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Options Trading and Stock Price Informativeness

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Abstract

We document the causal effects of single-name options trading on the absolute level of information content of prices (stock price informativeness) by exploiting the Penny Pilot Program as an exogenous shock to options trading volume. We find that options trading increases underlying stock price informativeness and information acquisition by both option and stock investors, consistent with the framework of Goldstein and Yang (2015). The findings are driven by firms for which options are more important sources of information and firms with more efficiently priced options. Options market introduction in a sample of 25 other economies also leads to higher price informativeness.

I. Introduction

Options improve the efficiency of an incomplete market by expanding investors' investment opportunity set (Ross (1976), Hakansson (1978)). Following this insight, many theoretical papers examine the trading motives and venues of informed and uninformed traders in stocks and options. For instance, Black (1975), Back (1993), and Biais and Hillion (1994) highlight the distinctive

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features of low transaction costs and high leverage from derivatives, and Figlewski and Webb (1993) show that options relax short-sale constraints. There is also a rich empirical literature that examines whether information is revealed first in options or in stocks. Using Hasbrouck (1995) information share approach, Chakravarty, Gulen, and Mayhew (2004) show that options markets contribute 17% to price discovery.

There is, thus, ample evidence of a rich interplay of information trading in options and stock markets. The weight of the evidence points to the fact that options trading increases market efficiency with respect to public information. Brunnermeier (2005) refers to this as informational efficiency (efficiency with respect to public information conditional on the existence of this information). Does options trading affect price informativeness, the absolute level of information content of prices?

Theoretical literature suggests that options motivate information acquisition. With low transaction costs and high leverage, options trading increases the reward for private information production (Biais and Hillion (1994), Cao (1999), and Massa (2002)). This view is also consistent with Grossman and Stiglitz (1980) intuition that the greater the rewards of acquiring information, the more efforts will be spent in collecting information. Despite this theoretical guidance, there are few empirical studies on whether options trading has an important impact on the equilibrium level of stock price informativeness. We attempt to fill this gap in our article.

Our hypothesis is that options trading, not just the existence of options,[1] increases underlying stock price informativeness. Our argument combines the insights of Grossman and Stiglitz (1980) and Goldstein and Yang (2015). While Grossman and Stiglitz (1980) study incentives to acquire only one type of information by only one type of investor, Goldstein and Yang (2015) argue that there are strategic complementarities in trading and information acquisition. Specifically, according to these latter authors, aggressive trading on information about one fundamental reduces uncertainty in trading on information about the other fundamental, encouraging more trading and information acquisition on that other fundamental.

We apply the Goldstein and Yang (2015) setting to our context by assuming two types of informed traders: options traders and stock traders. It is plausible that when options are more actively traded (i.e., there is high options volume, informed options traders receive more profits). They hence pay more effort in collecting information, as in the Grossman and Stiglitz (1980) model. However, options traders alone might not have a critical mass to affect stock price informativeness materially. According to the strategic complementarity argument of Goldstein and Yang (2015), the information collected by options traders reduces the uncertainty of informed stock traders in acquiring other information of interest, thus encouraging more information acquisition by stock traders. The implication for us is that high options trading volume increases the overall price informativeness due to the efforts of both options traders and stock traders.

[1]Hu (2018) finds that options listing increases both informed and uninformed trading. The ambiguous effect of options listing on underlying returns is also analyzed by Sorescu (2000) and Danielsen and Sorescu (2001).

We note that our hypothesis relates all derivatives trading activity to price informativeness. Options trading volume could reflect informed trading based on fundamentals, volatility trading, or uninformed trading. We are agnostic about the source of options trading as our goal is not to relate only informed trading in options to price efficiency in the stock market. As described in detail later, our tests are conducted at low frequency (annual). Thus, our analysis does not speak about the relatively more high-frequency speed of stock price adjustment. In other words, we contribute little to the ongoing debate on stock price efficiency. While we do affirm that under our hypothesis, it must also be true that options lead stocks in terms of price efficiency, in this article we take a step back and analyze whether derivatives change the amount of information (eventually) contained in stock prices.

We measure stock price informativeness using two measures. The first measure that we employ is stock return synchronicity to the market and industry return. Previous studies suggest that return synchronicity (related to R^2 of return regression) shows the relative amount of firm-specific information incorporated in stock price movement and indicates efficient capital allocation (Roll (1988), Morck, Yeung, and Yu (2000), Wurgler (2000), Jin and Myers (2006), and Chen, Goldstein, and Jiang (2007)).[2] For the second stock price informativeness measure, we relate our findings to those of Bai, Philippon, and Savov (2016), who find that overall market price informativeness has increased over the years. The intuition is that a more informative stock price should better predict future earnings. This measure is also used by Kacperczyk, Sundaresan, and Wang (2021). Our panel regressions find a strong and positive association between options trading volume and stock price informativeness.

Cognizant of endogeneity issues, to test our hypothesis, we rely on the Penny Pilot Program (henceforth PPP) launched by the Securities and Exchange Commission (SEC) as an exogenous shock on options trading volume. Starting from 2007, the major options exchanges gradually included options to the PPP, a reform of the tick size of options. In the PPP, options classes with prices less than \$3 could be quoted in 1-cent increments, while the tick size of those with prices greater than \$3 was changed to 5 cents. Outside the PPP, options were quoted in nickel and dime increments. The inclusion of the options in the PPP was not the firm's choice, and the SEC claimed that the PPP covered a diverse group of options with varying characteristics. Therefore, being a pilot firm can be viewed as an exogenous shock to the options trading volume of the firm and the options trading cost. Another important feature of the PPP is that it was implemented in a staggered fashion, in which different firms participated at different points of time.

We manually collect the options that are in the PPP from 2007 to 2016. After matching with the informativeness measure (by return synchronicity) and some basic filtering, we obtain 277 pilot firms whose options ever experienced a reduction in tick size after being included in the PPP. To test our hypothesis, we start with a 2-stage instrumental variable (IV) analysis. Specifically, we use the inclusion status in the PPP as the instrumental variable for options trading volume. In the first

[2]Even though several studies, cited above, use synchronicity as a measure of price informativeness, there is some debate in the literature about the interpretation of this measure (see, e.g., Hou, Peng, and Xiong (2013)).

stage, we find that the pilot firms experience a significant increase in their options trading volume after being included in the PPP, consistent with the objective of the PPP. In the second stage, we use instrumented options trading volume as the independent variable and examine its relation to our two informativeness measures. Consistent with our conjecture, we find that informativeness measured by return synchronicity significantly increases. We also find that the market valuation better predicts future earnings for stocks after the inclusion of their options in the PPP.

We then formally test our hypothesis using a difference-in-differences (DiD) approach, which helps us mitigate the differences between pilot and nonpilot firms before the event. We match pilot firms with nonpilot firms strictly according to firm fundamental characteristics in the year before the inclusion of the PPP. After verifying that there are no significant differences in firm characteristics (such as market capitalization, return volatility, past return, and institutional ownership), we find that pilot firms have an increase in options trading volume of \$397 million compared to the matched nonpilot firms in the 2 years after the shock (the average options trading volume for the matched sample is \$1,537 million). More importantly, pilot firms also experience a significant increase in stock price informativeness in the 2 years after the shock, compared with the nonpilot firms. In terms of economic significance, compared with the standard deviation of the average price informativeness measure (return synchronicity) before the shock, the absolute information level of piloting firms increases by 15% in the years after the PPP. The forecasting power of market valuation increases by almost 58% for pilot firms after the shock. We demonstrate that our results are robust to different matching methods, and the results do not change if we remove very few events after 2010.

We next test whether the increased options trading volume by the PPP motivates information acquisition by both options traders and stock traders. To test the theoretical predictions in Goldstein and Yang (2015), ideally one would need to identify the information that the options investors trade on and identify the other information acquired by other (stock) investors. This is a difficult, if not impossible, task. Nevertheless, we provide two suggestive pieces of evidence for the prediction in Goldstein and Yang (2015).

First, using our main matching approach and a set of robustness matching methods, we show that after the PPP, the pilot firms experience a significant increase in Google search compared to the matched nonpilot firms. The DiD analyses show that investors in general are incentivized to acquire more information. We believe that it is unlikely that the increase in Google website search is driven solely by options traders' information acquisition. Therefore, this evidence suggests that increased options volume leads to more information collection by stock market investors.

Second, we examine the behavior of financial analysts, who are important information providers and disseminate both public and private information to investors, especially those in the stock market. We first find that the analysts following pilot firms issue earnings forecasts more frequently than those following nonpilot firms, consistent with the notion that the analysts are making more efforts in providing information (see, e.g., Jacob, Lys, and Neale (1999), Merkley, Michaely, and Pacelli (2017)). Relatedly, we find the analyst forecasting dispersion increases for pilot firms after the PPP, compared with that of matched nonpilot firms. Chen and Jiang (2006) argue that analyst forecast dispersion reflects private information (see also Lang and Lundholm (1996)). Therefore, the patterns that we uncover are consistent with the notion that increased options trading volume motivates financial analysts, who provide information to stock investors, to acquire more private information.

So far, we have established that exogenously increased options trading volume by PPP increases the stock price informativeness, and motivates investors and analysts to acquire more information. We further check the robustness of our results by examining the positive effect of options trading on informativeness for different types of firms. A corollary of our hypothesis is that this effect is more significant for firms for which the information in options is more important. Therefore, we examine such a hypothesis from two perspectives, the stock trading volume and options trading volume. If investors cannot obtain sufficient information easily from the stock trading volume, then the incremental information from options trading volume has a greater impact on stock price informativeness. We find that the positive effect of the PPP on stock price informativeness is significant only among firms with low stock trading volume. Second, if the options market is inactive (has relatively low volume), then even if the options are included in the PPP, other investors might not pay much attention to collecting the information. Indeed, we find the positive effects of the PPP on stock price informativeness are more pronounced and significant only among firms with higher options trading volume.

Another corollary of our results is that the attractiveness of more efficiently priced options is higher than that of less efficiently priced options. For instance, if options market prices are noisy, then information acquisition may generate less profit for market participants. Thus, inefficient options markets might make investors less motivated to collect and produce information. Moreover, the trading of more efficiently priced options reduces more of the uncertainty faced by stock investors, thus motivating stock investors to acquire information. We employ Hasbrouck (1993) measure to proxy option pricing errors. We find that the positive effect of the PPP on stock price informativeness is more pronounced when the options are more efficiently priced than when they are less efficiently priced.

Finally, as an out-of-sample test (albeit not as a strict test of causality), we investigate whether the introduction of options to an economy's financial market improves the overall price informativeness. For 25 economies over a sample period of 1980 to 2016, we collect information on when these economies first listed options from the official website of their exchanges. For each economy, we compute our two proxies of stock price informativeness: the market synchronicity and the Bai et al. (2016) measure. Running a panel regression of price informativeness on a dummy variable, which equals 1 for years after options listing and 0 otherwise, we find an increase in both the measures after the introduction of options.

Overall, we contribute to the literature that studies the influence of options on the underlying stock market. Prior literature has mostly looked at where informed traders trade (by looking at the lead–lag relation between stock and option returns or by using option-related information to predict future stock returns). These studies establish the fact that informed traders sometimes trade in the options markets before the underlying markets. Thus, information is transmitted from the options markets to the stock markets. We, on the other hand, analyze whether options affect firms' information environment itself.

In a related study, Hu (2018) makes an important contribution by showing that options listing increases both informed and uninformed trading in the underlying stock market. Our article differs from his work in two main respects. First, we focus on the trading volume of options rather than the event of options listing per se. Our choice is motivated by both our theoretical foundation (i.e., Grossman and Stiglitz (1980), Goldstein and Yang (2015)), and the work of Roll, Schwartz, and Subrahmanyam (2009). Specifically, these latter authors argue that the incremental benefit from option listing should be related to whether the market for listed options has sufficient volume. The idea is that informed traders would be more active in high-volume markets. Indeed, Mayhew and Mihov (2005) document that the volume of newly listed options tends to be quite thin. Consistent with these arguments, Hu (2018) also finds that the impact of options listing is concentrated among stocks whose options are more actively traded after the listing events. Second, Hu (2018) examines the differential effect of options listing on informed and uninformed trading and finds (e.g., that even uninformed trading increases because of hedging demand).[3] His study is, thus, closer to the literature on the effects of options on Brunnermeier (2005) informational efficiency. Instead, as mentioned earlier, we focus on Brunnermeier (2005) price informativeness by looking at information acquisition by different investors. Importantly, we reach our conclusions by looking at two proxies for stock price informativeness and by establishing the causality of options trading's effect to mitigate endogeneity concerns. We also point out the channels through which options trading increases price informativeness. Overall, our article complements Hu (2018) on the effects of options on firm information environment, but, at the same time, differs from his in terms of theoretical motivation, measure selection, and empirical findings.

The remainder of our article proceeds as follows: Section II describes our sample, measure construction, and the institutional details of the PPP. Section III presents the IV and DiD results. Section IV explores the potential channels of the effect of options and conducts additional checks. A pseudo-out-of-sample international test is presented in Section V and Section VI concludes.

II. Data and PPP

A. Data, Measure, and Sample Construction

We collect data for both stocks and options for U.S. public firms. The data on trading volume, open interest, and strike prices for individual options are obtained from OptionMetrics from 2005 to 2016.[4] The data of returns, prices, and trading

[3]Kumar, Sarin, and Shastri (1998) find that options trading leads to a decline in the adverse component of spreads in stock markets, thus providing indirect evidence corroborating our results that options trading is beneficial to corporate information environment.

[4]Though OptionMetrics covers option data as early as 1996, we choose 2005 as the starting point of our sample as the PPP was launched in 2007. In our DiD framework, we analyze the effect of PPP within a window of 4 years around the events.

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volumes for individual stocks are obtained from CRSP. Accounting data are collected from Compustat. The quarterly institutional holdings are retrieved from Thomson Reuters (13F) database. The analyst coverage data are obtained from IBES. The market factor, risk-free rate, and Fama–French 48-industry classification are taken from Kenneth French's website. The option intra-day trades data are from the Options Price Reporting Authority (OPRA) database and start from 2004. We merge the stock sample with the options sample, and our sample only contains the stocks with positive options trading volume. We further require our sample stocks to be common stocks with CRSP share codes of 10 or 11. We also remove the observations with nonpositive book values.

We use stock return synchronicity as the first measure of stock price informativeness. Roll (1988) suggests that the stocks with relatively more firm-specific information incorporated into stock prices comove less with the other stocks. In other words, such stock prices have lower synchronicity with the market and the industry. Following this insight, there are many empirical studies that take synchronicity as a proxy for the extent to which firm-specific information is incorporated into the stock price.[5] We obtain firm-level synchronicity for each stock each year, by running the following regression:

$$R_{it} = \alpha_i + \beta_{1i} R_{m,t} + \beta_{2i} R_{ind,t} + u_{it}, \tag{1}$$

where R_{it} is stock i's return in week t, $R_{m,t}$ is the market return obtained from Kenneth French's website, and $R_{ind,t}$ is the return on the Fama–French 48-industry portfolio corresponding to stock i. We require a firm year to have a minimum of 26 valid weekly observations to run this regression. We then take a logarithmic transformation of the R^2 from this regression as $\ln\left(\left(1-R^2\right)/R^2\right)$, and label it as $-$SYNC: higher values imply more informative prices. After removing the firms without informativeness measures, we obtain a sample containing 23,174 firm-year observations from 3,591 unique firms.

Under a framework of q-theory/aggregate efficiency and information environment, Bai et al. (2016) derive a welfare-based measure of price informativeness: the predicted variation of future cash flows from current market prices. The intuition is that an informative stock price should have incorporated future earnings, therefore, the market valuation of stock could forecast future earnings. Formally, price informativeness is measured as forecasting price efficiency (FPE) as a scaled version of the coefficient b in the regression:

$$\ln\left(\frac{E_{i,t+1}}{A_{i,t}}\right) = a + b\ln\left(\frac{M_{i,t}}{A_{i,t}}\right) + cX_{i,t-1} + \varepsilon_{i,t+1}, \tag{2}$$

where $E_{i,t+1}$ is earnings before interest and taxes in the next year, $A_{i,t}$ is total assets in the current year, $M_{i,t}$ is the market capitalization in the current year, and $X_{i,t-1}$ is a vector composed of control variables (lagged). We control for a set of firm characteristics, including annual stock return, stock return volatility, institutional

[5]For an incomplete list, see Morck et al. (2000), Wurgler (2000), Jin and Myers (2006), Chen et al. (2007), Fernandes and Ferreira (2009), Ferreira, Ferreira, and Raposo (2011), and Bennett, Stulz, and Wang (2020).

TABLE 1
Summary Statistics

Table 1 presents the descriptive statistics. Our sample covers 23,174 firm-year observations from 2005 to 2016. We measure stock price informativeness using negative synchronicity (−SYNC). For each stock each year, we estimate R^2 by regressing weekly stock returns on the weekly market returns and the weekly returns of corresponding Fama–French 48 industry portfolios. We define −SYNC as $\ln\left((1-R^2)/R^2\right)$. A higher −SYNC indicates higher stock price informativeness. Options trading volume (OPTVOLM) is the annual dollar options trading volume in millions across all options for a given stock. Return (RET) is the annual stock return. Stock return volatility (STD) is the standard deviation of daily returns for a stock over a year. Institutional ownership (INSTOWN) is the ratio of the number of shares held by institutional investors divided by the total number of shares outstanding. Stock trading volume (STKVOLM) is the annual dollar trading volume of the stock. Return on assets (ROA) is the operating income before depreciation scaled by total assets. Market value (MV) is calculated as the natural logarithm of the product of price at calendar year-end and the number of shares outstanding. Book to market ratio (BTM) is the ratio of book value per share divided by price at calendar year-end. GOOGLE_TRENDS is the search index published by Google Trends service. Earnings forecast revision frequency (FREQ) is the average number of annual forecasts issued by analysts following the firm over a year. Earnings forecast dispersion (DISP) is the average standard deviation of analyst forecasts divided by the consensus forecast.

	Mean	Std. Dev.	25%	Median	75%
−SYNC	0.74	1.25	−0.11	0.63	1.45
OPTVOLM	141.74	469.43	1.08	7.42	55.72
RET	0.12	0.47	−0.16	0.08	0.32
STD	0.03	0.01	0.02	0.02	0.03
INSTOWN	0.72	0.21	0.59	0.75	0.87
STKVOLM	421.24	806.87	62.85	147.45	388.64
ROA	0.10	0.16	0.05	0.11	0.17
ln(MV)	7.38	1.65	6.23	7.27	8.40
BTM	0.55	0.40	0.27	0.45	0.71
GOOGLE_TRENDS	26.18	21.59	8.50	20.42	39.75
FREQ	4.15	1.43	3.25	3.96	4.80
DISP	0.25	0.49	0.03	0.07	0.19

ownership, stock trading volume, and return on assets (ROA) in the previous year. Kacperczyk et al. (2021) study the impact of foreign institutional ownership on stock price informativeness, and we follow their approach in studying the impact of options trading volume on this measure. We provide further details on the exact procedure in the methodology section.

We winsorize the data at the 1% and 99% levels and report summary statistics in Table 1. Firms in our sample are large firms given that we focus on firms with traded options: the average institutional holdings percentage is 72% and the average market capitalization is \$7.70 billion. On average, the annual options dollar trading volume is \$141.74 million, while the stock trading volume is \$421.24 million. However, the distribution of both stock and option volume is skewed and the median dollar option and stock trading volume are \$7.42 and \$147.45 million, respectively. This latter fact suggests that option traders will unlikely exert a strong influence by themselves on stock price informativeness. The average annual return is 12% and the average stock return volatility (calculated using daily returns) is 3%. The average ROA is 12% for our sample firms. −SYNC has a mean of 0.74 with a standard deviation of 1.25.

While the purpose of the article is to establish causality from options trading volume to stock price informativeness, we first run panel regressions to demonstrate the correlations. Specifically, we investigate the effect of options trading volume on informativeness measured by return synchronicity (−SYNC) in column 1 of Table 2. In column 2, we interact options trading volume with market valuation to study whether options trading volume enhances the predictability power of market valuation on future earnings (i.e., FPE). We take the natural logarithms of options

TABLE 2
Options Trading Volume and Stock Price Informativeness

Table 2 presents the firm-year level panel regression results. Our sample is from 2005 to 2016. For the convenience of reporting, we take the natural logarithms of options trading volume in the regressions. In column 1, we present the regression result by examining the effect of options trading volume (ln(OPTVOLM)) on stock price informativeness measured by −SYNC. In column 2, we present the regression result by examining the effect of options trading volume on stock price informativeness measured by the forecasting price efficiency (FPE). Control variables include stock return (RET), stock return volatility (STD), institutional ownership (INSTOWN), stock trading volume (STKVOLM), and return on assets (ROA). We control for firm and year-fixed effects. The *t*-statistics in parentheses are calculated from robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	_SYNC	FPE
	1	2
ln(OPTVOLM)×ln(M/A)	–	0.0029***
		(4.57)
ln(M/A)	–	0.0506***
		(16.22)
ln(OPTVOLM)	0.0261***	−0.0016*
	(4.17)	(−1.84)
RET	−0.2028***	0.0103***
	(−13.59)	(5.43)
STD	3.9546***	−0.0106
	(4.25)	(−0.08)
INSTOWN	−0.3599***	0.0045
	(−4.81)	(0.40)
STKVOLM	0.0000	0.0000**
	(0.21)	(2.00)
ROA	−0.6401***	0.0492**
	(−6.39)	(2.19)
Year/firm FE	Yes	Yes
No. of obs.	22,588	18,297
Adj. R^2	0.587	0.780

trading volume (in millions) and control for a set of firm characteristics including the annual stock return, stock return volatility, institutional ownership, stock trading volume, and ROA in the previous year. We also control for firm and year-fixed effects.[6] Table 2 shows that options trading volume has a positive and significant impact on stock price informativeness measured by both return synchronicity (−SYNC) and FPE. We formally establish causality by exploiting the PPP in Section III.

B. The Penny Pilot Program

The SEC launched the PPP in 2007 by allowing 13 options classes to be quoted in penny increments. Specifically, options classes with prices less than \$3 could be quoted in 1-cent increments, while the tick size of those with prices greater than \$3 was changed to 5 cents.[7] Another important feature of the PPP is that it was implemented in a staggered fashion, in which different firms participated at different points of time. Such staggered implementation further helps us to address the concerns of omitted variables. The initial plan began on Jan. 26, 2007, for only

[6]Our results hold if we use the options trading volume (in million) and control for additional firm characteristics such as market value and book to market.

[7]Except options overlying the QQQQ would be quoted and traded in minimum increments of \$0.01 for all series regardless of the price.

13 options classes. Then the exchanges proposed expanding the PPP to include more classes (in total 50) in two phases, one on Sept. 28, 2007, and the other on Mar. 28, 2008. While the PPP was supposed to expire on July 3, 2009, several exchanges proposed to extend and expand the number of issues included in the PPP. Therefore, from 2009 to 2010, 300 options classes were added to the PPP in four phases, leading to a total number of 363. The PPP expired on June 30, 2020, and the Penny Interval Program was adopted as the successor.

Anand, Hua, and McCormick (2016) show that the PPP effectively reduced the trading costs of options. A report by NYSE Arca shows that the PPP led to unprecedented volume increases. Moreover, the inclusion of the options in the PPP was not a choice of the firm; the SEC claimed that the PPP covered a diverse group of options with varying characteristics.[8] Therefore, being a pilot firm can be viewed as an exogenous shock to the options trading volume of the firm, as well as options trading cost.

We obtain the list of pilot firms and the associated dates from the CBOE and the International Securities Exchange (ISE) websites from 2007 to 2016. In total, we identify 351 unique common stocks whose options ever entered the PPP.[9] After matching with our sample described earlier, 277 unique firms in our sample are identified as pilot firms that ever entered the PPP.

III. Does Options Trading Volume Affect Stock Price Informativeness?

A. Evidence from an Instrumental Variable Approach

To investigate the effect of the PPP on options trading volume, and further on stock price informativeness, we first rely on an IV approach. Specifically, in the first stage, we use the pilot status as an IV for options trading volume:

$$\text{(3)}\qquad \text{OPTVOLM}_{i,t} = \alpha + \beta(\text{TREAT}_i \times \text{POST}_{i,t}) + \delta\text{CONTROLS}_{i,t-1} + \varepsilon_{i,t},$$

where TREAT is a dummy equal to 1 for pilot firms and 0 otherwise, and POST is a dummy equal to 1 for the years after a pilot firm enters the PPP (including the inclusion year), and 0 otherwise. We control for a set of firm characteristics including the annual stock return, stock return volatility, institutional ownership, stock trading volume, and ROA in the previous year.[10] We also control for firm and

[8]According to the documents of exchanges, option classes added to the PPP were the most actively traded, multiply listed options classes not yet included in the program.

[9]According to the CBOE and ISE website, from 2007 to 2016, 427 unique stocks and ETFs, including 382 stocks and 45 ETFs, entered the PPP. The number is higher than 363, which is officially reported. The reason is that some pilot option classes were later replaced. For example, there were other replacement clauses, including excluding high-priced underlying securities. The replacement issues would be added to the Pilot on the second trading day following Jan. 1, 2010, and July 1, 2010. The exchanges thereafter followed the semi-annual schedule to adjust the options classes on the second trading day after Jan. 1 and July 1 each year.

[10]Though the PPP inclusion is likely exogenous to individual firms, we control for stock return, stock return volatility, and stock trading volume to avoid the potential mechanical relation among stock return volatility, option/stock trading volume, and the informativeness measure. Institutional ownership is

TABLE 3

Penny Pilot Program and Stock Price Informativeness: IV Approach

Table 3 presents the 2SLS IV regression results by exploiting SEC's PPP as an exogenous shock to the options trading volume of pilot firms. Our sample is from 2005 to 2016. The PPP included 277 sample firms over this sample period. TREAT is a dummy equal to 1 if a firm is included in the PPP, and 0 otherwise. POST is a dummy equal to 1 for the years in and after the year the firm is included in the PPP, and 0 otherwise. Column 1 presents the first-stage result on the effect of PPP inclusion on options trading volume (OPTVOLM). In column 2, we present the second-stage result by examining the effect of instrumented options trading volume (PREDOPTVOLM) on stock price informativeness measured by −SYNC. In column 3, we present the second-stage result by examining the effect of instrumented options trading volume on stock price informativeness measured by the forecasting price efficiency (FPE). Control variables include stock return (RET), stock return volatility (STD), institutional ownership (INSTOWN), stock trading volume (STKVOLM), and return on assets (ROA). We control for firm and year-fixed effects. The *t*-statistics in parentheses are calculated from robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	First Stage	Second Stage	
	OptVolm	−SYNC	FPE
	1	2	3
PREDOPTVOLM × ln(M/A)	–	–	0.0001***
			(5.89)
ln(M/A)	–	–	0.0451***
			(12.12)
PREDOPTVOLM	–	0.0009**	0.0000
		(2.21)	(1.12)
TREAT × POST	106.9903***	–	–
	(2.74)		
Controls	Yes	Yes	Yes
Year/firm FE	Yes	Yes	Yes
No. of obs.	22,588	22,588	18,297
Adj. R^2	0.764	0.586	0.780

year-fixed effects. Therefore, the TREAT and POST dummies are absorbed and no longer included in the regression.

As shown in column 1 of Table 3, after being included in the PPP, the pilot firms have significantly higher options trading volume compared with that of the nonpilot firms. Specifically, we obtain an estimate of β equal to 106.9903 (significant at the 1% level) after controlling for firm and year-fixed effects and a set of firm fundamental variables. This implies that, on average, the annual options trading volume is \$106.99 million higher for pilot firms than that of nonpilot firms in the years after program inclusion, representing an 11.23% increase over the pre-PPP option trading volume of \$952.98 million. Consistent with previous literature that the PPP effectively reduces trading costs (Anand et al. (2016)), the pilot firms experience a sharp increase in their options trading volume.

Using the instrumented options trading volume from the first-stage regression, we next test whether the exogenously increased options trading volume would improve the stock price informativeness of pilot firms relative to nonpilot firms. We first run the second-stage regression for informativeness measured by return synchronicity (i.e., −SYNC). In column 2 of Table 3, we present the second-stage results.

controlled as institutions are better at acquiring and analyzing information. We also control for profitability in our main specification as it is one important firm fundamental and may affect information acquisition. Our results do not change if we further control for stock market capitalization (which is highly correlated with institutional ownership and stock trading volume), turnover, and beta in these regressions.

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Consistent with our expectation that an increased options trading volume would encourage (stock and options) investors to acquire more firm-specific information and hence more information would be incorporated in the stock prices, we find the instrumented options trading volume has a significant and positive impact on stock price informativeness. In other words, options trading volume reduces the return comovement of the underlying stocks with the market and industry.

To test whether increased options trading volume has a positive impact on the forecasting power of market valuation on future earnings, we follow the approach of Kacperczyk et al. (2021) and run the following second-stage regression counterpart of equation (4) as follows:

$$\ln\left(\frac{E_{i,t+1}}{A_{i,t}}\right) = a + b_1 \ln\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \text{PREDOPTVOLM}_{i,t} + b_2 \ln\left(\frac{M_{i,t}}{A_{i,t}}\right) + b_3 \text{PREDOPTVOLM}_{i,t} + cX_{i,t-1} + \varepsilon_{i,t+1}, \tag{4}$$

where PREDOPTVOLM is the instrumented options trading volume. We are interested in coefficient b_1, which measures the sensitivity of future earnings to current stock prices, conditional on the instrumented options trading volume. If our conjecture is correct, we would obtain a significantly positive b_1. This is exactly the result presented in column 3 of Table 3. We find that the positive shock on options trading volume leads to greater predictability by current market valuation for future earnings.[11]

B. Evidence from DiD Matching Estimates

The IV approach supports our argument that options trading volume improves stock price informativeness. However, it is not easy to interpret the economic magnitudes of the second-stage regressions, and the IV estimates are often inflated according to Jiang (2017). In this section, we conduct DiD analyses to investigate the effect of the PPP on stock price informativeness measured by both return synchronicity ($-$SYNC) and forecasting efficiency of market valuation (FPE).

We first match the pilot firms with nonpilot firms according to the characteristics in the year before the inclusion of pilot firms. Specifically, we match according to the stock market capitalization, stock return volatility, and stock return. The market capitalization captures the size of the firm and the stock market valuation. It is correlated with various aspects of firm fundamental characteristics, such as institutional ownership and information transparency. Therefore, matching according to market capitalization allows us to control for general firm heterogeneity. In the year before the inclusion, we classify our sample firms into 100 groups according to market cap. Then within each year and size percentile, we further classify our sample firms into 3-by-3 groups according to the stock return and stock return volatility in the year before the inclusion. Thus, every year, we split our sample firms into 900 groups according to market cap, stock return, and stock return volatilities in the prior year. Then we manually match the pilot and nonpilot firms

[11]Our results are robust if we examine the earnings 3 years later, rather than 1 year later.

by requiring them to be in the same year and the same market cap/return/return volatility group ranks.[12]

Note that the matching process requires the pilot and nonpilot firms to have nonmissing market cap, return, and return volatility before the year of the inclusion; therefore the number of qualified pilot firms reduces to 219 (the IV approach only requires the existence of pilot firms in the full sample). Our matching metrics are also very stringent. Therefore, after matching, we obtain 165 unique pilot firms matched with 295 nonpilot firms. We allow for 1-to-N matching. One-to-one matching yields similar results as we later show.

Panel A of Table 4 shows the quality of the matching. The differences in matching variables between the pilot and matched nonpilot (control) firms are negligible. For example, the logarithm of market cap for pilot firms is on average 9.26, while for control firms is 9.25, leading to a difference of 0.01. The return volatility and stock return are similar. We also check other important aspects such as institutional ownership, stock trading volume, and profitability. Though they are not in our matching metrics, the pilot and control firms are similar in these firm fundamentals.

We then verify the parallel trend assumption for the PPP as a valid natural experiment to study its impact on stock price informativeness. As the forecasting efficiency measure (FPE) is the coefficient from regressions, we can only demonstrate the parallel trends for the informativeness measured by return synchronicity ($-$SYNC). In Panel B of Table 4, we plot the average informativeness measures for the pilot and matched nonpilot firms for the 4 years around the program inclusion.[13] The informativeness levels of the pilot and nonpilot firms move in a parallel manner before the shock, but start to diverge in the year of inclusion. While the nonpilot firms experience a deterioration in informativeness, the pilot firms show an increase.[14] The trends of price informativeness not only confirm that the PPP is a valid quasi-natural experiment for our study, but also provide visual evidence of the effect of options trading volume on stock price informativeness.

Now we formally test the effect of the PPP on stock price informativeness. Similar to the first stage in IV regressions, we first show that the options trading volume of pilot firms significantly increases compared to the control firms after the shock. In column 1 in Panel C of Table 4, we tabulate the DiD matching estimate for options trading volume, which is the difference in options trading volume (Pilot $-$ Control) differences after and before the shock. In the 2 years post the shock, the pilot firms experience an increase of \$396.755 million in options trading volume, compared with matched control firms. In column 2, we present the matching estimate for informativeness measured by $-$SYNC. Consistent with the argument that options trading enhances stock price informativeness, we find the average price

[12]In 2012, NYSE ARCA applied make-take rules for nonpilot firms. Therefore, some nonpilot firms also experience reduction in trading cost (i.e., bid–ask spread). However, these confounding events work against us. Therefore, our results from the regressions and the DiD analysis are likely a lower bound of the PPP.

[13]Note that we denote the event year as year 1 because several inclusion phases occurred in the first half of the calendar year.

[14]As the PPP largely overlapped with the financial crisis, there is a downward trend of informativeness for our sample firms from 2005 to 2011.

TABLE 4

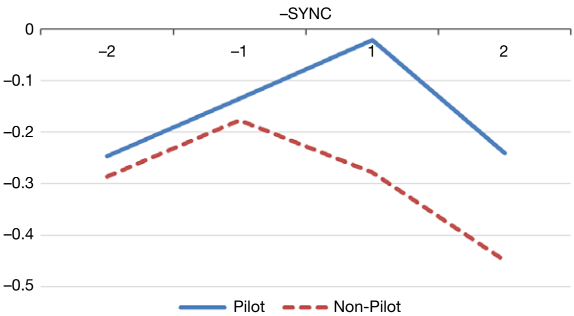
Penny Pilot Program and Stock Price Informativeness:
Difference-in-Differences Matching Approach

Table 4 presents the DiD estimates of stock price informativeness using the PPP as an exogenous shock to options trading volume. We match the pilot and nonpilot firms according to firm fundamentals before the inclusion. Specifically, we require the pilot and nonpilot firms to first be in the same size percentile. Then within the size percentile, we require the pilot and nonpilot firms to be in the same stock return and return volatility tercile. We match 165 unique piloting firms with 295 nonpiloting firms. Panel A reports the differences in firm characteristics between the pilot and nonpilot firms in the year before the events. Panel B plots the average differences in price informativeness measure (−SYNC) between the pilot and nonpilot firms in the years around the event. Panel C presents the difference-in-differences matching estimates for options trading volume (OPTVOLM) and informativeness measure (−SYNC), and the DiD regression results for the forecasting price efficiency (FPE). Specifically, we examine the 4-year window around the PPP inclusion. For the DiD regression, we include a set of control variables as in Table 1, and control for year-fixed effects. The *t*-statistics in parentheses are calculated from robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Balance Tests

	Pilot	Control	Difference	*t*-Stat.
ln(MV)	9.26	9.25	0.01	0.95
STD	0.04	0.04	0.00	−0.11
RET	0.44	0.58	−0.14	−1.32
INSTOWN	0.74	0.74	−0.01	−0.06
STKVOLM	2,480.82	2,634.32	−153.50	−0.60
ROA	0.12	0.13	−0.01	−0.69

Panel B. The Parallel Trends



Panel C. Difference-in-Differences Matching (Regression) Estimates

	OPTVOLM	_SYNC	FPE
	1	2	3
1–*N* matching	396.755***	0.128**	0.018**
	(3.10)	(2.33)	(2.19)
Removing events after 2010	394.816***	0.148***	0.017**
	(2.95)	(2.64)	(2.22)
1–1 matching	449.249**	0.168**	0.021**
	(2.52)	(2.44)	(2.57)

informativeness level of piloting firms increases by 0.128 compared with the control firms in the 2 years after the shock.[15] In terms of economic significance, compared with the standard deviation of average −SYNC (0.854) before the shock, the absolute information level of piloting firms increases by about 15% (0.128/0.854) in the years after the PPP.[16]

[15]Our results hold if we instead run a DiD regression.

[16]The average of −SYNC measure is −0.207 for the matched sample before the shock. We therefore interpret the economic magnitude by benchmarking with the standard deviation.

In column 3, we present the DiD regression result for forecasting efficiency. Specifically, we run the following regression:

$$\ln\left(\frac{E_{i,t+1}}{A_{i,t}}\right) = a + b_1 \ln\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \text{TREAT}_{i,t} \times \text{POST}_{i,t} + b_2 \ln\left(\frac{M_{i,t}}{A_{i,t}}\right) + b_3 \text{INTERACTIONS}_{i,t} + cX_{i,t-1} + \varepsilon_{i,t+1}, \quad (5)$$

where TREAT is a dummy equal to 1 for pilot firms and 0 for control firms, POST is a dummy equal to 1 for the years after the shock (including the year of the shock) and 0 otherwise, and INTERACTIONS is a vector containing interactions between market valuation, TREAT, and POST. We also include year-fixed effects to control for potential time trends over our sample period.

We are interested in the coefficient b_1 which captures the effect of PPP on the forecasting efficiency of market valuation. The coefficient is 0.018 with a t-statistic of 2.19, indicating that after being included in the PPP, the market valuation of pilot firms forecasts the future earnings significantly better than matched nonpilot firms. In the regression, the coefficient b_2 on market valuation is 0.031 (t-stat. = 8.23, not reported in the table). Therefore, in terms of economic magnitude, the PPP increases the forecasting efficiency by about 58% (0.018/0.031).[17]

Based on the matching metrics outlined above, we conduct two robustness checks for our empirical results in the lower part of Panel C of Table 4. First, we remove the shocks after 2010. Only 11 replacement events occurred after 2010, and removing these events has no impact on our documented patterns. Second, we require one pilot firm to be matched with only one nonpilot firm in the last rows of Panel C. When more than one nonpilot firms are matched with the pilot firm, we keep only one nonpilot firm with stock return volatility closest to the pilot firm. Again, our results are not impacted by this alternative matching procedure.

C. Robustness: Different Matching Metrics

In this subsection, we examine whether our DiD results are robust to alternative matching methods. On top of our baseline matching metrics (i.e., market cap, stock return volatility, and stock return), we further add one of the following characteristics as an additional matching variable, including options trading volume (OPTVOLM), return on assets (ROA), book-to-market (BTM), institutional ownership (INSTOWN), stock turnover (TURNOVER), and stock beta (BETA). Specifically, in the year before the inclusion, we first classify our sample firms into market cap percentiles. Then within the year and market cap percentile, we classify the firms into 2-by-2-by-2 groups according to the stock return volatility, stock return, and the additional matching variable. In Table 5, we present the DiD

[17]The DiD regression results also show that the interaction between POST and market valuation has a negative and significant coefficient. This is consistent with the fact that during our sample period, there is a deterioration of forecasting efficiency and informativeness. The insignificant coefficient for the interaction between TREAT and market valuation shows that there is no significant difference between pilot and control firms in forecasting efficiency before the PPP. Our results also hold if we replace 1-year-forward earnings with 3-year-forward earnings.

TABLE 5

Penny Pilot Program and Stock Price Informativeness: Alternative Difference-in-Differences Matching Approach

Table 5 presents the DiD estimates (regression results) of stock price informativeness using the PPP as an exogenous shock to options trading volume. We match the pilot and nonpilot firms in the same year according to different sets of matching variables in the year before the inclusion. Specifically, we require the pilot and nonpilot firms to be in the same size percentile. Then within the size percentile, we further require the pilot and nonpilot to be in the same group (2-by-2-by-2) classified by each of the other matching variables. We report the DiD matching estimates for informativeness measure (−SYNC), and the DiD regression results for the forecasting price efficiency (FPE). The *t*-statistics in parentheses are calculated from robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	_SYNC	FPE
	1	2
ln(MV)/STD/RET/OPTVOLM	0.106**	0.015**
	(2.45)	(2.01)
ln(MV)/STD/RET/ROA	0.116**	0.017**
	(2.34)	(2.46)
ln(MV)/STD/RET/BTM	0.096**	0.014**
	(2.06)	(2.13)
ln(MV)/STD/RET/INSTOWN	0.082*	0.015**
	(1.68)	(1.97)
ln(MV)/STD/RET/TURNOVER	0.102**	0.019**
	(2.55)	(2.54)
ln(MV)/STD/RET/BETA	0.077*	0.013*
	(1.86)	(1.71)

matching estimates for stock price informativeness (−SYNC) and the DiD regression results for forecasting efficiency (FPE) as described in equation (5).

As demonstrated in Table 5, our finding that the pilot firms' stock price informativeness increases compared to matched control firms after the inclusion of the PPP holds across different matching metrics. The DiD matching estimate for informativeness measured by return synchronicity ranges from 0.082 to 0.116, with *t*-statistics ranging from 1.68 to 2.55. The DiD regression coefficient (i.e., b_1 in equation (5)), ranges from 0.013 to 0.019, with *t*-statistics ranging from 1.71 to 2.54. Combined with Panel C of Table 4, it is unlikely that our matching results are dependent on one particular matching method.

IV. Possible Channels

We now explore the channels through which options trading increases stock price informativeness using the PPP as quasi-natural experiments. We first examine whether options trading volume increases information acquisition by general investors and financial analysts. Then we conduct subsample analyses to further understand the impact of options trading on stock price informativeness.

A. Does Options Trading Volume Facilitate Information Acquisition?

An active options market could motivate information acquisition by both option investors because of higher leverage and lower transaction costs (Grossman and Stiglitz (1980)) and by stock investors because of the information complementarity (Goldstein and Yang (2015)). To confirm the predictions from both models, we need to identify the information that the options investors trade on and to

TABLE 6

Penny Pilot Program and Information Acquisition

Table 6 presents the DiD estimates of information acquisition using the PPP as an exogenous shock to options trading volume. We match the pilot and nonpilot firms in the same year according to different sets of matching variables. Then within the size percentile, we further require the pilot and nonpilot to be in the same group (3-by-3 or 2-by-2-by-2) classified by each of the other matching variables. GOOGLE_TRENDS is the search index published by Google Trends service. Earnings forecast revision frequency (FREQ) is the average number of annual forecasts issued by analysts following the firm over a year. Earnings forecast dispersion (DISP) is the average standard deviation of analyst forecasts divided by the consensus forecast. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	GOOGLE_TRENDS	FREQ	DISP
	1	2	3
ln(MV)/STD/RET	3.310*** (2.86)	0.103* (1.66)	0.256*** (5.09)
ln(MV)/STD/RET/OPTVOLM	1.815** (2.27)	0.119** (2.05)	0.220*** (4.71)
ln(MV)/STD/RET/ROA	1.375* (1.81)	0.087* (1.68)	0.155*** (5.13)
ln(MV)/STD/RET/BTM	1.226 (1.40)	0.113* (1.71)	0.131*** (4.78)
ln(MV)/STD/RET/INSTOWN	1.966** (1.98)	0.097 (1.40)	0.180*** (4.18)
ln(MV)/STD/RET/TURNOVER	2.759*** (3.39)	0.127** (2.24)	0.245*** (5.97)
ln(MV)/STD/RET/BETA	1.826** (2.25)	0.136** (2.46)	0.250*** (6.06)

identify the other information acquired by other (stock) investors. This is virtually an impossible task. Nevertheless, we provide two suggestive pieces of evidence for the prediction in Goldstein and Yang (2015). Specifically, we examine the effect of the PPP on Google search volume and financial analyst behavior. The former captures the overall information acquisition by stock and option investors, and the latter captures information that is produced and acquired for the stock investors.

Google Trends search volume index (GOOGLE_TRENDS) measures the searching frequency of a keyword in Google and is provided by the Google Trends service.[18] Da, Engelberg, and Gao (2011) pioneer the use of the search volume index and interpret the index as a proxy for investors' attention, while we regard it as a direct measure of searching intensity. Following their setting, we employ the index of the stock symbols of firms instead of the index of company names. For each year and each firm, we obtain a Google search index that captures overall searching intensity by taking an average of the monthly search index.

In column 1 of Table 6, we report the DiD matching estimates for Google search volume. We match the pilot and nonpilot firms according to the main specification (market cap, stock return volatility, and stock return) and robustness matching metrics as we have discussed earlier. Though the magnitude of matching estimates varies (from 1.226 to 3.310) across different matching metrics, the matching results point out that after the inclusion in the PPP, the Google search volume for pilot firms significantly increases, compared to that for matched non-pilot firms.[19] In terms of economic magnitudes, the average Google search volume

[18]The service can be accessed via: https://trends.google.com/trends/.

[19]The only exception is the DiD matching estimate for the matching which further adds book to market as a matching metric. The *t*-statistic is 1.40.

for matched firms is 36.774; therefore, for our main specification, the DiD matching estimate represents an increase of 9% (3.310/36.774) of the mean. While this DiD analysis shows that investors in general are incentivized to acquire more information, we believe that it is unlikely that the increase in Google website search is driven solely by options traders' information acquisition. Therefore, this evidence suggests that an increase in options volume leads to more information collection by stock market investors as well.

In columns 2 and 3 of Table 6, we investigate the effect of the PPP on financial analyst forecast revision frequency and dispersion. Financial analysts provide both public and private information to investors, especially stock investors. Thus, analyzing their behavior helps us to focus on information production and acquisition primarily in the stock market. We rely on the average number of forecasts issued by the analysts following a firm within a year to capture analysts' efforts in information production. The results in column 2 show that financial analysts of pilot firms issue earnings forecasts more frequently compared to those of matched nonpilot firms after the PPP. To measure the unique information in earnings forecast by different financial analysts, we calculate the earnings forecast dispersion, which is the standard deviation of forecast scaled by the absolute mean of forecasts. Chen and Jiang (2006) argue that analyst forecast dispersion reflects private information. Relatedly, Lang and Lundholm (1996) show that different analysts make different forecasts primarily because of differences in nonfirm-provided information rather than the differences in the interpretation of common information. These studies suggest, therefore, that greater analyst forecast dispersion is due to differences in private information. The significant and positive DiD matching estimates in column 3, showing that the analyst forecast dispersion for pilot firms increases significantly compared to that for matched nonpilot firms after the PPP, confirm our conjecture.

To sum up, using the PPP as an exogenous shock to options trading volume, we find options trading volume increases information acquisition by the general public and private information production by financial analysts. The results are also robust to different matching metrics that we introduced earlier. These pieces of evidence lend support to the framework in Grossman and Stiglitz (1980) and Goldstein and Yang (2015), on which we build our research question and hypothesis.

B. The Role of Stock and Options Trading Volume

We build our hypothesis on the benefits of information acquisition (Grossman and Stiglitz (1980)) and information complementarity (Goldstein and Yang (2015)) because of options trading. A natural hypothesis is that our findings should be more pronounced when the information from other security trading is limited and/or when the options market has a greater role in information production. We, therefore, investigate the effects of the PPP on stock price informativeness conditional on the trading volume of underlying stocks and options, respectively.

In Panel A of Table 7, we split the matched pilot and control firms according to the trading volume of underlying stocks. Then we present the DiD results for the two subsamples, respectively. The DiD matching estimates for stock price

TABLE 7

The Effect of Stock Trading Volume and Options Trading Volume

Table 7 presents the impact of the PPP on stock price informativeness conditional on the trading volume of stocks and options before the shock. Specifically, we split our sample into two subsamples according to stock trading volume (options trading volume) in Panel A (B). We report the DiD matching estimates for informativeness measure (−SYNC), and the difference-in-differences regression results for the forecasting price efficiency (FPE). The *t*-statistics in parentheses are calculated from robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	–SYNC	FPE
	1	2
Panel A. Stock Trading Volume		
High	0.067	0.011
	(0.90)	(1.07)
Low	0.205**	0.037***
	(2.43)	(2.64)
Panel B. Options Trading Volume		
High	0.297***	0.023**
	(3.43)	(2.04)
Low	−0.029	−0.009
	(−0.41)	(−0.65)

informativeness measured by stock return synchronicity in column 1 and regression coefficients for forecasting efficiency in column 2 confirm that our documented results are more pronounced among firms with lower stock trading volume. For firms with high stock trading volume, the PPP has no significant effect on the stock price informativeness. For example, the DiD estimate for informativeness (−SYNC) is 0.205 for firms with low stock trading volume, almost 3 times the estimate for firms with high stock trading volume (0.067). When investors cannot obtain sufficient information from the stock market, the relative weight of information in options trading is higher.

In Panel B of Table 7, we report the results conditional on the options trading volume. In a similar vein, we split the sample according to the options trading volume and obtain the DiD matching estimates and regression results for the two subsamples, respectively. Our results show that the PPP increases the stock price informativeness only when options are of more importance in information production (i.e., when the options are actively traded). The DiD matching estimate for −SYNC is 0.297, significant at the 1% level among firms with high options trading volume but the estimate is −0.029 for firms with low options trading volume.

Taken together, we show in this section that the informational benefits associated with options trading volume depend on the relative importance of a firm's options market.

C. The Role of Options Price Efficiency

We now turn to the impact of price efficiency in the options market on our documented patterns. Our proxy for price efficiency is Hasbrouck (1993) pricing error, which captures temporary deviations from the efficient price due to various market frictions.

An actively traded options market is more attractive to option traders if options are also priced more efficiently. Such options, therefore, motivate option traders to

TABLE 8

The Effect of Option Pricing Error

Table 8 presents the impact of the PPP on stock price informativeness conditional on the option price efficiency before the shock. Option pricing error (PRCERR) is calculated as the average Hasbrouck (1993) pricing error measure across all options with the same underlying stock. A higher PRCERR indicates more noise in options trading. We split our sample into two subsamples according to the option pricing error (PRCERR). We report the DiD matching estimates for informativeness measure (−SYNC), and the difference-in-differences regression results for the forecasting price efficiency (FPE). The *t*-statistics in parentheses are calculated from robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	_SYNC	FPE
Option Pricing Error (PRCERR)	1	2
High	0.089	0.005
	(1.13)	(0.40)
Low	0.270**	0.031**
	(2.10)	(2.56)

acquire more information vis-a-vis options that are priced less efficiently. Moreover, when option prices reflect the newly acquired information from options traders, such information can be observed by other investors, such as stock traders. Thus, if options price is more efficient and reflects more accurate information, trading in the options market reduces even more uncertainty of stock traders in acquiring other information of interest, and encourages more information acquisition by stock traders.[20] Thus, our testable hypothesis is that the relation between stock price informativeness and options trading should be stronger for more efficiently priced options.

We construct the pricing error of options following Hasbrouck (1993). We obtain intra-day transaction records (execution price, associated quotes, and trading volumes for each transaction) of options from OPRA over a sample period of 2004 to 2015. We apply standard filters to transaction records.[21] We apply Lee and Ready (1991) algorithm to sign the transactions. We only include options with the number of transactions greater than 50 in the VAR estimation. Then for each stock, we compute the average of the pricing errors of all the options associated with it and name this variable PRCERR. A higher value of PRCERR indicates that the options are less efficiently priced.

In Table 8, we split the sample into two subsamples according to the pricing error of options and report the DiD results. We find that the positive effects of the PPP on stock price informativeness are only significant among firms with more efficiently priced options (i.e., ones with a low pricing error). For example, the DiD

[20]We recognize that not all options trading is information driven. However, if there is information-driven trading in the options market, the information will be more accurately reflected in the trading and observed by other investors when options are more efficiently priced.

[21]First, to avoid potential microstructure bias, we include only transaction records with positive price, trading volume, strike price, and bid–ask quotes. The standard of positive prices, quotes, and number of shares outstanding applies to the underlying stocks. We also require the bid price be strictly less than the ask price. Second, we eliminate all records with obvious arbitrage opportunities such as $S \geq C \geq \max(0, S-K)$ for a call option price C with the underlying price S and the strike price K. Third, to make the estimates of the VAR model with 5 lags exist, a minimum of 50 transactions per month is required for an individual option. Fourth, following Boehmer and Kelley (2009), we eliminate volatile execution price observations that exceed 130% of the previous price or precipitate below 70% of the previous price.

matching estimate of −SYNC is 0.270 (t-stat. = 2.10) for firms with efficiently priced options, which is 3 times the estimate for firms with less efficiently priced options (0.089).

Our results are, thus, consistent with the argument that the positive impact on stock price informativeness from options trading volume varies in the price efficiency of the options traded. If options are not efficiently priced, the attractiveness of options as an outlet for informed trading declines, and so does the strategic information complementarity to other investors.

V. International Evidence

We conduct an out-of-sample international analysis to investigate whether the introduction of the options market to an economy's financial market improves the overall price informativeness. Our sample of economies is similar to that of Leuz, Nanda, and Wysocki (2003) but with some modifications due to data availability. We collect information about when an economy first listed options from the official website of their exchanges.[22] The data on equity prices and firm fundamentals are obtained from Datastream over a sample period of 1980 to 2016. We require an economy to have the first listed option within our specific sample period. For example, Canada and Australia first listed options in 1975 and 1976, respectively. Both these countries are excluded from our sample. After filtering, we end up with a panel data set that covers 25 economies: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Israel, Italy, Japan, Korea, Malaysia, Mexico, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, Taiwan, and Turkey. Our sample spans a wide range of countries and regions that includes both developed and emerging economies. We do not notice any specific clustering of the time of the introduction of the options market. However, developed economies introduced options earlier than emerging economies. For example, options trading in Germany started in 1983 but Malaysia introduced an options market only in 2006.

For the economy-level analysis, we compute the same two proxies of stock price informativeness. First, for each economy in each year, we compute the market synchronicity, −SYNC, of all stocks in that country using the CAPM model at the weekly frequency. Second, we calculate the price informativeness measure, FPE, following Bai et al. (2016). The intuition is that future cash flows should be more sensitive to the current market value if the price informativeness for an economy is higher. We omit the industry dummies in their model due to the missing SIC codes of many firms. As options market introduction may have long-run effects on financial markets, we focus on the Bai et al. (2016) measure calculated with a 5-year horizon.

We examine the effect of options market introduction on price informativeness by running a panel regression with the dummy variable POST, which equals 1 for years after an economy introduces options, and 0 otherwise. To rule out the

[22]Some countries have markets in OTC options and/or warrants prior to the official introduction of exchange-listed options. To the extent that these derivative instruments facilitate price informativeness, we are biased against finding an effect in our analysis.

TABLE 9

Options Market and Price Informativeness: International Evidence

Table 9 presents the impact of options market introduction on stock price informativeness using data from 25 economies. The price informativeness is measured as −SYNC or the forecasting price efficiency FPE following Bai et al. (2016) with a 5-year horizon. POST is a dummy variable equal to 1 for years after the economy introduces the options market, and 0 otherwise. Control variables include the logarithms of purchasing power parity converted per capita GDP, GDP growth rate, the logarithm of total stock market capitalization, and the logarithm of number of stocks listed. The *t*-statistics in parentheses are calculated from robust standard errors clustered by economy. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 1981 to 2016 for the −SYNC measure, and 1981 to 2011 for the FPE measure.

	−SYNC	FPE
	1	2
POST	0.412***	0.035**
	(3.19)	(2.40)
ln(GDP_PER_CAPITA)	0.384	−0.057**
	(1.20)	(−2.25)
GDP_GROWTH_RATE	−1.711	−0.233
	(−1.24)	(−1.21)
ln(TOTAL_MARKET_CAP)	−0.079	0.009
	(−0.97)	(1.34)
ln(NUMBER_OF_STOCKS_LISTED)	0.461**	0.006
	(2.68)	(0.58)
Economy FE	Yes	Yes
No. of obs.	799	674
Adj. R^2	0.488	0.172

possibility that we have captured some fundamental changes at the economy level, we control for several macroeconomic variables as well as economy-fixed effects in our regression analysis. Following Morck et al. (2000), we include the logarithm of per capita GDP at purchasing power parity levels and the logarithm of numbers of listed stocks in our control variables. We also control GDP growth and the logarithm of total market capitalization. All control variables are lagged by 1 year. The sample period is from 1981 to 2016 for the −SYNC measure and 1981 to 2011 for the FPE measure. The results of the panel regression are reported in Table 9. We find that there is a significant increase in both price informativeness measures after the introduction of the options market. The coefficient on POST is statistically significant at the 1% level for −SYNC and at the 5% level for the FPE measure. Thus, consistent with our firm-level analysis, we find a positive impact of options on price informativeness in the international sample.

VI. Conclusion

We investigate the effect of options trading on stock price informativeness using the PPP as exogenous shocks to options trading volume. We find that options trading volume increases stock price informativeness measured by both the return synchronicity and the forecasting efficiency of market valuation. Specifically, using the PPP inclusion status as an instrumental variable for options trading volume and using a DiD matching approach, we find pilot firms' stock returns comove less with the market and industry returns, compared with the nonpilot firms. Therefore, stock prices of pilot firms contain more firm-specific information. Market valuation of pilot firms also better predicts the future earnings after inclusion in the PPP,

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consistent with higher stock price informativeness. Our results are robust to a set of alternative matching metrics.

We also show that exogenous increases in options trading lead to more information acquisition by investors, consistent with the theoretical channels in Grossman and Stiglitz (1980) and Goldstein and Yang (2015). Our cross-sectional analysis further supports the channels and shows that the effect of options trading on price informativeness is stronger for firms for which the information in options trading is more important, and for firms with more efficiently priced options.

Our findings reinforce the bright side of options trading documented by previous literature such as Cao (1999) and Pan and Poteshman (2006). Options trading reduces the information asymmetry in the underlying stock market and increases the informational efficiency from the substitutional effects to stock trading. We focus on the absolute level of information content of prices (i.e., Brunnermeier (2005) price informativeness). At the same time, it remains difficult to directly measure the proportion of information contained in the trading activities of different types of investors. It would be an interesting extension of our work to exactly classify and track investors, and to decompose the aggregate impact of different investors on stock price informativeness.

Variable Definitions

Dependent Variable (Measured in the Current Year)

−SYNC: Negative synchronicity: Negative synchronicity is defined as $\ln\left(\left(1-R^2\right)/R^2\right)$. The higher the value, the higher the stock price informativeness. R^2 of annual time-series regression of weekly stock returns on weekly returns of the value-weighted market portfolio, and Fama–French 48-industry portfolio. We require a minimum of 26 valid observations in a firm year.

Forecasting price efficiency (FPE) in Bai et al. (2016): Following Bai et al. (2016), the forecasting price efficiency (FPE) for the stock price to forecast future cash flow is calculated using cross-sectional regression within the stocks each year.

OPTVOLM: Options trading volume: The annual dollar options trading volume in millions across all options for a given stock.

Google Trends index (GOOGLE_TRENDS): Google Trends search volume index with category 7 (finance-related search). A higher index indicates higher search volume. Data are retrieved from the Google Trends service. Coverage: 2004–2016.

Analyst Forecast Revision Frequency (FREQ): The average number of annual forecasts issued by analysts following the firm over a year.

Analyst Forecast Dispersion (DISP): The average standard deviation of analyst forecasts is divided by the consensus forecast.

Independent Variable (Measured in the Previous Year)

RET: Annual stock returns.

STD: The standard deviation of daily stock returns.

INSTOWN: Institutional ownership: the ratio of institutional investors' holding the number of shares divided by the total number of shares outstanding.

STKVOLM: Annual stock trading volume (in millions).

ROA: The operating income before depreciation scaled by total assets.

ln(MV): The natural logarithm of market value, calculated as the product of price close at the calendar year and the total number of shares outstanding.

BTM: Book to market ratio: the ratio of book value per share divided by price close at the calendar year.

TURNOVER: The ratio of total trading volume divided by the total number of shares outstanding.

SKEW: The sample skewness of daily stock returns.

BETA: The year-end market beta of monthly stock returns.

PRCERR: The option pricing error measure is based on Hasbrouck (1993) and calculated monthly using intra-day option trades data. Averaged within each stock and year to be consistent with other measures. To ensure reasonable estimation, there must be over 50 transactions in each option month. Data are provided by the Options Price Reporting Authority (OPRA). Coverage: 2004–2015.

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