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Oil price uncertainty and stock price informativeness: Evidence from investment-price sensitivity in China

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ABSTRACT

We study the effects of oil price uncertainty (OPU) on stock price informativeness based on investment-price sensitivity. Using Chinese stocks from 2008 to 2021, we find a negative relationship between OPU and the strength of Tobin's q (a standardized measure of prices) for predicting investment opportunities. This finding is likely due to the crowding out of informed investors rather than the financial constraints brought by a higher cost of capital. Investment-price sensitivity also decreases more among firms in less-competition, high sales volatility, and lower analysts' attention. What is more, the reduction in investment-price sensitivity is more concentrated in public utilities, agriculture & livestock, and industry instead of in real estate or commerce industries. These findings indicate that OPU decreases the acquisition of information related to firms, and consequently, price informativeness for future investment decisions.

1. Introduction

Crude oil, which is one of the world's most momentous raw materials, exerts a significant impact on the world economy. Numerous studies have shown that the shock of oil price uncertainty (OPU) leads to economic recession and influences China's macroeconomic activities as well as macroeconomic policies (Tang, Wu, & Zhang, 2010; Xu, Fu, & Wang, 2022). Additionally, OPU also affects microeconomic activities, for example, firms' investment decisions (Maghyereh & Abdoh, 2020; Phan, Tran, & Nguyen, 2019), financing decisions (Haushalter, Heron, & Lie, 2002), and cash holdings (Zhang, Zhang, & Zhou, 2020). Hence, studying the influence of OPU is of great practical significance. Meanwhile, few research studies have examined the association between OPU and stock price information. Most of these studies have focused on spillover effects in different markets, but few have provided empirical evidence of the impact on investor behavior (Ågren, 2006; Chen, 2010).

In this paper, we primarily examine how OPU impacts stock price informativeness. When facing OPU, managers may rely on market information to optimize decision making (i.e., investment decisions). Thus, informed investors could increase or decrease in trading to change the stock price information and transmit their own expectations. Furthermore, managers can observe growth opportunities through learning price information and then making investment decisions. Therefore, based on the investment-price sensitivity framework, after testing the sample of Chinese listed companies from 2008 to 2021, we find a negative correlation between OPU and stock price informativeness (investment-price sensitivity, the strength of Tobin's q as a standardized evaluation of prices to predict investment opportunities). Our findings furnish evidence that OPU increases the discount rate of external investors, thus demotivating investors from gathering information and decreasing the stock price information that is not possessed by the manager.

Next, we apply four methods to check the robustness of our basic results. First of all, we use oil product pricing mechanism reform to examine whether OPU causes a change in investment-price sensitivity. After the reform of the refined oil product pricing mechanism, domestic crude oil prices were linked to international crude oil prices so that oil price adjustment became more frequent, and the price transmission

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channel was less obstructed. Therefore, if OPU is associated with making decisions based on information from informed investors, the oil price management method (OPMM) enhances the sensitivity of informed investors to oil price fluctuations. Next, to control for potential endogeneity, we use the instrumental variable method. Then, we adopt the high-dimensional fixed effects model to exclude the influence of unobservable firm characteristics. Fourth, we employ another approach to measure OPU to address the measurement error problem. Overall, our main results remain consistent.

Third, we conjecture two possible channels for the negative interrelationship between OPU and stock price informativeness. First, in the secondary market, OPU may crowd out informed investors and hence reduce stock price informativeness, which may lead to less dependence on stock price information for managers. This mechanism is similar to Jayaraman and Wu (2019). And that, according to Jayaraman and Wu (2019), we put forward the stock price information channel. In addition, in the primary market, OPU may coincide with a tightened set of financial constraints brought by a higher cost of capital, which would make it more difficult for managers to diversify investments in accordance with investment opportunities (Edmans, Jayaraman, & Schneemeier, 2017). We call this mechanism the financial constraints channel.

We follow the literature in using the measure of the probability of informed trading (*PIN*) and the shareholding proportion of institutional investors (*INS*) to capture informed trading and find supporting evidence for the channel of stock price information. Also, we utilize *SA* index and *KZ* index to measure financial constraints, and find little evidence for the channel of financial constraints brought by a higher cost of capital. Hence, we infer that the negative influence of OPU on stock price informativeness is probably due to the crowding out of informed investors instead of financial constraints brought by a higher cost of capital.

Fourth, we further check the impact of stock price information based on industry characteristics and firm characteristics on the correlation between OPU and stock price informativeness. Although the above empirical result shows an average negative relation between OPU and stock price informativeness, we could observe more negative sensitivity in the subsamples with managers relying more on price information when making decisions. First, Allen (1993) indicates that managers rely more on price information in firms belonging to less-competition industries, since managers can observe peer firms' behavior before they make investment decisions. Our empirical results also obtain a negative influence of OPU on stock price informativeness only in firms in industries with less competition (i.e., the Herfindahl-Hirschman index). Second, we split the full sample into two subsamples according to the extent of firm sales volatility. Following stock price information channel, managers rely more on market information in high production function uncertainty. In our research, the effect of OPU on price informativeness is only significant in firms with high sale volatility. Third, sell-side analysts play a role in communicating between firms and investors, thus leading firms with more analysts' attention to face low information asymmetry when OPU increases. It is found that investment-price sensitivity also significantly decreases more in firms with low analysts' attention. In short, by splitting our full sample into different industries or different firms, we check the stock price information channel driving the negative relation between OPU and stock price informativeness.

Fifth, we explore the impact of OPU on investment-price sensitivity among different industries. The results show that the reduction in investment-price sensitivity is more remarkable in public utilities, agriculture & livestock, and industry instead of in real estate or commerce industries. In addition, after excluding the influence of stock market crises and Chinese oil price uncertainty, the re-estimated results are still robust.

These findings suggest that OPU decreases the acquisition of information on firms and consequently price informativeness about future investment decisions.

We make several contributions to the literature. First, we contribute to the small but growing strand of literature on the real and financial effects of OPU by investigating its influence on stock price informativeness. To the best of our knowledge, although many studies have examined the interrelationship between the crude oil market and stock markets (e.g., Xiao, Zhou, Wen, & Wen, 2018), this research topic has not been asked in the literature, which has ignored the effect of OPU on investors, managers and market efficiency.

Second, we contribute to the finance literature on market efficiency and managerial learning (i.e., the real effects of stock prices on corporate decisions) from the perspective of OPU. The traditional finance literature only considers price informativeness as being how well prices reveal future cash flows, which is termed "forecasting price efficiency" (FPE) in Bond, Edmans, and Goldstein (2012). We follow his point and the subsequent literature to study an under-researched aspect of price informativeness, "revelatory price efficiency" (RPE): the degree to which prices reflect "new" information to managers (Edmans, Goldstein, & Jiang, 2015). This strand of literature on RPE is much smaller than that on FPE, and we adopt a new perspective.

Third, we contribute to the oil pricing literature generally by studying the second moment instead of the levels of crude oil prices, as the extreme event of a negative oil price in April 2020 has made many standard oil pricing methodologies (e.g., the ARCH and GARCH family of models) infeasible. Of course, there are more ways to circumvent this problem (such as simply treating the observation around this event as an outlier), but OPU has its own economic meaning beyond this single event. The importance of OPU has been highlighted since this event, and hence, people have become more interested in it.

Fourth, while most of the three strands of literature above focus on developed markets such as the U.S. (e.g., Alsalman, 2016; Zhang & Hamori, 2021), we provide fresh evidence from China, the largest emerging market in the world with the second-largest equity market capitalization. With the largest gross domestic product in terms of purchasing power parity (second-largest in terms of foreign exchange parity) and the highest proportion of the largest 500 companies in the world,[1] the equity markets in China are seriously under-researched relative to their size and importance (Fan, Zhang, & Zhao, 2021; Wang, Xiang, Ruan, & Hu, 2017; Zhu, Chen, Hau, & Chen, 2021). For example, it remains unclear whether the famous investment–price relationship holds in China as it does the U.S. ex ante. Hence, we contribute to the small but growing strand of studies on Chinese financial markets as well.

The rest of this paper is organized as follows. In Section 2, we review related literature and develop our hypothesis. Section 3 briefly introduces our data and methodology, while Section 4 presents our empirical results. In Section 5, we conclude the paper.

2. Literature review and hypothesis

2.1. Literature review on investment-price sensitivity

The idea of "investment-price sensitivity" dates back to Hayek (1945). He proposes that price pools the information of different participants in the financial market and eventually forms an accurate assessment of corporate value. This information, gathered from diverse investors, may be more informed than managers know, for example, by financial situation and consumer demand (Grossman, 1976; Hellwig, 1980). Therefore, when managers make an investment decision, they should consider the information they own and the incremental information revealed in prices (Bond et al., 2012). Accordingly, investment is sensitive to stock prices: managers can gain useful information from the

[1] Chinese (USA) companies accounted for 129 (121) firms on the 2019 Fortune Global 500 list by revenue. https://enapp.chinadaily.com.cn/a/201907/24/AP5d376510a3106b83cdbf8a27.html

stock price and make corresponding investment decisions.

However, not all information reflected in stock prices is valid. The stock price includes two kinds of information: fundamental information and private information owned by investors. Traditional studies focus mainly on the relationship between stock price and fundamental information of the company to predict the future cash flow of the company. Bond et al. (2012) term this as "forecast price efficiency" (FPE). In terms of the company's basic information, managers have more prominent information advantages than investors, so FPE is ineffective for making investment decisions. In contrast, investors' private information explains the information required by managers to make correct investment decisions and can reasonably predict firm value. Bond et al. (2012) term this as "revelatory price efficiency" (RPE), which is often adopted to evaluate market efficiency. Dow and Gorton (1997) establish a model in which managers learn from stock prices and discovered two equilibria. In the first equilibrium, investors in the market trade and produce information, and managers invest based on price. In the second equilibrium, investors do not deal, and managers do not invest. This model indicated that RPE is effective, whereas FPE is invalid.

Bond et al. (2012) also state that price information affects managers' behavior through two channels. The first is the learning channel. That is, price information affects managers' ability to invest effectively. The more private information is reflected in stock prices, the more useful information managers can obtain. Foucault and Gehrig (2008) suggest that cross-listing drives managers to gain useful information from stock prices and improves decision-making efficiency. The second channel is the incentive channel, which affects managers' motivation to invest efficiently. Since managers' contracts are linked to stock prices, they are more focused on movement in stock prices. That is, stock prices affect managerial incentives and drive managers to learn from the market. The stronger the managerial motivation is, the greater the investment-price sensitivity. Holmström and Tirole (1993) find that a prosperous incentive mechanism inspires managers to learn from markets and enhances investment-price sensitivity.

2.2. Literature review on OPU

With the financialization of commodities, the links between the commodity market and secondary markets are increasingly close. Demirer, Lee, and Lien (2015) note that investors have already regarded commodities as assets equivalent to financial assets such as stocks. And they hold positions in commodities to profit from them. Uncertainty in commodity markets is transmitted to secondary markets through investors. For example, crude oil, as an indispensable raw material in production activities, affects the production cost of firms (Phan et al., 2019; Xiao et al., 2018). Meanwhile, the profits and dividends of firms, which are vital drivers of stock prices, are impacted when they are unable to fully pass on costs to consumers. Ågren (2006) proves that there is dynamic linkage between OPU and stock market uncertainty. In particular, as uncertainty in the market increases, the costs of information transmission and of investors seeking information also increase (Xue, Ray, & Gu, 2011). In short, OPU augments information search cost.

Moreover, OPU not only affects stock price volatility but also influences corporate behavior. Some strands of literature discuss the influence of OPU on corporate activities (Maghyereh & Abdoh, 2020; Xiao et al., 2018). These studies show that firms tend to be more conservative when facing high uncertainty. Managers cannot easily make investment decisions and would like to "wait and see" rather than take action that may lead to losses. Thus, they delay investment (Bernanke, 1983). Since investment is irreversible, they may miss some projects that have positive net present value (NPV) (Gulen & Ion, 2016). Gao, Grinstein, and Wang (2017) state that firms facing uncertainty also confront uncertain future investment opportunities, uncertain operating cash flow, and uncertain external financing costs. To avoid risks, they are eager to hold cash rather than invest. These studies provide evidence that OPU drives managers to be more cautious.

2.3. Hypothesis development

Different information is gathered in the stock market, and then reflected in the stock price through investors' continuous trading (Jiang, Kim, & Pang, 2011). External informed investors have provided private information that internal investors do not know. Thus, managers have potential inspiration to learn from the private information held by informed investors through stock prices. Therefore, if pricing effectiveness increases based on aggregated information, stock price information helps managers to learn (e.g., Bai, Philippon, & Savov, 2016; Bond et al., 2012; Chen, Goldstein, & Jiang, 2007; Edmans et al., 2015, 2017; Ye, Zheng, & Zhu, 2019).

OPU may crowd out informed investors. Uncertainty in crude oil markets spreads to capital markets, further affecting the risk of financial assets (Alomran & Alsubaiei, 2022). With the increase in capital market uncertainty, it is more tough for investors to accurately assess firms' value, and the cost of searching for information increases, which leads to uncertain profits or losses. Therefore, investors' trading motivation weakens. Many studies indicate that due to the OPU, the challenge of predicting future cash flows and profitability decreases investors' trading motivation (Phan et al., 2019). As a result, informed investors may be crowded out of the stock market, and stock prices will then contain less private information from external investors.

OPU makes managers more conservative and impairs managerial learning motivation. Pindyck (1991) and Dixit and Pindyck (2012) indicate that firms facing uncertainty should delay making investment decisions until managers aggregate sufficient information. Uncertainty, such as political uncertainty (Gulen & Ion, 2016), enhances the option value of waiting for the investment and decreases the NPV of the investment. Managers are more likely to make mistakes in an uncertain environment. To avoid risks, managers prefer to "wait and see" rather than take a costly action with uncertain consequences (Bloom, Bond, & Van Reenen, 2007). Therefore, they are less likely to learn from the market. In addition, managers need more information to help them make appropriate investment decisions. Since OPU leads to noisy information, managers are expected to spend more to gather information and invest more effort in identifying the authenticity of the information, forcing them to pay a higher cost to obtain the information required (Bloom et al., 2007). Aiming to maximize their own benefits, managerial motivation to learn from stock prices weakens.

Based on the discussions above, OPU may crowd out informed investors and decrease stock price information. At the same time, OPU also stimulates managerial sensitivity to the aggregate information associated with making decisions regarding corporate investment. Facing OPU, the risk aversion of informed investors' conflicts with the managerial demand for information, which should weaken managerial learning from the market. As such, we propose the following hypothesis:

Hypothesis: OPU exerts a negative impact on investment-price sensitivity.

3. Data and methodology

3.1. Sample construction

We employ a sample of Chinese listed companies from 2008 to 2021. We obtain firm-level financial data and stock price data from the China Stock Market and Accounting Research (CSMAR) database. The crude oil volatility index data are extracted from the Chicago Board Options Exchange (CBOE).[2] Since the crude oil volatility index data are available from 2007, our sample period spans the period from 2008 to 2021.

[2] See https://cdn.cboe.com/api/global/us_indices/daily_prices/Oil price uncertainty_History.csv.

Following previous studies, firms in the financial industry and firms that have missing values are excluded. To eliminate the influence of outliers, all continuous variables are winsorized at their 1st and 99th percentiles. Consequently, our final sample includes 27,883 firm-year observations and 2403 firms.

Table 1 represents the summary statistics of all variables used in our study. For dependent variables, the means (medians) of *Inv1* and *Inv2* are 0.061 (0.040) and 0.062 (0.042), respectively. In addition, *Tobin's q* has a mean of 2.005 and a median of 1.599, while *OPU* (annual OPU) has a mean of 36.655 and a standard deviation of 10.454. Overall, the summary statistics of our variables are consistent with those reported in other relevant studies (López, 2018; Wang, Wang, & Wang, 2021; Yang, He, Zhu, & Li, 2018).

3.2. Methodology

The major variable of interest in our paper is *OPU*, which is used by the CBOE to measure annual OPU. The calculation formula of *OPU* is shown below:

$$OPU = \frac{1}{\mathrm{n}}\sum_{k=1}^{n} DailyOPV_{t,k} \tag{1}$$

where OPU_t is oil price uncertainty in year *t*. *OPV* is the daily oil price volatility, and *n* is the total trading days of year *t*.

To investigate the impact of *OPU* on investment-price sensitivity, we estimate the following baseline model:

$$\begin{aligned} INVi,t = \beta 0 + \beta 1Qi,t-1 + \beta 2OPUi,t-1 + \beta 3Qi,t-1 \times OPUi,t-1 + \beta 4CFi,t-1 \times OPUi,t-1 \\ + \beta 5CFi,t-1 + \beta 6Sizei,t-1 + \theta i + \mu t + \varepsilon i,t \end{aligned} \tag{2}$$

where $INV_{i,t}$ is corporate investment for firm *i* in year *t*. Following Bhandari and Javakhadze (2017), we adopt two variables to measure corporate investment: (i) capital expenditures (CAPX) scaled by lagged total assets and (ii) capital expenditures (CAPX) plus R&D scaled by lagged total assets. $Q_{i,t-1}$ is the Tobin's q of firm *i* in year *t-1*, which is defined as the market value of equity plus the book value of debt scaled by the book value of assets. Follow with Fama and French (1992) and Xing (2008), Tobin's q is associated with stock price and reflects the growth opportunity in the investors' view. Tobin's q has been used to measure stock prices in the empirical literature (e.g., Edmans et al., 2017; Jayaraman & Wu, 2019). In addition, we introduce several control variables to the traditional investment-price sensitivity model. The first control variable is cash flow (CF), which is related to the solvency of the company and is crucial to entity survival. Moreover, since firm size affects a firm's transaction costs and level of information asymmetry (Houston & James, 1996; Nooteboom, 1993), we also include *Size* as a control variable. Additionally, we include firm fixed effects (θ_i) and year fixed effects (μ_t). Detailed definitions of all variables employed in our paper are presented in the appendix.

We mainly focus on β_3, that is, the influence of *OPU* on investment-price sensitivity. According to the hypothesis, if *OPU* weakens stock price informativeness, β_3 is significantly negative.

4. Empirical results and analysis

4.1. Baseline results

Our paper first tests the influence of *OPU* on investment-price sensitivity. The regression results of the benchmark regression are shown in Table 2. In Column 1, the dependent variable is *INV1*, which refers to corporate annual capital expenditures. In Column 2, the dependent variable is *INV2*, which measures corporate annual capital expenditures and R&D investment.

In Column 1, the main coefficient of interest is that for the interaction between *Q* and *OPU*. The coefficient on $Q \times OPU$ is negative and

Table 1
Summary statistics.

Variable	N	Obs.	S.D.	Min	P25	P50	P75	Max
Dependent variables								
INV1	27,883	0.061	0.065	0.000	0.017	0.040	0.081	0.357
INV2	27,883	0.062	0.065	0.000	0.018	0.042	0.083	0.676
Independent variables								
Q	27,883	2.005	1.299	0.078	1.219	1.599	2.310	10.617
OPU	27,883	36.655	10.454	22.480	29.789	33.331	44.702	58.395
Channel variables								
PIN	27,883	0.315	0.037	0.000	0.299	0.323	0.339	0.443
INS	27,883	25.037	24.411	0.000	2.032	17.220	45.840	98.100
SA	27,883	−3.483	0.301	−4.358	−3.706	−3.464	−3.265	−1.750
KZ	27,883	1.396	2.399	−15.297	0.222	1.628	2.843	17.195
Control variables								
CF	27,883	0.044	0.073	−0.337	0.004	0.043	0.086	0.252
Size	27,883	22.157	1.348	19.222	21.207	21.991	22.916	26.709
HHI	27,883	0.125	0.146	0.016	0.049	0.077	0.144	1.000
Sale_Var	27,883	0.232	0.271	0.000	0.096	0.167	0.277	7.621
Report	27,883	15.854	23.639	0.000	1.000	6.000	21.000	253.000

This table shows the summary statistics for all variables used in our study. After excluding firms in the financial industry and those with missing values, our final sample consists of 27,883 firm-year observations covered by the CBOE and CSMAR databases over the period 2008–2021. All continuous variables are winsorized at their 1st and 99th percentiles. The exact definitions of all variables are shown in the Appendix.

Table 2
OPU and investment-price sensitivities.

	$INV1_t$	$INV2_t$
	(1)	(2)
Q_{t-1}	0.00713***	0.00790***
	(5.221)	(5.578)
OPU_{t-1}	−0.00064***	−0.00054***
	(−5.985)	(−4.890)
$OPU_{t-1} \times Q_{t-1}$	−0.00008***	−0.00008***
	(−2.732)	(−2.907)
$OPU_{t-1} \times CF_{t-1}$	−0.00007	−0.00010
	(−0.147)	(−0.209)
CF_{t-1}	0.04116**	0.04483**
	(2.178)	(2.319)
$Size_{t-1}$	−0.01050***	−0.01010***
	(−8.564)	(−7.831)
Constant	0.31700***	0.30470***
	(12.152)	(11.140)
Year effect	Yes	Yes
Firm fixed effect	Yes	Yes
Observations	27,883	27,883
R^2	0.101	0.096

This table shows the benchmark regression results for the influence of *OPU* on investment-price sensitivity. Our final sample consists of 27,883 firm-year observations with non-missing values for the period 2008–2021. The dependent variables are two measures of investment: *INV1* and *INV2*. The independent variable of interest is $Q \times OPU$. In both Columns, we include the year fixed effects and firm fixed effects to control the unobservable year-level and firm-level heterogeneity. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

statistically significant at less than the 1% level, indicating that *OPU* weakens investment-price sensitivity. The coefficient on CF×*OPU* is negative but not statistically significant. These results indicate that firms adjust their investment expenditures based on stock price information rather than their own cash flows. Similar to the study of Edmans et al. (2017), managers must establish a balance between learning information from stock prices and cash flows. According to our hypothesis, *OPU* may increase firm risk, crowd out informed investors, and, consequently, reduce stock price informativeness. Therefore, *OPU* could reduce investment-price sensitivity.

In addition, *Q* shows a positive relationship with investment, which is similar to the finding of Edmans et al. (2017). Consistent with Maghyereh and Abdoh (2020), *OPU* will limit the company's investment. In addition, *Size* is negatively correlated with investment, which is consistent with Foucault and Fresard (2012, 2014). CF is positively correlated with investment, which is in line with Ouyang and Szewczyk (2018).

To observe investment-price sensitivity comprehensively, we replace *INV1* with *INV2* and report the re-estimated results in Column 2. Compared with the independent variable *INV1*, *INV2* includes the R&D investment of firms. Chen et al. (2007) and Goldstein, Yang, and Zuo (2020) indicate that R&D investment is used to measure R&D activities and is regarded as a significant investment expenditure of firms. In Column 2, the coefficients of $Q \times OVX$ are still negative and statistically significant at less than the 1% level, which is similar to Column 1.

In regard to the economic significance of *OPU* in our manuscript, taking Column 1 in Table 2 as an example, with one standard deviation increasing of *OPU*, investment-price sensitivity will decrease by 11.78% $(-0.00008 \times 10.454)/0.0071 = 11.78\%$). Therefore, *OPU* is a crucial factor affecting stock price informativeness.

4.2. Endogeneity

In this section, we address some endogeneity issues. Our baseline results have shown that there is a negative relationship between *OPU* and investment-price sensitivity. However, this causal effect may arise from endogenous causes. First, the *Oil Price Management Method* (*Trial*, OPMM) bill issued in 2009 may exert an impact on our basic empirical results. Second, the correlation between *OPU* and investment-price sensitivity is likely affected by unobservable firm characteristics and unobserved heterogeneities. Third, the measurement of *OPU* may not be appropriate. Therefore, we adopt the event shock method, instrumental variable approach, high-dimensional fixed effects, and measurement error to eliminate possible endogeneity issues.

4.2.1. The impact of oil product pricing mechanism reform

On 7 May 2009, China issued the OPMM (*Trial, OPMM*), stipulating that crude oil prices would be formulated independently by enterprises according to international market prices. After the reform of the refined oil product pricing mechanism, domestic crude oil prices were linked to international crude oil prices so that oil price adjustment became more frequent, and the price transmission channel was less obstructed. Therefore, if *OPU* is related to informed investors' information decisions, *OPMM* will enhance the sensitivity of informed investors to oil price fluctuations. The increase in *OPU* crowds out informed investors, thus reducing stock price informativeness. Consequently, the implementation of a refined oil product pricing mechanism might strengthen the inhibitory effect of *OPU* on investment-price sensitivity.

We test this prediction by establishing the following model:

Table 3
The impact of oil product pricing mechanism reform.

	$INV1_t$	$INV2_t$
	(1)	(2)
Q_{t-1}	−0.00512	−0.00552
	(−1.055)	(−1.133)
OPU_{t-1}	−0.00058***	−0.00060***
	(−2.602)	(−2.669)
OPMM	0.18363***	0.15757***
	(5.157)	(4.347)
$OPMM \times Q_{t-1}$	0.01221**	0.01346***
	(2.479)	(2.708)
$OPMM \times CF_{t-1}$	−0.23780***	−0.24599***
	(−3.601)	(−3.684)
$OPMM \times Size_{t-1}$	−0.00916***	−0.00907***
	(−6.132)	(−5.969)
$OPMM \times OPU_{t-1}$	0.00018	0.00064***
	(0.790)	(2.780)
$OPMM \times OPU_{t-1} \times Q_{t-1}$	−0.00027**	−0.00030**
	(−2.105)	(−2.310)
$OPMM \times OPU_{t-1} \times CF_{t-1}$	0.00365**	0.00379**
	(2.480)	(2.535)
$OPU_{t-1} \times Q_{t-1}$	0.00019	0.00020
	(1.454)	(1.601)
$OPU_{t-1} \times CF_{t-1}$	−0.00374***	−0.00390***
	(−2.665)	(−2.750)
CF_{t-1}	0.26886***	0.28023***
	(4.234)	(4.375)
$Size_{t-1}$	−0.00244	−0.00211
	(−1.283)	(−1.081)
Constant	0.14479***	0.13837***
	(3.322)	(3.104)
Firm fixed effect	Yes	Yes
Year effect	Yes	Yes
Observations	27,883	27,883
R^2	0.107	0.102

This table explores the impact of the OPMM on the relationship between *OPU* and investment-price sensitivity. *OPMM* is an indicator variable equal to one for observations after 2009 (including 2009) and zero for those before 2009. In both Columns, we employ firm fixed effects and year fixed effects to exclude unobservable heterogeneity. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

$$INVi,t = \beta 0 + \beta 1Qi,t-1 + \beta 2OPUi,t-1 + \beta 3OPMM + \beta 4Qi,t-1 + \beta 4OPMM \times Qi,t-1 \\ + \beta 5OPMM \times CFi,t-1 + \beta 6OPMM \times Sziei,t-1 + \beta 7OPMM \times OPUi,t-1 \\ + \beta 8OPMM \times Qi,t-1 \times OPUi,t-1 + + \beta 9OPMM \times OPUi,t-1 \times CFi,t-1 \\ + \beta 10Qi,t-1 \times OPUi,t-1 + \beta 11CFi,t-1 \times OPUi,t-1 + \beta 11CFi,t-1 \\ + \beta 12Sizei,t-1 + \theta j + \mu t + \varepsilon i,t \quad (3)$$

where *OPMM* is an indicator variable equal to one for samples after 2009 (including 2009) and zero for those before 2009. All other variables are as defined previously. Our primary coefficient of interest in this model is the interaction variable *OPMM*×*Q* × *OPU*. If the OPMM makes informed investors more sensitive to *OPU*, we expect a negative coefficient on the interaction term ($\beta_8 < 0$).

Table 3 reports the regression results from estimating Eq. (3). We find that the coefficients on *OPMM* are positive and statistically significant at less than the 1% level in Columns 1 and 2, suggesting an increase in investment after the oil product pricing mechanism was implemented. The coefficients on the interaction term *Q* × *OPU* are not statistically significant. These results indicate that prior to the oil product pricing mechanism reform, *OPU* did not crowd out informed investors. The estimated coefficients of the interaction term *OPMM*×*Q* × *OPU* are negative and statistically significant. These results support our assumption that the reform of the refined oil product pricing mechanism enhances the negative relationship between *OPU* and investment-price sensitivity.

4.2.2. Instrumental variable approach

With the mutual penetration of the oil market and stock market, comovement between the two markets is more closely associated (Junttila, Pesonen, & Raatikainen, 2018). For example, during the global financial crisis, investors' emotions may have simultaneously impacted the oil and stock markets. Maghyereh and Abdoh (2020) point out that excessive investor sentiment during a crisis will not only affect stock returns but also contribute to short-term fluctuations in crude oil prices. Therefore, unobserved omitted variables may pose a problem that we need to address.

To control endogeneity concerns regarding unobserved omitted variables, we adopt an instrumental variable approach to re-estimate our benchmark hypothesis. We use *OPU* at period *t*-2 as the instrumental variable, which meets two conditions for the instrument variable. First, it meets the relevance criterion: *OPU* at period *t*-2 contains historical information on the oil price, which is highly correlated with the endogenous variable *OPU* at period *t*-1 in our paper. Second, it meets the exclusion restriction: *OPU* at period *t*-2 is not directly associated with investment decisions made in period *t*. Collectively, this instrumental variable can reduce endogeneity concerns in research design.

We present the results of the instrumental variable approach in Table 4. In the first-stage regression, we find a strong and positive relationship between *OPU* and its instrument, as expected. In the second-stage regression, we replace the original values of *OPU* with its fitted values from the first-stage regression. The coefficients estimated on instrumented *OPU* are positive and statistically significant at the 1% level. The results show that our baseline regression results are robust.

Table 4
Instrumental variable approach.

	$INV1_t$	$INV2_t$
	(1)	(2)
Q_{t-1}	0.02558***	0.03109***
	(3.874)	(4.588)
Instrumed-OPU$_{t-1}$	−0.02196***	−0.01876***
	(−5.529)	(−4.555)
Instrumed-OPU$_{t-1}$ × Q_{t-1}	−0.00056***	−0.00070***
	(−3.146)	(−3.826)
Instrumed-OPU$_{t-1}$ × CF_{t-1}	0.00755***	0.00767***
	(2.989)	(2.969)
CF_{t-1}	−0.25546***	−0.25736***
	(−2.745)	(−2.700)
$Size_{t-1}$	−0.00917***	−0.00867***
	(−7.586)	(−6.769)
Constant	1.04988***	0.92399***
	(7.910)	(6.738)
Firm Fixed Effect	Yes	Yes
Year Effect	Yes	Yes
Observations	25,480	25,480
R^2	0.082	0.078
First stage		
OVX_{t-2}	0.20933***	0.20933***
	(32.115)	(32.115)
R^2	0.032	0.032

This table reports the two-stage least squares regression results to examine endogeneity concerns regarding unobserved omitted variables. We adopt *OPU* at the t-2 period as the instrumental variable for *OPU*. In both Columns, we employ firm fixed effects and year fixed effects to exclude unobservable heterogeneity. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

4.2.3. High-dimensional fixed effects

A weakness of our model is that we only control for observable firm characteristics but ignore the unobserved heterogeneity across firms as well as time-invariant heterogeneity across industries (Gormley & Matsa, 2014). For example, during the COVID-19 period, some industries, including the airline and tourism industries, experienced

Table 5
High-dimensional fixed effects.

	$INV1_t$	$INV2_t$
	(1)	(2)
Q_{t-1}	0.00683***	0.00763***
	(4.847)	(5.315)
OPU_{t-1}		
OPU_{t-1} × Q_{t-1}	−0.00007**	−0.00008***
	(−2.397)	(−2.620)
OPU_{t-1} × CF_{t-1}	−0.00031	−0.00034
	(−0.661)	(−0.707)
CF_{t-1}	0.04994***	0.05355***
	(2.673)	(2.813)
$Size_{t-1}$	−0.01140***	−0.01097***
	(−11.036)	(−10.593)
Constant	0.30349***	0.29354***
	(13.117)	(12.652)
Firm fixed effect	Yes	Yes
Industry effect×Year effect	Yes	Yes
Observations	27,883	27,883
R^2	0.434	0.419

This table reports the high-dimensional fixed effects estimation results for the impact of *OPU* on investment-price sensitivity. In both Columns, we apply the firm fixed effect and interacted industry-year fixed effects. Our sample consists of 27,883 firm-year observations from 2008 to 2021. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 6
Measurement error.

	$INV1_t$	$INV2_t$
	(1)	(2)
Q_{t-1}	0.00715***	0.00882***
	(7.982)	(9.133)
$MOPU_{t-1}$	0.00243***	0.00257***
	(6.919)	(7.119)
$MOPU_{t-1} \times Q_{t-1}$	−0.00047***	−0.00064***
	(−3.831)	(−5.124)
$MOPU_{t-1} \times CF_{t-1}$	0.01037***	0.01050***
	(7.010)	(6.913)
CF_{t-1}	−0.02823***	−0.02620**
	(−2.633)	(−2.340)
$Size_{t-1}$	−0.01082***	−0.01045***
	(−9.021)	(−8.285)
Constant	0.27116***	0.26433***
	(9.575)	(8.879)
Year effect	Yes	Yes
Firm fixed effect	Yes	Yes
Observations	27,883	27,883
R^2	0.104	0.100

This table reports the results for the impact of *MOPU* on investment-price sensitivity. In both Columns, we apply the firm fixed effect and interacted industry-year fixed effects. Our sample consists of 27,883 firm-year observations from 2008 to 2021. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

shocks, so time-varying heterogeneity across industries may disturb the robustness of our empirical results. Following Gormley and Matsa (2014), our regression controls for the firm fixed effect and the interacted industry-year fixed effects.

In Table 5, we re-estimate the empirical correlation between *OPU* and investment-price sensitivity by controlling for high-dimensional fixed effects. Since *OPU* does not vary with the industry, there exists a collinearity issue with the industry fixed effect, so its results are omitted. The interrelationship between *OPU* and investment-price sensitivity is still negative and statistically significant at the 5% level and the 1% level in each Column, which confirms that our results are robust.

4.2.4. Measurement error

The construction of variables in our paper may exists the problem of measurement error, resulting in systematic deviation of the estimated results. First, the use of average values may misestimate the actual effect. And the analysis of volatility on an annual frequency may not able to provide sufficient useful information for volatility is a high frequency measure. Therefore, we change the calculation method for oil price uncertainty and the detailed calculation formula for *MOPU* is as follows:

$$MOPU_t = \frac{\sqrt{\sum_{i=1}^{n} OPV^2}}{n} \tag{4}$$

where $MOPU_t$ is oil price uncertainty in year *t*. *OPV* is the daily oil price volatility, and *n* is the total trading days of year *t*.

We replace *OPU* with *MOPU* and re-estimated the results, which is represented in Table 6. The coefficient on $Q \times MOPU$ is negative and statistically significant at less than the 1% level, indicating that *MOPU* weakens investment-price sensitivity. It proves that our basic results are robust.

4.3. Channels

In this section, we explicitly discuss whether the stock price information channel or financial constraints channel drives the impact of oil price uncertainty on investment-price sensitivity. On the one hand, the uncertainty faced by firms, such as oil prices and economic policy, increases the cost of gathering information for informed investors. Easley and O'Hara (2010) point out that uncertainty prevents informed investors from being involved in stock trading. Thus, if stock price information potentially impacts the association between oil price uncertainty and investment sensitivity to price, oil price uncertainty crowds out informed investors and dampens the reaction of stock prices. Therefore, oil price uncertainty may lead to the crowding out of informed investors and then reduce stock price informativeness, which is reflected in the decline of investment-price sensitivity.

On the other hand, firm uncertainty also causes financial constraints and restrains investment opportunities. Fazzari, Hubbard, Petersen, Blinder, and Poterba (1988) suggest that financial constraints restrict firms' ability to pursue the optimal investment level. Firms with serious financial constraints may often forgo prosperous investment opportunities due to insufficient funds. Thus, financial constraints may be an influence channel that drives the association between oil price uncertainty and investment-price sensitivity.

We take two variables to measure stock price informativeness. First, following Chen et al. (2007) and Jayaraman and Wu (2019), we adopt the *PIN* proposed by Easley, Kiefer, and O'hara, M., and Paperman, J. B. (1996) to measure stock price information, which includes information from informed investors. *PIN* is a direct and effective measure to estimate stock price information that is supported by a substantial number of papers (Chen et al., 2007). Furthermore, Easley, Hvidkjaer, and O'hara, M. (2002) find that *PIN* estimates are quite firm-specific and temporally stable. Moreover, institutional investors are regarded as the main informed investors. They inject their private information into the stock market through arbitrage trading to improve stock price informativeness (Bushee, 1998). Thus, for robustness, we adopt the shareholding proportion of institutional investors (*INS*) to measure stock price information as well. In addition, following Hadlock and Pierce (2010) and Kaplan and Zingales (1997), we take two indexes to proxy firms' financial constraints: *SA* and *KZ*. Definitions of all variables can be found in the Appendix.

Following Li and Zeng (2019), we use the two-stage least square method (2SLS) to estimate the impact channel of *OPU* on investment-price sensitivity. First, the first-stage regression equation in this section is as follows:

$$OPU_{i,t} = \beta_0 + \beta_1 Channel_{i,t} + \theta_i + \mu_t + \varepsilon_{i,t} \tag{5}$$

where *OPU* represents oil price uncertainty and *Channel* represents the stock price information channel (*TK*) and financial constraints channel (*FC*). θ_i represents firm fixed effects, and μ_t stands for time fixed effects. The residual term $\varepsilon_{i,t}$ represents the variation in *OPU* that cannot be explained by stock price informativeness or financial constraints. Then, we substitute the residual term (*Residual_IT*, *Residual_FC*) for *OPU* in the basic Eq. (2) as the second-stage equation. It is worth noting that, as for channel exploration, we do not need to add other variables that may affect *OPU* in the first-stage regression because the residual term includes all variables that exclude the *Channel* that may affect *OPU*.

Table 7 reports the regression results of the channel analysis. Columns 1 and 2 report the empirical results based on *Residual_IT*, Columns 3 and 4 report the empirical results based on *Residual_FC*, and Columns 5 and 6 report the empirical results based on both *Residual_IT* and *Residual_FC*. In particular, the coefficients of *Residual_IT*×*Q* are not statistically significant in all Columns, indicating that after excluding the channel of stock price information, *OPU* cannot impact investment-price sensitivity. The coefficients of *Residual_TK*×*Q* are significantly negative in all Columns, suggesting that after excluding the channel of financial constraints, *OPU* will still affect investment-price sensitivity. Therefore, our results offer evidence that stock price information rather than financial constraints drives the empirical correlation between oil price uncertainty and investment-price sensitivity.

Table 7
Channels: stock price informativeness or financial constraints.

	$INV1_t$	$INV2_t$	$INV1_t$	$INV2_t$	$INV1_t$	$INV2_t$
	(1)	(2)	(3)	(4)	(5)	(6)
Q_{t-1}	0.00389***	0.00437***	0.00622***	0.00669***	0.00592***	0.00634***
	(7.115)	(7.486)	(10.545)	(10.636)	(9.917)	(9.998)
$Residual\_IT_{t-1}$	−0.00135***	−0.00154***			−0.00124***	−0.00139***
	(−5.801)	(−6.551)			(−4.731)	(−5.162)
$Residual\_IT_{t-1} \times Q_{t-1}$	−0.00005	−0.00006			0.00009	0.00007
	(−1.445)	(−1.632)			(1.163)	(0.852)
$Residual\_IT_{t-1} \times CF_{t-1}$	−0.00073	−0.00079*			−0.00956***	−0.01022***
	(−1.636)	(−1.728)			(−5.028)	(−5.231)
$Residual\_FC_{t-1}$			0.03466***	0.03398***	0.03444***	0.03373***
			(13.174)	(11.977)	(12.999)	(11.855)
$Residual\_FC_{t-1} \times Q_{t-1}$			−0.00009***	−0.00010***	−0.00013**	−0.00012*
			(−3.310)	(−3.458)	(−2.018)	(−1.767)
$Residual\_FC_{t-1} \times CF_{t-1}$			0.0006	0.00056	0.01027***	0.01089***
			(1.277)	(1.168)	(5.136)	(5.330)
CF_{t-1}	0.03990***	0.04247***	−0.00279	0.00054	−0.00356	−0.00032
	(6.277)	(6.507)	(−0.407)	(0.076)	(−0.523)	(−0.046)
$Size_{t-1}$	−0.01087***	−0.01050***	−0.00917***	−0.00879***	−0.00948***	−0.00915***
	(−8.937)	(−8.233)	(−7.611)	(−6.907)	(−7.865)	(−7.221)
Constant	0.29344***	0.28317***	0.46798***	0.45534***	0.46224***	0.44913***
	(11.030)	(10.146)	(16.341)	(15.063)	(16.178)	(14.920)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,883	27,883	27,883	27,883	27,883	27,883
R^2	0.103	0.099	0.113	0.107	0.117	0.112

This table shows the baseline regression results for investment-price sensitivity given the variations in *OPU* that cannot be explained by stock price informativeness or financial constraints. Our sample consists of 27,883 firm-year observations from 2008 to 2021. The dependent variables are two measures of investment: *Inv1* and *Inv2*. The independent variables of interest are $Residual\_IT_{t-1}$ and $Residual\_FC_{t-1}$. The residual terms estimated in Eq. (5) in the Appendix show the exact definitions of all variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

4.4. Sub-sample analyses

We further explore the heterogeneous effects of *OPU* based on different subsamples. Considering the channel for stock price information, we split the total sample into two subsamples on the basis of the information environment: industry competition, sales volatility, and analysts' attention. In particular, we expect that the samples with a weak information environment will be more sensitive to stock price information, and thus the impact of *OPU* will be stronger.

4.4.1. Industry competition

Industry competition is associated with firms' information environment. Allen (1993) indicates that managers in less-competitive industries potentially have incentives to use information from stock prices when making decisions. In highly competitive industries, a manager can learn information from peers' decisions and behaviors, such as financing policy (Leary & Roberts, 2014), investment policy (Bustamante and Frésard, 2021), earnings management (Du & Shen, 2018) and corporate disclosure decisions (Seo, 2021). However, in less-competitive industries, managers have difficulty imitating rivals, so it is important to learn from the stock market. Thus, firms in less-competitive industries might be more responsive to stock price information. Then, following the stock price information channel, we may observe a greater influence of *OPU* on investment-price sensitivity of firms in less-competitive industries.

Follow with Edmans et al. (2017), we employ the Herfindahl–Hirschman Index (*HHI)* on the strength of total assets to evaluate industry competition. It is calculated as follows:

$$HHI = \sum_{i}^{n} s_i^2 \quad (6)$$

where s_i is the market share of firm *i*. A high value of the *HHI* indicates a lower degree of industry competition. We divide our samples into highly competitive industries and less-competitive industries according to the median of the *HHI* and then perform basic regression for each subsample.

Panel A of Table 8 shows that the estimated coefficients of the interaction term on $Q \times OPU$ are negative for both subsamples but only statistically significant in the less-competition subsample. Furthermore, based on the seemingly unrelated regression (SUR), there is a significant difference in the coefficient of $Q \times OPU$ between these two subsamples. This result confirms our prediction that the effect of *OPU* on investment-price sensitivity is more pronounced in less competitive industries.

4.4.2. Sales volatility

Sales volatility measures a firm's product market uncertainty, that is, the product market information environment. Compared with firms with stable sales, firms with high sales volatility show that their product market is more uncertain, which makes it more difficult for managers to predict future sales. Therefore, in firms with high sales volatility, managers possess stronger motivation to gain new information from the price to reduce the possible impact of product market uncertainty. In summary, we may observe a greater influence of *OPU* on investment-price sensitivity in firms with high sales volatility.

Following Bo (2001), we compute the 3-year moving variance of the natural logarithm of corporate sales to construct sales volatility (*Sale_Var*). Then, we split the total samples into two subsamples according to the median of the sales volatility.

Panel B of Table 8 reports the correlation between *OPU* and investment-price sensitivity between the high and low sales volatility subsamples. The estimated coefficients of the interaction term $Q \times OPU$ are negative and statistically significant only in the high sales volatility

Table 8
Subsample analyses.

Panel A				
	INV1$_t$		*INV2$_t$*	
	(1)	(2)	(3)	(4)
	High HHI	*Low HHI*	*High HHI*	*Low HHI*
$Q_{t\text{-}1}$	0.01080***	0.00376**	0.01104***	0.00500***
	(5.053)	(2.103)	(5.140)	(2.599)
$OPU_{t\text{-}1}$	−0.00071***	−0.00050***	−0.00066***	−0.00033*
	(−4.823)	(−2.967)	(−4.371)	(−1.871)
$OPU_{t\text{-}1} \times Q_{t\text{-}1}$	−0.00014***	−0.00001	−0.00015***	−0.00002
	(−3.175)	(−0.331)	(−3.328)	(−0.559)
$OPU_{t\text{-}1} \times CF_{t\text{-}1}$	0.00031	−0.00070	0.00019	−0.00057
	(0.516)	(−0.935)	(0.304)	(−0.723)
$CF_{t\text{-}1}$	0.03682	0.03848	0.04579*	0.03224
	(1.536)	(1.288)	(1.875)	(1.042)
$Size_{t\text{-}1}$	−0.00727***	−0.01576***	−0.00697***	−0.01540***
	(−4.564)	(−8.201)	(−4.239)	(−7.205)
Constant	0.24577***	0.42789***	0.23770***	0.41417***
	(7.147)	(10.592)	(6.709)	(9.270)
Firm fixed effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
Observations	15,651	12,232	15,651	12,232
R^2	0.088	0.122	0.088	0.108
Prob>chi2	0.0321		0.0417	

Panel B				
Variables	*INV1$_t$*		*INV2$_t$*	
	(1)	(2)	(3)	(4)
	High Sale_Var	*Low Sale_Var*	*High Sale_Var*	*Low Sale_Var*
$Q_{t\text{-}1}$	0.00938***	0.00263	0.01066***	0.00324
	(4.494)	(1.352)	(5.002)	(1.587)
$OPU_{t\text{-}1}$	−0.00054***	−0.00070***	−0.00040**	−0.00060***
	(−3.087)	(−4.423)	(−2.254)	(−3.710)
$OPU_{t\text{-}1} \times Q_{t\text{-}1}$	−0.00013***	0.00001	−0.00015***	0.00000
	(−2.979)	(0.173)	(−3.334)	(0.016)
$OPU_{t\text{-}1} \times CF_{t\text{-}1}$	−0.00001	−0.00005	−0.00002	−0.00010
	(−0.020)	(−0.075)	(−0.022)	(−0.131)
$CF_{t\text{-}1}$	0.03926	0.03452	0.04316	0.03780
	(1.348)	(1.253)	(1.475)	(1.324)
$Size_{t\text{-}1}$	−0.01011***	−0.01296***	−0.00983***	−0.01241***
	(−6.009)	(−7.508)	(−5.526)	(−6.996)
Constant	0.30710***	0.37287***	0.29574***	0.35739***
	(8.635)	(10.304)	(7.840)	(9.620)
Firm fixed effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
Observations	13,962	13,921	13,962	13,921
R^2	0.098	0.098	0.097	0.089
Prob>chi2	0.0219		0.0171	

Panel C				
Variables	*INV1$_t$*		*INV2$_t$*	
	(1)	(2)	(3)	(4)
	High Report	*Low Report*	*High Report*	*Low Report*
$Q_{t\text{-}1}$	0.00503***	0.00821***	0.00675***	0.00819***
	(2.955)	(3.761)	(3.880)	(3.625)
$OPU_{t\text{-}1}$	−0.00083***	−0.00002	−0.00074***	0.00011
	(−4.236)	(−0.112)	(−3.763)	(0.772)
$OPU_{t\text{-}1} \times Q_{t\text{-}1}$	−0.00001	−0.00013***	−0.00003	−0.00013***
	(−0.223)	(−2.602)	(−0.785)	(−2.628)
$OPU_{t\text{-}1} \times CF_{t\text{-}1}$	−0.00072	0.00046	−0.00056	0.00031
	(−1.163)	(0.659)	(−0.890)	(0.442)
$CF_{t\text{-}1}$	0.07898***	−0.00238	0.07753***	0.00269
	(3.089)	(−0.089)	(2.980)	(0.100)
$Size_{t\text{-}1}$	−0.01771***	−0.01265***	−0.01659***	−0.01335***
	(−7.845)	(−7.635)	(−7.401)	(−7.703)
Constant	0.50620***	0.32083***	0.47794***	0.33224***
	(11.024)	(8.862)	(10.468)	(8.844)
Firm fixed effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
Observations	13,159	14,724	13,159	14,724
R^2	0.154	0.066	0.149	0.062
Prob>chi2	0.0519		0.0929	

This table reports the cross-sectional analyses of the effect of industry competition (*HHI*), sales volatility (*Sale_Var*) and report attention (*Report*) on the relationship between *OPU* and investment-price sensitivity. Our sample consists of 27,883 firm-year observations from 2008 to 2021. In Panel A, we divide our sample into a highly competitive subsample and a less-competitive subsample according to the median of the *HHI*. In Panel B, we divide our sample into high and low sales volatility subsamples based on the median of *Sale_Var*. In Panel C, the sample is divided into low and high report attention subsamples based on the median of *Report*. In each Column, we employ firm fixed effects and year fixed effects to exclude unobservable heterogeneity. Prob>chi2" is used to verify the coefficient difference of *OPU*×Q between two groups based on the seemingly unrelated regression (SUR). The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

subsample. Moreover, the coefficient difference test also shows a significant difference in the coefficient of $Q \times OPU$ between these two subsamples. These results support our expectation that the impact of *OPU* on investment-price sensitivity is more obvious in firms with high sales volatility.

4.4.3. Analysts' attention

Analysts' attention is also a proxy variable for the market information environment. As an information intermediary in the stock market, analysts specialize in discovering and analyzing firm information. They can unearth undiscovered corporate information on the market and pass it to the public. Elton, Gruber, and Grossman (1986) indicate that analysts forecasts increase stock price informativeness. Ellul and Panayides (2018) further find that analysts can improve the arbitrariness of private information by promoting information competition among insiders, which makes more firm-specific information available to the public through analysts' reports. In particular, we employ analysts' reports to measure analysts' attention. Analysts' attention can ameliorate the information environment of firms, thereby reducing non-public information in the stock price. Thus, in firms with higher analysts' reports, the information reflected in the price may not be so "valuable". Then, the impact of *OPU* on investment-price sensitivity might be more remarkable in firms with low analysts' reports.

We measure Report attention (*Report*) by the number of reports that concentrated on a firm. We split our samples into above- and below-median subsamples according to the median of the report attention. Panel C of Table 8 shows that the estimated coefficients of $Q \times OPU$ are negative in both subsamples but only statistically significant in the low analysts' attention subsample. Additionally, the coefficient difference test between these two groups is significant. These findings suggest that analysts can weaken the negative effect of *OPU* on stock price sensitivity.

4.5. Further analysis

4.5.1. Industry differences

In this section, we examine whether the correlation between *OPU* and investment-price sensitivity is different for firms belonging to different industries. Oil is an important raw material for social production, and its price uncertainty exerts considerable impact on macroeconomic factors (Kilian, 2008). The impact of the *OPU* of firms among different industries may be different, thereby affecting the interrelationship between *OPU* and investment-price sensitivity. Particularly, in industries that are highly sensitive to oil prices, *OPU* may contribute to a greater impact on investment-price sensitivity. According to the industry classification standard from the China Securities Regulatory Commission (CSRC) at 2012, the total sample is divided into five industries: Public Utilities, Real Estate, Agriculture & Livestock, Industry and Commerce. Then, we re-estimate our basic regression based on the different industries.

Table 9 shows the impact of *OPU* on investment-price sensitivity among different industries. The estimated coefficients of the interaction term $Q \times OPU$ are negative and statistically significant for Public

Table 9
Industrial difference.

	Public utilities		Real estate		Agriculture & Livestock		Industry		Commerce	
	$INV1_t$	$INV2_t$	$INV1_t$	$INV2_t$	$INV1_t$	$INV2_t$	$INV1_t$	$INV2_t$	$INV1_t$	$INV2_t$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Q_{t\text{-}1}$	0.01096***	0.01249***	−0.00191	−0.00257	0.01076**	0.01243***	0.00616***	0.00684***	−0.00031	−0.00026
	(3.457)	(3.905)	(−0.197)	(−0.245)	(2.534)	(2.738)	(3.747)	(3.996)	(−0.056)	(−0.046)
$OPU_{t\text{-}1}$	−0.00082***	−0.00073**	−0.00002	0.00003	−0.00015	−0.00012	−0.00068***	−0.00057***	−0.00025	−0.00027
	(−2.602)	(−2.283)	(−0.071)	(0.101)	(−0.305)	(−0.230)	(−5.032)	(−4.020)	(−0.772)	(−0.830)
$OPU_{t\text{-}1} \times Q_{t\text{-}1}$	−0.00015**	−0.00017***	0.00019	0.00018	−0.00030**	−0.00032***	−0.00006*	−0.00006*	0.00005	0.00004
	(−2.352)	(−2.646)	(0.848)	(0.789)	(−2.528)	(−2.760)	(−1.661)	(−1.776)	(0.446)	(0.364)
$OPU_{t\text{-}1} \times CF_{t\text{-}1}$	0.00105	0.00122	−0.00071	−0.00077	0.00375	0.00345	−0.00081	−0.00085	−0.00028	−0.00045
	(0.796)	(0.921)	(−0.787)	(−0.854)	(1.520)	(1.358)	(−1.299)	(−1.312)	(−0.198)	(−0.320)
$CF_{t\text{-}1}$	0.02965	0.02667	0.04726	0.05236	−0.11147	−0.10040	0.06336**	0.06694***	0.06108	0.07075
	(0.559)	(0.493)	(1.402)	(1.550)	(−1.106)	(−0.942)	(2.511)	(2.588)	(1.134)	(1.349)
$Size_{t\text{-}1}$	−0.00592*	−0.00562	−0.00811***	−0.00947***	−0.01317*	−0.01076	−0.01373***	−0.01309***	−0.01256***	−0.01196***
	(−1.744)	(−1.647)	(−2.877)	(−3.192)	(−1.687)	(−1.407)	(−8.393)	(−7.373)	(−3.370)	(−3.159)
Constant	0.21859***	0.20909***	0.20583***	0.23580***	0.34327**	0.28874*	0.39735***	0.37970***	0.32750***	0.31566***
	(3.064)	(2.923)	(3.013)	(3.307)	(2.040)	(1.758)	(11.473)	(10.128)	(4.209)	(3.955)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4587	4587	1930	1930	812	812	18,812	18,812	1742	1742
R^2	0.077	0.075	0.092	0.100	0.085	0.073	0.123	0.116	0.099	0.105

This table represents the baseline regression results for investment-price sensitivity given *OPU* by industry based on the CSRC classification (2012). Our sample consists of 27,883 firm-year observations from 2008 to 2021. We divide our samples into five subgroups: public utilities, real estate, agriculture and livestock, industry, and commerce. In each Column, we employ firm fixed effects and year fixed effects to exclude unobservable heterogeneity. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 10
Stock market crises.

	$INV1_t$	$INV2_t$
	(1)	(2)
$Q_{t\text{-}1}$	0.00742***	0.00817***
	(5.097)	(5.392)
$OPU_{t\text{-}1}$	−0.00282***	−0.00243***
	(−7.185)	(−5.955)
$OPU_{t\text{-}1} \times Q_{t\text{-}1}$	−0.00010***	−0.00010***
	(−3.250)	(−3.199)
$OPU_{t\text{-}1} \times CF_{t\text{-}1}$	0.00014	0.00016
	(0.241)	(0.276)
$CF_{t\text{-}1}$	0.02077	0.02357
	(0.971)	(1.067)
$Size_{t\text{-}1}$	−0.01118***	−0.01054***
	(−8.230)	(−7.235)
Constant	0.46133***	0.42618***
	(17.300)	(15.196)
Firm fixed effect	Yes	Yes
Year effect	Yes	Yes
Observations	20,561	20,561
R^2	0.106	0.101

This table re-estimates the influence of *OPU* on investment-price sensitivity after excluding subsamples of stock market crises. Our subsample consists of 20,561 firm-year observations from 2009 to 2014 and 2017 to 2021. In both Columns, we employ firm fixed effects and year fixed effects to exclude unobservable heterogeneity. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Utilities, Agriculture & Livestock, and Industry, while the estimated coefficients of $Q \times OPU$ are not statistically significant for Real estate as well as Commerce. These results show that in Public Utilities, Agriculture & Livestock, and Industry firms, *OPU* exerts an impact on stock price information and investment-price sensitivity, which is similar to the findings of Maghyereh and Abdoh (2020).

4.5.2. Stock market crises

In this section, we explore whether the stock market crisis will disturb the correlation between *OPU* and stock price informativeness. During stock market crises, informed investors' trading may be restricted, as arbitrage activities will be limited when systematic risk exists (Barberis & Thaler, 2002). De Long, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1990) show that in a noisy trading environment, rational investors may be forced to liquidate their stock and be unable to trade based on their private information or firm fundamentals. Moreover, during stock market crises, it is difficult for managers to make optimal investment decisions when learning information from stock prices (Bond et al., 2012). Therefore, to eliminate the interference of financial crises and obtain the pure impact of *OPU*, we excluded the samples during the financial crisis (2007–2008) and the A-share crash (2015–2016) and re-estimated the basic regression in Table 10.

In Table 10, the estimated coefficients of $Q \times OPU$ are still negative and statistically significant at the 1% level, and the absolute value of the estimated coefficients is greater after removing the samples from the stock market crisis period. This result confirms that the influence of *OPU* on investment-price sensitivity is still robust.

4.5.3. Chinese oil price uncertainty

Zhang et al. (2020) take the crude oil volatility index from the CBOE (*OVX*) to detect the influence of international oil price uncertainty on the cash holdings of Chinese listed firms. They propose that *OVX* stands for both historical and future movement of oil price, which is considered to be an appropriate measure of oil price uncertainty. Following Zhang et al. (2020), we calculate annual *OPU* on the strength of international *OVX* rather than the Chinese crude oil volatility (*COVX*).

In addition, we attempt to construct a measure of Chinese oil price

Table 11
Chinese oil price uncertainty.

	$INV1_t$	$INV2_t$		$INV1_t$	$INV2_t$
	(1)	(2)		(1)	(2)
Q_{t-1}	0.00709***	0.00786***	Q_{t-1}	0.00357***	0.00442***
	(5.193)	(5.563)		(3.146)	(3.715)
OPU_{t-1}	−0.00059***	−0.00050***	$COVX_{t-1}$	−0.01497	−0.01111
	(−5.187)	(−4.236)		(−1.285)	(−0.899)
$OPU_{t-1} \times Q_{t-1}$	−0.00008***	−0.00008***	$COVX_{t-1} \times Q_{t-1}$	0.00092	−0.00010
	(−2.686)	(−2.877)		(0.364)	(−0.040)
$OPU_{t-1} \times CF_{t-1}$	−0.00007	−0.00010	$COVX_{t-1} \times CF_{t-1}$	−0.10728***	−0.11255***
	(−0.139)	(−0.203)		(−2.798)	(−2.871)
$COVX_{t-1}$	0.04107**	0.04476**			
	(2.173)	(2.315)			
CF_{t-1}	−0.01049***	−0.01009***	CF_{t-1}	0.07244***	0.07646***
	(−8.556)	(−7.822)		(5.105)	(5.289)
$Size_{t-1}$	−0.01325	−0.01093	$Size_{t-1}$	−0.01087***	−0.01045***
	(−1.203)	(−0.926)		(−8.913)	(−8.143)
Constant	0.31813***	0.30563***	Constant	0.31010***	0.29971***
	(12.184)	(11.182)		(11.516)	(10.625)
Firm fixed effect	Yes	Yes	Firm fixed effect	Yes	Yes
Year effect	Yes	Yes	Year effect	Yes	Yes
Observations	27,883	27,883	Observations	27,883	27,883
R^2	0.101	0.096	R^2	0.101	0.096

This table shows the influence of *OPU* on investment-price sensitivity after controlling for Chinese oil price uncertainty (*COVX*) and the influence of *COVX* on investment-price sensitivity. Our final sample consists of 27,883 firm-year observations with non-missing values over the period 2008–2021. In all Columns, we employ firm fixed effects and year fixed effects to exclude unobservable heterogeneity. The appendix shows the exact definitions of all variables. The t-statistics applying robust estimation are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

uncertainty. Since Chinese crude oil price data are available only from 2018, we take Chinese fuel price data from the Wind database to construct Chinese oil uncertainty (*COVX*). Following Phan et al. (2019) and Maghyereh and Abdoh (2020), taking the daily closing fuel oil price in China (p_t) for the period from January 2007 to December 2020, we measure the *COVX* with the following model:

$$COVX_t = \sqrt{\frac{1}{n-1} + \sum_{t=1}^{n} (r_t - E(r_t))^2} \times \sqrt{n} \tag{7}$$

where n represents the annual trading days of fuel, r_t is the daily fuel return computed as $r_t = \ln (p_t/p_{t-1})$, and p_t is the daily price.

The results considering *COVX* are reported in Table 11. Columns 1 and 2 show that the influence of *OPU* on investment-price sensitivity is also negative and statistically significant after controlling for Chinese oil price uncertainty (*COVX*). In addition, Columns 3 and 4 show that the coefficients on $Q \times COVX$ are negative but not statistically significant, which confirms that *COVX* exerts no significant impact on stock price informativeness. These results reveal that managers may pay more attention to the international oil price market than just the domestic market. Moreover, as shown in 4.2.1, *OPU* can weaken investment-price sensitivity only after domestic crude oil prices are linked to international crude oil prices, which also proves the importance of the international oil price market.

5. Conclusion

This study surveys the influence of the oil price uncertainty on stock price informativeness. We find a negative correlation between *OPU* and investment-price sensitivity. After investigating a large sample of Chinese listed companies during 2008–2021, we find that this effect comes from the stock price information channel based on informed investors rather than the financial constraints channel caused by high capital cost.

In addition, the negative influence of *OPU* on investment-price sensitivity is concentrated in Public Utilities, Agriculture & Livestock and Industry, rather than the Real Estate or Commerce. These findings show that the uncertainty of oil prices crowds out informed investors, thus reducing the information in the stock price that can guide firm investment strategies.

Our findings expand the cognition for investor and manager behavior when oil prices are uncertain. When the oil price is uncertain, the decrease in informed trading reduces market efficiency and increases market uncertainty. These findings can help peer investors, especially fund managers, make more efficient investment decisions. Furthermore, our findings can help policy makers understand how uncertainty from the commodity market impacts the stock market and firm decision making and improve second-market efficiency.

CRediT authorship contribution statement

Qi Zhu: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Sisi Jin:** Conceptualization, Data curation, Validation, Formal analysis, Investigation, Visualization, Writing – original draft, Visualization. **Yuxuan Huang:** Supervision, Validation, Writing – original draft, Writing – review & editing. **Cheng Yan:** Supervision, Validation, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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Appendix A

This table offers exact variable definitions and corresponding data sources. CSMAR refers to the China Stock Market and Accounting Research database, and CBOE refers to the Chicago Board Options Exchange.

Variables	Definitions	Source
Dependent variables		
INV1	Capital expenditures (*CAPX*) scaled by lagged total assets (*AT*).	CSMAR
INV2	Capital expenditures (*CAPX*) plus R&D expenditure scaled by lagged total assets (*AT*).	CSMAR
Independent variables		
Q	Defined as the market value of equity plus the book value of debt scaled by the book value of assets (*AT*). The market value of assets is the sum of long-term debt, short-term debt and the product of the stock price multiply by the number of shares outstanding.	CSMAR
OPU	Annual oil price uncertainty.	CBOE
Channel variables		
PIN	Defined as the probability of informed trading proposed by Easley et al. (1996) and used to measure informed investors' private information in the stock prices.	CSMAR
INS	Defined as the shares held by institutional investors divided by total shares of the firm.	CSMAR
SA	Defined as an index of financial constraints by Hadlock and Pierce (2010). The *SA* index tends to decrease with higher levels of financial constraints. $SA = -0.737 \times Size + 0.043 \times Size^2 - 0.04 \times Age$, *Age* refers to the listing period of the firm.	CSMAR
KZ	Defined as an index of financial constraints by Kaplan and Zingales (1997). The *KZ* index tends to increase with higher levels of financial constraints. $KZ = -1.001909 \times CF + 3.139193 \times TLTD - 39.36780 \times TDIV - 1.314759 \times CASH + 0.2826389 \times Q$. *TLTD* refers to the ratio of the long-term debt to total assets, *TDIV* refers to the ratio of total dividends to assets, and *CASH* is the ratio of liquid assets to total assets	CSMAR
Control variables		
CF	Defined as the cash flow from operations scaled by total assets (*AT*).	CSMAR
Size	Defined as the natural logarithm of the book value of total assets (*AT*).	CSMAR
HHI	Defined as the sum of squares of the total assets (*AT*) percentage of each competitive subject in the market in an industry and used to measure the dispersion of manufacturer size in the market.	CSMAR
Sale_Var	Defined as the degree of spread in sales over time. Lower sales volatility suggests more stable earnings.	
Report	The number of analysts' reports a firm.	CSMAR

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