Learning to innovate in recessions

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Abstract

Innovating in downturns can affect corporate success because it improves a firm's position relative to competitors during the recovery period. However, increased uncertainty and more binding financial constraints complicate such innovation activity. I find that past experience with innovation during recessions improves a firm's ability to invest in R&D when a new downturn hits. This result holds controlling for traditional drivers of innovation as cumulated innovations and financial constraints, as well as using variations of a firm's financial strength to mitigate endogeneity concerns. Moreover, difference-in-differences results show that past experience with innovation during recessions is beneficial to patent outcomes after a new recession. Overall, this paper provides novel evidence on how business cycles shape innovative capabilities.

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1. Introduction

Investment in research and development (R&D) is a key driver of technological progress and economic prosperity. It is therefore important to understand why some companies are more innovative than others. Toward that end, scholars have examined such various factors as cash flow and equity financing (Brown et al. 2009; Himmelberg and Petersen 1994), product market competition (Aghion et al. 2005), banking development (Amore et al. 2013; Chava et al. 2013; Cornaggia et al. 2014), labor laws (Acharya et al. 2013), managerial compensation (Manso 2011), ownership and governance characteristics (Aghion et al. 2013; Atanassov 2013; Ferreira et al. 2012) as well as CEO traits and expertise (Custodio et al. 2013; Galasso and Simcoe 2011). What emerges from these studies is that successful innovation is a highly complex process requiring a combination of favorable credit conditions, managerial incentives, and unique human and organizational capital.

It is difficult to develop successful innovations in normal times. During hard times, the challenge is likely amplified given demand uncertainty, revenue declines, and financial constraints. Despite these problems, firms aspire to innovate during recessions. According to Ken Chenault, the CEO of American Express, "a difficult economic environment argues for the need to innovate more, not pull back"; and Adalio Sanchez, general manager of IBM's System X server business, believes that "recession is a catalyst for increased innovation". In fact, more than 90% of executives surveyed by Booz & Company (2009) during the Great Recession remarked that their preparation for the upturn depended critically on innovation.

What drives innovative capabilities in recessions? I document that the experience of innovation during *past* recessions has a positive and significant effect on firms' innovative performance and recovery when a *new* downturn hits. In line with managerial theories of strategic persistence (see e.g. Audia et al. 2000), results suggest that undertaking innovative activities during downturns is a salient experience that contribute to develop specific competencies valuable to roar out of future recessions.

I conduct the empirical analysis using data on US-listed companies matched with the NBER patent data set. The sample period, from 1976 to 2006, includes three downturns of the US economy: the early 1980s, the early 1990s and 2001. I start by measuring investment in innovation inputs during the early 1980s recession. To this end, I construct a variable measuring R&D increases during recession. I then use this variable to predict R&D expenditures during the two post-1980s recession periods (namely early 1990s and 2001), after controlling for traditional drivers of innovation in hard times, e.g. financial constraints (Aghion et al. 2012; Campello et al. 2010) and knowledge stock (Archibugi et al. 2012).[1] These controls help address the concern that firms with innovation experience in past recessions may innovate more in a new recession *because* they are less financially constrained and/or endowed with a larger stock of innovations.[2]

Results indicate that having increased (reduced) innovative activities in the early 1980s recession has a positive (negative) and significant effect on R&D investment during subsequent recessions. I validate this result in several ways. First, I verify that results hold using national and state-specific recession periods. Second, I mitigate endogeneity concerns using pre-recession components of a firm's financial strength as instruments for the propensity to innovate in recession. Third, I check that R&D in *normal* years does not have a similar effect. Fourth, I show that innovation-*unrelated* investment during past recessions does not predict innovation in subsequent recessions.

These results are consistent with the notion of *strategic persistence* advanced by organizational and strategy scholars. This literature suggests that past strategies have bearing on the present (Boeker 1997) because, as result of organizational learning, firms tend to stick with actions that have worked in the past (Audia et al. 2000). Similarly, finance scholars have drawn on learning theories to understand whether experience generates persistent behaviors that

[1] Thus, the empirical setting is similar to Fahlenbrach et al. (2012), who use the stock market performance of banks during the 1998 crisis to predict bank performance during the 2008 crisis.
[2] Controlling for the stock of innovations is also important to rule out the possibility that firms innovating in past recessions had more existing patents that could be pledged as collateral, facilitating the credit access needed to fuel their innovation during the new downturn.

improve investors' strategies or whether those persistent behaviors would suffer from psychological biases detrimental to performance (see e.g. Chiang et al. 2011 on IPO auctions).

I discuss the performance implications of the findings so far from a learning lens. On the one hand, having conducted innovative activities during past recessions may have spurred the development of recession-specific competencies, for instance related to reallocating projects, dealing with financial constraints and retaining or attracting key innovative employees. This rational organizational learning predicts that, relative to firms with experience of innovation during past recessions, firms with such experience are better able to invest in high-quality R&D projects during a new recession and should thus exhibit better subsequent performance. On the other hand, firms with experience of innovation during past recessions may have become overly optimistic about the ability to successfully innovate again in similar situations. This naïve reinforcement organizational learning would induce a dysfunctional persistence whereby, during a new recession, firms that experienced innovation in past recession invest in R&D projects of both high and low quality and thus experience lower performance.

In other words, both rational learning and naïve reinforcement learning predict that firms with experience of innovation in past recessions engage more in R&D during a new recession; however, the performance effect are different (i.e. positive in rational learning and negative in naïve reinforcement learning).

I use a difference-in-differences model to discriminate between these two mechanisms. In particular, I interact a dummy variable set equal to 1 for the post-recession years with the variable measuring a firm's experience of innovation during previous recession. Results indicate that past experience of recession-R&D increases the quality of a firm's innovation outputs, as measured by future citations received (Trajtenberg 1990), and innovative efficiency, as measured by citations per R&D dollar (Hirshleifer et al. 2013).

This paper relates to a growing literature that documents how exposure to past recessions affects individual risk aversion (Malmendier and Nagel 2011), social preferences (Giuliano and Spilimbergo 2013), CEO style (Schoar and Zuo

2012), and inventors' productivity (Shu 2012). Specifically, the paper is closely related to Fahlenbrach et al. (2012), who adopt an organizational viewpoint and show that banks performing the worst in the 1998 crisis (following Russia's default on some debt obligations) also performed the worst during the 2008 crisis. The paper is also close to Cronqvist et al. (2009), who document a strong persistence of investment and financing policies, possibly attributable to corporate culture. I contribute to this research by identifying a specific mechanism, namely persistence of innovative behavior over business cycles, as one that helps understand the heterogeneous response of firms to recession periods.

This paper is also related to a research on the differences between innovative and non-innovative firms. Geroski et al. (1993) find that the profit margin of innovative companies is less sensitive to cyclical downturns. Archibugi et al. (2012) show that compared with non-innovative firms, innovative firms implemented less extensive reductions in innovation activities during the economic crisis of 2008. I extend these insights by showing that the innovative capabilities most valuable for overcoming a new recession are specifically those that were built during past recessions. In other words, the accumulation of innovative experience over different stages of the business cycle strongly shapes the effect of past innovative knowledge on future innovation performance.

2. Data and variables

Firm-level data come from the Compustat dataset. I exclude companies with nonpositive values of revenues, companies with missing R&D[3], and companies headquartered outside the US. I then follow the procedure in Bessen (2009) to match Compustat firms with patent data from the National Bureau of Economic Research (NBER) dataset. This dataset contains information on all the patents awarded by the US Patent and Trademark Office (USPTO)—and on the citations made to these patents—for the period 1976–2006 (Hall et al. 2001). Recession periods for the US economy are identified in two ways. First, I follow Owyang et

[3] In robustness checks, I verify that results are robust to treating missing-R&D firms in different ways as proposed by existing works.

al. (2005) to identify recession years specific to a given state. Second, I use the official NBER business cycle dates and classify as recessionary a year in which at least two quarters were in recession. Given the time period covered in the NBER patent dataset, the analysis includes three recession periods: the downturn of the early 1980s, which initiated in 1980 and, after a mild recovery in 1981, bottomed out in 1982; the early 1990s recession (from July 1990 to March 1991); and the tech bubble of 2001.

I restrict the analysis to firms that are present in the sample for at least one year prior to the early 1980s recession and one year after the early 1990s recession. This restriction is necessary because the goal is to analyze firms that changed R&D during recession and that were affected by more than one recession over the period considered. However, I check that this restriction has no meaningful effect on the paper's main findings.

For the empirical analysis, I need an explanatory variable measuring those innovation activities specific to a given recession. Patent applications in recession years may be helpful; however, it is hard to establish whether the innovative process behind the patent application was initiated in the same (recession) year of the application or in previous (non-recession) years. To overcome this limitation, I measure innovation in hard times using innovation inputs. Specifically, I construct an indicator equal to one for firms that undertake an (average) relevant increase in R&D expenditures during the early 1980s recession, relative to the previous non-recession year; and equal to zero for firms that do not report any relevant increase in R&D expenditures. Similar to Eberhart et al. (2004), I classify as economically relevant those R&D increases of at least 5% in both the dollar amount of R&D expenses and the ratio of R&D expenses to the book value of total assets. While I adopt these criteria to construct the main explanatory variable, in additional tests I verify the robustness to the use of alternative thresholds (e.g. 3% or 7%).

As main measure of innovation inputs, I use the logarithm of 1 plus R&D (rather than simply R&D) so as to avoid dropping firms with zero R&D expenses. I also involve in the analysis innovation outputs constructed using patent data, which is a common approach in the innovation literature (Griliches 1990).

Following that literature, I date patents by the year of application, which is a more accurate indication (than is the granting year) of when the innovation process actually took place. I then consider patent counts weighted by the number of citations appearing in later patent applications. Using those subsequent patent citations is useful to account for differences in the quality of patents. Forward citations have been shown to reflect both the technological importance (Jaffe et al. 2000) and economic significance (Hall et al. 2005; Trajtenberg 1990) of patents. To mitigate any bias from later-filed patents having less time to be cited, I adjust citations using the truncation weights from the NBER data set (Hall et al. 2001, 2005).

Finally, I construct a number of variables suited to capturing differences in size, profitability, and financial constraints across firms. Specifically, I measure firm size as the logarithm of a firm’s revenues. Firm age is computed as the logarithm of the number of years a firm has been in Compustat; controlling for age is important also because firm age, like firm size, is a key determinant of financial constraints (Hadlock and Pierce 2010). Capital-to-labor ratio is computed as the logarithm of property, plants, and equipment divided by the number of employees. Profitability is measured by the return on assets (ROA), which is calculated as earnings before interest, taxes, depreciation and amortization (EBITDA) divided by total assets.

Summary statistics for these variables (as of 1982) are reported in Table 1, and detailed definitions are in Appendix 1.

3. Recession-specific innovation and R&D in next recessions

3.1. Main finding

The goal of this section is to establish whether innovation increases during past recessions affect the propensity to invest in R&D during a new recession. To this end, I estimate the following model:

$$\mathrm{Ln}[1+(\mathrm{R\&D})_{i,t}] = \alpha + \beta v_{82} + \mathrm{X}_{i,t}\delta + \gamma_j + \lambda_t + \varepsilon_{i,t} \qquad (1)$$

Here the main explanatory variable, v_{82}, is the dummy equal to one for R&D increases in the early 1980s recession. The dependent variable is the logarithm of 1 plus R&D expenditures for firm i when time t is equal to the early 1990s or 2001 recession years, i.e. the next downturns after 1982.

Firms that innovated in a previous recession may be larger, less financially constrained, and endowed with more innovative knowledge than their non-innovating peers—all factors that enable the innovators to respond more successfully to the next recession (Archibugi et al. 2012; Geroski et al. 1993). Hence it is crucial to control for a wide array of firm characteristics, which are included in the X vector. Specifically, I control for firm sales, firm age, capital/labor ratio, and ROA to absorb differences in profitability and other firm characteristics;[4] I also control for a firm's stock of existing knowledge by using the logarithm of cumulated patent counts. Finally, the model incorporates year dummies, to absorb the specific effect of each recession year, as well as 2-digit SIC dummies, γ_j, to control to sectoral heterogeneity (note that I cannot control for firm fixed effects because the main explanatory variable, v_{82}, is time invariant). Standard errors are clustered at the firm level to allow for firm-level correlation of residuals across the two recession years (in Section 3.5, I confirm the main findings while computing the standard errors in alternative ways).

As shown in columns (1)-(2) of Table 2, Panel A, firms that increased R&D in the past downturn invest more in R&D also during the new state-specific recession years. This result is obtained controlling for firm size, capital to labor ratio, firm age, ROA and the stock of innovation. I find that, consistently with results reported in the extant literature, there is a strong positive correlation between a firm's innovation stock and its R&D expenditures. Even so, the effect of previous recession-innovation remains both positive and statistically significant.

Results reported so far are obtained pooling early 1990s and 2001 recessions. In columns (3) and (4), I estimate the model separately for those two

[4] The baseline specification controls for current firm characteristics; however, in robustness regressions I validate the main finding while controlling for both current and 1982 firm characteristics.

recession periods. As expected, the effect of innovation during the 1980s recession is strong on R&D expenses during the 1990 recession, and, while the effect remains positive, it is smaller and statistically less significant on R&D in the 2001 recession. In Panel B, I confirm these results using national, rather than state-specific, recession years

3.2. Alternative channels

One concern with findings so far is that corporate innovators during past recessions were less affected by a subsequent recession—for example, because existing patents protected them from rivals' actions during periods of shrinking demand. Controlling for a firm's cumulated knowledge and ROA increases confidence that the main result is driven in particular by the firm's innovation effort during the previous recession. Yet, to rule out this concern more explicitly, I check for whether the recession periods of early 1990s and 2001 affected firms differently according as whether or not they increased innovation during the early 1980s recession. Using *t*-tests to assess the difference, I find that the drop in profits (as measured by earnings before interest, taxes and depreciation) experienced by the two firm types is not statistically significant.

Next, I address the concern that the findings in Table 2 are not specific R&D undertaken in recession but rather driven by a general propensity to innovate (in normal and recession years). To this end, I construct the average increase of R&D investment in the normal years of 1984 and 1985, and include this variable in the baseline regression. As shown in Table 3, column (1), the effect of such variable is statistically and economically insignificant, while the effect of R&D increase in the 1980s recession remains economically and statistically significant.

An important question is whether the findings of the previous section are specific to R&D, or whether they are more generally driven by corporate investment undertaken in past recessions. To shed light on this question, I construct a variable measuring recession-time increases in capital expenditures (capex), similar to the one used for R&D in Table 2. Results in Table 3, column

(2), indicate that, even though all the controls are of a similar magnitude and have the same sign as their counterparts reported in previous columns (e.g. the coefficient for the stock of innovation remains positive and strongly significant), capex increases in recession do not have the same significant effect of R&D increases.

While in the main specification I adopt as explanatory variable an indicator for R&D expenses increased in recession, I verify that the results hold using alternative variables. Specifically, I adopt a measure of recession-time drops in R&D (computed similar to R&D increases but using negative rather than positive changes). Results reported in Table 3, column (3), show that dropping R&D in the early-1980s downturn had a negative and statistically significant effect on R&D spending in the next recessions.

3.3. Endogeneity

R&D increases during the 1980s recession had a positive and significant effect on R&D spending during the early 1990s and 2001 recessions. However, the decision to innovate in the 1980s was an endogenous one that could be correlated with confounding factors. To resolve this problem, I adopt an instrumental variables approach exploiting predetermined drivers of a firm's financial strength at the onset of the 1980s recession.

It has been shown that cash holdings improve a firm's financial strength, which is in turn useful to face turbulent times. For instance, Fresard (2010) documents that, when product market competition increases, companies with large cash reserves gain market shares at the expenses of competitors. These insights suggest that large liquid holdings can serve as a valid instrument as they make firms better able to invest in R&D during recession periods. This argument is indeed consistent with the existing finding that the negative effect of recessions on R&D spending is smaller for financially unconstrained firms (Campello et al. 2010).

However, one drawback of using cash holdings as an instrument for recession-specific R&D spending is that cash holdings in recession are likely endogenous themselves (i.e. firms with large and small cash reserves may differ due to characteristics other than the ones included as regression controls). To mitigate this concern, I follow Fresard (2010) and use as instruments pre-shock averages of cash holdings, to capture systematic differences in cash levels, and asset tangibility, which forces the exogenous variations of financial strength to explain the dependent variable. To absorb industry-specific differences in cash holdings, I subtract industry averages from firm-level values.

There are two identifying requirements for the validity of this approach. The first is that pre-recession financial strength, as proxied by industry-adjusted cash and tangible assets, should correlate with recession-specific R&D investment. I check whether this is the case by running an OLS regression with R&D expenses as dependent variable and the two proxies of financial strength together with the controls used in Table 2 as explanatory variable. Results indicate that both pre-recession cash and tangibility have a statistically significant effect (1% and 5% respectively) on recession-specific R&D. The second requirement is that a firm's cash holdings and asset tangibility prior to a recession should not have a direct influence on R&D during a recession that takes place after a decade. This condition is likely satisfied given that the instruments are constructed around 10 years prior to the dependent variable, and also given that the regression includes for a host of firm-level controls contemporaneous to the dependent variable (thus controlling for e.g. the fact that firms with more liquid holdings in the previous recession may end up being larger or financially constrained in the next one).[5]

Given the binary nature of the endogenous variable, I use a treatment effect model estimated with maximum likelihood. In this model, the first stage is a probit regression of the innovation increase in the early 1980s recession on the above-described instruments and the controls of Table 2, whereas the second stage regresses R&D in the recession years of 1990 and 2001 on the predicted R&D

[5] One potential concern though has to do with the persistence of financing policies (e.g. cash-rich firms in early 1980s could also be cash-rich in the early 1990s). To rule out this concern, in unreported tests I verify that results hold controlling for leverage (both current and in the early 1980s recession) and current cash holdings.

increases from the first stage (and on the controls). Results are reported in Table 4, column (2). For comparison purposes, column (1) reports OLS results on the same sample. As shown, the IV estimates are positive, statistically significant at the 1% level and around 3 times larger than the OLS estimates. In unreported tests, I have confirmed the robustness of this finding using a 2SLS regression, i.e. estimating the first stage regression with a linear probability model rather than probit.

Overall, instrumental variable analyses confirm the main finding that innovative effort in the early 1980s recession has a positive effect on R&D spending in subsequent recessions.

3.4. Robustness

This section presents various tests that further validate the finding established so far. These tests are summarized in Table 5. I start by using an alternative estimation strategy. Row (1) shows a positive and significant effect of R&D increases in past recession once using a negative binomial model in which the dependent variable is the raw dollar amount of R&D.

In the baseline specification, I measure knowledge stock as the cumulated number of patent counts. Yet I establish that the main result remains statistically significant when the patent stock is computed using the perpetual inventory method and a constant annual depreciation rate of 15% (see e.g. Cockburn and Griliches 1988; Hall 1990), or when I use the stock of citations rather than patent stock (rows 2 and 3).

Next, I deal with the concern of influential observations in the key explanatory variable measuring R&D increases in recession. To this end, in row (4), I show that findings are robust to the exclusion of 1% observations in the extreme left and right tails of R&D increases, as described in Section 2.

Next, I present results obtained using a more comprehensive set of controls. In row (5), I augment the main specification with state-specific dummies; in row (6), I control for state–year dummies to accommodate the possibility that each considered recession year had dynamic effects on individual states differently.

Similarly, in row (7) I include industry–year dummies to allow for recessions to affect differently industries in different years (e.g., the 2001 recession hit tech firms the hardest). Row (8) controls for industry structure by including as an explanatory variable the Herfindahl–Hirschman index (HHI), which measures the concentration of revenues in each 3-digit SIC industry. Row (9) controls for growth opportunities by including a firm's market-to-book ratio. Finally, row (10) includes both controls contemporaneous to the dependent variable, as in all previous regressions, and control values specific to the early 1980s recession (computed by taking the average value of each variable from 1980 to 1982). This procedure captures differences across firms in the early 1980s recession that may have led to innovation during that period.

Next, I deal with the computation of standard errors. In row (11), I provide estimates obtained while clustering residuals at the state level; this method is useful in case a recession's differential effects across areas cause the residuals to be correlated by geography. Finally, rows (12) and (13) report results obtained when clustering by industry–year and state–year, respectively.

I then evaluate robustness with respect to a variety of subsamples. In row (14), I exclude firms headquartered in California and Massachusetts, which are among the most innovative of US states. I also deal with the concern of product cycles, i.e. that some firms may reduce R&D less across certain recession periods because their product development cycles are relatively long and/or inflexible (i.e., invariant with respect to recessions). In this case, the documented persistence of innovation across recession periods could be attributed to product cycle lengths. First, I clarify that controlling for industry fixed effects should mitigate this concern to the extent that product development cycles are industry-specific. Second, in row (15) I follow Bilir (2013) to classify industries by their product lifecycle and show that results hold excluding industries with intermediate (around 9 years) to long product cycles (between 10 and 11 years).

It is common to firms in Compustat dataset to have missing R&D. For instance, in the whole sample of Compustat firms from 1976 and 2006, after excluding firms with zero and negative assets and sales, and firms in financial and utility industries, about 50% of firms do not report R&D. This reporting problem may bias empirical findings that rely on R&D-specific variables. While in the baseline analyses I have excluded firms with missing R&D, in rows (16)-(17) I check the robustness to treating these firms differently, e.g. replacing missing values in R&D with zeros, or replacing missing values with industry average as recently proposed in Koh and Reeb (2014).

4. Post-recession results

Section 3 showed that firms able to increase R&D in recessions invest more in innovation inputs during new downturns. As discussed in the introduction, this effect is consistent with strategic persistence, i.e. a tendency of firms to stick with given corporate policies under same circumstances.

However, the performance implications of this tendency can be positive or negative depending on whether the persistence in recession-specific innovation is driven by rational or naïve reinforcement processes of organizational learning. The former process predicts that by innovating in past recession, firms developed specific competencies that, during a new recession, make them able to undertake high-quality R&D projects leading to higher performance. On the contrary, the latter process predicts that the experience of innovation in past recessions may induce firms to become overly optimistic about their ability to successfully innovate again in similar averse conditions, which in turn implies that firms invest in R&D projects of both high and low quality leading to lower performance.

To shed light on the performance effect, I focus on innovation outcomes. If R&D projects undertaken in recession (i.e. the dependent variable of previous regressions) were of high quality, innovation outcomes (and especially their quality) should increase in the aftermath of recessions. By contrast, if projects were of low quality, then the change in innovation outputs should be insignificant, because many of those R&D projects failed to generate the desired output or were discontinued.

Innovation outputs are measured using patent counts weighted by future citations received, which better reflect the economic and technological importance of the patented innovations. Specifically, I estimate the following model:

$$\text{Ln}(1+\text{Innovation quality}_{i,t}) = \alpha + \beta(\text{Post}\times v_{82}) + \text{X}_{i,t}\delta + \theta_i + \lambda_t + \varepsilon_{i,t} \qquad (2)$$

where the dependent variable is the quality of patenting activity of a firm *i* in the recession periods of early 1990s and 2001 and afterwards. Following the literature (e.g., Fang et al. 2013), I take the logarithm when modeling the right-skewed distribution of patent counts/citations and also use 1 plus the patent counts to preclude dropping firms with zero patent counts/citations.

As for the explanatory variables, I first construct a dummy Post set equal to 1 for years up to five after the recession shock (and set to 0 for the recession years). Then I interact the post-recession indicator with v_{82}; recall that this variable is an indicator for firms with experience of R&D increases in the early 1980s recession. The approach can thus be viewed as a difference-in-differences model in which the Post variable and the v_{82} variable provide (respectively) the longitudinal and cross-sectional variation around the recession. I include firm and year fixed effects (τ_i and θ_t respectively) and also include time-varying controls as in Table 3. Standard errors are clustered at the firm level.

Results reported in Table 6, column (1), show that the interaction term is positive and statistically significant at the 1% level. This means that firms with experience of increased innovation in past downturns are significantly more likely to generate higher-quality patents.

In Columns (2) and (3), I confirm this finding using proxies for a firm's innovative efficiency, obtained by scaling the patent citations by the number of patent counts, or by the amount of R&D expenses (Hirshleifer et al. 2013). Results indicate that firms able to increase R&D in recession are also more efficient in generating innovation outcomes in the aftermath of a new shock.

5. Conclusion

What determines firms' innovative behavior in hard times? Previous research has focused on such traditional factors as financial constraints and cumulated innovations; in this paper, I investigate the dynamic effect of innovative experience over the business cycle.

Using data on US listed firms during the major downturns of the US economy from the early 1980s to 2001, I find firms that increased innovative effort during *past* downturns are significantly more likely to invest in R&D expenditures when a *new* recession hits. This finding holds controlling for financial constraints, firm profitability, and cumulated innovations—thereby addressing the concern that previously innovating firms may have been so simply because they were financially stronger or endowed with a larger knowledge stock.

Innovation experience in normal years does *not* affect subsequent recession-period innovation, which supports the hypothesis that innovating during a recession has a distinctly identifiable effect on firms' later innovative behavior. Also, I mitigate endogeneity problems by using predetermined drivers of a firm's financial strength.

Finally, I use a difference-in-differences model to show that firms with past experience of innovation exhibit significantly better patent outcomes and superior innovative efficiency after a new recession.

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Table 1. Summary statistics

This table reports summary statistics for the main firm characteristics as of 1982. Ln (Sales) is the logarithm of a firm's revenues. Ln (*K*/*L*) is the logarithm of capital to labor, computed as the ratio of property, plants, and equipment to the number of employees. Firm age is the number of years a firm has been in Compustat. ROA is the return on assets, computed as the ratio of EBITDA to total assets. Ln (1+R&D) is the logarithm of 1 plus R&D expenditures. Ln (1+Patent counts) is the logarithm of 1 plus a firm's number of patents. R&D/Assets is the ratio of R&D expenses to the book value of total assets.

	Mean	s.d.	Median
Ln (Sales)	4.647	2.322	4.610
Ln (*K*/*L*)	2.665	0.880	2.687
Firm age	16.211	9.920	14.5
ROA	0.124	0.116	0.140
Ln (1+R&D)	1.450	1.568	0.835
R&D/Assets	0.041	0.046	0.027

Table 2. Effect of recession-R&D on innovative behavior in future recessions

This table reports results from OLS regressions. The dependent variable is the logarithm of 1 plus R&D expenditures in the recession period of the early 1990s and 2001. R&D increase in the 1980s recession is a dummy equal to one if a firm has experienced an increase of R&D in the recession period of the early 1980s relative to the previous non-recession year; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets. Panel A uses state-specific recession years from Owyang et al. (2005), whereas Panel B uses national recession years as defined by the NBER. Ln (Sales) is the logarithm of a firm's revenues. Ln (*K*/*L*) is the logarithm of capital to labor, computed as the ratio of property, plants, and equipment to the number of employees. Firm age is the number of years a firm has been in Compustat. ROA is the return on assets, computed as the ratio of EBITDA to total assets. Each regression includes 2-digit SIC dummies and year dummies. Standard errors are clustered by firm. *, **, and *** denote significance at (respectively) the 10%, 5%, and 1% level. Details on the construction of each variable are reported in Appendix 1.

Panel A. State-specific recession years

Dependent variable: Ln (1+R&D)

	Early 1990s and 2001 recessions		Early 1990s	2001
	(1)	(2)	(3)	(4)
R&D increase in 1980s recession	0.206***	0.137**	0.151**	0.095
	(0.075)	(0.065)	(0.071)	(0.091)
Ln (Sales)	0.517***	0.573***	0.593***	0.584***
	(0.038)	(0.034)	(0.034)	(0.048)
Ln (*K*/*L*)	-0.008	0.053	0.060	0.055
	(0.045)	(0.052)	(0.058)	(0.076)
Firm age	-0.004	0.001	-0.002	0.000
	(0.006)	(0.005)	(0.006)	(0.007)
ROA	-0.674**	-0.827***	-0.736**	-1.091**
	(0.311)	(0.254)	(0.304)	(0.446)
Innovation stock	0.246***	0.187***	0.153***	0.243***
	(0.028)	(0.024)	(0.027)	(0.034)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	1395	1395	1013	382

Panel B. National recession years

Dependent variable: Ln (1+R&D)

	Early 1990s and 2001 recessions		Early 1990s	2001
	(1)	(2)	(3)	(4)
R&D increase in 1980s recession	0.131*	0.142**	0.152**	0.142
	(0.074)	(0.068)	(0.068)	(0.096)
Ln (Sales)	0.502***	0.579***	0.615***	0.575***
	(0.035)	(0.033)	(0.032)	(0.049)
Ln (*K*/*L*)	-0.032	0.043	0.049	0.045
	(0.048)	(0.055)	(0.060)	(0.079)
Firm age	-0.002	0.001	-0.002	0.001
	(0.006)	(0.006)	(0.006)	(0.007)
ROA	-1.034***	-1.161***	-1.137***	-1.099**
	(0.310)	(0.284)	(0.384)	(0.461)
Innovation stock	0.265***	0.193***	0.144***	0.245***
	(0.024)	(0.022)	(0.022)	(0.034)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	947	947	580	367

Table 3. Additional evidence

This table reports results from OLS regressions. The dependent variable is the logarithm of 1 plus R&D expenditures in the state-specific recession years of early 1990s and 2001. R&D increase in the 1980s recession is a dummy equal to one if a firm has experienced an increase of R&D in the recession period of the early 1980s relative to the previous non-recession year; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets. R&D increase in normal years is a dummy equal to one if a firm has experienced an increase of R&D in the non-recession year of 1985 relative to the previous non-recession year of 1984; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets. Capex increase in 1980s recession is computed similar to the R&D increase in 1980s recession using capital expenditures instead of R&D expenses. R&D drop in the 1980s recession is a dummy equal to one if a firm has experienced a reduction of R&D in the recession period of the early 1980s relative to the previous non-recession year; R&D drop is defined as a reduction of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets. Ln (Sales) is the logarithm of a firm's revenues. Ln (*K*/*L*) is the logarithm of capital to labor, computed as the ratio of property, plants, and equipment to the number of employees. Firm age is the number of years a firm has been in Compustat. ROA is the return on assets, computed as the ratio of EBITDA to total assets. Each regression includes 2-digit SIC dummies and year dummies. Standard errors are clustered by firm. *, **, and *** denote significance at (respectively) the 10%, 5%, and 1% level. Details on the construction of each variable are reported in Appendix 1.

Dependent variable: Ln (1+R&D)			
	(1)	(2)	(3)
R&D increase in 1980s recession	0.135**	0.146**	
	(0.066)	(0.066)	
R&D increase in normal years	0.060		
	(0.069)		
Capex increase in 1980s recession		-0.072	
		(0.067)	
R&D drop in 1980s recession			-0.293***
			(0.096)
Ln (Sales)	0.586***	0.570***	0.564***
	(0.034)	(0.034)	(0.038)
Ln (*K*/*L*)	0.052	0.057	0.061
	(0.054)	(0.052)	(0.057)
Firm age	-0.000	0.000	-0.000
	(0.005)	(0.005)	(0.006)
ROA	-0.887***	-0.815***	-0.714***
	(0.259)	(0.257)	(0.271)
Innovation stock	0.179***	0.191***	0.176***
	(0.024)	(0.024)	(0.028)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	1354	1380	1131

Table 4. Instrumental variables results

This table reports results from OLS and instrumental variables regressions. Column (1) shows estimates obtained estimating a model similar to the one in the Column (2) of Table 2, Panel A. Results in column (2) are obtained from a treatment effect model estimated with maximum likelihood. In particular, the model estimates a first stage with the dummy for R&D increase in 1980s recession as dependent variable and with explanatory variables the firm-level controls reported in the table as well as two instruments, namely (1) pre-recession cash holdings, computed by taking the average over the years prior to the early 1980s recession and adjusted for industry effects by subtracting the industry average from firm values; and (2) asset tangibility, computed as the average over the years up to 1982. The second stage uses the predicted values of the endogenous variable in a regression similar to Column (1). Ln (Sales) is the logarithm of a firm's revenues. Ln (*K*/*L*) is the logarithm of capital to labor, computed as the ratio of property, plants, and equipment to the number of employees. Firm age is the number of years a firm has been in Compustat. ROA is the return on assets, computed as the ratio of EBITDA to total assets. Each regression includes 2-digit SIC dummies and year dummies. Standard errors are clustered by firm. *, **, and *** denote significance at (respectively) the 10%, 5%, and 1% level. Details on the construction of each variable are reported in Appendix 1.

Dependent variable: Ln (1+R&D)		
	OLS	IV
	(1)	(2)
R&D increase in 1980s recession	0.078**	0.670**
	(0.039)	(0.293)
Ln (Sales)	0.591***	0.591***
	(0.021)	(0.020)
Ln (*K*/*L*)	0.054*	0.053*
	(0.029)	(0.029)
Firm age	-1.357***	-1.353***
	(0.178)	(0.176)
ROA	-0.001	-0.001
	(0.003)	(0.003)
Cash holdings	1.170***	1.135***
	(0.168)	(0.166)
Innovation stock	0.177***	0.177***
	(0.015)	(0.015)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	1665	1665

Table 5. Robustness

This table reports results from OLS regressions. Unless otherwise specified, the dependent variable is the logarithm of 1 plus R&D expenditures in the state-specific recession years of early 1990s and 2001. R&D increase in the 1980s recession is a dummy equal to one if a firm has experienced an increase of R&D in the recession period of the early 1980s relative to the previous non-recession year; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets. Each specification includes the same firm controls as in column (2) of Table 2, Panel 2, plus additional controls depending on the specification. To save space, the table only reports the coefficient for the main explanatory variable, the standard errors (SEs), and the number of observations. In row 1, I use the raw amount of R&D expenditures (rather than the logarithm of 1 plus R&D) as the dependent variable, and estimate the regression using a negative binomial model. In rows 2 and 3, I use the stock of cumulated patents (or patent citations) computed using the perpetual inventory method and assuming a 15% depreciation rate. In row 4, I drop observations with increases in R&D expenses or R& to assets in the extreme 1% of the left and right tails of the distribution. In rows 6–8, I use a combination of state, industry, and year dummies. Row 9 includes as a further control the industry HHI. In row 10, I add the market-to-book ratio, and in row 10 I control for firm characteristics at the 1980s recession by including the average of all controls in column (2) of Table 2, Panel A, computed in the state-specific recession years of the early 1980s. In rows 11–13, I cluster standard errors by various combinations of industry, state, and year dummies. In row 14, I exclude firms headquartered in California or Massachusetts; in row (15), I exclude firms in SIC industries with intermediate (SIC 359, 289, 384, 352, 363) and long (SIC 344, 342, 345, 341, 343) product lifecycles (Bilir 2013). In row (16), I replace missing R&D values with zeros; while in row (17) I replace missing values with SIC-year averages. Standard errors are clustered at the firm level unless stated otherwise. *, **, and *** denote significance at (respectively) the 10%, 5%, and 1% level. Details on the construction of each variable are reported in Appendix 1.

	R&D increase in 1980s	Standard Errors (SEs)	Observations
1. Alternative estimation model	0.145**	(0.063)	1389
2. Patent-based innovation stock (perpetual inventory method)	0.145**	(0.063)	1389
3. Citation-based innovation stock (perpetual inventory method)	0.153**	(0.071)	1254
4. Dropping influential observations	0.136**	(0.067)	1336
5. Controlling for state dummies	0.219***	(0.073)	1395
6. Controlling for state × year dummies	0.220***	(0.074)	1395
7. Controlling for industry × year dummies	0.135**	(0.067)	1395
8. Controlling for current HHI	0.135**	(0.065)	1395
9. Controlling for current growth opportunities	0.136**	(0.065)	1195
10. Controlling for firm characteristics in the 1980s recession	0.130**	(0.065)	1360
11. SEs clustered by state	0.137*	(0.074)	1395
12. SEs clustered by state × year	0.137***	(0.048)	1395
13. SEs clustered by industry × year	0.137**	(0.052)	1395
14. Removing firms headquartered in California and Massachusetts	0.173**	(0.070)	1265
15. Removing firms with intermediate/long product lifecycles	0.164**	(0.072)	1253
16. Including missing R&D firms I	0.229***	(0.074)	1724
17. Including missing R&D firms II	0.179***	(0.0637)	2834

Table 6. Post-recession patenting

This table reports results from OLS regressions. In column (1), the dependent variable is the logarithm of 1 plus patent citations; in column (2) is the logarithm of 1 plus citations per patent; in column (3) is the logarithm of 1 plus citations scaled by R&D expenses. R&D increase in the 1980s recession is a dummy equal to one if a firm has experienced an increase of R&D in the recession period of the early 1980s relative to the previous non-recession year; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets. Post is a dummy variable set equal to 1 for the recession the five years following the early 1990s and 2001 recession years (and to 0 for recession years). Each regression includes firm fixed effects and year dummies. Standard errors are clustered by firm. *, **, and *** denote significance at (respectively) the 10%, 5%, and 1% level. Details on the construction of each variable are reported in Appendix 1.

Dependent variable:	Ln (1+citations)	Ln (1+citations per patent)	Ln (1+citations per R&D dollar)
	(1)	(2)	(3)
Post × R&D increase in 1980s recession	0.229**	0.142**	0.152**
	(0.103)	(0.065)	(0.065)
Ln (Sales)	0.187	0.044	-0.050
	(0.130)	(0.069)	(0.074)
Ln (*K*/*L*)	-0.078	-0.054	-0.058
	(0.111)	(0.062)	(0.063)
Firm age	-0.282***	-0.138***	-0.105***
	(0.018)	(0.010)	(0.010)
ROA	-0.462	-0.166	0.115
	(0.446)	(0.255)	(0.241)
Innovation stock	0.883***	0.329***	0.351***
	(0.114)	(0.075)	(0.061)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	4852	4852	4852

Appendix 1. Variable description

Name	Description	Source
Ln (Sales)	Logarithm of a firm's sales	Compustat
Ln (*K*/*L*)	Logarithm of the ratio of capital (property, plants, and equipment) to labor (employees)	Compustat
Firm age	Number of years a firm has been in Compustat	Compustat
ROA	EBITDA (earnings before interest, taxes, depreciation and amortization) divided by the book value of total assets	Compustat
R&D increase in 1980s recession	Dummy equal to one if a firm has experienced an increase of R&D in the recession period of the early 1980s relative to the previous non-recession year; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets	Compustat
R&D increase in normal years	Dummy equal to one if a firm has experienced an increase of R&D in the non-recession year of 1985 relative to the non-recession year of 1984; R&D increases are defined as an increase of at least 5% in both the dollar amount of R&D and the ratio of R&D to the book value of total assets	Compustat
Capex increase in 1980s recession	Dummy equal to one if a firm has experienced an increase of capex in the recession period of the early 1980s relative to the previous non-recession year; capex increases are defined as an increase of at least 5% in both the dollar amount of capex and the ratio of capex to the book value of total assets	Compustat
Ln (1+R&D)	Logarithm of 1 plus a firm's R&D expenditures	Compustat
Ln (1+citations)	Logarithm of 1 plus the count a firm's number of patent cites, adjusted for truncation as described in Hall et al. (2001; 2005)	NBER
Ln (1+citations per patent)	Logarithm of 1 plus the count a firm's number of patent cites, adjusted for truncation as described in Hall et al. (2001; 2005) and divided by the number of a firm's patents	NBER
Ln (1+citations per R&D dollar)	Logarithm of 1 plus the count a firm's number of patent cites, adjusted for truncation as described in Hall et al. (2001; 2005) and divided by the dollar amount of R&D expenses	NBER
Innovation stock	Logarithm of 1 plus the cumulated number of patents (or citations). When specified in the table, the stock is computed using the perpetual inventory method assuming a 15% depreciation rate	NBER
Post	Dummy variable set equal to 1 for the 5 years following the early 1990s and 2001 recessions, and zero for the relative recession years	NBER
Market to book	Market price of common shares at the end of the fiscal year times the number of common shares outstanding divided by the book value of equity. The variable is trimmed between 0 and 10	Compustat
Asset tangibility	1 minus intangible assets divided by total assets. Values outside the [0, 1] range are excluded	Compustat
Cash holdings	Cash and marketable securities divided by total assets. Values outside the [0,	Compustat

	1] range are excluded	
Leverage	Sum of financial debt due in one year plus long-term financial debt divided by total assets. Values outside the [0, 1] range are excluded	Compustat
Year fixed effects	Full set of year dummies	Compustat
State fixed effects	Full set of state-of-headquarter dummies, where headquarter corresponds to the last state of headquarter as reported in Compustat	Compustat
Industry fixed effects	Logarithm of 1 plus a firm's R&D expenditures	Compustat
Firm fixed effects	Full set of firm-specific dummies	Compustat