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Firm-level R&D after periods of intense technological innovation: The role of investor sentiment

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Abstract

Following periods of intense technological innovation, R&D is a critical driver of technology diffusion, but it is subject to frictions that can lower it below the level firms would undertake otherwise. We study whether sentiment can counterbalance these frictions and thus strengthen the link between firm-level R&D and lagged aggregate innovation. We find a positive answer for low-tech firms, which represent the main conduit for technology diffusion. The effect is stronger in the presence of informational externalities, that is when the results of experimentation funded by a company are observable by competitors. In contrast to the literature on sentiment and capital expenditures, the effect is weaker for financially constrained firms.

JEL classification: G02; G31; O32; O33.
Keywords: Investor sentiment; technological innovation; R&D.

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1 Introduction

In the aftermath of rapid technological progress, firm-level R&D serves two important purposes in the technology-diffusion process. First, firms engage in small-scale experimentation (which is booked as R&D; see FASB, 2010), to understand whether they should incorporate recent innovations in their current products or processes. This activity is key for technology diffusion, because it minimizes the risk that productive innovations are rejected or that unproductive innovations are adopted (Bolton and Harris, 1999). Second, some firms invest in R&D to imitate technological leaders (Mukoyama, 2003).

Certain frictions can reduce R&D below the level firms would normally choose. First, the imperfect appropriability of knowledge produced through R&D gives rise to informational externalities, meaning that the outcome of R&D undertaken by a company can also inform the decisions of other firms that have *not* spent resources on R&D.[1] These externalities lower the incentive to experiment and to better understand a new technology (Bolton and Harris, 1999). Second, managers can cater to investors with short-term horizons by diverting resources away from useful but hard-to-evaluate R&D, including experimentation.[2] Third, financing constraints can, in principle, limit the ability to fund otherwise viable projects. While studies indicate that financing constraints often reduce corporate investment (Rauh, 2006), their effect on R&D is less clear in principle, especially as it pertains to technology

[1]See Adams and Jaffe (1996); Benkard (2000); Bernstein (1989); Bernstein and Nadiri (1989); Bhattacharya, Chatterjee, and Samuelson (1986); Gruber (1998); Hall (1996); Irwin and Klenow (1994); Jovanovic and MacDonald (1994); Reinganum (1983); Thornton and Thompson (2001); Zimmerman (1982). While informational externalities generally discourage firms from engaging in R&D, there is an exception when, in order to exploit the information produced by their competitors, firms need to maintain a certain level of technical proficiency known as absorptive capacity (Cohen and Levinthal, 1989).

[2]The interaction of managerial career concerns and short-termist or failure-averse investors is the subject of a large literature, including Aggarwal and Hsu (2013), Ferreira, Manso, and Silva (2014), He and Tian (2013), Asker, Farre-Mensa, and Ljungqvist (2015), Bernstein (2015), and Tian and Wang, 2014.

diffusion, because these expenses are inherently small.

In the context of technology diffusion, we ask whether investor sentiment strengthens the relation between firm-level R&D and lagged aggregate innovation, measured with changes in granted patents. We are particularly interested in firms subject to frictions that can weaken their incentive to engage in experimentation after periods of technological innovation. Sentiment can be interpreted as "propensity to speculate" (Baker and Wurgler, 2006), or the tendency of investors' decision making to deviate from rationality.[3] Sentiment can offset frictions that affect R&D in different ways. Investors are likely to be particularly interested in a new technology when sentiment is high, not least because both sentiment and investors' attention are partly driven by the financial media's coverage of popular topics (Barber and Odean, 2008 and Tetlock, 2007). Managers can cater to this interest by exploring the new technology, all the while maximizing short-term stock prices and their own compensation (Polk and Sapienza, 2009, and Grundy and Li, 2010). For managers with behavioral traits, sentiment can reinforce overconfidence and their appetite for risky innovative projects (Hirshleifer, Low, and Teoh, 2012).

We find that investor sentiment, measured with the index of Baker and Wurgler (2006), reinforces the effect of lagged aggregate innovation on R&D, especially for low-tech[4] companies subject to informational externalities. Importantly, the effect is stronger for firms with *looser* financing constraints. On a average, these firms engage in more R&D than their con-

[3]The findings of Baker and Wurgler (2006) have been extended to option pricing by Han (2008) and to an international setting by Baker, Wurgler, and Yuan (2012). Yu and Yuan (2011) show that the relation between expected excess returns and conditional variance only holds during periods of low sentiment, consistent with less-than-rational investment decisions at times of high sentiment. Hwang (2011) finds that the attitudes of the American public toward other countries affect the price of securities referencing assets in those countries (like CCEF, or country closed-end funds, and ADR, or American Depositary Receipts).

[4]Following Brown, Fazzari, and Petersen (2009), high-tech firms are those for which the first three SIC digits are equal to 283, 357, 366, 367, 382, 384, and 737. The remaining firms are considered low-tech.

strained counterparts. This second result sets our work apart from McLean and Zhao (2014), who find that investor sentiment can increase investment by loosening financing constraints.[5] It also confirms our conjecture that, as it pertains to small-scale experimentation, financing constraints are a friction of secondary importance. Consistent with higher R&D reflecting experimentation, which is by definition a small-scale activity, a 1-standard deviation increase in innovation raises R&D by 5 basis points after two years, if sentiment is 1 standard deviation above the mean. While the figure is roughly 2% of average R&D, the information gathered from small-scale experimentation is crucial for an efficient technology-diffusion process (Bolton and Harris, 1999). These findings are robust to a variety of alternative measures of sentiment and innovation.

A prime concern for our work is that the proxy for investor sentiment that we use might reflect growth expectations. In this case, apparently irrational price movements could actually be the result of rational learning about a disruptive technology (Johnson, 2007 and Pastor and Veronesi, 2009). Baker and Wurgler (2006) orthogonalize their index with respect to business-cycle variables and provide cross-sectional results indicating that it is informative about sentiment, and not expected growth. Still, the index might reflect growth expectations specifically related to newly available technologies. As a result, in some specifications we orthogonalize the index with respect to the stock-return spread between high-tech and low-tech firms, which should be particularly large if a newly available technology is expected to

[5] A related literature studies the effect of mispricing on investment. Equity-dependent firms issue more equity and invest more when their stock is overvalued (Baker, Stein, and Wurgler, 2003). Indicating that unusually high investment could be wasteful when equity is overvalued, Polk and Sapienza (2009) find that companies with mispriced stock experience low returns following abnormally high investment. High dispersion in investor beliefs, which can give rise to stock overvaluation, is linked to higher investment (Gilchrist, Himmelberg, and Huberman, 2005). Similarly, Chirinko and Schaller (2011) find that misvaluation has a significant effect on investment in a panel of U.S. firms. Chirinko and Schaller (2001) provide international evidence by focusing on the Japanese stock market bubble of the late 1980s.

be very profitable.

Our results complement those of two related papers that focus on the link between asset valuations and innovation at the *invention* stage, when new technologies are developed, rather than at the *diffusion* stage, as we do, when the broader universe of firms decide how to best incorporate innovations in their existing products or processes. Jerzmanowski and Nabar (2008) develop a theoretical model where the adverse effect of informational externalities is countered by stock market overvaluation. From an empirical point of view, Nanda and Rhodes-Kropf (2013) study how "hot markets," where investors are willing to finance a large number of start-ups, affect the type of firms that file for initial public offerings. On average, companies have higher valuations and produce more highly-cited patents. These results are also consistent with a positive effect of investor sentiment on the process of technological innovation and diffusion.

2 Data and research design

We are interested in how firm-level R&D is affected by the interaction of lagged innovation and investor sentiment. The analysis revolves around a set of panel regressions based on the empirical analysis of Brown, Fazzari, and Petersen (2009), who, in turn, build on the model of the financial determinants of corporate investment introduced by Bond and Meghir (1994) and Bond, Elston, Mairesse, and Mulkay (2003). In our setup, the dependent variable is R&D and the covariates include controls for both firm-specific and aggregate investment opportunities. Appendix A provides details on the construction of the firm-level controls and on the filters used to clean the data, which are from Compustat through Wharton Research Data Services (WRDS). The main specification of the panel regressions is (we omit subscripts when possible to simplify the notation):

$$RD_{i,t} = \beta \cdot \mathbf{X}_{i,t-1} + \sum_{j=1,2} (\gamma_1 \cdot ADS_{t-j} + \gamma_2 \cdot S_{t-j} + \gamma_3 \cdot \Delta P_{t-j} + \gamma_4 \cdot I_{t-j}) + \varepsilon_{i,t}, \qquad (1)$$

where $RD_{i,t}$ is R&D for firm i at time t, ADS_{t-j} is the lagged control for macroeconomic conditions (the yearly average of the daily Aruoba, Diebold, and Scotti, 2009 index of economic activity), S_{t-j} is the lagged sentiment index, ΔP_{t-j} is the lagged change in patents, and I_{t-j} is the product of S_{t-j} and ΔP_{t-j}. The baseline set of firm-specific controls, $\mathbf{X}_{i,t-1}$, includes the variables used by Brown, Fazzari, and Petersen (2009) in their study of the 1990s R&D boom. These variables are lagged and squared lagged R&D ($RD_{i,t-1}$ and $RD^2_{i,t-1}$; the latter reflects quadratic adjustment costs), lagged stock issuance ($stk_{i,t-1}$), lagged gross cash flows ($GCF_{i,t-1}$), and lagged sales scaled by assets ($SRa_{i,t-1}$). In robustness checks, we use variables proposed by Gala, Gomes, and Liu (2020) in the context of the corporate investment literature. These variables are lags of the log sales-to-capital ratio ($ln(SRk)_{i,t-1}$), of leverage ($lev_{i,t-1}$), and of log-capital ($ln(K)_{i,t-1}$). The two versions of the sales ratio are calculated in slightly different ways to follow the definitions provided in the two articles.

In most cases, the proxy for technological innovation is ΔP, the log-change in the number of patents granted by the United States Patent and Trademark Office (USPTO), which we obtain from the USPTO website (see Griliches, 1990 for a detailed discussion on patents as economic indicators).[6] In Section 3.2, we explore the sensitivity of the results to an alternative measure that does not rely on patent counts.

We use granted patents rather than patent applications because they measure innovation that is ready for adoption. Companies that push the technological frontier often file

[6] "Table of Annual U.S. Patent Activity Since 1790." Granted patents are the variable "Utility Patents," while applications are the variable "Utility Patent Applications."

patents on technologies that are still under development, typically to defend or to improve their market position (see, for instance, Hall and Ziedonis, 2001). As a consequence, patent applications can lead the actual availability of a technology. We do not use citation-weighted patents (Trajtenberg, 1990) because future citations are not part of the information set available to firms when they make their decisions on experimentation.

Table 1 shows that the number of granted patents increases at an annual average rate of 3.79% over the 1965-2015 sample. Griliches (1990) notes that the variation in granted patents at the end of the 1970s, and especially in 1979, was affected by staffing and budget issues at USPTO. To make sure that this spurious variation is not driving the results, we multiply the change in patents for the years 1979 and 1980 by 30% unless noted otherwise. The results are robust to not multiplying the observations by 30%, to multiplying them by 10%, and to excluding them altogether.[7]

One important point to discuss is the link between the state of the economy and the change in the number of granted patents. In a "demand pull" framework, the business cycle affects the resources spent on R&D, and the production of patents could depend, with a lag, on the amount of R&D, so that the innovation proxy could be interpreted as a business cycle indicator. In "supply push" models, innovation is driven by exogenous and unpredictable advances in scientific knowledge. Geroski and Walters (1995) find that demand plays a modest role relative to supply side factors.

The main measure for investor sentiment is the yearly average of the monthly $SENT^{\perp}$ index of Baker and Wurgler (2006). We download the index from Jeffrey Wurgler's website.

[7] The conclusions are also unaffected when excluding the years from 1975 to 1980. These results are not reported for space reasons, and are available upon request. Griliches (1990) notes that the variation in granted patents throughout the second half of the 1970s was affected by staffing and budget issues at USPTO, which culminated in the large 1979 drop in ΔP. 1975 is the first year in which the number of USPTO examiners starts to decline (see Figure 8 on page 1691 in Griliches, 1990).

We also evaluate the robustness of the results to using the University of Michigan Index of Consumer Sentiment, obtained from the FRED database of the Federal Reserve Bank of St. Louis. The sentiment index of Baker and Wurgler (2006) is the first principal component of variables that the literature has linked to investor sentiment, like the closed-end fund discount. In order to remove the potential influence of business-cycle fluctuations, Baker and Wurgler (2006) orthogonalize the constituent variables with respect to industrial production growth, growth in consumer durables, nondurables and services, and a dummy for NBER recessions. As shown in the bottom panel of Table 1, ΔP, ADS, and the sentiment index S are weakly correlated. The correlation between ΔP and ADS is 17%, and the correlation between ADS and S is -18%.

Table 2 reports summary statistics for the firm-level variables. The R&D intensity has an average of 2.69% for low-tech firms and 12.43% for high-tech firms. Brown, Fazzari, and Petersen (2009) report that the average R&D ratio of high-tech firms, over their 1990-2004 sample, is a comparable but larger 17%.

In most cases, we calculate the coefficients in Equation (1) with the Arellano and Bond (1991) first-difference GMM procedure for dynamic panels, as Brown, Fazzari, and Petersen (2009) do. For comparison, we also discuss results based on firm fixed-effects regressions and 2SLS on first differences.[8] Standard errors are double clustered by firm and year, using the procedure in Cameron, Gelbach, and Miller (2011). Since we report double-clustered standard errors, only the one-step GMM procedure is feasible. The reason is that the weight matrix in the second step of efficient GMM changes with the variable by which standard errors are clustered, and with two-step GMM there would be three different coefficient estimates

[8]For the 2SLS estimates, we use the ivreg2 Stata command (Baum, Schaffer, and Stillman, 2002). The GMM estimates and the Arellano-Bond tests for autocorrelation are obtained with, respectively, the xtabond2 (Roodman, 2003) and abar (Roodman, 2004) Stata commands.

for each specification.

3 Results

In this section, we discuss how the interaction of lagged innovation and sentiment affects the R&D intensity of Compustat firms. The first two columns of Table 3 show results from firm fixed-effects regressions, one for low-tech firms and one for high-tech firms. All coefficients are in percent. The magnitudes of the coefficients on lagged R&D and lagged squared R&D are consistent with the values predicted by the structural model referenced by Brown, Fazzari, and Petersen (2009) and developed by Bond and Meghir (1994) and Bond, Elston, Mairesse, and Mulkay (2003). The second lag of the interaction of innovation and sentiment has a positive effect on R&D for low-tech firms, but not for high-tech firms.

The next four columns are 2SLS estimates on first differences, where the instruments are lagged levels of firm-level regressors. The second and third lags are used in the first two specifications, while the third and fourth lags are used in the two other specifications. The second interaction lag remains strongly statistically significant for low-tech firms. The first lag is now statistically significant for low-tech firms when using the second and third lags as instruments.

The last four columns of Table 3 report Arellano-Bond one-step first-difference GMM estimates, where the instruments are either the second through fourth or the third and fourth level lags of the firm-specific regressors. Note that we use the second and third lags as instruments for 2SLS regressions and the second through the fourth as instruments for the GMM specifications because the GMM implementation replaces missing values of the instruments with zeroes. As a result, it is possible to include longer lags without reducing the sample, as reflected in the larger number of observations. The coefficient on the second interaction lag remains positive and statistically significant for low-tech firms under both GMM specifications. The point estimate is remarkably similar across the fixed-effects, 2SLS, and GMM specifications.

For low-tech firms, the marginal effect of a 1-standard deviation increase in innovation (first-difference GMM estimation, 2-4 lags of instruments included) is about 6 basis points when sentiment is 1-standard deviation above the mean. This figure amounts to approximately 2% of the average R&D intensity (Table 2). As discussed in Section 1, the modest size of the marginal effect of innovation is consistent with our hypothesis that firms engage in experimentation after periods of sustained technological innovation. Experimentation is booked as R&D and it is, by definition, a small-scale activity.

A set of statistics reported in Table 3 confirm the appropriateness of the instruments. The Hansen tests never reject the validity of the overidentifying restrictions, while the Kleibergen-Paap statistics, which should be at least 10 to rule out weak instruments (Baum, Schaffer, and Stillman, 2007), indicate that it is best to include the second lag of the firm-level variables in the instrument set. In addition, first order autocorrelation in the residuals is expected in first-difference GMM, and the null of no autocorrelation is rejected in each specification.

In the remainder of the analysis, we investigate whether the first and second interaction lags of innovation and sentiment remain statistically significant under a variety of specifications, sample periods, firm-specific controls, measures of investor sentiment, and proxies for technological innovation. We also discuss further the economic significance of the marginal effect of innovation on R&D conditional different levels of investor sentiment. All these results are based on first-difference GMM specifications with second to fourth lags of firm-level variables as instruments. This choice reflects the size of the Kleibergen-Paap statistics with and without the second instrument lag, and the results of the overidentifying-restrictions tests discussed above. Brown, Fazzari, and Petersen (2009) also use the same lags for low-tech firms.

The first three columns of Table 4 address the robustness of the lagged interaction coefficient to spurious variation in the number of patents due to staffing issues at USPTO (Griliches, 1990). In specification (1), the 1979 and 1980 observations of ΔP are not multiplied by 30%, while in (2) they are multiplied by 10%. In (3), observations for which any lags of the regressors include 1979 or 1980 are excluded. The coefficients on both the first and second lags of the interaction are equal to about 0.5% and are statistically significant in each of the three specifications, in line with the results shown in Table 3. The magnitude and statistical significance of the coefficients are also robust to excluding the bottom 10% of the time-t distribution of log-capital (specification (4)), and to excluding 1995 (specification (5)). In 1995, the R&D expense of high-tech firms starts to trend upwards rapidly (see Figure 1 in Brown, Fazzari, and Petersen, 2009), and this year might have had a disproportionate effect on our results.

Table 5 summarizes the marginal effect of innovation on R&D intensity, conditional on investor sentiment, as estimated across the various specifications. While the coefficients on the interaction between innovation and investor sentiment are statistically significant, the coefficient on lagged ΔP is typically statistically insignificant. As a result, the marginal effect of innovation on R&D intensity is statistically significant (when investor sentiment is 1 standard deviation above the mean) only for the two-year lag. The average marginal effect across the six specifications is 0.51% (0.78% if sentiment is 1.5 standard deviations above the mean), which implies an increase in R&D intensity of about 5 (8) basis points, or 2% (3%) of the average R&D intensity reported in Table 2. On balance, the marginal effects are remarkably similar for the various specifications.

3.1 Financing constraints and informational externalities

As noted in Section 1, investor sentiment has the potential to counteract frictions, like financing constraints and informational externalities, that can negatively affect the level of R&D firms undertake. If investor sentiment does indeed counteract these frictions, the interaction of innovation and sentiment should have a stronger effect on R&D intensity for firms that face tighter financing constraints or that are more susceptible to informational externalities.

We measure financing constraints with the Kaplan and Zingales (1997) index (henceforth, KZ index; see the Appendix in Lamont, Polk, and Saá-Requejo, 2001 for details on its construction), or with a combination of the KZ index and of the more recent measure developed by Hoberg and Maksimovic (2015). We classify firms as highly susceptible to informational externalities if they belong to an industry that past studies have found to be relatively more affected by R&D spillovers. Appendix B provides a detailed discussion of this classification.

The top left chart of Figure 1 shows the coefficient on the first lag of the interaction of innovation and sentiment for firms that face progressively milder financing constraints in year t-1. The leftmost point shows the coefficient for all the firms for which the lagged KZ index can be calculated. This coefficient is very close to that shown in Table 3. Moving to the right, the coefficients are estimated on samples that include firms with increasingly looser financing constraints, from the bottom 80% most financially constrained firms to the bottom 20% most financially constrained firms, in 5% increments.

The coefficients increase steadily as financing constraints become less binding, and they increase sharply for the least financially constrained firms. In contrast to the results of several studies on the relation between investment and investor sentiment (e.g., McLean and Zhao, 2014), this pattern clearly indicates that the effect of investor sentiment on the relation between innovation and R&D intensity does not operate through financing constraints. As shown in Figure 2, firms with loose financing constraints have a lower investment-to-assets ratio (about 6%) than the full sample (about 9%). The decline from 9% to 6% is steady as one focuses on firms with progressively slacker financing constraints. R&D intensity behaves in exactly the opposite way. It increases from about 2.5% in the full sample to just under 4% for the least financially constrained firms. The pattern of investment and R&D is robust to removing the smallest firms (top right chart), the most leveraged firms (bottom left), and those more susceptible to informational externalities (bottom right). These results highlight that the impact of investor sentiment on the relation between R&D and innovation is stronger for the most R&D-intensive firms, which also have looser financing constraints.

In the bottom left chart of Figure 1, we evaluate how the results change when using a different measure of financing constraints than the KZ index. Hoberg and Maksimovic (2015) quantify the tightness of the financing constraints faced by a company by analyzing the text of 10-K regulatory disclosures. They make their financing constraints score available starting from 1997. We use their measure of investment delays arising from liquidity issues to build the cross-sectional distribution of financing constraints from 1997 onward.[9] Before 1997, we use the KZ index. We can combine the two measures because we use their lagged values to partition the sample, and neither enters the analysis as an explanatory variable. The bottom left chart of Figure 1 shows that the broad trend of an increasing coefficient on the interaction term I_{-1} remains when including the Hoberg and Maksimovic (2015) index, although statistical significance is generally weaker and the relation is noisier than when using only the KZ index.

In the top right chart of Figure 1, we estimate the coefficient on the first lag of the interaction of innovation and sentiment separately for firms that are most and least susceptible to informational externalities. The coefficient for firms affected by informational externalities is more than double the one for all firms, and the coefficient for firms least affected by informational externalities is smaller than the full-sample counterpart and also statistically insignificant. The effect of informational externalities on R&D could be compounded in the presence of short-termist shareholders: not only are the benefits of R&D less appropriable, but R&D funds could be used to increase short-term performance and boost the career prospect of managers who face investors focused on short-term results (see the discussion in Section 1).

In the bottom right chart of Figure 1, we partition the sample on the basis of both the susceptibility of informational externalities and share turnover in year $t-1$ (the yearly average of shares traded daily over shares outstanding). Firms with high turnover are those with turnover above the median. The coefficient on the first lag of the innovation/sentiment inter-

[9] About 15% of the companies that had a KZ index have a missing Hoberg and Maksimovic (2015) index. The authors note that companies for which they cannot calculate their index are unlikely to face financing constraints. As such, we assign the companies in question to the bottom quintile of financially constrained firms.

action is four times larger than in the full sample for firms that are subject to informational externalities *and* that have high share turnover.

3.2 Robustness checks

We first evaluate the effect of a different set of firm-specific controls, replacing the variables used by Brown, Fazzari, and Petersen (2009) with the controls proposed by Gala, Gomes, and Liu (2020): the levels and squared values of size ($ln(K)$), of leverage (lev), and of an alternative definition of the sales ratio ($ln(SRk)$). In order to preserve degrees of freedom, we drop GCF and SRa and include either $ln(K)$ and $ln(K)^2$, or lev and lev^2, or $ln(SRk)$ and $ln(SRk)^2$. As shown in the first three columns of Table 6, the coefficients on the first and second lags of the interaction between S and ΔP remain positive and statistically significant, with magnitudes comparable to those reported thus far.

The specifications in the remaining four columns of Table 6 include not two but three lags of S, ΔP, and $S \cdot \Delta P$. As indicated, the firm-specific controls are also different in each case. Two results stand out. First, the third interaction lag is negative in all cases and statistically significant in one, suggesting that the effect of sentiment on the relation between innovation and R&D intensity is temporary. Second, in two instances the second lag of the interaction between sentiment and innovation is not statistically significant, albeit by a small margin. In these two specifications, however, the null that the overidentifying restrictions are valid is rejected when standard errors are clustered by firm.

The investor sentiment index of Baker and Wurgler (2006) is, by construction, orthogonalized relative to indicators of macroeconomic conditions. However, it might also reflect growth expectation specifically related to newly available technologies. In our setting, such possibility is clearly a concern, which we address by orthogonalizing the sentiment index with respect to a variable meant to capture these growth expectations. The variable is the difference between the weighted-average stock returns of high-tech firms and the weighted-average stock returns of low-tech firms (we obtain stock returns from CRSP through WRDS). Weights are based on log capital in the previous year. High-tech firms are more likely to benefit from a particularly productive new technology than low-tech firms are, and the stock returns of high-tech firms should exceed those of low-tech firms if investors expected strong growth as a result of technological developments. In Table 7, we show the first and second lags of the orthogonalized sentiment/innovation interaction coefficients for a variety of specifications that reflect many of the robustness checks performed so far. These coefficients are very similar to those discussed above, highlighting that investor sentiment does not proxy for growth expectations arising specifically from technological innovation.

In a further set of robustness checks, we discard firms in the top 10% of the distribution of, first, discretionary accruals in $t-1$ and, second, of sales growth (average sales-to-assets ratio in $t+2$ and $t+1$ minus the average sales-to-assets ratio in t and $t-1$). The reason for doing so is that managers might use R&D expenses to manipulate earnings (Bushee, 1998), because R&D is expensed rather than amortized and it has a significant impact on current earnings. If this were the case, discretionary accruals, which are another measure of earnings management (Polk and Sapienza, 2009), would also be high. The exclusion of firms with high sales growth is meant to address the possibility that changes in R&D intensity reflect the commercialization of new products in the aftermath of periods of technological innovation. For instance, firms might develop new products but delay the final stages of R&D and commercialization until their customers are receptive enough. The first two columns of Table 8 show that excluding firms with high discretionary accruals and sales growth reduces the magnitude and statistical significance of the interaction coefficients, but the t-statistics are still between about 1.80 and 1.90.

In the third column of Table 8, the investor sentiment index is orthogonalized with respect to three price and quantity measures of corporate financing conditions. The purpose of this specification is to evaluate whether the results are driven by time-varying credit availability, which could be reflected in investor sentiment (McLean and Zhao, 2014 find that firms can more easily finance investment when investor sentiment is high). The three variables are: the spread of the Moody's Seasoned Baa Corporate Bond index over the 10-year Treasury rate, the real log-change in Commercial and Industrial loans held by commercial banks, and the real log-change in Real Estate loans held by commercial banks. The coefficients on the interaction lags remain strongly statistically significant. This result is consistent with the finding discussed in Section 3.1 that the effect of investor sentiment, in our framework, is not driven by financing constraints. In the fourth specification shown in Table 8, sentiment is measured with the University of Michigan Index of Consumer Sentiment. The first lag of the interaction between innovation and sentiment is not statistically significant any longer, but the second lag is with a t-statistic of 1.73. The first lag of the sentiment index is, unlike in the results so far, statistically significant and negative.

San Miguel (1977) studies the quality of the R&D data reported in Compustat in 1972. He finds discrepancies, sometimes notable, between the data in Compustat and in 10-K forms filed by a sample of companies. He attributes these discrepancies, at least in part, to changes in regulatory disclosures that required disaggregated reporting of R&D expenses. He notes that Compustat quickly addressed certain reasons for discrepancy. As discussed in Section 2, Griliches (1990) highlights that variation in granted patents in the late 1970s was affected by staffing issues at USPTO. In this paper, so far we dealt with possible noise in the late

1970s patent data by underweighting the affected patent observations. In light of the issues described by San Miguel (1977) and Griliches (1990), in column (5) of Table 8 we restrict the sample to the years between 1983 and 2015, thus excluding early R&D data that could be of lower quality and excluding the patent observations affected by USPTO staffing issues. Starting in 1983 means that patent data from 1979 are not used, because the second lag of patent changes (1981) is based on observations in 1980 and 1981. In column (6) of Table 8 we also discard small firms, defined as the bottom 10% of the size distribution in year $t-1$, because the quality of the R&D data might be better for larger firms. The sample size decreases by 31% and 35% in columns (5) and (6), respectively, but the coefficient on the second interaction of innovation and sentiment is somewhat larger than discussed so far, and it is still statistically significant.

In the last two columns of Table 8, we measure technological innovation not with granted patents but with the difference in the growth of the sales-to-assets ratio between high-tech and low-tech firms ($\Delta SR^{HT/LT}$). When the broader universe of firms start adopting a new technology, the sales of high-tech firms should increase faster than the sales of low-tech firms. Since we are interested in when firms start experimenting with a new technology, rather than when they start adopting it, we use leads of the difference in sales growth: a large gap in sales growth in year t means that firms started experimenting with a new technology before year t. In column (7) of Table 8, $\Delta SR^{HT/LT}$ is the difference in the growth of the sales-to-asset ratio in $t+1$, while in column (8) it is the difference in year $t+2$. In the first case, the first lag of the interaction term is positive and statistically significant, while in the second case it is the second lag that is positive and statistically significant. One caveat of using lead values of $\Delta SR^{HT/LT}$ is that the sales of high-tech firms will increase only if the broader universe of firms adopt a technology. On the contrary, the number of patents would increase while the technology is developed even if, ex post, the technology were not be adopted.

4 Conclusions

Following periods of intense technological progress, firms engage in small-scale experimentation to understand how to best use a new technology. This activity, which is booked as R&D, is an important element of the technology diffusion process. However, certain frictions can reduce it to below the level that firms would normally undertake. In this paper, we investigate whether investor sentiment can offset these frictions, at least partially.

We find that, for low-tech firms, investor sentiment reinforces the effect of aggregate technological innovation on two-year-ahead firm-level R&D. The effect is stronger for companies subject to informational externalities and whose shareholders have short investment horizons. Unlike in the literature on investor sentiment and investment, the results are not driven by binding financing constraints that become looser when investor sentiment is more buoyant – indicating that R&D is subject to a distinct set of frictions than investment.

The findings are robust to a variety of controls and specifications that address the possibility that investor sentiment might proxy for growth expectations and for credit availability. The results are also robust to alternative measures of investor sentiment and of technological innovation.

Appendix A

Definition of firm-specific variables

The definition of firm-level variables follows Polk and Sapienza (2009), Gala, Gomes, and Liu (2020), and Brown, Fazzari, and Petersen (2009). Compustat variable names are in italics, and subscripts indicate whether the variables are lagged and by how many years. R&D intensity (RD) is xrd_t divided by at_{t-1}. Log-capital ($ln(K)$) is the logarithm of net property, plant and equipment ($ppent_t$). Gross cash flows (GCF) are the sum of income before extraordinary items (ib_t), depreciation and amortization (dp_t), and research and development expense (xrd_t) over beginning of year total book assets (at_{t-1}). The log-sales ratio ($ln(SRk)$) is the natural logarithm of the ratio of net sales/turnover ($sale_t$) divided by lagged capital ($ppent_{t-1}$). The sales ratio (SRa) is the ratio of net sales/turnover ($sale_t$) divided by lagged total book assets (at_{t-1}). Leverage is total debt over total book assets (at_t). Total debt is the sum of total debt in current liabilities (dlc_t) and total long term debt ($dltt_t$). Discretionary accruals are defined as in the Appendix of Polk and Sapienza (2009).

Filters applied to firm-specific variables

We apply several filters to the data, in order to reduce the effect of recording errors and noisy observations. The filters are also largely from Polk and Sapienza (2009), Gala, Gomes, and Liu (2020), and Brown, Fazzari, and Petersen (2009). We exclude firms incorporated outside the U.S., with a fiscal year not ending in December, with negative *at*, *ppent*, *capx*, *sale*, *xrd*, and total debt. We drop regulated utilities and financials, with SIC codes in the ranges 4900-4949 and 6000-6999 (see Helwege, Pirinsky, and Stulz, 2007). We filter out cases in which *gvkey* does not uniquely identify a firm-year observation. Before calculating the accounting ratios described in the previous paragraph, we drop observations in the bottom 1% of the yearly distributions of the two variables used in the denominators (*ppent* and *at*). While the analysis focuses on gross cash flows, we drop observations for which cash flows are, in absolute values, greater than 10. This filter matches the maximum and minimum reported by Polk and Sapienza (2009). Cash flow (CF) is the sum of income before extraordinary items (ib_t) and depreciation and amortization (dp_t) over beginning of year capital ($ppent_{t-1}$). Note that GCF is defined with at at the denominator (following Brown, Fazzari, and Petersen, 2009), while CF is defined with $ppent$ at the denominator (following Polk and Sapienza, 2009). We further exclude observations (a) in the top or bottom 1% of the yearly distribution of GCF, $ln(SRk)$, and SRa, and (b) the top 2% of the yearly distribution of leverage and RD. This last set of filters reduce the sample by 6%.

Appendix B

Identifiying firms that are most susceptible to informational externalities

Extant studies identify industries that are particularly subject to informational externalities, and we rely on these studies to classify firms into two catgories: most and least susceptible to informational externatities. We use two- and three-digit SIC codes (henceforth, SIC2 and SIC3, respectively) to classify firms, and we refine the classification using four-digit codes (SIC4). These refinements reflect the fact that SIC2 and SIC3 often include firms that manufacture complex products and firms that manufacture more standard products, and, as implied by Zimmerman (1982), product complexity contributes to informational externalities. As an example, we consider SIC3 382 (Laboratory Apparatus And Analytical, Optical, Measuring, and Controlling Instruments) as susceptible to informational externalities. However, we exclude, among others, SIC4 3821 (Laboratory Apparatus and Furniture) because it includes manufacturers of items like worktables and furniture and we include, among others, SIC 3826, which covers manufacturers of spectrometers and electron microscopes.

The literature highlights that informational externalities play a particularly significant role for the following industries: chemicals (Adams and Jaffe, 1996; Bernstein, 1989; Bernstein and Nadiri, 1989), rubber and plastics (Bernstein, 1989), petroleum (Bernstein, 1989; Bernstein and Nadiri, 1989), non-electrical machinery (Bernstein, 1989), computer components (Gruber, 1998; Irwin and Klenow, 1994), aircraft manufacturing (Benkard, 2000), shipbuilding (Thornton and Thompson, 2001), instruments (Bernstein and Nadiri, 1989), and power generation (Zimmerman, 1982; note that we exclude utilities as discussed in Appendix A). Bernstein and Nadiri (1989) use two-digit SIC codes to identify chemicals (28), petroleum

(29), machinery (35), and instruments (38). SIC3 283 (Drugs) is not classified as susceptible to informational externalities because patents are an effective way of protecting R&D returns for pharmaceutical companies (Levin, Klevorick, Nelson, and Winter, 1987).

Chemicals

SIC3 281 (Industrial Inorganic Chemicals).

SIC3 284 (Soap, Detergents, And Cleaning Preparations; Perfumes, Cosmetics, and Other Toilet Preparations).

SIC3 285 (Paints, Varnishes, Lacquers, Enamels, And Allied).

SIC3 286 (Industrial Organic Chemicals).

SIC3 287 (Agricultural Chemicals).

SIC3 289 (Miscellaneous Chemical Products).

Rubber and plastics

SIC3 282 (Plastics Materials And Synthetic Resins, Synthetic).

Petroleum

SIC2 29 (Petroleum Refining And Related Industries).

Non-electrical machinery

SIC3 352 (Farm And Garden Machinery And Equipment) except SIC4 3524 (Lawn and Garden Tractors and Home Lawn and Garden Equipment).

SIC3 353 (Construction, Mining, And Materials Handling) except SIC4 3534 (Elevators and Moving Stairways).

SIC3 354 (Metalworking Machinery And Equipment) except SIC4 3543 (Industrial Patterns), 3544 (Special Dies and Tools, Die Sets, Jigs and Fixtures, and Industrial Molds), and 3546 (Power-Driven Handtools).

SIC3 355 (Special Industry Machinery, Except Metalworking).

SIC3 356 (General Industrial Machinery And Equipment) except SIC4 3562 (Ball and Roller Bearings), 3564 (Industrial and Commercial Fans and Blowers and Air Purification Equipment), 3567 (Industrial Process Furnaces and Ovens), 3568 (Mechanical Power Transmission Equipment, Not Elsewhere Classified).

Computers

SIC3 357 (Computer And Office Equipment) excluding SIC4 3578 (Calculating and Accounting Machines, Except Electronic Computers) and 3579 (Office Machines, Not Elsewhere Classified).

SIC3 365 (Household Audio And Video Equipment, And Audio).

SIC3 367 (Electronic Components And Accessories) excluding SIC4 3671 (Electron Tubes), 3675 (Electronic Capacitors), 3676 (Electronic Resistors), 3677 (Electronic Coils, Transformers, and Other Inductors), 3678 (Electronic Connectors).

Aircraft manufacturing

SIC3 372 (Aircraft And Parts).

Shipbuilding

SIC3 373 (Ship And Boat Building And Repairing).

Instruments

SIC3 381 (Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems and Instruments).

SIC3 382 (Laboratory Apparatus And Analytical, Optical, Measuring, and Controlling Instruments) except SIC4 3821 (Laboratory Apparatus and Furniture), 3822 (Automatic Controls for Regulating Residential and Commercial Environments and Appliances), 3824 (Totalizing Fluid Meters and Counting Devices).

SIC3 384 (Surgical, Medical, And Dental Instruments And Supplies) except SIC4 3841 (Surgical and Medical Instruments and Apparatus), 3842 (Orthopedic, Prosthetic, and Surgical Appliances and Supplies), 3843 (Dental Equipment and Supplies).

SIC3 386 (Photographic Equipment And Supplies).

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Figure 1: The role of financing constraints and informational externalities.

The charts show GMM coefficients on the lagged interaction of S and ΔP for firms sorted by financing constraints and susceptibility to informational externalities. Financing constraints are measured with the Kaplan and Zingales (1997) index as of year $t-1$. See Appendix B for how firms are classified according to susceptibility to informational externalities. In the top left chart, the leftmost point is the coefficient estimated on all firms for financing constraints can be calculated. The point immediately to the right (the rightmost point) is based on firms in the top 80% (top 20%) of the distribution of the negative of the Kaplan and Zingales (1997) index, so that the least constrained forms are shown in the rightmost point. In the bottom left chart, the yearly distribution of financing constraints is based on the Kaplan and Zingales (1997) index through 1996, and on the Hoberg and Maksimovic (2015) measure from 1997. In the bottom right chart, firms are classified according to the susceptibility to informational externalities and according to the average daily ratio of shares traded to shares outstanding in year $t-1$. Double-clustered t-statistics are reported next to the data points. The regressors are those shown in Table 4. The sample includes 1965 to 2015.

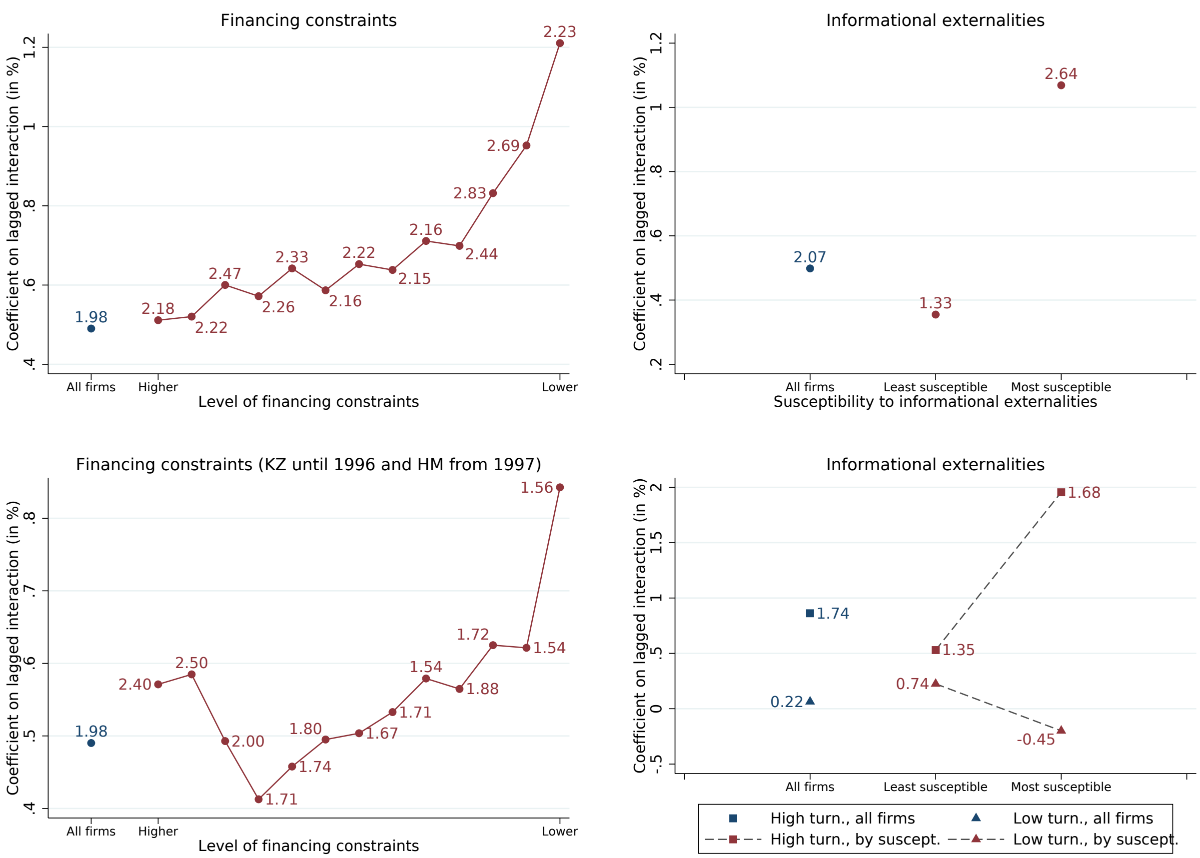

Figure 2: Average investment and R&D across financing constraints.

The charts show the average investment/lagged assets (blue hollow circles) and the average RD (red solid circles) for firms sorted by financing constraints. Financing constraints are measured with the Kaplan and Zingales (1997) index as of year $t-1$. In the top left chart, the leftmost point is the average over all firms for financing constraints can be calculated. The point immediately to the right (the rightmost point) is based on firms in the top 80% (top 20%) of the distribution of the negative of the Kaplan and Zingales (1997) index, so that the least constrained forms are shown in the rightmost point. In the top right chart, firms in the bottom 20% of the distribution of log capital in year $t-1$ are excluded. In the bottom left chart, firms in the top 20% of the distribution of leverage in year $t-1$ are excluded. In the bottom right chart, the firms most subject to informational externalities are excluded. See Appendix B for how firms are classified according to their susceptibility to informational externalities. The sample includes 1965 to 2015.

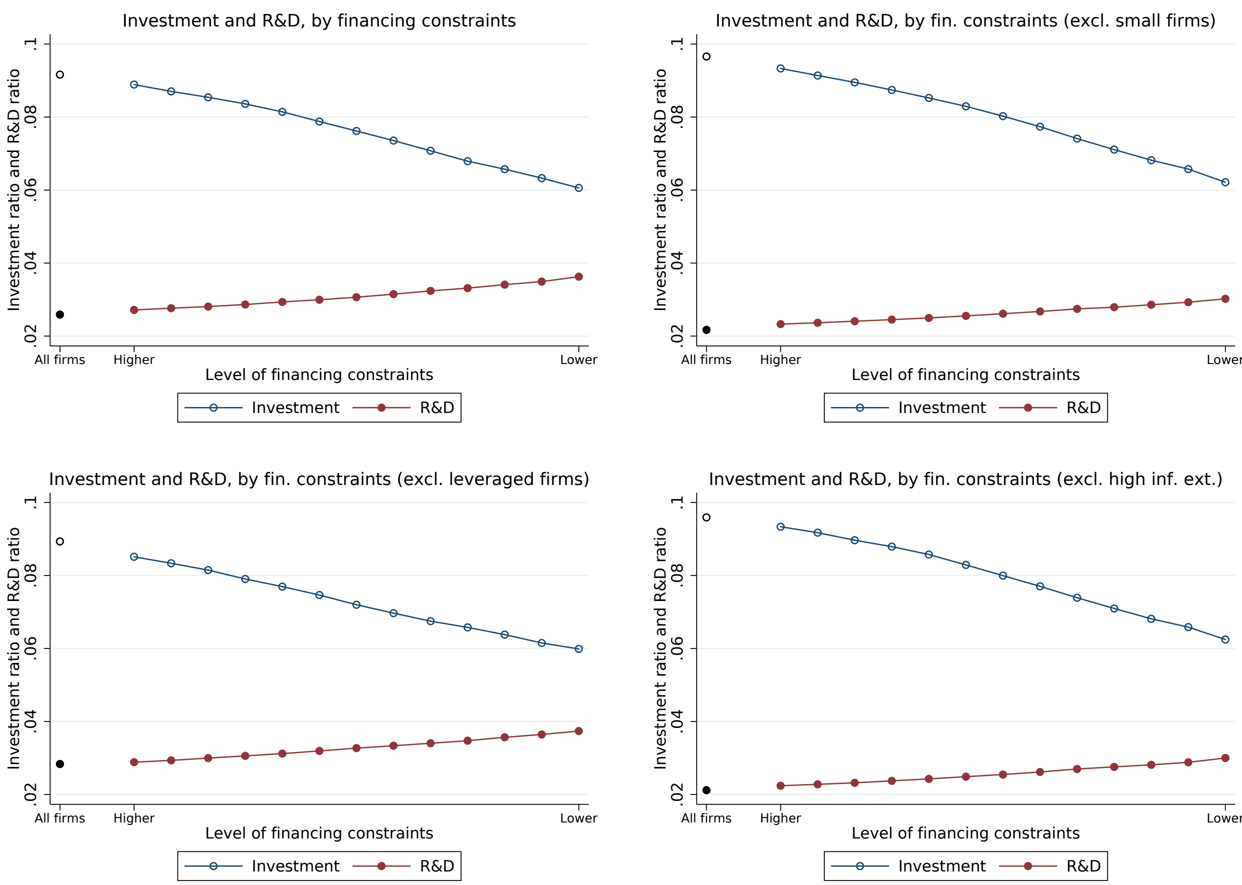

Table 1: Summary statistics: macro variables.

The table reports the mean, standard deviation, and selected percentiles for ADS (yearly average of the daily values of the Aruoba, Diebold, and Scotti, 2009 index of economic activity), S (yearly average of the monthly values of the $SENT^{\perp}$ sentiment index of Baker and Wurgler, 2006), and ΔP (log-changes in the number of patents granted by USPTO). The sample includes 1965 to 2015.

Summary statistics					
	μ	σ	10^{th}	50^{th}	90^{th}
ADS	-0.0266	0.6578	-0.9621	0.0216	0.7354
S	-0.0189	0.9876	-1.606	0.0243	0.9094
ΔP	0.0379	0.1013	-0.082	0.0216	0.1922

Correlations			
	ADS	S	ΔP
ADS	100		
S	-18	100	
ΔP	17	5	100

Table 2: Summary statistics: firm-level variables.

The table reports the mean, standard deviation, selected percentiles, and the number of observations for the following firm-level variables: research and development intensity (RD), gross cash flows (GCF), sales ratio (SRa, scaled by assets), log-sales ratio ($ln(SRk)$, scaled by capital), leverage (lev), log-size ($ln(K)$), and stock issuance (stk). Low-tech and high-tech firms are classified following Brown, Fazzari, and Petersen (2009). See Appendix A for details on how the variables are constructed. The sample includes 1965 to 2015.

Low-tech firms						
	μ	σ	10^{th}	50^{th}	90^{th}	obs
RD	0.0269	0.0454	0.0000	0.0131	0.0661	26,470
GCF	0.1059	0.1172	-0.0102	0.1138	0.2236	26,564
SRa	1.3565	0.8352	0.4002	1.2424	2.3985	61,586
$ln(SRk)$	1.3341	1.1712	-0.3149	1.4215	2.7587	61,449
lev	0.2738	0.2010	0.0102	0.2549	0.5469	67,856
$ln(K)$	4.0316	2.3830	1.0217	3.9339	7.1903	68,326
stk	0.0203	0.1610	-0.0260	0.0000	0.0383	53,860
High-tech firms						
	μ	σ	10^{th}	50^{th}	90^{th}	obs
RD	0.1243	0.1088	0.0224	0.0967	0.2588	16,725
GCF	0.1421	0.1822	-0.0856	0.1582	0.3475	17,197
SRa	1.0829	0.6362	0.3614	0.9998	1.8653	19,005
$ln(SRk)$	1.8943	0.9631	0.7390	1.9116	3.0938	18,989
lev	0.1520	0.1792	0.0000	0.0888	0.4027	22,697
$ln(K)$	2.5279	2.2024	-0.0534	2.2787	5.5709	22,811
stk	0.0573	0.2688	-0.0406	0.0035	0.1390	16,297

Table 3: Innovation and firm-level R&D intensity: low-tech and high-tech firms. The table shows the effect of the interaction between S and ΔP and controls on RD. See Tables 1 and 2 for definitions. High-tech and low-tech firms are classified following Brown, Fazzari, and Petersen (2009). The first two columns show fixed-effect regressions. The next four columns report 2SLS estimates, using 2-3 or 3-4 level lags of firm-level regressors as instruments. The last four columns show Arellano and Bond (1991) first-difference GMM estimates, using 2-4 or 3-4 level lags of firm-level regressors as instruments. t-statistics are based on double clustering by time and firm. HJ is the p-value of the Hansen test that overidentifying restrictions are valid. WI is the Kleibergen-Paap Wald rk F statistic. The subscripts y, f, and i indicate that the statistics refer to specifications with errors clustered by year, firm, or the intersection of year and firm. m1 and m2 are the p-values of Arellano-Bond tests of no first- and second-order autocorrelation in the residuals (when the errors are clustered by firm). Coefficients in %. The sample includes 1965 to 2015.

	Firm FE, levels		2SLS, differences				1-step GMM, Arellano-Bond			
			2-3		3-4		2-4		3-4	
	Lo	Hi	Lo	Hi	Lo	Hi	Lo	Hi	Lo	Hi
RD_{-1}	87.11	85.13	61.02	35.46	61.97	4.79	69.05	47.07	79.89	55.75
	13.97	15.04	2.13	1.80	0.90	0.07	1.98	1.57	1.22	0.95
RD^2_{-1}	-94.58	-71.92	-91.18	-14.34	133.42	34.60	-71.09	-34.71	16.71	-36.87
	-3.68	-5.14	-2.24	-0.53	0.68	0.31	-1.30	-0.82	0.10	-0.34
stk_{-1}	-1.95	-4.27	-1.36	-2.47	-12.16	-0.71	-1.71	-2.81	-6.97	-6.37
	-3.62	-9.34	-3.29	-4.46	-1.55	-0.11	-3.11	-3.46	-1.97	-1.45
GCF_{-1}	-0.15	-2.25	1.79	2.86	2.90	6.03	1.40	2.87	-5.53	4.36
	-0.30	-2.93	2.08	1.52	0.40	0.95	1.22	3.07	-0.92	0.88
SRa_{-1}	-0.14	0.19	-0.18	-0.36	0.30	-1.56	0.04	-0.35	1.96	-1.26
	-2.13	0.84	-0.43	-0.33	0.15	-1.07	0.09	-0.60	1.04	-1.06
ADS_{-1}	0.08	0.33	0.03	0.07	-0.04	0.13	0.03	0.01	0.06	0.02
	3.66	2.44	1.06	0.78	-0.56	1.22	0.92	0.10	0.88	0.21
ADS_{-2}	-0.08	-0.08	-0.09	-0.11	-0.25	0.02	-0.11	-0.18	-0.26	-0.21
	-4.26	-0.65	-3.81	-0.98	-1.88	0.10	-3.72	-1.41	-2.12	-1.64
S_{-1}	0.04	-0.06	0.03	-0.18	0.05	-0.16	0.02	-0.08	0.06	-0.11
	1.31	-0.42	0.81	-1.54	0.84	-1.15	0.77	-0.70	1.14	-1.00
ΔP_{-1}	-0.32	-1.21	-0.23	-1.31	-0.69	-0.93	-0.31	-1.13	-0.36	-1.56
	-2.00	-1.52	-1.30	-1.41	-1.84	-0.70	-1.57	-1.32	-1.11	-1.60
I_{-1}	0.18	-1.07	0.32	0.43	0.37	-0.60	0.50	0.87	0.48	0.41
	0.69	-0.87	1.79	0.40	1.11	-0.38	2.07	0.71	1.21	0.25
S_{-2}	0.00	0.15	0.03	0.15	-0.05	0.25	0.03	0.19	-0.02	0.09
	0.16	1.31	1.08	1.57	-0.85	1.29	0.98	1.66	-0.37	0.54
ΔP_{-2}	-0.10	-0.37	-0.06	-0.22	-0.80	-0.31	-0.04	-0.19	-0.04	-0.69
	-0.73	-0.38	-0.31	-0.27	-1.94	-0.21	-0.20	-0.22	-0.10	-0.63
I_{-2}	0.52	-0.56	0.39	-0.45	1.02	-1.27	0.60	0.59	0.76	0.66
	2.48	-0.48	2.03	-0.59	2.30	-1.09	2.49	0.68	1.96	0.65
Obs.	21,026	12,171	15,653	8,358	13,622	7,053	18,065	10,014	18,065	10,014
HJ_y			0.86	0.96	0.78	0.42	0.56	0.88	0.76	0.78
HJ_f			0.84	0.93	0.52	0.43	0.51	0.83	0.46	0.80
HJ_i			0.90	0.95	0.66	0.39	0.60	0.97	0.64	0.87
WI_y			16.93	12.37	0.70	0.68				
WI_f			14.44	15.06	1.09	1.36				
WI_i			12.52	11.57	0.68	0.83				
m1			0.00	0.00	0.02	0.01	0.00	0.00	0.02	0.00
m2			0.63	0.67	0.13	0.86	0.25	0.78	0.25	0.99

Table 4: Innovation and R&D intensity: additional results.

The table shows the effect of the interaction between S and ΔP and controls on RD for low-tech firms, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 2-to-4 level lags of firm-level regressors as instruments. See Tables 1 and 2 for variable definitions, and Table 3 for details on m1, m2, the HJ statistics, and on the t-statistics. Low-tech firms are identified following Brown, Fazzari, and Petersen (2009). In (1) the 1979-80 observations of ΔP are *not* multiplied by 30%, while in (2) they are multiplied by 10%. In (3) observations for which lags of the regressors include 1979 or 1980 are excluded. In (4) firms in the bottom 10% of the size distribution as of t are excluded (the percentile is calculated on the overall sample, including both high- and low-tech firms). In (5), the sample excludes 1995. Coefficients in %. The sample includes 1965 to 2015.

	(1)	(2)	(3)	(4)	(5)
RD_{-1}	69.14	69.01	71.65	62.75	56.56
	1.99	1.98	1.93	1.49	1.97
RD^2_{-1}	-71.27	-71.00	-77.35	-44.58	-58.36
	-1.31	-1.29	-1.32	-0.66	-1.21
stk_{-1}	-1.72	-1.70	-1.84	-1.51	-1.84
	-3.16	-3.10	-3.21	-2.36	-4.89
GCF_{-1}	1.38	1.41	1.37	2.03	0.81
	1.18	1.23	1.09	2.50	0.62
SRa_{-1}	0.05	0.03	0.13	-0.16	0.22
	0.13	0.07	0.29	-0.55	0.45
ADS_{-1}	0.03	0.03	0.05	0.00	0.03
	0.98	0.92	1.75	0.12	1.14
ADS_{-2}	-0.11	-0.10	-0.11	-0.11	-0.09
	-3.90	-3.62	-3.46	-3.26	-3.86
S_{-1}	0.03	0.02	0.01	0.01	0.01
	1.01	0.70	0.18	0.34	0.28
ΔP_{-1}	-0.25	-0.29	-0.25	-0.29	-0.33
	-1.59	-1.47	-1.34	-1.61	-2.06
I_{-1}	0.47	0.47	0.61	0.55	0.41
	1.96	2.02	3.05	2.22	1.85
S_{-2}	0.02	0.03	0.02	0.01	0.04
	0.70	1.04	0.97	0.23	1.61
ΔP_{-2}	-0.08	0.01	-0.02	-0.15	-0.02
	-0.53	0.04	-0.11	-0.77	-0.09
I_{-2}	0.75	0.51	0.58	0.45	0.51
	3.14	2.22	2.27	2.27	2.28
Obs.	18,065	18,065	15,953	17,032	16,237
HJ_y	0.57	0.55	0.67	0.65	0.69
HJ_f	0.53	0.49	0.70	0.13	0.54
HJ_i	0.62	0.59	0.76	0.33	0.75
m1	0.00	0.00	0.00	0.00	0.00
m2	0.25	0.25	0.22	0.36	0.49

Table 5: Innovation and R&D intensity, conditional on investor sentiment.

The table shows the marginal effect of the first and second lags of ΔP on RD when the first and second lags of S are equal to one or one and a half standard deviations above the mean. The results are shown only for low-tech firms. The coefficients are estimated from specifications that include the same variables (and lags) as in Table 4, and are estimated with the Arellano and Bond (1991) first-difference GMM procedure, where the instruments are 2-to-4 level lags of firm-level regressors. Column (1) corresponds to the fourth-to-last specification of Table 3. In (2) the 1979-80 observations of ΔP are *not* multiplied by 30%, while in (3) they are multiplied by 10%. In (4) observations for which lags of the regressors include 1979 or 1980 are excluded. In (5) firms in the bottom 10% of the size distribution as of t are excluded (the percentile is calculated on the overall sample, including both high- and low-tech firms). In (6), the sample excludes 1995. Coefficients in %. The sample includes 1965 to 2015.

	First lag						
	(1)	(2)	(3)	(4)	(5)	(6)	Average
$1\ \sigma$	0.18	0.21	0.17	0.36	0.25	0.07	0.21
	0.58	0.68	0.55	1.18	0.80	0.24	
$1.5\ \sigma$	0.42	0.44	0.40	0.66	0.52	0.27	0.45
	1.04	1.06	0.99	1.72	1.24	0.71	

	Second lag						
	(1)	(2)	(3)	(4)	(5)	(6)	Average
$1\ \sigma$	0.54	0.65	0.51	0.55	0.29	0.49	0.51
	1.75	2.11	1.64	1.65	1.17	1.62	
$1.5\ \sigma$	0.83	1.02	0.76	0.84	0.51	0.74	0.78
	2.07	2.46	1.89	1.91	1.60	1.89	

Table 6: Innovation and R&D intensity: alternative specifications.

The table shows the effect of the interaction between S and ΔP and controls on RD, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 2-to-4 level lags of firm-level regressors as instruments. See Tables 1 and 2 for variable definitions, and Table 3 for details on m1, m2, the HJ statistics, and on the t-statistics. Coefficients on the lags of ADS are omitted for space reasons. The baseline firm-specific controls GCF and SRa are those used in the previous tables. The alternative firm-specific controls $ln(SRk)$, $ln(K)$, and lev are based on Gala, Gomes, and Liu (2020). Coefficients in %. The sample includes 1965 to 2015.

	Alternative controls			Including three lags, with baseline and alternative controls			
X_1	$ln(SRk)$	$ln(K)$	lev	X_1=GCF	X_1=$ln(SRk)$	X_1=$ln(K)$	X_1=lev
X_2	$ln(SRk)^2$	$ln(K)^2$	lev^2	X_2= SRa	X_2=$ln(SRk)^2$	$X_2 = ln(K)^2$	$X_2 = lev^2$
RD_{-1}	71.89	71.12	55.12	69.08	71.76	71.50	54.90
	2.26	2.40	2.36	1.99	2.27	2.41	2.38
RD^2_{-1}	-75.51	-76.63	-47.03	-71.03	-75.21	-77.38	-46.49
	-1.51	-1.75	-1.17	-1.30	-1.52	-1.77	-1.18
stk_{-1}	-1.71	-1.54	-1.58	-1.69	-1.71	-1.53	-1.58
	-2.58	-2.33	-2.82	-3.15	-2.60	-2.33	-2.82
$X_{1,-1}$	0.93	0.54	-4.71	1.46	0.87	0.58	-4.98
	1.30	0.70	-1.30	1.28	1.29	0.76	-1.37
$X_{2,-1}$	-0.23	-0.05	3.63	0.01	-0.22	-0.05	3.88
	-1.88	-0.76	1.11	0.01	-1.94	-0.80	1.22
ADS	Lags 1 and 2 (not reported)			Lags 1 to 3 (not reported)			
S_{-1}	0.02	0.01	0.00	0.02	0.02	0.01	0.00
	0.67	0.47	-0.15	0.74	0.74	0.40	-0.06
ΔP_{-1}	-0.28	-0.25	-0.17	-0.24	-0.23	-0.20	-0.09
	-1.57	-1.38	-1.04	-1.17	-1.23	-1.02	-0.51
I_{-1}	0.49	0.44	0.34	0.44	0.40	0.32	0.34
	1.85	1.88	1.75	2.13	1.64	1.46	1.73
S_{-2}	0.03	0.02	0.03	0.02	0.02	0.02	0.02
	1.24	0.86	1.71	0.78	0.82	0.56	0.97
ΔP_{-2}	-0.04	0.00	0.06	0.09	0.05	0.06	0.25
	-0.18	0.01	0.33	0.35	0.21	0.25	1.10
I_{-2}	0.56	0.52	0.39	0.49	0.48	0.39	0.33
	2.08	1.98	2.02	2.44	2.00	1.65	1.62
S_{-3}				0.02	0.02	0.01	0.02
				0.52	0.87	0.41	0.68
ΔP_{-3}				0.17	0.13	0.10	0.23
				0.97	0.73	0.55	1.60
I_{-3}				-0.27	-0.29	-0.31	-0.22
				-1.53	-1.50	-1.86	-1.44
Obs.	18,070	18,071	18,034	18,065	18,070	18,071	18,034
HJ_y	0.36	0.77	0.40	0.54	0.38	0.78	0.42
HJ_f	0.42	0.09	0.00	0.53	0.44	0.09	0.01
HJ_i	0.49	0.59	0.37	0.61	0.51	0.59	0.39
m1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m2	0.24	0.26	0.27	0.25	0.24	0.27	0.27

Table 7: Orthogonalizing sentiment relative to the high-tech/low-tech return spread.

The table shows the coefficients on the interaction between S and ΔP, estimated with the Arellano and Bond (1991) first-difference GMM procedure using the indicated specifications. The coefficients on the firm-specific and economic-activity controls are not reported. Lags 2 to 4 of firm-level regressors are used as instruments, unless specificied otherwise. See Tables 1 and 2 for variable definitions, and Table 3 for details on m1, m2, the HJ statistics, and on the t-statistics. Investor sentiment is measured with the residuals from regressions of S on the difference between the weighted average return on high-tech firms and the weighted average return on low-tech firms. In all cases, weights are based on log-capital (see Appendix A). Low-tech and high-tech firms are identified following Brown, Fazzari, and Petersen (2009). In the baseline specification, the 1979-80 observations of ΔP are multiplied by 30%. Small firms are those in the bottom 10% of the size distribution as of year t (the percentile is calculated on the overall sample, including both high- and low-tech firms). Coefficients in %. The sample includes 1965 to 2015.

	Baseline	1979-80: 100%	1979-80: 10%	1979-80: drop
I_{-1}	0.49	0.46	0.46	0.60
	2.03	1.94	1.98	3.03
I_{-2}	0.63	0.78	0.55	0.62
	2.59	3.19	2.34	2.35
Obs.	18,065	18,065	18,065	15,953
HJ_y	0.57	0.58	0.56	0.67
HJ_f	0.52	0.54	0.51	0.70
HJ_i	0.61	0.63	0.60	0.76
m1	0.00	0.00	0.00	0.00
m2	0.25	0.25	0.25	0.22
	3-4 lags as instruments	**Exclude 1995**	**Drop small firms**	**Only manuf.**
I_{-1}	0.48	0.39	0.53	0.61
	1.20	1.79	2.16	2.45
I_{-2}	0.81	0.56	0.48	0.56
	2.04	2.44	2.38	2.14
Obs.	18,065	16,237	17,032	12,549
HJ_y	0.76	0.70	0.65	0.47
HJ_f	0.47	0.58	0.13	0.36
HJ_i	0.64	0.77	0.34	0.63
m1	0.02	0.00	0.00	0.00
m2	0.25	0.49	0.36	0.11

Table 8: Innovation and R&D intensity: additional robustness checks.

The table shows Arellano and Bond (1991) first-difference GMM coefficients for low-tech firms. Lags 2 to 4 of firm-level regressors are used as instruments. In (1), firms in the top 10% of the distribution of sales changes are excluded. In (2), firms in the top 10% of the distribution of discretionary accruals are excluded. In (3), the sentiment index S is orthogonalized relative to the spread of the Moody's Seasoned Baa Corporate Bond index over the 10-year Treasury rate, the real log-change in Commercial and Industrial loans held by commercial banks, and the real log-change in Real Estate loans held by commercial banks. In (4), investor sentiment is measured with yearly average values of the University of Michigan Index of Consumer Sentiment. In (5), the sample covers 1983 to 2015. In (6), the sample covers 1983 to 2015, and small firms are excluded (see Table 7 for the definition of small firms). In (7), innovation in year t is measured not with granted patents, but with the year $t+1$ difference between the high-tech and low-tech capital-weighted average year-on-year change in the sales ratio (SR). In (8), innovation in year t is measured with the sales-ratio difference as of year $t+2$. See Tables 1, 2, and Appendix A for variable definitions, and Table 3 for details on m1, m2, the HJ statistics, and on the t-statistics. Low-tech are identified following Brown, Fazzari, and Petersen (2009). Coefficients in %. The sample includes 1965 to 2015.

	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)
RD_{-1}	70.67	44.66	68.88	68.16	71.38	64.25		68.55	66.45
	2.11	1.07	1.98	2.01	1.71	1.31		2.02	2.02
RD^2_{-1}	-64.02	-44.46	-70.72	-69.09	-75.95	-47.69		-69.84	-67.47
	-1.41	-0.74	-1.28	-1.29	-1.15	-0.61		-1.30	-1.27
stk_{-1}	-1.71	-1.30	-1.69	-1.66	-1.79	-1.64		-1.66	-1.56
	-2.55	-1.83	-3.07	-3.16	-2.91	-2.37		-3.21	-3.45
GCF_{-1}	1.77	2.06	1.43	1.47	1.45	1.93		1.44	1.59
	1.87	2.62	1.25	1.26	1.17	2.05		1.24	1.35
SRa_{-1}	-0.01	0.00	0.02	-0.04	0.03	-0.06		-0.01	-0.12
	-0.05	0.01	0.04	-0.09	0.08	-0.19		-0.02	-0.28
ADS_{-1}	0.02	0.03	0.03	0.09	0.02	-0.04		0.05	0.06
	0.70	0.97	1.03	2.26	0.56	-0.72		1.71	2.55
ADS_{-2}	-0.11	-0.09	-0.10	-0.07	-0.09	-0.14		-0.07	-0.09
	-3.62	-2.79	-3.70	-1.98	-1.83	-2.40		-3.06	-3.26
S_{-1}	0.03	0.01	0.01	-0.67	-0.01	0.00		0.00	0.01
	1.15	0.24	0.47	-1.85	-0.14	0.12		-0.07	0.25
ΔP_{-1}	-0.30	-0.22	-0.29	-0.18	-0.06	0.03	$\Delta SR^{HT/LT}_{-1}$	0.54	-0.51
	-1.64	-1.12	-1.45	-0.92	-0.24	0.12		1.66	-1.42
I_{-1}	0.36	0.41	0.61	1.32	0.47	0.64		0.76	0.48
	1.93	1.81	2.52	1.32	1.16	1.55		2.33	0.80
S_{-2}	0.01	0.02	0.04	0.28	0.02	-0.01		0.00	-0.01
	0.23	0.68	1.40	1.11	0.76	-0.14		-0.04	-0.27
ΔP_{-2}	-0.16	-0.03	-0.02	0.06	0.16	0.13	$\Delta SR^{HT/LT}_{-2}$	0.38	0.44
	-0.85	-0.16	-0.11	0.34	0.65	0.56		0.90	1.32
I_{-2}	0.39	0.45	0.49	2.26	0.64	0.64		-0.29	1.23
	1.79	1.85	2.01	1.73	1.90	1.99		-0.60	2.31
Obs.	15,064	15,404	18,065	18,065	12,473	11,785		18,065	17,700
HJ_y	0.19	0.54	0.54	0.47	0.50	0.77		0.57	0.57
HJ_f	0.29	0.35	0.49	0.38	0.68	0.21		0.43	0.42
HJ_i	0.19	0.46	0.59	0.54	0.63	0.49		0.57	0.59
m1	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00
m2	0.56	0.90	0.25	0.26	0.22	0.28		0.27	0.30

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