Policy uncertainty and peer effects: Evidence from corporate investment in China[a]

Hyun Joong Im[b], Jia Liu[c], Young Joon Park[d]

Abstract

This study investigates whether economic policy uncertainty (EPU) magnifies peer effects in corporate investment in China and the economic mechanisms through which EPU may act upon this property. We examine this relationship by analysing a large sample of publicly listed companies in China for the period of 2009–2019, adopting the peer-firm-average idiosyncratic stock return to capture exogenous variations in peer firms' investment activities. We demonstrate that peer effects are stronger when EPU is increasing in intensity. We also find that high EPU magnifies peer effects by decreasing the accuracy of firms' signals regarding their investment opportunities, asymmetrically impacting their capacity to acquire information and exacerbating managers' career concerns. We further show that increased EPU magnifies peer effects only for underinvesting firms, causing underinvestment to persist and retarding recovery from an economic downturn. Our investigation provides original evidence of how EPU influences corporate investment decisions through peer effects, contributing to the continuing debate on the role of EPU and corporate investment efficiency by establishing that the adoption of consistent and transparent economic policies optimize returns on a company's investments, especially during an economic downturn.

JEL classifications: G31, E22, D81, G32

Keywords: corporate investment policy, peer effects, economic policy uncertainty, underinvestment, information cascade

---

[a]We are grateful for valuable comments from Steve Bond, Guojun Chen, Steven Davis, Jun-koo Kang, Rui Shen, Bohui Zhang, Jake Zhao, Hong Zhu, and seminar participants at Peking University and Renmin University of China, as well as to conference participants at the 2017 Asian Meeting of the Econometric Society, the 2017 PKU-NUS International Conference on Quantitative Finance and Economics, the 2017 Financial Management Association Asia Pacific Meeting, and the 2017 China Meeting of the Econometric Society. We are also grateful to Ya Kang and Lewis Linghu for excellent research assistance.

[b]Address: School of Business Administration, University of Seoul, Dongdaemun District, Seoul, Korea, 02592. Email: hyun.im@uos.ac.kr.

[c]Address: Business School, University of Portsmouth, Portsmouth, U.K. Email: jia.liu@port.ac.uk.

[d]Corresponding author. Address: HSBC Business School, Peking University, Shenzhen, China, 518055. Email: yjpark@phbs.pku.edu.cn. Tel.: +86 (0)755 2603 2019.

1. Introduction

Research has established that a firm's investment decision is influenced by its peers' stock prices (Foucault and Fresard, 2014) and peer firms' investments (Chen and Ma, 2017),[1] while further studies have demonstrated that economic policy uncertainty (EPU) influences corporate investment (e.g. Gulen and Ion, 2016; Wang et al., 2014; Kang et al., 2014; An et al., 2016). A government's macroeconomic or industrial policies often impact the business environment, creating uncertain business conditions for firms that affect the costs of production, productivity, market demand, and competitive advantage (Baker et al., 2016). Intuitively, uncertain business conditions increase agency conflicts and the cost of investment decisions, because acquiring information becomes more expensive in an unstable environment. In such cases, "Following Your Peers" will be a cheaper option to choose. Arguably, peer effects are likely to be more severe when EPU intensifies. However, extant research has not yet investigated the influence of EPU on peer effects in corporate investment decisions. In this study, therefore, we examine whether increased EPU magnifies peer effects in corporate investment, and analyse the economic mechanisms through which EPU may act upon this property.

Studies suggest several possible mechanisms through which EPU influences peer effects, and one possibility is suggested by the information cascade perspective. Bikhchandani et al. (1992) and Zhang (1997) demonstrate that rational agents engage in herding behaviour, making sequen-

[1] A peer effect is said to exist when an agent's decision is influenced by its peers' decisions. There is an increasing body of literature regarding the peer effect in financial decisions, such as capital structure (Leary and Roberts, 2014), corporate investment (Foucault and Fresard, 2014; Chen and Ma, 2017), institutional investment (Choi and Sias, 2009), analysts' behaviour (Jegadeesh and Kim, 2010), and stock-split behaviour (Kaustia and Rantala, 2015). Several rationales behind peer effects have been proposed in the microeconomics literature. First, an individual agent's decision and its peers' decisions could be correlated positively or negatively depending on whether they are strategic complements or strategic substitutes (Bulow et al., 1985). In such a strategic setting, game-theoretic models predict a company's best response to others' decisions would naturally take a form similar to a typical peer effect. Second, the information cascade model suggests that herd behaviour can arise due to the belief that peers have made their decisions based on superior information (Bikhchandani et al., 1992). Third, due to agency motives, decision-makers may have incentives to mimic peers (Scharfstein and Stein, 1990). For example, a manager who is concerned about his or her own reputation with an eye toward future employment opportunities may make choices similar to those of peer firms to avoid blame regarding their managerial ability if their decisions turn out to be suboptimal.

tial decisions only when receiving incomplete private signals regarding the true state of the world. When EPU increases, the accuracy of the private signal upon which a firm bases a decision is expected to decrease (Leahy and Whited, 1996). Thus, EPU would magnify peer effects in investment choices. Another plausible mechanism through which EPU influences peer effects in corporate investment decisions is related to the asymmetric impact of higher EPU on firms with different capacities for acquiring information. Firms with longer histories possess superior connections through accumulated experience (Stinchcombe, 1965), and larger firms are commonly endowed with greater resources (Penrose, 2009). Particularly in China, where political connections are much more important for obtaining information than in developed countries, an inability to gain access might have profoundly negative consequences. With higher EPU, firms with superior access to information are more likely to maintain their informational advantage. Thus, firms with inferior information capacities would have an increased tendency to follow such advantaged companies (Zhang, 1997). The third mechanism is related to managerial career concerns. Peer effects can be intensified by higher EPU in firms with managers who are anxious about their career development. Scharfstein and Stein (1990) and Trueman (1994) design models in which managers, influenced by career ambitions, may choose to mimic other firms' decisions to avoid making unusual choices. When the evaluation scheme of a firm does not reward success as highly as it punishes failure, managers are reluctant to make an unorthodox decision that can be deemed to be risky (Thaler and Ganser, 2015). Given the foregoing discussion, we argue that higher EPU increases risk in such cases, so that the higher the degree of EPU, the more severe the peer effect will be.

In this study, we address the question of whether heightened EPU magnifies peer effects in corporate investment behaviour, first by identifying the directional effect of increased EPU on the magnitude of peer effects, and then by considering whether the directional effect is consistent with any of the mechanisms stated above.

We select China because peer effects in this country are likely to be highly pronounced for the reasons we discuss below. First, China's corporate environment is demonstrably the most dynamic in the world, with a significant share of global manufacturing output in recent decades. Second, China's political system is relatively stable in comparison to other sizable economies and, unlike them, does not undergo regular election cycles, therefore experiencing fewer repercussions in its stock markets. According to Baker et al. (2016), the US economic policy uncertainty index has spikes surrounding close presidential elections. Durnev (2010) reports that elections, particularly tight ones, lower the sensitivity of investment to stock prices, and concludes the decrease in investment-to-price sensitivity is due to stock prices becoming less informative during election years, making them noisier signals for managers to follow. Since our identification method requires the causal effect of stock returns on investment decisions to be established, investigating cases in China allows us to avoid such potential confounding effects.

The problem we must surmount in identifying the directional effect is endogeneity. Despite abundant microeconomic studies on peer effects, their use in corporate investment policy has been understudied due to potential endogeneity issues such as the reflection problem. The reflection problem (Manski, 1993) refers to the problem that arises when one tries to infer whether the average behaviour of a group influences the behaviour of a group member. The problem arises because it cannot be distinguished whether the group affects the individual behaviour or the group behaviour is merely a reflection of individual behaviours.[2] Foucault and Fresard (2014) show that a company's investment is influenced by the stock prices of its peers. Their model describes the situation where a firm's manager gains information from its own and its peers' stock prices, empirically showing that a firm's investment is positively related to the stock prices of its peers. Generally, however, peer firms' stock prices or stock returns can be affected by common factors that also determine investment. To address this endogeneity issue, we utilize peer-firm-average

[2]See Manski (1993), Leary and Roberts (2014), and Angrist (2014) for more detail on endogeneity issues.

idiosyncratic return shock, as proposed by Leary and Roberts (2014), as an instrumental variable (IV) for an *ex post* peer-firm investment measure. Using this approach, we show that peer effects are significantly stronger when EPU is greater.

We also explore whether EPU influences peer effects asymmetrically between firms that overinvest relative to optimal investment levels and firms that underinvest relative to optimal investment levels. Although both overinvestment and underinvestment would generate undesirable results, our findings further suggest the consequences from a change in EPU would have an asymmetric impact. Prior studies, such as Bernanke (1983), Julio and Yook (2012), Wang et al. (2014), Kang et al. (2014), Gulen and Ion (2016), and An et al. (2016), document that economic and policy-related uncertainty affects corporate investment negatively. However, there are few prior studies that investigate what asymmetric impact economic and policy uncertainty may have on peer effects between overinvesting and underinvesting firms. This study finds that the effects of EPU on investment peer effects are stronger for underinvesting firms. This research adds to the literature on investment (in)efficiency by providing evidence that EPU has more severe consequences for the peer effects of underinvesting firms.

In addition, we show that the aforementioned effect—EPU magnifying peer effects—is more prevalent for state-owned enterprises (SOEs). SOEs have stronger ties to the government and their businesses are closely related to governmental policies. Thus, managers of SOEs are more inclined to follow the directions of the government, and thus they are likely to follow peers' actions especially if economic policy made by government is uncertain. When EPU is high, the managers would not be confident with their information set and the tendency to mimic peers will be magnified.

We also show that our results are robust to the use of micro-level uncertainty measures. Our main results are based on a macro-level uncertainty measure, i.e. the EPU index, to measure the overall market-level uncertainty. However, the peer effects in corporate investment policy could also depend on micro-level uncertainty measures which are heterogenous across individual firms. Our robustness tests confirm that micro-level uncertainty also magnifies peer effects. Finally, analyzing several possible mechanisms for magnifying effects, we find evidence supporting all three mechanisms—information cascade mechanism, asymmetric capacity for information acquisition mechanism, and career concerns mechanism.

This study contributes to the literature in several ways. First, in respect to the relationship between uncertainty and corporate investment, although a number of studies provide evidence that greater uncertainty leads to reduced corporate investment (Bernanke, 1983; Julio and Yook, 2012; Wang et al., 2014; Kang et al., 2014; Gulen and Ion, 2016; An et al., 2016), few studies specify the role of peer effects in this process. In fact, corporate investment can decrease because individual firms decide to reduce investment due to decreased investment opportunities and peer effects magnify these changes. Most of the existing studies report the overall tendency of decreased corporate investment, but they do not focus on identifying the causes. Using the peer-firm-average idiosyncratic return shock as an IV, our research attempts to verify whether such peer effects become more severe as EPU increases. This study is the first to demonstrate that EPU amplifies peer effects in corporate investment policy, suggesting that peer effects could exacerbate reduced corporate investment driven by heightened EPU.

Second, this study identifies the mechanisms through which EPU magnifies investment peer effects. We propose and test three mechanisms: *i)* information cascade, *ii)* the asymmetric capacity of information acquisition, and *iii)* the career concerns of managers. Our investigation improves our understanding of the impact that EPU has on the magnitude of peer effects by documenting empirical evidence on the effectiveness of these three mechanisms.

The third contribution of this study to the literature is regarding investment inefficiency. Following the classical theory on costly external finance (Myers, 1977), several theories of investment distortion, such as those based on empire building (Baumol, 1959; Jensen, 1986), overconfidence

(Malmendier and Tate, 2005), and short-term reputation (Narayanan, 1985; Stein, 1989), have been put forth. While some studies propose peer effects as another source of investment distortion (Foucault and Fresard, 2014; Chen and Ma, 2017), this study examines whether increased EPU magnifies peer effects in inefficient investment behaviour. Our study analyses both overinvesting and underinvesting behaviours, and we find evidence that EPU magnifies peer effects only in underinvesting firms, clearly demonstrating that higher EPU, by magnifying peer effects, can cause underinvestment problems to last longer, slowing down recovery from an economic downturn.

2. Literature review and hypothesis development

2.1. The effect of EPU on peer effects of investment decisions

Economic policy, especially industrial policy, often alters the business environment, and thus, uncertain economic policies bring about business uncertainty to firms. Baker et al. (2016) contend that both types of uncertainty, economic uncertainty and policy uncertainty, lead to lower levels of investment.[3] Higher EPU can decrease firms' investment levels for two reasons: 1) individual firms' decisions to decrease investment levels due to reduced optimal investment levels and 2) peer effects that magnify the aforementioned changes. Most of the existing literatures report the overall tendency of decreased investment levels, but they do not separately identify the two effects. We hypothesize that higher EPU magnifies the peer effects among firms and further reduce the investment levels. Thus, we propose our first and main hypothesis below:

Hypothesis 1. *Higher EPU magnifies peer effects on firms' investment policy.*

Real-options-based investment theories suggest that higher EPU is likely to magnify peer effects more strongly for underinvesting firms than for overinvesting firms (e.g. Bloom et al., 2007).

[3] See Bernanke (1983); Julio and Yook (2012); Wang et al. (2014); Kang et al. (2014); Gulen and Ion (2016); An et al. (2016).

On the one hand, if a higher level of EPU results in a lower level of investment (i.e. a significantly negative direct effect) and a strong peer effect (i.e. a significantly negative peer effect), the effect of EPU on underinvestment is likely to be significant. That is, when underinvestment is prevalent, a stronger peer effect would further drive a firm's investment down to a level below optimal investment. On the other hand, when a lower level of EPU results in a greater level of investment (i.e. a significantly positive direct effect) and a less strong peer effect (i.e. a weakly positive peer effect), the effect of EPU on overinvestment is less likely to be significant due to a weaker peer effect. Thus, we propose our second hypothesis below:

Hypothesis 2. *EPU's magnifying effect is more pronounced for underinvesting firms than for overinvesting firms.*

2.2. Economic mechanisms

Consider there are multiple firms competing in an industry. Each has a manager who is in charge of making investment decisions. In each period, the manager exerts efforts to acquire information about various conditions (e.g. financial and product markets, cash flows of companies, and available investment projects) to make and execute optimal investment decisions. The manager makes investment decisions based on his or her own judgment on the basis of the acquired information. Alternatively, the manager may try to observe the decisions made by competitors before making his or her decisions. There are several plausible mechanisms through which EPU influences peer effects. Specifically, we consider the following three possible mechanisms: information cascade, asymmetric capacity for information acquisition, and managers' career concerns.

The first possible mechanism is the information cascade mechanism. Since the seminal work by Bikhchandani et al. (1992), the information cascade theory has been used to explain economic agents' herding behaviour in various settings. According to the model, when there are multiple decision-makers who are making decisions sequentially and each of them receives only an incomplete private signal regarding the true state of the world, herding behaviour will arise as a result of rational choices. In this setting, an agent who makes decisions later can observe those decisions already made by others. Although the agent cannot observe other agents' private information, he or she can make inferences from observed decisions. Once the degree of precision of the information revealed by the choices of others is sufficiently high and the information outweighs the agent's own private signals, a rational agent would mimic others' choices while ignoring his or her own signals. Thus, when an accumulation of certain choices is observed in the market, agents will start to follow these choices regardless of their private information. Zhang (1997) further develops this idea and verifies that the herding behaviour that the information cascade model predicts will arise when agents can choose when to make an investment decision. When the degree of accuracy of the private signal is high, it is less likely that information cascading will arise because agents acting later would need to observe an accumulation of more opposing choices to start mimicking them.

Given the foregoing discussion, we argue that higher EPU will reduce the ability for managers to make accurate investment decisions when firms face a higher level of EPU. With the reduced accuracy, firms would have stronger incentive to mimic their peers and that can increase the peer effects. Thus, we propose our third hypothesis below:

Hypothesis 3. *Higher EPU reduces the accuracy of firms' investment opportunity estimates.*

Another mechanism through which higher EPU can magnify peer effects in investment decisions is based on the asymmetric capacity of information acquisition. Different firms have different capacities for acquiring relevant information to make optimal investment decisions. Companies with a longer history are likely to have more experience in investment-decision process. Similarly, larger firms could have better access to information due to more abundant resources. Zhang (1997) confirms that firms with better information would lead in the decision-making process, while firms with inferior information would follow by mimicking the leaders' decisions.[4]

[4] Bikhchandani et al. (1992) also wrote: "While the order of moves is exogenous in [their] model, it is plausible that

We conjecture that higher EPU will also affect the ability to acquire information across firms. We argue that higher EPU would widen the asymmetry of the capacity to acquire information. Firms with information advantages would still be able to obtain valuable information under higher EPU, whereas the opposite holds for firms with a lower capacity for information acquisition. Consequently, firms with inferior capacity would rely more on mimicking leading firms. Thus, the asymmetric capacity of information acquisition mechanism predicts that firms with a longer history and of larger size will have better access to important information regarding economic policies. This implies when EPU is higher, peer effects in corporate investment are more likely to be stronger for smaller and younger firms, as they are at a disadvantage in terms of information acquisition; and therefore, they are more likely to rely on peers' behaviours to make decisions. Given the foregoing discussion, we propose our fourth hypothesis below:

Hypothesis 4. *Higher EPU magnifies peer effects more significantly for smaller and younger firms.*

The third mechanism that EPU may influence peer effects relates to the career concerns of managers (Scharfstein and Stein, 1990; Trueman, 1994; Chevalier and Ellison, 1999). In modern organizations, managers are routinely evaluated. In many cases, their evaluation depends not only on their own firm performance but also on their firm performance relative to the performance of peer firms.

Scharfstein and Stein (1990) and Trueman (1994) document that managers who have concerns regarding their own careers may engage in herd behaviour in investment decisions. Consider a manager who has received a signal that indicates that a certain decision is the optimal one for the firm. If this manager also observes that many of his or her competitors have made opposing decisions, it would be a challenge to follow his or her own signal. Following own judgement would

the individual with the most precise information decides first. Consider a more general setting in which all individuals have the choice to decide or to delay, but there is a cost of delaying a decision. All individuals have an incentive to wait in the hope of free-riding on the first to decide. However, other things being equal, the cost of deciding early is the lowest for the individual with the most accurate information" (p. 1002).

provide the opportunity to achieve a rare success, but it would also mean that there is a possibility of an unusual failure (Thaler and Ganser, 2015). Following the majority would make the manager's decision outcome a rather common one (again, either a success or a failure). When the manager's job security is linked to the evaluation of the firm's relative performance, he or she might make a suboptimal decision and mimic others despite his or her own private signal.

Chevalier and Ellison (1999) empirically verify this observation using the behaviour of mutual fund managers. They find that managers with less experience are more likely to be "terminated" and this induces less experienced managers to avoid unsystematic risk when selecting their portfolios.[5] Kahneman and Lovallo (1993) describe such organizational motivation as being derived by a behavioural bias called "narrow framing."

Although an organization's investment objective is supposed to focus on the overall performance of all investment decisions, the evaluations carried out by managers are commonly conducted on the basis of individual projects. Thus, we hypothesize that managers tend to make a safer decision—following others rather than acting according to their own signals—even though they are aware that this is not the best decision for the whole organization.[6] In such circumstances, managers may prefer the option of "moderate success or failure" rather than "extreme success or failure" as described by Thaler and Ganser (2015).

Higher EPU will naturally increase the volatility of investment returns, which would increase the risk of extreme losses in investment performance, thus increasing career concerns for managers. As discussed above, when the manager's job security is linked to the evaluation of the firm's relative performance, he or she might mimic others despite his or her own private signal. Therefore,

[5]Refer to page 391 of Chevalier and Ellison (1999) for the definition of being "terminated".

[6]Describing the findings of Kahneman and Lovallo (1993), Thaler and Ganser (2015) writes: "Each manager is loss-averse regarding any outcomes that will be attributed to him. In an organizational setting, the natural feeling of loss aversion can be exacerbated by the system of reward and punishment. In many companies, creating a large gain will lead to modest rewards, while creating an equal-sized loss will get you fired. Under those terms, even a manager who starts out risk neutral, willing to take any bet that will make money on average, will become highly risk-averse. Rather than solving the problem, the organizational structure is making things worse" (p. 187).

it is likely that the effect of EPU on the magnitude of peer effects are greater for firms with higher managerial career concerns. Thus, we propose our fifth hypothesis below:

Hypothesis 5. *Higher EPU increases peer effects more significantly for firms with higher managerial career concerns.*

3. Research design

3.1. Data and sample

Our primary source of data is the CSMAR database, which contains financial statements and stock market information for Chinese companies. This study covers the sample period 1999–2019 for all nonfinancial firms listed in the Shanghai and Shenzhen exchanges.[7] We select our sample using the following criteria. First, we exclude information on B-share stocks, as B-share stocks are restricted to foreign investors. Second, we also exclude firms listed on ChiNext, widely known as the Growth Enterprises Market Board (GEM), because GEM is the second-board market and its listing rules are qualitatively different from the rules for the main-board market. For instance, there is no cash flow requirement for GEM firms, while firms on the main board are expected to have more than $8 million for the last three accounting periods.[8] Third, we exclude special treatment (ST) firms, as these firms have suffered losses for two or more consecutive years and are not comparable with non-ST firms due to their high default and delisting risk (Jiang et al., 2009).

We use the EPU index constructed by Baker et al. (2016) as a proxy for the degree of EPU prevalent in the economy. We adopt the Chinese EPU index calculated using the text-based analysis of the frequency of EPU being discussed in the *South China Morning Post*, a leading English-

[7] Stock return data start in 1990, the year the Chinese stock market opened, but cash flow data begins in 1998, as companies were required to report cash flow statements from 1997 onwards. For more details, see the State Administration of Taxation website: http://www.chinatax.gov.cn/jypx/jckj/jxnr/1/kjfg03.htm.

[8] For more details, see the Shenzhen Stock Exchange website: http://www.szse.cn/main/en/.

language newspaper in Hong Kong.[9] Figure 1 reveals there are five spikes in the EPU index during our sample period: China's entry into the World Trade Organization (WTO) in 2001 (marked as A); declining exports and a US $580 billion rescue package due to the global financial crisis in 2008 (marked as B); the Euro debt crisis and trade protectionism, economic growth slowdown expectations, anti-corruption campaign, and political elections in 2011–2012 (marked as C); the first sub-7% GDP growth rate for the first time in 25 years in 2016 (marked as D); and the trade war against the United States in 2018–2020 (marked as E).

[Insert Figure 1 Here]

The final sample consists of 16,642 firm-year observations, corresponding to 1,981 firms. The total number of industries (i.e. peer groups) is 71, with on average 33 firms per industry-year subsample. Peer groups are defined by the industry code C (i.e. *nnindcd* in CSMAR). Panel A of Table 1 provides definitions of variables, and Panel B of Table 1 presents summary statistics with respect to firm-specific and peer-firm-average variables. We winsorize all continuous variables at the 1st and 99th percentiles.

[Insert Table 1 Here]

3.2. Baseline model specification

To examine whether peer firms influence corporate investment policy, we first extend the empirical model used by Hubbard (1998) and Richardson (2006) by adding an *ex post* peer-firm investment

[9] Baker et al. (2016) construct the EPU indices for major economies in the world based on a textual analysis of economic policy news. The original EPU index has a large variation across time periods, ranging from 9 to 971, and its mean value is 196. As the EPU index is a monthly measure, we first take its annual average, and then divide the annualized EPU index by 100 to obtain our proxy for EPU, EPU_t, as in Wang et al. (2014). See the website for detailed information: http://www.policyuncertainty.com/china_monthly.html.

measure to capture peer effects.[10] Our baseline model is specified as follows:

$$INV_{i,t} = \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 INV_{i,t}^{peer} + \beta'_{CONTROLS}\textbf{CONTROLS} + \textit{Firm Fixed Effects} + \textit{Year Fixed Effects} + \varepsilon_{i,t}, \quad (1)$$

where $INV_{i,t}$ is defined as firm i's net capital expenditure plus net acquisitions, less sales of fixed assets at the end of year t, scaled by total assets at the beginning of year t (Richardson, 2006; Bloom et al., 2007). $INV_{i,t}^{peer}$ is defined as the average of the investment rates of all firms in firm i's peer group, excluding itself.

We expect β_2 or the coefficient of $INV_{i,t}^{peer}$ to be significantly positive. Following Richardson (2006), we include the following control variables: the natural logarithm of total assets ($SIZE_{i,t-1}$), Tobin's q ($Q_{i,t-1}$), leverage ($LEV_{i,t-1}$), cash holdings to total assets ($CASH_{i,t-1}$), the natural logarithm of the time elapsed since the stock listing date ($AGE_{i,t-1}$), and earnings before interest and taxes to total assets ($EBIT_{i,t-1}$). To examine whether a firm reacts to peer firms' characteristics in addition to peer firms' investment decisions, we also include peer-firm-average characteristics, such as $SIZE_{i,t-1}^{peer}$ and $Q_{i,t-1}^{peer}$, in all regression models.

3.3. Addressing endogeneity concerns

In respect of Eq. (1), the inclusion of a peer-firm-average investment measure ($INV_{i,t}^{peer}$) on the right-hand side of the regression equation is subject to endogeneity problems in that (*i*) there could be confounding effects, as firms within the same peer group are exposed to the same or a similar investment environment, and (*ii*) there may be reverse causality, i.e. $INV_{i,t}$ might cause $INV_{i,t}^{peer}$. To address these endogeneity concerns, we adopt the peer-firm-average idiosyncratic return shock as an IV for the peer-firm-average investment ratio $INV_{i,t}^{peer}$, similar to Leary and Roberts (2014).

[10] The endogeneity problems will be discussed in the following subsection.

In principle, the identification of peer effects requires an exogenous peer firm characteristic, but a peer-firm-average characteristic is not exogenous with respect to firm i's investment (or financing) policy. We follow Leary and Roberts' (2014) approach. First, we begin with a known determinant of investment, i.e. stock returns. We then extract the idiosyncratic variation in stock returns using the residual from a traditional asset pricing model that also incorporates an industry factor to remove common variation among peers. We use the peer-firm-average idiosyncratic return shock to capture exogenous variation in peer firms' characteristics.

A crucial condition for this approach to be effective is a causal relation between stock returns and investment decisions. A number of studies provide evidence that stock returns influence investment decisions. Chen et al. (2007) show empirical evidence that managers learn from private information in stock prices when they make investment decisions, suggesting that stock prices or stock returns are an important determinant of corporate investment. Similarly, Hau and Lai (2013), using the 2007–2009 financial crisis as a natural experiment for large-scale stock mispricing, establish a causal effect of stock prices on corporate investment, which is consistent with well-established theoretical literature (Dow and Gorton, 1997; Subrahmanyam and Titman, 1999) on the relation between stock prices/returns and corporate investment. This theory contends that stock prices aggregate information from many different participants who do not have channels for communication with the firm outside the trading process. Thus, stock prices may contain the information that managers do not have. In turn, this information can guide managers in making corporate decisions, such as corporate investment decisions.[11] In this spirit, Foucault and Fresard (2014) provide a theoretical model in which peer firms' stock prices influence a firm's investment because the firm learns from its peers' stock prices. In addition, they provide empirical evidence

[11]Stock prices in the Chinese stock market have become increasingly informative since China opened its stock market in 1990, followed by a series of market reforms including the Split Share Structure Reform. Recent studies such as Carpenter et al. (2021) demonstrate that China's stock market has become as informative as the US stock market in reflecting firm fundamentals such as future earnings. Moreover, they find a strong relation between stock price informativeness and corporate investment efficiency in China. Recent studies regarding the informational efficiency of the Chinese stock market support our empirical design.

that a firm's investment is positively related to the stock prices of peer firms.

Leary and Roberts (2014) argue that this approach has several advantages. First, the measure is available for a broad panel of firms and thus mitigates statistical power and external validity concerns. Second, compared to other investment determinants, such as leverage, profitability, and other accounting measures, stock returns are relatively free from manipulation. Third, stock returns impound many, if not all, value-relevant events, including those stated above. Finally, a vast body of asset pricing literature focuses on estimating the expected and idiosyncratic components of returns. Intuitively, our identification strategy builds on the event-study approach by addressing its shortcomings. The key problem is that the aforementioned value-relevant events affect both the idiosyncratic and the common components of stock returns. Our identification strategy is to eliminate this common variation to capture only the firm-specific variation and identify peer effects. Thus, our identification strategy relies on isolating the firm-specific variation in stock returns rather than relying on particular firm-specific economic events.

To address these problems, we use the peer-firm-average idiosyncratic return shock ($IDIO_{i,t-1}^{peer}$) as an IV.[12] We consider the following two model specifications with the IV as a key variable:

Reduced-form dynamic panel IV specification

$$\begin{aligned} INV_{i,t} &= \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 IDIO_{i,t-1}^{peer} + \beta'_{CONTROLS}\mathbf{CONTROLS} \\ &\quad + \textit{Firm Fixed Effects} + \textit{Year Fixed Effects} + \varepsilon_{i,t}; \end{aligned} \tag{2}$$

Two-stage dynamic panel IV specification

$$\begin{aligned} INV_{i,t} &= \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 \widehat{INV_{i,t}^{peer}} + \beta'_{CONTROLS}\mathbf{CONTROLS} \\ &\quad + \textit{Firm Fixed Effects} + \textit{Year Fixed Effects} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

[12] The procedure to construct the instrumental variable is described in the following subsection.

where $\widehat{INV}^{peer}_{i,t}$ is the fitted values from the first-stage regression in which $IDIO^{peer}_{i,t-1}$ is used as an IV.[13]

We employ system GMM (generalized methods of moments) methods to ensure that peer effects or the impact of EPU on the magnitude of the peer effects are not due to the choice of estimation methods.[14]

There is a need to resolve an important estimation issue arising from the simultaneous inclusion of fixed effects and lagged dependent variables as in standard dynamic panel regression models. The most important issue is that ordinary least squares (OLS) and fixed effects (FE) estimators of the coefficient of the lagged dependent variable tend to be biased upwards and downwards, respectively. This is particularly true when the dataset has a short panel length (Nickell, 1981; Bond, 2002). Therefore, the coefficients of the other variables are also likely to be biased. Using simulated panel data, Flannery and Hankins (2013) show that the estimation performance of various econometric methodologies varies substantially depending on data complications, such as fixed effects, the persistence of the dependent variable, endogenous independent variables, and error term autocorrelations. They find that the system GMM estimator (Arelleno and Bover, 1995; Blundell and Bond, 1998) appears to be the best choice in the presence of endogenous independent variables and even second-order serial correlation if the dataset includes shorter panels. Thus, we employ the system GMM estimator throughout this study.

[13] We have qualitatively similar results when the contemporaneous peer-firm-average idiosyncratic return shock is used as an IV.

[14] Although the difference GMM estimators developed by Arellano and Bond (1991) are consistent provided the instruments are valid, the instruments become weak if the series is highly persistent (Blundell and Bond, 1998). In this case, the system GMM estimator, proposed by Arelleno and Bover (1995) and developed by Blundell and Bond (1998), is potentially more efficient than the difference GMM estimator. This estimator augments the system of equations in first differences by additional equations in levels and uses the lagged first difference of the dependent variable and explanatory variables as instruments for the equations in levels.

3.4. Construction of the instrumental variable

To eliminate common variation among peers, we start by estimating the following asset pricing model that incorporates a market factor and an industry factor:

$$r_{ijt} = \alpha_{ijt} + \beta_{ijt}^{MKT}(r_{mt} - r_{ft}) + \beta_{ijt}^{IND}(\bar{r}_{-ijt} - r_{ft}) + \eta_{ijt}, \tag{4}$$

where i, j and t denote firm i, peer group j and month t, respectively. r_{ijt} is firm i's monthly return. r_{mt} refers to the monthly market return, and r_{ft} refers to the monthly risk-free rate. $\bar{r}_{-ijt}$ is the peer-firm-average monthly return for firm i (excluding firm i's own monthly return). In fact, Eq. (4) is a revised capital asset pricing model in which one additional component—excess peer group return $(\bar{r}_{-ijt} - r_{ft})$—is added to capture the common factors within the same peer group.

This model is estimated on a rolling annual basis using monthly returns during the previous five-year period (with at least 24 observations). On average, the adjusted R^2 value is as high as 51.6%. Notably, a firm's monthly stock returns are weighted averages of market factors and industry factors, with approximately one-third and two-thirds being weights, respectively, given that the constant is close to zero and the sum of the two factor loadings is almost one. The mean idiosyncratic return is approximately -20 basis points, which is comparable to that of US firms, as reported in Leary and Roberts (2014). The results of regressions to estimate return shocks are reported in Table A1.

[Insert Table A1 Here]

For each firm, expected monthly returns are estimated from Eq. (4). Firm i's monthly idiosyncratic shocks are estimated as the difference between the realized monthly returns and expected monthly returns. Peer-firm-average idiosyncratic return shocks denoted by $IDIO_{i,t-1}^{peer}$, our IV, are then obtained by taking the average of the peer firms' *annualized* idiosyncratic shocks in year $t-1$

(excluding firm *i*'s).

4. Empirical results and discussions

4.1. Baseline analyses of the peer effects in corporate investment policy

Before investigating whether EPU magnifies peer effects in corporate investment policy, we must first investigate whether peer effects exist in firms' investment decision-making. To determine whether peer firms influence corporate investment policy, we consider examining whether the peer-firm-average investment ($INV_{i,t}^{peer}$) has a significant effect on a firm's investment. Table 2 presents the estimation results of dynamic panel regression models. Column (1) presents the system GMM estimation result of the baseline dynamic panel regression model (without an external IV).[15] The results show that the coefficient estimate of peer-firm-average investment is positive and significant at the 1% level, providing strong evidence for peer effects in corporate investment policy. Estimated coefficients for the control variables suggest that larger firms and firms with more investment opportunities, greater cash holdings, and higher profitability tend to invest more, while older firms in the later period of their life cycle invest less.

[Insert Table 2 Here]

However, as discussed earlier, endogeneity problems arise if a peer-firm-average investment measure is included in the right-hand side of the equation, with a firm's investment measure being the dependent variable. Similar to Leary and Roberts's (2014) study, we use the peer-firm-average

[15]The GMM-style instruments used in column (1) are the contemporaneous value and all available lags of peer-firm-average investment rate and the second to sixth lags of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average investment rate, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. Year dummies are used as instruments for the equations in levels only. The Sargan-Hansen test of over-identifying restrictions does not reject this specification, and there is no significant evidence of the second-order serial correlation in the first-differenced residuals.

idiosyncratic return shock ($IDIO_{i,t-1}^{peer}$) as an IV to capture the exogenous variation of the peer-firm-average investment. We estimate both the reduced-form dynamic panel IV model and the two-stage dynamic panel IV model using the system GMM.[16] The dynamic panel IV approach allows us to address endogeneity concerns related to the short panel bias and the reflection problem mentioned earlier. Column (2) presents the reduced-form IV regression results, and columns (3) through (4) present the two-stage IV regression results as in Leary and Roberts's (2014) and Foucault and Fresard's (2014) studies.

The results for the reduced-form IV specification (i.e. IV-SGMM) are reported in column (2) of Table 2.[17] The result shows that $IDIO_{i,t-1}^{peer}$ is significantly positive, indicating that there are strong *causal* peer effects in corporate investment decisions. In columns (3) and (4), we report results for the two-stage IV specification (i.e. two-stage IV-SGMM) described above. To implement this approach, we use an FE regression at the first stage, with $IDIO_{i,t-1}^{peer}$ as the instrument. Then, at the second stage, the fitted values of $INV_{i,t}^{peer}$ are incorporated to estimate a dynamic panel regression model using system GMM.[18] The coefficient of $IDIO_{i,t-1}^{peer}$ from the first-stage regression in column (3) is positive and significant at the 1% level, indicating that $IDIO_{i,t-1}^{peer}$ is a valid IV for $INV_{i,t}^{peer}$. Consistent with the reduced-form specification results, the coefficient of $\widehat{INV_{i,t}^{peer}}$ in column (4) is positive and significant at the 5% level, and its magnitude is far greater than the coefficient for the first-lagged investment rate, confirming there are strong *causal* peer effects in corporate investment decisions.

Overall, our empirical findings based on the baseline model, the reduced-form model, and the

[16]The two-stage system GMM estimation is a combination of IV estimation and system GMM estimation. To implement this approach, we use the FE estimator at the first stage, with $IDIO_{i,t-1}^{peer}$ as the instrument. Then, at the second stage, we use the fitted values of $INV_{i,t}^{peer}$ to estimate a dynamic panel regression model using the system GMM.

[17]The GMM-style instruments used in these two models are the same as those in column (1), except that instruments related to peer-firm-average investment rate are replaced by those related to peer-firm-average idiosyncratic return shock. Again, the requirements of the Sargan-Hansen test and Arellano-Bond test are satisfied.

[18]The instruments used to estimate a dynamic panel regression model in column (4) are the same as those used in column (2). The requirements of the Sargan-Hansen and Arellano-Bond tests are again satisfied.

second-stage model of the two-stage model unanimously demonstrate that peer firms' investment decisions, a neglected factor in classical investment theories, play a very important role in determining a firm's investment policy.

4.2. Impacts of EPU on peer effects in corporate investment policy

To examine whether EPU is the main driver of peer effects, we test whether greater uncertainty in economic policy magnifies peer effects in corporate investment policy. We use three different specifications to capture a more comprehensive picture. First, we consider the following specification:

$$\begin{aligned} INV_{i,t} &= \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 HighEPU_t + \beta_3 IDIO^{peer}_{i,t-1} + \beta_4 HighEPU_t \times IDIO^{peer}_{i,t-1} \\ &\quad + \beta'_{CONTROLS}\mathbf{CONTROLS} + \mathit{Firm\ Fixed\ Effects} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where $HighEPU_t$ equals 1 if the annualized EPU measure divided by 100 (EPU_t) is higher than its historical median and 0 otherwise. Next, we consider the following specification:

$$\begin{aligned} INV_{i,t} &= \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 LogEPU_t + \beta_3 IDIO^{peer}_{i,t-1} + \beta_4 LogEPU_t \times IDIO^{peer}_{i,t-1} \\ &\quad + \beta'_{CONTROLS}\mathbf{CONTROLS} + \mathit{Firm\ Fixed\ Effects} + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where $LogEPU_t$ is the natural logarithm of EPU_t. Finally, we consider the following specification:

$$\begin{aligned} INV_{i,t} &= \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 IncEPU_t + \beta_3 IDIO^{peer}_{i,t-1} + \beta_4 IncEPU_t \times IDIO^{peer}_{i,t-1} \\ &\quad + \beta'_{CONTROLS}\mathbf{CONTROLS} + \mathit{Firm\ Fixed\ Effects} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $IncEPU_t$ is computed as the first difference of EPU_t. The first two specifications help us identify how much the level of EPU affects the magnitude of peer effects, while the third specification captures how much the increase in the level of EPU affects the magnitude of peer effects.

Table 3 reports the estimation results. The models in odd-numbered columns include $IDIO^{peer}_{i,t-1}$ and one of the following three EPU measures: $HighEPU$, $LogEPU$, or $IncEPU$. The models in even-numbered columns additionally include the terms interacting $IDIO^{peer}_{i,t-1}$ with $HighEPU$, $LogEPU$, and $IncEPU$, respectively, to measure the effect of EPU on the magnitude of peer effects. All empirical models control for firm-specific and peer-firm-average characteristics.[19] Our results show that $HighEPU_t$ and $LogEPU_t$ have significantly negative signs, confirming the findings of the existing literature on the effect of economic policy on corporate investment.[20] On the other hand, $IncEPU_t$, which measures the change in EPU rather than the level of EPU, has no significant effect on corporate investment. The results indicate that firms' investment decisions tend to be affected more by the level of EPU rather than the change in EPU.

More importantly, we find that the coefficient of $HighEPU_t \times IDIO^{peer}_{i,t-1}$ is positive and significant at the 1% level. The corresponding coefficients for $LogEPU_t \times IDIO^{peer}_{i,t-1}$ and $IncEPU_t \times IDIO^{peer}_{i,t-1}$ are smaller but still positive and significant at the 10% level. The significantly positive coefficients of $HighEPU_t \times IDIO^{peer}_{i,t}$ or $LogEPU_t \times IDIO^{peer}_{i,t}$ suggest higher EPU amplifies peer effects in corporate investment policy, supporting our main hypothesis (Hypothesis 1). Similarly, the significantly positive coefficient of $IncEPU_t \times IDIO^{peer}_{i,t}$ suggests that a large increase in EPU amplifies peer effects in corporate investment policy. Overall, our analyses demonstrate that both a high level of EPU and a large change in EPU magnify peer effects in corporate investment policy.

[Insert Table 3 Here]

[19] The requirements of the Sargan-Hansen and Arellano-Bond tests are again satisfied. Refer to Table 3 for the list of instruments included.

[20] For example, Gulen and Ion (2016), Wang et al. (2014), and Kang et al. (2014) find a negative relation between EPU and corporate investment.

4.3. Cross-sectional heterogeneity of the impacts of EPU on peer effects

While our analysis confirms the existence of EPU's magnifying effect on investment peer effects in China, there may exist cross-sectional heterogeneity across firms. Particularly, we analyse whether there is systematic heterogeneity between state owned enterprises (SOEs) and non-SOEs. Chen et al. (2017) show that Chinese SOEs have a significantly weaker sensitivity of investment expenditure to investment opportunities. If SOEs react differently to investment opportunities, they may react differently to both EPU and peer firms' actions as well. Thus, it is possible that the impact of EPU on the peer effects of SOEs is very different from that for non-SOEs. We estimate the impacts of EPU on the magnitude of peer effects separately for SOEs and non-SOEs.

The estimation results are reported in Table 4.[21] Columns (1) and (2) show the results for SOEs, and columns (3) and (4) show the results for non-SOEs. We can verify that higher EPU reduces investment levels for both types of firms. However, the effects of higher EPU on peer effects are heterogenous between SOEs and non-SOEs. The significantly positive coefficient of $HighEPU_t \times IDIO^{peer}_{i,t-1}$ for SOEs indicates that the reduction in their investments are mainly due to the peer effects. On the contrary, the coefficient of $HighEPU_t \times IDIO^{peer}_{i,t-1}$ for non-SOEs is nonsignificant, which might suggest that non-SOEs reduce investment due to higher EPU, but the reduction of their investments is not due to the increased peer effects.

China's SOEs have been considered as having inefficient operations (Liu and Pang, 2009; Lin et al., 2020). Similarly, Jiang et al. (2010) point out that government intervention leads to inefficient operation and investment behaviour. The unique objectives of SOEs could also hinder efficient investment. Since SOEs are controlled by the government or politicians, they are often requested to operate for social or political benefits instead of corporate profits (Fan et al., 2007; Lin et al.,

[21] We classify firms into SOEs and non-SOEs based on the nature of the ultimate owners available through the CSMAR. Based on our regression sample, approximately 64% of firm-years are classified as SOEs and the rest are classified as non-SOEs. However, along with the privatization process in China, the proportion of SOEs has decreased each year in recent decades. For example, the proportion of SOEs was approximately 75% in 2003, while the proportion of SOEs was approximately 52% in 2019.

1998). Our results are in line with these findings in that SOEs suffer from stronger peer effects compared to non-SOEs in our sample.

[Insert Table 4 Here]

4.4. Firm-specific uncertainty measures

Our main results are based on a macro-level uncertainty measure, i.e. the EPU index, to measure the overall market-level uncertainty. However, the peer effects in corporate investment policy could also depend on micro-level (or idiosyncratic) uncertainty measures that are heterogenous across individual firms. As a robustness test, we examine the effect of micro-level uncertainty on peer effects. Specifically, we measure micro-level uncertainty in two ways: 1) 5-year moving standard deviation of cash flows from operations (scaled by total assets) from year $t-5$ to year $t-1$ and 2) 5-year moving standard deviation of sales (scaled by total assets) from year $t-5$ to year $t-1$. We construct two dummy variables $HighSdCFO_{i,t}$ and $HighSdSALE_{i,t}$ based on the two micro-uncertainty measures. Each of the measures has a value of one if the corresponding uncertainty measure is above the sample median, and a value of zero otherwise.

Table 5 reports the estimation results. The results in columns (1) and (3) indicate that a high level of micro-level uncertainty reduces the level of corporate investment. More importantly, columns (2) and (4) show that a high level of micro-level uncertainty magnifies the peer effects in corporate investment using both measures of micro-level uncertainty. These findings are consistent with our main results based on the EPU measure. That is, both macro-level and micro-level uncertainty magnify peer effects in corporate investment.

[Insert Table 5 Here]

4.5. EPU and peer effects in overinvestment and underinvestment

To examine whether the impact of EPU on peer effects is asymmetric between overinvesting firms and underinvesting firms, we repeat the analyses separately. We follow Biddle et al. (2009) to measure overinvestment ($OverInv_{i,t}$) and underinvestment ($UnderInv_{i,t}$). We first obtain the residuals from industry-year cross-sectional regressions of firm i's investment rate ($INV_{i,t}$) on its lagged Tobin's q, where $INV_{i,t}$ is defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of year t. We then define $OverInv_{i,t}$ ($UnderInv_{i,t}$) as the absolute value of the residual for firm-years with positive (negative) residuals.

The estimation results are reported in Table 6. First of all, we find that peer effects, as measured by the coefficients of $IDIO^{peer}_{i,t-1}$, are stronger for underinvesting firms than for overinvesting firms. In addition, the interaction term, $HighEPU_t \times IDIO^{peer}_{i,t-1}$, is significantly positive for firms in the underinvestment subsample but nonsignificant for firms in the overinvestment subsample, indicating that the result in the full sample is mainly driven by underinvesting firms. This finding implies when EPU is greater, underinvesting firms react to their peers' underinvestment behaviour. This result is consistent with the real-options-based investment theory (Dixit et al., 1994; Bloom et al., 2007). Greater uncertainty deters investment due to the irreversible nature of corporate investment. An underinvesting firm's peer effect increases with an increase in EPU. In other words, when economic policy becomes more uncertain, firms are more likely to mimic their peers and give up some of their valuable (i.e. positive NPV) investment opportunities.

[Insert Table 6 Here]

Our findings are also consistent with Hypothesis 2. When EPU increases, a firm's investment decreases and peer effects increases. Greater peer effects accompanied by a firm's lower investment implies the overall level of underinvestment can be quite large when EPU is high. In other words, once peer firms tend to lower their investment levels, peer effects would further decrease investment. Therefore, firms in the underinvestment subsample are more significantly affected by EPU. When EPU decreases, however, peer effects would decrease while investment increases. Since peer effects are not as prevalent as before, a further increase in investment levels would be limited.

5. Possible mechanisms

In this section, we examine the mechanisms through which higher EPU magnifies peer effects in corporate investment policy. We propose and test the following three mechanisms: *i)* information cascade, *ii)* the asymmetric capacity of information acquisition, and *iii)* the career concerns of managers.

5.1. Information cascade mechanism

When EPU increases, the accuracy of the information that each firm possesses decreases because greater EPU makes it more difficult for firms to predict future investment opportunities. Consequently, overall peer effects can become more severe. Thus, the information cascade mechanism suggests that greater EPU actually increases the noise in investment opportunities which we measure using Tobin's q. To test this hypothesis, we adopt a two-stage regression framework. In the first stage, we estimate an AR(1) or AR(2) model of Tobin's q to obtain firm-year-specific residuals. In the second stage, we regress the absolute value of the residual on a measure of EPU, i.e. $HighEPU_t$. The empirical framework is specified below:

$$\begin{aligned} Q_{i,t} &= \alpha_0 + \alpha_1 Q_{i,t-1} (+\alpha_2 Q_{i,t-2}) + \alpha'_{CONTROLS}\mathbf{CONTROLS} \\ &\quad + \mathit{Firm\ Fixed\ Effects} + \mathit{Year\ Fixed\ Effects} + \varepsilon_{i,t}; \end{aligned} \tag{8}$$

$$|\widehat{RES_{i,t}}| = \beta_0 + \beta_1 HighEPU_t + Firm\ Fixed\ Effects + \varepsilon_{i,t}, \quad (9)$$

where the control variables include firm-specific characteristics and peer-firm-average characteristics.

Table 7 presents the estimation results. Column (1) reports the first-stage estimation results for the AR (1) model. We use the system GMM to estimate Eq. (8) for the AR(1) model of Tobin's q. The goodness-of-fit score for the AR(1) model is 0.688, and the requirement of the Sargan-Hansen test is also satisfied (p-value=0.180). The absolute value of the residual from Eq. (8), $|\widehat{RES_{i,t}}|$, is used as the dependent variable in Eq. (9). A positive sign of $HighEPU_t$ indicates that higher EPU decreases the accuracy of the signal. The second-stage results reported in column (2) show that there is a positive relation between $HighEPU_t$ and $|\widehat{RES_{i,t}}|$. The results based on the AR(2) model in the first stage are similar, as shown in column (3). The goodness-of-fit score for the AR(2) model is 0.684, and the requirement of the Sargan-Hansen test is satisfied (p-value=0.142). Again, the second-stage result reported in column (4) shows that there is a positive relation between $HighEPU_t$ and $|\widehat{RES_{i,t}}|$.

[Insert Table 7 Here]

In summary, we find evidence that EPU affects the magnitude of peer effects by influencing the accuracy of firms' signals regarding their investment opportunities. This evidence supports the information cascade mechanism. Specifically, consistent with Hypothesis 3, higher EPU decreases the accuracy of investment opportunities information; therefore, higher EPU makes it more difficult for firms to predict future investment opportunities, and thus, the peer effects in corporate investment policy would become more severe.

5.2. Asymmetric capacity of information acquisition mechanism

Next, the second mechanism through which higher EPU magnifies peer effects in investment decisions is based on the asymmetric capacity of information acquisition. To examine if the mechanism is supported, we examine whether the effects of EPU on the peer effects are heterogenous between small and young firms and large and old firms, and between small and young SOEs and large and old SOEs. A firm is classified as young (old) if its firm age is below (above) the median in the same peer group and small (large) if its firm size is below (above) the median in the same peer group.

Table 8 presents the estimation results. Columns (1) and (2) report the subsample estimation results for all firms, while columns (3) and (4) report the subsample estimation results for SOEs. In all four columns, the dynamic panel regression models are estimated using the system GMM. Firm-specific characteristics and peer-firm-average characteristics are included as control variables in all four columns. The results of columns (1) and (2) show that $HighEPU_t \times IDIO_{i,t-1}^{peer}$ is positive and statistically significant at the 5% level for small and young firms but is not significant for large and old firms. The results indicate that high EPU increases the peer effects of small and young firms but not the peer effects of large and old firms. Further, these distinctive effects of EPU on peer effects are also found between small and young SOEs and large and old SOEs, as shown in columns (3) and (4).

[Insert Table 8 Here]

Overall, our results demonstrate that higher EPU, indeed, amplifies the peer effects of small and young firms more prominently than the peer effects of large and old firms, supporting Hypothesis 4 that firms with superior information are able to keep or even enlarge their edge over other firms.

5.3. Career concerns mechanism

The third mechanism that could explain the relation between EPU and peer effects relates to the career concerns of managers. We use the firm-average tenure of directors or the industry-average tenure of directors as proxies for managers' career concerns.[22] We hypothesize that managers in a firm with shorter historical average tenure or managers in a firm that belongs to an industry with shorter historical average tenure will feel more concerned about their future careers. Arguably, such concerns would be materialized more prominently when the EPU increases in the economy. Thus, the peer effects of these firms will be amplified more significantly with higher EPU.

To verify the validity of the career concern mechanism, we examine whether the effects of EPU on the peer effects are heterogenous between short-tenure firms and long-tenure firms and between short-tenure industries and long-tenure industries. A firm is classified as a short-tenure (long-tenure) firm if its three-year moving-average directors' tenure is below the lower tercile (above the upper tercile); while an industry is classified as a short-tenure (long-tenure) industry if the cross-firm average of three-year moving-average directors' tenures is below the lower tercile (above the upper tercile).

Table 9 presents the estimation results. Columns (1) and (2) report the subsample estimation results for short-tenure firms and long-tenure firms, respectively, while columns (3) and (4) report the subsample estimation results for short-tenure industries and long-tenure industries, respectively. Column (1) shows that short-tenure firms have a significantly positive coefficient on the interaction term, $HighEPU_t \times IDIO^{peer}_{i,t-1}$, while the corresponding coefficient for long-tenure firms is not significant in column (2). The results indicate that high EPU magnifies short-tenure firms' peer effects significantly, while there is no such evidence for long-tenure firms. We also

[22] There are alternative measures for managers' career concerns. For instance, Chevalier and Ellison (1999) use managers' age as a proxy for career concerns. In our analysis, career concerns stem from the risk of being fired. Thus, we believe that the firm-average tenure of directors or the industry-average tenure of directors is a better measure for managers' career concerns. We appreciate Hong Zhu for giving us this suggestion.

find similar heterogeneity in the effect of high EPU on peer effects between firms in short-tenure industries and firms in long-tenure industries. Specifically, higher EPU magnifies peer effects only for firms in short-tenure industries. Thus, our results are consistent with Hypothesis 5.

[Insert Table 9 Here]

Overall, our investigation of the possible mechanisms reveals that EPU magnifies peer effects through the three channels we have proposed: 1) by decreasing the accuracy of firms' signals regarding their investment opportunities; 2) by asymmetrically impacting firms in terms of their capacity to acquire information; and 3) by exacerbating managers' career concerns.

6. Conclusion

Although an increasing body of literature links EPU to firms' investment decisions and considers whether there are peer effects in investment policies, few studies have investigated if and how EPU influences peer effects. Using the system GMM estimator combined with the IV method, we show peer effects are significantly stronger when EPU is greater. We further analyse three mechanisms for such effects, i.e. information cascade mechanism, asymmetric capacity of information acquisition mechanism, and career concerns mechanism, and find evidence supporting them. Particularly, we document that EPU magnifies peer effects of corporate investment since higher EPU amplifies the noise of the information that firms use to make investment decisions and eventually magnifies peer effects. We also find that such peer effects are more prevalent among firms with inferior information acquisition capacities and firms whose managers have stronger career concerns. Further, using subsamples of overinvesting and underinvesting firms, we find evidence that EPU magnifies peer effects only in underinvesting firms. This result suggests that higher EPU could cause underinvestment problems to last longer, slowing down recovery from an economic downturn. Based on our empirical findings, we argue that economic policies should be planned and executed in a consistent, reliable and transparent manner, especially during an economic downturn.

Appendix

Table A1. Stock return factor regression results

The sample consists of all listed nonfinancial firms in the CSMAR database between 1999 and 2019. The table presents mean factor loadings and adjusted R^2 from the regression

$$r_{ijt} = \alpha_{ijt} + \beta_{ijt}^{MKT}(r_{mt} - r_{ft}) + \beta_{ijt}^{IND}(\bar{r}_{-ijt} - r_{ft}) + \eta_{ijt},$$

where i, j and t denote firm i, peer group j and month t, respectively. r_{ijt} is firm i's monthly return in year t. r_{mt} denote the monthly market return in year t and r_{ft} denote the monthly risk-free rate in year t. $\bar{r}_{-ijt}$ is the peer-firm-average monthly return for firm i (excluding firm i's own monthly return) in year t, where peer groups are defined by the industry code C (i.e. *nnindcd* in CSMAR). The regression model is estimated for each firm on a rolling annual basis using historical monthly returns during the five-year period. We require at least 24 months of historical data for the estimation. Expected returns were computed using the estimated factor loadings and realized factor returns one year hence. Idiosyncratic returns were computed as the difference between realized returns and expected returns.

Variables	Mean	Std. Dev.	Q1	Median	Q3
Regression summary					
α_{ijt}	0.003	0.012	-0.004	0.002	0.009
β_{ijt}^{MKT}	0.284	0.642	-0.098	0.247	0.625
β_{ijt}^{IND}	0.727	0.575	0.407	0.757	1.070
Observations per regression	59.39	2.37	60.00	60.00	60.00
Adjusted R^2	0.516	0.154	0.419	0.528	0.629
Summary statistics					
Avg. monthly return	0.012	0.046	-0.019	0.005	0.036
Avg. expected monthly return	0.014	0.043	-0.012	0.007	0.035
Avg. idiosyncratic monthly return	-0.002	0.031	-0.019	-0.002	0.014
Sample characteristics					
Number of firm-year observations	16,642				
Number of firms	1,981				

References

An, H., Chen, Y., Luo, D., Zhang, T., 2016. Political uncertainty and corporate investment: Evidence from China. Journal of Corporate Finance 36, 174–189.

Angrist, J. D., 2014. The perils of peer effects. Labour Economics 30, 98–108.

Arellano, M., Bond, S., 1991. Some tests of specification for panel carlo application to data: Evidence and an employment equations. The Review of Economic Studies 58 (2), 277–297.

Arelleno, M., Bover, O., 1995. Another look at instrumental variable estimation of error component models. Journal of Econometrics 68 (1), 29–51.

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics 131 (4), 1593–1636.

Baumol, W. J., 1959. Business behavior, value and growth.

Bernanke, B. S., 1983. Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics 98 (1), 85–106.

Biddle, G. C., Hilary, G., Verdi, R. S., 2009. How does financial reporting quality relate to investment efficiency? Journal of Accounting and Economics 48 (2-3), 112–131.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy 100 (5), 992–1026.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. The Review of Economic Studies 74 (2), 391–415.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87 (1), 115–143.

Bond, S. R., 2002. Dynamic panel data models: A guide to micro data methods and practice. Portuguese Economic Journal 1 (2), 141–162.

Bulow, J. I., Geanakoplos, J. D., Klemperer, P. D., 1985. Multimarket oligopoly: Strategic substitutes and complements. Journal of Political Economy 93 (3), 488–511.

Carpenter, J. N., Lu, F., Whitelaw, R. F., 2021. The real value of China's stock market. Journal of Financial Economics 139 (3), 679–696.

Chen, N., Sung, H.-C., Yang, J., 2017. Ownership structure, corporate governance and investment efficiency of Chinese listed firms. Pacific Accounting Review 29 (3), 266–282.

Chen, Q., Goldstein, I., Jiang, W., 2007. Price informativeness and investment sensitivity to stock price. The Review of Financial Studies 20 (3), 619–650.

Chen, S., Ma, H., 2017. Peer effects in decision-making: Evidence from corporate investment. China Journal of Accounting Research 10 (2), 167–188.

Chevalier, J., Ellison, G., 1999. Career concerns of mutual fund managers. The Quarterly Journal of Economics 114 (2), 389–432.

Choi, N., Sias, R. W., 2009. Institutional industry herding. Journal of Financial Economics 94 (3), 469–491.

Dixit, R. K., Dixit, A. K., Pindyck, R. S., 1994. Investment under uncertainty. Princeton university press.

Dow, J., Gorton, G., 1997. Stock market efficiency and economic efficiency: Is there a connection? The Journal of Finance 52 (3), 1087–1129.

Durnev, A., 2010. The real effects of political uncertainty: Elections and investment sensitivity to stock prices. Available at SSRN 1549714.

Fan, J. P., Wong, T. J., Zhang, T., 2007. Politically connected CEOs, corporate governance, and post-IPO performance of China's newly partially privatized firms. Journal of Financial Economics 84 (2), 330–357.

Flannery, M. J., Hankins, K. W., 2013. Estimating dynamic panel models in corporate finance. Journal of Corporate Finance 19, 1–19.

Foucault, T., Fresard, L., 2014. Learning from peers' stock prices and corporate investment. Journal of Financial Economics 111 (3), 554–577.

Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. The Review of Financial Studies 29 (3), 523–564.

Hau, H., Lai, S., 2013. Real effects of stock underpricing. Journal of Financial Economics 108 (2), 392–408.

Hubbard, R. G., 1998. Capital-market imperfections and investment. Journal of Economic Literature 36 (1), 193–225.

Jegadeesh, N., Kim, W., 2010. Do analysts herd? An analysis of recommendations and market reactions. The Review of Financial Studies 23 (2), 901–937.

Jensen, M. C., 1986. Agency costs of free cash flow, corporate finance, and takeovers. The American Economic Review 76 (2), 323–329.

Jiang, F., Yi, Z., Su, F., 2009. Management background and corporate overinvestment behaviors. Management World 1, 130–139.

Jiang, G., Lee, C. M., Yue, H., 2010. Tunneling through intercorporate loans: The China experience. Journal of Financial Economics 98 (1), 1–20.

Julio, B., Yook, Y., 2012. Political uncertainty and corporate investment cycles. The Journal of Finance 67 (1), 45–83.

Kahneman, D., Lovallo, D., 1993. Timid choices and bold forecasts: A cognitive perspective on risk taking. Management Science 39 (1), 17–31.

Kang, W., Lee, K., Ratti, R. A., 2014. Economic policy uncertainty and firm-level investment. Journal of Macroeconomics 39, 42–53.

Kaustia, M., Rantala, V., 2015. Social learning and corporate peer effects. Journal of Financial Economics 117 (3), 653–669.

Leahy, J. V., Whited, T. M., 1996. The effect of uncertainty on investment: Some stylized facts. Journal of Money, Credit and Banking 28 (1), 64–83.

Leary, M. T., Roberts, M. R., 2014. Do peer firms affect corporate financial policy? The Journal of Finance 69 (1), 139–178.

Lin, J. Y., Cai, F., Li, Z., 1998. Competition, policy burdens, and state-owned enterprise reform. The American Economic Review 88 (2), 422–427.

Lin, K. J., Lu, X., Zhang, J., Zheng, Y., 2020. State-owned enterprises in China: A review of 40 years of research and practice. China Journal of Accounting Research 13 (1), 31–55.

Liu, J., Pang, D., 2009. Financial factors and company investment decisions in transitional China. Managerial and Decision Economics 30 (2), 91–108.

Malmendier, U., Tate, G., 2005. CEO overconfidence and corporate investment. The Journal of Finance 60 (6), 2661–2700.

Manski, C. F., 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60 (3), 531–542.

Myers, S. C., 1977. Determinants of corporate borrowing. Journal of Financial Economics 5 (2), 147–175.

Narayanan, M., 1985. Managerial incentives for short-term results. The Journal of Finance 40 (5), 1469–1484.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica 49 (6), 1417–1426.

Penrose, E., 2009. The Theory of the Growth of the Firm. Oxford university press.

Richardson, S., 2006. Over-investment of free cash flow. Review of Accounting Studies 11 (2-3), 159–189.

Scharfstein, D. S., Stein, J. C., 1990. Herd behavior and investment. The American Economic Review 80 (3), 465–479.

Stein, J. C., 1989. Efficient capital markets, inefficient firms: A model of myopic corporate behavior. The Quarterly Journal of Economics 104 (4), 655–669.

Stinchcombe, A. L., 1965. Organizations and social structure. Handbook of organizations 44 (2), 142–193.

Subrahmanyam, A., Titman, S., 1999. The going-public decision and the development of financial markets. The Journal of Finance 54 (3), 1045–1082.

Thaler, R. H., Ganser, L., 2015. Misbehaving: The making of behavioral economics. WW Norton New York.

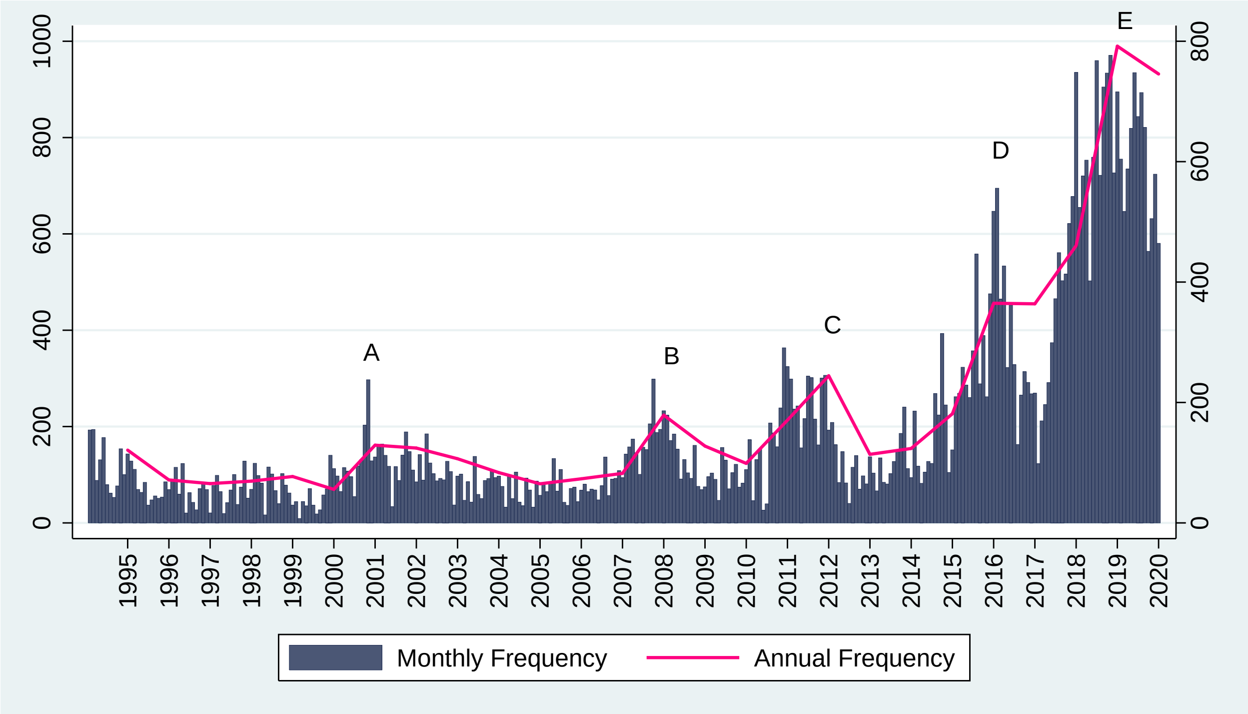
Trueman, B., 1994. Analyst forecasts and herding behavior. The Review of Financial Studies 7 (1), 97–124.

Wang, Y., Chen, C. R., Huang, Y. S., 2014. Economic policy uncertainty and corporate investment: Evidence from China. Pacific-Basin Finance Journal 26, 227–243.

Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics 126 (1), 25–51.

Zhang, J., 1997. Strategic delay and the onset of investment cascades. The RAND Journal of Economics 28 (1), 188–205.

Figure 1. Economic policy uncertainty index for the Chinese market



Notes. This figure depicts the Baker et al. (2016) economic policy uncertainty (EPU) index for the Chinese market during the period from January 1999 to December 2019, both in monthly frequency (the left axis) and in yearly frequency (the right axis). The dark blue bar presents monthly EPU index, while the pink solid line presents the average of monthly EPU index for each year.

Table 1. Variable definitions and summary statistics

This table shows the definitions and summary statistics of variables used in this study. The sample consists of all listed nonfinancial firms in the CSMAR database between 1999 and 2019. Panel A provides definitions of and formulas for the main variables used in this study. Panel B presents means, standard deviations, medians, lower quartiles (Q1), and upper quartiles (Q3) for the variables.

Panel A. Variable definitions

Abbreviation	Definition	Calculation
Firm-specific variables		
$INV_{i,t}$	Investment rate	Net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of year t
$INV_{i,t-1}$	Lagged investment rate	Net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of year $t-1$
$SIZE_{i,t-1}$	Firm size	Natural logarithm of total assets
$Q_{i,t-1}$	Investment opportunities	Tobin's q
$LEV_{i,t-1}$	Leverage	Book leverage ratio
$EBIT_{i,t-1}$	Profitability	Earnings before interest expenses and taxes divided by total assets at the beginning of year t
$CASH_{i,t-1}$	Cash holdings	Cash plus tradable financial assets divided by total assets
$AGE_{i,t-1}$	Age	Natural logarithm of the time elapsed since stock listing
Peer-firm-average variables		
$INV_{i,t}^{peer}$	Peer-firm-average investment rate	Peer-firm-average $INV_{i,t}$ (excluding firm i)
$SIZE_{i,t-1}^{peer}$	Peer-firm-average firm size	Peer-firm-average $LNTA_{i,t-1}$ (excluding firm i)
$Q_{i,t-1}^{peer}$	Peer-firm-average investment opportunities	Peer-firm-average $TQ_{i,t-1}$ (excluding firm i)
$LEV_{i,t-1}^{peer}$	Peer-firm-average leverage	Peer-firm-average $LEV_{i,t-1}$ (excluding firm i)
$EBIT_{i,t-1}^{peer}$	Peer-firm-average profitability	Peer-firm-average $EBIT_{i,t-1}$ (excluding firm i)
$CASH_{i,t-1}^{peer}$	Peer-firm-average cash holdings	Peer-firm-average $CASH_{i,t-1}$ (excluding firm i)
$AGE_{i,t-1}^{peer}$	Peer-firm-average age	Peer-firm-average $LNAGE_{i,t-1}$ (excluding firm i)
$IDIO_{i,t-1}^{peer}$	Peer-firm-average idiosyncratic return shock	Peer-firm-average $IDIO_{i,t-1}$ (excluding firm i) where $IDIO_{i,t-1}$ is the annualized idiosyncratic stock return constructed as in Leary and Roberts (2014)

Panel B. Summary statistics

Variables	Mean	Std. Dev.	Q1	Median	Q3
Firm-specific variables					
$INV_{i,t}$	0.056	0.070	0.012	0.036	0.078
$INV_{i,t-1}$	0.060	0.073	0.013	0.039	0.084
$SIZE_{i,t-1}$	22.100	1.297	21.180	21.940	22.840
$Q_{i,t-1}$	1.751	0.986	1.142	1.414	1.966
$LEV_{i,t-1}$	0.195	0.145	0.070	0.184	0.298
$EBIT_{i,t-1}$	0.066	0.066	0.031	0.056	0.092
$CASH_{i,t-1}$	0.156	0.106	0.082	0.131	0.204
$AGE_{i,t-1}$	2.257	0.508	1.792	2.303	2.708
Peer-firm-average variables					
$INV_{i,t}^{peer}$	0.058	0.032	0.037	0.053	0.071
$SIZE_{i,t-1}^{peer}$	22.030	0.827	21.400	21.980	22.520
$Q_{i,t-1}^{peer}$	1.785	0.597	1.315	1.619	2.099
$LEV_{i,t-1}^{peer}$	0.196	0.074	0.143	0.190	0.247
$EBIT_{i,t-1}^{peer}$	0.062	0.030	0.045	0.060	0.076
$CASH_{i,t-1}^{peer}$	0.156	0.043	0.126	0.154	0.180
$AGE_{i,t-1}^{peer}$	2.188	0.346	1.958	2.204	2.432
$AGE_{i,t-1}^{peer}$	2.206	0.333	1.977	2.216	2.443
$IDIO_{i,t-1}^{peer}$	-0.071	0.143	-0.103	-0.048	-0.008
Industry characteristics					
Number of firms per industry-year	33.15	23.52	13.00	28.00	47.00
Number of industries	71				
Sample characteristics					
Number of firm-year observations	16,642				
Number of firms	1,981				

Table 2. Identification of peer effects in corporate investment decisions—Dynamic panel IV regression results

This table presents the estimation results of three specifications of dynamic panel regression models. The sample consists of all nonfinancial firms in the CSMAR database between 1999 and 2019 with non-missing data for all regression variables. Column (1) presents the estimation result of the baseline dynamic panel regression model (without an external IV), Column (2) presents the reduced-form IV regression results, and columns (3) through (4) present the two-stage IV regression results. The baseline model, the reduced-form model, and the second-stage model of the two-stage model are estimated using the system GMM estimator. In estimating the first-stage model in the two-stage specification, we use an FE regression to obtain the predicted values of peer-firm-average investment rate ($\widehat{INV}_{i,t}^{peer}$), and the coefficient estimates and standard errors clustered by firms are presented in column (3). Columns (1), (2), and (4) present two-step system GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The dependent variable is firm i's investment rate ($INV_{i,t}$) defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of the year t. All explanatory variables are described in Panel A of Table 1. Year dummies are included in all regression models. GMM-style instruments used in system GMM are the contemporaneous value and all available lags of peer-firm-average investment rate or idiosyncratic return shock and the second to sixth lags of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average investment rate or idiosyncratic return shock, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. Note that year dummies are treated as instruments for the equations in levels only. We report p-values for the Arellano-Bond test for second-order serial correlation in first-differenced residuals and the Sargan-Hansen test of overidentifying restrictions. Overall goodness-of-fit scores measured as $[Corr(INV_{i,t}, \widehat{INV}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Model	SGMM	IV-SGMM	Two-stage IV-SGMM	
			First stage	Second stage
	(1)	(2)	(3)	(4)
Lagged dependent variable				
$INV_{i,t-1}$	0.358***	0.396***		0.396***
	(0.014)	(0.014)		(0.014)
Peer-effect-related variable				
$INV_{i,t}^{peer}$	0.504***			
	(0.040)			
$IDIO_{i,t-1}^{peer}$		0.008**	0.010***	
		(0.004)	(0.003)	
$\widehat{INV}_{i,t}^{peer}$				0.844**
				(0.416)
Firm-specific characteristics				
$SIZE_{i,t-1}$	0.004***	0.003**	0.001	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
$Q_{i,t-1}$	0.005***	0.005***	0.000	0.005***
	(0.001)	(0.001)	(0.000)	(0.001)
$LEV_{i,t-1}$	-0.008	-0.004	0.001	-0.004
	(0.009)	(0.009)	(0.003)	(0.009)
$EBIT_{i,t-1}$	0.124***	0.120***	0.005	0.116***
	(0.014)	(0.014)	(0.004)	(0.014)
$CASH_{i,t-1}$	0.061***	0.061***	0.002	0.059***
	(0.011)	(0.011)	(0.003)	(0.011)
$AGE_{i,t-1}$	-0.010***	-0.010***	-0.004**	-0.006***
	(0.001)	(0.002)	(0.002)	(0.002)
Peer-firm-average characteristics				
$SIZE_{i,t-1}^{peer}$	-0.002	0.006***	0.004***	0.002
	(0.002)	(0.002)	(0.002)	(0.003)
$Q_{i,t-1}^{peer}$	-0.004*	0.003	0.013***	-0.008
	(0.002)	(0.002)	(0.001)	(0.006)
$LEV_{i,t-1}$	0.015	0.062***	0.026**	0.040**
	(0.018)	(0.017)	(0.013)	(0.020)
$EBIT_{i,t-1}^{peer}$	-0.043	0.128***	0.231***	-0.067
	(0.030)	(0.029)	(0.020)	(0.099)
$CASH_{i,t-1}^{peer}$	-0.047*	-0.043*	0.059***	-0.093***
	(0.027)	(0.025)	(0.013)	(0.034)
$AGE_{i,t-1}^{peer}$	0.007	-0.019***	-0.027***	0.004
	(0.005)	(0.004)	(0.003)	(0.013)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	16,642	16,642	16,642	16,642
Number of firms	1,981	1,981	1,981	1,981
Second-order ser. corr. (p-value)	0.982	0.719		0.719
Sargan-Hansen (p-value)	0.391	0.361		0.361
Goodness-of-fit score/R-squard	0.327	0.327	0.303	0.327

Table 3. Impacts of EPU on peer effects in corporate investment decisions

This table presents the estimation results of reduced-form dynamic panel IV regression models designed to estimate the impacts of EPU on peer effects in corporate investment decisions. The sample consists of all nonfinancial firms in the CSMAR database between 2001 and 2019 with non-missing data for all regression variables. In the first two columns, we present the following regression specification: $INV_{i,t} = \beta_0 + \beta_1 INV_{i,t-1} + \beta_2 IDIO^{peer}_{i,t-1} + \beta_3 HighEPU_t (+\beta_4 HighEPU_t \times IDIO^{peer}_{i,t-1}) + \beta'_{CONTROLS}\mathbf{CONTROLS} + \mathit{Firm\ Fixed\ Effects} + \varepsilon_{i,t}$, where $HighEPU_t$ equals 1 if the annualized EPU measure divided by 100 (EPU_t) is higher than its historical median and 0 otherwise. We use $LogEPU_t$ and $IncEPU_t$ (i.e. the first difference of EPU_t) in place of $HighEPU_t$ in Columns (3) and (4) and Columns (5) and (6), respectively. In all columns, we present two-step system GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The dependent variable is firm i's investment rate ($INV_{i,t}$) defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of the year t. All control variables are described in Panel A of Table 1. GMM-style instruments in the first two columns (the last four columns) are the contemporaneous value and all available lags of peer-firm-average idiosyncratic return shock and the corresponding EPU measure and the second to sixth lags (the second to fifth lags) of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average idiosyncratic return shock and the corresponding EPU measure, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. We report p-values for the Arellano-Bond test for second-order serial correlation in first-differenced residuals and the Sargan-Hansen test of overidentifying restrictions. Overall goodness-of-fit scores measured as $[Corr(INV_{i,t}, \widehat{INV}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Model	IV-SGMM (1)	IV-SGMM (2)	IV-SGMM (3)	IV-SGMM (4)	IV-SGMM (5)	IV-SGMM (6)
Lagged dependent variable						
$INV_{i,t-1}$	0.405***	0.405***	0.406***	0.407***	0.406***	0.407***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
EPU and peer-effects variables						
$IDIO^{peer}_{i,t-1}$	0.006*	-0.009	0.005	0.001	0.005	0.000
	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
$HighEPU_t$	-0.005***	-0.003**				
	(0.001)	(0.001)				
$HighEPU_t \times IDIO^{peer}_{i,t-1}$		0.023***				
		(0.007)				
$LogEPU_t$			-0.002**	-0.002**		
			(0.001)	(0.001)		
$LogEPU_t \times IDIO^{peer}_{i,t-1}$				0.009*		
				(0.005)		
$IncEPU_t$					-0.000	-0.000
					(0.000)	(0.000)
$IncEPU_t \times IDIO^{peer}_{i,t-1}$						0.006*
						(0.004)
Firm-specific characteristics						
$SIZE_{i,t-1}$	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Q_{i,t-1}$	0.005***	0.005***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$LEV_{i,t-1}$	-0.004	-0.004	-0.007	-0.007	-0.006	-0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$EBIT_{i,t-1}$	0.119***	0.118***	0.118***	0.116***	0.118***	0.117***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$CASH_{i,t-1}$	0.064***	0.064***	0.067***	0.067***	0.067***	0.067***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$AGE_{i,t-1}$	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Peer-firm-average characteristics						
$SIZE^{peer}_{i,t-1}$	0.004**	0.004**	0.004**	0.004***	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Q^{peer}_{i,t-1}$	0.001	0.001	0.000	0.000	-0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
$LEV^{peer}_{i,t-1}$	0.091***	0.089***	0.089***	0.088***	0.096***	0.095***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
$EBIT^{peer}_{i,t-1}$	0.139***	0.137***	0.135***	0.133***	0.140***	0.138***
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
$CASH^{peer}_{i,t-1}$	0.003	0.002	0.008	0.008	0.009	0.007
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
$AGE^{peer}_{i,t-1}$	-0.010***	-0.012***	-0.010***	-0.011***	-0.011***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of observations	16,642	16,642	16,642	16,642	16,642	16,642
Number of firms	1,981	1,981	1,981	1,981	1,981	1,981
Second-order ser. corr. (p-value)	0.748	0.715	0.772	0.751	0.791	0.769
Sargan-Hansen (p-value)	0.776	0.777	0.629	0.611	0.617	0.602
Goodness-of-fit score	0.323	0.323	0.321	0.321	0.321	0.322

Table 4. Cross-sectional heterogeneity of the impacts of EPU on peer effects: SOEs versus non-SOEs

This table presents the estimation results of reduced-form dynamic panel IV regression models separately for state-owned enterprises (SOEs) and non-SOEs. The sample consists of all nonfinancial firms in the CSMAR database between 2003 and 2019 with non-missing data for all regression variables. Columns (1) and (2) report the results for SOEs, while columns (3) and (4) report the results for non-SOEs. Firms are classified as SOEs if ultimate controllers are the central government, a local government, or a centrally controlled corporation. In all columns, we present two-step system GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The dependent variable is firm i's investment rate ($INV_{i,t}$) defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of the year t. All control variables are described in Panel A of Table 1. GMM-style instruments in all four models are the contemporaneous value and the first to fourth lags of peer-firm-average idiosyncratic return shock and $HighEPU$ and the second to fourth lags of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average idiosyncratic return shock and $HighEPU$, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. We report p-values for the Arellano-Bond test for second-order serial correlation in first-differenced residuals and the Sargan-Hansen test of overidentifying restrictions. Overall goodness-of-fit scores measured as $[Corr(INV_{i,t}, \widehat{INV}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Sample	SOEs		Non-SOEs	
Model	IV-SGMM (1)	IV-SGMM (2)	IV-SGMM (3)	IV-SGMM (4)
Lagged dependent variable				
$INV_{i,t-1}$	0.428***	0.426***	0.348***	0.348***
	(0.017)	(0.017)	(0.024)	(0.024)
Uncertainty and peer-effects variables				
$IDIO^{peer}_{i,t-1}$	0.008*	-0.012	0.007	0.004
	(0.004)	(0.008)	(0.006)	(0.011)
$HighEPU_t$	-0.004**	-0.002	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
$HighEPU_t \times IDIO^{peer}_{i,t-1}$		0.032***		0.004
		(0.010)		(0.012)
Firm-specific characteristics				
$SIZE_{i,t-1}$	0.000	0.000	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
$Q_{i,t-1}$	0.003	0.003	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
$LEV_{i,t-1}$	0.011	0.011	-0.002	-0.002
	(0.012)	(0.012)	(0.014)	(0.014)
$EBIT_{i,t-1}$	0.147***	0.145***	0.106***	0.106***
	(0.020)	(0.020)	(0.022)	(0.022)
$CASH_{i,t-1}$	0.065***	0.065***	0.049***	0.049***
	(0.016)	(0.016)	(0.016)	(0.016)
$AGE_{i,t-1}$	-0.006***	-0.007***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.003)	(0.003)
Peer-firm-average characteristics				
$SIZE^{peer}_{i,t-1}$	0.006**	0.006***	-0.002	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)
$Q^{peer}_{i,t-1}$	0.003*	0.004*	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
$LEV^{peer}_{i,t-1}$	0.063***	0.059***	0.053**	0.053**
	(0.020)	(0.020)	(0.026)	(0.026)
$EBIT^{peer}_{i,t-1}$	0.117***	0.115***	0.078	0.078
	(0.032)	(0.032)	(0.049)	(0.048)
$CASH^{peer}_{i,t-1}$	-0.086***	-0.089***	0.001	0.001
	(0.032)	(0.032)	(0.040)	(0.040)
$AGE^{peer}_{i,t-1}$	-0.020***	-0.022***	-0.005	-0.005
	(0.004)	(0.004)	(0.006)	(0.006)
Number of observations	9,723	9,723	5,385	5,385
Number of firms	1,131	1,131	1,018	1,018
Second-order serial correlation (p-value)	0.891	0.847	0.538	0.539
Sargan-Hansen (p-value)	0.377	0.361	0.994	0.994
Goodness-of-fit score	0.363	0.363	0.290	0.291

Table 5. Robustness tests—Firm-specific uncertainty measures

This table presents the robustness tests using two firm-specific uncertainty measures. The first two columns report the results based on the 5-year moving standard deviation of cash flows from operations (scaled by total assets) from year $t-5$ to year $t-1$, while the last two columns report the results based on the 5-year moving standard deviation of sales (scaled by total assets) from year $t-5$ to year $t-1$. In all columns, we present two-step system GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The dependent variable is firm i's investment rate ($INV_{i,t}$) defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of the year t. All control variables are described in Panel A of Table 1. GMM-style instruments used in system GMM are the contemporaneous value and all available lags of peer-firm-average idiosyncratic return shock and $HighSdCFO_{i,t}$ or $HighSdSALE_{i,t}$ and the second to fifth lags of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average idiosyncratic return shock and $HighSdCFO_{i,t}$ or $HighSdSALE_{i,t}$, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. We report p-values for the Arellano-Bond test for second-order serial correlation in first-differenced residuals and the Sargan-Hansen test of overidentifying restrictions. Overall goodness-of-fit scores measured as $[Corr(INV_{i,t}, \widehat{INV}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Firm-specific uncertainty measure	Cash flow volatility		Sales volatility	
Model	IV-SGMM (1)	IV-SGMM (2)	IV-SGMM (3)	IV-SGMM (4)
Lagged dependent variable				
$INV_{i,t-1}$	0.417***	0.416***	0.416***	0.416***
	(0.014)	(0.014)	(0.014)	(0.014)
Uncertainty and peer-effects variables				
$IDIO^{peer}_{i,t-1}$	0.008**	-0.008	0.008**	-0.002
	(0.004)	(0.006)	(0.003)	(0.006)
$HighSdCFO_{i,t}$	-0.006***	-0.003*		
	(0.002)	(0.002)		
$HighSdCFO_{i,t} \times IDIO^{peer}_{i,t-1}$		0.031***		
		(0.010)		
$HighSdSALE_{i,t}$			-0.004***	-0.003*
			(0.001)	(0.002)
$HighSdSALE_{i,t} \times IDIO^{peer}_{i,t-1}$				0.022**
				(0.010)
Firm-specific characteristics				
$SIZE_{i,t-1}$	0.003***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Q_{i,t-1}$	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$LEV_{i,t-1}$	-0.010	-0.010	-0.008	-0.007
	(0.009)	(0.009)	(0.009)	(0.009)
$EBIT_{i,t-1}$	0.119***	0.120***	0.116***	0.117***
	(0.014)	(0.014)	(0.014)	(0.014)
$CASH_{i,t-1}$	0.068***	0.068***	0.065***	0.065***
	(0.012)	(0.012)	(0.012)	(0.012)
$AGE_{i,t-1}$	-0.011***	-0.011***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Peer-firm-average characteristics				
$SIZE^{peer}_{i,t-1}$	0.003**	0.003*	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
$Q^{peer}_{i,t-1}$	0.001	0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
$LEV^{peer}_{i,t-1}$	0.100***	0.101***	0.100***	0.098***
	(0.016)	(0.016)	(0.015)	(0.015)
$EBIT^{peer}_{i,t-1}$	0.150***	0.152***	0.153***	0.151***
	(0.027)	(0.027)	(0.027)	(0.027)
$CASH^{peer}_{i,t-1}$	-0.016	-0.014	0.004	0.002
	(0.024)	(0.024)	(0.023)	(0.023)
$AGE^{peer}_{i,t-1}$	-0.014***	-0.014***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.003)	(0.003)
Number of observations	14,595	14,595	14,731	14,731
Number of firms	1,839	1,839	1,840	1,840
Second-order serial correlation (p-value)	0.911	0.920	0.971	0.998
Sargan-Hansen (p-value)	0.757	0.741	0.975	0.973
Goodness-of-fit score	0.331	0.331	0.329	0.329

Table 6. Impacts of EPU on peer effects in corporate investment inefficiency

This table presents the estimation results of reduced-form dynamic panel IV regression models designed to estimate the impacts of EPU on peer effects in corporate investment inefficiency. The sample consists of all nonfinancial firms in the CSMAR database between 1999 and 2019 with non-missing data for all regression variables. We measure overinvestment ($OverInv_{i,t}$) and underinvestment ($UnderInv_{i,t}$) using the residuals from industry-year cross-sectional regressions of firm i's investment rate ($INV_{i,t}$) on its lagged Tobin's q, where $INV_{i,t}$ is defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of year t. Specifically, $OverInv_{i,t}$ ($UnderInv_{i,t}$) is defined as the absolute value of the residual for firm-years with positive (negative) residuals. This table presents fixed effects regression results based on the two subsamples for the following regression model: $OverInv_{i,t}$ (or $UnderInv_{i,t}$) $= \beta_0 + \beta_1 IDIO^{peer}_{i,t-1} + \beta_2 HighEPU_t + \beta_3 HighEPU_t \times IDIO^{peer}_{i,t-1} + \beta'_{CONTROLS}\mathbf{CONTROLS} + Firm\ Fixed\ Effects + \varepsilon_{i,t}$, where $HighEPU_t$ equals 1 if the annualized EPU measure divided by 100 (EPU_t) is higher than its historical median and 0 otherwise. All four columns present fixed effects regression estimates with standard errors clustered for firms. The dependent variable is $OverInv_{i,t}$ in the first two columns and $UnderInv_{i,t}$ in the last two columns. All control variables are described in Panel A of Table 1. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable Model	$OverInv_{i,t}$ FE (1)	$OverInv_{i,t}$ FE (2)	$UnderInv_{i,t}$ FE (3)	$UnderInv_{i,t}$ FE (4)
Uncertainty and peer-effects variables				
$IDIO^{peer}_{i,t-1}$	0.006	0.013	0.005**	-0.004
	(0.008)	(0.016)	(0.002)	(0.005)
$HighEPU_t$	0.001	0.001	-0.001	-0.000
	(0.002)	(0.003)	(0.001)	(0.001)
$HighEPU_t \times IDIO^{peer}_{i,t-1}$		-0.009		0.013**
		(0.018)		(0.005)
Firm-specific characteristics				
$SIZE_{i,t-1}$	-0.022***	-0.021***	-0.003***	-0.003***
	(0.004)	(0.004)	(0.001)	(0.001)
$Q_{i,t-1}$	0.002	0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
$LEV_{i,t-1}$	-0.032**	-0.032**	0.007*	0.008*
	(0.015)	(0.015)	(0.004)	(0.004)
$EBIT_{i,t-1}$	0.103***	0.103***	-0.045***	-0.045***
	(0.028)	(0.028)	(0.007)	(0.007)
$CASH_{i,t-1}$	0.072***	0.071***	-0.003	-0.004
	(0.019)	(0.019)	(0.005)	(0.005)
$AGE_{i,t-1}$	0.024***	0.024***	0.007***	0.007***
	(0.008)	(0.008)	(0.002)	(0.002)
Peer-firm-average characteristics				
$SIZE^{peer}_{i,t-1}$	-0.010	-0.010	-0.005***	-0.005***
	(0.007)	(0.007)	(0.002)	(0.002)
$Q^{peer}_{i,t-1}$	-0.000	-0.001	0.005***	0.005***
	(0.003)	(0.003)	(0.001)	(0.001)
$LEV^{peer}_{i,t-1}$	0.083*	0.083*	0.047***	0.046***
	(0.047)	(0.047)	(0.016)	(0.016)
$EBIT^{peer}_{i,t-1}$	-0.024	-0.021	0.167***	0.163***
	(0.068)	(0.068)	(0.024)	(0.024)
$CASH^{peer}_{i,t-1}$	0.112	0.114	0.101***	0.098***
	(0.072)	(0.072)	(0.019)	(0.019)
$AGE^{peer}_{i,t-1}$	0.002	0.002	-0.004	-0.005
	(0.013)	(0.013)	(0.004)	(0.004)
Number of observations	4,295	4,295	7,401	7,401
R-squared	0.081	0.081	0.078	0.079

Table 7. Testing the information cascade mechanism

This table presents the results of the two-stage regressions designed to test the information cascade mechanism. The sample consists of all nonfinancial firms in the CSMAR database between 1999 and 2019 with non-missing data for all regression variables. At the first stage, we estimate the AR(1) or AR(2) model of Tobin's q using system GMM. The model is specified as in Eq. (8). GMM-style instruments used in column (1) (column (3)) are the second to all available lags (the third to all available lags) of Tobin's q and peer-firm-average Tobin's q and the second to sixth lags of firm-specific and peer-firm-average control variables for the equations in first differences and the first lags of the change in Tobin's q, the change in peer-firm-average Tobin's q, and the changes in all firm-specific and peer-firm-average variables for level equations. Year dummies are treated as instruments for the equations in levels only. Columns (1) and (3) report the estimation results for the AR (1) and AR (2) models of Tobin's q, respectively. In columns (2) and (4), the dependent variables are the absolute values of the residuals ($|\widehat{RES_{i,t}}|$) of the AR (1) and AR (2) models, respectively. In the first stage, two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005) are reported. In the second stage, FE coefficients and standard errors that control for firm-level clustering are reported. Overall goodness-of-fit scores measured as $[Corr(Q_{i,t}, \widehat{Q}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	AR(1) model for Tobin's q		AR(2) model for Tobin's q	
Dependent variables	$Q_{i,t}$	$\|\widehat{RES_{i,t}}\|$	$Q_{i,t}$	$\|\widehat{RES_{i,t}}\|$
Model	(1)	(2)	(3)	(4)
$HighEPU_t$		0.032***		0.025***
		(0.006)		(0.007)
$Q_{i,t-1}$	0.567***		0.487***	
	(0.018)		(0.022)	
$Q_{i,t-2}$			0.053***	
			(0.017)	
$Q^{peer}_{i,t-1}$	0.034		0.051*	
	(0.023)		(0.029)	
$Q^{peer}_{i,t-2}$			-0.005	
			(0.023)	
$SIZE_{i,t-1}$	-0.181***		-0.186***	
	(0.017)		(0.018)	
$LEV_{i,t-1}$	-0.304***		-0.283***	
	(0.078)		(0.079)	
$EBIT_{i,t-1}$	0.318**		0.416***	
	(0.139)		(0.143)	
$CASH_{i,t-1}$	0.172*		0.116	
	(0.094)		(0.095)	
$AGE_{i,t-1}$	0.018		0.021	
	(0.015)		(0.016)	
$SIZE^{peer}_{i,t-1}$	0.006		-0.004	
	(0.023)		(0.025)	
$LEV^{peer}_{i,t-1}$	-0.607***		-0.532***	
	(0.167)		(0.172)	
$EBIT^{peer}_{i,t-1}$	-0.014		0.083	
	(0.275)		(0.279)	
$CASH^{peer}_{i,t-1}$	0.291		0.178	
	(0.291)		(0.312)	
$AGE^{peer}_{i,t-1}$	0.037		0.006	
	(0.050)		(0.052)	
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
Number of observations	16,814	16,814	16,785	16,785
Number of firms	1,987	1,987	1,986	1,986
Second-order serial correlation (p-value)	0.778		0.051	
Third-order serial correlation (p-value)			0.968	
Sargan-Hansen (p-value)	0.180		0.142	
Goodness-of-fit [R-squared]	0.688	[0.002]	0.684	[0.001]

Table 8. Testing the asymmetric capacity for information acquisition mechanism

This table presents the estimation results of reduced-form dynamic panel IV regression models separately for different types of firms: small and young firms versus large and old firms; and small and young SOEs versus large and old SOEs. The sample consists of all nonfinancial firms in the CSMAR database between 1999 and 2019 (in the first two columns) or between 2003 and 2019 (in the last two columns) with non-missing data for all regression variables. A firm is classified as young (old) if its firm age is below (above) the median in the same peer group and small (large) if its firm size is below (above) the median in the same peer group. In all columns, we present two-step system GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The dependent variable is firm i's investment rate ($INV_{i,t}$) defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of the year t. All control variables are described in Panel A of Table 1. GMM-style instruments in all four models are the contemporaneous value and the first to fourth lags of peer-firm-average idiosyncratic return shock and $HighEPU$ and the second to fourth lags of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average idiosyncratic return shock and $HighEPU$, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. We report p-values for the Arellano-Bond test for second-order serial correlation in first-differenced residuals and the Sargan-Hansen test of overidentifying restrictions. Overall goodness-of-fit scores measured as $[Corr(INV_{i,t}, \widehat{INV}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Sample	Small & young firms	Large & old firms	Small & young SOEs	Large & old SOEs
Model	IV-SGMM	IV-SGMM	IV-SGMM	IV-SGMM
	(1)	(2)	(3)	(4)
Lagged dependent variable				
$INV_{i,t-1}$	0.328***	0.420***	0.382***	0.438***
	(0.025)	(0.024)	(0.035)	(0.030)
Uncertainty and peer-effects variables				
$IDIO^{peer}_{i,t-1}$	-0.029***	0.005	-0.028*	0.001
	(0.011)	(0.011)	(0.015)	(0.013)
$HighEPU_t$	0.000	-0.005**	-0.002	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
$HighEPU_t \times IDIO^{peer}_{i,t-1}$	0.033**	0.010	0.042**	0.008
	(0.014)	(0.012)	(0.021)	(0.015)
Firm-specific characteristics				
$SIZE_{i,t-1}$	0.005	-0.001	-0.004	-0.004
	(0.004)	(0.003)	(0.006)	(0.003)
$Q_{i,t-1}$	0.005*	0.010***	0.008*	0.002
	(0.003)	(0.003)	(0.005)	(0.003)
$LEV_{i,t-1}$	0.024*	0.009	0.039	-0.004
	(0.014)	(0.014)	(0.024)	(0.019)
$EBIT_{i,t-1}$	0.172***	0.061**	0.221***	0.095***
	(0.023)	(0.027)	(0.041)	(0.032)
$CASH_{i,t-1}$	0.072***	0.010	0.060**	0.013
	(0.018)	(0.019)	(0.025)	(0.028)
$AGE_{i,t-1}$	-0.012***	-0.007**	-0.012**	-0.011***
	(0.004)	(0.003)	(0.005)	(0.004)
Peer-firm-average characteristics				
$SIZE^{peer}_{i,t-1}$	0.009**	0.004	0.008	0.007*
	(0.004)	(0.003)	(0.005)	(0.003)
$Q^{peer}_{i,t-1}$	-0.002	0.001	-0.003	0.004
	(0.004)	(0.003)	(0.006)	(0.003)
$LEV^{peer}_{i,t-1}$	0.074***	0.098***	-0.002	0.117***
	(0.025)	(0.024)	(0.040)	(0.031)
$EBIT^{peer}_{i,t-1}$	0.104**	0.103**	0.107	0.111**
	(0.043)	(0.044)	(0.068)	(0.054)
$CASH^{peer}_{i,t-1}$	0.030	0.005	-0.140**	0.003
	(0.037)	(0.041)	(0.063)	(0.042)
$AGE^{peer}_{i,t-1}$	-0.017***	-0.015**	-0.019**	-0.015*
	(0.006)	(0.006)	(0.009)	(0.008)
Number of observations	4,499	6,149	1,999	4,177
Number of firms	1,302	1,169	642	714
Second-order serial correlation (p-value)	0.111	0.944	0.636	0.959
Sargan-Hansen (p-value)	0.994	0.998	0.993	0.797
Goodness-of-fit score	0.262	0.362	0.341	0.377

Table 9. Testing the career concerns mechanism

This table presents the estimation results of reduced-form dynamic panel IV regression models separately for different types of firms: short-tenure firms versus long-tenure firms; and short-tenure industries versus long-tenure industries. The sample consists of all nonfinancial firms in the CSMAR database between 1999 and 2019 with non-missing data for all regression variables. A firm is classified as a short-tenure (long-tenure) firm if its three-year moving-average directors' tenure is below the lower tercile (above the upper tercile), while an industry is classified as a short-tenure (long-tenure) industry if the cross-firm average of three-year moving-average directors' tenures is below the lower tercile (above the upper tercile). In all columns, we present two-step system GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The dependent variable is firm i's investment rate ($INV_{i,t}$) defined as net capital expenditures plus net acquisitions less sales of fixed assets divided by total assets at the beginning of the year t. All control variables are described in Panel A of Table 1. GMM-style instruments in all four models are the contemporaneous value and the first to fourth lags of peer-firm-average idiosyncratic return shock and $HighEPU$ and the second to fourth lags of the investment rate and the firm-specific and peer-firm-average control variables for equations in first differences and the first lag of the change in peer-firm-average idiosyncratic return shock and $HighEPU$, the first lag of the change in investment rate, and the first lag of the change in all firm-specific and peer-firm-average control variables for level equations. We report p-values for the Arellano-Bond test for second-order serial correlation in first-differenced residuals and the Sargan-Hansen test of overidentifying restrictions. Overall goodness-of-fit scores measured as $[Corr(INV_{i,t}, \widehat{INV}_{i,t})]^2$ are also reported. Superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Sample	Short-tenure firms	Long-tenure firms	Short-tenure industries	Long-tenure industries
Model	IV-SGMM	IV-SGMM	IV-SGMM	IV-SGMM
	(1)	(2)	(3)	(4)
Lagged dependent variable				
$INV_{i,t-1}$	0.345***	0.437***	0.365***	0.398***
	(0.026)	(0.028)	(0.021)	(0.031)
Uncertainty and peer-effects variables				
$IDIO^{peer}_{i,t-1}$	-0.015	-0.012	0.007	-0.029
	(0.010)	(0.020)	(0.008)	(0.021)
$HighEPU_t$	-0.006***	-0.003	-0.006**	0.003
	(0.002)	(0.003)	(0.002)	(0.003)
$HighEPU_t \times IDIO^{peer}_{i,t-1}$	0.044***	0.024	0.024**	0.034
	(0.014)	(0.022)	(0.011)	(0.022)
Firm-specific characteristics				
$SIZE_{i,t-1}$	0.006**	0.004*	0.007***	0.007***
	(0.003)	(0.002)	(0.003)	(0.002)
$Q_{i,t-1}$	0.007**	0.004*	0.009***	0.004**
	(0.003)	(0.002)	(0.003)	(0.002)
$LEV_{i,t-1}$	-0.023	-0.019	-0.003	-0.019
	(0.016)	(0.018)	(0.015)	(0.019)
$EBIT_{i,t-1}$	0.112***	0.107***	0.157***	0.063***
	(0.025)	(0.031)	(0.020)	(0.016)
$CASH_{i,t-1}$	0.077***	0.004	0.046**	0.018
	(0.024)	(0.020)	(0.023)	(0.014)
$AGE_{i,t-1}$	-0.013***	-0.010***	-0.010***	-0.009***
	(0.003)	(0.002)	(0.003)	(0.002)
Peer-firm-average characteristics				
$SIZE^{peer}_{i,t-1}$	0.007*	-0.004	0.005	-0.011***
	(0.004)	(0.003)	(0.003)	(0.003)
$Q^{peer}_{i,t-1}$	0.007**	0.001	-0.001	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)
$LEV^{peer}_{i,t-1}$	0.095***	0.090***	0.084***	0.053*
	(0.032)	(0.030)	(0.024)	(0.031)
$EBIT^{peer}_{i,t-1}$	0.172***	0.030	0.135***	0.113***
	(0.048)	(0.047)	(0.038)	(0.042)
$CASH^{peer}_{i,t-1}$	-0.104**	0.025	-0.054	-0.072
	(0.046)	(0.055)	(0.039)	(0.048)
$AGE^{peer}_{i,t-1}$	-0.018***	0.003	-0.014***	0.007
	(0.007)	(0.008)	(0.005)	(0.006)
Number of observations	3,990	4,242	5,425	4,914
Number of firms	1,153	1,317	1,198	1,551
Second-order serial correlation (p-value)	0.493	0.103	0.392	0.144
Sargan-Hansen (p-value)	0.830	0.954	0.244	0.399
Goodness-of-fit score	0.302	0.355	0.331	0.317