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R&D and Firm Resilience During Bad Times *

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Abstract

Can being innovative help firms to shield themselves from the disruptive effects of a recession? Using data for Spanish manufacturing firms, this paper finds that innovative firms suffered considerably less compared to non-innovative firms during the Great Recession. The operating mechanism for the resilience of innovative firms to market disruption during a recession is product differentiation, and not reduction in marginal cost of production and prices with process innovation. The data does not support alternative explanations such as better access to capital, or difference in labour moving costs for innovative firms. The results provide evidence for the role of innovation in making firms dynamically capable and resilient to large negative shocks.

JEL Classification: L25, O30, O31, E32

Keywords: Innovation, Recession, Resilience, Product differentiation, Dynamic capability

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1 Introduction

The positive relationship between innovation, firm performance and aggregate economic growth has long been understood (Schumpeter, 1934; Romer, 1990). Our understanding of this relationship is framed with a focus on long run growth absent of business cycle fluctuations. Whether being innovative matters for firm performance even when an economy is hit by a large negative shock, an event that dramatically lowers demand and rapidly modifies existing markets, remains an open question.[1] This paper analyses if firms with a strong innovative potential and hence a large knowledge base suffer lesser or equivalently adapt better to large and sudden changes in the external environment during a recession.

The paper focusses on the deepest recession in the last 70 years, the Great Recession of 2008, and use firm-level data for Spain, an economy that was severely affected by it. Exploiting variation in the intensity of the recession across different industries, I find that innovative firms were less adversely affected compared to their non-innovative counterparts during the recession. The resilience of innovative firms operates through product differentiation, and not through lowering of cost of production and selling price with process innovation. The finding is supported by a strand of management literature which suggests that R&D investment contributes towards making a firm dynamically capable, that is being innovative makes a firm capable of reconfiguring and renewing itself to adapt to and capitalise on sudden changes in the external environment (Wang and Ahmed, 2007; Winter, 2003). As recessions are accompanied by rapid and extreme change in markets, being innovative might help a firm to adapt its products and processes to meet new consumer needs, and hence cope better. In my knowledge, this paper is one of the first empirical works to provide robust evidence and highlight the operating mechanism of how being innovative makes firms resilient and dynamically capable.

[1] In the aftermath of a large negative shock, the economic environment changes dramatically as disposable income gets redistributed across consumer groups, unproductive firms exit creating 'vacant markets' ready for capture, asset prices decline, and existing firm-customer relationships break (Fajgelbaum et al., 2011; Krugman, 2000; Canton and Uhlig, 1999).

The empirical strategy studies the relationship between firm performance *during* the recession, measured by real sales growth, and the innovative potential of firm, measured by its R&D intensity *prior* to the recession. For identification, I exploit variation in the severity of the Great Recession across industries. The Great Recession acts as a natural experiment to study the relationship between firm growth in bad times and its innovative potential since it was largely unexpected and precipitated rather quickly, making it seemingly impossible for firms to change their R&D strategy in expectation of a large market disruption. I measure the intensity of the recession shock as deviation from trend in exports from Spain to the world at industry level. Since exports are more likely to be driven by demand in the world markets than by internal supply shocks, the intensity of the shock in all probability is exogenous to Spanish firm performance. The empirical framework controls for confounding firm characteristics like firm size and physical productivity, compares firms in the same industry at the same time, and controls for any regional differences in the impact of the recession shock. Moreover, R&D is known to be persistent over time due to high sunk costs, attenuating the concerns of unobservable firm-level time variant characteristics driving the results. Finally, the definition of firm performance in terms of real sales *growth* differences out any time-invariant unobservable firm characteristics affecting the *level* of sales of a firm.

Using data from the *Encuesta sobre Estrategias Empresariales* (ESEE) for Spanish manufacturing firms, I find convincing evidence that innovative firms in sectors most affected by the recession suffered lesser than non-innovative firms. This is a noteworthy finding because the literature on reallocation of resources during recessions has hitherto abstracted away from the *capabilities* firms develop to react and adapt in bad times (Caballero and Hammour, 1994; Foster et al., 2016). The magnitude of the resilience of innovative firms is large. The analysis shows that a 1% drop in demand lowers the output sold of an average firm with no R&D by 0.79 percentage points, but lowers the output sold of a firm with 1% R&D intensity by 0.64 percentage points. Resilience increases with the innovative potential of firms.

To address concerns that the measure of recession shock calculated as the deviation from trend in exports from Spain and the relatively better performance of innovative firms could be endogenous, I instrument the shock with the corresponding decline in exports from the US to the world except Spain. There is high correlation between the IV and baseline measure of recession shock across industries, and results with the IV are similar to the baseline specification. I also show that the baseline measure of recession shock is not picking up unobserved industry heterogeneity such that innovative firms always perform better in the industries that suffered more during the recession with a placebo test. Further, I show that the growth rate of innovative firms is not less volatile, that is although they suffer lesser in bad times, their growth rate is not relatively muted in good times. The results are conditional on survival of firms during the recession, and can suffer from selection if only successful innovators survive, and those with unsuccessful R&D effort perish. To allay this concern, I study the likelihood of survival, and find that survival of innovative firms is higher in sectors that were severely affected by the recession. The baseline results are robust to using alternative measures of firm performance, firm innovativeness, and crisis intensity, and accounting for industrial characteristics such as external financial dependence.

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 invest relatively more in *innovation* when hit by a large negative shock. The answer is yes. Investment in R&D can improve firm performance by allowing firms to differentiate its products, improve its processes and lower costs, or both. This paper provides evidence that the resilience of innovative firms to negative shocks operates through product differentiation.

I follow the approach of Rauch (1999) to divide my sample by the relative importance of product differentiation across industries. While innovative firms in industries with a higher scope for product differentiation are able to cushion the negative effects of a recession, those in homogeneous goods industries are not. Moreover, during bad times innovative firms invest more in R&D, and specifically in product differentiation, measured as the expenditure on capital goods for product and process improvement, and on advertisement, only when they operate in industries that have a high scope for product differentiation. These effects are not found for firms operating in homogeneous goods industries, thus highlighting that product differentiation is key for resilience of innovative firms to negative shocks.

Another mechanism 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 following De Loecker and Warzynski (2012). Innovative firms in sectors most affected during the recession, contrary to expectation, experience an increase in marginal cost. The increase in marginal costs is compensated partially by an increase in selling price, lowering the markup at which products are sold. The findings show that altering products to adapt to a changed market environment supersedes the need to improve efficiency through process innovation for growth in bad times.

In arguing that being innovative makes firms resilient through product differentiation, I recognise the need to be cautious in interpreting firm R&D intensity only as a measure of innovative potential. I carefully check if alternative theories suggested in the literature, and applicable to Spain's market structure can attenuate the findings of this paper. First, the recession of 2008 in Spain was accompanied by a sudden drying up of liquidity in financial markets which could have directly affected growth of financially constrained firms. If innovative firms are systematically less financially constrained, they could have invested more in innovation and grown relatively more during the recession because of better access to capital, and not because of their innovative potential. Second, R&D could be picking up the effect of innovative successes prior to the crisis, and not potential to innovate. Third, Spain has a two-tier labour market with large differences in the cost of firing permanent versus temporary employees. Thus, any differences in labour composition of innovative and non-innovative firms, and the consequent incentives for hoarding of employees could explain the findings. Lastly, 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. Even after accounting for these alternative theories, being innovative continues to plays a crucial role in the ability of firms to invest in product differentiation, and grow relatively more during a recession.

Thus, firms are not passive in bad times, they react to changes in the economic environment in the aftermath of a recession. An important characteristic contributing to this capability of firms, as shown in this paper, is their innovative potential. 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; Coad and Rao, 2008) , 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). This paper highlights the third face of R&D, its role in making firms resilient and dynamically capable (Wang and Ahmed, 2007). It also provides empirical evidence for the knowledge based view of a firm which 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).

The paper also contributes to understanding the firm-level prerequisites for product differentiation and growth in periods of economic turmoil. Recent work by Bernard and Okubo (2016) shows that product level churning increases after the peak of a recession, and promotes firm level growth. 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. Recent work by Hombert and Matray (2018) and Bloom et al. (2016) shows that being innovative and technologically advanced is what allows firms to upgrade their products and compete successfully against a surge in low-cost import competition. I complement this literature by showing that being innovative is important too for being able to engage in product differentiation and grow in recessions, when the economy is more uncertain and disruptive as compared to when the economy is growing. Unlike when firms are dealing with low-cost competition, the resilience in bad times is not necessarily complemented by scaling up and climbing the quality ladder, but due to reallocation of factors of production within a firm towards production of products differentiated to meet changed consumer preferences, and market conditions.

Finally, in showing the importance of being innovative for resilience, the paper adds to the literature studying attributes of a firm and its environment that lower the impact of a recession on its performance. A seminal paper by Chodorow-Reich (2014) shows that firms that had pre-recession relationships with less healthy lenders had a lower likelihood of obtaining a loan following the Lehman bankruptcy, and suffered more. Giroud and Mueller (2017) find that highly leveraged firms experienced significantly larger employment losses in response to declines in local consumer demand. Recent papers also highlight the importance of firm ownership, and a decentralised decision-making process within firms in allowing firms to attenuate the negative effects of a recession (Alviarez et al., 2017; Alfaro and Chen, 2012; Aghion et al., 2020).

The rest of the paper is structured as follows. Section 2 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 section 6 discusses alternate theories that could explain the findings. Section 7 concludes and offers ideas for future work.

2 Empirical identification

To investigate if innovative firms are capable of shielding themselves from the negative effects of a recession, I focus on performance of manufacturing firms in Spain in the aftermath of the collapse of Lehman Brothers in late 2008. I use the case of the Great Recession to study a large negative shock since the Recession was largely unanticipated, especially for the manufacturing sector, and hence acts like a natural experiment to study the relationship between firm growth and innovativeness in bad times. It was the biggest recession in the last 80 years, and Spain is one of the countries where the effects of the recession were particularly severe, and where it lasted for several years allowing us to study firm growth in a period of depressed demand. Moreover, Spain provides an appropriate setting to study questions regarding R&D since it is neither a technological leader, nor the lowest ranked in terms of its R&D spending.

2.1 Econometric specification

The key interest of this paper is to understand whether being innovative makes a firm resilient and capable of adapting to large and sudden changes in its economic environment as a result of a recessionary shock. The paper focusses on the relationship between innovation and firm performance in bad times only because the dynamics of a recession are qualitatively different from those of booms (Hamilton, 1989). For instance, negative shocks are sharp and sudden leading to high uncertainty, while positive shocks are typically smoother, more predictable transitions allowing firms to plan ahead. To identify the resilience of innovative firms, I study how the performance of a firm during bad times is associated with its innovative potential, and the intensity of recession and consequent market disruption it experiences. Specifically, l use the following econometric framework.[2]

$$\Delta Y_{ijt+1} = Y_{ijt+1} - Y_{ijt-1} = \alpha + \beta R_{ijt-1} + \gamma R_{ijt-1} * Shock_j + \\ x_{ijt-1} * Shock_j + Controls_{ijt-1} + \phi_{jt} + \phi_l + \epsilon_{ijt} \quad (1)$$

where Y is a measure of overall product market performance of firm i in industry j measured from $t-1$ to $t+1$. In the baseline, I focus on real sales growth measured

[2]Bloom et al. (2016) use a similar econometric strategy to show that import competition from China led to reallocation of employment towards more technologically advanced firms.

at a two year horizon to give firms the time to adapt to a shock that hits the firm between $t-1$ and $t+1$.

R is the innovative potential of firm i measured at $t-1$. I measure firms' innovative potential *a priori* to the shock so that it is weakly exogenous to firm performance. The fact that the Great Recession was largely unanticipated and precipitated rather quickly makes it unlikely that firms would have changed their innovation strategies in $t-1$ in expectation of a business cycle downturn. In the baseline, I use R&D expenditure of a firms as a percentage of sales as a measure of innovative potential. This relies on the idea that higher expenditure on R&D today translates into a higher probability of innovation and higher potential revenue from innovation tomorrow. Moreover, R&D values tend to be smooth due to high adjustment costs (Bloom, 2007), whereas other readily available variables like patents tend to be more volatile. Thus, R&D expenditure is most appropriate to capture the overall ability to innovate, and the tacit knowledge base of a firm.

Shock is a measure of the intensity of the Great Recession varying at industry level j. Higher the drop in demand in the recession, higher will be the value of *Shock*. The direct effect of *Shock* on firm performance gets absorbed by industry-year fixed effects in the regression specification. The key hypothesis I examine in this paper is whether $\gamma > 0$, which would show that firms with high innovative potential facing the biggest recession *Shock*, and hence a sudden and extreme change in their economic environment, adapt and perform better than their counterparts.

x_{ijt-1} includes firm size and physical total factor productivity, and the interaction of both with the measure of recession shock. These interactions controls for the high correlation between firm size, productivity, and R&D. $Controls_{ijt-1}$ include firm age and export to sales ratio to account for determinants of firm growth recognised in the literature.[3] Using growth as the dependent variable differences out time-invariant firm characteristics affecting the *level* of sales of a firm.

[3] See Fort et al. (2013); Almunia et al. (2017); Foster et al. (2016) for how size, age, exports, and TFP matter for growth during a recession.

ϕ_{jt} are industry-by-year dummies such that γ is identified from comparing firms within the same industry-year. This is important because if innovative *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 capabilities. ϕ_l are location dummies, and they absorb any region-specific policies that could differentially affect the growth of innovative and non-innovative firms during the recession.[4] As suggested by Abadie et al. (2017), standard errors are clustered at industry level, the level of variation of *Shock*, and I adjust degrees of freedom if the number of clusters is small.

2.2 Data description

Firm level data

The analysis in this paper relies on a longitudinal survey of Spanish manufacturing firms named *Encuesta sobre Estrategias Empresariales* (ESEE).[5] 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. On average 1800 firms respond to the survey each year. New firms are incorporated to minimise the deterioration of the initial sample, and to maintain representativeness with respect to the reference population.[6] The survey is oriented towards capturing information about firms' strategies, its external environment, and also includes information on the firms' balance sheet together with the profit and loss statements.

The survey reports changes in input and output prices at firm level, which I use to

[4] This could include R&D tax credits for example, however in Spain the variation across regions in R&D tax credit is not high.

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

[6] 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 investment in tangible and intangible assets and growth (for example Guadalupe et al. (2012), Doraszelski and Jaumandreu (2013), and Garicano and Steinwender (2016).)

calculate *firm level* price indices. To measure product market performance abstracting away from changes in prices, I calculate firm growth by deflating firm sales by firm specific output price index.[7]. Firm specific price information also makes it possible to calculate *physical* total factor productivity following Ackerberg et al. (2015), and marginal cost 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.

The survey provides detailed information on technological activities of a firm. I measure innovative potential as the annual total expenditure on internal and external R&D as a percentage of annual sales. Approximately 34-37% firms every year report positive R&D expenditures. In addition, I use information on innovation output, investment in capital for innovation, advertisement expenses. Finally, firm accounting data such as number of employees, value added, and profit margin, and detailed information about a firms financial position, employment contracts, and market environment allows me to check the robustness of my results to various confounding factors.

Firms in the sample belong to twenty manufacturing industries based on two-digit Classification of Economic Activities in the European Community (NACE) classification. This is the most disaggregated level of industry classification available in this survey, and I exploit variation in the intensity of the recession shock across these industry groups to identify resilience of innovative firms. I use the location of the main plant of a firm to define nineteen location dummies for the regions of Spain.

To proceed with the analysis, 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 trim all growth variables at 0.05% on both tails for data from 2000-2014. To maximise the use of data for the period of the Great Recession, I pool data for two cross sections, $t \in 2008, 2009$. In this paper I focus on the Great Recession, which started in late 2008 and was followed by a Sovereign

[7]Results are similar when I use the growth of nominal value of sales.

Debt Crisis in some European countries, including Spain in 2011.[8]

Table 1 presents summary statistics for the sample used in the baseline regression analysis. Independent variables are measured prior to the peak of the recession (see Figure 2 in Appendix A), and dependent variables are measured during the recession. The mean R&D intensity of firms is 0.71% before the recession. Firm real sales during the recession declined on average by 27.08%, and employment declined on average by 11.09%.

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 recession as the baseline measure following Aghion et al. (2020). In using export growth as a measure of recession intensity, an identifying assumption I make is that exports are driven by demand in the world markets, and not by internal supply shocks which are endogenous to domestic 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. I relax this assumption of exogeneity of export shock 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 annual Consumer Price Index of Spain to obtain real exports. Figure 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

[8]Since the recession had started in the fourth quarter of 2008 I check the robustness of the analysis to excluding the cross section for $t = 2009$.

as follows:

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

To measure the *intensity* of recession shock, I calculate the deviation of export growth during the recession from average growth prior to the recession. Specifically, *Shock* is defined as follows:

$$Shock = \frac{\sum_{2004}^{2006} Xgr_t}{3} - Xgr_{2008} \tag{2}$$

Thus the larger the deviation from trend, the bigger and more impactful is the recession *Shock*. Figure 3 plots the recession shock for 19 industries in the data[9]. For all indusries, except Leather and Beverages, export growth was below trend during the recession. 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) find similar patterns of trade collapse across industries during the recession of 2008 using French customs data.

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 with above and below mean pre-recession R&D intensity into 2 industry groups each; those that experienced a high intensity shock during the recession (above mean *Shock*), and those that experienced a relatively mild recession shock (below mean *Shock*). I plot the average real sales growth during the recession of these four groups of firms on the y-axis, and show

[9] 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.

95% confidence intervals. The average decline in real sales of more innovative firms in industries hit by a 'high' shock is 24.2%, and that of less innovative firms is 38.8%, while in 'low' shock industries the decline is 12.5% and 17% respectively. Thus, as excepted there is a decline in growth for all four groups during the recession, and it is sharper for firms operating in industries that were hit harder. However, innovative firms suffer significantly lesser than others in sectors that were hit severely during the recession. This shows that innovative firms were able to shield themselves from adverse outcomes of a recession.

3.2 Baseline result

To begin with, I study the relationship between *ex-ante* R&D intensity, recession shock, and real sales growth of a firm during the recession in Table 2, column (1). I find that on average R&D intensive firms performed significantly better during the recession. A one percent increase in R&D intensity is associated with a 2.24 percent increase in growth. As expected, the relationship between intensity of recession $Shock$ and firm growth is negative. A one percent increase in intensity of recession shock is associated with a 0.73 percent decrease in firm growth.

In Column (2), I introduce an interaction between firms' R&D intensity and the recession shock. The coefficient for R&D intensity is not statistically significant, which shows that innovative firms did not grow differentially from non-innovative firms in the sectors that were not hit by the recession. The coefficient on the interaction term, $R\&D * Shock$ is 0.148 with a standard error of 0.060. It is positive and significant which shows that innovative firms in industries that experienced a bigger recession shock were resilient and grew relatively more than their counterparts. The magnitude of resilience of innovative firms is not trivial and shows that a shock of 1% lowered the growth of an average firm with no R&D by 0.79 percentage points, but for a firm with 1% R&D intensity by 0.64 percentage points. The resilience of innovative firms increases as the intensity of R&D increases.

In column (3), I control for firm size and productivity, and their interaction with

Shock. I also include age, export-sales ratio as controls and industry-year and location fixed effects following equation 1. I find that the coefficient on R&D$*$*Shock* decreases to 0.106, but remains positive and significant. Thus, after controlling for potentially confounding firm-level variables, being innovative remains an important factor in making a firm capable of cushioning the negative effects of a large recession shock.[10]

Instrumental variable

The relationship between firm performance and $R\&D * Shock$ could be endogenous if for example 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. To allay this concern, I use an instrument for decline in industry-level exports of Spain.

It could also be that when firms innovate successfully, that is when realised returns to R&D are higher, exports increase in that industry. Thus export growth at industry level and real sales growth of innovative 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 recession assuming that the ranking of 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 industry-wise impact of recessions dependent on characteristics of an industry, and

[10]Although not reported in the table, the coefficient on the interaction of firm size and *Shock* is negative but not significant (p-value, 0.32), and the coefficient on the interaction of productivity and *Shock* is positive but not significant (p-value, 0.79). This also mitigates the concern that the result is getting driven by quality of firm management. The survey does not provide a direct measure for management quality at firm level. However, Bloom et al. (2013) suggests that well managed firms are causally more productive, and since I do not find any significant effect of the interaction of recession shock with productivity, it is unlikely that management quality is driving the result. I also use labour productivity to study the role of firm productivity in resilience during bad times and find no significant relationship.

not a country.

The exclusion restriction required for this instrument to work is that supply shocks to firm level performance in Spain are uncorrelated with decline in US exports during the recession. It is unlikely that US exports are affected by Spanish supply side factors since Spain is 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.

The instrument is calculated by deflating US exports by the annual Consumer Price Index of the US, and following the formula shown in equation 2. Figure 4 shows the correlation between the baseline measure of recession intensity, and that of the IV. The instrument is highly positively correlated with baseline measure of recession shock, suggesting that the intensity with which industries were hit across the world during the recession was similarly ranked.

Column (4) in Table 2 shows the results for the instrument variable regression. The null for weak instruments is rejected with a p-value tending to zero. The F-statistic is 31.36, thus showing that the first stage is valid. The interaction term is positive and significant showing that innovative firms in industries that are affected more by a recession shock perform better than their non-innovative counterparts. The coefficient for the interaction term using IV estimation is similar to that obtained in column (3). The Durbin-Wu-Hausman test comparing the OLS and IV results 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 the deviation from trend of exports from Spain to the world to measure the recession shock across industries.[11]

4 Robustness tests

In this section, I test for robustness of the resilience of innovative firms when hit by a negative shock with a placebo test, by using alternative measures of firm perfor-

[11] All the subsequent results with IV estimation are available upon request.

mance, firm innovativeness, and *Shock*, and accounting for industry level structural heterogeneity.

Placebo test

A possible concern with the baseline measure of recession shock, and the instrument used in the previous section could be that it is picking up a time-invariant industry characteristic such that innovative firms perform better in sectors that were hit during the recession irrespective of the macroeconomic environment. For instance, if the recession shock was more severe in industries with a high dispersion of R&D expenses, and innovative 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, firm innovativeness and *Shock* as described in equation 1, but for *pre-recession years*. If $R\&D * Shock$ is positive and significant for explaining firm growth prior to the recession, then this would suggest that R&D firms always perform better in industry groups that also happened to be hit during the recession.

I pool firm-level data for two cross sections, $t \in 2004.2005$, and use *Shock* as defined in section 2.2. Spain experienced strong economic growth in this period as seen in Figure 2, and studying this period can highlight how being innovative matters for growth during recessions and booms comparatively. 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 the Great Recession across industries. Although innovative 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 more adverse shock during the recession (coefficient on interaction term is not significant). This shows that the measure of recession shock is not picking up unobserved industry heterogeneity.

Are innovative firms particularly resilient to *bad* shocks, or is it that their growth is less volatile, and hence the interaction term is negative? To study this, I pool data for pre-recession and recession years that is $t \in \{2004 : 2009\}$. I study the relationship between firm growth, firm R&D intensity in $t-1$, and add an interaction of R&D intensity with a dummy for the Great Recession, labelled GFC ($t \in \{2008, 2009\}$). I control for industry-year and location fixed effects and firm level controls as in the baseline specification shown in equation 1. Column (3) of Table 3 shows that innovative firms are associated with higher growth on average, and this effect is significantly stronger when $GFC = 1$, that is being innovative seems to matter for growth significantly more during bad times. Thus the relationship between R&D and firm performance is not symmetric in booms and recessions. In bad times, in addition to a direct impact of R&D on growth of firms, being innovative makes firms capable of adapting to changes in the external environment.

Survival and sample selection

Studying firm growth in the baseline specification is conditional on survival of firms during the recession and this could lead to a selection bias if only firms that successfully innovated prior to the recession 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 leading to firm closure in the event of unsuccessful R&D effort. Thus, if the probability of successfully innovating and surviving given R&D expenditure is 0.5, then the result of resilience of R&D intensive firms during the recession would be due to sample selection of successful innovators. 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 attenuated.

To define exit, I use a variable from the survey that identifies if a firm closes down, changes to non-manufacturing activity, or is taken over. The aggregation of three different changes in firm status into one category is not ideal but there is no variable in the survey that identifies only firm closure. 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 exit in t or $t+1$. I use a probit model to study firm survival as the dependent variable with the same independent variables as described in equation 1. Column (1) in Table 4 shows that the interaction of R&D and recession shock is positive and significant showing that innovative firms were also more likely to survive in sectors that were severely hit during the recession. Thus conditioning on survivors in the baseline regression is, if anything, attenuating, the effect of R&D on firm resilience.

Alternative measures of firm performance

Columns (2) and (3) in Table 4 show the results for alternative measures of overall firm performance: (a) change in log of value-added from $t-1$ to $t+1$ and (b) change in cumulative profit from $t-1$ to $t+1$, respectively. The interaction term is positive and significant for value added growth but not for profit margin. Thus even though innovative firms sell relatively more, it does not translate into higher profits. This is interesting because if it were the case that innovative firms in particular were not affected by the recession, they would have performed well along all metrics of firm performance.

In columns (4) and (5), I explore if innovative firms hire or invest relatively more to perform relatively well in a recession. In column (4), I estimate equation 1 with difference in log 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 stickier than firm sales. 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 (5), I estimate the effect on capital expenditures by using the cumulative investment in capital goods over two years (in t, and $t+1$) normalised by sales in $t-1$ as the dependent variables in equation 1.[12] The interaction term is positive, but

[12] I cumulate investment variables, here and in subsequent analysis, because of high prevalence of zeroes in investment data. When the dependent variable is cumulated over t and $t+1$ and normalised by sales in $t-1$, I control for the corresponding variable as a percentage of sales in $t-1$ as an independent variable.

not statistically significant. This shows that the resilience of innovative firms is not complemented by employing more factors of production, and scaling up, but possibly due to reallocation of factors of production and changing firm operations strategically.

Alternative measurement of *Shock* and firm innovativeness

I check the robustness of the result to changes in the measurement of recession shock, and innovativeness of a firm. Results are shown in Table 5. In column (1), recession shock is measured as the decline in exports (Xgr) without subtracting trend growth, and I find that innovative firms hit by a large negative shock perform better than their counterparts. In column (2), instead of exploiting industry level variation in intensity of recession, I study determinants of growth of a sub-sample of firms that report that decrease in demand in 2008 and/or 2009 was the main change in their largest market.[13] For this sub-sample, I find that the coefficient on R&D intensity is positive and significant, showing that innovative firms performed better than their non-innovative counterparts when there is a large decline in demand. In column (3), I make a modification in the IV to account for the fact that US exports to important trading partners of Spain, and they could be influenced by supply side shocks to Spanish firms. Specifically, I subtract exports from the US to Spain *and* its main trading partners, France, Germany, Italy and Portugal to calculate Xgr. I find that R&D*Shock is positive and significant using this modified IV.

In column (4), I measure firm innovative effort by adding R&D expenses of a firm from the first time a firm reports it to $t-1$ and depreciate it annually at 15% to calculate R&D stock. I normalise R&D stock by sales in $t-1$. I find that firms with a high R&D stock show resilience during bad times. In column (5), I use the R&D intensity of firms measured in $t-5$ to measure innovative potential. While using R&D expenditure in $t-5$ reduces the sample size significantly, it reduces concerns of R&D being endogenous to unobservable time-variant firm characteristics. In column (6),

[13]In ESEE, firms are asked to report the main change that occurred in the market during the year, and choose from the following options: Variation in the prices of domestic competitors, variation in the prices of the imported equivalent products, appearance of new products or competitors, demand increase demand decrease. This variable is self-reported and suffers from comparability across firms.

I measure innovative potential by normalising R&D expenditure with total employment. Finally, in column (7) I use a dummy for positive R&D expenditure in $t-1$ to study if the extensive margin of R&D matters. The interaction of different measures of R&D intensity and recession shock remains significant in all these modifications of the baseline specification.

Accounting for industrial heterogeneity

In Table 6, I check the robustness of the baseline results to accounting for industry level structural heterogeneity. I do this by augmenting the baseline regression with interactions of firm-level R&D intensity and industry characteristics measured at a two-digit NACE level.[14] In column (1), I control for external financial dependence of an industry measured as the difference between a firm's capital expenditures minus cash flows, divided by capital expenditures following Rajan and Zingales (1998). External financial dependence is suggestive of the degree of financial constraints faced within an industry as changes in the supply of finance are more likely to affect industries that are more dependent on external financing. The coefficient for interaction between R&D and measure of external financial dependence is positive but not significant, suggesting that financing constraints did not matter differently for performance of innovative and non-innovative firms during the recession. Moreover, the main interaction term remains positive and significant in the augmented regression, thus showing that the baseline measure of demand shock is not picking up industrial heterogeneity in financial dependence. In the subsequent columns, I control for interactions of R&D intensity and b) Labour costs measured as the ratio of total compensation to employees to gross value added, c) Capital intensity measured as the ratio of gross fixed capital formation to gross value added, and d) ICT intensity measured as the ratio of gross value of ICT equipment to gross value added. I find

[14] I borrow the measure for financial dependence from Sharma and Winkler (2018), and use the mean value at NACE two-digit level. I measure labour costs using national account data from the Spanish Statistical Agency, INE, and use the average value of the ratio of compensation to employees to gross value added from 1995 to 2005 for each two-digit NACE industry. Capital intensity and ICT intensity are measured using data from EUROSTAT, averaged over 1995-2005 for all European countries.

that accounting for heterogeneity in dependence on different factors of production across industries does not importantly alter the value and statistical significance of the main interaction term, R&D*Shock.

Summarising the robustness checks:

The basic character of results is consistently obtained across the range of robustness checks shown above. Innovative firms, defined as firms with high R&D intensity prior to the recession, were able to cushion the negative effects of the recession as compare to their non-innovative counterparts.

5 Mechanism

This section explores the mechanism that allows innovative firms to cushion the disruptive effects of a large recession 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 7 estimates equation 1 with R&D expenses in t normalised by pre-recession sales as the dependent variable in column (1), and R&D expenses cumulated over t and $t+1$ normalised by pre-recession sales in column (2).[15] The table shows that R&D expenses during the recession were higher for innovative firms (coefficient on R&D is positive and significant in both the columns). As column)2) shows, a one percent increase in R&D intensity for a firm experiencing no shock is associated with 0.66 percentage points increase in its R&D intensity over a two year interval. This is in line with Archibugi et al. (2013), who find that in-house R&D activity is an important predictor of innovation expenditure during a recession. Moreover, the innovation expenditure is significantly higher for innovative firms in industries that were hit more severely during the recession, that is firms with one percent R&D intensity hit by a one percent *Shock* increase their R&D intensity by 0.05 percentage

[15] The survey does not report employment in R&D on an annual basis, but every four years starting in 1990. Thus I don't have this measure during the recession years.

points over a two year interval. This is in line with the theory of opportunity cost of productivity enhancing investment which states that the opportunity cost of doing R&D falls in recessions as return from production declines, and hence firms invest more in R&D (Aghion and Saint-Paul, 1998). This paper adds to the literature on countercyclical investment in R&D by showing that having an innovation base, as measured by ex-ante R&D intensity, is important for firms to swiftly move resources from production to innovation when times are bad.

Investing in R&D can improve firm performance by allowing it to differentiate its products, improve its production processes, or both. In times of a recession, product differentiation can help a firm to enter markets that continue to do well, access markets left vacant by exiting firms, and adapt according to changed consumer preferences. An article by the Harvard Business Review titled 'Roaring Out of Recession' presents a case study of a company named Target that grew in terms of sales by 40% over the course of the Great Recession by partnering with new designers, and expanding new merchandise segments, thereby differentiating its products.[16] Process innovation, on the other hand, could enable firms to reduce the cost of production and sell more of their existing products at a lower price. In the following section, I explore the possible operating mechanisms of resilience of innovative firms.

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 the liberal RAUCH classification available for SITC Revision 2, map it to two-digit NACE Revision 2 and divide industries by the relative prevalence of differentiated and homogenous goods. The measurement is described in detail in Appendix B and Table 17 shows the classification of industries into differentiated and homogeneous good industries. According to this classification, Machinery and equipment is one of the

[16] See https://hbr.org/2010/03/roaring-out-of-recession.

most differentiated industry, and Meat Products is one with the most homogeneous goods.

Table 8 shows the result for resilience using equation 1 for the two sub-samples, where firm real sales growth is the dependent variable. Innovative firms in differentiated products industry show resilience when they are hit by a large recession shock (column 1), however this is not the case for firms in industries with homogeneous products (column 2).

I further investigate if firms in industries with a high scope for product differentiation innovate their way out of the crisis. Columns (3) and (4) of Table 8 show the results for cumulative expenditure on R&D in t and $t+1$ normalised by pre-recession sales for the two sub-samples. The coefficient for R&D*Shock is positive and statistically significant at the 1% level in column (3), but not so in column (4). Thus the scope for product differentiation is key for firms to innovate and grow relatively more in a recession.

Do innovative firms invest more in product differentiation?

To investigate directed effort at product differentiation by firms during the recession, I use two variables: (a) value of machinery and equipment bought by a firm specifically for improving or making new products or processes, and (b) the value of advertisement expenses. [17] Capital investment in product/process improvement measures the intensity of effort firms put to *change* their products or processes, and advertisement expenditure measures the effort firms put to disseminate information about their products. To understand the role of product differentiation, I test whether

[17]Papers studying product differentiation use detailed 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 at a aggregated two-digit NACE level. Having only total number of products masks any changes in product composition, and availability at two-digit industry level masks changes at finer levels of industry classification. Hence I do not use number of products to study product differentiation. Other variables like a binary indicator for product innovation is also not suitable to study product differentiation because, first, it is not comparable across firms as the definition of what constitutes an innovation is not defined by the survey, and secondly because it masks the degree of product differentiation. Table 15 shows results for binary indicator of whether a firm recorded a product innovation (column 1) as the dependent variable in equation 1. The coefficient for R&D*Shock is positive but not significant.

innovative firms invest in capital for product/process improvement, and in advertisement during the recession only when there is scope for product differentiation, and/or in homogenous goods industries too.

I estimate equation 1 with the cumulative capital expenditure for product/process improvement in t and $t+1$ normalised by pre-recession sales as the dependent variable for the two sub samples. I find that in industries with a high scope for product differentiation, innovative firms invest more capital in product/process improvement when hit by a large recession shock (column 5), while in industries with homogenous goods, there is no significant difference between the response of innovative and non-innovative firms (column 6). Next, I estimate equation 1 with the cumulative advertisement expenses in t and $t+1$ normalised by pre-recession sales as the dependent variable for the two sub samples. Again, I find that only in industries with a high scope for product differentiation, innovative firms invest more in advertising when hit by a large recession shock (column 7 and 8). The above results suggest that product differentiation is an important operating mechanism for resilience of innovative firms in bad times.[18]

I check the robustness of product differentiation as an operating mechanism of resilience in Table 9. Instead of splitting the sample using an industry-level measure for product differentiation, I split the sample using a firm reported measure on whether their products are designed for specific customers, hence differentiated, or whether they sell similar products to all buyers, hence homogenous. This measure is self-reported, and could suffer from comparability across firms. In column (1), (3), (5) and (7), I find that innovative firms with customised products showed resilience during the recession through investing more in R&D, and in capital goods for the purpose of product/process improvement, and in advertising than their non-innovative counterparts. This is not the case for firms selling standardised products (columns 2, 4, 6, 8). Thus the operating mechanism of product differentiation is robust to using a

[18] The evidence in section 5.2 suggests that process innovation is unlikely to be the operating mechanism of resilience of innovative firms. Thus, it can be inferred that during bad times firms invest in capital goods for the purpose of improvement of products, not processes, and on advertisement, possibly for disseminating information about newly differentiated products, and not lower prices.

firm-reported measure of whether their products are homogenous or differentiated.

5.2 Effect on cost and prices

Another possible mechanism for how being innovative fosters resilience in bad times could be cost reduction through process innovation. Lower cost of production can be passed onto consumers in the form of lower prices, and could lead to better product market performance. I study this operating mechanism by evaluating if innovative firms in sectors severely affected by the recession lower their marginal cost of production, and sell at a lower price.

In Table 10, I estimate equation 1 for the percentage change in marginal cost over a two year horizon as the dependent variable. Marginal cost is calculated following De Loecker and Warzynski (2012), explained in detail in Appendix B. Results in column (1) show that the marginal cost of innovative firms that were hit severely by the recession increased more than their counterparts. Jaumandreu and Lin (2018) use the same dataset to show that process innovation generally leads to a decline in marginal costs. Thus increase in marginal costs suggests that resilience of innovative firms is not operating through process innovation.[19]

Column (2) shows the results for the percentage change in output price over a two year horizon as the dependent variable in equation 1. The interaction term, R&D*Shock, is positive and significant showing that innovative firms hit by a severe shock sell their products at a marginally higher price. Thus innovative firms don't seem to perform relatively better because of lower selling price. Moreover, the increase in selling price does not seem to be due to innovative firms buying expensive higher-quality inputs. Column (3) shows that the coefficient on R&D*Shock for change in input prices is positive but not significant.

As can be seen in the table, the increase in output price is not as high as the increase

[19] I do not use a binary variable for process innovation since it masks the success of process innovation across firms which is captured by change in marginal cost and prices. Results for the binary indicator of process innovation is reported in Table 15. The coefficient for the key interaction term is positive but not significant (column 3).

in marginal cost, suggesting that innovative firms lower their markup. In column (4), I estimate equation 1 with the percentage change in markup over a two year horizon. I find that the interaction term is negative but not significant (p-value, 0.14).[20] Thus, the evidence in this section goes against resilience operating through process innovation. In fact, increase in marginal cost supports the finding that product differentiation allows innovative firms to adapt in a recession. This is because inexperience in production of a new product can lead to inefficiency and increase the cost of production. 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. Productivity is likely to suffer as a result".

6 Alternative explanations

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

Financing constraints

During the Great Recession, liquidity froze and financially constrained firms 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 invest in innovation grow could have been driven by their ability to raise enough capital during the recession. I study this by augmenting the baseline regression described in equation 1 with

[20]The larger decline in marginal costs as compared to prices could also explain why profits are not higher for innovative firms even though they sell relatively more than their counterparts during the recession (see Table 4).

an interaction of the recession shock and a measure of firm financing constraint in $t-1$. I do this with four measures of financing constraints identified in the literature (Garicano and Steinwender, 2016; Almeida and Campello, 2007).

Table 11 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 percentage of foreign ownership of firms where foreign owned firms are expected to be less constrained. Column (3) uses firms debt to equity ratio as a measure of firm leverage, where firms with higher leverage are likely to be more financially constrained. Column (4) uses the ratio of tangible assets to total assets of a firm to measure its ability to raise capital against collateral. 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. Foreign owned firms, as seen by Alfaro and Chen (2012), and firms part of a business group, also perform relatively better in sectors most hit during the recession, however being innovative continues to matter for firm resilience.

Innovative potential versus past innovative success

While R&D expenditure is a measure of overall innovative effort of a firm, it is highly correlated with the innovative outcomes of a firm. Thus, if firms with successful innovations *prior* to the recession are likely to grow more during the recession because of higher demand for their new innovations, then the resilience of innovative firms would not be an outcome of their ability to adapt, but an outcome of their pre-existing innovative success. I study this by augmenting the baseline regression with measures of past innovative success of a firm in Table 12. I augment the baseline regression in columns (1) to (3) with an interaction of the baseline measure of recession shock and the following variables: a) a dummy for product innovation b) a dummy for process innovation, and c) log of the total number of patents filed. I find that the coefficient on the interaction term, R&D*Shock remains positive and significant, and the economic value of the coefficient also remains similar when past innovative success is accounted for. This shows that having the potential to innovate is important for 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 firing 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 labour moving costs, then the baseline result could be driven by the presence of 'trapped factors' in a recession. I study this in Table 13 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, $R\&D * Shock$ remains positive and significant, and the additional interaction terms are not statistically significant.

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 14, I add an interaction of *Shock* and number of products as an indicator of diversity of output and input markets (column 1), number of international markets of the firm (column 2), and export intensity as a measure of international market diversification (column 3), all measured in $t-1$. The coefficients on the additional interaction terms are not significantly different from zero (columns 1-3), suggesting that there were no important diversification benefits for innovative firms specifically. Importantly, the coefficient on interaction of R&D and demand shock remains positive and significant with additional control for technological diversification.[21]

I test the robustness of product differentiation as the operating mechanism in Table 16. I estimate equation 1 with a) cumulative R&D expenses in t and $t+1$ in columns (1) and (2) b) cumulative expenditure on product/process improvement in t and $t+1$ in columns (3) and (4), and c) cumulative advertisement expenditure in t and $t+1$ in columns (5) and (6), all normalised by pre-recession sales in $t-1$ as dependent variables, augmented with interactions of firm level characteristics capturing the explanations discussed above. 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 innovation, product/process improvement, and advertisement in differentiated products industries, but not in homogeneous products industries.

[21]Almunia et al. (2017) show that export markets were a means for Spanish firms to cushion the negative 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. However, the results in column (3) of Table 14 shows that firms with high export intensity prior to the recession did not perform relatively better in industries that were hit by a large trade-induced demand shock.

7 Conclusion

This paper analyses if being innovative makes firms resilient to large negative shocks, and if yes, how. I focus on the Great Recession of 2008, and use data for Spanish manufacturing firms. For identification, I use decline in the exports from Spain to the world by industry to exploit variation in the severity of the Great Recession across industries. The main finding of this paper is that innovative firms, defined as *ex-ante* R&D intensive firms, were able to cushion the disruptive effects of the recession as compared to their non-innovative counterparts. The results are robust to a battery of tests accounting for potential endogeneity in the measure of recession shock, controlling for confounding firm and industry characteristics, sample selection bias, and altering measurement of firm performance, being innovative and recession $Shock$.

The data shows that product differentiation is an important operating mechanism for the resilience of innovative firms. Specifically, I find that innovative firms in industries with a high scope for product differentiation show resilience to a negative shock, while those in homogenous goods industries do not perform significantly better than their non-innovative counterparts. Moreover, innovative firms with a scope for product differentiation invest more in research and development, and specifically in product differentiation measured by the investment in capital goods for improving products and processes and advertisement. I do not find evidence for innovative firms reducing their marginal cost of production with process innovation, and consequently reducing prices to sell more. Alternative theories such as better access to capital, past innovative success, difference in labour moving costs, or higher technological diversification for innovative firms do not attenuate the findings in the paper.

This paper, in my knowledge, is one of the first empirical works to unravel the role of R&D in making firms resilient and capable of renewing themselves to adapt to changes in the external environment. Literature in management has discussed how innovation is a key component of the capabilities firms develop to deal with extreme changes in the external environment, and this paper presents a systematic rigorous analysis of this role of being innovative using rich survey data for the period of the Great Recession. This research has important policy implications for managers, firms and governments deciding how much to invest in R&D. It suggests that firms that are innovative prior to a recession are capable of coping with a recession better than other firms. Thus R&D expenditure *today* acts as a stabilising tool in turbulent times, and this should be taken into consideration when evaluating investment alternatives and policy options.

There are several directions for future work. First, it is important to understand the channels that allow R&D firms to be more resilient to demand shocks. The paper presents evidence that product differentiation is important for resilience of innovative firms in times of crises, and future research could study 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, detailed input and output prices 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 avenue for research is the general equilibrium effect of this channel of resilience to large negative shocks. This could provide an understanding for whether higher R&D spending by all firms attenuates the aggregate disruptive effects of a recession.

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8 Tables and Figures

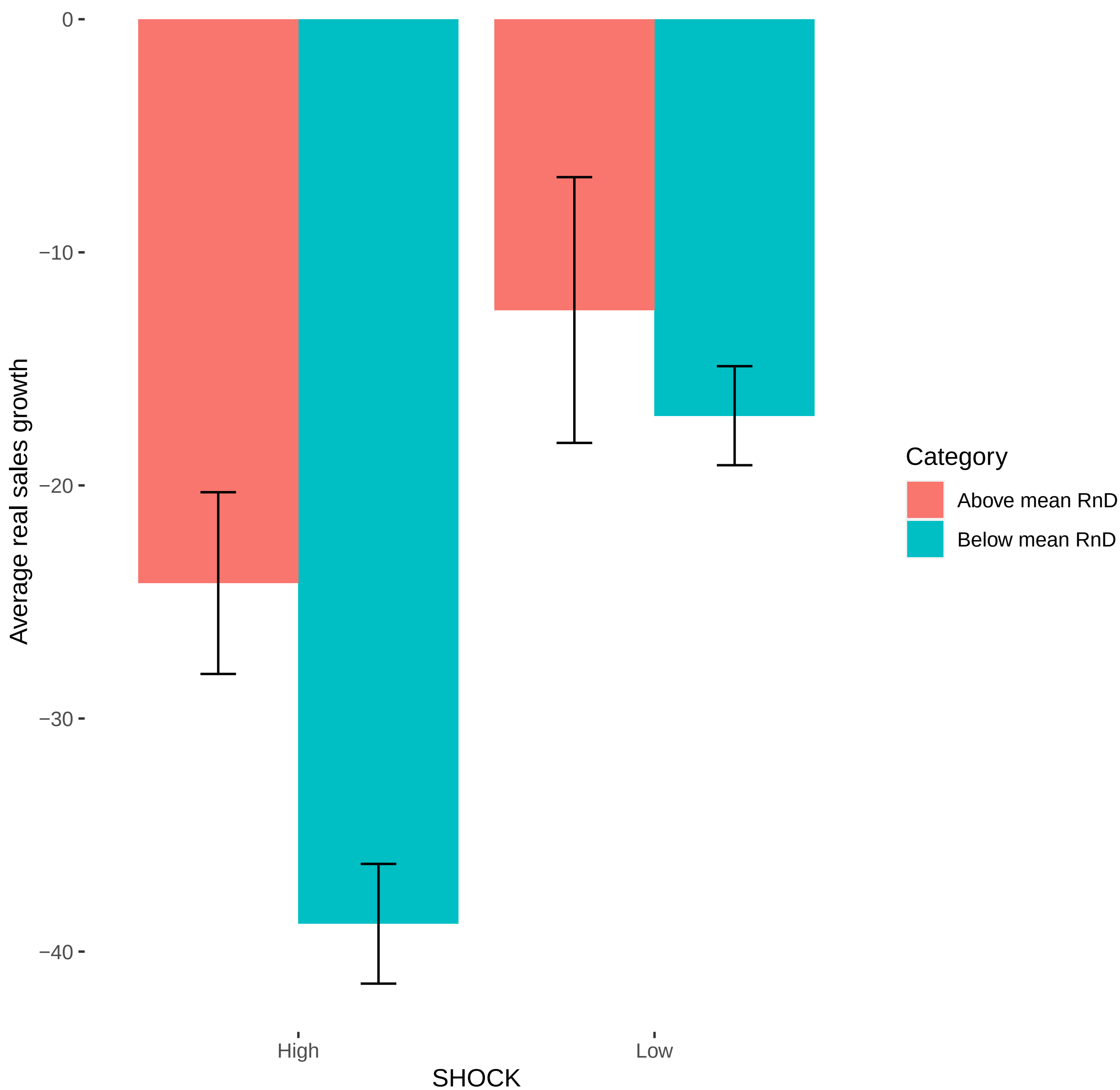
Table 1: Summary statistics

Independent variable	Mean	Median	SD	Observed
R&D to sales (%)	0.71	0.00	1.96	3026
Employment	242.07	51.50	794.33	3026
Physical TFP	-1.70	-0.74	3.09	3026
Age	31.46	25.00	21.84	3026
Export to sales (%)	19.16	4.45	26.71	3026
Belongs to a group	0.36	0.00	0.48	3017
Foreign ownership	14.37	0.00	34.17	3026
Leverage	385.57	128.84	2358.01	2958
Asset tangibility	87.61	96.11	18.00	3026
Product innovation	0.19	0.00	0.40	3026
Process innovation	0.37	0.00	0.48	3026
Log of patents (plus one)	0.10	0.00	0.44	3026
Temporary workers	12.34	7.14	16.07	3026
Part-time workers	2.57	0.00	5.72	3026
Employee training to sales	0.06	0.00	0.77	3026
No. of international markets	0.80	0.00	1.06	3026
No. of products	1.18	1.00	0.47	3026

Dependent variables	Mean	Median	SD	Obs.
Real sales growth (two year difference)	-27.08	-23.53	36.83	3026
Employment growth (two year difference)	-11.09	-10.32	21.51	3003
Capital investment (cumulated for two years) to sales	4.67	2.12	8.56	3026
Value-added growth (two year difference)	-8.89	-17.36	54.70	2990
Profit growth (cumulated for two years)	32.03	11.04	673.34	2984
R&D expenses (cumulated for two years) to sales	1.41	0.00	4.29	3026
Product improvement cost (cumulated for two years) to sales	0.93	0.00	3.52	3026
Advertisement expenses (cumulated for two years) to sales	179.71	36.82	484.77	3026
Growth in marginal cost (two year difference)	1.64	1.06	11.64	2980
Growth in markups (two year difference)	0.12	-0.10	12.18	2976
Growth in output prices (two year difference)	0.89	0.00	6.36	2966
Growth in input prices (two year difference)	5.55	4.00	8.06	2969

Note: The table presents summary statistics for two cross sections for $t \in 2008, 2009$ for the ESEE dataset. Independent variable data is measured in $t-1$. Dependent variables are measured as two year differences from $t-1$ to $t+1$. Variables are cumulated over t and $t+1$ and normalised by sales in $t-1$.

Figure 1: Change in sales by *Shock* and R&D



Note: The figure uses data for real sales growth of firms measured for two cross sections over 2007-09 and 2008-10. Firms are divided into two groups, those that were hit by a above mean shock (labelled High), and below 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 resilience-Baseline results

	Dependent variable: Sales Growth (Two year difference)			
	OLS	*OLS*	*OLS*	*instrumental variable*
	(1)	(2)	(3)	(4)
R&D$_{t-1}$	2.242***	−0.625	−0.434	−0.624
	(0.333)	(1.332)	(1.036)	(0.984)
Shock	−0.733***	−0.786**		
	(0.061)	(0.307)		
R&D$_{t-1}$*Shock		0.148**	0.106**	0.115***
		(0.060)	(0.041)	(0.039)
Industry by year FE	*No*	*No*	*Yes*	*Yes*
Plant location FE	*No*	*No*	*Yes*	*Yes*
Firm controls	*No*	*No*	*Yes*	*Yes*
Weak instruments				0
Observations	3,026	3,026	3,026	3,026
R^2	0.054	0.058	0.235	0.234

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. Data is pooled for $t \in 2008, 2009$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. The IV in column (4) is *Shock* calculated for the exports from United States of America to the World minus to Spain. Column (3) and (4) contain log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age 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

	Dependent variable: Sales Growth (Two year difference)		
	(1)	(2)	(3)
R&D	1.409***	1.451**	0.934***
	(0.262)	(0.712)	(0.206)
R&D*Shock		−0.011	
		(0.029)	
R&D*GFC			0.729**
			(0.360)
Industry by year FE	*Yes*	*Yes*	*Yes*
Plant location FE	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*
Observations	2,330	2,287	8,400
R^2	0.091	0.096	0.286

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. Data is pooled for $t \in 2004, 2005$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. Columns (2) and (3) contain log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. Standard errors are clustered at industry level in columns (2) and (3), and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 4: Alternative firm level outcomes

	Dependent variable:				
	Survival	Value added	Profit	Employment growth	Capital expenditure
	probit	*OLS*	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)	(5)
R&D*Shock	0.005**	0.128**	−1.215	0.001	0.021
	(0.002)	(0.063)	(1.064)	(0.027)	(0.016)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,395	2,990	2,984	3,003	3,026
R^2		0.091	0.018	0.123	0.117
Log Likelihood	-1,052.427				
Akaike Inf. Crit.	2,228.853				

Note: The dependent variable in column (1) is 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 $t+1$. The dependent variable in column (2) is difference in log value of value added from $t-1$ to $t+1$. Column (3) dependent variable is change in cumulative profit from $t-1$ and $t+1$. Profit is the value of sales minus intermediate consumption and labour costs. 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 $t-1$. R&D is firm level R&D as a percentage of sales, measured at $t-1$. *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, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age. Column (4) controls for investment to sales ratio in $t-1$. Standard errors are clustered at industry level in all columns, and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 5: Changing measurement of *Shock* and Innovativeness

	Dependent variable: Sales Growth (two year difference)						
	Shock without detrending	Demand decrease	Modified IV	With R&D stock	With R&D in t-5	R&D Employment ratio	R&D Dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R&D*Shock			0.117***				
			(0.038)				
R&D*Shock (no detrending)	0.107**						
	(0.049)						
R&D	1.484***	2.208*	−0.661				
	(0.442)	(1.148)	(0.993)				
$R\&D_{t-5}$*Shock					0.120**		
					(0.060)		
R&D stock*Shock				2.975**			
				(1.211)			
R&DEmp*Shock						0.00004**	
						(0.00001)	
R&D> 0*Shock							0.302**
							(0.131)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Plant location FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,026	358	3,026	3,026	1,572	3,026	3,026
R^2	0.235	0.329	0.234	0.231	0.251	0.233	0.229

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. In column (1), the recession shock is measured as the decline in exports (Xgr) without subtracting trend growth. In column (2), the sample contains firms that report that decrease in demand in 2008 and/or 2009 was the main change in their largest market. In column (3), the IV is calculated with US exports to world minus Spain, France, Germany, Italy and Portugal. In column (4), firm innovative effort is cumulated R&D expenses of a firm depreciated annually at 15%. In column (5), R&D intensity of firms is measured in $t-5$. In column (6), R&D intensity is R&D expenditure as a ratio of total employment. In column (7) firm innovativeness is measured using a dummy equal to one if firm has positive R&D expenditure in $t-1$. *Shock* is two-digit NACE 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. All columns control for log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. Column (2) does not include interactions of firm level variables with *Shock*. Standard errors are clustered at industry level in all columns, except column (2), and are reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 6: Accounting for industrial heterogeneity

	Dependent variable: Sales Growth (Two year difference)			
	(1)	(2)	(3)	(4)
R&D*Shock	0.106**	0.092**	0.091**	0.111***
	(0.042)	(0.042)	(0.046)	(0.040)
R&D*Financial Dependence	0.092			
	(0.164)			
R&D*Capital Intensity		−0.029		
		(0.048)		
R&D*Labour costs			0.075	
			(0.088)	
R&D*ICT intensity				−0.248
				(0.563)
Industry by year FE	Yes	Yes	Yes	Yes
Observations	3,026	3,026	3,026	3,026
R^2	0.235	0.238	0.237	0.235

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. External financial dependence is the difference between a firm's capital expenditures minus cash flows, divided by capital expenditures. I borrow the measure from Sharma and Winkler (2018), and use the mean value at NACE two-digit level. I measure labour costs using national account data from the Spanish Statistical Agency, INE, and use the average value of the compensation to employees as a percentage of gross value added from 1995 to 2005 for each two-digit NACE industry. Capital intensity and ICT intensity are measured using data from EUROSTAT at two-digit NACE level, averaged over 1995-2005 for all European countries. Capital intensity is the gross fixed capital formation as a percentage of gross value added, and ICT intensity is the gross ICT equipment as a percentage of gross value added. All columns control for log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. Standard errors are clustered at industry level in all columns, and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 7: R&D spending during the recession

	Dependent variable:	
	R&D (One year horizon)	R&D (Two year horizon)
	(1)	(2)
R&D	0.463***	0.657*
	(0.140)	(0.374)
R&D*Shock	0.016**	0.045**
	(0.007)	(0.020)
Industry by year FE	*Yes*	*Yes*
Location FE	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*
Observations	3,000	3,026
R^2	0.604	0.582

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-recession sales. R&D is firm level R&D as a percentage of sales, measured at $t-1$. *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, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age 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: Resilience and innovation effort by scope for product differentiation

	Sales Growth		R&D		Capital purchases for product/process improvement		Advertisement expenses	
	Differentiated	Homogenous	Differentiated	Homogenous	Differentiated	Homogenous	Differentiated	Homogenous
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D*Shock	0.167**	0.038	0.079***	0.017	0.045**	0.002	0.452***	0.020
	(0.070)	(0.048)	(0.024)	(0.018)	(0.022)	(0.003)	(0.143)	(0.605)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,627	1,399	1,627	1,399	1,627	1,398	1,627	1,399
R^2	0.171	0.224	0.598	0.586	0.095	0.072	0.533	0.748

Note: Columns are split using the RAUCH classification for identifying sectors with differentiated products and those with homogeneous products. The dependent variable in columns(1) and (2) is firm real sales growth measured from from $t-1$ to $t+1$ by deflating firm sales with firm level prices. In columns (3) and (4), dependent variable is R&D expenditure cumulated over t and $t+1$ as a percentage of pre-recession sales. The dependent variable in columns (5) and (6) is cumulative expenditure on product improvement in t and $t+1$ normalised by pre-recession sales. The dependent variable in columns (7) and (8) is cumulative advertisement expenditure in t and $t+1$ normalised by pre-recession sales. R&D is firm level R&D as a percentage of sales, measured at $t-1$. *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, its interaction with *Shock*, physical total factor productivity, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. Columns (5) and (6) contain the capital expenses for product/process improvement as a percentage of sales in $t-1$ as a control, and Columns (7) and (8) contain the advertisment expenses as a percentage of sales in $t-1$ as a control. Standard errors are clustered at industry level in all columns except column (2), and reported in parentheses. $*$, $**$, $***$ mean statistically different from zero at 10, 5, and 1% level of significance.

Table 9: Resilience and innovation effort by product customisation

	At a two-year horizon							
	Sales Growth		R&D		Capital purchases for product/process improvement		Advertisement expenses	
	Customised	Standardised	Customised	Standardised	Customised	Standardised	Customised	Standardised
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D*Shock	0.138	0.035	0.075***	0.013	0.035*	0.002	0.449***	−0.153
	(0.087)	(0.067)	(0.022)	(0.018)	(0.021)	(0.003)	(0.143)	(0.605)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,291	1,724	1,291	1,724	1,291	1,723	1,291	1,724
R^2	0.209	0.296	0.613	0.563	0.106	0.075	0.444	0.754

Note: Columns are split using a firm reported measure of whether they product customised products, or standardised products. The dependent variable in columns(1) and (2) is firm real sales growth measured from from $t-1$ to $t+1$ by deflating firm sales with firm level prices. In columns (3) and (4), dependent variable is R&D expenditure cumulated over t and $t+1$ as a percentage of pre-recession sales. The dependent variable in columns (5) and (6) is cumulative expenditure on product/process improvement in t and $t+1$ normalised by pre-recession sales. The dependent variable in columns (7) and (8) is cumulative advertisement expenditure in t and $t+1$ normalised by pre-recession sales. R&D is firm level R&D as a percentage of sales, measured at $t-1$. *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, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. Columns (5) and (6) contain the capital expenses for product/process improvement as a percentage of sales in $t-1$ as a control, and Columns (7) and (8) contain the advertisment expenses as a percentage of sales in $t-1$ as a control 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: Change in prices, marginal cost, and markup

	Dependent variable:			
	Marginal cost	OutputPrice	InputPrice	Markup
	(1)	(2)	(3)	(4)
R&D*Shock	0.029**	0.007*	0.0004	−0.024
	(0.013)	(0.004)	(0.010)	(0.016)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,883	2,883	2,883	2,883
R^2	0.071	0.070	0.113	0.108

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 change in markup from $t-1$ to $t+1$. A sample with no missing observations for either of the four dependent variables is used. R&D is firm level R&D as a percentage of sales, measured at $t-1$. *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, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age 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: Financing constraints and growth

	Dependent variable: Sales Growth (Two year difference)			
	(1)	(2)	(3)	(4)
R&D*Shock	0.106***	0.108***	0.108***	0.105**
	(0.043)	(0.040)	(0.042)	(0.041)
GROUP*Shock	0.206***			
	(0.116)			
Foreign Own*Shock		0.005***		
		(0.002)		
Leverage*Shock			−0.00001	
			(0.00003)	
Asset tangibility*Shock				−0.004
				(0.003)
Industry by year FE	*Yes*	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,017	3,026	2,958	3,026
R^2	0.236	0.237	0.240	0.235

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. All columns contain log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. GROUP is equal to 1 for firms that belong to a business group. 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. 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 12: Innovative potential versus past innovation success

	Dependent variable: Sales growth (Two year difference)		
	(1)	(2)	(3)
R&D*Shock	0.105**	0.104**	0.110***
	(0.040)	(0.042)	(0.042)
Product innovation*Shock	−0.067		
	(0.180)		
Process innovation*Shock		0.067	
		(0.132)	
Total Patents*Shock			−0.178
			(0.132)
Industry-year FE	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*
Observations	3,026	3,026	3,026
R^2	0.235	0.235	0.235

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. All columns contain log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. Product innovation is a categorical variable for whether the firm reported a product innovation in $t-1$. Process innovation is a categorical variable for whether the firm reported a process innovation in $t-1$. Total patents is the log of patents filed in Spain or elsewhere in $t-1$ plus one. Sales growth is the growth of sales in $t-1$. 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 13: Trapped factors and growth

	Dependent variable: Sales Growth (Two year difference)		
	(1)	(2)	(3)
R&D*Shock	0.103**	0.106**	0.105**
	(0.042)	(0.042)	(0.041)
Temporary staff*Shock	−0.004		
	(0.005)		
Part-time staff*Shock		−0.008	
		(0.010)	
Employee training expenses*Shock			0.386
			(0.693)
Industry by year FE	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*
Observations	3,026	3,026	3,026
R^2	0.236	0.235	0.235

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. All columns contain log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. 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 $t-1$. 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.

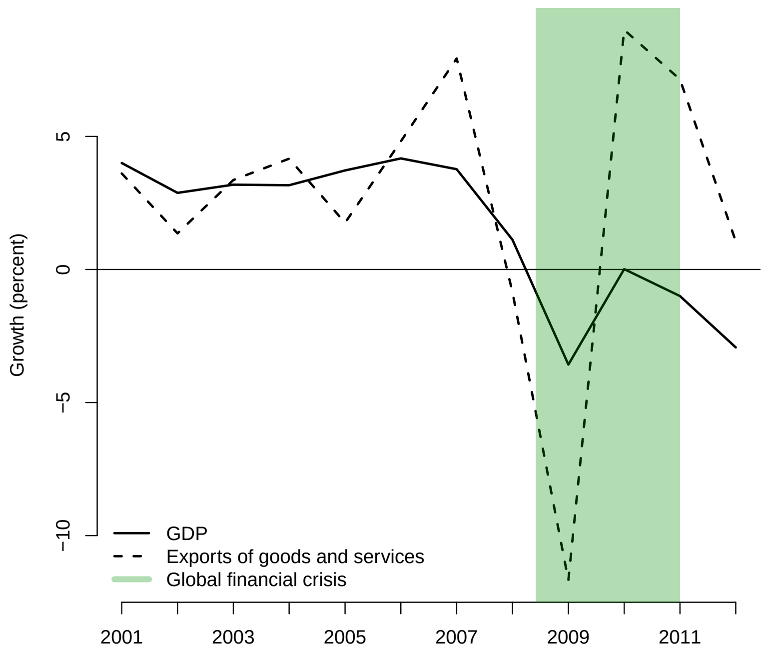
Table 14: Diversity of inputs and growth

	Dependent variable: Sales growth$_{t+2,t}$		
	(1)	(2)	(3)
R&D*Shock	0.107**	0.109***	0.104**
	(0.041)	(0.041)	(0.043)
No. of products*Shock	0.061		
	(0.135)		
No. of international markets*Shock		−0.031	
		(0.059)	
Export Intensity*Shock			0.002
			(0.003)
Industry by year FE	*Yes*	*Yes*	*Yes*
Location FE	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*
Observations	3,026	3,026	3,026
R^2	0.236	0.236	0.235

Note: The dependent variable is real sales growth measured by deflating firm sales with firm level prices. Growth is measured from $t-1$ to $t+1$. R&D intensity is firm level R&D as a percentage of sales, measured at $t-1$. *Shock* is two-digit NACE 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. All columns contain log of number of employees, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age as controls. 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. Number of industrial plants is the number of plants operational by the firm in Spain. Export intensity is export sales as a percentage of total sales. 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.

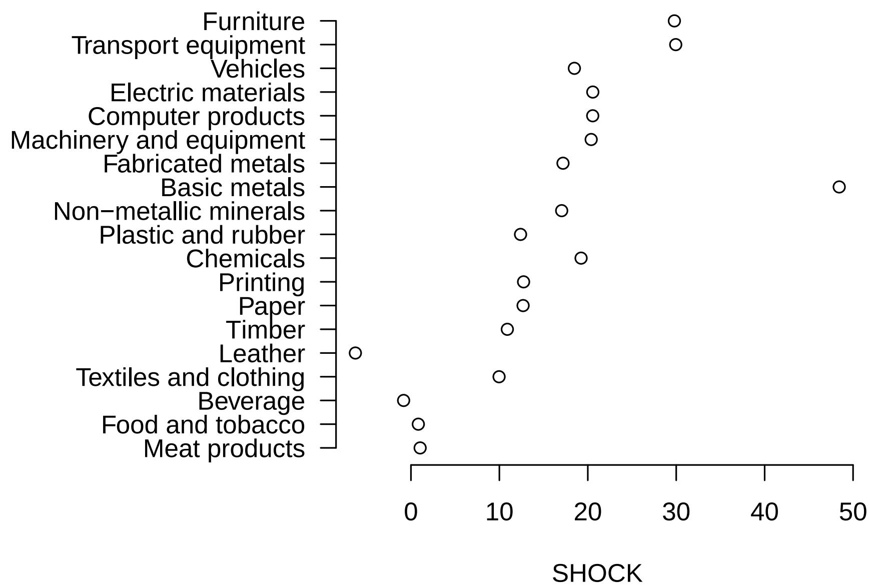
A Appendix: Additional tables

Figure 2: Spain: Aggregate performance indicators



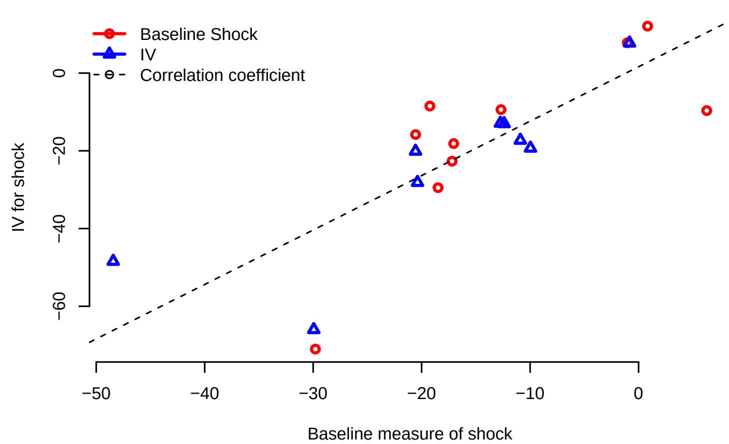
The data is from World Bank's databank, World Development indicators. Both series are measured at constant 2010 USD.

Figure 3: Crisis shock by industry



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 4: Baseline measure and IV for crisis intensity



Note: The figure shows deviation of export growth from trend for Spain during the crisis on the x-axis, and deviation of export growth from trend for the US to the world minus Spain on the y-axis for 19 industry groups. The dotted line shows the slope coefficient of a linear regression of *Shock* and the IV.

Table 15: Product and process innovation

	Dependent variable:	
	Product inn	Process inn
	(1)	(2)
R&D*Shock	0.001	0.0004
	(0.001)	(0.001)
Industry by year FE	Yes	Yes
Plant location FE	Yes	Yes
Firm controls	Yes	Yes
Observations	3,026	3,026
R^2	0.438	0.379

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 $t-1$. *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, its interaction with *Shock*, physical total factor productivity as controls, its interaction with *Shock*, exports as a percentage of sales, and log of age 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 16: Product differentiation: Controlling for additional firm characteristics interacted with Shock

	R&D expenses		Improvement expenses		Advertisement expenses	
	Differentiated	Homogenous	Differentiated	Homogenous	Differentiated	Homogenous
	(1)	(2)	(3)	(4)	(5)	(6)
GROUP	0.08 (0.025) **	0.017 (0.018)	0.046 (0.023) *	0.002 (0.003)	0.471 (0.152) **	0.001 (0.574)
Foreign own	0.08 (0.025) **	0.016 (0.018)	0.046 (0.023) *	0.002 (0.003)	0.478 (0.149) **	-0.026 (0.574)
Leverage	0.065 (0.015) ***	0.017 (0.018)	0.029 (0.009) ***	0.002 (0.003)	0.493 (0.163) **	0.013 (0.601)
Asset tangibility	0.078 (0.024) ***	0.017 (0.018)	0.045 (0.021) *	0.002 (0.003)	0.441 (0.153) **	-0.055 (0.528)
Product innovation	0.081 (0.024) ***	0.017 (0.018)	0.046 (0.022) *	0.005 (0.004)	0.426 (0.146) **	0.371 (0.717)
Process innovation	0.08 (0.024) ***	0.018 (0.018)	0.046 (0.022) *	0.004 (0.005)	0.415 (0.123) ***	0.137 (0.682)
Total Patents	0.079 (0.026) **	0.013 (0.015)	0.046 (0.025) *	0.002 (0.003)	0.44 (0.168) **	-0.075 (0.57)
Temporary staff	0.079 (0.023) ***	0.017 (0.018)	0.044 (0.021) *	0.002 (0.003)	0.445 (0.151) **	0.001 (0.593)
Part-time staff	0.079 (0.024) ***	0.017 (0.018)	0.045 (0.022) *	0.002 (0.003)	0.448 (0.15) **	0.017 (0.602)
Employee training expenses	0.079 (0.024) ***	0.017 (0.018)	0.045 (0.022) *	0.002 (0.003)	0.458 (0.143) **	0.046 (0.605)
No. of products	0.079 (0.024) ***	0.017 (0.018)	0.045 (0.022) *	0.002 (0.003)	0.461 (0.144) **	0.022 (0.612)
No. of international markets	0.079 (0.024) ***	0.018 (0.018)	0.045 (0.022) *	0.002 (0.003)	0.451 (0.145) **	0.052 (0.631)
Export intensity	0.079 (0.024) ***	0.018 (0.018)	0.044 (0.022) *	0.002 (0.003)	0.455 (0.145) **	0.056 (0.625)

Note: Each cell in columns 1-6 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 1 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. In columns (1) and (2), dependent variable is R&D expenditure cumulated over t and $t+1$ as a percentage of pre-recession sales. The dependent variable in columns (3) and (4) is cumulative expenditure on product/process improvement in t and $t+1$ normalised by pre-recession sales. The dependent variable in columns (5) and (6) is cumulative advertisement expenses in t and $t+1$ normalised by pre-recession sales. GROUP is equal to 1 for firms that belong to a business group. Foreign Ownership is the percentage of foreign shareholding in a firm. Leverage is the ratio of total debt to stockholder's equity in a firm. Asset tangibility is the ratio of fixed assets in total assets of a firm. Product innovation is a categorical variable for whether the firm reported a product innovation. Process innovation is a categorical variable for whether the firm reported a process innovation. Total Patents is the log of patents filed in Spain or elsewhere in $t-1$ plus one. 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. Number of industrial plants is the number of plants operational by the firm in Spain. Export intensity is export sales as a percentage of total sales. All columns contain log of number of employees, exports as a percentage of sales, log of age, and physical total factor productivity as controls.

B Appendix: Data description

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). NACE is derived from the International Standard Industrial Classification of All Economic Activities (ISIC), but is more detailed than 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 from ESEE to export growth available at SITC (2 digit, Revision 3), I follow a probability based concordance. I use concordance tables from UN Stats.[22] Since there is no direct concordance table available between NACE and SITC, I map from NACE to ISIC Revision 3 to SITC Rev 3.

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. 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.1 Calculating TFP, marginal cost, and markups

Firm level output and input price index

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

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 input's 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.

B.2 Classifying industries into differentiated and homogenous products

I use the liberal classification of Rauch (1999) for SITC Revision 2 classification, and map it to SITC Revision 3 classification using the merge code provided. [23]. I mark a two-digit SITC group as a differentiated industry when more than 50% of four-digit SITC products within it are differentiated as opposed to homogenous or reference-priced. I map SITC two-digit to NACE two-digit using a probability concordance as described above. For each two-digit NACE group, if the difference between the probability with which differentiated and homogeneous SITC industries map into

[23] https://econweb.ucsd.edu/~jrauch/rauch_classification.html

that group is greater than the median difference across industries, then I call it a differentiated sector. Thus, the classification into differentiated and homogeneous is relative to other industries. It is important to note that the RAUCH classification classifies goods traded on an exchange as homogeneous goods. This includes several basic metals. Products that are not branded and for which a price can be quoted without mentioning a manufacturer are classified as products with a reference price. This includes several chemicals like polymers, and copolymers. Table 17 shows the classification of industries according to the calculation above.

Table 17: 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	Chemicals
Electric materials	Food and tobacco
Transport equipment	Beverage
Textiles and clothing	Paper
Leather	Furniture
Timber	Printing
Vehicles	

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