Weaker today, stronger tomorrow: peer learning and firm innovation after the Great Recession

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Abstract

Can a recession have a positive, long-term impact on firm innovation? A downturn represents an opportunity for firms to learn from their peers and try to understand the main drivers of resilience. If they deem R&D capital one of them, they may raise innovation in the following years, in order to be better shielded from future crisis. In this paper, I provide evidence of this effect in the aftermath of the Great Recession. I do so by assuming that firms learned from their best peers and by examining the characteristics of these companies. I first look at their level of R&D capital and find that firms with high-R&D best peers raised intangible investment 5 percent more than others after 2008. I then examine the top competitors' type of R&D capital and show that companies raised innovation only in the case of high-productivity (as opposed to high-product differentiation) best peers. Using alternative tests, I find a positive (negative) relationship between productivity (product differentiation) and company performance during the crisis, which supports the fact that companies learned from their peers and raised innovation only when they deemed it a source of resilience to the downturn. Finally, I examine whether the increase in innovation improved firm resilience and show that it did: companies raised sales growth, profitability and international recognition and were less likely to fail.

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1 Introduction

Most of the studies on the relationship between economic downturns and firm innovation focus on how R&D investment behaves during periods of stagnation. They find that, though from a theoretical point of view intangible investment should be countercyclical and thus increase, it often declines due to credit constraints, uncertainty, or the fact that firms fail to discount future R&D benefits (Aghion et al., 2012; Bloom et al., 2007; Barlevy, 2007). But what about the long-run relation between downturns and innovation? A recession, indeed, may also have a prolonged impact on R&D investment, as it represents an opportunity for firms to learn from their peers and try to understand the main drivers of resilience. If they deem knowledge capital one of them, they may raise R&D investment in the years that follow the slowdown, in order to be better shielded from future crisis. In this paper, I provide evidence of this effect in the aftermath of the Great Recession.

I start the analysis by comparing firm intangible investment before and after the downturn. I show that firms increased R&D spending in the five years that followed the crisis relative to the previous years, and that such raise is not due to expansionary monetary policy, industry growth or the possibility that the recession acted as a stimulus for companies to innovate. I then focus on the learning-from-peers hypothesis outlined in the previous paragraph. This explanation has a main concern: learning from competitors is not measurable and thus requires a proxy. I choose to use firms' peers that best performed during the downturn. The reason for this is that, while firms can learn from any competitor, they likely pay more attention to the best ones, as they represent an example of success. Thus, if companies tried to acquire information on resilience during the Great Recession, it is reasonable to assume that they examined primarily the characteristics of their strongest peers. Of course, this approach is imperfect, as it potentially captures only part of firm learning. For this reason I perform, in Section 7, an ancillary analysis that tests the validity of the learning channel from a different perspective, focusing, rather than on the best-performing peers, on the likelihood that firms learned from other companies.

The identification I use follows three steps. First, I define a firm's peers/competitors

as the companies that belong to the same 5-digit NAICS. This choice is a compromise between an optimal universe of competitors (that is, companies that belong to the same specific industry and have the same scope) and a reliable sample size. Second, I select a firm's best-performing peers during the recession as the firms that are in the top quartile of 2007-2008 sales growth. The reason for this is that I want to focus on resilience to a negative demand shock, and sales growth is a better proxy for it than profitability measures. Last, I examine the R&D capital of the best competitors, using knowledge capital estimates developed by Peters et al. (2017). Specifically, I compare their R&D capital with the one of all other firms in the industry. Intuitively, if the best peers had a high level of innovation within their industry, other firms may have inferred that knowledge capital was a source of resilience to the crisis and thus raised intangible investment after the downturn.

I begin by looking at the best competitors' level of R&D capital, regardless of its type, and find that firms with a large share of high-R&D best peers raised intangible investment almost 5 percent more than other companies after 2008. This finding is useful as a broad test of the learning-from-peers channel, but it provides little insight on why, assuming they did, companies considered R&D a source of resilience during the recession. For this reason, I pursue the analysis by looking at the type of the best peers' innovation. In general, R&D capital can improve firms' performance in two ways: through higher productivity, as in Aghion and Howitt (1992), or through higher product differentiation, as in Sutton (1991). To distinguish the two, I rely on the Text-based Network Industry Classification of Hoberg and Phillips (2016) described in part 3.3. I define product differentiation as one minus the pairwise similarity score and calculate, for each firm, its average product differentiation among all U.S. firms in 2007. I then classify a company as a high-differentiation firm if both its R&D ratio and its differentiation in 2007 are above the industry median, and as a high-productivity firm if its R&D ratio in 2007 is above median and its differentiation in 2007 is below median. Companies that belong to the latter category have higher total factor productivity than other ones, thus supporting the identification. I find that firms with high-differentiated best peers did not raise intangi-

ble investment more than other companies after 2008. Those with high-productivity top competitors, instead, did so, by 3 percent. This different firm response to the best peers' type of R&D capital has two potential explanations: either (i) the learning channel is not valid or (ii) firms observed the top companies' productivity and product differentiation and deemed only the former a source of resilience to the downturn. Since it is not feasible to evaluate explanation (i) directly, I focus on explanation (ii) and perform three alternative tests on the relationship between a firm's type of R&D capital and its performance during the recession. In the first test, I examine the link between a firm's type of innovation and the probability that it was among the worst performers during the recession (i.e. that it was in the bottom quartile of the 2007-2008 sales growth). I find a positive and significant likelihood for high-differentiated firms and a non-significant one for high-productivity companies. As a second test, I study the relationship between a firm's type of R&D capital and its 2007-2008 domestic sales growth. The Great Recession, indeed, was a global recession, but hit the U.S. more than other countries. As a result, firms that maintained their pre-crisis domestic sales growth should be considered more resilient than those that decreased it. Using data from Compustat Historical Segments, I show that high-differentiation firms decreased domestic sales growth by 3.4 percent during the recession, while high-productivity companies didn't. As a last test, I examine the link between a firm's type of R&D capital in 2007 and the growth in sales from new customers between 2007 and 2008. Intuitively, companies that decreased sales from new customers should be considered less resilient than those that didn't. I calculate sales from new customers from Compustat Customer Segments and find that high-differentiation companies lowered their sales growth from new customers, while high-productivity ones managed to maintain their pre-crisis sales growth. The results of the three tests all indicate a negative relationship between product differentiation and company performance during the Great Recession and therefore suggest that explanation (ii) is the valid one: firms learned from their best-performing peers, and raised intangible investment only when they deemed their top competitors' R&D capital a source of resilience to the downturn.

As a complementary analysis of the learning-from-peers channel, I then examine the type

of innovation that firms acquired after 2008. If the channel is valid, i.e. companies raised intangible investment because they deemed their best-performing peers' productivity a source of resilience to the downturn, we would expect that they invested mainly in productivity. To see if this is the case, I first focus on total-factor-productivity (TFP), both at the firm level and at the industry level. I show that firms (industries) with a large share of high-productivity best peers increased their TFP more than other companies (industries) after 2008, in line with the learning channel. I then look at product-related and process-related measures. The reason for this is that investment in product quality normally entails a change in the type and variety of a firm's products, while investment in productivity often affects the production process, through expenditures on new equipment, software or structures aimed at maximizing efficiency. Examining product-related and process-related outcomes, therefore, can help deduce the type of innovation that firms acquired. I use, as product-related measures, three different variables: product differentiation, firm scope, as estimated by Hoberg and Phillips (2024), and firm's business segments. The latter are subsections of the companies associated with specific product lines and are provided by Compustat Historical Segments. None of the three estimates is significant, suggesting that firms' innovation after 2008 did not affect the type of products they sold. To size a potential change in the production process, I use firm asset redeployability estimates from Kim and Kung (2017). These estimates are constructed from capital expenditures of the Bureau of Economic Analysis (BEA) capital flow tables, and measure how easily a firm can sell its assets in the case of need. They capture, therefore, two components: asset specificity and asset liquidity. A change in a firm's production process may affect the first component and, as a result, overall asset redeployability. I find that asset redeployability decreased for all firms after 2008, but it declined 0.9 percent more for firms in industries with high-productivity best performers. This indicates that the type of innovation that companies acquired after the recession affected their asset composition and, therefore, suggests that firms invested primarily in productivity. To corroborate this result, I also estimate a regression of asset redeployability on product differentiation for the whole period of analysis. The coefficient estimate for product differentiation is not

significant, indicating that investment in product quality does not affect firms' asset composition. Overall, these results suggest that firms invested mainly in productivity after 2008 and thus support the learning channel hypothesis that companies raised innovation only when they deemed their top peers' R&D capital a source of resilience to the crisis.

Having shown that firms raised intangible investment in industries with high-productivity best-performing companies and that this increased their productivity, a question remains open: did innovation improve their strength, allowing them to be more resilient in the event of a downturn? I try to answer this question by analyzing several measures related to firm performance: sales growth, efficiency, profitability, likelihood of closure or contraction, international recognition and human capital. I find that companies with high-productivity best peers increased sales growth 3 percent more than other companies after 2008 and even managed to improve sales growth from their weakest product lines, defined as the least profitable segments in the years that preceded the recession. Higher sales translated into higher profitability: treated companies raised profits 1.3 percent more than other companies after the downturn. They also translated into a lower likelihood of insolvency or contraction: using data from the Business Dynamics Statistics (BDS), I show that, in industries with a large share of high-productivity best peers, company closures decreased 6 percent more than in other areas, establishment contractions by 3 percent and employment contractions by 11 percent. As an additional measure related to resilience, I then examine firm global recognition: did firms manage to attract new foreign customers after 2008? Answering this question is not straightforward, because firms differ in the products or services they provide and some of them can only serve a local market. Including all companies in an analysis on global attractiveness, therefore, hardly makes sense. To address this problem, I use data from Compustat Historical Segments and look at companies' geographical segments in the 5 years prior to the recession, that is from 2003 and 2007. I assume that firms with no foreign segments in this period can only serve a local market and thus exclude them from the analysis. I find that companies with high-productivity peers raised foreign sales growth 2.3 percent more than others after 2008 and had a 10 percent higher probability of increasing their foreign segments. Both

results show an enhancement in international recognition and thus suggest an improved strength. The last outcome variable that I examine is employment. A priori, there is no reason why innovation should affect the level of employment. It may, instead, affect workers' composition, because R&D capital usually requires talent. I measure employee skills in several ways, both at firm level and at the industry level. For the former, I use the stock compensation ratio, due to the fact that high-skilled workers are often compensated with equity (Eisfeldt et al., 2022; Dottling and Ratnovski, 2022), and the pension-to-employees ratio, due to the fact that an increase in this ratio may signal a higher share of skilled employment. As for industry-level measures, I use the share of non-production workers and the ratio of non-production workers salary to value added, calculated from the NBER-CES Manufacturing Industry Database, and the share of workers with a college degree, calculated from the Quarterly Workforce Indicators (QWI) of the U.S. Census Bureau. All the coefficient estimates point to a shift in workforce composition towards higher skills, in line with a stronger focus on knowledge capital.

Overall, the results on sales growth, efficiency, profitability, likelihood of closure or contraction, international recognition and human capital indicate an improvement in firm performance and thus suggest a stronger resilience to future downturns.

This paper contributes to the innovation literature in two ways. First, it contributes to studies on the determinants of innovation. The literature has focused primarily on the relationship between foreign competition and innovation, due to the fact firms often postpone R&D investment until they feel pressure to do it, as in the case of higher competition (Bloom et al., 2016a; Autor et al., 2013). This analysis complements these studies by exploring another determinant: learning from best-performing peers during a recession. Second, the paper contributes to the understandings of the potential benefits of innovation. Specifically, the analysis adds to this literature by showing that R&D capital in terms of high productivity may provide stronger benefits than the one in terms of high product quality, both during a downturn and subsequently.

The rest of the paper is organized as follows. Section 2 illustrates the data used. Section 3 examines firm innovation before and after the Great Recession and explores potential

explanations for the increase. Section 4 focuses on the learning channel hypothesis and examines firm reaction to their best peers' R&D capital. Section 5 studies the type of innovation that firms chose after the recession. Section 6 examines whether innovation was effective in improving companies' resilience to negative demand shocks. Section 7 presents robustness checks. Specifically, it examines the learning channel from a different perspective, focusing on the likelihood that firms acquired information from their competitors. Finally, Section 8 presents the conclusions.

2 Data

Data comes from different sources.

2.1 Firm-level data

2.1.1 Intangible investment

The main dependent variable throughout the analysis is intangible investment. I follow Peters et al. (2017) and define it as the sum between research and development expense and 30% of selling, general and administrative expense, scaled by lagged intangible capital. The idea is that R&D expense captures investment in knowledge, while a share of SG&A expense reflects investment in brand and organizational capital. I take the first two variables from Compustat IQ, while for intangible capital I use the estimates of Peters et al. (2017). They construct it by capitalizing intangible investment using depreciation rate estimates and adding on-balance sheet intangibles, mostly goodwill. Table 2 shows the summary statistics for intangible investment, winsorized at 1%.

2.2 Main firm-level measures

All the main firm-level variables other from intangible investment come from the annual financial statements of Compustat IQ.

In most of the regressions, I control for the market-to-book ratio, sales growth, cash flow, cash, leverage, total assets, age and the Herfindahl-Hirschman Index (HHI). The market-to-book ratio is the total market value of equity (common shares outstanding times the end-of-year close price of common shares) plus the book value of debt and quasi equity (book value of assets, minus common equity, minus deferred taxes), normalized by total assets. Cash flow is the sum between income before extraordinary items and depreciation, scaled by total assets. Cash is cash scaled by total assets. Leverage is debt due in one year divided by total assets.

Table 2 shows the main summary statistics for these variables. Assets have been winsorized at 5%.

2.3 Scope

For the analysis of firm innovation type in Section 5, I use firm scope data developed by Hoberg and Phillips (2024). Based on product description in firms' 10-Ks, the data contains, for each year, the number of product markets a firm operates in.

2.4 Product differentiation

For the analysis of product similarity in part 3.3, of productivity vs. product differentiation in Section 4.2 and of firm type of innovation in Section 5, I use the Text-based Network Industry Classification developed by Hoberg and Phillips (2016). Based on product description in firms' 10-Ks, the data contains pairwise word similarity scores for each pair of U.S. public firms, starting from 1996. This similarity score ranges from zero to one: two firms are deemed to be closer in the product market space when their product

similarity score is closer to one and more differentiated when their score is closer to zero. For the analysis in part 3.3, I use product similarity, while for the other analysis I use one minus the similarity score and refer to it as product differentiation.

2.5 Sales and profits by segment

For the analysis of productivity vs. product differentiation in Section 4.2, of firm type of innovation in Section 5 and of firm outcomes in Section 6, I use data from Compustat Historical Segments. The data provides firm sales by year and segment. Each segment is classified as either business, geographic, operating and state. When the purpose of the analysis is to examine a firm's product lines, I consider only business segments. When the purpose of the analysis is to examine a firm's geographical distribution or to calculate domestic and foreign sales growth, I consider only geographical segments.

2.6 Sales by customer

For the analysis of sales to foreign customers and foreign areas in Section 6, I use data from Compustat Customer Segments. The data provides firm sales by year and customer, including the customer geographical area and area type (ISO for countries, REGION for world big areas such as North America, and STATE for U.S. states). Both the geographical area and the area type are missing most of time but it is possible to partially retrieve them from the customer identifier (a customer may have a non-missing area and area type in one year, and missing in all other years). I exclude all customers for which it is not possible to retrieve information on the geographical area and define a customer as foreign if its area type is not the U.S. or if its area type is not STATE.

2.7 Asset redeployability

For the analysis of type of innovation in Section 5, I use asset redeployability measures developed by Kim and Kung (2017). The data is based on expenditures on new equipment, software, and structures from the Bureau of Economic Analysis (BEA) capital flow tables, and provides an estimate of easily a firm can sell its assets in the case of need. It comprises, therefore, two components: asset specificity and asset liquidity.

2.8 Industry-level data

2.9 Business Dynamics Statistics (BDS)

For the analysis of firm closures and contractions in part 6.4 and in the robustness checks of Section 7, I use the Business Dynamics Statistics (BDS) of the U.S. Census Bureau. The data provides information on firm births, firm deaths, establishment entry and establishment exit at the 4-digit NAICS.

2.10 NBER-CES Manufacturing Industry Database

For the analysis of industry-level total factor productivity in Section 5 and of skilled employment in part 6.6, I use data from the NBER-CES Manufacturing Industry Database. The data provides industry-level TFP estimates as well as information of the number and wages of production and non-production workers at all NAICS levels.

2.11 Quarterly Workforce Indicators (QWI)

For the analysis of skilled employment in part 6.6, I use data from the Quarterly Workforce Indicators (QWI) of the U.S. Census Bureau. The data provides information on employment, hiring, firing and earnings by worker characteristics (sex, age, education,

race, ethnicity) at the 4-digit NAICS.

3 Intangible investment after the Great Recession

To see whether the Great Recession had an impact on U.S. firms' innovation, I begin the analysis by estimating the following relationship:

$$IntangInv_{i,j,t} = \beta_0 + \beta_1 \cdot After + \beta_2 \cdot \mu_{i,j,t-1} + \lambda_i + \nu_t + \epsilon_{i,j,t} \quad (1)$$

where $IntangInv_{i,j,t}$ is intangible investment of firm i in NAICS industry (5-digit NAICS) j in year t. I follow Peters et al. (2017) and define intangible investment as the sum between research and development expense and 30% of selling, general and administrative expense, scaled by lagged intangible capital. The idea is that R&D expense captures investment in knowledge, while a share of SG&A expense reflects investment in brand and organizational capital. I take the two expenses from Compustat IQ, and intangible capital from Peters et al. (2017). $After$ is a dummy variable equal to 1 for every year starting from 2008, and 0 otherwise. $\mu_{i,j,t-1}$ are lagged firm-level (or industry-level) controls. They include the market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of the Herfindahl-Hirschman Index (HHI). λ_i are firm fixed effects, which absorb all time-invariant factors of intangible investment at the firm level. ν_t are year fixed effects, that control for determinants of the dependent variable that are specific to certain periods. The period of analysis comprises a 5-year window around the start of the Great Recession, that is from 2003 to 2012. I exclude the finance, construction and the utilities sectors and all the firms that have missing values in their assets and I focus only on firms with market capitalization greater than 10 millions.
Table 3 shows the main results. In the first column, I estimate Equation 1 on all firms. The coefficient of After is positive and significant, indicating that intangible investment increased in the years that followed the recession.

Clearly, the increase may be due to a change in firm composition between the years that preceded the recession and the ones that followed. The downturn, indeed, caused many bankruptcies; if the companies that went out of business had lower intangible investment rates than the surviving ones, this would induce a positive estimate of After. Furthermore, firms failures during the crisis and expansionary monetary policy in the subsequent years may have encouraged firm entry. Since young firms have higher productivity than more mature ones (Foster et al., 2008) and productivity is often correlated with innovation, higher entry may have contributed to the raise in intangible investment after 2008. In the second column of the table, I estimate Equation 1 excluding firms that declared insolvency in 2008. The coefficient of After is extremely similar to the one for the whole sample, suggesting that firm bankruptcies doesn't explain the change in innovation pre and post 2008. In the third column, instead, I exclude new firms after 2008. Again, the coefficient of After is almost identical to the one for all firms. As a last test on firm composition, in the last column of the table I further restrict the sample to firms that were active during the whole period of analysis, that is, between 2003 and 2012. The coefficient of After is equal to 0.21, confirming that most of the increase in innovation after 2008 came from existing firms.

A raise in intangible investment by existing firms may be due to a variety of reasons. In the next parts of this section, I consider three main ones: expansionary monetary policy, industry growth and the possibility that the recession acted as a stimulus for companies to innovate.

3.1 Monetary policy stimulus

One potential explanation for the fact that U.S. companies raised innovation in the years that followed the recession is expansionary monetary policy. So far, the empirical evidence has found a weak response of intangible investment to monetary policy, for two main reasons: (i) a weak credit channel, due to difficulty in pledging intangible capital as collateral (Dottling and Ratnovski, 2022) and (ii) a low interest rate sensitivity

of intangible investment, due to the fact that intangible assets have high depreciation rates (Crouzet and Eberly, 2019; Dottling and Ratnovski, 2022). Still, it is possible that the Fed's asset purchases programs introduced in 2008 allowed firms to increase R&D spending. To see if this is the case, I examine intangible investment of financially constrained and unconstrained firms. If monetary policy stimulated innovation, we would expect a stronger response for the former than for the latter. There are several measures of firm financial constraints used in the literature. The most common ones are young age (Cloyne et al., 2018; Hadlock and Pierce, 2010) and small size (Gertler and Gilchrist, 1994; Kashyap et al., 1994), because young and small firms usually have difficulty in getting external financing due to high asymmetric information and uncertain returns. Another frequent proxy for financial constraints is high cash holdings, as financially constrained companies accumulate more cash for precautionary reasons (Cunha and J., 2019). A last approach uses firm dividends, assuming that companies that don't pay dividends are financially constrained (Otto and Thorsten, 2024). Since each method is potentially imperfect (Farre-Mensa and Ljungqvist, 2016), I use all the above proxies except for age. Firm age, indeed, has two main shortcomings. First, it may be correlated with innovation activities, given that young firms have high productivity and investment rates than more mature ones. Second, some young firms may grow quickly and not be financially constrained in the subsequent years (Dottling and Ratnovski, 2022). Panel A of Table 4 estimates Equation 1 on sub-samples of financially constrained firms, defined as companies (i) whose book values of assets in 2007 is below median, (ii) whose cash-to-assets ratio in 2007 is below median or (iii) with no dividends in 2007, and unconstrained firms. The intangible investment response after 2008 is the same for the two groups, as shown by the p-value of the difference between the coefficients. In Panel B, I estimate the same equation using, as dependent variable, tangible investment. In this case, there is a different response between financially constrained and unconstrained companies, with the former increasing investment significantly more than the latter. The results of the two panels validate the empirical evidence that intangible intangible investment responds weakly to monetary policy and suggest that the increase in innovation after 2008 is not due to the

Fed's expansionary policies.

3.2 Industry growth

Another potential explanation for the post-recession raise in intangible investment is industry technological change: it is possible that the result is driven by firms in industries that experienced a rapid technological change or growth after 2008, with no specific link to the downturn. To see whether this is true, I use two alternative measures of industry growth: Tobin's Q and sales growth. Table 5 estimates Equation 1 adding the interaction between After and a dummy variable that identifies industries whose Tobin's Q (sales growth) between 2008 and 2012 is above median. The interaction term is negative for the former, and positive for the latter, but with very small magnitude compared to the one of After alone. This suggests that industry growth explains, if any, only a small part of the raise in intangible investment after 2008.

3.3 Recession as a stimulus to innovate

Firms often postpone long-term projects and start innovating when they feel the pressure to do it. For example, they frequently raise R&D investment after an increase in competition, to get stronger than competitors (Bloom et al., 2016b). It is therefore possible that the recession, with its disruptive effects, acted as a sort of stimulus for companies to stop postponing R&D projects and start innovating. I analyze this possibility with four alternative tests.

The first one is based on firms' level of innovation prior to the crisis. If companies already had, at the start of the crisis, high R&D capital, it is unlikely that the downturn prompted them to further raise it. In other words, if the recession acted as a stimulus for innovation, we would expect a stronger response from low-R&D firms. In Panel A of Table 6, I estimate Equation 1 on firms whose R&D capital in 2007 is below (above) median, using knowledge capital estimates from Peters et al. (2017). The coefficient of

After is the same for the two groups, as shown by the p-value of the difference between the coefficients.

As a second test, I focus on how severely industries were hit by the downturn. If the recession represented a stimulus for firms to innovate, we would expect a stronger response from companies in industries that were severely affected by the crisis. Indeed, it is unlikely that firms marginally damaged by the negative demand shock reacted to it. To perform this analysis, I use a dummy variable that identifies industries whose average 2007-2008 sales growth is below median. Panel B of Table 6 estimates Equation 1 by adding the interaction with these dummy variables. The coefficient of the interaction with After is negative, which contradicts the previous reasoning.

As a third test, I examine industry competition prior to the recession. A negative demand shock represents a bigger risk for firms with many competitors. As a result, we would expect companies in industries with high competition to react more strongly to the recession, in order to be better shielded from future demand shocks. In the first column of Panel C of Table 6, I estimate equation 1 by interacting After with the Herfindahl-Hirschman Index (HHI) in 2007. The interaction term is positive and significant, equal to 0.8 percent. Thus, innovation increased more in industries with low, rather than high, competition.

As a final test, I focus on an industry's average product similarity among its firms. If companies in a given industry produce very similar products, they are at greater risk in the case of a negative demand shock. As a result, if the recession acted as a stimulus for firms to innovate, we would expect a stronger response in industries where firms produce similar goods. To see whether this is the case, I use the Text-based Network Industry Classification developed by Hoberg and Phillips (2016). Based on product description in firms' 10-Ks, the data contains pairwise word similarity scores for each pair of U.S. public firms, starting from 1996. This similarity score ranges from zero to one: two firms are deemed to be closer in the product market space when their product similarity score is closer to one and more differentiated when their score is closer to zero. I calculate, for each industry, the average similarity among its firms and construct a dummy variable

that identifies industries whose similarity in 2007 is above median. In the last column of Panel C of Table 6, I estimate equation 1 interacting After with this dummy variable. The interaction term is significant, but negative, equal to almost -3 percent. Thus, innovation increased more in industries with low product similarity.

Overall, the results of Table 7 suggest that the raise in intangible investment after 2008 is not explained by the fact that the recession acted as a stimulus for firms to innovate.

4 Learning from peers

Section 3 shows that U.S. firms raised intangible investment after 2008, and that such raise is not due to expansionary monetary policy, industry technological growth or a stimulus to innovate induced by the recession. In this and the following sections, I focus on another potential explanation for the increase: learning from peers. During a downturn, indeed, firms may compare their performance to the ones of their competitors and try to understand the main drivers of resilience. If the comparison leads them to deem knowledge capital a source of strength during the crisis, they may raise R&D investment in the following years, in order to be better shielded from future downturns.

This explanation has a main concern: learning from peers is not measurable and thus requires a proxy. I choose to use firms' peers that best performed during the recession. The reason for this is that, while firms can learn from any competitor, they likely pay more attention to the best ones, as they represent an example of success. Thus, if companies tried to acquire information on resilience during the Great Recession, it is reasonable to assume that they examined primarily the characteristics of their strongest peers. Of course, this approach is imperfect, as it potentially captures only part of firm learning. For this reason I perform, in Section 7, an ancillary analysis that tests the validity of the learning channel from a different perspective, focusing, rather than on the best-performing peers, on the likelihood that firms learned from other companies.

Examining the learning channel using firms' best-performing peers during the Great Re-

cession requires addressing two main points: (i) choosing an appropriate definition of a company's peers, and (ii) selecting the ones that were more resilient to the recession. Regarding the first point, I define a firm's peers/competitors as the companies that belong to the same 5-digit NAICS. This choice is a compromise between an optimal universe of competitors (companies that belong to the same 5-digit NAICS and have the same scope, meaning they operate in the same number of product markets) and a reliable sample size (using both industry and scope would generate in most cases extremely small groups of firms). As for point (ii), I define a firm's best-performing peers during the recession as the firms that are in the top quartile of 2007-2008 sales growth. The reason for this is that I want to focus on resilience to a negative demand shock, and sales growth is a better proxy for it than profitability measures.

Having selected firms' benchmark, I examine the R&D capital of these companies. Specifically, I compare the top peers' R&D capital with the one of all other firms in the industry. Intuitively, if the best companies had a high level of innovation within their industry, other firms may have inferred that knowledge capital was a source of resilience to the crisis and thus raised R&D investment after the downturn.

In this subsection, I focus on the best competitors' level of R&D capital, as general test of the learning from peers channel. In part 4.2, instead, I look at its type. This allows me to understand why, assuming they deed, firms considered their top peers' innovation a source of resilience to the downturn. In both parts, I estimate of the following relationship:

$$\begin{aligned} IntangInv_{i,j,t} &= \beta_0 + \beta_1 \cdot After + \beta_2 \cdot InnovBest_{j,07} + \beta_3 \cdot After \cdot InnovBest_{j,07} \\ &\quad + \beta_4 \cdot \mu_{i,j,t-1} + \omega_{s,t} + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

where $InnovBest_{j,07}$ is a measure that identifies the best-performing companies' innovation in industry j in year 2007, the year that precedes the recession.

4.1 Broad R&D capital

As mentioned in the previous paragraph, I start the analysis by focusing on the level of R&D capital. I use R&D capital estimates from Peters et al. (2017), as outlined in part 3.3, and calculate, for each firm, its R&D ratio in 2007, defined as R&D capital scaled by the sum of tangible and intangible capital. I then classify a company as high-R&D if its ratio is above the industry median. Since I want to examine firms' learning from the top peers, I exclude the best-performing companies from the analysis (here and in each of the following analysis) and estimate Equation 2 using, as $InnovBest_{j,07}$, either the share of an industry's high-R&D best peers or a dummy variable equal to 1 if an industry' share of high-R&D best peers is equal or greater than 0.5, and 0 otherwise. The first column of Table 7 presents the results. In Panel A, we can see that a one standard deviation increase in the share of an industry's high-R&D best peers leads to almost a 10 percent raise in intangible investment by other firms in the industry after 2008. A similar finding is obtained when using a dummy variable, in the first column of Panel B: firms with a large share of high-R&D best peers raised intangible investment almost 5 percent more than other companies after 2008. These results are in line with the learning from peers channel, as they suggest that firms observed the characteristics of the top companies and raised intangible when they hypothesized R&D capital a source of strength during the crisis.

4.2 Productivity and Product differentiation

The previous results focus on the level of best peers' R&D capital. While they are useful as a test of the learning-from-peers channel, they provide little insight on why, assuming they did, companies considered R&D a source of resilience during the recession. In this part, I try to improve such understanding by looking at the type of the top-performing firms' innovation.

In general, R&D capital can improve firms' performance in two ways: through higher

productivity, as in Aghion and Howitt (1992), or through higher product differentiation, as in Sutton (1991). To distinguish the two, I rely on the Text-based Network Industry Classification of Hoberg and Phillips (2016) described in part 3.3. I define product differentiation as one minus the pairwise similarity score and calculate, for each firm, its average product differentiation among all U.S. firms in 2007. I then classify a company as a high-differentiation firm if both its R&D ratio and its differentiation in 2007 are above the industry median, and as a high-productivity firm if its R&D ratio in 2007 is above median and its differentiation in 2007 is below median. This identification may raise concerns about whether the combination of high R&D capital and low product differentiation truly captures firm productivity. Table 8 shows the estimates of total factor productivity (TFP) between 2003 and 2007 for the two types of high-R&D companies. TFP is positive and significant for high-productivity firms, while it is not significant for high-differentiation firms. This suggests that the approach correctly identifies the two types of R&D capital. In Section 5, I further try to alleviate these concerns by examining the type of innovation that firms acquired after 2008.

Following the same approach outlined in part 4.1 for broad R&D capital, I calculate, for each industry, the share of best-performing firms that are high-differentiated (high-productivity) and re-estimate Equation 2 using both the share and a dummy variable equal to 1 if the share is equal or greater than 0.5. Columns (2) and (3) of Table 7 show the results. Firm with high-differentiated best peers did not raise intangible investment more than other companies. Those with high-productivity best peers, instead, did so: as shown by Panel B, firms with a large share of high-productivity best peers raised intangible investment almost 3 percent more than other companies.

This different firm response to the top peers' type of R&D capital has two potential explanations: either (i) the learning channel is not valid or (ii) firms observed the top companies' productivity and product differentiation and deemed only the former a source of resilience to the downturn. Since it is not feasible to test explanation (i), I focus on explanation (ii). Specifically, I perform three alternative tests on the relationship between a firm's type of R&D capital and its performance during the recession. If they all point

out a significantly better performance in the case of high productivity, it is likely that explanation (ii) is the valid one.

In the first test, I examine the link between a firm's type of innovation and the probability that it was among the worst performers during the recession (i.e. in the bottom quartile of the 2007-2008 sales growths). The first column of Table 8 shows the results. High-differentiated firms had a 23 percent higher probability of ending up among the worst performers, while high-productivity companies did not differ significantly from other firms. The standard deviation of the two coefficient estimates is very similar, indicating that the disparity between the two types of R&D capital is not due to different sample sizes. This result suggests that product differentiation did not improve firm resilience to the downturn.

As a second test, I study the relationship between a firm's type of R&D capital and its 2007-2008 domestic sales growth. The Great Recession, indeed, was a global recession, but was more severe in the U.S. than in other countries. As a result, firms that maintained their pre-crisis domestic sales growth should be considered more resilient than those that decreased it. To perform this analysis, I use data from Compustat Historical Segments, which provides firm sales by segment. Each segment is classified as business, geographical or operating segment. I focus only on geographical segments and calculate sales growth of U.S. segments. The third column of Table 9 shows the coefficient estimates. High-differentiation firms decreased domestic sales growth by 3.4 percent during the recession, while high-productivity companies didn't. As for the previous analysis, the disparity is not caused by different sample sizes and suggests a negative relationship between product differentiation and firm performance during the crisis.

As a last test, I examine the link between a firm's type of R&D capital in 2007 and the growth in sales from new customers between 2007 and 2008. Intuitively, companies that decreased sales from new customers should be considered less resilient than those that didn't. To perform this analysis, I use data from Compustat Customer Segments, which provides firm sales by year and customer. The last column of Table 9 displays the results. High-differentiation companies lowered their sales growth from new customers,

while high-productivity ones did not.

The results of the three tests all point to a negative relationship between product differentiation and company performance during the Great Recession and thus suggest that explanation (ii) is the valid one: firms learned from their best-performing peers, and raised intangible investment only when they deemed their peers' R&D capital a source of resilience to the downturn.

5 What type of innovation did firms choose?

Section 4 shows that firms raised intangible investment in the case of high-productivity best peers. In this section, I examine the implications of this for the type of innovation that firms acquired after 2008. If the learning channel is valid, i.e. firms raised intangible investment because they deemed their best-performing peers' productivity a source of resilience to the downturn, we would expect that they invested mainly in productivity. To see whether this is true, I estimate the following relationship:

$$\begin{aligned} Y_{i,j,t} &= \beta_0 + \beta_1 \cdot After + \beta_2 \cdot BestHighProd_{j,07} + \beta_3 \cdot After \cdot BestHighProd_{j,07} \\ &\quad + \beta_4 \cdot \mu_{i,j,t-1} + \nu_s + \omega_t + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

where $Y_{i,j,t}$ is a firm-level measure that allows to understand the type of innovation that firms acquired and $BestHighProd_{j,07}$ is a dummy variable equal to 1 if the share of industry j's high-productivity best peers is equal or greater than 0.5, and 0 otherwise.

I begin the analysis by using, as dependent variable, total factor productivity (TFP). To do so, I estimate firm-level TFP based on Olley-Pakes, Levinshon-Petrin and Wooldridge, using data from Compustat IQ. This approach has, however, two main concerns. The first one relates to the employment variable. TFP is usually measured using the number of hours worked; since Compustat IQ does not provide this information I use, as a proxy, the number of employees. The second concern, which applies only to the latter two estimates,

relates to the choice of intermediate inputs. TFP estimation based on Levinshon-Petrin and Wooldridge requires the use of intermediate inputs, which are usually the cost of material or the cost of energy. I use, as a proxy for these variables, operating expenses. Given these concerns, I complement the analysis with industry-level TFP provided by the NBER-CES Manufacturing Industry Database. The drawback of this is that it provides information only on manufacturing industries and, since it is at industry level, it doesn't allow the exclusion of the best-performing firms. Panel A of Table 10 displays the results. All the three firm-level analysis indicate that firms with high-productivity best peers increased their TFP more than other companies after 2008. A similar result is obtained for industry-level TFP. Overall, these finding support the learning channel that companies analyzed their top peers' characteristics, hypothesized that productivity was a source of resilience to the crisis and thus raised investment in this type of R&D capital.

As an additional analysis to understand the type of innovation that firm chose after 2008, I examine product-related and process-related measures. The reason for this is that investment in product quality normally entails a change in the type and variety of a firm's products, while investment in productivity often affects the production process, through expenditures on new equipment, software or structures aimed at maximizing efficiency. Examining product-related and process-related outcomes, therefore, can help deduce the type of innovation that firms acquired after the Great Recession.

I use, as product-related measures, three different variables: product differentiation, scope and the number of business segments. Product differentiation is taken from the Text-based Network Industry Classification developed by Hoberg and Phillips (2016), as outlined in part 4.2. Firm scope represents the number of product markets in which a company operates and is taken from scope data developed by Hoberg and Phillips (2024). Finally, business segments are subsections of the companies associated with specific product lines and are provided by Compustat Historical Segments. In the first three columns of Panel B of Table 10, I estimate Equation 3 using these three product-related measures as dependent variables. None of the coefficient estimates is significant for the interaction term, suggesting that firms' innovation did not affect the type of products they sold.

To size a potential change in the production process, I use firm asset redeployability estimates from Kim and Kung (2017). These estimates are constructed from capital expenditures of the Bureau of Economic Analysis (BEA) capital flow tables, and measure how easily a firm can sell its assets in the case of need. They capture, therefore, two components: asset specificity and asset liquidity. A change in a firm's production process may affect the first component and, as a result, overall asset redeployability. The fourth column of Panel B displays the results when estimating Equation 3 with asset redeployability as dependent variable. Asset redeployability decreased for all firms after 2008, but it declined 0.9 percent more for firms in industries with high-productivity best performers. This indicates that the type of innovation that companies acquired after the recession affected their asset composition and, therefore, suggests that firms invested primarily in productivity. To corroborate this result I also estimate, in the last column of the panel, a regression of asset redeployability on product differentiation for the whole period of analysis (i.e., from 2003 to 2012). The coefficient of product differentiation is not significant, indicating that investment in product quality does not affect a firm's asset composition. Hence, the decline of 0.9 percent in asset redeployability of the fourth column is likely to reflect an investment in productivity.

Overall, the results of Table 10 support the learning channel, as it suggests that firms raised intangible investment only when they deemed their top peers' R&D capital a source of resilience to the crisis.

6 Learning outcomes

Having shown that firms increased intangible investment in the case of high-productivity best peers and that this raised their productivity, a question remains open: did innovation improve their strength, allowing them to be more resilient in the event of a downturn? In this section, I try to answer this question by analyzing several measures: sales growth, efficiency, profitability, likelihood of closure or contraction, international recognition and

human capital.

6.1 Sales

As first measure of resilience, I focus on sales growth and estimate Equation 3 using this as dependent variable. Column 1 of Table 11 shows the results. Firms with high-productivity best peers increased sales growth 3 percent more than other companies after 2008. While this finding provides a general indication of improved strength, it raises concerns due to the fact that firms differ in their foreign operations. A company, for instance, may exhibit a surge in sales due to an increase in foreign operations with customers located in areas with stable economic conditions and this can't be considered a sign of resilience. To address this concerns, I estimate Equation 3 with domestic sales growth as dependent variable, using data from Compustat Historical Segments. The second column of the table shows the results, which are very similar to the ones for total sales growth: firms with high-productivity best peers raised their domestic sales growth almost 3 percent more than others.

6.2 Efficiency

As a second outcome variable, I focus on efficiency. We know, from Section 4, that firms invested primarily in productivity after 2008. Did this make their production process more efficient? To answer this question, I use again data from Compustat Historical Segments, and focus on business segments (which are, as outlined in Section 5, subsections of the companies associated with specific product lines). I look at a firm business segments' profitability between 2003 and 2007 and classify a segment as weak if its average gross profitability in these years is below the firm median. I then estimate Equation 3 using, as dependent variable, sales growth from weak segments. The third column of Table 11 displays the coefficient estimates. Treated companies increased sales growth of the weak segments 2.6 percent more than others. The fact that firms managed to improve their weakest lines suggests that companies increased overall efficiency of the production pro-

cess after 2008.

6.3 Profitability

Part 6.1 shows that firms increased their market share. Did this translate into higher profitability? The first column of Panel A of Table 12 shows the estimates of Equation 3 when using, as dependent variable, profitability, defined as net income scaled by assets. Firms with high-productivity best peers raised profits 1.3 percent more than other companies after 2008. In the second column of the panel, I examine the profitability of firms' weakest business segments, defined as in subsection 6.2. Treated firms raised profitability of their weakest product lines 3.4 percent more than others in the years that followed the recession.

6.4 Firm closures and contractions

Higher sales growth and profitability may translate into a lower likelihood of insolvency or contraction. In order to see whether this is the case, I use data from the Business Dynamics Statistics (BDS), which provides industry-level information on firm closures, establishment exits and employment changes from new, existing or closed firms. Specifically, I focus on three different variables: firm closures (the ratio between an industry's number of firm deaths and the total number of firms), establishment contractions (the ratio between an industry's number of closed establishments and the total number of establishments) and employment contractions (the ratio between an industry's firing from existing firms and total employment). Panel B of Table 12 displays the coefficient estimates. In industries with a large share of high-productivity best performers, company closures decreased 6 percent more than in other areas, establishment contractions by 3 percent and employment contractions by 11 percent.

6.5 Global recognition

Table 11 indicates that, in industries with high-productivity best performers, firms improved their domestic market share. What about their international recognition? Did they manage attract new foreign customers? Answering this question is not straightforward, because firms differ in the products or services they provide and some of them can only serve a local market. Including all companies in an analysis on global attractiveness, therefore, hardly makes sense. To address this problem, I use data from Compustat Historical Segments and look at companies' geographical segments in the five years prior to the recession, that is from 2003 and 2007. I assume that firms with no foreign segments in this period can only serve a local market, and thus exclude them from the analysis. I then estimate Equation 3 on the remaining companies using, as dependent variable, foreign sales growth (sales growth from non-U.S. geographical segments). Column 1 of Panel A of Table 13 shows the coefficient estimates. Firms with high-productivity peers increased foreign sales growth 2.3 percent more than others after 2008, suggesting an improvement in international recognition.

As a complementary test, I then look at the probability that firms increased their foreign segments after the downturn. As before, I restrict the analysis to firms with at least one foreign segment between 2003 and 2007 and estimate Equation 3 with both OLS and probit regressions. The second and third columns of Panel A show the results. Treated companies had, after 2008, a 10 percent higher probability of increasing their foreign segments than other firms. This finding is in line with the one of the first column and suggests an improvement in global attractiveness.

A raise in a firm's foreign segments may indicate an increase in a firm's foreign customers. To see whether this is true, I use data from Compustat Customer Segments. The data provides firm sales by customer, including the customer geographical area and area type. I exclude all customers for which it is not possible to retrieve information on the geographical area, and define a customer as foreign if its area is the U.S. or if its area type is STATE (which identifies customers by U.S. state). I then estimate the probability of firms to find new foreign customers after 2008. The first two columns of Panel B of Table 13

display the results. As expected, firms with high-productivity top peers were 26 percent more likely to have a new foreign customer than other companies after 2008.

As a last test on international recognition, I examine whether firms were more likely to sell to new geographical areas, using again data from Compustat Customer Segments. The last two columns of Panel B display the coefficient estimates. Treated firms had a 23 percent higher probability of expanding their sales geographically, supporting the evidence of an improved international recognition.

6.6 Employment

The last outcome variable that I examine in this section is employment. A priori, there is no reason why innovation should affect the level of employment. It may, instead, affect workers' composition, because R&D capital usually requires talent.

Measuring employee skills at firm level is not easy, because Compustat IQ provides only the total number of workers and all the variables related to wages are missing most of the time, making it is impossible to derive a measure of talent based on salary. I therefore use two alternative proxies for skilled human capital. The first one is the ratio between a firm's stock compensation and its number of employees. Since many skilled employees are rewarded with stock compensation, an increase in this ratio should signal higher workers skills (Eisfeldt et al., 2022; Dottling and Ratnovski, 2022). A potential concern with this approach is that the results are not driven by an actual increase in talent, but increased firing of unskilled workers during the recession. In order to mitigate this concern, I estimate Equation 3 both on all firms and on a sub-sample of firms that did not reduce their number of employees in 2008. Columns (1) and (2) of Panel A of Table 14 display the results. Companies with a large share of high-productivity best peers raised the stock compensation ratio 20 percent more than other firms after 2008. Within companies that did not contract employment in 2008, treated ones raised the ratio 15 percent more than others.

As a second proxy of firm-level employee skills, I use the ratio between a firm' pension

and retirement expense and its employees. An increase in this ratio, indeed, may signal a higher share of skilled employment, due to the fact that pension benefits are positively correlated with workers skills. It must be noted that this approach has two potential concerns. The first one is that, in the case of defined benefit pension plans, some firms report the actual pension expense, while others the net periodic pension cost, making cross-sectional comparability hard to interpret. The use of a difference-in-differences methodology should alleviate this problem. The second concern is similar to the one for the stock compensation ratio, i.e. that the result is biased by an increased firing of young workers during the recession. As before, I address this potential problem by estimating Equation 3 both on all firms and on firms that did not reduce their employment force between 2007 and 2008. The last two columns of Panel A of Table 14 show the main findings. Firms with high-productivity best peers raised the pension-to-employees ratio 10 or 12 percent more than other companies after 2008. This finding, combined with the one for the stock compensation ratio, suggests that treated firms changed their workforce composition, shifting towards a higher share of skilled human capital.

Since the stock compensation ratio and the pension ratio are imperfect proxies for employee skills, I complement the analysis with industry-level measures. These come from two different data sources. The first one is the NBER-CES Manufacturing Industry Database, which provides information on production and non-production workers, as well as their respective payroll. I use two proxies for workers skills. The first one is the share of non-production workers, while the second one, following Pierce and Schott (2016), is the ratio of non-production workers salary (total payroll minus production workers wages) to value added. As for the firm-level analysis, estimating Equation 3 with these measured may lead to biased results due to firing of unskilled workers during the recession. To alleviate this concern, I estimate the equation both on all manufacturing industries and only on industries in which firms didn't considerably reduce their workforce during the crisis. I construct this latter sample using firm deaths from the Business Dynamics Statistics (BDS) and selecting industries whose firing share from existing firms in 2008 is below median. Panel B of Table 14 shows the results. In treated industries, the skilled labor

share increased 2 percent more than in others areas, while the skilled income labor share by 2.5 percent. When only industries with low firing in 2008 are included, the raise is even higher, equal to 1.3 and 5 percent, respectively. These findings confirm the ones at firm level and point to a shift in firms' workforce composition towards higher skills.

The second data source that I use to measure workers skills at the industry level is the Quarterly Workforce Indicators (QWI) of the U.S. Census Bureau. This data provides information on firm employment, hiring and firing by employee characteristics (sex, age, education and ethnicity). I use two proxies for skills: the share of workers with a college degree and the average worker age. College represents the highest education in the data, so an increase in its share should signal an increase in an industry's worker skills. Similarly, a raise in the average age should signal an increase in employees' experience. I calculate the two proxies using both total employees and hired employees. The reason for this is that the former gives a general indication of workers skills, while the latter allows me to exclude the potential bias from firing of less-skilled workers during the recession. Panel C of Table 14 displays the results. In treated industries, college share of total employees increased 1.4 percent more than in other ones, while the one of hired employees by 1.7 percent. A similar finding is obtained when using average worker age: in treated industries, age of all employees increased 6.5 percent more, and age of hired ones by 5.7 percent. These results are in line with the other ones of the table, and signal an increase in skilled human capital in the years that followed the recession.

6.7 Concluding remarks on learning outcomes

In this section, I examined a variety of measures related to firm performance: sales growth, efficiency, profitability, likelihood of closure or contraction, international recognition and human capital. All the results indicate an improvement in firm strength and thus suggest a stronger resilience to future negative demand shocks.

7 Robustness

The main analysis of Sections 4, 5 and 6 examines the learning channel by using, as a mean of comparison for firms, their best-performing peers during the recession. Since this approach may raise concerns on whether the results fully capture learning, I here complement the analysis with ancillary tests on the likelihood that firm learned from other companies. Learning from competitors, indeed, depends on a variety of factors. There can be situations in which acquiring information from other companies is straightforward, and others in which it is difficult or even meaningless. The tests of this section analyze some of these situations.

One factor that may affect the likelihood of firm learning is how an industry's sales distribution changed during the downturn. Let us suppose, as an extreme case, that the crisis caused a fall in average sales growth, with no change in the firms' relative market shares. In this case, there was no reason for companies to analyze their peers' performance. If, instead, the downturn altered firms' market shares, it is possible that firms interpreted the change as a sign of relative strength or weakness and thus tried to learn from their competitors. The deeper the change, the stronger firms' incentive to observe their peers' performance and try to understand the drivers of resilience. This leads to the following prediction:

Prediction 1: *Intangible investment after the Great Recession should be stronger in industries where the downturn severely altered firms' market shares.*

To test this prediction, I calculate, for each industry, the difference between the 2008 sales growth dispersion and the 2007 one. In the first column of Panel A of Table 15, I estimate Equation 1 by adding the interaction of After with this difference. The coefficient of the interaction is positive and significant, in line with the prediction: a one standard deviation increase in the delta dispersion leads to almost a 3 percent raise in intangible investment. As an additional test, I calculate, for each industry, the average change in firms' market shares between 2007 and 2008 and estimate Equation 1 by adding the interaction with a

dummy variable that identifies industries whose change is above median. If Prediction 3 is correct, we would expect a positive estimate of the interaction between After and this dummy variable. This is the case: as shown in the second column of Panel A, firms in industries with a high change in market shares raised intangible investment 2.3 percent more than others after 2008.

Another factor that may affect the likelihood of firm learning is companies' own performance during the recession. A firm that improved or maintained its market share during the crisis had little motive to observe its peers. A company the worsened its share, instead, had a high incentive to understand the reasons for the decline and learn from its competitors. This motivates:

Prediction 2: *Intangible investment after the Great Recession should be stronger for firms that worsened their market share.*

In Panel B of Table 15, I estimate Equation 1 on two sub-samples: companies that decreased their market share between 2007 and 2008 and companies that didn't. The estimate of After is almost 33 percent for the former and only 19 percent for the latter, and the difference is significant, as shown by the p-value between the coefficients. This confirms the prediction: firms that deteriorated their sales share raised innovation more than other companies after 2008.

Predictions 1 and 2 focus on firm or industry sales during the recession. In addition to this, learning from peers may depend on factors that affect the learning potential of the comparison. Firms, indeed, differ in characteristics that may be correlated to their resilience to a downturn. When these differences are substantial, it may be difficult or useless for a company to analyze its peers' performance, because the learning potential is low. Hence, we would expect learning to be stronger in situations where firms can easily compare their performance to the ones of their competitors and acquire useful information from such comparison.

One factor that may affect the learning potential of peers' comparison relates to the type of demand that an industry faces. The more similar is output demand, the easier it is for a firm to compare its performance to the one of its peers. Tradable industries depend on national demand, while the non-tradable ones rely on on local demand, which was impacted by the recession in a heterogeneous way, due to the different declines in house prices (Mian and Sufi, 2014). Hence, we would expect a higher raise of innovation in tradable industries. In other words:

Prediction 3: *Intangible investment after the Great Recession should be stronger in tradable industries.*

In Panel C of Table 15, I estimate Equation 1 on tradable and non-tradable industries. The coefficient of After for tradable industries has a double magnitude than the one for non-tradable industries, and this difference is significant, in line with the prediction.
Another factor that can affect the learning potential of peers' comparison is an industry stage in the life cycle. Firm age and size, indeed, may affect their resilience to a downturn in several ways. Young firms have higher productivity than mature companies and this may allow them to sell their products at lower prices and keep serving costumers in spite of the reduced demand. Older firms, instead, can be more resilient to a recession thank to their solid reputation. Similarly, small companies may have higher flexibility and adapt more easily to changed economic conditions, while large ones can be more resilient thank to their reputation or a wider geographical distribution, which makes them less exposed to local demand. If age and size affect resilience, we would expect firms to learn from their peers in industries where their competitors have a similar stage in the life cycle; in this case, indeed, it would be easier for them to disentangle the main determinants of resilience and acquire useful information from other companies. This motivates:

Prediction 4: *Intangible investment after the Great Recession should be stronger in industries where firms have a similar age or size.*

I test this prediction with two different data sources. The first one is the Business Dynamics Statistics (BDS) of the U.S. Census Bureau, which provides the number of firms by detailed age and employee size. Unfortunately, the data is at 4-digit NAICS and this may raise a concern on whether firms can be considered as peers. To alleviate this problem, I also use, for the analysis on size, data from the County Business Patterns (CPB) of the U.S. Census Bureau, which provides information on the number of establishments by employee size at the all NAICS levels up to the 6-digit. It's drawback, however, is that it is at the establishment level, so it can't be considered a perfect measure of firm size. For each data source, I construct a dummy variable that identifies industries whose age (size) dispersion in 2007 is below median and interact it with After in Equation 3. Panel B of Table 16 shows the results. In industries with low age dispersion, intangible investment increased 2.5 percent more than in others after 2008. Similarly, in industries with low age dispersion, it increased 3.7 or 2.4 percent more than in the remaining areas. Both findings confirm Prediction 3.

A last element that can affect the learning potential of peers' comparison is firm turnover. An industry with high entry and exit is usually an industry with high dynamic change. In a such a context, it may be useless, for a firm, to analyze its peers' performance, as the drivers of resilience can change shortly as the industry evolves. This leads to:

Prediction 5: *Intangible investment after the Great Recession should be stronger in industries with low firm turnover.*

To assess this prediction, I use again data from the Business Dynamics Statistics (BDS). I define turnover as the sum between firms with an age of less that on year and firms that closed (firm deaths), scaled by the lagged number of total firms. I then estimate Equation 1 interacting After with a dummy variable equal to 1 for industries whose turnover in 2007 is below median. Table 17 displays the results. The coefficient of the interaction term is significant and equal to 3 percent, thus validating the prediction.

Overall, the results of Tables 15, 16 and 17 show that firms raised intangible investment when it was easier or more likely that they learned from other companies and thus support the findings of the main analysis.

8 Conclusions

This paper analyzes the long-term relationship between economic downturns and firm innovation, in the context of the Great Recession. During a recession, indeed, firms have the opportunity to learn from their peers and try to understand the main drivers of resilience. If they deem knowledge capital one of them, they may raise R&D investment in the years that follow the slowdown, in order to be better shielded from future crisis. Assuming that firms learn primarily from their best peers, I show that firms with high-R&D top peers raised intangible investment 5 percent more than others after 2008. When looking at the type of the top competitors knowledge capital, I find that companies raised innovation only in the case of high-productivity (as opposed to high-product differentiation) best peers. Using three alternative tests, I show that, in general, product differentiation was negatively correlated with firm performance during the crisis. Hence, the different companies' response to their top competitors type of R&D capital supports the learning channel hypothesis that firms raised innovation only when they deemed it a source of resilience to the downturn.

As a complementary analysis of the learning channel, I examine the type of innovation that firms acquired after 2008. If the mechanism is valid, we would expect that they invested mainly in productivity. I find that this is the case: treated firms raised their total factor productivity after 2008 more than others, and they also altered their asset structure, in line with the fact that investment in productivity often involves a change in the production process.

In the last part of the paper, I study whether innovation improved firms resilience to future downturns. I find positive outcomes on sales growth, efficiency, profitability, likelihood of

closure or contraction, international recognition and human capital, thus suggesting that R&D investment was effective in improving company performance.

These results can have policy implications for the design of research subsidies to firms, in two ways. First, they may help improve the timing of these grants, by taking into account how companies adjust their R&D capital after periods of slowdown. Second, and more important, they can provide insightful information on the design of such subsidies. If, as shown by the results of part 4.2, productivity provides more benefits than product differentiation, institutions may want to take this into account when choosing how firms can make use of the grants.

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Table 1: Appendix: Variable Definitions

Variable	**Definition**
After	A dummy variable which takes the value of 1 from the first year of the recession (2008) onward, and 0 otherwise
Average Age	The average workers' age in an industry, using data from the Quarterly Workforce Indicators (QWI)
College Share	The log of the ratio between an industry's workers with a college degree and total workers, using data from the QWI
Closures Share	The ratio between an industry's failed firms to total firms
Contractions Share	The log of the ratio between an industry's exited establishment to total establishments
$DeltaDisp_{j,07-08}$	The difference between an industry's 2008 and 2007 sales growth dispersions
Domestic Firm	A U.S. firm that doesn't have any segment outside the U.S. between 2003 and 2007
Domestic Sales Growth	Sales growth from U.S. geographical segments
Est Exit Share	The log of the ratio between an industry's establishment exited to total establishments
FiringExist Share	The log of the ratio of an industry's firing from existing firms to total employment
Firm with foreign operations	A U.S. firm that has at least one segment outside the U.S. between 2003 and 2007
Foreign Sales Growth	Sales growth from non-U.S. geographical segments
$HighGrowth^{MB}_{j,08-12}$	A dummy variable equal to 1 if an industry' market-to-book between 2008 and 2012 is above median, and 0 otherwise
$HighGrowth^{Sales}_{j,08-12}$	A dummy variable equal to 1 if an industry' sales growth between 2008 and 2012 is above median, and 0 otherwise
$HighDiff_{i,j,07}$	A dummy variable equal to 1 if both a firm's R&D ratio and product differentiation in 2007 are above the NAICS industry median, and 0 otherwise
$HighDiffBest^{S}_{j,07}$	The share of an industry's best-performing firms that are high-differentiation
$HighDiffBest_{j,07}$	A dummy variable equal to 1 if an industry' share of best-performing firms that are high-differentiation is equal or greater than 0.5, and 0 otherwise

Variable	Definition
$HighDistrChange_{j,07-08}$	A dummy variable equal to 1 if an industry's change of firm market shares between 2007 and 2008 is above median, and 0 otherwise
$HighProd_{i,j,07}$	A dummy variable equal to 1 if a firm's R&D ratio in 2007 is above the NAICS industry median and its product differentiation is below median, and 0 otherwise
$HighProdBest^{S}_{j,07}$	The share of an industry's best-performing firms that are high-productivity
$HighProdBest_{j,07}$	A dummy variable equal to 1 if an industry' share of best-performing firms that are high-productivity is equal or greater than 0.5, and 0 otherwise
$HighRD_{i,j,07}$	A dummy variable equal to 1 if a firm's R&D ratio in 2007 is above the NAICS industry median, and 0 otherwise
$HighRDBest^{S}_{j,07}$	The share of an industry's best-performing firms that are high-R&D
$HighRDBest_{j,07}$	A dummy variable equal to 1 if an industry' share of best-performing firms that are high-R&D is equal or greater than 0.5, and 0 otherwise
Intangible investment	The sum of R&D expense and 30% of SG&A expense, scaled by lagged intangible capital
$HighSimil_{j,07}$	A dummy variable equal to 1 if an industry's product similarity in 2007 is above median, and 0 otherwise
$HighTurnover_{j,07}$	A dummy variable equal to 1 if an industry's average firm turnover (the sum between new firms and firm deaths scaled by lagged total firms) in 2007 is below median, an 0 otherwise, using data from Business Dynamics Stratistics (BDS)
$LowAgeDispj, 07$	A dummy variable equal to 1 if an industry's standard deviation of firm age in 2007 is below median, an 0 otherwise
$LowSales_{j,08}$	A dummy variable equal to 1 if an industry's difference between the 2008 and 2007 sales growths is below median, and 0 otherwise
$LowSizeDisp^{BDS}_{j,07}$	A dummy variable equal to 1 if an industry's standard deviation of firm employee size in 2007 is below median, and 0 otherwise, using data from Business Dynamics Stratistics (BDS) of the U.S Census Bureau

Variable	Definition
$LowSizeDisp_{j,07}^{CPB}$	A dummy variable equal to 1 if an industry's standard deviation of establishments employee size in 2007 is below median, an 0 otherwise, using data from the Conty Business Patterns (CBP)
New Foreign Area	A dummy variable equal to 1 if a firm has at least one new customer in a new foreign area in a given year, and 0 otherwise
New Foreign Customer	A dummy variable equal to 1 if a firm has at least one new non-U.S. customer in a given year and 0 otherwise
New Foreign Segment	A dummy variable equal to 1 if a firm has at least one new non-U.S. segment in a given year and 0 otherwise
Pension Ratio	The log of the ratio between pension expense and the number of employees
Product differentiation	The average differentiation (1 minus average similarity estimated by Hoberg and Phillips (2016)) among all U.S. firms
Profitability	Operating income before depreciation minus depreciation and scaled by assets
R&D capital	Knowledge capital as estimated by Peters et al. (2017)
R&D ratio	R&D capital divided by the sum of tangible and intangible capital
Skilled Share	The log of the ratio between an industry's non-production workers and total workers, using data from the NBER-CES Manufacturing Industry Database
SkilledIncome Share	The log of the ratio between an industry's non-production wages (total payroll minus production workers wages) and value added, using data from the NBER-CES Manufacturing Industry Database
Stock Ratio	The log of the ratio between stock compensation and the number of employees
Weak Segment	A business segment whose average profitability between 2003 and 2007 is below a firm median

Table 2: Summary statistics

This table provides the main summary statistics. Market-To-Book is total market value of equity plus the book value of debt and quasi equity, normalized by total assets. Cash Flow is income before extraordinary items, plus depreciation, scaled by assets. Cash is cash scaled by total assets. Leverage is debt due in one year divided by total assets. Intangible Investment is the sum between research and development expense and 30% of selling, general and administrative expense scaled by lagged intangible capital, using intangible capital measures from Peters et al. (2017). R&D Ratio is the ratio between R&D capital and the sum of tangible and intangible capital, using estimates from Peters et al. (2017). Product Differentiation is one minus product similarity as estimated by Hoberg and Phillips (2016). Scope is the number of product markets in which a firm operates, using data from Hoberg and Phillips (2024). Business Segments is the number of firm business segments, using data from Compustat Historical Segments. Geographic Segments is the number of firm geographic segments, using data from Compustat Historical Segments. Asset redeployability is a measure of how easily a firm can sell its assets, estimated by Kim and Kung (2017). Assets have been winsorized at 5%, while Intangible Investment at the 1%, in order to remove outliers.

	Mean	St. Dev.	25^{th}	50^{th}	75^{th}	N. Obs.
Market-To-Book	2.536	3.890	1.141	1.610	2.640	47,058
Sales Growth	0.121	0.593	-0.021	0.087	0.230	46,014
Cash Flow	-0.033	0.859	-0.043	0.066	0.124	51,794
Cash	0.168	0.204	0.030	0.098	0.229	51,731
Leverage	0.032	0.167	0	0.001	0.020	51,398
Assets	1841.733	3595.786	53.981	267.502	1417.450	52,105
Intangible Investment	0.468	0.338	0.299	0.396	0.528	25,510
R&D Ratio	0.149	0.237	0	0.002	0.240	50,860
Product Differentiation	0.959	0.038	0.950	0.970	0.980	44,851
Scope	8.177	5.922	3	7	11	67,327
Business Segments	2.221	1.878	1	1	3	72,548
Geographic Segments	2.769	2.702	1	2	4	58,245
Asset redeployability	0.458	0.199	0.340	0.423	0.538	92,591

Table 3: Intangible investment after the Great Recession

In this table, I estimate Equation 1 on various samples of firms. Intangible Investment is the sum between research and development expense and 30% of selling, general and administrative expense scaled by lagged intangible capital, using intangible capital data from Peters et al. (2017). $After$ is a dummy variable which takes the value of 1 from the first year of the recession (2008) onward, and 0 otherwise. Column (1) includes all firms, Column (2) excludes firms that failed in 2008, Column(3) excludes new firms after 2008 and Column (4) includes only firms that operated for the whole period 2003-2012. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
	Intangible Investment			
	All	Excl failed in 08	Excl new after 08	Stayed 03-12
$After$	0.297***	0.297***	0.030***	0.213***
	(0.015)	(0.015)	(0.015)	(0.019)
$M/B_{i,j,t-1}$	0.009***	0.009***	0.009***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
$SalesGrowth_{i,j,t-1}$	0.047***	0.047***	0.047***	0.070***
	(0.002)	(0.002)	(0.003)	(0.004)
$CashFlow_{i,j,t-1}$	0.034***	0.033***	0.034***	0.031***
	(0.005)	(0.005)	(0.005)	(0.007)
$Cash_{i,j,t-1}$	0.028***	0.030***	0.028***	0.017
	(0.010)	(0.010)	(0.010)	(0.012)
$Leverage_{i,j,t-1}$	-0.070**	-0.071***	-0.069***	-0.102***
	(0.014)	(0.014)	(0.014)	(0.019)
$TotAssets_{i,j,t-1}$	0.048***	0.048***	0.048***	0.068***
	(0.003)	(0.003)	(0.003)	(0.004)
$Age_{i,j,t-1}$	-0.538***	-0.539***	-0.540***	-0.447***
	(0.018)	(0.018)	(0.018)	(0.024)
$HHI_{j,t-1}$	-0.011*	-0.011*	-0.009	-0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
Firm FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
R^2	0.136	0.148	0.148	0.151
N. Obs.	21,860	21,748	21,576	12,538

Table 4: Intangible investment - Monetary policy stimulus

In this table, I show the results of the analysis in part 3.1. Small (Big) firms are firms whose book value of assets is below (above) median in 2007. High cash (Low cash) firms are firms whose cash-to-assets ratio in 2007 is above (below) median. No dividend (Dividend) firms are forms that did not pay (that payed) dividends in 2007. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. Non-interacted terms are included but not reported. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
	Intangible Investment					
	Small	Big	High cash	Low cash	No dividend	Dividend
After	0.251***	0.233***	0.227***	0.240***	0.240***	0.205***
	(0.030)	(0.024)	(0.025)	(0.028)	(0.023)	(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.121	0.079	0.096	0.111	0.142	0.079
N. Obs.	4,810	6,748	7,023	5,535	7,406	5,152
p-val of coeff. similarity		0.633		0.501		0.276
			Panel B			
	Tangible Investment					
	Small	Big	High cash	Low cash	No dividend	Dividend
After	0.396***	0.225***	0.453***	0.113***	0.375***	0.151***
	(0.080)	(0.026)	(0.055)	(0.029)	(0.051)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.087	0.150	0.094	0.118	0.115	0.100
N. Obs.	6,306	10,724	10,799	12,231	12,391	10,639
p-val of coeff. similarity		0.062		0.043		0.038

Table 5: Intangible investment - Industry growth

In this table, I show the results of the analysis in part 3.2. $HighGrowth_{j,08-12}$ is a dummy variable equal to 1 if an industry' market-to-book (sales growth) between 2008 and 2012 is above median, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. Non-interacted terms are included but not reported. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)
	Intangible Investment	
$After$	0.581**	0.545**
	(0.263)	(0.264)
$HighGrowth^{MB}_{j,08-12}$	0.321*	
	(0.173)	
$After \cdot HighGrowth^{MB}_{j,08-12}$	-0.020**	
	(0.007)	
$HighGrowth^{Sales}_{j,08-12}$		0.204*
		(0.112)
$After \cdot HighGrowth^{Sales}_{j,08-12}$		0.035***
		(0.007)
Controls	Yes	Yes
Sector-Year FE	Yes	Yes
R^2	0.205	0.203
N. Obs.	21,749	21,749

Table 6: Intangible investment - Recession as a stimulus to innovate

In this table, I show the results of the analysis in part 3.3. $LowSales_{j,08}$ is a dummy variable equal to 1 if an industry's difference between the 2008-2007 and 2007-2006 sales growths is below median, and 0 otherwise. $HighSimil_{j,07}$ is a dummy variable equal to 1 if an industry's product similarity in 2007 is above median, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. Non-interacted terms are included but not reported. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)
Panel A		
	Intangible Investment	
	Low R&D	High R&D
$After$	0.280***	0.283***
	(0.030)	(0.017)
Controls	Yes	Yes s
Firm FE	Yes	Yes
Year FE	Yes	Yes
R^2	0.159	0.121
N. Obs.	6,724	9,670
p-val of coeff. similarity		0.362
Panel B		
	Intangible Investment	
$After$	0.731**	
	(0.269)	
$After \cdot LowSales_{j,08}$	-.014**	
	(0.007)	
Controls	Yes	
Sector-Year FE	Yes	
R^2	0.189	
N. Obs.	21,414	
Panel C		
	Intangible Investment	
$After$	-0.018	0.034**
	(0.075)	(0.011)
$After \cdot HHI_{j,07}$	0.008**	
	(0.004)	
$After \cdot HighSimil_{j,07}$		-0.028***
		(0.006)
Controls	Yes	Yes
Sector-Year FE	Yes	Yes
R^2	0.183	0.172
N. Obs.	20,583	21,307

Table 7: Learning from peers

In this table, I estimate Equation 2. Panel A shows the results for the share of an industry's best-performing firms that are high-R&D (high-differentiation, high-productivity). Panel B shows, instead, the results for a dummy variable equal to 1 if the industry share of best-performing firms that are high-R&D (high-differentiation, high-productivity) is equal or greater than 0.5, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)
Panel A: using shares			
	Intangible Investment		
$After$	-0.015	0.012	-0.020
	(0.079)	(0.007)	(0.082)
$HighRDBest^{S}_{j,07}$	-0.071***		
	(0.011)		
$After \cdot HighRDBest^{S}_{j,07}$	0.093***		
	(0.017)		
$HighDiffBest^{S}_{j,07}$		0.017	
		(0.014)	
$After \cdot HighDiffBest^{S}_{j,07}$		-0.012	
		(0.020)	
$HighProdBest^{S}_{j,07}$			-0.075***
			(0.19)
$After \cdot HighProdBest^{S}_{j,07}$			0.098***
			(0.027)
Controls	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
R^2	0.192	0.198	0.199
N. Obs.	15,842	15,710	14,848
Panel B: using dummy variables			
	Intangible Investment		
$After$	-0.001	0.011	-0.016
	(0.079)	(0.077)	(0.082)
$HighRDBest_{j,07}$	-0.060***		
	(0.006)		
$After \cdot HighRDBest_{j,07}$	0.046***		
	(0.009)		
$HighDiffBest_{j,07}$		-0.005	
		(0.006)	
$After \cdot HighDiffBest_{j,07}$		-0.004	
		(0.010)	
$HighProdBest_{j,07}$			-0.036***
			(0.006)
$After \cdot HighProdBest_{j,07}$			0.028***
			(0.009)
Controls	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
R^2	0.194	0.198	0.200
N. Obs.	15,842	15,710	14,848

Table 8: TFP of high-differentiation and high-productivity firms

In this table, I estimate total factor productivity (TFP) for high-differentiated and high-productivity firms based on Olley-Pakes (OP), Levinshon-Petrin (LP) and Wooldridge (WRDG). $HighDiff_{i,j,07}$ is a dummy variable equal to 1 if a firm has both R&D ratio and product differentiation above its industry median in 2007, and 0 otherwise. $HighProd_{i,j,07}$ is a dummy variable equal to 1 if a firm has R&D ratio above its industry median and product differentiation below its industry median in 2007, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period goes from 2003 to 2007. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)
Panel A			
	Ln(TFP)		
	OP	LP	WRDG
$HighDiff_{i,j,07}$	-0.020	0.030	0.025
	(0.027)	(0.029)	(0.031)
R^2	0.078	0.095	0.093
N. Obs.	12,758	12,758	12,758
Panel B			
	Ln(TFP)		
	OP	LP	WRDG
$HighProd_{i,j,07}$	0.255***	0.255***	0.254***
	(0.025)	(0.027)	(0.028)
R^2	0.085	0.101	0.098
N. Obs.	12,758	12,758	12,758

Table 9: Resilience of high-differentiation and high-productivity firms

In this table, I analyze the link between a firm's type of R&D capital in 2007 and its performance in 2008. Bottom is a dummy variable equal to 1 if a firms is in the bottom quartile of the sales growth between 2007 and 2008. Dom Sales Growth is the sales growth to U.S. customers between 2007 and 2008. New Cust Sales Growth is the sales growth to new customers between 2007 and 2008. $HighDiff_{i,j,07}$ is a dummy variable equal to 1 if a firm has both R&D ratio and product differentiation above its industry median in 2007, and 0 otherwise. $HighProd_{i,j,07}$ is a dummy variable equal to 1 if a firm has R&D ratio above its industry median and product differentiation below its industry median in 2007, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
	Panel A			
	Bottom		Dom Sales Growth	New Cust Sales Growth
	OLS	Probit		
$HighDiff_{i,j,07}$	0.040**	0.234**	-0.034*	-0.497**
	(0.020)	(0.087)	(0.019)	(0.234)
Controls	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.157	0.202	0.079	0.128
N. Obs.	2,403	2,403	1,989	278
	Panel B			
	Bottom		Dom Sales Growth	New Cust Sales Growth
	OLS	Probit		
$HighProd_{i,j,07}$	0.012	0.004	-0.012	0.197
	(0.019)	(0.084)	(0.018)	(0.210)
Controls	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.155	0.199	0.077	0.115
N. Obs.	2,403	2,403	1,989	278

Table 10: Innovation type in industries with high-productivity best performers

In this table, I estimate Equation 3 using firm-level TFP, industry-level TFP, product differentiation, scope, the number of business segments and asset redeployability. Firm-level TFP is estimated based on Olley-Pakes (OP), Levinshon-Petrin (LP) and Wooldridge (WRDG). Industry-level TFP is taken from the NBER-CES Manufacturing Industry Database. Prod Diff is product differentiation, Scope is the log of firm scope, New Bus Seg is the probability of having at least one new business segment (estimated with probit) and Redeployability is asset redeployability. $HighProdBest_{j,07}$ is a dummy variable equal to 1 if an industry' share of best-performing firms that are high-productivity is equal or greater than 0.5, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)	
	Panel A: TFP				
	Firm-level Ln(TFP)			Industry-level Ln(TFP)	
	OP	LP	WRDG		
$After$	0.523***	0.533***	0.522***	0.062***	
	(0.035)	(0.038)	(0.038)	(0.014)	
$HighProdBest_{j,07}$	-0.237***	-0.239***	-0.222***	-0.013	
	(0.021)	(0.023)	(0.022)	(0.009)	
$After \cdot HighProdBest_{j,07}$	0.073**	0.074**	0.074**	0.026*	
	(0.030)	(0.033)	(0.033)	(0.014)	
Controls	Yes	Yes	Yes	Yes	
Sector FE	Yes	Yes	Yes	Yes	
R^2	0.079	0.125	0.138	0.054	
N. Obs.	27,280	27,280	27,280	1,830	
	Panel B: product and process measures				
	Prod Diff	Scope	New Bus Seg	Redeployability	
$After$	0.020	0.560	-0.017*	-0.009***	
	(0.029)	(0.632)	(0.063)	(0.002)	
$HighProdBest_{j,07}$	-0.001	-0.004	0.023	-0.013***	
	(0.001)	(0.017)	(0.036)	(0.001)	
$After \cdot HighProdBest_{j,07}$	-0.001	0.006	-.0144	-0.006***	
	(0.001)	(0.025)	(0.051)	(0.001)	
$ProdDiff_{i,t}$					0.008
					(0.006)
Controls	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes
Firm FE	No	No	No	No	Yes
R^2	0.095	0.122	0.023	0.506	0.031
N. Obs.	17,291	19,923	22,313	24,977	24,655

Table 11: Outcomes - Sales growth and Efficiency

In this table, I show the results of the analysis outlined in parts 6.1 and 6.2. The sample includes all U.S firms. Domestic Sales Growth is sales growth from U.S. segments. Weak Seg Sales Growth is sales growth of a firm's least profitable segments in the period 2003-2007. The time period goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)
	Sales Growth	Domestic Sales Growth	Weak Seg Sales Growth
$After$	0.034**	0.033**	-0.023
	(0.013)	(0.014)	(0.015)
$HighProdBest_{j,07}$	-0.023**	-0.023**	-0.004
	(0.008)	(0.008)	(0.008)
$After \cdot HighProdBest_{j,07}$	0.031**	0.032**	0.026**
	(0.011)	(0.010)	(0.012)
$M/B_{i,j,t-1}$	0.004***	0.017***	0.008***
	(0.001)	(0.001)	(0.001)
$CashFlow_{i,j,t-1}$	-0.031***	-0.012	-0.023**
	(0.005)	(0.007)	(0.006)
$Cash_{i,j,t-1}$	0.051***	-0.041**	-0.004
	(0.015)	(0.015)	(0.016)
$Leverage_{i,j,t-1}$	-0.056**	-0.017	-0.065**
	(0.022)	(0.020)	(0.021)
$TotAssets_{i,j,t-1}$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
$Age_{i,j,t-1}$	-0.175***	-0.108***	-0.151***
	(0.007)	(0.008)	(0.008)
$HHI_{j,t-1}$	-0.007**	-0.002	-0.008**
	(0.004)	(0.003)	(0.004)
Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
R^2	0.070	0.051	0.066
N. Obs.	27,174	22,833	20,244

Table 12: Outcomes - Profitability and Firm closures/contractions

In this table, I show the results of the analysis of parts 6.3 and 6.4. Profitability is operating income before depreciation minus depreciation and scaled by assets. Weak Seg Profitability is gross profitability (sales minus cost of goods sold scaled by assets) of a firm's least profitable segments in the period 2003-2007. Closures Share is the ratio between an industry's failed firms to total firms. Est Exit Share is the ratio between an industry's establishment exited to total establishments. FiringExist Share is the ratio of an industry firing from existing firms to total employment. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel A: profitability

	Profitability	Weak Seg Profitability
$After$	-0.063***	-0.049**
	(0.009)	(0.016)
$HighProdBest_{j,07}$	-0.025***	-0.019**
	(0.005)	(0.009)
$After \cdot HighProdBest_{j,07}$	0.013*	0.034**
	(0.007)	(0.012)
Controls	Yes	Yes
Year FE	Yes	Yes
Sector FE	Yes	Yes
R^2	0.437	0.214
N. Obs.	26,498	14,210

Panel B: closures and contractions

	Closures Share	Est exit Share	FiringExist Share
$After$	-0.201***	-0.289***	-0.488***
	(0.008)	(0.007)	(0.011)
$HighProdBest_{j,07}$	0.082***	0.046***	0.104***
	(0.005)	(0.004)	(0.007)
$After \cdot HPBest_{j,07}$	-0.061***	-0.028***	-0.111***
	(0.006)	(0.006)	(0.009)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
R^2	0.502	0.555	0.315
N. Obs.	24,663	24,786	24,790

Table 13: Outcomes - Global recognition

In this table, I show the results of the analysis outlined in part 6.5. The sample includes U.S firms with foreign operations, defined as firms with at least one foreign segment between 2003 and 2009. New Foreign Segment is a dummy variable equal to 1 if a firm has at least one new geographical segment outside the U.S in a given year, and 0 otherwise. New Foreign Cust is a dummy variable equal to 1 if a firm has at least one new foreign customer in a given year, and 0 otherwise. New Foreign Area is a dummy variable equal to 1 if a firm has at least one new customer in a new foreign area in a given year, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth (except when the dependent variable is foreign sales growth), cash flow, cash, log of total assets, log of age and log of HHI. The time period goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel A

	Foreign Sales Growth	New Foreign Segment	
		OLS	Probit
$After$	-0.040**	-0.043**	-0.210**
	(0.018)	(0.017)	(0.081)
$HighProdBest_{j,07}$	-0.006	0.006	0.028
	(0.010)	(0.009)	(0.041)
$After \cdot HighProdBest_{j,07}$	0.023*	0.022*	0.102*
	(0.013)	(0.013)	(0.059)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
R^2	0.051	0.008	0.009
N. Obs.	15,461	11,652	11,630

Panel B

	New Foreign Customer		New Foreign Area	
	OLS	Probit	OLS	Probit
$After$	-0.045	-0.140	-0.054	-0.203
	(0.056)	(0.167)	(0.051)	(0.177)
$HighProdBest_{j,07}$	-0.042	-0.120	-0.051*	-0.166
	(0.034)	(0.100)	(0.031)	(0.104)
$After \cdot HighProdBest_{j,07}$	0.086**	0.258**	0.065*	0.230*
	(0.043)	(0.128)	(0.039)	(0.135)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.043	0.034	0.041	0.037
N. Obs.	1,823	1,822	1,823	1,823

Table 14: Outcomes - Human capital

In this table, I show the results of the analysis outlined in part 6.6. Stock Ratio is the stock compensation divided by the number of employees. Pension Ratio is the pension expense divided by the number of employees. Skilled Share is non-production workers divided by total workers. SkilledIncome Share is non-production wages (total payroll minus production workers wages) divided by value added. College Share is workers with a college degree divided by total workers. Average Age is the average workers' age. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period goes from 2003 to 2012. Non-interacted terms are included but not reported. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel A: Compustat IQ measures

	Stock Ratio		Pension Ratio	
	All	No emp decr	All	No emp decr
$After$	0.791**	0.790**	0.164***	0.107
	(0.029)	(0.030)	(0.051)	(0.084)
$After \cdot HProdB_{j,07}$	0.198*	0.154*	0.099***	0.126**
	(0.052)	(0.085)	(0.038)	(0.027)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.371	0.410	0.319	0.352
N. Obs.	14,777	5,490	13,702	5,194

Panel B: NBER measures

	Skilled Share		SkilledIncome Share	
	All	Low Firing	All	Low Firing
$After$	0.027**	0.026**	-0.086***	-0.096***
	(0.009)	(0.009)	(0.015)	(0.016)
$After \cdot HighProdBest_{j,07}$	0.019**	0.013***	0.025**	0.051***
	(0.007)	(0.007)	(0.011)	(0.012)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.219	0.242	0.490	0.525
N. Obs.	13,294	11,406	13,294	11,406

Panel C: QWI measures

	College Share		Average Age	
	Emp	Hiring	Emp	Hiring
$After$	-0.007	-0.069***	0.041***	0.125***
	(0.009)	(0.002)	(0.023)	(o.024)
$After \cdot HighProdBest_{j,07}$	0.014*	0.017	0.064***	0.056***
	(0.007)	(0.007)	(0.020)	(0.021)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
R^2	0.577	0.548	0.520	0.608
N. Obs.	24,708	23,621	23,621	23,621

Table 15: Robustness: Likelihood of learning from peers

In this table, I show the tests of Predictions 1 and 2 outlined in Section 7. $DeltaDisp_{j,07-08}$ is the difference between an industry's 2008 and 2007 sales growth dispersions. $HighDistrChange_{j,07-08}$ is a dummy variable equal to 1 if an industry's change of firm market shares between 2007 and 2008 is above median, and 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel A: Prediction 1

	Intangible Investment	
$After$	-0.126	0.707**
	(0.294)	(0.269)
$DeltaDisp_{j,07-08}$	0.031**	
	(0.011)	
$After \cdot DeltaDisp_{j,07-08}$	0.029*	
	(0.016)	
$HighDistrChange_{j,07-08}$		-0.002
		(0.009)
$After \cdot HighDistrChange_{j,07-08}$		0.022*
		(0.013)
Controls	Yes	Yes
Sector-Year FE	Yes	Yes
R^2	0.190	0.189
N. Obs.	20,974	21,414

Panel C: Prediction 2

	Intangible Investment	
	Worsened	Improved
$After$	0.329***	0.191***
	(0.026)	(0.022)
Controls	Yes	Yes
Firm FE	Yes	Yes
R^2	0.155	0.092
N. Obs.	7,617	8,283
p-val of coeff. similarity		0.042

Table 16: Robustness: Likelihood of learning from peers (cont)

In this table, I show the tests of Predictions 3 and 4 outlined in Section 7. $LowAgeDispj,07$ is a dummy variable equal to 1 if an industry's standard deviation of firm age in 2007 is below median, an 0 otherwise. $LowSizeDispj,07$ is a dummy variable equal to 1 if an industry's standard deviation of firm (establishments) employee size in 2007 is below median, an 0 otherwise, using data from the Business Dynamics Statistics (BDS) or and County Business Patterns (CPB). The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

Panel B: Prediction 3

	Intangible Investment		
	All	Tradable	Non-Tradable
$After$	0.297***	0.316***	0.153***
	(0.015)	(0.016)	(0.048)
Controls	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
R^2	0.137	0.141	0.113
N. Obs.	21,854	19,725	2,129
p-val of coeff. similarity			0.042

Panel B: Prediction 4

	Intangible Investment		
$After$	-0.113	-0.111	-0.117
	(0.293)	(0.292)	(0.294)
$LowAgeDisp_{j,07}$	0.001		
	(0.007)		
$After \cdot LowAgeDisp_{j,07}$	0.025**		
	(0.010)		
$LowSizeDisp^{BDS}_{j,07}$		0.033***	
		(0.007)	
$After \cdot LowSizeDisp^{BDS}_{j,07}$		0.036***	
		(0.011)	
$LowSizeDisp^{CBP}_{j,07}$			0.022**
			(0.008)
$After \cdot LowSizeDisp^{CBP}_{j,07}$			0.023*
			(0.012)
Controls	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
R^2	0.195	0.199	0.192
N. Obs.	19,802	19,802	17,336

Table 17: Robustness: Likelihood of learning from peers (cont)

In this table, I show the tests of Prediction 5 outlined in Section 7. $HighTurnover_{j,07}$ is a dummy variable equal to 1 if an industry's average firm turnover (the sum between firms less than one year old and firm deaths scaled by lagged total firms) in 2007 is below median, an 0 otherwise. The specifications control for the lagged market-to-book ratio, sales growth, cash flow, cash, leverage, log of total assets, log of age and log of HHI. The time period of the analysis goes from 2003 to 2012. Heteroskedasticity-robust standard errors are reported in parentheses. *, ** and *** denote respectively statistical significance at the 10%, 5% and 1% levels.

	Intangible Investment
$After$	-0.138
	(0.298)
$HighTurnover_{j,07}$	-0.015*
	(0.008)
$After \cdot HighTurnover_{j,07}$	0.030**
	(0.012)
Controls	Yes
Sector-Year FE	Yes
R^2	0.199
N. Obs.	20,058