Do Insider Trading Patterns Indicate a Firm's R&D Productivity: Evidence from U.S. Patenting Firms

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It is hard to evaluate a firm's R&D performance in a timely manner due to the uncertainties involved in the R&D process. By examining the U.S. listed firms with heavy patenting during 1987-1998, I find that the effects of a firm's insider trading patterns are significant in explaining the contemporaneous fluctuations in its R&D productivity. This finding is consistent with the hypothesis that management has considerable information about its R&D productivity beyond what is known to outside investors.

INTRODUCTION

It is well known that "corporate insiders"[1] are better informed, and they tend to earn abnormal returns by trading the securities of their firms. Actually, ample evidence shows that insider trading outperforms the market over various time horizons (e.g., Jaffe, 1974; Finnerty, 1976; Seyhun, 1986; Jeng, Metrick and Zeckhauser, 2003). Studies also document that insiders trade prior to various corporate events, of which they may be informed in advance.[2]

However, R&D, as an important source of information asymmetry and insider gains, has not been comprehensively investigated. Among the few, Aboody and Lev (2000) demonstrate that R&D is a major contributor to information asymmetry by finding that insider gains in R&D firms are substantially larger than those in firms conducting no R&D.[3] In this paper, I further examine a specific dimension to this R&D-related information asymmetry, i.e., R&D productivity, among 88 U.S. listed firms with the heaviest patenting for the period of 1987 to 1998.[4] Here, R&D productivity is defined as a firm's R&D output relative to its R&D expenditures. Following the literature, I use the count of a firm's granted patents to measure its R&D output (e.g., Scherer, 1965; Schmookler, 1966; Griliches, 1995).

The methodology in this paper follows Romer and Romer (2000). They investigate the Federal Reserve's privileged information about inflation by examining whether an individual could make better predictions about inflation if he knew the Federal Reserve's forecasts. I apply their approach by examining whether investors would know better about a firm's R&D productivity if they knew its insider trading patterns.

Specifically, I ask whether a firm's insider trading patterns are significant in explaining the *unexpected* fluctuations in its patent output with control for the effect of its R&D expenditures. To analyze this question, I first regress a firm's patent counts on its R&D expenditures, and use the estimated residual to measure the unexpected fluctuations of its R&D productivity. Then I regress this residual on contemporaneous insider trading patterns. Consistent with my hypothesis, I find that the effects of insider trading patterns are significant in explaining this residual whereas the effects of abnormal stock returns are insignificant. These results are robust across different model specifications and across different time scales.

Further examinations reveal that the explanatory power of insider trading patterns is more significant among firms with heavier patenting. Moreover, this explanatory power is stronger when insider purchases and sales are measured separately. I also find that, before 1994, the explanatory power of insider trading patterns came from the *purchases* while insider *sales* appeared to have little power. However, the later turned to be influential after 1994.

The rest of the paper is organized as follows. Section II describes the data and variables. Section III reports the empirical results. Section IV concludes.

DATA AND VARIABLES

The variables used in this paper are taken from four major data sources. One is the NBER patent data, which includes information on granted patents and their citations up to 2006. Another is firm-level financial data from the COMPUSTAT. The third is stock return information from the CRSP. The last is insider trading data from the Thomson Financial (TFN) starting in 1986.

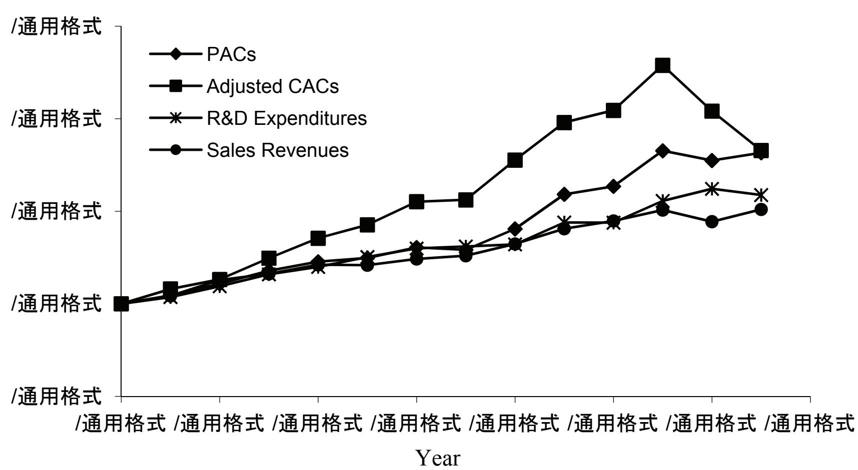
My examination focuses on heavy-patenting firms, in which the fluctuations in R&D productivity should have significant impacts on the stock value. To do so, I only include firms with average patent annual counts (hereafter, PACs) greater than 30 for the years 1987-1994.[5] PACs refer to the number of granted patents applied for in a given year. Further deleting firms with no record of insider trading, I end up with 88 firms. A list of these firms is given in Appendix A.

Patent Output

One limitation of PACs as the measure of patent output is the large variance in the value of individual patents. To account for this heterogeneity, I use citation-weighted patent counts, or so called “citation annual counts” (CACs). CACs refer to the summed citation counts of those patents that are applied for in a given year. The number of citations subsequently received by a patent is often interpreted as a signal of its economic importance (Albert, Avery, Nari and McAllister, 1991). Hall, Jaffe and Trajtenberg (2005) find that patent citations are a useful way to measure the importance of a firm’s patents as the intangible assets of knowledge.

This figure shows mean characteristics of the 88 firms for 1986-1999, including PACs, CACs, R&D expenditures, and sales revenues. Each variable is normalized by its 1986 value.

FIGURE 1
MEAN CHARACTERISTICS OF THE 88 FIRMS FOR 1986-1999



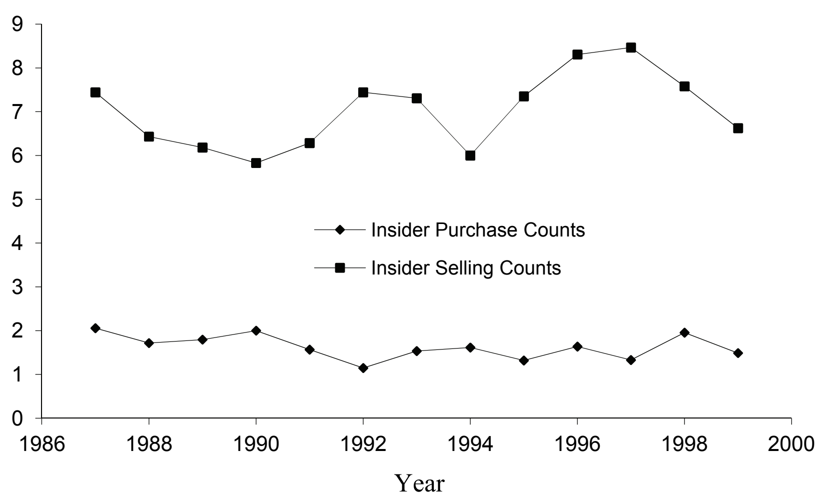
Another concern with the validity of PACs is that some firms have a higher propensity to apply for "small" patents. For example, Eastman Kodak had on average 826 PACs and 8528 CACs for the years 1987-1994; Intel had 162 PACs and 4105 CACs. The citation counts per patent in Eastman Kodak are almost 60% lower than Intel's. Adding firm dummies does not solve this problem because the propensity mainly influences the coefficient on R&D expenditures.

The number of citations received by a patent is truncated because there could be more citations in the future. This truncation effect is biased since the citation counts received by a 1987 patent are less likely to be affected than those associated with a 1994 patent. I use the CACs that are adjusted for this truncation effect by the HJT (an abbreviation for Hall, Jaffe and Trajtenberg) weights.[6] As suggested by Hall, Jaffe and Trajtenberg (2001), the adjusted CACs (later briefed as CACs) are inaccurate for the last three years of the sample (2004-2006), as three years is too short a time to get a reliable estimate of actual citations. We treat this issue more conservatively by having the latest observation year in 1998. Doing so allows for at least eight years of citation records for each patent. Keeping a wide observation window is essential to the validity of CACs. Hall, Jaffe and Trajtenberg (2001) document that it took over ten years for a 1975 patent to receive 50% of its citations, the total of which is measured within a 35-year time window.[7] Another reason that I truncate the data in 1998 is that there was the dot-com bubble in 1999, which should not be considered as a stationary state.

Figure 1 shows mean characteristics for the 88 firms during 1986-1999. Each variable is normalized by its 1986 value. R&D expenditures and sales revenues are doubled from 1986 to 1999. The upward trend in PACs becomes flattened after 1997 whereas a reversal in CACs happens in 1997. This is because the patent granting and citation records in the NBER data discontinue after 2006. Due to the truncation bias, the trend of CACs is more sensitive to this discontinuity. This explains why a reversal happened in CACs but not in PACs. This reversal further validates my treatment of ending the investigation in 1998.

This figure shows annual means of insider purchase counts and insider selling counts of the 88 firms for 1987-1999.

FIGURE 2
INSIDER TRADING COUNTS FOR 1987-1999



Insider Trading Patterns

In the U.S., insiders were required to inform the Securities and Exchange Commission (SEC) of any trades in the firm's stock by filing a "Statement of Change in Beneficial Ownership of Securities" form by the tenth of the month[8] following the month in which they trade. Trading on privileged information is illegal by Sections 17(a) and 10(B) of the Securities and Exchange Act of 1934 and SEC Rule 10(b)-5. In practice, legal enforcement focuses on trades driven by knowledge of specific corporate events. It is less likely to face legal jeopardizes when insiders trade on R&D related information given that R&D is performed continuously in a firm.

Only corporate officers and directors are counted for insiders in this paper for my research purpose.[9] Two types of insider transactions are kept. They are "open market or private purchase of non-derivative or derivative security" and "open market or private sale of non-derivative or derivative security", respectively. In practice, derivatives are not included in these two types. Approximately 16% of trading records remain after the screening process.

In business practice, it is common to measure insider trading patterns by the number of insiders that trade rather than the value of those trades. Insider trading newsletters, such as *Insiders' Chronicle* and *Insider Indicator*, compute insider trading measures based on the number of buyers and sellers. Figure 2 shows the annual means of insider purchase counts (IPCs) and insider selling counts (ISCs) of the 88 firms for 1987-1999. IPCs refer to the number of insiders who are net buyers of the stock in a given year; analogously, ISCs refer to the number of insiders who are net sellers of the stock. I omit observations in 1986 because both counts are significantly lower than the following years, indicating that some records are missing. As show in Figure 2, neither curve reveals a strong trend. The mean of ISCs is much higher than IPCs because stock compensation arrangements lead to routine insider sales.

EMPIRICAL RESULTS

Model Specification

The rational expectations hypothesis implies that investors react only to unexpected shocks. This logic applies precisely to insider trading versus R&D productivity. To investigate the relationship between these two, one should first identify the unexpected component of a firm's R&D productivity. To do so, I first estimate how these expectations on a firm's R&D productivity are formed based on public information. Pakes and Grilliches (1980) provide an empirical model to estimate the relationship between patents and R&D expenditures and find it statistically significant. I use a similar model to formulate market expectations on a firm's patent output. In my specification, I choose a linear production function instead of a Cobb-Douglas primarily because OLS results demonstrate a larger R^2 under the linear specification. The first-stage estimation model is

$$CAC_{i,t} = \alpha_1 + \theta RD_{i,t} + \eta_1 FIRM_i + \eta_2 YEAR_t + \varepsilon^1_{i,t}, \quad (1)$$

where $CAC_{i,t}$ is firm i's CACs in year t. It measures the value of firm i's patents that are applied for in year t. The value of $CAC_{i,t}$ is unobservable in year t because no one instantly knows the exact value of these patents. $RD_{i,t}$ represents firm i's R&D expenditures in year t. It measures firm i's patent-related R&D input. Actually, R&D outputs should depend on a distributed lag of R&D expenditures, but most of the weight appears to fall on the current R&D (Hall, Griliches and Hausman, 1986). $FIRM_t$ is a vector of firm dummies to control for firm fixed effects. $YEAR_t$ is a vector of year dummies to control for year fixed effects, such as annual differences in the patent granting process and the business cycle. Finally, $\varepsilon^1_{i,t}$ represents unobserved factors, such as uncertainties in the R&D process.

In the second stage, I use the estimated residual from model (1), ($CAC_{i,t} - \hat{CAC}_{i,t}$), to measure the unexpected fluctuations in R&D productivity. Some managers would appropriate through insider trading if they have better knowledge about their firms' R&D productivity. Thus, one should expect that insider trading patterns be significant in explaining the contemporaneous ($CAC_{i,t} - \hat{CAC}_{i,t}$).

Since my focus is on management's timely knowledge about its R&D productivity, I only include the measures of insider trading patterns in the years around the observation year. Insider trading in later years may help to explain ($CAC_{i,t} - \hat{CAC}_{i,t}$) either because additional information about patent output is released or because managers strategically delay their reactions. Since it is impossible to distinguish between these two effects, I focus on their immediate reactions. I use the following empirical model to examine how well insider trading patterns explain ($CAC_{i,t} - \hat{CAC}_{i,t}$).

$$CAC_{i,t} - \hat{CAC}_{i,t} = \alpha_2 + \sum_{j=-1}^{1} \beta_j IPC_{i,t+j} + \sum_{j=-1}^{1} \gamma_j ISC_{i,t+j} + \varepsilon_{i,t}^2, \tag{2}$$

where IPCs and ISCs from year $t-1$ to $t+1$ are included. I treat insider purchases and insider sales separately in case they have different explanatory power. There has been empirical evidence on this difference. By examining listed firms in the U.S. during 1975-95, Lakonishok and Lee (2001) find that any informative content from insider activities in predicting stock returns comes from purchases; insider sales appear to have no predictive power. Jeng, Metrick and Zeckhauser (2003) report that the abnormal returns on insider purchases for a one-year holding period are 0.4 percent per month while the abnormal returns on sales are insignificant.

There is evidence that insiders are contrarian investors (Rozeff and Zaman, 1998; Lakonishok and Lee, 2001). It is possible that there is some correlation between a firm's stock price and its R&D productivity. Without control for the price effect, it is possible the estimated effect of insider trading patterns may only reflect their correlation with the stock price. Therefore, I further estimate the following model.

$$CAC_{i,t} - \hat{CAC}_{i,t} = \alpha_3 + \sum_{j=-1}^{1} \beta_j IPC_{i,t+j} + \sum_{j=-1}^{1} \gamma_j ISC_{i,t+j} + \sum_{j=-1}^{1} \delta_j \left(R_{i,t+j} - R_{t+j}^m \right) + \varepsilon_{i,t}^3, \tag{3}$$

where stock abnormal returns in year $t-1$ to $t+1$ are included. $R_{i,t}$ is the rate of return on firm *i*'s stock in year *t*. R_t^m is the average return of its primary industry in year *t*. I use the Fama and French (1997) 49 industry classifications based on the 4-digit SIC code. I expect that the effects of abnormal returns be insignificant for the following reason. The stock market generally does not capture the fluctuations in R&D productivity in a timely manner. Therefore, one should not expect that these shocks be instantly priced in the market. That is, the abnormal returns should not contemporarily reflect these fluctuations.

TABLE 1
SUMMARY STATISTICS OF FIRMS FOR 1987-1994

Variable	PACs>30		10<PACs< 30	
PACs	153	(215)	18.7	(11.4)
Adjusted CACs	3090	(5446)	383	(400)
R&D expenditures (100 mil. $)	5.4	(9.4)	0.5	(0.8)
Sales revenues (10 bil. $)	1.2	(2.0)	0.2	(0.4)
Abnormal returns	0.03	(0.34)	0.04	(0.34)
ISCs	6.6	(6.6)	4.3	(4.0)
IPCs	1.7	(1.8)	1.6	(1.9)
Firm counts	88		68	

Standard deviations are in parentheses. This table provides summary statistics of the 88 firms for 1987-1994. For comparison, I also report the summary statistics of the 68 firms with average PACs between 10 and 30.

Baseline Estimation

Table 1 provides summary statistics for the 88 firms during 1987-1999. The definition of each variable is given in Appendix B. R&D expenditures and sales revenues are in real value (in 2000 dollars). For comparison, I also report the summary statistics of 68 firms with average PACs between 10 and 30. The 88 firms are more R&D intensive, with the ratio of R&D expenditures to sales revenues equal to 4.5%, compared to 2.5% for the 68 firms. Meanwhile, their average patenting propensity to R&D expenditures is lower while the citation counts per patent are close, indicating that the 88 firms are less productive in R&D. ISCs were much higher in the 88 firms while IPCs were similar. This may be due to the fact that firms with heavier patenting are more likely to use stock-related compensation arrangements, resulting in routine insider sales and a lower propensity for management to purchase.[10]

In Table 2, I briefly report the first-stage estimation with the 88-firm observations for 1987-1994.[11] The R^2 indicates that the model accounts for 83% of the variance in CACs. The estimated coefficient on R&D expenditures is significantly positive. The estimated coefficients on firm and year dummies are suppressed in the table for the sake of brevity, as is the intercept.

Insider trading patterns are different across firms due to various factors, such as compensation arrangements. These differences are irrelevant to management's attitude toward a firm's profitability, thus should be eliminated. Therefore, I standardize insider trading counts by calculating the difference between its current value and the firm mean, then by dividing it by the firm's standard deviation.

TABLE 2
EXPLANATORY POWER OF INSIDER TRADING COUNTS ON CACS

Stage	Variable		Regular Residual		Standardized Residual	
			(1)	(2)	(3)	(4)
1st	R&D		285***			
			(47)			
	Adjusted R^2		0.83			
	Observations		704			
2nd	Abnormal return	t-1		-49.439		-0.011
				(153.962)		(0.102)
		t		56.872		0.004
				(197.589)		(0.119)
		t+1		46.802		0.042
				(267.219)		(0.129)
	ISC	t-1	-55.872	-51.849	0.015	0.016
			(125.473)	(131.351)	(0.044)	(0.044)
		t	-16.480	-13.079	-0.022	-0.020
			(65.045)	(72.046)	(0.041)	(0.042)
		t+1	-86.843	-91.886	-0.076	-0.077*
			(96.796)	(92.994)	(0.047)	(0.046)
	IPC	t-1	241.938**	239.221**	0.137***	0.134***
			(92.515)	(94.971)	(0.046)	(0.047)
		t	216.064**	217.530**	0.101**	0.101**
			(95.870)	(96.065)	(0.043)	(0.044)
		t+1	211.150*	210.972*	0.121***	0.124***
			(118.216)	(116.444)	(0.043)	(0.043)
	Adjusted R^2		0.028	0.024	0.054	0.049
	Observations		616	615	616	615

This table reports the first-stage estimation of CACs with the 88-firm observations for 1987-1994. Firm fixed effects are controlled for. It also reports the second-stage estimations of the CACs residual. First, I use the residual directly from the first-stage estimation. Then I standardize the residual by dividing by its firm standard deviation, and repeat the regressions using the standardized residual.

Table 2 also reports the second-stage estimation results. In Table 2, as well as all the following tables, *, ** and *** indicate the coefficient is statistically significant at the 10%, 5% and 1% significance level, respectively; standard errors are in parentheses; for robustness, estimated standard errors are clustered at the firm level. In columns (1) and (2), I use the estimated residual from the first-stage regression directly. In column (1), all estimated coefficients on IPCs are significant with the expected sign. This is consistent with the hypothesis that management possesses timely considerable information about the fluctuations of its R&D productivity and trades accordingly. In contrast, the effects of ISCs are less influential. This difference may come from stock-related compensations. Take stock bonuses for example. Suppose that the annual bonus shares are more than what managers want to add to their portfolios. In a regular year, we should expect that managers routinely sell their stock. Managers may reduce the amount of sales when they think the stock is underpriced. Only when the magnitude of this underpricing is great enough would they switch to purchases. Therefore, having one more net-buyer indicates deeper underpricing than the situation of having one less net-seller.

In column (2), I include abnormal returns. None of the estimated coefficients on abnormal returns is significant while the effects of IPCs persist significant. This difference in explanatory power further confirms that management does possess timely considerable information about its R&D productivity. Notice that these results mainly reflect management's privileged knowledge about its own R&D productivity rather than other firms' R&D productivity. With the inclusion of firm dummies in the first-stage estimation, the mean difference of CACs across firms has been eliminated from the estimated residual.

Consider two identical firms except that one is twice as large. The observations from these two firms should be weighted equally in the second-stage estimation. However, using the estimated residual directly gives a heavier weight to the large firm because the variation of CACs in the large firm is twice as large as the small one. Whereas, the variation of insider trading measures is the same because of the standardization. Therefore, the explanatory power of insider trading patterns in the smaller firm is underestimated. I thus standardize the estimated residual by dividing by its firm standard deviation so as to impose a heavier weight on firms with less patenting. The second-stage estimations using the standardized residual are reported in columns (3) and (4) of Table 2. The patterns previously found in columns (1) and (2) persist. Moreover, the R^2 increases with this standardization, indicating that patterns in firms with less patenting were overwhelmed.

Robustness Check

For the first-stage estimation, the R&D production function may take other forms. In columns (1) and (2) of Table 3, I include a quadratic term for R&D expenditures. Though the quadratic effect is significant, it does not sizably improve the estimation. In column (1) I use the regular residual while in column (2) I use the standardized one. The major results persist. Further examinations reveal that using a Cobb-Douglas production function or including lagged R&D expenditures has little impact on the major results.

Another concern with the first-stage estimation is that the propensities of patent output to R&D expenditures may vary across industries. Following Hall, Jaffe and Trajtenberg (2001), I classify the 88 firms into five categories. They are Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, and Mechanical & Others. I rerun the first-stage estimation by categories.[12] Then using the residual, I rerun the second-stage estimations in Table 3. In column (3) I use the regular residual while in column (4) I use the standardized one. In either case, the effects of IPCs are significantly positive.

I then expand the observation year to 1998 to investigate how persistent the explanatory power of insider trading patterns would be after 1994. With the expanded observations of 1987-1998, I repeat the regressions in Table 2 and report the estimation results briefly in columns (5) and (6) of Table 3. For the convenience of comparison, I restrict my sample to the same 88 firms. In column (6) I standardize the residual while in column (5) I do not. In column (5), the estimated coefficients on IPCs persist significant but only for year $t-1$ and t, indicating that management reacts more promptly after 1994. The estimated coefficients on some ISCs turn to significant with the expected sign, indicating that the effects of ISCs became influential after 1994. I speculate that this change may come from an accelerating adoption of stock options in executive compensation beginning in the mid-1990s.[13] Moreover, the R^2 increases significantly when I switch to the standardized residual, indicating that the explanatory power of insider trading patterns in firms with less patenting was overwhelmed when using the regular residual in column (5).

TABLE 3
FURTHER ESTIMATIONS ON THE EFFECTS OF INSIDER TRADING COUNTS

Stage	Variable		Quadratic Effects		By Industries		Expanded Observations	
			(1)	(2)	(3)	(4)	(5)	(6)
	R&D		612***				215***	
			(96)				(38)	
1st	R&D*R&D		-5.35***				-	
			(1.38)					
	Adjusted R^2		0.83				0.77	
	Observations		704				880	
	Abnormal return	t-1	-15.259	0.017	1.008	0.005	84.524	0.105
			(154.826)	(0.107)	(148.943)	(0.106)	(220.060)	(0.091)
		t	75.460	0.063	-16.100	-0.084	-46.940	0.061
			(196.944)	(0.138)	(163.613)	(0.118)	(317.842)	(0.095)
		t+1	85.010	0.073	109.108	-0.047	-203.506	-0.084
			(264.217)	(0.122)	(215.020)	(0.142)	(280.370)	(0.093)
2nd	ISC	t-1	-46.644	0.013	-118.767	-0.012	-68.457	0.034
			(133.429)	(0.046)	(110.155)	(0.049)	(181.306)	(0.042)
		t	3.562	-0.012	33.736	0.062	-45.374	-0.072*
			(70.221)	(0.043)	(55.093)	(0.044)	(74.113)	(0.038)
		t+1	-93.199	-0.080*	-75.026	-0.039	-184.898*	-0.151***
			(88.073)	(0.045)	(72.529)	(0.050)	(109.864)	(0.040)
	IPC	t-1	233.651**	0.122**	179.403*	0.083*	358.831**	0.132***
			(93.412)	(0.047)	(94.452)	(0.043)	(169.442)	(0.039)
		t	207.658**	0.075	218.806**	0.088*	260.601**	0.105***
			(95.091)	(0.045)	(88.641)	(0.051)	(109.345)	(0.033)
		t+1	200.358*	0.104**	197.066*	0.099**	53.611	0.070*
			(118.547)	(0.044)	(105.611)	(0.046)	(113.102)	(0.040)
	Adjusted R^2		0.021	0.032	0.025	0.016	0.021	0.076
	Observations		615	615	615	615	788	788

First, I include a quadratic term for R&D expenditures in the first-stage estimation. Second, I classify the 88 firms into five categories, and rerun the first-stage estimation by categories. Last, I repeat the estimations with the observation year expanded to 1998.

I also repeat the regressions based on the 68 firms with less patenting. The effects of insider trading patterns turn insignificant, consistent with my former argument that the explanatory power if insider trading patterns is more likely to exist among firms with heavy patenting. To further confirm this, I divide the 88 firms into two groups based on the mean PACs, with the highest 44 firms in one and the lowest 44 firms in the other. I rerun the regressions for each group, and report the second-stage estimations in Table 4. Consistent with my expectation, the effects of IPCs are significantly positive among the highest 44 firms but not among the lowest 44 firms. In the estimations of the highest 44 firms, the R^2 rises significantly from 0.05 to 0.11 when switching from using the regular residual to the standardized one.

This indicates that the explanatory power of IPCs is stronger in firms with less patenting among the highest 44 firms.[14]

In the literature, the net purchase ratio (NPR) is commonly used to measure insider trading patterns at the firm level (Lakonishok and Lee, 2001; Rozeff and Zaman, 1998). The NPR in a certain period is defined as the ratio of net purchase volume (insider purchase volume minus insider sales volume) to total trading volume (insider purchase volume plus insider sales volume) in this time period. One limitation of this measure is that it is a single index and cannot capture the characteristics of insider purchases and insider sales separately.

TABLE 4
THE INFLUENCE OF PATENTING DENSITY

Stage	Variable		Highest 44 Firms		Lowest 44 Firms	
			(1)	(2)	(3)	(4)
1st	R&D		218***		603***	
			(69)		(114)	
	Adjusted R^2		0.83		0.87	
	Observations		352		352	
2nd	Abnormal return	t-1	-81.737	-0.014	-259.651	-0.014
			(302.866)	(0.173)	(190.492)	(0.132)
		t	-283.366	-0.168	201.041	0.158
			(496.709)	(0.217)	(143.086)	(0.157)
		t+1	-290.365	0.016	309.515	0.097
			(423.987)	(0.123)	(357.037)	(0.189)
	ISC	t-1	-34.333	0.106*	-18.701	-0.098
			(235.117)	(0.056)	(39.244)	(0.070)
		t	21.589	0.012	-19.824	-0.061
			(118.936)	(0.058)	(65.459)	(0.065)
		t+1	-257.463	-0.105	-9.959	-0.075
			(179.343)	(0.066)	(56.542)	(0.059)
	IPC	t-1	430.677**	0.190***	11.831	0.004
			(163.111)	(0.056)	(59.507)	(0.074)
		t	362.815**	0.166***	74.849	0.016
			(163.709)	(0.057)	(49.989)	(0.070)
		t+1	390.385*	0.178***	31.817	0.047
			(215.963)	(0.060)	(43.728)	(0.062)
	Adjusted R^2		0.045	0.112	0.022	-0.002
	Observations		308	308	307	307

I divide the 88 firms into two groups based on the mean PACs, with the highest 44 firms in one group and the lowest 44 firms in the other. I rerun the estimations for each group, respectively.

In Table 5, I replace IPCs and ISCs with the NPR as the measure of insider trading patterns and repeat the regressions in Table 2. Similarly, I standardize the NPR.[15] The first-stage estimation remains the same, thus only the second-stage estimations are reported. In columns (1) and (2) I use the regular residual while in columns (3) and (4) I use the standardized one. In any case, though the estimated coefficients on the NPR have the expected sign, their significance is marginal. In columns (5) and (6), I restrict my sample to the highest 44 firms, but there is little improvement in the estimation with the sample change. Overall, these results indicate that the explanatory power of the NPR on the fluctuations in R&D productivity is minor if there is any.

The explanatory power of insider trading patterns seems to be stronger when using IPCs and ISCs as the measure than using the NPR. The reason may lie in the heterogeneous characteristics between net sellers and net buyers. The validity of the NPR relies on an implicit assumption that these two types of insiders are homogeneous thus their trade volumes are addable. However, the previous results indicate that these two types of insiders at least differ in their explanatory power on R&D productivity. Specifically, the explanatory power of IPCs is stronger than ISCs.[16]

TABLE 5
EXPLANATORY POWER OF THE NPR ON CACS

Variable		Regular Residual		Standardized Residual		Highest 44 Firms	
		(1)	(2)	(3)	(4)	(5)	(6)
Abnormal return	t-1		-123.932		-0.063	-52.109	0.012
			(137.094)		(0.107)	(285.630)	(0.195)
	t		10.367		-0.053	-261.300	-0.197
			(172.632)		(0.116)	(374.494)	(0.199)
	t+1		7.509		0.018	-399.250	-0.060
			(267.695)		(0.134)	(440.225)	(0.145)
NPR	t-1	118.900	113.449	0.061	0.058	207.638	0.086
		(96.198)	(99.127)	(0.043)	(0.045)	(171.752)	(0.061)
	t	94.984	90.814	0.026	0.020	227.452	0.089
		(130.364)	(135.472)	(0.043)	(0.045)	(253.496)	(0.059)
	t+1	87.510	86.077	0.079	0.077	244.635	0.101
		(111.790)	(106.203)	(0.048)	(0.049)	(196.702)	(0.065)
Adjusted R^2		0.001	-0.003	0.006	0.001	-0.000	0.012
Observations		616	615	616	615	308	308

This table reports the estimations of CACs using the NPR to measure insider trading patterns. First, I include all the 88 firms. Then, I include only the 44 highest firms. In column (5) I use the regular residual. In column (6) I use the standardized one.

CONCLUSIONS

By examining 88 U.S. listed firms with the heaviest patenting for the period of 1987 to 1998, I found strong evidence that a firm's insider trading patterns are significant in explaining the contemporaneous fluctuations in its patent output when controlling for R&D input effects. These results are consistent with the hypothesis that management has privileged knowledge about its R&D productivity.

The market value of a firm's shares should ultimately reflect the value of all its net assets. When a firm has a high proportion of intangible assets, the task of equity valuation becomes complicate. The rise in the importance of R&D firms raises a practical question of how to timely and accurately evaluate their intangible R&D capital, especially their R&D performance. As far as business practice is concerned, my findings suggest that, to evaluate a firm's R&D performance, it is advantageous to take account of insider trading patterns. Moreover, this approach should be more effective when evaluating firms with heavy patenting. My estimation results also indicate that the explanatory power of insider trading patterns is stronger when using two separate measures (IPCs and ISCs) than using an integral one (NPRs). Additionally, the finding that the effects of insider trading counts are significant also supports the business convention of using the number of insiders engaged in trading.

In this study I do not broach the debate on the social consequences of insider trading. However, for those concerned with this issue, my results do point to an important source of private information: R&D productivity. Management's better knowledge about R&D productivity may come from their earlier access to patent-related information. According to the U.S. Patent and Trademark Office (USPTO) website, there is an average lag between the application time and the granted time (the grant lag) of 24.6 months. The grant rate historically was about 66%, and has recently dropped to 54%, as reported by the

USPTO. Before November 2000, patent applications in the U.S. were kept secret until the patent is granted. The USPTO only published granted patents. Access to pending patent applications in the USPTO was governed by 35 USC 122, which states:

> Applications for patents shall be kept in confidence by the Patent and Trademark Office and no information concerning the same given without authority of the applicant or owner unless necessary to carry out the provisions of any Act of Congress or in such special circumstances as may be determined by the Commissioner.

In contrast, the information about patent applications is available to management as early as when a firm is preparing for the related documents. Based on application counts, management might have a timely and reliable estimation about its patent output. Therefore, improving disclosure requirements of relevant information, such as releasing patent application information in a timely manner, may be considered a means to reduce the R&D-related information asymmetry.

ENDNOTES

1. Corporate insiders are defined by the 1934 Securities and Exchange Act as corporate officers, directors, and owners of 10 percent or more of any equity class of securities.
2. Such as bankruptcy (Seyhun and Bradley, 1997), dividend announcement (John and Lang, 1991), seasoned equity offerings (Karpoff and Lee, 1991; Gombola, Lee and Liu 1997), stock repurchases (Lee, Mikkelson and Partch 1992), future cash flow news (Jiang and Zaman, 2010), private renegotiation (Yur-Austin, 1998), and takeover (Seyhun, 1990).
3. Meanwhile, there is evidence that the stock market has been attempting to reduce this R&D-related information asymmetry. Analyst coverage is larger for R&D intensive firms (Barth, Kasznik and McNichols, 2001), and R&D intensive firms have more conference calls with analysts (Tasker, 1998).
4. Other dimensions include the absence of organized R&D markets and the ambiguity of R&D accounting rules, which further exacerbate the information asymmetry associated with R&D, as argued by Aboody and Lev (2000).
5. I rerun the regressions based on the observations extended to 1999. The major results persist.
6. The HJT weight is a multiplier that can be applied to citations from US patents through 2006 received by the patent, in order to correct for the truncation of post-2006 citations using the methodology described in Hall, Jaffe and Trajtenberg (2001). They estimate a six-field specific obsolescence-diffusion model with year dummies and used the estimated model to predict a factor for the citations based on the patent's grant year and technology category.
7. In contrast, the length of observation time is not so demanding when calculating PACs. More than 95% of patent applications during 1973-1975 were granted in four years.
8. Effective on August 29, 2002, insiders must report to the SEC certain changes in their beneficial ownership of their company's securities within two business days after the date of the transaction.
9. Specifically, I exclude the following insider personals: SH, AF, B, UT, T, R, TR, GC, CP, AI, and IA. About 6% of the total transaction counts are eliminated. See TFN Insider Filing Data for details.
10. Ofek and Yermack (2000) examine whether stock-related compensation drives insider trading. They find that for executives with large pre-existing positions in firm stocks, new grants of equity incentives are associated with stock sales.
11. The reason I do not use the results with expanded observations up to 1998 as the baseline is because the reliability of the CACs is the key to robustness. Even though the NBER 2006 patent data has ameliorated the truncation bias, its reliability is still a concern when the shortest observation window for CACs is only eight years.
12. The estimated propensities of CACs to R&D expenditures vary across categories. The highest is 403 in the Electrical & Electronic category, and the lowest is -90 in the Drugs & Medical category. This negative sign may indicate that larger firms in Drugs & Medical were less productive in R&D. To verify that the effects of IPCs do not come from the poor estimation in the Drugs & Medical category, I exclude this category and rerun the regressions. The major results persist.
13. Frydman and Saks (2007) show that the share of stock options granted in total executive compensation in the 50 largest U.S. listed firms increased dramatically in the mid-90s.

14. Concerned that a number of firms with a nearly perfect correlation between the CACs residual and IPCs would lead to the same R^2 level, I exclude four firms with the highest correlation in the highest 44 firms and rerun the second-stage estimations. The effects of IPCs are persistently significant. This indicates that the explanatory power of IPCs is not unique among the highest 44 firms.
15. The major results persist without the standardization of the NPR.
16. I also use another pair of proxies to measure insider trading patterns. They are insider purchase value and insider selling value. The insider purchase value (IPV) refers to the sum of the value of each insider purchase transaction within a given year. The insider selling value (ISV) refers to the sum of the value of each insider sale transaction within a given year. The value of an insider transaction equals the transaction volume times the transaction price. Similarly, I standardize both measures. The major results are similar to those when using IPCs and PSCs.

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APPENDIX A

A List of the 88 Firms by Categories

Chemical
AIR PRODUCTS & CHEMICALS
AMOCO CORP
ATLANTIC RICHFIELD CO
BETZDEARBORN INC
COLGATE-PALMOLIVE CO
DOW CHEMICAL
DRESSER INDUSTRIES INC
DU PONT (E I) DE NEMOURS
FMC CORP
GOODYEAR TIRE & RUBBER C
HERCULES INC
INTL PAPER CO
KIMBERLY-CLARK CORP
LUBRIZOL CORP
MEAD CORP
NALCO CHEMICAL CO
PPG INDUSTRIES INC
PROCTER & GAMBLE CO
ROHM AND HAAS CO
SCHLUMBERGER LTD
TEXACO INC
UNION CARBIDE CORP

Drugs & Medical
ABBOTT LABORATORIES
ALZA CORP
BAXTER INTERNATIONAL INC
BECTON DICKINSON & CO
BRISTOL-MYERS SQUIBB CO
JOHNSON & JOHNSON
LILLY (ELI) & CO
MEDTRONIC INC
MERCK & CO
PFIZER INC
SCHERING-PLOUGH
U S SURGICAL CORP
WARNER-LAMBERT CO

Electrical & Electronics
EASTMAN KODAK CO
EMERSON ELECTRIC CO
GENERAL ELECTRIC CO
RAYCHEM CORP
TEKTRONIX INC
WHIRLPOOL CORP
ZENITH ELECTRONICS CORP

Computers & Communications
AT&T CORP
ADVANCED MICRO DEVICES
AMP INC
APPLE COMPUTER INC
COMPAQ COMPUTER CORP
CORNING INC
DIGITAL EQUIPMENT
GTE CORP
HARRIS CORP
HEWLETT-PACKARD CO
HONEYWELL INC
INTEL CORP
INTL BUSINESS MACHINES C
MICRON TECHNOLOGY INC
MOLEX INC
MOTOROLA INC
NATIONAL SEMICONDUCTOR C
RAYTHEON CO
SEAGATE TECHNOLOGY-OLD
SUN MICROSYSTEMS INC
TEXAS INSTRUMENTS INC
UNISYS CORP
VLSI TECHNOLOGY INC
XEROX CORP

Mechanical & Others
BAKER HUGHES INC
BOEING CO
BRUNSWICK CORP
CATERPILLAR INC
CHRYSLER CORP
DANA CORP
DEERE & CO
EATON CORP
FORD MOTOR CO
GENERAL MOTORS CORP
GOODRICH CORP
HALLIBURTON CO
ILLINOIS TOOL WORKS
LITTON INDUSTRIES INC
MCDONNELL DOUGLAS CORP
OLIN CORP
OUTBOARD MARINE CORP
PITNEY BOWES INC
SUNDSTRAND CORP
TRW INC
TEXTRON INC
UNITED TECHNOLOGIES CORP

APPENDIX B

Variable Description

The specific variables used in the paper are defined as follows:

. *Patent Annual Counts* (PACs) is defined as the number of granted patents applied for in a given year.

. *Citation Annual Counts* (CACs) is defined as the summed citation counts of those granted patents applied for in a given year. Here, citation counts of a patent are the number of citations the patent received up to August 2006.

. *R&D Expenditures* is R&D expenditures (COMPUSTAT item 46) in the fiscal year.

. *Sales Revenues* is sales revenues (COMPUSTAT item 12) in the fiscal year.

. *Abnormal Return* is the difference between the return on the stock and the equal-weighted average return of the industry in a given year. I use the Fama and French (1997) 49 industry classifications, which are based on the 4-digit SIC code.

. *Insider Selling Counts* (ISCs) is the number of insiders who are net sellers of the stock in a given year.

. *Insider Purchase Counts* (IPCs) is the number of insiders who are net buyers of the stock in a given year.

. *Net Purchase Ratio* (NPR) is the ratio of net purchase volume (insider purchase volume minus insider sales volume) to total trading volume (insider purchase volume plus insider sales volume) in a given year.