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Innovation, investor sentiment, and firm-level experimentation

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Abstract

Due to frictions like informational externalities, firms invest too little in learning the productivity of newly available technologies through small-scale experimentation. I study the effect of investor sentiment on the relation between technological innovation and future firm-level R&D expenses, which include the resources used for small-scale experimentation. I find that rapidly improving investor sentiment strengthens the effect of technological innovation on one-year-ahead R&D expenses, and that the effect is more pronounced for high-tech firms with tighter financing constraints. The results are not driven by sentiment proxying for technological innovation or by sentiment and R&D expenses being jointly determined. The evidence is consistent with the hypothesis that sentiment counteracts frictions in the process of technology diffusion.

JEL classification: G02; G31; O32; O33; O40.
Keywords: Investor sentiment; technological innovation; R&D.

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1 Introduction

I study how changes in investor sentiment affect the relation between technological innovation and future firm-level research and development (R&D) expenses, which include the resources firms invest in small-scale experimentation to understand whether they should incorporate technological innovations in their current production process.[1] Due to frictions like informational externalities, firms typically invest too little in small-scale experimentation, which can lead to sub-optimal technology adoption decisions.

As detailed in Section 2, the literature has found that mispricing and investor sentiment can increase corporate investment. The hypothesis at the heart of this paper is that investor sentiment may counteract the effects of frictions that characterize the technology diffusion process and increase experimentation, as reflected in R&D expenses. Investor sentiment would play a role similar to that of the subsidies that governments often provide to not only foster technological innovation but also to promote its adoption (Evenson (1967), Hall (2003), Rustichini and Schmilz (1991)).

I find that the interaction of innovation and sentiment changes has, after one year, a positive and statistically significant effect on the R&D of both high-tech and low-tech firms. The unconditional effect of innovation is, however, estimated imprecisely, which means that sentiment changes have to be large to make the conditional effect of innovation on R&D positive. Conditional on sentiment changes being one and a half standard deviations from the mean, the marginal effect of a one-standard deviation increase in innovation on R&D is, after one year, an increase of 0.42 percentage points for high-tech firms, and of

[1] Accounting standards (FASB (2010)) prescribe that activities like the search for "applications of new research findings," the "evaluation of product or process alternatives," or the "operation of a pilot plant," should be classified as R&D.

0.11 percentage points for low-tech firms (the corresponding sample averages are 11.60% and 2.61%). The modest size of the effect of investor sentiment is consistent with the hypothesis that sentiment increases the impact of innovation on experimentation, because experimentation is by definition a small-scale activity.

Firms engaged in technological innovation at the *invention* stage – that is, when a new technology is developed by a relatively small group of firms – face a free-rider problem, because the benefits of innovation are not completely appropriable. The consequence is that, even though patent protection and first-mover advantages can reduce the impact of informational externalities (Johnson (2007)), private returns to innovation are lower than social returns (Griliches (1992)), and the equilibrium level of innovation is lower than the social optimum (Jones and Williams (1998)).

Even in the absence of externalities, other market failures can constrain the level of innovation below the social optimum. Asymmetric information can make financing constraints bind (Hall (2002)), in particular for young firms (Brown, Fazzari, and Petersen (2009)). In addition, career concerns can make managers reluctant to undertake risky but innovative R&D. For instance, pressure to meet short-term goals[2] can reduce incentives to innovate, and so can less failure-tolerant investors (Tian and Wang (2014)) and shareholders that are less able to distinguish poor R&D choices from bad outcomes of risky but ex-ante optimal R&D.[3]

The *adoption* stage – when the larger population of firms decides whether and how to invest in a new technology – is also characterized by informational externalities, in particular

[2] Aggarwal and Hsu (2013), Ferreira, Manso, and Silva (2014), He and Tian (2013), Asker, Farre-Mensa, and Ljungqvist (2015), Bernstein (2015).

[3] Fang, Tian, and Tice (2014), Lerner, Sorensen, and Stromberg (2011), Aghion, VanReenen, and Zingales (2013).

when the productivity of the new technology is uncertain.[4] Bolton and Harris (1999), for instance, solve a problem where firms decide how much to produce with the old and with the new technology, and where experimentation provides information about the productivity of the new technology, but it is subject to informational externalities. They show that, in general, the equilibrium level of experimentation falls short of the social optimum, and the resulting reduction in the flow of information can lead to the rejection of a productive technology or to the adoption of an unproductive one. Financing constraints and career-concern problems can also limit the amount of experimentation at the adoption stage.

The reinforcing effect that investor sentiment has on the impact of innovation on R&D could simply be the result of investor sentiment being a proxy for growth expectations, in which case the results of the paper should be interpreted along the lines of Johnson (2007) and Pastor and Veronesi (2009), in whose setting large and apparently irrational price movements are the result of rational learning about a potentially disruptive technology.[5] The sentiment proxies used in the paper (Baker and Wurgler (2006)) are by construction orthogonalized with respect to business cycle variables, and the results in Baker and Wurgler (2006) imply that the proxies are informative about investor sentiment, rather than growth expectations.

Similarly, the results could be due to investor sentiment being a better proxy for innovation than changes in the number of granted patents. As discussed in Section 4.1, the results are unaffected if sentiment changes are orthogonalized with respect to several alternative measures of innovation. In the same section, I also address the possibility that R&D and sentiment changes are jointly determined by exploiting the negative correlation between

[4] Bhattacharya, Chatterjee, and Samuelson (1986), Jovanovic and MacDonald (1994), Reinganum (1983); for empirical studies, see Zimmerman (1982) and Thornton and Thompson (2001).

[5] Similar contributions where expectations of high productivity growth or low financing costs can generate apparently irrational market valuations are, for instance, Caballero, Farhi, and Hammour (2006) and Jermann and Quadrini (2007).

sentiment changes and lagged sentiment levels that arises because of the mean reversion of sentiment levels. The results are largely unchanged, especially for low-tech firms.

The link between stock market valuations and R&D has been studied, from a theoretical point of view, by Jerzmanowski and Nabar (2008). In their model, innovation is below the social optimum because of the inappropriability of the positive externalities that current innovation has for future innovation. Stock market overvaluation increases the amount of resources expended at the invention stage, which in turns boosts innovation and increases productivity growth. Besides its empirical focus, this paper differs from Jerzmanowski and Nabar (2008) because it concentrates on the technological diffusion stage, with innovation available for adoption being used as an explanatory variable for experimentation, as measured by R&D.

Nanda and Rhodes-Kropf (2013) study how "hot markets," defined on the basis of how many startups obtain initial early stage financing in a given quarter, affect the type of startups funded by venture capital companies. They find that a higher proportion of novel firms are financed, and these firms are less likely to file for an initial public offering (IPO). However, conditional on doing so, they have higher IPO valuations, produce more patents, and these patents have more citations. Nanda and Rhodes-Kropf (2013, p.405) interpret their results as evidence that hot markets are a "critical aspect of the process through which new technologies are commercialized," because they "seem to facilitate the experimentation that is important for the [...] diffusion of radical new technologies." The focus of Nanda and Rhodes-Kropf (2013) is different from this paper's, because they study the early financing of startups which *invent* new technologies, while I am interested in the later *adoption* stage by the broader cross-section of firms. To the extent that hot markets were a manifestation of investor sentiment, however, their results would be complementary to this paper's, because they would also characterize investor sentiment as an important catalyst in the technological invention and diffusion process.[6]

Finally, the analysis focuses on sentiment changes, rather than levels, in light of the relatively high persistence of sentiment levels: the main proxy used throughout the paper has a level autocorrelation of about 55%. Robustness checks suggest that sentiment levels may also play a role in amplifying the effect of innovation on R&D, although the evidence is weaker.

In Section 2, I review the literature on investor sentiment and discuss the channels through which investor sentiment can affect R&D decisions. Section 3 describes the data. Section 4 present the effect of the interaction of innovation and investor sentiment on R&D. Section 5 concludes.

2 Investor sentiment

Sentiment can be interpreted as the time-varying tendency of investors' decision making to deviate from rationality: Baker and Wurgler (2006) define sentiment as the "propensity to speculate," while in Dumas, Kurshev, and Uppal (2009) sentiment is reflected in the overconfidence of some investors about a noisy public signal. Baker and Wurgler (2006) build a proxy for investor sentiment from variables that the literature has linked to investors' irrational behavior, like the closed-end fund discount (Lee, Shleifer, and Thaler (1991)), and find that stocks more attractive to speculators, like those of small, young firms, earn low future returns when the sentiment proxy is high, and viceversa – which is consistent with an

[6] Hot markets that coincide with periods of technological innovation could also be the result of herding, or of rational responses to fundamentals. See Nanda and Rhodes-Kropf (2011), Scharfstein and Stein (1990), Pastor and Veronesi (2009).

over-/under-valuation generated by high/low sentiment.

The findings of Baker and Wurgler (2006) have been extended to an international setting by Baker, Wurgler, and Yuan (2012), and confirmed in a mean-variance framework by Yu and Yuan (2011), who show that the relation between expected excess returns and conditional variance only holds during periods of low sentiment, in line with the hypothesis that sentiment traders invest in a less than rational fashion. The reaction of financial markets to specific negative events also suggests that investor sentiment is at play. Hwang (2011), for instance, studies the relation between the attitudes of the American public toward other countries and the price of several securities referencing assets in those countries (like CCEF, or country closed-end funds, and ADR, or American Depositary Receipts). One of the findings is that the "France Growth Fund" CCEF traded at an increasingly large discount in early 2003, when American perceptions toward France kept deteriorating in the weeks leading to the Iraq War. In addition, Kaplanski and Levy (2010) show that stock market losses following aviation disasters are much larger than the direct economic impact would imply, and that such negative returns tend to reverse after two days.

The literature has also focused on the role played by the news media in generating and conveying investor sentiment. A textual analysis of the "Abreast of the Market" column in the Wall Street Journal reveals a *pessimism* factor, which temporarily depresses asset prices (Tetlock (2007)). Dongal, Engelberg, Garcia, and Parsons (2012) exploit the scheduling of "Abreast of the Market" columnists to causally link the identity of financial journalists – and their bullishness/bearishness – to short-term stock returns.

There are a number of reasons why the mispricing caused by investor sentiment may not be quickly eliminated by arbitrageurs. Arbitrage is risky if the persistence of mispricing is uncertain (DeLong, Shleifer, Summers, and Waldmann (1990), Dumas, Kurshev, and Uppal (2009)). Information and agency problems make it difficult for arbitrageurs to raise capital through closed-end funds, with the consequence that they are exposed to the risk of capital redemption. The ensuing need to take the performance-flow relation into account (Shleifer and Vishny (1997)) can reduce the incentive to take a stand on potentially long lasting mispricing. Even if rational investors collectively have the resources to immediately eliminate deviations from fundamental values, coordination problems can delay arbitrage, and may actually be an incentive to trade on a continuation of mispricing (Abreu and Brunnermeier (2003)). Brunnermeier and Nagel (2004) and Lakonishok, Lee, Pearson, and Poteshman (2007) provide evidence that, during the late 1990s, sophisticated investors tried to realize short-term profits by accommodating what they perceived as mispricing. The effectiveness of arbitrage is further dampened when mispricing affects firms that just underwent an IPO, because a large part of the floated capital is usually held in lock-up agreements for at least 6 months (Hong, Scheinkman, and Xiong (2005)).

2.1 The real effects of mispricing

Polk and Sapienza (2009) focus on the cross-sectional relation between discretionary accruals and investment, in particular for firms where capital misallocation is more difficult to identify (companies with high R&D expenses), and whose shareholders are more likely to have a short investment horizon (companies with high share turnover). Discretionary accruals are used as a proxy for firm-level mispricing because they measure the extent of possible earnings manipulation (Sloan (1996)). Consistent with the hypothesis that mispricing affects both the quantity and quality of investment, their results show that investment by firms with either high R&D or high turnover is more sensitive to discretionary accruals, and these firms have low returns following abnormally high investment.

Gilchrist, Himmelberg, and Huberman (2005) use a panel VAR to investigate the relation between investment and belief dispersion, a variable that, in their model, can cause stock prices to exceed their fundamental value. They find that higher dispersion is indeed linked to higher investment. Baker, Stein, and Wurgler (2003) also study the relation between non-fundamental stock valuation and investment, finding that equity dependent firms issue more equity and invest more when their stock is likely overvalued, as measured by a high Tobin's Q and low future stock returns. More recently, Chirinko and Schaller (2011) also find that misvaluation has a significant effect on investment in a panel of U.S. firms.

Schaller (2012) studies investment hurdle rates (see Stein (1996)) during periods of high sentiment and low sentiment (using the Baker and Wurgler (2006) index), and finds that hurdle rates are lower during periods of high sentiment, in particular for sentiment-sensitive firms with poor investment opportunities. The results in Chirinko and Schaller (2001) also support the hypothesis that sentiment affects investment. They analyze the Japanese stock market bubble of the late 1980s, and find that it increased business fixed investment by about 5%-10%.

A few studies have also focused on the macroeconomic implications of the sensitivity of investment to mispricing. In Jerzmanowski and Nabar (2008), informational externalities negatively affect the resources devoted to R&D at the invention stage, and stock market overvaluation increases innovation and productivity growth. In Olivier (2000), bubbles can enhance growth because high stock valuations increase the creation of firms and investment. This conclusion, however, is unambiguous only for small open economies, where the interest rate is loosely dependent on domestic investment. For large economies, the increase in interest rates potentially offsets the effect of additional investment on growth.

In Farhi and Panageas (2004) mispricing can relax financing constraints, and its aggregate effect depends on the proportion of newly available funds that finance efficient and wasteful investments. Their empirical analysis shows that the net macroeconomic effect is negative. More precisely, they estimate a vector auto-regression for NYSE aggregate profits and turnover (turnover is a function of mispricing, as in Scheinkman and Xiong (2003)), and the impulse response function of shocks to turnover on profits is negative.

Investor sentiment can act as a subsidy to R&D through several channels. First, behavioral biases that affect investors allow rational managers to obtain funds at reduced cost (Baker, Stein, and Wurgler (2003)), which can relax financing constraints or offset the costs related to informational externalities. Such funds could simply be held in cash (see Chirinko and Schaller (2001), for instance), although rational managers may be willing to invest in projects that cater to investors' interest in the new technology, in order to maximize short-term stock prices (along the lines of Polk and Sapienza (2009) and Jensen (2005)). News coverage that highlights the novelty of the new technology can catalyze the interest of investors in the technology, thus opening the catering channel to which managers respond. Barber and Odean (2008) show that investors focus on stocks that grab their attention, such as when a stock is featured prominently in the news.

Second, managers themselves may be less than fully rational and exhibit behavioral traits, like overconfidence. The literature has linked overconfidence to corporate investment (Malmendier and Tate (2005), Ben-David, Graham, and Harvey (2013)), and in particular to the willingness to undertake risky but innovative projects (Hirshleifer, Low, and Teoh

(2012)). To the extent that sentiment reinforces overconfidence, a large increase in investor sentiment can affect experimentation, because it biases managers' beliefs about the productivity of the new technology upward.

3 Data

3.1 Innovation and the business cycle control

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 I obtain from the USPTO website (see Griliches (1990) for a detailed discussion on patents as economic indicators).[7]

Granted patents measure innovation that is ready for adoption by the larger population of firms. Companies often use patents strategically to defend or to improve their market position (see, for instance, Hall and Ziedonis (2001)). Strategic motives could provide an incentive to apply for patents when innovations are still under development, rather than when they are ready for adoption, so that applications could lead the actual availability of a technology. I do not use citation-weighted patents (Trajtenberg (1990)), because future citations are not part of the information set available to firms when making their R&D decisions.

Table 1 shows that the number of granted patents has grown at an annual average rate of 2.18% over the sample period I study. The statistics in Table 1 are based on observations

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

from 1952 onwards, because I use data from 1950 only, and the business cycle control (see below) is calculated from first order autoregressive residuals of changes in several macroeconomic variable, hence it is only available from 1952.

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 the USPTO. As the bottom left panel of Figure 1 illustrates, 1979 and 1980 do show extreme changes. To make sure that this spurious variation is not driving the results, I multiply the change in patents for the years 1979 and 1980 by 30%. Robustness checks show that the results are robust to not multiplying the observations by 30%, to multiplying them by 10%, and to excluding them altogether.[8]

One important point to discuss is the link between the state of the economy and the change in the number of granted patents, which I use as a proxy for technological innovation. 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, on the other hand, 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 business cycle proxy is based on four of the macroeconomic indicators typically considered by the NBER dating committee, that are reported as "economic indicators" by the Federal Reserve Bank of St. Louis on its "Tracking the Economy - United States" webpage:

[8] 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 the 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)).

Industrial Production, Real Gross Domestic Product, Employment, and Real Retail Sales, whose St. Louis FRED mnemonics are INDPRO, GDPC1, and PAYEMS. Real Retail Sales are RETAIL (until discontinued) and RSAFS deflated by CPIAUCSL.[9] Note that I replace the Real Disposable Personal Income indicator in the St. Louis Fed's list with Real Gross Domestic Product. I run a first-order vector auto-regression (selected on the basis of Akaike's information criterion and Schwarz's Bayesian information criterion) on log-changes in the four macroeconomic indicators, and define the business cycle control as the first principal component of the residuals. The bottom right panel of Figure 1 shows its time-series.

3.2 Investor sentiment

The results presented in the paper are based on the annual investor sentiment indexes proposed by Baker and Wurgler (2006). When calculating sentiment changes, I mostly use their extended 1934-2005 index (I refer to this proxy a ΔS^e), which I prefer to their 1965-2010 index because of the longer time series. Changes based on the 1965-2010 index (ΔS) are used in a set of robustness checks. The indexes, which are available on the website of Jeffrey Wurgler, are first principal components of variables that the literature has linked to investor sentiment. The shorter index is based on six variables: NYSE share turnover, the dividend premium, the closed-end fund discount, the number of IPOs, the average first day return on IPOs, and the equity share in new issues. The longer index builds on the three variables for which an extended time series is available: the closed-end fund discount, the equity share in new issues, and NYSE share turnover. 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

9 http://research.stlouisfed.org/economy

services, and a dummy for NBER recessions.

The top left panel of Figure 1 shows the time series of the two Baker and Wurgler (2006) indexes. They overlap for most of the sample, with the index based on six variables being noticeably lower than the one based on three variables in the mid-1960s, the 1970s, and the early 2000s. Both indexes are quite persistent, with the autocorrelation for S^e being slightly more than 55% between 1950 and 2005. The right top panel of Figure 1 shows the corresponding index changes (ΔS^e and ΔS). They are particularly volatile through the 1970s and, in the case of ΔS, around the year 2000 as well. The linear correlation between the sentiment indexes is 81%, while it is 70% between ΔS^e and ΔS (Table 2).

3.3 R&D and other firm-level variables

The empirical analysis focuses on how firm-level R&D is affected by the interaction between innovation and sentiment changes. The research design is based on a set of panel regressions, where the covariates include controls for both aggregate and firm-specific investment opportunities. In most specifications, the latter are the variables used by Brown, Fazzari, and Petersen (2009) in their study of the 1990s R&D boom, while in robustness checks I include the variables proposed by Gala and Gomes (2013) in the context of the corporate investment literature.

The first group of controls, from Brown, Fazzari, and Petersen (2009), includes lags of R&D and R&D squared, of gross cash flows (GCF), and of sales scaled by assets (SR_a). The second group of controls includes lags of R&D and R&D squared, and, from Gala and Gomes (2013), lags of the log of the sales-to-capital ratio ($\ln(SR_k)$), of leverage (lev), and of log-capital ($\ln(K)$). The two versions of the sales ratio are calculated in slightly different ways in order to exactly follow the definitions provided in the two articles. A number of specifications also include lagged stock issuance (stk), following Brown, Fazzari, and Petersen (2009). Appendix A provides details on the construction of firm-level controls, and on the filters used to remove outliers.

The R&D ratio is typically defined by scaling current R&D expenses with lagged assets, as in, for instance, Brown, Fazzari, and Petersen (2009). The reason is that it takes time to complete the budgeting and implementation process, so that there is a lag between the time when R&D decisions are made and when they are carried out. The ratio can also be defined by using current assets, as in the case of Polk and Sapienza (2009), where R&D is used as a measure for firm opacity, rather than as a choice variable for managers.

In the empirical analysis that follows, I use R&D scaled by current assets ($\text{R\&D}_c$) as the dependent variable. The reason is that small-scale experimentation requires, by definition, comparatively low resources, and does not need to be well integrated into the ongoing R&D activity – which presumably reduces the R&D implementation delay. Such added flexibility is likely more important in the case of firms with a higher technological intensity, whose R&D expense is a much larger fraction of assets. Indeed, using R&D scaled by lagged assets ($\text{R\&D}_l$) renders the effect of the interaction between innovation and sentiment changes statistically insignificant for high-tech firms, although the interaction coefficient remains significant and of about the same magnitude in the case of low-tech firms.[10]

Table 3 reports summary statistics for the firm-level variables. $\text{R\&D}_c$ and $\text{R\&D}_l$ have about the same distributional properties, with an average of around 6% per year. The R&D ratio for high-tech firms, which are about 37% of the sample, has much larger average and

[10] High-tech firms are identified following Brown, Fazzari, and Petersen (2009), while low-tech firms are the remaining sample. High-tech firms are those whose first three SIC digits are 283, 357, 366, 367, 382, 384, and 737.

volatility, with the average being 11.60% for high-tech firms, and 2.61% for low-tech firms (volatility is, respectively, 10.30% and 4.48%). 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%, with the volatility also being higher at 21%. Table 3 also shows that the full-sample averages of gross cash flows and of the sales ratio SR_a are 13.16% and 1.36; the corresponding values for high-tech firms in Brown, Fazzari, and Petersen (2009) are 20.50% and 1.21. The alternate sales ratio, $\ln(\mathrm{SR}_k)$ has an average of 1.42, with the corresponding value in Gala and Gomes (2013) being 1.72, while average log-capital is 3.64 in Table 3 and 3.56 in Gala and Gomes (2013).

4 Results

In this Section, I discuss how the interaction of innovation and sentiment changes affects the R&D expenses of a panel of Compustat firms. The analysis is largely based on the Arellano and Bond (1991) first-difference GMM procedure for dynamic panels, following Brown, Fazzari, and Petersen (2009). I also discuss results estimated with firm-fixed effects regressions, and 2SLS on first differences.[11] All specifications include lagged R&D, which gives rise to the need of instrumental variables in first-difference specifications. I also include squared values of lagged R&D, following Brown, Fazzari, and Petersen (2009). In most specifications, the regressions include lagged gross cash flows and the lagged sales ratio SR_a, again following Brown, Fazzari, and Petersen (2009). In order to assess the robustness of the results, some specifications include variables that Gala and Gomes (2013) use as controls in

[11] For the 2SLS estimates, I 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.

investment regressions: the sales ratio $\ln(\text{SR}_k)$, leverage, and log-capital.

The response of R&D to the macroeconomic variables is likely correlated across firms, hence the t-statistics reported in Tables 4 to 9 are based on standard errors double-clustered by firm and year, using the procedure in Cameron, Gelbach, and Miller (2011). Each covariance matrix is calculated by adding the matrix based on clustering by year to the matrix based on clustering by firm, then subtracting the matrix based on clustering by the intersection of year and firm. The diagonal elements of the resulting matrices are positive in every specification, but the covariance matrices are relatively often non positive-semidefinite. In such cases, following Cameron, Gelbach, and Miller (2011), the covariance matrices are recalculated after setting the negative eigenvalues to zero. The resulting t-statistics are very similar if not virtually identical to the t-statistics based on the original covariance matrices, which are available upon request. The use of double-clustered standard errors implies that, in the case of GMM estimation, only the one-step procedure is feasible. The reason is that the weight matrix in the second step of efficient GMM changes on the basis of the variable by which standard errors are clustered, and with two-step GMM I would have three different coefficient estimates for each specification.

The first two columns of Table 4 show results from two firm fixed-effects regressions, one for high-tech firms and one for low-tech firms. The coefficient on lagged $\text{R\&D}_c$ is close to one in both specifications, while that on lagged squared $\text{R\&D}_c$ is slightly larger than -1 for high-tech firms, and smaller than -1 for low-tech firm. Such estimates are in line with the values predicted by the structural model from which the regression specification is derived (1 for lagged R&D, and -1 for lagged R&D squared – see Brown, Fazzari, and Petersen (2009)). The first lag of the interaction of innovation and sentiment changes has a positive effect on $\text{R\&D}_c$. The coefficient is about one order of magnitude larger for high-tech firms than for low-tech firms.

The next four columns are 2SLS estimates on first differences, where the instruments are lagged levels of the 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 first interaction lag remains strongly statistically significant, although the coefficient is now smaller for high-tech firms. The second lag is still statistically significant only for high-tech firms, with the coefficient about half as large as in the fixed-effects estimation.

The last four columns 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-level regressors. Note that the first two GMM specifications use three instrument lags, while the corresponding 2SLS specifications only two. The reason is that the GMM implementation replaces missing values of the instruments with zeroes, hence it is possible to include longer lags without reducing the sample, as reflected in the larger number of observations. The statistical significance of the first interaction lag remains strong, with the effect being about six times larger for high-tech firms than for low-tech firms.

Table 4 also reports a series of statistics that allow to evaluate the appropriateness of the chosen instruments. First, it shows the p-values of Hansen tests that the overidentifying restrictions are valid. Second, it reports Kleibergen-Paap Wald rk F statistics for the 2SLS estimates, that help understand whether the instruments are weak. The table shows three versions of each statistic, corresponding to the three types of clustering that are used in the calculation of the double-clustered standard errors, as described above. Note that both statistics are based on two-step GMM estimates corresponding to the indicated 2SLS/one-step GMM specifications. Third, Table 4 shows the p-values of Arellano-Bond tests that the residuals have no first order and no second order autocorrelations. First order autocorrelation is expected in the Arellano-Bond estimation, and the null is rejected in all specifications but one.

The Hansen test p-values reject the validity of the overidentifying restrictions in only two of the 24 cases, while the Kleibergen-Paap statistics, which should be at least 10 to rule out weak instruments (see Baum, Schaffer, and Stillman (2007)), suggest that omitting the second instrument lag could be especially problematic for low-tech firms. This is the reason why, in the remainder of the analysis, I follow Brown, Fazzari, and Petersen (2009) in the case of high-tech firms and use lags three and four as instruments, while for low-tech firms I include the second lag as well.

In Table 5, I provide a number of additional results for high-tech firms. The first three columns address the robustness of the lagged interaction coefficient to spurious variation in the number of patents. 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 coefficient on the first lag of the interaction is statistically significant in each of the three specifications, and it is equal to about 3%, as in Table 4. The significance of the first interaction lag is also robust to excluding the bottom 10% of the time t distribution of log-capital, to excluding 1995 – the year in which the R&D expense of high-tech firms starts to trend upwards rapidly (see Figure 1 in Brown, Fazzari, and Petersen (2009)) – and to including lagged stock issuance to control for access to capital markets.

The first interaction lag is not statistically significant when using ΔS as a proxy for sentiment changes (specification (7)). The second interaction lag, however, is now strongly statistically significant and, at 6.57%, larger than any of the interaction coefficients estimated with ΔS^e. Note that, in this specification, observations with lags corresponding to the years 1968 and 1971 are excluded because, as shown in Figure 2, these years are outliers for the interaction of innovation and sentiment changes. Replacing sentiment changes with levels, as in (8) and (9), also yields a statistically significant coefficient on the first interaction lag, but only when including lagged stock issuance.

Table 6 has the same structure as Table 5, but it shows results for low-tech firms. The pattern is similar to the case of high-tech firms, with the first interaction lag being statistically significant, and of the same magnitude as in Table 4, when sentiment changes are proxied with ΔS^e. When using ΔS, the first lag is not statistically significant, but the second is. In the case of sentiment levels, however, neither lag is significant, even when including lagged stock issuance.

The effect of lagged patent changes on RD_c is estimated imprecisely in all the specifications in Tables 4 through 6, with the t-statistics often less than one in absolute value. For high-tech firms, the marginal effect is not statistically significant in any of the five specifications in Table 7 if sentiment changes are one standard deviation above the mean.

If they are one and a half standard deviations above the mean, two of the five specifications yield statistically significant positive interactions. The average marginal effect is 3.27%, which implies that a one-standard deviation increase in innovation raises $R\&D_c$ by 0.42 percentage points (the sample average is 11.60%). The statistical significance of the marginal effect is stronger in the case of low-tech firms, with four specifications being statistically significant when sentiment changes are one and a half standard deviations above the mean. The average marginal effect is 0.88%, so that a one standard deviation increase in innovation raises R&D$_c$ by about 0.11 percentage points (the sample average is 2.61%). In the case of both high-tech and low-tech firms, the marginal effect of innovation conditional on large contemporaneous sentiment changes is about 4% of the average R&D ratio.

4.1 Robustness checks

As noted in Section 3, the analysis largely focuses on the ratio of R&D expenses scaled by current assets, under the assumption that the particular nature of R&D related to experimentation can shorten implementation lags, especially in the case of high-tech firms. In the first set of robustness checks, the dependent variable is the ratio of R&D to lagged assets (R&D$_l$) rather than the ratio of R&D to current assets. The results in Table 8 show that, in the case of high-tech firms, the first interaction lag is not significant, while the second lag turns negative and statistically significant in the two specifications that do not exclude the years for which regressor lags include 1979 and 1980. In the case of low-tech firms, however, the coefficient of the first interaction lag is positive and statistically significant in the two specifications that include lagged stock issuance, with the magnitude being comparable to the results reported so far.

In the second set of robustness checks, the dependent variable is again R&D scaled by current assets, but the firm-level controls are those used by Gala and Gomes (2013) in the context of investment regressions. The set of control variables includes log-size, leverage, and a different definition of the sales ratio – scaled by capital rather than assets – together with the square of each control. As shown in Table 9, the main results still hold, and the coefficient on the first interaction lag remains positive and statistically significant, with magnitudes comparable to those reported in the previous tables. The only exception is specification

(3), where including lagged stock issuance makes the coefficient marginally insignificant for high-tech firms. The p-values of the Hansen and Arellano-Bond tests, however, point to issues with this particular specification, because, the Hansen test is close to rejecting the null when clustering by year, while the residuals exhibit second order autocorrelation.

The investor sentiment index of Baker and Wurgler (2006) is by construction orthogonalized with respect to indicators of macroeconomic conditions, but it may contain information about future technological innovation, including its expected productivity, that could affect R&D decisions. In Table 10, I show results from the same dynamic panel specifications discussed so far, where sentiment changes are first orthogonalized with respect to the contemporaneous values of one of three variables that should capture expectations about the future path of technological innovation or its productivity.

These variables are: changes in the weighted-average R&D expenses of high-tech firms; changes in the weighted-average R&D expenses of high-tech firms in the top 30% of the yearly cross-sectional distribution of stock returns; and the difference between the weighted-average stock returns of high-tech firms and the weighted-average returns of low-tech firms. Weights are based on log capital in the previous year. The adjusted R^2s and the *t*-statistics of the unreported orthogonalizing regressions show that the three measures of expected innovation explain very little of the time series of sentiment changes. As a consequence, the coefficients reported in Table 10 are very similar to those discussed so far, suggesting that investor sentiment does not proxy for expected technological innovation.

I now discuss whether the results could be due to sentiment and R&D trends being jointly determined. I exploit the mean reversion in investor sentiment levels, which induces negative correlation between changes and lagged levels, to proxy for sentiment changes with twice-lagged levels.[12] In the left panels of Table 11, I replace $t-1$ changes with $t-3$ levels and $t-2$ changes with $t-4$ levels (the interaction terms are the product of $t-1$ patent changes and $t-3$ sentiment levels, and $t-2$ changes and $t-4$ levels).

Lagged sentiment levels might affect R&D expenses directly, and not only through their correlation with sentiment changes, to the extent that they measure innovation that impacts R&D with a substantial delay. I can rule out this hypothesis for two reasons. First, the results discussed just above suggest that sentiment does not proxy for innovation expectations. Second, the sign of the coefficients on the interaction terms shown in the left panels of Table 11 is negative, while it should be positive if past lagged levels measured innovation or expectations thereof that affect R&D with a delay. The negative coefficients, however, are consistent with low lagged levels proxying for higher future changes, given that the coefficients on the interaction of sentiment changes and patent changes are positive in all the specifications discusses previously. One notable difference between Table 11 and the results discussed in the previous section is that the coefficient on the interaction is not statistically significant for high-tech firms when using the firm-specific controls of Brown, Fazzari, and Petersen (2009).

In the right panels of Table 11 sentiment changes are not replaced with lagged levels, but with the fitted values of regressions of sentiment changes on twice-lagged levels. As expected, the coefficients on the interaction term switch sign, and the results are in line with those discussed just above.

As noted in Section 2.1, one way changes in investor sentiment could increase the sen-

[12] Over the sample starting in 1950, the correlations between sentiment changes and once-, twice-, and thrice-lagged levels are -48%, -43%, and -14%, respectively. A regression of sentiment changes on twice-lagged levels with two-lag Newey-West standard errors yields a coefficient of -38.83%, a t-statistic of -4.41, and an F statistic equal to 19.42.

sititvity of R&D to innovation is by relaxing financing constraints. In Table 12, I evaluate whether the coefficient on the interaction between sentiment changes and innovation is larger for more financially-constrained firms. I measure financing constraints with the Kaplan and Zingales (1997) index, and estimate the dynamic panel regressions for high-tech and low-tech firms that are in the top 30%, 25%, or 20% of the cross-sectional distribution of the Kaplan and Zingales (1997) index in the previous year. The thresholds are calculated separately for high-tech and low-tech firms. As shown in the top panel of Table 12, the coefficient on the interaction between sentiment changes and innovation is higher the tighter the financing constraints are for high-tech firms, and this result holds with both sets of firm-specific controls. For the 20% most constrained firms, the coefficient is more than double the full-sample estimate. The evidence is different for low-tech firms, because the estimates are typically not statistically significant for the most constrained firms. These results are consistent with the finding that it is easier for high-tech firms to overcome financing constraints by issuing equity rather than debt (Carpenter and Petersen (2002)) and that equity issuance tends to be higher when investor sentiment is higher (Baker and Wurgler (2000)).

5 Conclusions

Due to frictions like informational externalities, firms invest too little in learning the productivity of newly available technologies through small-scale experimentation. The literature has highlighted that mispricing and investor sentiment can increase corporate investment, and the hypothesis at the heart of this paper is that investor sentiment may counteract the effects of the frictions that characterize technology diffusion.

I study the effect of investor sentiment on the relation between technological innovation and future firm-level R&D expenses, which include the resources used for small-scale experimentation. I find that, unconditionally, innovation does not have a statistically significant effect on one-year-ahead R&D expenses. When contemporaneous sentiment changes are sufficiently large, however, the marginal effect of innovation becomes positive. The effect is also stronger for high-tech firms subject to financing constraints. The results are not driven by sentiment proxying for technological innovation or by sentiment and R&D expenses being jointly determined.

Appendix A

Definition of firm-specific variables

The definition of firm-level variables largely follows Polk and Sapienza (2009), Gala and Gomes (2013), and Brown, Fazzari, and Petersen (2009). Compustat variable names are in italics. R&D$_c$ is research and development expense (*xrd* in t) divided by total book assets (*at* in t), while R&D$_l$ is *xrd* in t divided by *at* in t-1. Log-capital (ln(K)) is the logarithm of net property, plant and equipment (*ppent*). Gross cash flow (GCF) is the sum of income before extraordinary items (*ib* in t), depreciation and amortization (*dp* in t), and research and development expense (*xrd* in t) over beginning of year total book assets (*at* in t-1). The log-sales ratio (ln(SR$_k$)) is the natural logarithm of the ratio of net sales/turnover (*sale* in t) divided by lagged capital (*ppent* in t-1). The sales ratio (SR$_a$) is the ratio of net sales/turnover (*sale* in t) divided by lagged total book assets (*at* in t-1). Leverage is total debt over total book assets (*at* in t). Total debt is the sum of total debt in current liabilities (*dlc* in t) and total long term debt (*dltt* in t).

Filters applied to firm-specific variables

I apply several filters to the sample, in order to reduce the effect of recording errors and noisy data. The filters are also largely from Polk and Sapienza (2009), Gala and Gomes (2013), and Brown, Fazzari, and Petersen (2009). I 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. I drop regulated utilities and financials, with SIC codes in the ranges 4900-4949 and 6000-6999 (see Helwege, Pirinsky, and Stulz (2007)). I filter out cases in which *gvkey* does not uniquely identify a firm-year observation. Before calculating the accounting ratios described in the previous paragraph, I 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, I 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* in t) and depreciation and amortization (*dp* in t) over beginning of year capital (*ppent* in 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)). I further exclude observations (a) in the top or bottom 1% of the yearly distribution of GCF, $\ln(\mathrm{SR}_k)$, and SR_a, and (b) the top 2% of the yearly distribution of leverage and $\mathrm{R\&D}_c$. This last set of filters reduces the sample by 6%.

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Figure 1: Sentiment, patent changes, and the business cycle control.

The top panels show the time series of investor sentiment (S^e and S) and of changes in investor sentiment (ΔS^e and ΔS). The bottom left panel depicts log-changes in the number of patents granted by the USPTO. The vertical lines highlight the years 1979 and 1980, which are strongly affected by spurious variation generated by USPTO staffing problems in 1979 (Griliches (1990)). The bottom right panel shows the business cycle control, which is the principal component of the autoregressive residuals of selected macroeconomic variables. The frequency is annual for all variables. See Section 3 for definitions.

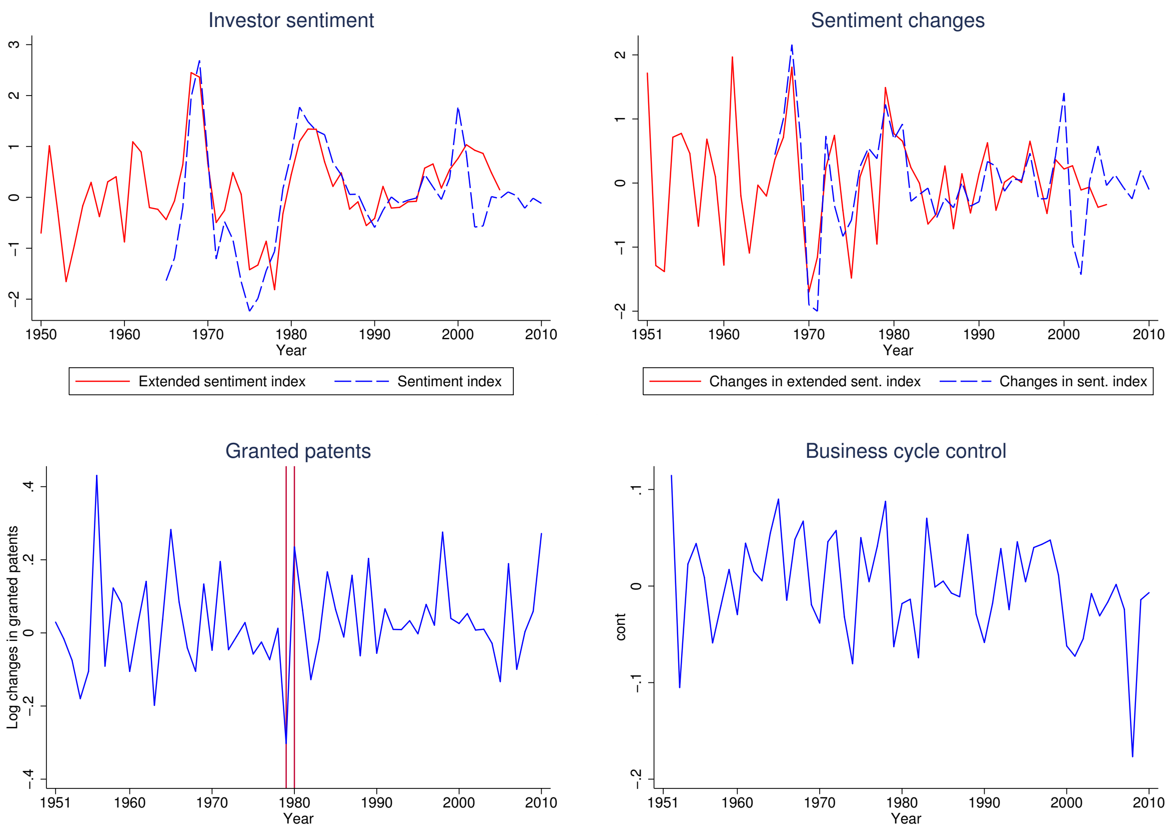

Figure 2: Interaction between innovation and sentiment changes.

The two panels plot the time series of the interaction of innovation and (top to bottom) ΔS^e and ΔS. In 1979 and 1980 ΔP is multiplied by 30%, in order to minimize the effect of USPTO staffing issues in 1979 (Griliches (1990)). See Section 3 for definitions.

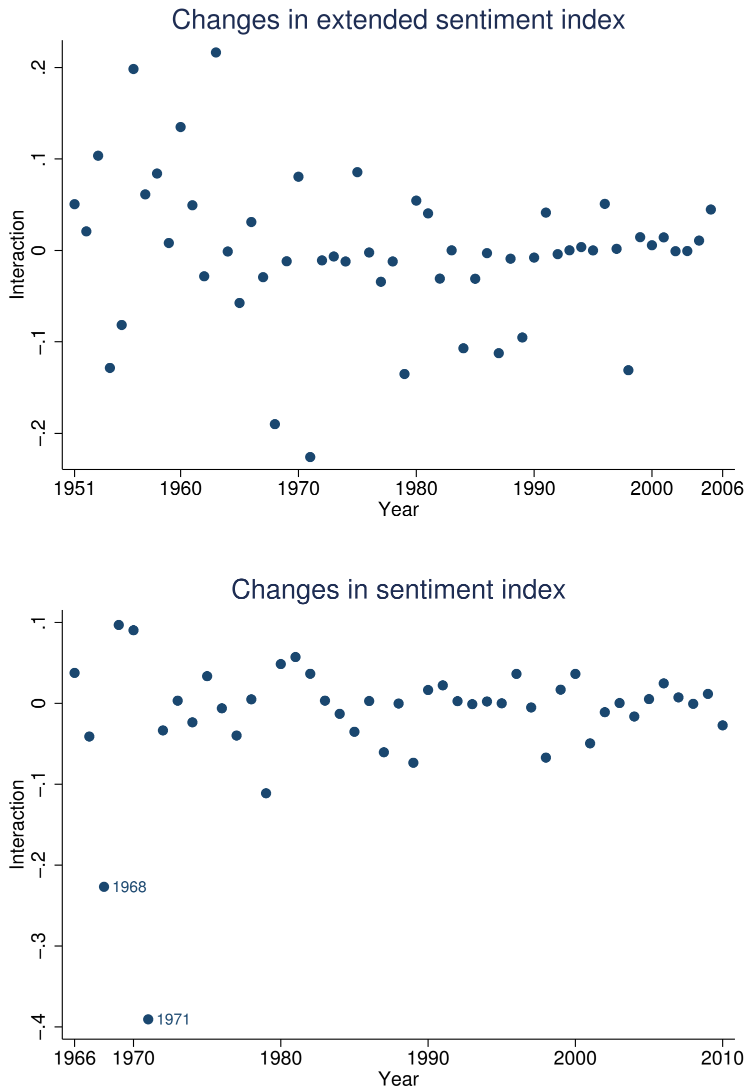

Table 1: Summary statistics: macro variables.

The table reports the mean, standard deviation, and selected percentiles for: levels and changes of the Baker and Wurgler (2006) sentiment and extended sentiment indexes (S, S^e, ΔS, ΔS^e); log-changes in the number of patents granted by the USPTO (ΔP); the business cycle control. In order to use data from 1950 onwards, the sample starts in 1952 (the business cycle control is based on a one-lag vector autoregression of the changes of selected macroeconomic variables), and ends in 2005, when the last observation for ΔS^e is available (1965-2005 for S, 1966-2005 for ΔS).

	μ	σ	10^{th}	50^{th}	90^{th}
S	0.0185	1.1026	-1.4401	-0.0131	1.4876
S^e	0.1497	0.8470	-0.8752	0.1648	1.0918
ΔS	0.0403	0.8127	-0.8861	0.0130	0.9612
ΔS^e	-0.0160	0.7700	-1.1577	0.0476	0.7434
ΔP	0.0218	0.1279	-0.1053	0.0098	0.1952
cont	0.0041	0.0484	-0.0620	0.0045	0.0575

Table 2: Correlations: macro variables.

The table reports linear correlations (in %) among the following variables: levels and changes of the Baker and Wurgler (2006) sentiment and extended sentiment indexes (S, S^e, ΔS, ΔS^e); log-changes in the number of patents granted by the USPTO (ΔP); the business cycle control. 1966-2005.

	S	S^e	ΔS	ΔS^e	ΔP	cont
S	100					
S^e	81	100				
ΔS	33	21	100			
ΔS^e	30	39	70	100		
ΔP	8	3	-24	-31	100	
cont	-14	-21	20	-7	9	100

Table 3: Summary statistics: firm-level variables.

The table reports the mean, standard deviation, minimum/maximum, selected percentiles, and the number of observations for the following firm-level variables: R&D intensity scaled by contemporaneous assets (R&D$_c$) and by lagged assets (R&D$_l$), lagged gross cash flows (GCF), lagged sales ratio (SR$_a$, scaled by assets), lagged log-sales ratio (ln(SR$_k$), scaled by capital), lagged leverage, and lagged log-size. Statistics for R&D$_c$ are also reported separately for high-tech and low-tech firms. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). See Appendix A for details on how the variables are constructed. 1955-2006.

	μ	σ	min	25^{th}	50^{th}	75^{th}	max	obs
R&D$_c$	0.0598	0.0844	0.0000	0.0071	0.0280	0.0766	0.7275	39,044
R&D$_c$ (high-tech)	0.1160	0.1030	0.0000	0.0451	0.0874	0.1519	0.7275	14,628
R&D$_c$ (low-tech)	0.0261	0.0448	0.0000	0.0022	0.0131	0.0312	0.6072	24,416
R&D$_l$	0.0613	0.0903	0.0000	0.0076	0.0289	0.0782	1.9275	34,418
GCF	0.1316	0.1341	-0.8735	0.0746	0.1327	0.1964	0.7072	30,078
SR$_a$	1.3619	0.7791	0.0240	0.8238	1.2675	1.7435	5.9278	59,717
ln(SR$_k$)	1.4208	1.0580	-2.2588	0.7959	1.5006	2.0952	4.6387	59,600
lev	0.2362	0.1812	0.0000	0.0814	0.2204	0.3539	0.9303	65,623
ln(K)	3.6292	2.2855	-3.4112	1.9728	3.4485	5.1595	11.7603	66,378

Table 4: Innovation and firm-level R&D intensity: high-tech and low-tech firms. The table shows the effect of ΔP, ΔS^e, and controls on $R\&D_c$. See Tables 1 and 3 for definitions. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%. The first two columns show fixed-effect regressions. The next four columns report 2SLS estimations, 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 estimations, 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 (Cameron, Gelbach, and Miller (2011)). HJ is the p-value of the Hansen test that overidentifying restrictions are valid, while WI is the Kleibergen-Paap Wald rk F statistic; both are from the two-step GMM estimation corresponding to the reported 2SLS/one-step GMM estimations. 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 from Arellano-Bond tests of the null of no first and second order autocorrelation in the residuals of the specification with errors clustered by firm. Coefficients in %. 1955-2006.

	Firm FE, levels		2SLS, differences				1-step GMM, Arellano-Bond			
			2-3		3-4		2-4		3-4	
	Hi	Lo	Hi	Lo	Hi	Lo	Hi	Lo	Hi	Lo
RD_{-1}	81.65	88.53	89.21	108.85	28.27	14.75	50.91	76.95	27.01	70.32
	12.37	15.86	3.80	6.71	0.50	0.32	1.01	2.23	0.29	1.33
RD^2_{-1}	-97.41	-120.83	-101.04	-154.12	21.57	16.00	-36.65	-109.19	-17.34	-162.26
	-5.92	-5.10	-2.70	-3.82	0.19	0.18	-0.51	-2.29	-0.10	-1.10
GCF_{-1}	0.07	0.10	-0.70	0.56	11.33	9.46	1.36	0.84	9.52	6.00
	0.09	0.27	-0.33	0.36	1.72	1.47	1.09	0.88	1.89	1.29
$SR_{a,-1}$	-0.29	-0.06	1.07	0.25	-3.96	-1.52	-1.03	0.05	-3.64	-0.81
	-1.33	-1.20	1.17	0.82	-1.98	-1.16	-1.36	0.25	-1.83	-0.95
$cont_{-1}$	-1.21	0.08	-2.48	-0.20	-2.85	-0.50	-2.95	0.00	-3.42	-0.30
	-0.62	0.22	-2.02	-0.61	-1.82	-1.07	-2.52	0.01	-1.95	-0.66
$cont_{-2}$	4.54	0.43	1.78	-0.10	0.93	-0.38	2.79	0.20	1.60	0.00
	1.83	1.07	1.05	-0.36	0.39	-0.90	1.49	0.78	0.61	0.00
ΔS^e_{-1}	0.41	0.04	0.01	0.04	0.07	0.04	0.13	0.03	0.17	0.03
	3.02	1.76	0.09	1.65	0.75	1.18	0.80	0.98	1.39	0.94
ΔP_{-1}	1.10	0.23	-1.02	0.17	-0.94	0.30	-0.66	0.11	-0.26	0.10
	1.23	1.10	-1.30	0.84	-1.08	1.25	-0.76	0.53	-0.30	0.46
I_{-1}	5.01	0.47	2.91	0.73	2.66	0.51	3.89	0.61	3.49	0.54
	3.43	1.99	2.76	3.47	2.68	2.48	2.80	2.93	2.41	2.43
ΔS^e_{-2}	0.20	0.03	0.08	0.00	0.16	0.01	0.05	0.01	0.08	0.02
	1.30	1.27	0.83	-0.02	1.55	0.44	0.47	0.49	0.69	0.68
ΔP_{-2}	-0.90	-0.10	-2.10	-0.01	-2.01	0.14	-2.28	-0.08	-1.87	-0.07
	-0.88	-0.45	-3.44	-0.05	-2.59	0.73	-3.29	-0.43	-1.98	-0.34
I_{-2}	2.90	0.16	1.38	0.23	1.61	0.31	1.26	0.29	1.49	0.31
	2.39	0.71	1.83	1.06	1.76	1.49	1.57	1.28	1.62	1.23
Obs.	10,511	19,622	7,447	15,091	6,325	13,334	8,793	17,157	8,793	17,157
HJ_y			0.36	0.63	0.83	0.16	0.73	0.55	0.89	0.27
HJ_f			0.04	0.37	0.60	0.33	0.41	0.14	0.82	0.06
HJ_i			0.19	0.63	0.53	0.57	0.68	0.37	0.84	0.19
WI_y			*13.82*	*17.33*	*1.80*	*2.06*				
WI_f			*22.11*	*12.51*	*6.22*	*2.81*				
WI_i			*16.75*	*10.43*	*2.95*	*2.47*				
m1			0.00	0.00	0.00	0.07	0.00	0.00	0.02	0.40
m2			0.71	0.34	0.88	0.60	0.71	0.20	0.43	0.25

Table 5: Innovation and R&D intensity: additional results for high-tech firms.

The table shows the effect of ΔP, ΔS^e, ΔS and S^e, and controls on R&D$_c$, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 3 and 4 level lags of firm-level regressors as instruments. See Tables 1 and 3 for variable definitions, and Table 4 for details on m1, m2, the HJ statistics, and on the *t*-statistics. High-tech firms are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%, unless specified otherwise. 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, while (6) includes lagged stock issuance as an additional explanatory variable. In (7) sentiment changes are measured with ΔS, and lags corresponding to 1968 and 1971 are excluded. 1968 and 1971 are outliers in the distribution of the interaction of ΔP and ΔS (see Fig. 2). In (8) and (9) S^e is in levels. Coefficients in %. 1955-2006 (1968-2010 for (7)).

	(1)	(2)	(3)	(4)	(5)	(6)		(7)		(8)	(9)
stk_{-1}						3.21					2.94
						0.63					0.59
RD_{-1}	25.95	27.56	27.80	-6.44	60.71	12.74		-22.90		29.63	17.39
	0.27	0.29	0.29	-0.05	0.61	0.20		-0.27		0.31	0.25
RD^2_{-1}	-15.10	-18.49	-18.83	48.79	-114.77	27.40		94.99		-22.74	18.85
	-0.09	-0.11	-0.11	0.19	-0.59	0.21		0.58		-0.13	0.13
GCF_{-1}	9.46	9.55	10.04	10.50	10.94	5.19		6.42		9.39	5.72
	1.82	1.90	2.03	3.06	1.37	0.99		1.06		1.84	1.12
$SR_{a,-1}$	-3.59	-3.64	-3.57	-4.19	-3.19	-3.57		-3.52		-3.48	-3.62
	-1.73	-1.84	-2.20	-1.76	-0.87	-1.39		-1.94		-1.66	-1.43
$cont_{-1}$	-3.44	-3.36	-4.62	-2.10	-3.76	-4.14		0.85		-3.56	-3.87
	-1.88	-1.94	-2.44	-1.05	-2.15	-2.09		0.33		-2.09	-1.68
$cont_{-2}$	1.37	1.43	1.30	2.44	0.15	3.03		1.73		0.66	2.13
	0.52	0.57	0.49	0.85	0.08	1.28		0.95		0.31	1.10
ΔS^e_{-1}	0.19	0.15	0.18	0.14	0.11	0.06	ΔS_{-1}	0.03	S^e_{-1}	0.08	0.01
	1.52	1.19	1.05	1.03	0.74	0.38		0.16		0.49	0.04
ΔP_{-1}	-0.61	-0.37	-0.54	-0.34	-0.70	-0.10		0.25		-1.44	-1.63
	-0.92	-0.37	-0.40	-0.40	-0.82	-0.09		0.21		-1.36	-1.32
I_{-1}	2.30	3.48	3.04	2.76	3.10	4.20		4.39		1.57	2.90
	2.51	2.31	1.77	1.85	1.81	1.92		1.66		1.50	2.02
ΔS^e_{-2}	0.07	0.10	0.11	0.12	0.04	0.06	ΔS_{-1}	0.64	S^e_{-1}	0.02	0.18
	0.63	0.92	0.82	0.80	0.27	0.43		5.22		0.12	0.89
ΔP_{-2}	-1.64	-2.05	-1.65	-1.70	-2.25	-1.44		0.91		-2.66	-2.58
	-2.61	-1.90	-1.50	-1.46	-2.74	-1.08		0.65		-3.28	-2.43
I_{-2}	1.82	1.11	1.71	1.72	1.36	1.26		6.57		-0.05	0.40
	3.93	0.93	1.32	1.67	1.61	1.09		2.43		-0.07	0.32
Obs.	8,793	8,793	8,084	7,391	7,416	7,177		9,842		8,793	7,177
HJ_y	0.89	0.89	0.88	0.94	0.40	0.32		0.93		0.87	0.35
HJ_f	0.83	0.82	0.83	0.93	0.39	0.44		0.81		0.84	0.47
HJ_i	0.85	0.84	0.86	0.94	0.49	0.30		0.81		0.85	0.33
m1	0.02	0.02	0.02	0.09	0.12	0.01		0.02		0.02	0.01
m2	0.43	0.43	0.38	0.61	0.49	0.28		0.61		0.41	0.31

Table 6: Innovation and R&D intensity: additional results for low-tech firms.

The table shows the effect of ΔP, ΔS^e, ΔS and S^e, and controls on R&D$_c$, 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 3 for definitions, and Table 4 for details on m1, m2, the HJ statistics, and on the t-statistics. High-tech firms are identified following Brown, Fazzari, and Petersen (2009). The structure of the Table is the same as in Table 5. The 1979-80 observations of ΔP are multiplied by 30%, unless specified otherwise, as in (1), where they are *not* multiplied by 30%, and (2), where 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, while (6) includes lagged stock issuance as an additional regressor. In (7) sentiment changes are measured with ΔS, and observations with regressor lags that include 1968 and 1971 are dropped. 1968 and 1971 are outliers in the distribution of the interaction (see Fig. 2). In (8) and (9) S^e is in levels. Coefficients in %. 1955-2006 (1968-2010 for (7)).

	(1)	(2)	(3)	(4)	(5)	(6)		(7)		(8)	(9)
stk$_{-1}$						-0.94					-0.91
						-1.68					-1.63
RD$_{-1}$	77.02	76.85	85.34	86.38	77.01	71.14		60.57		76.80	69.79
	2.20	2.23	2.52	2.84	2.08	1.90		1.37		2.16	1.81
RD$^2_{-1}$	-109.33	-109.02	-124.01	-71.00	-116.68	-102.33		-89.24		-108.82	-99.67
	-2.26	-2.30	-2.74	-1.66	-2.09	-1.93		-1.45		-2.18	-1.79
GCF$_{-1}$	0.84	0.84	0.76	0.63	1.21	1.40		1.05		0.86	1.46
	0.87	0.88	0.77	0.54	0.99	1.26		1.18		0.86	1.27
SR$_{a,-1}$	0.05	0.05	0.19	-0.06	0.05	0.22		-0.10		0.04	0.17
	0.20	0.26	0.73	-0.22	0.21	0.73		-0.46		0.15	0.58
cont$_{-1}$	-0.03	0.10	0.14	0.18	-0.03	-0.50		0.24		0.12	0.06
	-0.08	0.28	0.35	0.51	-0.08	-1.14		0.60		0.32	0.12
cont$_{-2}$	0.18	0.18	0.29	0.04	0.12	0.11		-0.13		0.11	-0.07
	0.64	0.71	1.05	0.16	0.48	0.40		-0.58		0.43	-0.24
ΔS$^e_{-1}$	0.02	0.04	0.03	0.05	0.02	0.02	ΔS$_{-1}$	0.03	S$^e_{-1}$	0.03	0.03
	0.70	1.10	0.66	1.89	0.52	0.56		1.02		0.74	0.56
ΔP$_{-1}$	-0.06	0.16	0.12	0.13	-0.06	0.20		0.11		-0.08	-0.17
	-0.38	0.71	0.37	0.66	-0.34	0.76		0.70		-0.34	-0.61
I$_{-1}$	0.29	0.70	0.74	0.51	0.48	1.18		0.53		0.10	0.24
	1.79	3.02	2.39	2.50	2.46	3.47		1.07		0.60	0.64
ΔS$^e_{-2}$	0.01	0.02	0.02	0.03	0.01	-0.02	ΔS$_{-2}$	0.09	S$^e_{-2}$	0.01	0.03
	0.34	0.86	0.58	1.00	0.47	-0.55		2.82		0.52	0.78
ΔP$_{-2}$	-0.13	-0.03	-0.02	0.01	-0.17	-0.18		0.25		-0.15	-0.19
	-0.92	-0.12	-0.06	0.03	-0.88	-0.77		1.22		-0.70	-0.75
I$_{-2}$	0.18	0.37	0.42	0.34	0.24	0.23		1.01		0.10	0.32
	1.28	1.31	1.30	1.74	1.13	0.79		2.22		0.72	1.03
Obs.	17,157	17,157	14,899	16,183	15,068	14,901		17,255		17,157	14,901
HJ$_y$	0.54	0.55	0.57	0.91	0.84	0.50		0.48		0.54	0.45
HJ$_f$	0.15	0.14	0.23	0.92	0.21	0.36		0.25		0.13	0.31
HJ$_i$	0.37	0.36	0.50	0.98	0.44	0.48		0.50		0.35	0.45
m1	0.00	0.00	0.00	0.00	0.00	0.00		0.01		0.00	0.00
m2	0.20	0.20	0.17	0.11	0.27	0.76		0.17		0.20	0.74

Table 7: Innovation and R&D intensity, conditional on sentiment changes.

The table shows the marginal effect of the first lag of the demeaned ΔP on R&D$_c$ when the first lag of the demeaned ΔS^e is equal to one or one and a half standard deviations above the (zero) mean. The coefficients are estimated from specifications that include the same variables (and lags) as in Tables 5 and 6, and are estimated with the Arellano and Bond (1991) first-difference GMM procedure, where the instruments are 3 and 4 level lags (for high-tech firms) and 2 to 4 level lags (for low-tech firms) of firm-level regressors. Column (1) corresponds to the second-to-last specification of Table 4 for high-tech firms, and to the third-to-last specification of Table 4 for low-tech firms. In (2) observations for which lags of the regressors include 1979 or 1980 are excluded. In (3) firms in the bottom 10% of the distribution as of t are excluded (the percentile is calculated on the overall sample, including both high- and low-tech firms). In (4) the sample excludes 1995, while (5) includes lagged stock issuance as an additional explanatory variable. Coefficients are in %. 1955-2006. Note that calculating the marginal effects with the standard deviation of ΔS^e shown in Table 1 yields results slightly different from those reported here. The reason is that the standard deviation of ΔS^e is calculated over the actual sample of each panel regression, while Table 1 reports statistics for the 1952-2005 sample. For instance, specification (2) excludes observations for which regressor lags include 1979 or 1980, and the ΔS^e standard deviation used in calculating the marginal effects is based on such reduced sample.

	High-tech firms					
	(1)	(2)	(3)	(4)	(5)	Average
1sd	2.32	1.63	1.69	1.62	3.00	2.05
	1.51	0.72	1.23	0.88	1.52	
1.5sd	3.61	2.72	2.71	2.78	4.56	3.27
	1.81	0.97	1.47	1.14	1.70	
	Low-tech firms					
	(1)	(2)	(3)	(4)	(5)	Average
1sd	0.56	0.66	0.51	0.30	1.07	0.62
	1.95	1.29	2.34	1.38	2.52	
1.5sd	0.79	0.92	0.70	0.48	1.51	0.88
	2.26	1.52	2.66	1.77	2.83	

Table 8: Innovation and R&D intensity: scaling R&D by lagged assets.

The table shows the effect of ΔP, ΔS^e, and controls on $R\&D_l$, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 3 and 4 level lags (2 to 4 for low-tech firms) of firm-level regressors as instruments. See Tables 1 and 3 for variable definitions, and Table 4 for details on m1, m2, the HJ statistics, and on the *t*-statistics. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%. Specifications (1) to (3) are estimated on high-tech firms, while (4) to (6) are estimated on low-tech firms. Specifications (2)-(3) and (5)-(6) include lagged stock issuance as an additional explanatory variable, and in (3) and (6) observations for which lags of the regressors include 1979 or 1980 are excluded. Coefficients in %. 1955-2006.

	High-tech			Low-tech		
	(1)	(2)	(3)	(4)	(5)	(6)
stk_{-1}		-2.36	-3.90		-1.58	-1.71
		0.26	-0.42		-3.13	-3.56
RD_{-1}	52.82	12.98	14.23	63.14	58.24	59.50
	0.78	0.36	0.51	3.52	2.70	2.84
RD^2_{-1}	-46.51	28.27	36.05	-78.74	-50.81	-54.67
	-0.58	0.35	0.46	-2.15	-1.02	-1.14
GCF_{-1}	5.56	4.89	1.71	2.46	3.58	3.49
	0.95	0.53	0.14	2.26	3.20	2.97
$SR_{a,-1}$	-2.62	-2.37	-1.22	-0.27	-0.29	-0.14
	-1.27	-0.65	-0.22	-0.82	-1.04	-0.44
$cont_{-1}$	-1.08	-2.03	-1.15	0.28	-0.06	0.71
	-0.34	-0.84	-0.39	0.82	-0.14	1.82
$cont_{-2}$	-0.37	0.27	0.76	-0.32	-0.34	-0.28
	-0.16	0.12	0.34	-1.10	-1.22	-1.09
ΔS^e_{-1}	-0.18	-0.23	-0.34	0.03	0.01	0.07
	-1.12	-1.94	-1.37	0.72	0.27	1.58
ΔP_{-1}	-0.66	-1.49	-3.20	-0.13	-0.02	0.60
	-0.34	-0.66	-0.89	-0.44	-0.06	1.70
I_{-1}	-1.27	-0.44	-2.30	0.34	0.67	1.39
	-1.08	-0.15	-0.82	1.25	1.90	2.91
ΔS^e_{-2}	-0.24	-0.36	-0.51	-0.04	-0.08	-0.07
	-1.40	-1.90	-2.28	-1.90	-3.28	-1.56
ΔP_{-2}	0.09	-1.86	-3.61	-0.21	-0.29	0.08
	0.04	-0.60	-0.79	-0.91	-0.96	0.30
I_{-2}	-2.19	-2.81	-4.59	-0.18	-0.37	0.08
	-1.70	-2.15	-1.52	-0.77	-1.57	0.25
Obs.	8,793	7,177	6,522	17,157	14,901	12,788
HJ_y	0.68	0.44	0.48	0.92	0.64	0.82
HJ_f	0.54	0.25	0.09	0.90	0.52	0.58
HJ_i	0.77	0.29	0.26	0.89	0.59	0.69
m1	0.00	0.00	0.00	0.00	0.00	0.00
m2	0.59	0.83	0.95	0.99	0.43	0.39

Table 9: Innovation and R&D intensity: alternative firm-specific controls.
The table shows the effect of ΔP, ΔS^e, and controls on R&D_c, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 3 and 4 level lags (2 to 4 for low-tech firms) of firm-level regressors as instruments. The firm-specific controls are used in the investment regressions of Gala and Gomes (2013). See Tables 1 and 3 for variable definitions, and Table 4 for details on m1, m2, the HJ statistics, and on the t-statistics. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%. Coefficients on lags of the business cycle control are omitted for space reasons. Specifications (1) to (3) are estimated on high-tech firms, while (4) to (6) are estimated on low-tech firms. In specifications (2) and (5) observations for which lags of the regressors include 1979 or 1980 are excluded. Specifications (3) and (6) include lagged stock issuance as an additional explanatory variable. Coefficients in %. 1955-2006.

	High-tech			Low-tech		
	(1)	(2)	(3)	(4)	(5)	(6)
stk_{-1}			4.31			-0.83
			0.68			-1.44
RD_{-1}	47.93	48.45	33.45	82.82	89.44	70.78
	0.53	0.59	0.56	2.32	2.44	1.89
RD^2_{-1}	-75.22	-74.57	-57.43	-117.52	-128.66	-100.88
	-0.47	-0.51	-0.48	-2.32	-2.50	-1.75
$\ln(\text{SR}_k)_{-1}$	-0.16	0.26	-3.34	1.38	1.70	1.49
	-0.16	0.12	-0.76	3.10	2.95	2.41
$\ln(\text{SR}_k)^2_{-1}$	-0.13	-0.25	0.33	-0.28	-0.34	-0.32
	-0.24	-0.58	0.36	-2.96	-2.74	-3.05
$\ln(\text{K})_{-1}$	1.58	1.65	1.67	0.34	0.38	0.25
	5.12	4.91	2.96	2.09	1.99	1.42
$\ln(\text{K})^2_{-1}$	-0.13	-0.14	-0.10	-0.02	-0.03	-0.02
	-2.38	-2.61	-1.81	-1.24	-1.76	-0.74
lev_{-1}	-2.39	-2.35	0.37	0.20	0.21	0.09
	-1.09	-1.03	0.08	0.20	0.20	0.10
lev^2_{-1}	-0.39	-0.36	-3.63	0.13	0.22	0.01
	-0.14	-0.12	-0.91	0.12	0.18	0.01
ΔS^e_{-1}	0.10	0.07	-0.05	0.02	0.03	0.03
	0.72	0.38	-0.25	0.82	0.70	0.73
ΔP_{-1}	-0.72	-1.19	-0.46	0.05	0.12	0.22
	-0.92	-1.01	-0.38	0.26	0.37	0.80
I_{-1}	3.62	3.26	3.82	0.57	0.72	0.99
	2.60	2.04	1.61	2.60	2.48	2.86
ΔS^e_{-2}	0.03	0.04	0.02	0.00	0.01	-0.02
	0.26	0.24	0.15	-0.01	0.13	-0.68
ΔP_{-2}	-2.22	-2.40	-1.68	-0.18	-0.08	-0.21
	-2.74	-2.52	-1.16	-0.84	-0.26	-0.77
I_{-2}	1.31	1.07	1.34	0.27	0.45	0.22
	1.55	0.87	1.26	1.07	1.31	0.72
Obs.	8,737	8,033	7,144	17,110	14,860	14,879
HJ_y	0.70	0.71	0.13	0.64	0.74	0.67
HJ_f	0.61	0.66	0.17	0.73	0.84	0.52
HJ_i	0.73	0.75	0.20	0.62	0.83	0.50
m1	0.10	0.10	0.13	0.00	0.00	0.00
m2	0.24	0.23	0.07	0.32	0.31	0.94

Table 10: Orthogonalizing sentiment relative to alternative measures of innovation.

The table shows the effect of ΔP, $\Delta S^{e,\perp}$, and controls on R&D$_c$, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 3 and 4 level lags (2 to 4 for low-tech firms) of firm-level regressors as instruments. See Tables 1 and 3 for variable definitions, and Table 4 for details on m1, m2, the HJ statistics, and on the t-statistics. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%. $\Delta S^{e,\perp}$ are changes in the extended sentiment index orthogonalized relative to one of several measures of innovation. In (1) and (4) $\Delta S^{e,\perp}$ is the residual from regressing ΔS^{e} on the change in the weighted average R&D ratio of high-tech firms. In (2) and (5) the residuals are relative to the change in weighted average R&D ratio of high-tech firms whose stock returns in a given year are in the top 30% of the cross-sectional distribution of high-tech firm returns. In (3) and (6) the residuals are relative to 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). Coefficients in %. 1955-2006.

	High-tech			Low-tech		
	(1)	(2)	(3)	(4)	(5)	(6)
RD_{-1}	30.12	35.85	24.07	76.88	77.34	76.81
	0.32	0.38	0.26	2.24	2.25	2.23
RD^2_{-1}	-23.92	-36.27	-10.98	-109.08	-109.86	-108.98
	-0.14	-0.21	-0.06	-2.32	-2.31	-2.29
GCF_{-1}	9.58	9.40	9.54	0.84	0.82	0.85
	1.85	1.86	1.90	0.87	0.85	0.89
$SR_{a,-1}$	-3.59	-3.42	-3.70	0.05	0.06	0.05
	-1.84	-1.62	-1.88	0.22	0.26	0.24
$cont_{-1}$	-3.64	-3.96	-3.17	0.02	-0.13	0.02
	-1.99	-2.29	-1.86	0.06	-0.37	0.07
$cont_{-2}$	1.51	1.33	1.69	0.23	0.23	0.19
	0.58	0.51	0.65	0.89	0.97	0.71
$\Delta S^{e,\perp}_{-1}$	0.04	0.05	0.22	0.02	0.00	0.04
	0.26	0.41	1.88	0.60	0.03	1.30
ΔP_{-1}	-0.66	-0.79	-0.10	0.06	-0.03	0.15
	-0.78	-0.88	-0.12	0.32	-0.14	0.76
I_{-1}	3.04	3.60	3.47	0.54	0.51	0.65
	2.16	2.09	2.49	2.39	2.40	3.25
$\Delta S^{e,\perp}_{-2}$	0.09	-0.08	0.10	0.03	0.00	0.01
	0.61	-0.61	0.85	1.05	0.08	0.35
ΔP_{-2}	-2.05	-2.47	-1.73	-0.06	-0.19	-0.07
	-2.37	-2.85	-1.74	-0.35	-0.99	-0.35
I_{-2}	1.24	1.06	1.52	0.32	0.12	0.30
	1.39	1.08	1.68	1.53	0.56	1.31
Obs.	8,793	8,793	8,793	17,157	17,157	17,157
HJ_y	0.90	0.89	0.89	0.54	0.55	0.55
HJ_f	0.84	0.84	0.82	0.14	0.13	0.15
HJ_i	0.86	0.85	0.84	0.36	0.36	0.37
m1	0.02	0.02	0.02	0.00	0.00	0.00
m2	0.42	0.39	0.45	0.20	0.20	0.20

Table 11: Proxying for sentiment changes with twice lagged sentiment levels.

The table shows the effect of ΔP_{-1} and S^e_{-3} or $\Delta\widehat{S^e}_{-1}$ (firm-specific and business-cycle controls are included in the regressions but not reported) on $R\&D_c$, estimated with the Arellano and Bond (1991) first-difference GMM procedure, and using 3 and 4 level lags (2 to 4 for low-tech firms) of firm-level regressors as instruments. See Tables 1 and 3 for variable definitions, and Table 4 for details on m1, m2, the HJ statistics, and on the *t*-statistics. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%. In the top panel the firm-specific controls are those shown in all tables but Table 9, while in the bottom panels the controls are those in Table 9. The twice lagged value of the sentiment level can predict sentiment changes, and it is used as a proxy for current sentiment changes that is not affected by current changes in granted patents. In the right panels, the predicted sentiment change from a regression of sentiment changes on twice-lagged levels is used as the measure of sentiment changes. Coefficients in %. 1955-2006.

Firm controls set #1					
	High-tech	Low-Tech		High-tech	Low-Tech
S^e_{-3}	-0.10	0.00	$\Delta\widehat{S^e}_{-1}$	0.26	0.00
	-0.60	-0.05		0.60	0.05
ΔP_{-1}	-1.46	-0.01	ΔP_{-1}	-1.41	0.01
	-1.80	-0.07		-1.73	0.05
$I_{(\Delta P, S^e)}$	-0.88	-0.38	$I_{(\Delta P, \Delta\widehat{S^e})}$	2.28	0.97
	-1.33	-2.41		1.33	2.42

Firm controls set #2					
	High-tech	Low-Tech		High-tech	Low-Tech
S^e_{-3}	-0.06	0.02	$\Delta\widehat{S^e}_{-1}$	0.14	-0.06
	-0.37	0.91		0.37	-0.91
ΔP_{-1}	-1.63	-0.06	ΔP_{-1}	-1.56	-0.03
	-2.06	-0.29		-1.96	-0.18
$I_{(\Delta P, S^e)}$	-1.34	-0.39	$I_{(\Delta P, \Delta\widehat{S^e})}$	3.46	0.99
	-1.79	-2.80		1.79	2.80

Table 12: Coefficients on financially constrained firms.

The table shows the coefficients and t-statistics on the interaction between ΔP_{-1} and ΔS^{e}_{-1} when considering only firms in the top 30%, top 25%, or top 20% of the cross-sectional distribution of the Kaplan and Zingales (1997) index of financing constraints in the previous year. The results are estimated with the Arellano and Bond (1991) first-difference GMM procedure, using 3 and 4 level lags (2 to 4 for low-tech firms) of firm-level regressors as instruments. See Tables 1 and 3 for variable definitions, and Table 4 for details on the t-statistics. High-tech firms (and, by exclusion, low-tech firms) are identified following Brown, Fazzari, and Petersen (2009). The 1979-80 observations of ΔP are multiplied by 30%. The unreported firm-specific controls are those shown in all tables but Table 9 for panels 1a) and 2a), while the controls are those in Table 9 for panels 1b) and 2b). The corresponding results for the full sample of firms, which are reported for comparison, are from Tables 4 and 9. Coefficients in %. 1955-2006.

		High-tech firms			
		All firms	30% most constrained	25% most constrained	20% most constrained
	I_{-1}	3.49	3.95	4.66	9.06
1a)		2.41	1.65	1.88	1.46
	Obs.	8,793	1,656	1,288	980
	I_{-1}	3.62	4.85	5.13	9.76
2a)		2.60	1.94	1.86	2.64
	Obs.	8,737	1,621	1,253	946

		Low-tech firms			
		All firms	30% most constrained	25% most constrained	20% most constrained
	I_{-1}	0.61	-0.13	0.79	0.55
1b)		2.93	-0.27	1.51	0.88
	Obs.	17,157	3,068	2,531	2,074
	I_{-1}	0.57	-0.12	1.10	0.20
2b)		2.60	-0.18	1.79	0.19
	Obs.	17,110	3,036	2,500	2,044