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Innovation and Price Informativeness

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# Abstract

We study whether the innovation decisions of a firm are improved as a result of information reflected in the firm's stock price. We show that firms with more informative stock prices, as measured by price nonsynchronicity, have better innovation outcomes, as measured by the number of patents and patent citations. Our results are not driven by managerial private information and are robust to various alternative specifications. We also find that price informativeness is more important to innovation when managers are less experienced or face greater uncertainty about the optimal innovation strategy, and that these effects are primarily observed in small- and mid-sized firms where additional information may be of greater value. Our results are consistent with the notion that capital markets can have real effects on the economy.

Innovation has often been cited as a key driver of economic growth (Schumpeter, **1934**; Solow, **1957**). However, investment in innovation is risky and may take many years. As such, it is often foregone due to capital markets’ emphasis on firms’ short-term performance. The existing literature indicates that takeover threats, pressure from financial analysts, and short-term performance-based trading by institutional investors aggravate managerial myopia and impede firm innovation (Stein, **1988**; Holmstrom, **1989**; He and Tian, **2013**; Fang, Tian, and Tice, **2014**). Departing from the literature on the negative externality of capital markets, we investigate whether capital markets can also benefit firm innovation through the informational role of stock prices.

It has been long believed that stock prices aggregate all market participants’ information through trading and, as such, represent a rich source of information about firm fundamentals (Hayek, **1945**; Grossman and Stiglitz, **1980**). A growing strand of the literature argues that stock prices do not merely reflect the outcomes of corporate real decisions, but can also guide corporate real decision making (see Bond, Edmans, and Goldstein, **2012**, for a recent survey of the literature).**1** One argument is that value-maximizing managers can learn from the private information in stock prices, which is communicated to the managers only via the trading process, to optimize corporate real decisions.**2** We extend the literature by examining whether firms make better innovation decisions when managers learn from private information embedded in stock prices (learning hypothesis). Given that investments in innovation are very risky and uncertain, with a failure rate between 50% and 80% (Asplund and Sandin, **1999**; Cozjinsen, Vrakking, and IJerzloo, **2000**), we expect managers to have a strong incentive to utilize information in stock prices when making innovation decisions.

To test the learning hypothesis, we first must determine when stock prices are more informative, conveying private information that is new to managers. While it is inherently difficult to measure unobserved private information, we follow the existing literature and use price nonsynchronicity as a proxy for stock price informativeness. Price nonsynchronicity captures firm-specific stock return variations that are unexplained by market movements and has been shown to be a good indicator of stock price informativeness (see Section **I.**.C for a detailed discussion). As is typical in the innovation literature, we measure innovation outcomes as the number of patents and nonself-citations per patent. To provide enough time to observe the effect of managerial learning on innovation outcomes, we examine the impact of contemporaneous stock price nonsynchronicity on our measures of innovation outcomes three years in the future.**3**

Consistent with the learning hypothesis, we find that greater price nonsynchronicity is associated with more patents and nonself-citations per patent after controlling for other predictors of innovation outcomes and firm fixed effects. The economic significance of price nonsynchronicity is comparable to that of other important determinants of innovation, such as the market-to-book ratio and research and development (R&D) expenses. These results extend the work of Chen, Goldstein, and Jiang (**2007**) and Bakke and Whited (**2010**) who find that more informative stock prices lead to greater investment stock price sensitivity. Instead of focusing on investment input, we examine the impact of price informativeness on a vital type of investment outcome, innovation productivity.

While our baseline model suggests a positive relationship between stock price informativeness and innovation outcomes, it may not warrant a causal inference that managers learn information embedded in stock prices and make more efficient innovation decisions. Therefore, we adopt an instrumental variable (IV) approach to address the potential endogeneity problem. We instrument for price nonsynchronicity using two IVs: (1) a measure of information opacity and (2) a dummy variable for inclusion in the S&P 500 index. Both variables are known to be correlated with price informativeness, but neither has been used in the literature to explain innovation.**4** Our results support the interpretation that greater stock price informativeness improves innovation outcomes. To address the concern that firm-specific information in stock prices may reflect only private information that is already known to management, we control for the amount of managerial private information as measured by insider trading activity and earnings surprise. We find that price nonsynchronicity remains a strong predictor of innovation outcomes after their inclusion indicating that stock prices contain valuable information beyond the private information possessed by managers.

We test cross-sectional predictions of the learning hypothesis to provide further support. Hambrick and Fukutomi (**1991**) argue that more experienced chief executive officers (CEOs) are less likely to utilize external information sources due to their increased reliance on their own experience and expertise. As such, we predict that younger or less tenured CEOs are more likely to consider outside sources, including information in the stock price, when making innovation decisions. Consistent with our prediction, we find that the positive association between price nonsynchronicity and innovation outcomes is stronger when the CEO is younger or less tenured. Allen (**1993**) asserts that industries with a greater divergence of opinions about the optimal investment strategy derive more benefit from information conveyed by capital markets. Thus, we hypothesize that stock price informativeness is more important to innovation outcomes for firms in innovative industries, which face greater uncertainty in selecting the optimal projects from the set of available innovation projects. We find some supportive evidence that the positive relationship between price nonsynchronicity and innovation outcomes is more pronounced for firms in innovative industries.

We examine the robustness of our results to alternative specifications. While our findings are robust to most of the additional checks, there is one important caveat to our results. When we divide our sample into three size terciles based on firm sales, we find that price nonsynchronicity is significantly positively related to innovation outcomes for small- and mid-sized firms, but is insignificantly positive for large firms. Managers of larger firms may rely less on learning from stock prices as they have greater access to other sources of information.

We contribute to the literature in the following ways. First, our study expands the literature regarding how capital markets affect firms’ real decisions. While some studies argue that capital markets can enhance the efficiency of asset allocation thus improving real decision efficiency, others find that capital markets create negative externalities in firms’ real decision making by exerting too much pressure on firms’ short-term performance. Our study adds to the debate by demonstrating that firms make more efficient real decisions when their stock price is more informative. In documenting a positive impact of the stock market on firm innovation productivity, our study further extends the literature on innovation. While investment in innovation involves a great deal of complexity and uncertainty, we find that an efficient stock market can convey valuable information to managers and help them make more efficient innovation decisions. Our findings suggest that it is important to maintain an efficient and orderly capital market. This is particularly true for small- and mid-size firms.

The paper proceeds as follows. In Section **I.**, we discuss the sample and variable construction. In Section **II.**, we present the baseline empirical specification and results. Section **III.** addresses potential endogeneity concerns by introducing the IV approach and additional controls. Section **IV.** presents the cross-sectional analyses of the learning hypothesis. Section **V.** discusses additional robustness tests, while Section **VI.** provides our conclusions.

# I. Sample and Variable Construction

## Sample Selection

Our sample consists of US firms from 1994 to 2005 that have at least 60 days of trading activity within the year and a fiscal year-end price of at least $1 per share. We merge data from several sources to create our variables of interest and controls. We collect financial statement data from Compustat, stock price information from the Centre for Research in Security Prices (CRSP), analyst coverage data from Thomson Reuters, Fama-French (**1993**) factors from Kenneth French's Web site, and information on patent grants and citations from the National Bureau of Economic Research (NBER) Patent Citation database and from the Harvard Business School (HBS) patent database. Our main sample is an unbalanced panel of 27,686 firm-year observations. For some tests, we augment the sample with data on CEO compensation from ExecuComp, insider trading data from Thomson Reuters, and word counts from annual 10-K financial reports as provided on Feng Li's Web site.

## Measuring Innovation Outcomes

Following the existing literature (Seru, **2014**; Aghion et al., **2005**), we measure a firm's innovation outcomes by its patent activity using the NBER Patent Citation database. The NBER Patent Citation database was originally created by Hall, Jaffe, and Trajtenberg (**2001**). It contains patent information from 1976 to 2006 including the patent assignee name, the filing year, the grant year, the number of patents granted, and the number of citations received by each patent. Our first measure of innovation outcome is the number of patents filed in a given year that are eventually granted (*Patent*), which gauges a firm's overall innovation productivity in raw numbers.**5** Our second measure is the number of nonself-citations per patent (*CitePat*) that captures the significance of a firm's granted patents. Due to the positive skew in patent grants and citations, we use the natural logarithm of one plus the raw value for both patent variables in our regressions (*LnPatentt* and *LnCitePatt*). We investigate the effect of contemporaneous firm characteristics on innovation outcomes three years in the future. This accounts for the long process required to turn innovation investment into patents.

We follow He and Tian (**2013**) to adjust for two truncation problems inherent to the NBER Patent Citation database. Since patents appear in the database only after they are granted, many patents that were filed but still under review at the end of 2006 would be excluded from the NBER database. Therefore, we supplement the data from NBER using the HBS patent database that contains information on patents granted through 2010. The addition of the HBS data allows us to capture patent grants and citations for patents filed on and before 2005 and minimizes the first truncation issue. The second truncation issue arises when examining patent citations. Patents may be cited over many years, but we observe only the subset of total citations that occurred during our sample period. We correct for the truncation in citation counts by estimating the shape of the citation-lag distribution and using the distribution to estimate total citation counts.

## Measuring Stock Price Informativeness and Control Variables

We use price nonsynchronicity, the portion of stock return variations unexplained by systematic factors, as our main measure of stock price informativeness. Roll (**1988**) introduced price nonsynchronicity as an indication of private information and empirically demonstrated that price nonsynchronicity has only a very small correlation with public news. While Roll (**1988**) acknowledges that price nonsynchronicity can also be driven by occasional frenzy unrelated to information, a number of subsequent studies find additional evidence that price nonsynchronicity measures more private information than noise (e.g., Durnev et al., **2003**; Durnev, Morck, and Yeung, **2004**; Veldkamp, **2006**).**6** Therefore, many empirical studies use price nonsynchronicity to measure the private information in stock prices (e.g., Ferreira and Laux, **2007**; Fresard, **2012**; Foucault and Fresard, **2014**).

As in Ferreira, Ferreira, and Raposo (2011), we compute price nonsynchronicity (*Ψ*) for each firm-year as a logistic transformation of one minus the *R*2 from the Fama-French (1993) three-factor model. For each firm-year, we estimate the *R*2 from the following equation:

(1)

where  is the excess return of stock *i* on day *d*,  is the market risk premium on day *d*, and  and  are the small-minus-big size factor return and high-minus-low book-to-market factor return on day *d*, respectively. We estimate price nonsynchronicity as:

(2)

A greater value of *Ψ* means there are more firm-specific return variations relative to the market-related return variation indicating that more private information about firm fundamentals is moving the stock price.**7**

Following the literature, we control for a number of firm characteristics that could affect innovation outcomes in our baseline regression. These firm characteristics include firm size (*LnSale*), age (*LnAge*), property, plant and equipment (*PPE*), leverage (*Leverage*), R&D expense (*R&D*), capital expenditures (*Capex*), return on assets (*ROA*), market-to-book ratio (*TobinQ*), institutional ownership (*IO*), the KZ index (*KZindex*) measure of financial constraint as proposed by Kaplan and Zingales (**1997**), the Herfindahl Index measure of industry concentration (*HHI*), the squared Herfindahl Index (*HHI\_Square*), and analyst coverage (*Analyst*). Detailed variable definitions can be found in Appendix **A**.

## Summary Statistics

Table **I** provides details about our sample. Panel A presents summary statistics on the variables used in the baseline regression. The average number of patents granted to a firm (*Patentt*+3) is 8.6 per year, while the median is zero. A firm's nonself-citations per patent (*CitePatt*+3) has an average (median) of 2.9 (0). These summary statistics suggest that the number of patents and nonself-citations per patent are positively skewed and a logarithm transformation of the patent variables is warranted. The mean (median) value of *Ψ* is 2.679 (2.570). Examining the control variables, the average firm in our sample has annual sales of $1,751.2 million, is 16.3 years old, and has average annual R&D expenses (*R&D*) and capital expenditures (*Capex*) of 5.5% and 6.7% of firm assets, respectively.**8** Our sample characteristics are generally consistent with those reported in the existing literature.

In Panel B of Table **I**, we compare firms that are more productive in innovation (patent counts or nonself-citations per patent greater than the sample median) with those that are less productive (patent counts or nonself-citations per patent less than or equal to the sample median).**9** Consistent with the previous literature (Aghion, Van Reenen, and Zingales, **2013**), we observe that firms with greater innovation productivity are larger, older, and have greater analyst coverage, institutional ownership, industry concentration, and market-to-book ratio. Firms with greater patent counts, but fewer nonself-citations per patent incur higher R&D expenses confirming the importance of examining the two distinct aspects of innovation outcomes. The first row suggests that more innovative firms have lower average *Ψ*, which is counter to our learning hypothesis. However, this univariate result should be interpreted with caution as other variables may affect the relationship between innovation and price nonsynchronicity.

Panel C of Table **I** reports the time-series distribution of the sample. For each year, we report the sample mean of contemporaneous price nonsynchronicity (*Ψ*), patent counts (*Patentt*), and nonself-citations per patent (*CitePatt*). We also include the market capitalization of our sample firms as a percentage of the CRSP-Compustat Merged universe in each year to gauge the representativeness of our sampled firms. Consistent with the pattern observed in Brandt et al. (**2010**), price nonsynchronicity was high in the mid-to-late 1990s, but decreased after the year 2000. As in Bernstein (**2015**), we note that average patent counts increased through 2000 before declining over the rest of the sample.**10** Average patent citations also declined over the sample period. Given these time series patterns, it is important that we include firm and year fixed effects in our regressions.

**Table I.**Summary Statistics

This table presents summary statistics for our sample of US firms from 1994 to 2005. Panel A provides the 10th percentile (P10), median, mean, 90th percentile (P90), and standard deviation for all of the variables in our baseline regression. *Patent* measures the number of patents filed (and eventually granted). *CitePat* is the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted). *Ψ* measures stock price informativeness as the annual logistic transformation of one minus the estimated *R*2 from the Fama-French (1993) three-factor model. Panel B presents information on the cross-sectional differences between firms by innovation productivity. The rows report the mean of each variable in the subsample specified in Columns (1), (2), (4), and (5). Columns (3) and (6) report the difference in the sample characteristics between the high and low innovation productivity firms, as well as the statistical significance of the *t*-test for the difference in means. Panel C displays the distribution of the sample by year. Specifics of the variable definitions can be found in Appendix A.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **P10** | **Median** | **Mean** | **P90** | **SD** |  |
| ***Panel A. Summary Statistics for the Full Sample (27,686 Observations)*** |  |  |  |  |  |  |
| *Patentt*+3 | 0.000 | 0.000 | 8.571 | 6.000 | 82.354 |  |
| *CitePatt*+3 | 0.000 | 0.000 | 2.943 | 7.864 | 11.721 |  |
| *Ψ* | 1.018 | 2.570 | 2.679 | 4.497 | 1.358 |  |
| *LnSale* | 2.916 | 5.361 | 5.400 | 8.030 | 2.058 |  |
| *LnAge* | 1.386 | 2.398 | 2.446 | 3.638 | 0.857 |  |
| *PPE* | 0.052 | 0.214 | 0.281 | 0.640 | 0.225 |  |
| *Leverage* | 0.000 | 0.021 | 0.076 | 0.212 | 0.141 |  |
| *R&D* | 0.000 | 0.004 | 0.055 | 0.170 | 0.099 |  |
| *Capex* | 0.013 | 0.046 | 0.067 | 0.146 | 0.067 |  |
| *ROA* | −0.085 | 0.125 | 0.090 | 0.245 | 0.229 |  |
| *TobinQ* | 0.907 | 1.526 | 2.135 | 4.059 | 1.773 |  |
| *IO* | 0.063 | 0.406 | 0.415 | 0.772 | 0.264 |  |
| *KZindex* | −13.040 | −1.280 | −5.774 | 0.557 | 17.038 |  |
| *HHI* | 0.024 | 0.043 | 0.063 | 0.112 | 0.060 |  |
| *HHI\_Square* | 0.001 | 0.002 | 0.008 | 0.013 | 0.028 |  |
| *Analyst* | 0.000 | 1.099 | 1.107 | 2.197 | 0.791 |  |
|  | **Full Sample** |  |  | **Firms with at Least One Patent** |  |  |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|  | ***Patentt*+3 ⩽ Median (0) (21,468 Observations)** | ***Patentt*+3 > Median (0) (6,218 Observations)** | **Difference (2) – (1)** | ***CitePatt*+3 ⩽ Median (6.523) (3,109 Observations)** | ***CitePatt*+3 > Median (6.523) (3,109 Observations)** | **Difference (5) – (4)** |
| ***Panel B. Firm Characteristics by Innovation Productivity*** |  |  |  |  |  |  |
| *Ψ* | 2.812 | 2.217 | −0.595\*\*\* | 2.402 | 2.007 | −0.395\*\*\* |
| *LnSale* | 5.241 | 5.950 | 0.710\*\*\* | 5.456 | 6.513 | 1.057\*\*\* |
| *LnAge* | 2.387 | 2.649 | 0.261\*\*\* | 2.590 | 2.715 | 0.124\*\*\* |
| *PPE* | 0.291 | 0.244 | −0.048\*\*\* | 0.242 | 0.245 | −0.003 |
| *Leverage* | 0.076 | 0.076 | 0.000 | 0.069 | 0.084 | 0.015\*\*\* |
| *R&D* | 0.045 | 0.090 | 0.046\*\*\* | 0.097 | 0.082 | −0.016\*\*\* |
| *Capex* | 0.069 | 0.062 | −0.007\*\*\* | 0.058 | 0.068 | 0.010\*\*\* |
| *ROA* | 0.089 | 0.091 | 0.002 | 0.059 | 0.128 | 0.070\*\*\* |
| *TobinQ* | 1.985 | 2.653 | 0.668\*\*\* | 2.606 | 2.706 | 0.100\* |
| *IO* | 0.393 | 0.458 | 0.065\*\*\* | 0.429 | 0.492 | 0.064\*\*\* |
| *KZindex* | −5.549 | −6.546 | −0.997\*\*\* | −7.182 | −5.823 | 1.359\*\*\* |
| *HHI* | 0.067 | 0.047 | −0.020\*\*\* | 0.046 | 0.048 | −0.002\*\* |
| *HHI\_Square* | 0.009 | 0.003 | −0.005\*\*\* | 0.003 | 0.003 | 0.000 |
| *Analyst* | 1.023 | 1.396 | 0.373\*\*\* | 1.237 | 1.576 | 0.339\*\*\* |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Year** | ***Ψt* (Mean)** | ***Patentt* (Mean)** | ***CitePatt* (Mean)** | **Number of Firms** | **Total Market Capitalization as a Percentage of the CRSP-Compustat Merged Universe** |
| ***Panel C. Sample Distribution by Year*** |  |  |  |  |  |
| 1994 | 3.123 | 8.705 | 10.274 | 2,638 | 76% |
| 1995 | 3.376 | 10.347 | 10.064 | 2,765 | 75% |
| 1996 | 2.964 | 10.246 | 10.298 | 2,884 | 74% |
| 1997 | 2.786 | 11.896 | 9.352 | 3,050 | 72% |
| 1998 | 2.301 | 11.822 | 7.936 | 2,997 | 75% |
| 1999 | 2.973 | 12.560 | 6.798 | 2,853 | 80% |
| 2000 | 2.660 | 14.110 | 5.068 | 2,711 | 72% |
| 2001 | 2.276 | 13.700 | 3.542 | 2,775 | 70% |
| 2002 | 2.061 | 12.475 | 2.048 | 2,667 | 71% |
| 2003 | 2.157 | 8.389 | 1.101 | 2,730 | 71% |
| 2004 | 2.029 | 3.840 | 0.320 | 2,688 | 70% |
| 2005 | 2.176 | 1.191 | 0.105 | 2,272 | 62% |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

# II. Baseline Empirical Specification and Results

Our baseline model is specified as follows:

(3)

where *i* indexes the firms and *t* indexes the year. The dependent variables are innovation outcomes: the natural logarithm of one plus the number of patents filed (and eventually granted) (*LnPatent*) and the natural logarithm of one plus the number of nonself-citations per patent filed (and eventually granted) (*LnCitePat*). As discussed in Section I..B, we examine innovation outcomes three years in the future to account for the long-term nature of innovation activity. The control variables are discussed in Section I..C with their definitions specified in Appendix A.

We include firm fixed effects, denoted by *di*, in our regression model to absorb the time-invariant aspects of a firm, such as its business model, disclosure policy, and corporate culture, which may influence both innovation outcomes and stock price informativeness. We also control for time fixed effects, denoted by *dt*, to account for changes in the macroeconomic climate that may simultaneously affect a firm's innovation opportunities and information contained in stock prices. As innovation may be autocorrelated over time, we cluster standard errors by firm (Petersen, **2009**). If greater stock price informativeness enhances innovation efficiency, then *β*1 should be positive and statistically significant.

The results of our baseline regression are reported in Table **II**. In Columns (1) and (2), the dependent variable is the number of patents (*LnPatentt*+3). Column (1) indicates a negative and statistically significant coefficient estimate on price nonsynchronicity (*Ψ*) when we include all of the control variables and year fixed effects in the regression. Once we include firm fixed effects and estimate the full model in Column (2), we find a positive and statistically significant coefficient estimate on *Ψ*. The change in the coefficient estimate on *Ψ* suggests that unobservable time-invariant firm characteristics that are correlated with both *Ψ* and patent counts bias our coefficient estimate of *Ψ* downward. The results in Column (2) suggest that, on average, an increase in *Ψ* from the 10th to 90th percentile is associated with an 8.16% increase in the number of patents, when patent counts are at their unconditional mean.**11** For comparison, an increase in R&D expense (market-to-book ratio) from the 10th to 90th percentile predicts a 9.32% (10.91%) increase in patent counts. This puts the economic importance of price nonsynchronicity in line with other economically important factors in firm innovation outcomes.

**Table II.**Baseline Regression

This table provides the coefficient estimates from the ordinary least squares regression specified in Equation 3. In Columns (1) and (2), the dependent variable is *LnPatentt+3* defined as the natural logarithm of one plus the number of patents filed (and eventually granted) at year *t* + 3. In Columns (3) and (4), the dependent variable is *LnCitePatt+3* defined as the natural logarithm of one plus the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) at year *t* + 3. *Ψ* measures stock price informativeness as the annual logistic transformation of one minus the estimated *R*2 from the Fama-French (1993) three-factor model. All independent variables are measured at time *t*. Specifics of the variable definitions are available in Appendix A. Standard errors are clustered by firm and *t*-statistics are reported in parentheses.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ***LnPatentt*+3** |  | ***LnCitePatt*+3** |  |
|  | **(1)** | **(2)** | **(3)** | **(4)** |
| *Ψ* | −0.050\*\*\* | 0.021\*\*\* | −0.048\*\*\* | 0.016\*\* |
|  | (−6.073) | (4.337) | (−7.222) | (2.487) |
| *LnSale* | 0.149\*\*\* | 0.018 | 0.081\*\*\* | 0.010 |
|  | (11.347) | (1.207) | (9.581) | (0.550) |
| *LnAge* | 0.179\*\*\* | 0.287\*\*\* | 0.121\*\*\* | 0.319\*\*\* |
|  | (10.004) | (6.865) | (9.167) | (6.005) |
| *PPE* | −0.283\*\*\* | 0.335\*\*\* | −0.274\*\*\* | 0.438\*\*\* |
|  | (−4.550) | (3.467) | (−5.943) | (3.389) |
| *Leverage* | 0.459\*\*\* | −0.012 | 0.162\*\*\* | −0.079 |
|  | (4.342) | (−0.285) | (2.669) | (−1.356) |
| *R&D* | 2.771\*\*\* | 0.491\*\*\* | 1.923\*\*\* | 0.424\*\* |
|  | (15.042) | (3.007) | (13.058) | (2.044) |
| *Capex* | 0.471\*\* | 0.053 | 0.228 | 0.104 |
|  | (2.474) | (0.528) | (1.643) | (0.759) |
| *ROA* | 0.285\*\*\* | 0.108 | 0.266\*\*\* | 0.127 |
|  | (3.417) | (1.623) | (3.366) | (1.613) |
| *TobinQ* | 0.054\*\*\* | 0.031\*\*\* | 0.030\*\*\* | 0.019\*\*\* |
|  | (6.609) | (5.979) | (5.055) | (2.955) |
| *IO* | −0.219\*\*\* | −0.069 | −0.094\* | −0.186\*\* |
|  | (−3.203) | (−1.043) | (−1.898) | (−2.240) |
| *KZindex* | −0.001\*\* | −0.001\*\*\* | −0.000 | −0.002\*\*\* |
|  | (−2.269) | (−3.186) | (−1.002) | (−3.196) |
| *HHI* | −4.242\*\*\* | −1.170\*\* | −3.001\*\*\* | −0.726 |
|  | (−11.256) | (−2.330) | (−11.549) | (−0.811) |
| *HHI\_Square* | 5.546\*\*\* | 0.911 | 3.425\*\*\* | −0.635 |
|  | (7.984) | (1.046) | (8.430) | (−0.331) |
| *Analyst* | 0.175\*\*\* | −0.010 | 0.085\*\*\* | −0.020 |
|  | (7.051) | (−0.546) | (4.696) | (−0.914) |
| Constant | −0.806\*\*\* | −0.122 | −0.234\*\*\* | 0.129 |
|  | (−8.772) | (−1.106) | (−4.060) | (0.903) |
| YEAR FE | YES | YES | YES | YES |
| FIRM FE | NO | YES | NO | YES |
| Observations | 27,686 | 27,686 | 27,686 | 27,686 |
| Adj. *R*2 | 0.256 | 0.755 | 0.200 | 0.503 |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

In Columns (3) and (4), we present the regression results when the number of nonself-citations per patent *(LnCitePatt*+3) is the dependent variable. Similar to the results on patent counts, Column (3) indicates that there is a negative and significant association between *Ψ* and nonself-citations per patent when we exclude firm fixed effects. When we estimate the full model including firm fixed effects in Column (4), we find that greater *Ψ* predicts more future patent nonself-citations. Economically, an increase in *Ψ* from the 10th to the 90th percentile is associated with a 7.46% increase in the number of nonself-citations per patent when nonself-citations per patent are at their unconditional mean. The economic significance of *Ψ* in Column (4) is comparable to that of other important factors, such as R&D expense and the market-to-book ratio.**12** Since we control for innovation inputs (R&D expense and capital expenditures), our results in Table **II** indicate that for a given level of innovation investment, managers are able to enhance innovation productivity by learning from information conveyed by the stock price.

The signs on the control variables for our full model (Columns (2) and (4)) are consistent with the existing literature with two notable exceptions. The first is the effect of institutional ownership (*IO*), which has a negative and sometimes statistically significant impact on innovation outputs in our sample. This contrasts the findings of Aghion et al. (**2013**) that large levels of institutional ownership are associated with greater innovation outputs. However, our finding of a negative coefficient on institutional ownership is consistent with Adhikari and Agrawal (**2016**). This is likely due to issues of sample selection.**13** The second difference is the sign and statistical significance of analyst coverage (*Analyst*) on innovation output. In Table **II**, Columns (2) and (4), we find a negative, but statistically insignificant coefficient estimate on analyst coverage after controlling for firm fixed effects.**14** Our results may be due to two confounding effects of analyst coverage discussed in the literature. While He and Tian (**2013**) find that analyst coverage reduces innovation through increased managerial myopia, Goldman and Peress (**2015**) argue that analyst coverage leads to improved innovation efficiency as firms can receive more future capital for successful projects from better informed financiers.

# III. Extensions to the Baseline Model

## IV Approach

While our baseline results provide some primary support for the learning hypothesis, it is possible that reverse causality or omitted variables drive our results. For example, it may be that more informed investors are attracted to more innovative firms. Alternatively, price nonsynchronicity may be correlated with disagreement among investors, which tends to be higher among innovative firms due to the uncertainty involved in innovation. Although regressing innovation outcomes in year *t* + 3 on stock price nonsynchronicity in year *t* and including firm fixed effects in the baseline regressions can alleviate endogeneity concerns to some degree, we adopt an IV approach to further establish causality.

We instrument for price nonsynchronicity with a measure of firm information opacity and a dummy variable for inclusion in the S&P 500 index. Jin and Myers (**2006**) model the joint effects of transparency and investor protection on the firm-specific information in stock prices and show that even in markets with perfect investor protection, more opaque firms have lower price nonsynchronicity (higher *R*2). We proxy for the opacity of firm disclosures using the natural log of the number of words in the annual 10-K filing (*LnNum\_words*). As in Li (**2008**), we expect that firms with a greater number of words in their financial statements are more opaque, which obscures firms’ fundamental value and decreases the stock price informativeness. Our second instrument is inclusion in the S&P 500 (*SP500\_Dummy*). Empirical evidence suggests that S&P 500 inclusion distorts firms’ stock prices. Wurgler (**2011**) finds that stock returns of newly added S&P 500 firms become more correlated with other firms in the index and less correlated with the rest of the market causing their prices to become more reflective of supply and demand in the index than firm-specific information. Morck and Yang (**2001**) note a significant price premium for those stocks in the S&P 500 index indicating that their prices are detached from fundamentals. However, neither the number of words in the annual report nor inclusion in the S&P 500 has been used in the literature to explain innovation and is expected to have no direct impact on innovation outcomes.**15**

In Table **III**, we report the first- and second-stage results when instrumenting for *Ψ*. As expected, Column (1) indicates that both *LnNum\_words* and *SP500\_Dummy* are significantly negatively related to *Ψ* in the first stage, controlling for all other regressors in Equation **3**. Columns (2) and (3) demonstrate that the positive and statistically significant relationship between *Ψ* and innovation outcomes remains even after we instrument for *Ψ*.**16** These results alleviate the reverse causality and omitted variables concerns and provide further support for our hypothesis.

## Controlling for Managerial Private Information

Another alternative explanation for our results is that managers’ private information is correlated with the information embedded in stock prices and drives the relationship between price nonsynchronicity and innovation. To address this concern, we include two measures of managers’ private information as additional controls as in Chen et al. (**2007**). The first measure is the intensity of insider trading (*Insider*) calculated as net insider transactions as a percentage of the number of shares outstanding. While there are a number of reasons that managers may trade, we expect that managers are likely to trade more, on average, when they have more private information. The second measure is earnings surprise (*ERC*) constructed as the abnormal stock return around earnings announcements. Higher earnings surprise indicates that managers as corporate insiders possess more private information compared to outside investors.

Table **IV** presents the results of the extended baseline model controlling for managers’ private information. We find that the coefficient on *Ψ* remains significantly positive in all specifications with an economic significance comparable to that in the baseline regression. Consistent with the findings of Levine, Chen, and Wei (**2015**), insider trading (*Insider*) is negatively associated with innovation outcomes. It is possible that greater insider trading discourages the information acquisition of outside investors. Consequently, this may lead to greater price misevaluation and less efficient investment decisions (Merton, **1987**). Overall, the results in Table **IV** suggest that managers learn valuable information from their firms’ stock prices that is beyond the private information set they already possess.

**Table III.**Instrumental Variable Approach

This table reports the results of the first and second stage in a two-stage least squares model. The results of the first stage are reported in Column (1). The results of the second stage are reported in Columns (2) and (3). The dependent variable of the first stage in Column (1) is *Ψ*, the annual logistic transformation of one minus the estimated *R*2 from the Fama-French (1993) three-factor model. The instrumental variables in the first stage are *LnNum\_words* and *SP500\_Dummy*. *LnNum\_words* is measured as the natural logarithm of the word count from the firm's annual 10-K filing. *SP500\_Dummy* is a binary variable equal to one when the firm is included in the S&P 500 index and zero otherwise. The dependent variable of the second stage in Column (2) is *LnPatentt+3* defined as the natural logarithm of one plus the number of patents filed (and eventually granted) at year *t* + 3. The dependent variable of the second stage in Column (3) is *LnCitePatt+3* defined as the natural logarithm of one plus the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) at year *t* + 3. In the second stage, *Ψ* is the instrumented variable from the first-stage regression. All of the control variables from the baseline model are included in the regressions, but are unreported in this table. All independent variables are measured at time *t*. Specifics of the variable definitions are available in Appendix A. Standard errors are clustered by firm and *t*-statistics are reported in parentheses.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **First Stage** |  | **Second Stage** |
|  | ***Ψt*** | ***LnPatentt*+3** | ***LnCitePatt*+3** |
|  | **(1)** | **(2)** | **(3)** |
| *LnNum\_words* | −0.050\*\*\* |  |  |
|  | (−3.643) |  |  |
| *SP500\_Dummy* | −0.165\*\*\* |  |  |
|  | (−3.052) |  |  |
| *Ψ* |  | 1.038\*\*\* | 1.321\*\*\* |
|  |  | (3.242) | (3.271) |
| CONTROLS | YES | YES | YES |
| YEAR FE | YES | YES | YES |
| FIRM FE | YES | YES | YES |
| Observations | 19,497 | 19,497 | 19,497 |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

**Table IV.**Controlling for Managers’ Private Information

This table reports the coefficient estimates from the augmented ordinary least squares regression in Equation 3 controlling for managerial private information. In Columns (1) and (2), the dependent variable is LnPatentt+3 defined as the natural logarithm of one plus the number of patents filed (and eventually granted) at year t + 3. In Columns (3) and (4), the dependent variable is LnCitePatt+3 defined as the natural logarithm of one plus the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) at year t + 3. Ψ measures stock price informativeness as the annual logistic transformation of one minus the estimated R2 from the Fama-French (1993) three-factor model. Insider measures insider trading defined as Σ(shares purchasedd /shares outstandingd) – Σ(shares soldd/shares outstandingd), where the sum is over each firm's insiders over all days d in year t, and shares outstanding is the number of shares outstanding on the date of the insiders’ transaction. ERC is the earnings surprise, which is defined as the average cumulative abnormal stock returns (CAR [–1,1]) over the four quarterly earnings announcements in year t. All of the control variables from the baseline model are included in the regressions, but are unreported in this table. All of the independent variables are measured at year t. Specifics of the variable definitions are available in Appendix A. Standard errors are clustered by firm and t-statistics are reported in parentheses.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ***LnPatentt*+3** |  | ***LnCitePatt*+3** |  |
|  | **(1)** | **(2)** | **(3)** | **(4)** |
| *Ψ* | 0.021\*\*\* | 0.021\*\*\* | 0.017\*\* | 0.016\*\* |
|  | (4.370) | (4.343) | (2.524) | (2.487) |
| *Insider* | −0.189\*\* |  | −0.284\*\* |  |
|  | (−2.369) |  | (−2.498) |  |
| *ERC* |  | −0.083 |  | 0.012 |
|  |  | (−1.011) |  | (0.108) |
| CONTROLS | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES |
| FIRM FE | YES | YES | YES | YES |
| Observations | 27,686 | 27,686 | 27,686 | 27,686 |
| Adj. *R*2 | 0.755 | 0.755 | 0.503 | 0.503 |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

# IV. Cross-Sectional Tests

We conduct cross-sectional tests to provide further support for the learning hypothesis. Our first cross-sectional test examines the role of CEO experience in the relationship between stock price informativeness and innovation outcomes. Hambrick and Fukutomi (**1991**) find that more experienced CEOs rely more heavily on their own experience and expertise than external information sources for decision making. Therefore, we expect a stronger relationship between stock price informativeness and innovation when CEOs are less experienced as they place greater weight on learning from outside sources including stock prices. We measure CEO experience using the natural logarithm of CEO tenure at the firm (*LnCEO\_Tenure*) and the natural logarithm of CEO age (*LnCEO\_Age*).**17** In addition to the control variables from the baseline model, we also control for other CEO characteristics that could impact innovation outcomes to mitigate concerns about omitted variables.**18** These additional controls are CEO overconfidence (*ConfidentCEO*), pay-performance sensitivity (*LogDelta*), and pay-volatility sensitivity (*LogVega*).**19**

The results of the first cross-sectional test are reported in Table **V**. Consistent with our hypothesis, the interaction between *Ψ* and *LnCEO\_Tenure* (*LnCEO\_Age*) is significantly negative across all four specifications suggesting that less experienced CEOs rely more heavily on information learned from the stock price than more experienced CEOs. Furthermore, we find that both CEO tenure and age are positively associated with innovation outcomes indicating that managerial experience is valuable in making good innovation decisions. Our results also support the findings of Hirshleifer, Low, and Teoh (**2012**) and Galasso and Simcoe (**2011**) that overconfident CEOs underestimate the risk of innovation and are more productive in innovation. Finally, we find that pay-performance sensitivity decreases the quantity and quality of innovation outputs, which may be related to the managerial myopia induced by stock markets (Holmstrom, **1989**).

**Table V.**Impact of CEO Characteristics on Managerial Learning

This table reports the coefficient estimates from the augmented ordinary least squares regression in Equation 3, testing the cross-sectional effect of CEO experience on managerial learning. In Columns (1) and (3), the dependent variable is LnPatentt+3 defined as the natural logarithm of one plus the number of patents filed (and eventually granted) at year t + 3. In Columns (2) and (4), the dependent variable is LnCitePatt+3 defined as the natural logarithm of one plus the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) at year t + 3. Ψ measures stock price informativeness as the annual logistic transformation of one minus the estimated R2 from the Fama-French (1993) three-factor model. LnCEO\_Tenure is the natural logarithm of the number of years that the CEO has held the position at the firm. LnCEO\_Age is the natural logarithm of CEO age. Ψ × LnCEO\_Tenure (LnCEO\_Age) is the interaction of Ψ and LnCEO\_Tenure (LnCEO\_Age). ConfidentCEO is a binary variable of the options-based measure of CEO overconfidence equal to one for overconfident CEOs and zero otherwise. LogDelta is defined as the natural logarithm of the CEO delta measured as the dollar change in the CEO's stock and option portfolio for a 1% change in stock price in thousands of 2006 dollars. LogVega is the natural logarithm of the CEO vega measured as the dollar change in the CEO option holdings for a 1% change in stock return volatility in thousands of 2006 dollars. All of the control variables from the baseline model are included in the regressions, but are unreported in this table. All of the independent variables are measured at year t. Specifics of the variable definitions are available in Appendix A. Standard errors are clustered by firm and t-statistics are reported in parentheses.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ***LnPatentt*+3** | ***LnCitePatt*+3** | ***LnPatentt*+3** | ***LnCitePatt*+3** |
|  | **(1)** | **(2)** | **(3)** | **(4)** |
| *Ψ × LnCEO\_Tenure* | −0.025\*\* | −0.027\* |  |  |
|  | (−1.963) | (−1.824) |  |  |
| *Ψ × LnCEO\_Age* |  |  | −0.315\*\*\* | −0.343\*\*\* |
|  |  |  | (−3.495) | (−3.199) |
| *Ψ* | 0.056\*\* | 0.068\*\* | 1.319\*\*\* | 1.453\*\*\* |
|  | (2.054) | (2.171) | (3.504) | (3.259) |
| *LnCEO\_Tenure* | 0.080\* | 0.101\*\* |  |  |
|  | (1.728) | (2.017) |  |  |
| *LnCEO\_Age* |  |  | 0.611\*\* | 0.847\*\*\* |
|  |  |  | (2.343) | (2.996) |
| *Confident CEO* | 0.148\*\*\* | 0.142\*\*\* | 0.116\*\*\* | 0.130\*\*\* |
|  | (3.251) | (2.903) | (2.899) | (2.997) |
| *LogDelta* | −0.059\*\*\* | −0.051\*\* | −0.044\*\*\* | −0.034\* |
|  | (−2.739) | (−2.185) | (−2.606) | (−1.791) |
| *LogVega* | −0.006 | −0.023 | −0.004 | −0.018 |
|  | (−0.351) | (−1.164) | (−0.290) | (−1.074) |
| CONTROLS | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES |
| FIRM FE | YES | YES | YES | YES |
| Observations | 8,678 | 8,678 | 9,851 | 9,851 |
| Adj. *R*2 | 0.797 | 0.594 | 0.797 | 0.585 |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

In our second cross-sectional test, we investigate whether stock price informativeness is more important to innovation success when firms face greater uncertainty surrounding the optimal managerial strategy. Allen (**1993**) argues that the role of the stock market in allocating resources is particularly valuable in industries with a greater divergence of opinions as to the optimal investment strategy. Firms in innovative industries are likely to have more innovation opportunities and greater uncertainty in innovation outcomes resulting in a greater tendency to learn from information embedded in stock prices. Accordingly, we posit that stock price informativeness is more important to innovation outcomes for firms in innovative industries. We define an industry as innovative if the average innovation input (R&D expense) or output (patent counts or citations) of the industry is above the median for all industries and noninnovative otherwise. The industry classification is defined using the two-digit standard industrial classification (SIC) code.

Table **VI** presents the results of the baseline model for firms in innovative and noninnovative industries. The results in Columns (1)–(4) demonstrate that *Ψ* is more important in predicting the number of patents for firms in innovative industries, as defined by both greater R&D expense and patent output. The importance of *Ψ* to the nonself-citations per patent is greater for firms in high R&D expense industries (Columns (5) and (6)), but *Ψ* is an insignificant predictor of nonself-citations per patent for high patent output industries (Columns (7) and (8)). Overall, the results of Table **VI** provide some evidence that stock price informativeness has a greater impact on innovation outcomes when firms face greater uncertainty as to the optimal investment strategy amidst many innovation opportunities.

**Table VI.**Subsample Analysis by Innovative and Noninnovative Industries

This table provides the coefficient estimates from the ordinary least squares regression in Equation 3 performed on the subsample of firms in innovative and noninnovative industries as defined by R&D expense and patent output. An industry is defined as high (low) R&D if the average R&D expense in the industry is greater than (less than or equal to) the median across all industries defined by the two-digit SIC code. An industry is defined as high (low) patent output if the average number of patents or nonself-citations per patent in the industry are greater than (less than or equal to) the median across all industries defined by the two-digit SIC code. In Columns (1)–(4), the dependent variable is LnPatentt+3 defined as the natural logarithm of one plus the number of patents filed (and eventually granted) at year t + 3. In Columns (5)–(8), the dependent variable is LnCitePatt+3 defined as the natural logarithm of one plus the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) at year t + 3. Ψ measures stock price informativeness as the annual logistic transformation of one minus the estimated R2 from the Fama-French (1993) three-factor model. All of the control variables from the baseline model are included in the regressions, but are unreported in this table. All independent variables are measured at time t. Specifics of the variable definitions are available in Appendix A. Standard errors are clustered by firm and t-statistics are reported in parentheses.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***LnPatentt*+3** |  |  |  | ***LnCitePatt*+3** |  |  |  |
|  | **High R&D** | **Low R&D** | **High Patent Output** | **Low Patent Output** | **High R&D** | **Low R&D** | **High Patent Output** | **Low Patent Output** |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| Ψ | 0.043\*\*\* | 0.002 | 0.016\*\*\* | 0.003 | 0.026\*\* | −0.002 | 0.008 | 0.003 |
|  | (5.060) | (0.374) | (2.685) | (0.812) | (2.478) | (−0.269) | (0.868) | (0.781) |
| CONTROLS | YES | YES | YES | YES | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES | YES | YES | YES | YES |
| FIRM FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 13,572 | 14,114 | 19,345 | 8,341 | 13,572 | 14,114 | 19,345 | 8,341 |
| Adj. *R*2 | 0.761 | 0.762 | 0.821 | 0.482 | 0.526 | 0.52 | 0.641 | 0.493 |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

# V. Additional Robustness Checks

We perform several additional tests to ensure the robustness of our results. First, we examine whether the relationship between stock price informativeness and innovation outcomes varies across firms of different size, which may have heterogeneous access to information sources other than the stock price. In Appendix **B**, we report the baseline model results after dividing the sample into size terciles.**20** We find that the coefficient on *Ψ* is positive and statistically significant in the first two terciles (small- and mid-sized firms), but positive and statistically insignificant in the third tercile (large firms). It is possible that managers of large firms rely less on information contained in stock prices because they have more sources of information. For instance, they can obtain information through greater media coverage or the advice and expertise of a larger board with more outside directors.**21** Alternatively, the reduced significance may be due to the smaller sample size in each tercile as compared to the full sample.

To preserve space, the results of the remaining robustness tests are not presented in this paper but are available from the authors upon request. We assess the robustness of our results to alternative innovation measures. We re-estimate our baseline model with the dependent variable measured at year *t* + 2 and at year *t* + 4 and find that the coefficient on *Ψ* remains positive and statistically significant. We also rerun our regression models using a smoothed measure of patent outcomes where we define total patent counts (citations) over a rolling three-year window from *t* + 2 to *t* + 4.**22** Our results remain qualitatively unchanged.

We further check the sensitivity of the results to our proxy for stock price informativeness. First, we verify that we obtain consistent results when using an extended market model, including market and industry returns, in the estimation of price nonsynchronicity. Next, we retabulate all of our results with another measure of stock price informativeness, probability of informed trading (PIN). The PIN measure was first developed by Easley et al. (**1996**) and Easley, Kiefer, and O'Hara (**1996**) and captures order flow imbalance that is likely due to informed trading. We confirm that the qualitative results across all reported tables are unaffected by this change.**23** We also address the concerns of Li, Rajgopal, and Venkatachalam (**2014**) that price nonsynchronicity may be confounded with systematic risk resulting in biased coefficient estimates. Following their recommendation, we control for the natural log of the firm's squared beta to account for the systematic risk. Our results remain quantitatively and qualitatively similar.

In our final robustness check, we control for the effect of stock liquidity on innovation since both measures of price informativeness and innovation may be related to stock liquidity. The existing literature has found mixed results regarding the impact of stock liquidity on price informativeness. While Holmstrom and Tirole (**1993**) model stock liquidity as positively related to the information content of stock prices, Duarte and Young (**2009**) argue that PIN is priced due to its negative relationship with stock liquidity. Fang, Tian, and Tice (**2014**) find that an increase in stock liquidity reduces future innovation. As such, stock liquidity could confound the impact of stock price informativeness on innovation outcomes. After including stock liquidity as an additional control in the baseline model, we find that stock price informativeness remains as a significant predictor of innovation outcomes.

# VI. Conclusions

In this study, we investigate whether firms with more informative stock prices have better innovation outcomes. Specifically, we hypothesize that managers learn from their stock prices and make better investments in innovation (learning hypothesis). Consistent with the learning hypothesis, we find that firms with more informative stock prices, measured by greater price nonsynchronicity, are able to generate a greater number of granted patents and nonself-citations per patent, ceteris paribus. Our results are robust to the use of an IV approach and remain strong after controlling for managerial private information.

To provide further evidence for the learning hypothesis, we test its cross-sectional predictions. We find that firms take greater advantage of information in stock prices in making innovation decisions when their CEOs are relatively inexperienced. We also find some evidence that stock price informativeness has a greater impact on innovation among firms in more innovative industries, where there is likely to be greater uncertainty about the optimal innovation strategy. While our main finding is robust to a battery of additional tests, we find that the importance of stock price informativeness to innovation outcomes is statistically significant only in small- and mid-sized firms.

Overall, we contribute to two strands of the finance literature. First, we document an additional effect of the capital markets on the real economy. Our findings support the literature on the real effect of stock prices on corporate decisions and provide further evidence that the stock market is more than a sideshow. In addition, we contribute to the growing literature on firm innovation. Understanding the relationship between innovation and capital markets is important given the vital role of innovation to economic growth. While some studies have shown negative effects of the stock market on innovation, our paper suggests that an efficient and orderly stock market conveys valuable information and enhances corporate innovation productivity.

# Notes

1 For example, Luo (2005) finds that managers are more likely to cancel an acquisition that is viewed unfavorably by the market.

2 Managers do not have to be less informed than market participants to learn information from stock prices. So long as managers do not have the perfect information and market participants collectively possess some private information beyond the managers’ information set, managers can learn useful information from stock prices to make better real decisions. Such private information can be future investment opportunities, consumer demands for firms’ products, and position of competitors.

3 As discussed in Section V., our results remain qualitatively unchanged when we measure innovation output two or four years in the future, or over a rolling three-year window from year two to year four in the future.

4 Jin and Myers (2006) argue that greater information opacity results in less firm-specific information generation and lower stock price informativeness. Vijh (1994), Barberis, Shleifer, and Wurgler (2005), and Wurgler (2011) find that inclusion in the S&P 500 index reduces stock price informativeness as included stocks become more correlated with each other due to index trading.

5 We focus on when patents are filed rather than when they are granted since filing dates better describe the timing of innovation activity (Griliches, Pakes, and Hall, 1988).

6 Durnev et al. (2003) find that price nonsynchronicity is positively correlated with future earnings information contained in current stock prices indicating that firm-specific return variations reflect private information possessed by investors. Durnev et al. (2004) confirm that industries with greater price nonsynchronicity display greater investment efficiency, as measured by a deviation in Tobin's Q from its optimal level. Veldkamp (2006) demonstrates theoretically that when information production involves high fixed costs, rational investors acquire information common to many firms instead of private information on individual firms resulting in greater price comovements and less price nonsynchronicity.

7 As with any paper utilizing a model of expected returns, we acknowledge that our results are subject to the joint hypothesis problem in which we must assume that our model of returns is correct to make any claims on interpreting deviations from the model. In Section V., we discuss the robustness of our results to alternate price informative measures.

8 Firms in our sample are comparable to the CSRP-Compustat merged universe though they are somewhat larger and more mature. For example, the mean sales and age of firms in our sample are $1,752.1 million and 16.34 years, respectively, compared to $1,379.4 million and 13.52 years for the CRSP-Compustat merged universe. The average firm in our sample also has slightly larger investments in R&D and capital expenditures than the average CRSP-Compustat firm.

9 In examining nonself citations per patent, we restrict the sample to firms with at least one patent.

10 The time series distribution of the number of patents is reported in Table A1 of the Internet appendix of Bernstein (2015).

11 If we define patent counts as the *y* variable and price nonsynchronicity (*Ψ*) as the *x* variable of interest, then the coefficient on *Ψ* of 0.021 represents dln(1 + *y*)/d*x*. To find the change in *y* (d*y*), we derive it as d*y* = [dln(1 + *y*)/d*x*]\*d*x*\*(1 + *y*). Assuming *x* changes from its 10th to its 90th percentile (3.479) and *y* is at its unconditional mean (8.571), d*y* = [dln(1 + *y*)/d*x*]\*d*x*\*(1 + *y*) = 0.021\*3.479\*(1+8.571) = 0.699248. This represents an 8.16% (0.699248/8.571) increase at the mean of patent counts. The economic significance of *Ψ* in Column (4) when the dependent variable is nonself citations per patent is calculated similarly.

12 An increase in R&D expense (market-to-book ratio) from the 10th to 90th percentile predicts a 9.66% (8.03%) increase in nonself citations per patent when nonself citations per patent are at their unconditional mean.

13 When we restrict the sample to firms with nonzero patents as in Aghion et al. (2013), we find that the effect of institutional ownership is positive and significant. We also continue to observe a positive and statistically significant coefficient on price nonsynchronicity. Nonetheless, excluding firms with zero patents creates a sample selection issue. For instance, a disproportionally high number of small firms may be excluded given that small firms (with lower sales) tend to have fewer patents as illustrated in Panel B of Table I. Therefore, we include firms with zero patents in our sample.

14 In Columns (1) and (3), the coefficient on analyst coverage is positive and statistically significant when firm fixed effects are not controlled. Certain omitted time-invariant firm characteristics, such as corporate culture of greater risk tolerance, may attract more analyst coverage and generate more innovation outputs and bias upward the coefficient estimates on analyst coverage.

15 Given that firm size is related to the relationship between price nonsynchronicity and innovation outcomes, as discussed in Section V., we investigate the impact of the correlation between firm size (*LnSale*) and our IVs on the IV results. The pairwise correlation between *SP500\_Dummy* and *LnSale* is 0.44 and between *LnNum\_words* and *LnSale* is 0.16 suggesting that a substantial amount of the variation in our IVs is not correlated with firm size. The fact that both firm size and IVs are significantly associated with price nonsynchronicity in the first-stage regression also indicates that correlations between firm size and IVs are not likely to be severe. Furthermore, as multicollinearity inflates the standard errors, but does not bias the point estimates (Gujarati, 2004, p. 350), correlations between firm size and the IVs should not affect the consistency of the estimated coefficients in the second stage and should, if anything, bias toward finding insignificant coefficients on the instrumented price nonsynchronicity.

16 The *p*-value of the *F* statistics is less than 1% in the first stage indicating that our instruments are not weak and are highly correlated with *Ψ*. The Hansen overidentification tests have a *p*-value greater than 10% in the second stage and fail to reject the null hypothesis that the instruments are valid.

17 We use both CEO tenure and age because they each capture different aspects of CEO experience. For example, an older CEO with shorter tenure at the firm may have greater general management experience, but less firm or industry-specific experience than a younger CEO with longer tenure. We take the logarithm of both variables to ensure a normal distribution and to alleviate the influence of outliers.

18 The inclusion of CEO characteristics in the baseline model substantially reduces our sample size as the ExecuComp data only covers current and former S&P 1500 companies. In unreported tests, we confirm that the baseline results remain qualitatively similar when we include the CEO characteristic variables.

19 We include CEO overconfidence because Galasso and Simcoe (2011) find that overconfident CEOs are more productive in innovation. We also control for pay-performance sensitivity and pay-volatility sensitivity since CEO compensation structure can impact innovation outcomes (Chen, Chen, and Chih-Kang, 2014). Detailed variable definitions are available in Appendix A.

20 Size is measured based on firm sales (*LnSale*) as defined in Appendix A. Our sampled small-, mid-, and large-sized firms comprise 2.3%, 5.4%, and 63.9% of the aggregate market capitalization of the CRSP-Compustat merged universe, respectively.

21 Fang and Peress (2009) find that large firms are much more likely to be covered by the media and Liu and McConnell (2013) demonstrate that greater media coverage can improve managers’ capital allocation decisions. Cole, Daniel, and Naveen (2008) find that large firms have larger boards with more outside directors, which enhances their financial performance.

22 We thank the referee for suggesting both this robustness check and the test by firm size.

23 Stephen Brown generously provides PIN data on his Web site. His PIN construction follows Venter and de Jongh (2006) and is used in Brown and Hillegeist (2007).

# Appendix A: Variable Definitions

|  |  |
| --- | --- |
| **Variable Name** | **Description** |
| **Measures of innovation** |  |
| *Patentt*+3 | Total number of patents filed (and eventually granted) in year *t* + 3 |
| *CitePatt*+3 | Total number of nonself-citations received on the firm's patents filed (and eventually granted), scaled by the number of the patents filed (and eventually granted) in year *t* + 3 |
| *LnPatentt*+3 | Natural logarithm of one plus total number of patents filed (and eventually granted) in year *t* + 3 |
| *LnCitePatt*+3 | Natural logarithm of one plus total number of nonself-citations received on the firm's patents filed (and eventually granted), scaled by the number of the patents filed (and eventually granted) in year *t* + 3 |
| **Measure of stock price informativeness** |  |
| *Ψt* | Annual logistic transformation of one minus the estimated *R*2 from the Fama-French (1993) three-factor model, measured at year *t* |
| **Control variables** |  |
| *LnSalet* | Natural logarithm of the book value of sales (*sale*) measured at the end of fiscal year *t* |
| *LnAget* | Natural logarithm of the number of years since the stock was first included in the Compustat database, measured at the end of fiscal year *t* |
| *PPEt* | Net property, plant, and equipment (*ppent*) divided by book value of total assets (*at*), measured at the end of fiscal year *t* |
| *Leveraget* | Leverage ratio defined as the ratio of long-term debt (*dltt*) divided by book value of total assets (*at*), measured at the end of fiscal year *t* |
| *R&Dt* | Research and development expenditure (*xrd*) divided by book value of total assets (*at*) measured at the end of fiscal year *t*, where *xrd* is replaced with 0 if missing |
| *Capext* | Capital expenditures (*capx*) divided by book value of total assets (*at*), measured at the end of fiscal year *t* |
| *ROAt* | Return-on-assets ratio defined as operating income before depreciation(*oibdp*) divided by book value of total assets (*at*), measured at the end of fiscal year *t* |
| *TobinQt* | Market-to-book ratio defined as market value of equity (*prcc* × *csho*) plus book value of assets (*at*) minus book value of equity (*ceq*) minus balance sheet deferred taxes (*txdb*, replaced with 0 if missing), divided by book value of assets (*at*), measured at the end of fiscal year *t* |
| *IOt* | The institutional holdings (%) over fiscal year *t*, calculated as the average of the four quarterly institutional holdings reported on form 13F |
| *KZindext* | KZ index defined as –1.002 × Cash Flow ((*ib*+*dp*)/*ppent*) + 0.283 × Q ((*at*+*prcc*×*csho*-*ceq-txdb*)/*at*) + 3.139 × Leverage ((*dltt* + *dlc*)/(*dltt*+*dlc* + *seq*)) – 39.368 × Dividends ((*dvc*+*dvp*)/*ppent*) – 1.315 × Cash holdings (*che*/*ppent*), where *ppent* is lagged and all other variables are measured at the end of fiscal year *t* |
| *HHIt* | Herfindahl index of two-digit SIC industry to which the firm belongs in fiscal year *t* |
| *HHI\_Squaret* | The square of Herfindahl index in fiscal year *t* |
| *Analystt* | Analyst coverage defined as the natural logarithm of (1 + number of estimates), where the number of estimates is the arithmetic mean of the 12 monthly numbers of earnings forecasts extracted from the I/B/E/S summary file over fiscal year *t* |
| *SP500\_Dummyt* | A binary variable equal to one when the firm is included in the S&P 500 in fiscal year *t* and zero otherwise |
| *LnNum\_wordst* | The natural logarithm of the word count from the firm's annual 10-K file for fiscal year *t* from Li (2008) |
| *Insidert* | Insider trading defined as Σ(shares purchased*d*/shares outstanding*d*) – Σ(shares sold*d*/shares outstanding*d*), where the sum is across all insiders over all days, *d*, in year *t*, and where shares outstanding is the number of shares outstanding on the date of the insiders' transaction |
| *ERCt* | Earnings surprise defined as the average of the cumulative abnormal stock returns (CAR [–1,1]) over the four quarterly earnings announcements in fiscal year *t* |
| *LnCEO\_Tenuret* | Natural logarithm of the number of years that the CEO has served as CEO at the end of fiscal year *t* |
| *LnCEO\_Aget* | Natural logarithm of the age of the CEO at the end of fiscal year *t* |
| *ConfidentCEOt* | A binary variable of options-based measure of CEO overconfidence equal to one for overconfident CEOs and zero otherwise. As in Malmendier and Tate (2005), a CEO is defined as overconfident in all years after holding options that are at least 67% in the money at the end of fiscal year *t* |
| *LogDeltat* | Natural logarithm of CEO delta in fiscal year *t*, where CEO delta is measured as the dollar change in the CEO's stock and option portfolio for 1% change in stock price, in thousands of 2006 dollars |
| *LogVegat* | Natural logarithm of CEO vega in fiscal year *t*, where CEO vega is measured as the dollar change in CEO option holdings for a 1% change in stock return volatility, in thousands of 2006 dollars |

Compustat variable names are given in italics.

# Appendix B: Baseline Regression—Size Tercile Subsamples

This table presents the coefficient estimates from the baseline regression specified in Equation (3) for three subsamples based on size terciles. In Columns (1)–(3), the dependent variable is LnPatentt+3 defined as the natural logarithm of one plus the number of patents filed (and eventually granted) at year t + 3. In Columns (4)–(6), the dependent variable is LnCitePatt+3 defined as the natural logarithm of one plus the total number of nonself-citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) at year t + 3. All independent variables are measured at year t. Size terciles are defined by firm sales with T1 as the smallest and T3 as the largest size tercile. Specifics of the variable definitions are available in Appendix Appendix A. Standard errors are clustered by firm. t-Statistics are reported in parentheses.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | ***LnPatentt*+ 3** |  |  | ***LnCitePatt*+ 3** |  |  |
|  | **T1** | **T2** | **T3** | **T1** | **T2** | **T3** |
|  | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| *Ψ* | 0.009\*\* | 0.013\*\* | 0.000 | 0.020\* | 0.016\* | 0.010 |
|  | (2.083) | (2.278) | (0.031) | (1.877) | (1.876) | (0.740) |
| *LnSale* | 0.010 | 0.056 | 0.192\*\*\* | 0.003 | 0.015 | 0.162\*\* |
|  | (0.518) | (1.354) | (3.201) | (0.147) | (0.255) | (2.389) |
| *R&D* | 0.092 | 0.786 | 2.702\*\* | 0.016 | 0.270 | 1.747 |
|  | (0.622) | (1.457) | (2.480) | (0.067) | (0.453) | (1.515) |
| *LnAge* | −0.118\*\* | 0.121\* | 0.521\*\*\* | −0.163\*\* | 0.256\*\*\* | 0.563\*\*\* |
|  | (−2.389) | (1.935) | (4.708) | (−2.135) | (2.637) | (4.475) |
| *ROA* | 0.029 | 0.060 | 0.503 | 0.003 | 0.085 | 1.189\*\*\* |
|  | (0.673) | (1.016) | (1.619) | (0.039) | (0.978) | (3.746) |
| *PPE* | 0.032 | 0.307\*\* | 0.786\*\* | −0.093 | 0.527\*\* | 1.064\*\*\* |
|  | (0.288) | (2.096) | (2.524) | (−0.563) | (2.144) | (3.053) |
| *Leverage* | −0.101\*\* | −0.035 | 0.258\*\* | −0.075 | −0.089 | 0.033 |
|  | (−2.028) | (−0.616) | (2.061) | (−0.971) | (−0.888) | (0.239) |
| *Capex* | 0.060 | 0.210 | −0.163 | 0.176 | 0.108 | −0.301 |
|  | (0.489) | (1.461) | (−0.463) | (0.959) | (0.473) | (−0.784) |
| *IO* | −0.533\*\*\* | −0.179\*\* | 0.441\*\*\* | −0.572\*\*\* | −0.287\*\* | 0.294\* |
|  | (−5.301) | (−1.996) | (3.120) | (−4.161) | (−2.107) | (1.878) |
| *TobinQ* | 0.015\*\* | 0.046\*\*\* | 0.039\*\* | 0.013 | 0.040\*\*\* | −0.020 |
|  | (2.527) | (5.057) | (2.284) | (1.592) | (3.102) | (−1.200) |
| *KZindex* | −0.001\* | −0.001 | −0.000 | −0.001 | −0.001 | −0.003 |
|  | (−1.955) | (−0.882) | (−0.053) | (−1.223) | (−1.032) | (−1.580) |
| *HHI* | −1.792\*\* | −0.854 | 1.325 | −3.538\*\*\* | 1.482 | 3.729\*\* |
|  | (−2.504) | (−1.256) | (1.051) | (−2.900) | (1.221) | (2.402) |
| *HHI\_Square* | 1.673\*\* | 0.540 | −4.788\*\* | 3.730\*\*\* | −4.366\* | −11.254\*\*\* |
|  | (2.072) | (0.412) | (−2.038) | (2.822) | (−1.739) | (−3.717) |
| *Analyst* | 0.005 | −0.039\* | −0.006 | −0.006 | −0.023 | −0.022 |
|  | (0.195) | (−1.676) | (−0.146) | (−0.165) | (−0.664) | (−0.502) |
| Constant | 0.640\*\*\* | −0.149 | −2.223\*\*\* | 1.114\*\*\* | −0.016 | −2.127\*\*\* |
|  | (6.668) | (−0.747) | (−4.675) | (7.056) | (−0.050) | (−3.957) |
| YEAR FE | YES | YES | YES | YES | YES | YES |
| FIRM FE | YES | YES | YES | YES | YES | YES |
| Observations | 9,226 | 9,231 | 9,229 | 9,226 | 9,231 | 9,229 |
| Adj. *R*2 | 0.608 | 0.672 | 0.806 | 0.415 | 0.463 | 0.604 |

\*\*\*Significant at the 0.01 level.

\*\*Significant at the 0.05 level.

\*Significant at the 0.10 level.

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