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Investor short-termism and real investment☆

Dominik M. Rösch [a], Avanidhar Subrahmanyam [b], Mathijs A. van Dijk [c,*]

[a] State University of New York, Buffalo, USA
[b] UCLA Anderson School, USA
[c] Rotterdam School of Management, Erasmus University, Netherlands

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ABSTRACT

Short-term traders could affect the informativeness of stock prices about long-run fundamentals. Less (more) short-termism may thus induce managers to rely more (less) on stock prices in real investment decisions. Supporting this notion, we show that the investment-to-price sensitivity is inversely related to two short-termism proxies (controlling for firm size): institutional churn and liquidity. We confirm this finding using decimalization and an increase in mutual fund disclosure frequency as exogenous shocks to short-termism. Furthermore, short-termism is associated with an increased likelihood of voluntary capital expenditure forecasts by managers, suggesting a greater tendency to solicit market feedback when short-termism is high.

1. Introduction

The effect of investors' short-termism (broadly defined as investors pursuing uninformative short-term speculation and neglecting long-run fundamentals) on firms is of interest to regulators as well as practitioners. Bhide (1993) indicates that short-term traders may impede corporate governance because short-horizon traders care more about obtaining favorable prices than about corporate monitoring. Short-term traders can lead to market inefficiencies, herding, and speculative bubbles (Tirole, 1982; Dow and Gorton, 1994). Furthermore, these short-term traders may in part consist of noise traders, who trade for non-information reasons or are less than fully rational (Summers and Summers, 1989). Such traders can cause market prices to deviate from fundamentals, deter arbitrageurs from correcting market inefficiencies, and generate excess volatility (Black, 1986; DeLong et al., 1990).

In this paper, we examine a consequence of short-termism that, to the best of our knowledge, has not been investigated to date. We begin with the argument that a short-term focus might attenuate the incorporation of long-term fundamentals into prices (Froot et al., 1992). This would affect the efficacy of corporate resource allocation via the reliance of real investment on stock prices, because managers would be less able to learn from the stock price (Bond et al., 2012). This argument implies a stronger dependence of real investment on market prices for stocks with less short-termism, and vice versa. This forms our main hypothesis. In a contrary hypothesis, however, greater short-term noise trading might subsidize information collection, which implies that greater levels of such trading might improve stock price informativeness and thus increase the sensitivity of real investment to stock prices (Subrahmanyam and Titman, 1999).

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* Corresponding author.
E-mail addresses: drosch@buffalo.edu (D.M. Rösch), subra@anderson.ucla.edu (A. Subrahmanyam), madijk@rsm.nl (M.A. van Dijk).

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We test these competing hypotheses by investigating how the sensitivity of corporate investment to market valuations as measured by Tobin's Q (the investment-to-price sensitivity) is affected by two proxies for short-termism: market (il)liquidity and the institutional investor churn ratio. First, inspired by Bhide (1993), we use two key measures of a stock's illiquidity based on intraday trade and quote data (using 41.3 billion transactions in total): the proportional quoted bid-ask spread and the proportional effective spread. Bhide (1993) argues that liquid markets may encourage short-term trading behavior, while illiquidity might induce investors to hold the stock long-term. Subrahmanyam (1998) presents a model where increasing liquidity via lowering transaction taxes promotes the collection of short-term information signals at the expense of long-term ones, while Black (1986, p. 532) argues that "[w]hat's needed for a liquid market causes prices to be less efficient". Our second proxy for short-termism is the institutional investor churn ratio of Cella et al. (2013). Greater values of a stock's churn ratio indicate a shorter trading horizon of the institutional investors holding the stock.

Following Chen et al. (2007, henceforth CGJ), we measure the investment-to-price sensitivity using three different measures of corporate investment: the sum of capital expenditure and R&D expenses, capital expenditure, and the change in book assets, all scaled by beginning-of-year book assets. We construct a large sample of firm-quarter observations on the short-termism proxies, corporate investment, and Tobin's Q of all NYSE and NASDAQ stocks that survive our data screens over 1983–2016.

We first show that real investment is less sensitive to market valuations for stocks that are characterized by more short-termism. We estimate cross-sectional Fama and MacBeth (1973) regressions of the three investment measures on lagged Q, lagged illiquidity, and the interaction of lagged Q with lagged illiquidity. The coefficient on the interaction term is consistently and significantly positive for both of our illiquidity measures, even after including the control variables used by CGJ. We also find that the investment-to-price sensitivity decreases with the institutional churn ratio. Our main results are robust to controlling for firm size as well as firm complexity, to estimating the investment-to-price sensitivity separately for different industries, and throughout our sample period 1983–2016. In addition, higher values of the component of illiquidity that is explained by the churn ratio are associated with a greater investment-Q sensitivity, indicating that liquidity is related to the investment-to-price sensitivity in part through institutional churn.

We investigate how our results relate to the finding of CGJ that the investment-to-price sensitivity is greater for stocks with greater stock price nonsynchronicity – or the 1-R^2 measure of Morck et al. (2000). The notion is that less synchronous stock prices contain more stock-specific information and thus 1-R^2 is positively related to stock price informativeness. Consistent with our association of illiquidity with short-termism, the cross-sectional correlations of 1-R^2 with our two illiquidity measures are positive and significant. We control for 1-R^2 and its interaction with lagged Q in all our regressions and indeed obtain a positive and significant coefficient on the interaction term throughout, but our main results are not affected. When we sort stocks into 3×3 portfolios based on their 1-R^2 and illiquidity, we observe that our proposed relation holds within each 1-R^2 portfolio and vice versa. Thus, our results obtain after accounting for the effect of 1-R^2 on the investment-price sensitivity. A potential explanation for this result is that 1-R^2 is a general proxy for informativeness (both short-term and long-term), while our analysis supports the notion that liquidity is associated with short-termism, thereby affecting the incorporation of information about long-term fundamentals in particular (the type of information that should be most relevant for investment decisions).

To address identification, we supplement our cross-sectional regressions by three difference-in-differences (DiD) schemes. We first conduct an analysis around two events that exogenously increased liquidity: decimalization and an exogenous shock to analyst coverage. We first consider decimalization, which represented a secular decrease in bid-ask spreads (Bessembinder, 2003). We find evidence that stocks that experienced the greatest increase in liquidity around the decimals shift also experienced the greatest decline in the investment-to-price sensitivity. We obtain similar results when using another shock to the liquidity of individual stocks: the termination of analyst coverage of individual stocks due to the closing of the research departments of a number of U.S. brokerage firms during our sample period (following Kelly and Ljungqvist, 2012).[1]

Next, we address the concern that while illiquidity and institutional churn ratio are proxies for the horizon of the investors active in a stock, investors with short horizons may not necessarily ignore long-term fundamentals. In particular, we consider the scenario suggested by Agarwal et al. (2018, henceforth AVV),[2] who consider a regulation that required mutual funds to disclose their holdings more frequently. AVV argue that this regulation tended to make mutual fund managers more myopic (short-term oriented), which discouraged the filing of firm patents. Consistent with this argument, we find that the investment sensitivity to Q decreased following the regulatory shift for stocks held predominantly by funds that were most affected by this regulation. This finding supplements the results of our baseline short-termism proxies and indicates that, indeed, the presence of more short-term-oriented investors is associated with a lower investment-to-price sensitivity.

Although our results are suggestive of more short-termism being associated with stock prices that are noisier (i.e., less informative about fundamentals) and thus with a lower investment-to-price sensitivity, they do not provide direct evidence on the notion that short-termism induces noise in stock prices. Indeed, in Kyle (1985) the causality is reversed, and noise traders improve market liquidity. In Bhattacharyya and Nanda (2013), short-termism induces greater liquidity, whereas in Admati and Pfleiderer (1988), greater noise trading subsidizes more information collection. To address this concern, as a supplementary test, we follow Jayaraman and Wu (2020), who argue that firms are more likely to issue a forecast of capital expenditures when stock prices are noisier. This voluntary disclosure serves as a mechanism to solicit feedback from informed traders, who are attracted to analyze and interpret the

[1] The implicit argument is that less public information produced by analysts following the brokerage closures increase information asymmetry (Easley et al., 1998), and thus increase illiquidity and raise costs of informationless short-term trading. We are very grateful to Feng (Jack) Jiang for sharing the list of control and treated firms used in Harford et al. (2019), who use data similar to Kelly and Ljungqvist (2012).

[2] See also Agarwal et al. (2015) and Agarwal et al. (2020). We are very grateful to Vikas Agarwal for sharing the list of affected firms used in AVV.

disclosure (Fishman and Hagerty, 1989). Such feedback is especially valuable when stock prices are noisy. This argument can be used to test our implicit hypothesis that stock prices are noisier when there is more short-termism. We find that, indeed, managers of firms with greater institutional churn and greater liquidity are more likely to issue a capital expenditures forecast.[3]

In our final test, we examine how the earnings response coefficient (ERC) varies with stock liquidity and institutional churn. The ERC measures the stock price response to earnings surprises around the days surrounding the announcements and is inversely related to stock price informativeness. The idea is that a greater ERC indicates a lesser degree of informed trading before the earnings announcement and thus less incorporation of information into the stock price (Brennan et al., 2018). We find that the ERC is greater for stocks that are more liquid and have greater institutional churn. We also perform a DiD for the ERC around decimalization and around the AVV event, and find that the ERC increased the most for stocks that were affected the most by these regulatory shifts. These findings lend further support to our conjecture that more short-termism is associated with stock prices that are less informative about long-term fundamentals, and thus a lower investment-to-price sensitivity.

Our analysis points at a consequence of investor short-termism, which attenuates the ability of managers to learn about long-term fundamentals from stock prices. Our work links to at least three lines of the literature. First, many papers have linked the investment-to-price sensitivity to managerial learning from stock prices (e.g., Bakke and Whited, 2010; Foucault and Frésard, 2012; Goldstein et al., 2013). The line of studies most closely related to our paper examines how the investment-to-price sensitivity varies across firms and over time. For example, CGJ relate the sensitivity of investment to Q to price informativeness proxies. In other work, Dessaint et al. (2019) study how firms' investments respond to non-fundamental drops in the stock price of their product-market peers. They do not investigate the relation of the investment-to-price sensitivity with liquidity and, theoretically, this relation is ambiguous. Thus, liquidity can be associated with greater price informativeness due to greater competition between informed traders in Kyle-type settings (Admati and Pfleiderer, 1988) or lower price informativeness in bid-ask spread-based models (Glosten and Milgrom, 1985). Our result linking high liquidity as a short-termism proxy to reduced investment-price sensitivity[4] adds to the understanding of how reducing market frictions affects managerial learning from stock prices.[5]

The second line of work investigates various implications of investor short-termism. Chakrabarty et al. (2017) find that the majority of short-term institutional trades lose money and thus that there is no evidence that short-term investors are informed. Cremers and Pareek (2015) show that stock market anomalies are stronger among stocks held primarily by short-term investors and interpret their results as evidence of overconfident short-term traders reducing market efficiency. Cella et al. (2013) show that investors with short horizons demand liquidity in times of financial market turmoil, thereby amplifying negative market shocks. Harford et al. (2018) find that long-term investors enhance governance, innovation, and profitability. On the other hand, Giannetti and Yu (2020) find that firms with more short-term investors adapt better to changes in their competitive environment. Our paper also relates to the work of Weller (2018), who does not focus on short-term trading in general but on algorithmic trading in particular and shows that it is associated with lower price informativeness. We contribute to this strand of the literature by analyzing how investor short-termism affects corporate resource allocation.

We also add to a third line of research on the relation between the short-termism/liquidity pathway and corporate finance. Fang et al. (2014) show that liquidity reduces the number of patent filings and citations per patent. While this finding is important, it does not consider how liquidity might affect stock price informativeness, and, in turn, the efficacy of total resource allocation. Our economic pathway explicitly focuses on how the sensitivity of aggregate capital investment to market valuations is moderated by short-termism, which, in turn, may be related to liquidity and institutional churn.[6]

2. Data and methods

In this section, we discuss our data sources, variable definitions, and empirical methods. In Subsection 2.1, we describe the construction of our proxies for short-termism. In Subsection 2.2, we discuss how we estimate the investment-to-price sensitivity based on quarterly accounting and stock price data. In Subsection 2.3, we outline how we estimate the earnings response coefficient. In Subsection 2.4, we explain how we address identification in each of our analyses by conducting difference-in-differences tests. In Subsection 2.5, we discuss summary statistics of the variables included in our analyses. In Subsection 2.6, we examine whether our premise that more liquid stocks attract investors with shorter horizons holds in our sample.

[3] This result obtains after controlling for the Jayaraman and Wu (2020) measure of the noise-to-signal ratio, which is the ratio of the portions of the firm's Q that can and cannot be predicted from mutual fund flows.

[4] Kerr et al. (2020) find that returns of more liquid stocks are more informative about one-year-ahead earnings growth. The findings in this paper on the relation between our short-termism measures (including liquidity) and the investment-to-price sensitivity, stock price nonsynchronicity, capital expenditure forecasts, and the earnings response suggest that these measures have an adverse effect on informativeness about signals that are useful for real investment. A likely explanation is that information other than annual earnings growth might be useful for corporate resource allocation. Such information might involve profit margins and cash flows over horizons other than one year.

[5] After completing the first version of our paper, we became aware of a related paper by Ye et al. (2019), who find that the investment-to-price sensitivity is greater for firms whose share price is more discrete. Their paper focuses on the 2016 Tick Size Pilot Program by the SEC, while we analyze the relation between the investment-to-price sensitivity and short-termism more generally.

[6] We do understand that one benefit of improved liquidity is a reduction in expected or required rates of return; viz. Amihud and Mendelson (1986). We do not take a position on whether, on net, liquidity is beneficial or harmful to firms. Liquidity might also alter the incentives of other agents. For example, Pasquariello (2007) indicates that central banks often intervene in currency markets. Liquidity might change the frequency of these interventions, thus affecting their efficacy.

2.1. Short-termism proxies

Our sample consists of firm-quarter observations on our proxies for short-termism, corporate investment, and Tobin's Q of all NYSE and NASDAQ stocks that survive our data screens over the 1983–2016 period. We use two proxies for short-termism: illiquidity and institutional churn. Tick-by-tick transaction and quote data to compute our measures of a stock's illiquidity are from the Institute for the Study of Security Markets (ISSM) and the NYSE Trade and Quote (TAQ) databases. Our data include all best bid and offer (BBO) quotes on all U.S. exchanges, from which we construct national best bid and offer (NBBO) quotes following Holden and Jacobsen (2014). Pre-1993 trade and quote data are from ISSM. For data before 1996, we delay quotes by 5 seconds following Lee and Ready (1991). We use monthly TAQ data from 1993 to 2014, with trades and quotes timestamped by the second, and daily TAQ data from 2014 onwards. We apply the Holden and Jacobsen (2014) interpolated time technique for all data from 1983 to 2014. We follow the data filters of Rösch et al. (2017) in dealing with the tick-by-tick transaction data. We adjust trading volume data for NASDAQ stocks before 2004 following Gao and Ritter (2010).

We use two measures of a stock's market illiquidity: the proportional quoted bid-ask spread (*PQSPR*; the quoted bid-ask spread scaled by the quote midpoint), reflecting the costs of a round-trip transaction at the inside bid and ask quote, as well as the proportional effective spread (*PESPR*; two times the absolute difference between the transaction price and the quote midpoint, scaled by the quote midpoint) as an illiquidity measure that measures actual transaction costs, taking into account price impact. *PQSPR* and *PESPR* are computed daily for each stock in the sample as, respectively, the time-weighted average quoted spread over the trading day and the average effective spread across all trades on a day – and are subsequently aggregated to the monthly frequency by averaging across days within the month, and to the quarterly frequency by averaging across months within the quarter.

As a more specific proxy for the average trading horizon of the institutional investors holding a certain stock, we adopt the *Churn* ratio of Cella et al. (2013). In particular, following their approach, we first estimate, for each institutional investor, the average fraction of its shareholdings it trades in a given quarter based on quarterly holdings data for the universe of 13F institutional investors (which include mutual funds, hedge funds, trust companies, pension funds, insurance companies, and registered investment advisers) from Thomson Financial. We refer to the equation on page 1612 of Cella et al. (2013) for a definition of the churn ratio of an individual institutional investor. We compute the stock-level *Churn* ratio as the weighted average of the total portfolio churn ratio across all institutional investors holding that stock (see the equation on p. 1615 of Cella et al., 2013, where we choose $M = 1$). We cross-sectionally winsorize the stock-level *Churn* ratio at the 99% level each quarter to mitigate the influence of outliers.

In our initial tests to ascertain our premise that more liquid stocks attract investors with shorter horizons, we also use the quarterly *Turnover* (the number of shares traded within the quarter as a fraction of total shares outstanding, both from CRSP) of each stock in our sample as a crude but direct indicator of how often the average share of a firm changes hands each quarter.

2.2. Estimation of the investment-to-price sensitivity

We follow Chen et al. (2007) for the estimation of the investment-to-price sensitivity. Our baseline regression is as follows:

$$Inv_{i,q} = \beta_{0,q} + \beta_{1,q} ST_{i,q-1} \times Q_{i,q-1} + \beta_{2,q} ST_{i,q-1} + \beta_{3,q} Q_{i,q-1} + \Sigma \beta_q Contr_{i,q-1} + \varepsilon_{i,q}, \tag{1}$$

where *Inv* is corporate investment for firm *i* in quarter *q*, *ST* is one of our three proxies for short-termism (*PQSPR*, *PESPR*, or *Churn*), Q is Tobin's Q which we use as a measure of firm *i*'s stock market valuation, and *Contr* is a set of control variables. We estimate Eq. (1) cross-sectionally each quarter using the Fama and MacBeth (1973) approach.

The coefficient β_3 is the investment-to-price sensitivity, which, in line with previous studies, we expect to be positive. Further, β_1 measures how the investment-to-price sensitivity varies with our short-termism proxies. Our main hypothesis is that the investment-to-price sensitivity is lower for stocks with greater market liquidity and greater short-termism, which would imply that β_1 is positive for *PQSPR* and *PESPR*, and negative for *Churn*.

We obtain accounting data from Compustat and exclude firm-quarters in the financial industries (SIC code 6000–6999) and utility industries (SIC code 4200) as well as firm-quarters with book assets below US$ 10 million. Following CGJ, we use three different corporate investment measures: the sum of capital expenditure and R&D expenses (*CAPXRND*), capital expenditure (*CAPX*), and the change in book assets (*CHGASSET*), all scaled by beginning-of-year book assets. Following Himmelberg et al. (1999) and Edmans et al. (2017a), we set missing R&D expenses to zero. *CAPXRND* and *CAPX* are direct measures of a firm's real investment and R&D activities, respectively, while *CHGASSET* is a broader measure of investment that includes acquisition and divestiture activities.

Stock price and return information is from CRSP. We estimate Tobin's Q as the market value of equity (price times shares outstanding from CRSP) plus the book value of assets minus the book value of equity, scaled by book assets. In other words, $Q = (mktcap + ATQ - bvse)/ATQ$, where *ATQ* is quarterly total assets from Compustat, and *bvse* is stockholders' equity from Compustat, if available; otherwise, we use the book value of common equity plus the par value of preferred stock, or the book value of assets minus total liabilities (in that order).

Following CGJ, we include the 1-R^2 stock price nonsynchronicity measure of Morck et al. (2000), as well as its interaction with Q, as a control variable in all our regressions. We estimate 1-R^2 by stock-quarter in time-series regressions of the daily returns of individual stocks (from CRSP) on market and industry returns (from Ken French's website). We also include lagged cash flows (*CF*), computed as the sum of net income before extraordinary items, depreciation, and amortization expenses, and R&D expenses, scaled by book assets, to account for the effect of cash flows on investment (e.g., Fazzari et al., 1988), as well as the interaction of *CF* with *ST* and with 1-R^2 as further control variables in equation (1). Again following CGJ, we also include the inverse of lagged quarterly total assets ($1/ATQ$) to isolate the correlation between *Inv* and *Q* induced by their common scaling variable, and we include abnormal future stock returns (*AR*; the market-adjusted cumulative return over the next quarter) to control for managers' market timing of investment (Loughran and Ritter, 1995; Baker and Wurgler, 2002; Baker et al., 2003).

We cross-sectionally winsorize *CAPXRND*, *CAPX*, *CHGASSET*, Tobin's *Q*, 1-R^2, *CF*, 1/*ATQ*, and *AR* at the 1% and 99% levels each quarter to mitigate the influence of outliers. In line with CGJ, we subtract cross-sectional medians from all multiplicative variables in front of *Q* and *CF*, such that the coefficient on *Q* (*CF*) can be interpreted as the investment sensitivity to *Q* (*CF*) for a firm with median characteristics.

2.3. Estimation of the earnings response coefficient

We follow Imhoff and Lobo (1992) for the estimation of the earnings response coefficient (ERC). In particular, we estimate the following cross-sectional regression each quarter:

$$CAR_{i,q} = \gamma_{0,q} + \gamma_{1,q}ST_{i,q-1} \times SUE_{i,q} + \gamma_{2,q}ST_{i,q-1} + \gamma_{3,q}SUE_{i,q} + \eta_{i,q}, \tag{2}$$

where again *ST* is one of our three proxies for short-termism (*PQSPR*, *PESPR*, or *Churn*) for firm *i* in quarter *q*. *CAR* is the cumulative abnormal return in a two- or three-day window around quarterly corporate earnings announcements from Compustat, where abnormal returns are constructed using a market model estimated over a window from 50 through three days before the announcement date, and *SUE* is the standardized unexpected earnings corresponding to the earnings announcement, computed as the difference between actual earnings and the average analyst earnings forecast from IBES scaled by the stock price two trading days before the announcement date, as in Imhoff and Lobo (1992). We cross-sectionally winsorize *CAR* and *SUE* at the 1% and 99% levels each quarter. We subtract cross-sectional medians from all multiplicative variables in front of *SUE*.

Coefficient γ_3 is the ERC, which, in line with the literature, we expect to be positive. Coefficient γ_1 measures how the ERC varies with our short-termism proxies. We hypothesize that the ERC is greater for stocks with greater market liquidity and greater short-termism, which would imply that γ_1 is negative for *PQSPR* and *PESPR*, and positive for *Churn*.

2.4. Difference-in-differences analyses

Our main analyses described so far examine how the investment-to-price sensitivity and the earnings response coefficient vary with our proxies for short-termism. A potential concern about these analyses is the endogeneity of these short-termism proxies. For example, corporate investment may respond to stock liquidity (and its interaction with Tobin's *Q*), but liquidity, in turn, may also be dependent on (expected) investment. We address these concerns in a number of DiD analyses that exploit various exogenous shocks to illiquidity or short-termism. In particular, we use two events that prior studies have used as exogenous shocks to illiquidity: decimalization [following Fang et al. (2009) and Fang et al. (2014)] and the termination of analyst coverage due to the closing of a number of brokerage research departments [following Kelly and Ljungqvist (2012)]. Inspired by AVV, we also use a 2004 securities market regulation that required mutual funds to disclose their holdings more frequently (from semiannual to quarterly reporting) as an exogenous shock to investor short-termism. In this subsection, we describe the set-up of our DiD analyses around decimalization. Our DiD analyses based on the other events have a similar set-up and are discussed in more detail in Sections 3 and 4.

It is well-established that regulatory changes in the minimum tick size (in particular, the switch to decimalization in 2001) were associated with a large exogenous increase in the market liquidity of individual stocks, and that the magnitude of the increase varied considerably in the cross-section (Bessembinder, 2003; Furfine, 2003). Furthermore, it is unlikely that decimalization directly influenced any of the dependent variables in our two main analyses described so far (i.e., corporate investment and earnings announcement returns). In the spirit of Fang et al. (2014), we compare the change in the investment-to-price sensitivity from the eight quarters before to the eight quarters after the decimals shift for the tercile of stocks that experienced the greatest increase in liquidity in that period (the treatment group) with the change in the investment-to-price sensitivity for the tercile of stocks that experienced the smallest increase in liquidity (the control group). We conduct a similar DiD for the earnings response coefficient. We limit our sample in these DiD analyses to NYSE stocks, since Bessembinder (2003) documents that the impact of decimalization on liquidity was the greatest for NYSE stocks.

We conduct these DiD analyses using the following fixed effect panel regressions based on all NYSE-listed firms for which we have valid observations on the dependent and independent variables in each of the eight quarters before 2001:Q1 and the eight quarters after 2001:Q2 (to make sure the panel regressions are based on a balanced sample):

$$\begin{aligned} Dep_{i,q} \quad &= \sum_i \lambda_i + \sum_q \lambda_q + \lambda_1 Post_{i,q} \times Treat_{i,q} \times Ind_{i,q-1} + \lambda_2 Ind_{i,q-1} + \\ &+ \lambda_3 Post_{i,q} \times Ind_{i,q-1} + \lambda_4 Treat_{i,q} \times Ind_{i,q-1} + \lambda_5 Post_{i,q} \times Treat_{i,q} + \omega_{i,q}, \end{aligned} \tag{3}$$

where λ_i and λ_q are, respectively, firm fixed effects and quarter fixed effects. *Dep* is the dependent variable in each of our two main analyses (i.e., *Inv* or *CAR*) for firm *i* in quarter *q*; *Ind* is the corresponding independent variable (i.e., *Q* or *SUE*; we note that the independent variable is not lagged for the earnings response coefficient). *Post* is a dummy variable equal to one after decimalization, and *Treat* is a treatment dummy variable equal to one for firms whose stock liquidity improved the most around decimalization (defined as the tercile of stocks with the greatest decrease in average *PQSPR* from the eight quarters before to the eight quarters after decimalization).

Table 1

Summary statistics. This table reports the cross-sectional (across the 6,281 firms in the sample) mean, standard deviation ("SD"), first quartile ("25%"), median, and third quartile ("75%") of the time-series average by firm of the following quarterly variables: the sum of capital expenditure and R&D expenses (*CAPXRND*), capital expenditure (*CAPX*), and change in book assets (*CHGASSET*), all scaled by beginning-of-year book assets; Tobin's Q (*Q*); cash flows scaled by book assets (*CF*); total assets in US$m. (*ATQ*); stock price nonsynchronicity ($1 - R^2$); the proportional quoted bid-ask spread (*PQSPR*); the proportional effective spread (*PESPR*); as well as the quarterly number of shares traded over shares outstanding (*Turnover*) and weighted average churn ratio across all institutional investors holding the stock (*Churn*). See Section 2 for details on data screens and variable definitions.

	#Firms	Mean	SD	25%	Median	75%
CAPXRND	4,741	3.523	3.043	1.315	2.544	4.924
CAPX	4,741	1.643	1.581	0.683	1.221	2.037
CHGASSET	4,823	5.222	7.394	1.589	3.457	6.787
Q	4,828	2.292	1.534	1.286	1.792	2.837
CF	4,736	0.020	0.033	0.010	0.023	0.038
ATQ	4,828	2.223	10.308	0.130	0.341	1.096
$1 - R^2$	6,277	0.818	0.115	0.763	0.846	0.902
PQSPR	5,982	1.226	1.207	0.406	0.859	1.653
PESPR	5,326	1.101	2.185	0.397	0.784	1.426
Turnover	6,219	0.547	0.591	0.237	0.410	0.689
Churn	6,220	0.219	0.079	0.174	0.217	0.258

Table 2

Illiquidity and investor horizon. This table reports the average estimates of two proxies for investor horizon (*Turnover* in Panel A and *Churn* in Panel B) for 3 × 3 portfolios of stocks independently sorted on previous quarter firm size (quarterly total assets or *ATQ*, in rows) and on previous quarter illiquidity (*PESPR*; in columns). A stock's *Turnover* is the number of shares traded within the quarter as a fraction of total shares outstanding. A stock's *Churn* ratio is the weighted average churn ratio across all institutional investors holding the stock. For ease of interpretation, both *Turnover* and *Churn* are expressed in percentage terms in this table. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1 (Liquid)	2	3 (Illiquid)	*Liq − Illiq*
Panel A: Turnover for portfolios sorted on firm size and illiquidity				
1 (*Small*)	110.6%	74.4%	33.9%	76.7%***
2	73.7%	53.3%	25.3%	48.5%***
3 (*Big*)	51.8%	48.4%	30.8%	21.0%***
Big − Small	−58.7%***	−26.0%***	−3.1%**	
Panel B: Churn ratio for portfolios sorted on firm size and illiquidity				
1 (*Small*)	27.6%	24.3%	17.9%	9.7%***
2	24.6%	22.8%	19.3%	5.3%***
3 (*Big*)	22.2%	23.0%	20.4%	1.8%***
Big − Small	−5.4%***	−1.3%***	2.6%***	

Coefficient λ_1 measures the DiD effect of an exogenous increase in stock liquidity on the relation between the dependent and the independent variable. Our hypotheses suggest that λ_1 is negative for the investment-to-price sensitivity and positive for the earnings response coefficient.

2.5. Summary statistics

Table 1 presents summary statistics of the main variables included in our analyses. For each variable, the table reports cross-sectional summary statistics (the mean, standard deviation, as well as the median and the 25th and 75th percentiles) of the firm-by-firm time-series averages. The first column reports the total number of firms for which each variable can be computed over at least part of our 1983–2016 sample period. Depending on data availability and data screens, the coverage in terms of the total number of firms varies across the different variables. The variables that are based on quarterly accounting data are available for close to 5000 unique firms over at least part of our sample period. We can compute the illiquidity and *Churn* measures for around 5000 to 6000 firms. Our analyses are based on the greatest number of firm-quarters for which observations on all variables included in the regression are available, which means that the total number of observations differs somewhat across the different specifications. Overall, the summary statistics in Table 1 accord well with those reported in prior papers based on these variables, including CGJ, Cella et al. (2013), and Rösch et al. (2017).

2.6. Liquidity and investor horizon

Before we turn to our main analyses in Section 3, we want to check our basic premise that more liquid stocks attract investors with shorter horizons. Although this argument dates back to at least Amihud and Mendelson (1986), we are not aware of studies that directly assess it empirically and we want to make sure it holds in our sample. To this end, Table 2 shows how our two proxies for

Table 3

Short-termism and the investment-to-price sensitivity. This table reports the average coefficient estimates from the quarterly Fama-Macbeth regressions in equation (1), in which firm-level investment is regressed on lagged Tobin's Q, the interaction of lagged Q with lagged short-termism, and several control variables:

$Inv_{i,q} = \beta_{0,q} + \beta_{1,q}ST_{i,q-1} \times Q_{i,q-1} + \beta_{2,q}ST_{i,q-1} + \beta_{3,q}Q_{i,q-1} + \Sigma\beta_q Contr_{i,q-1} + \varepsilon_{i,q}$,

where *Inv* is one of the three corporate investment measures (*CAPXRND*, *CAPX*, or *CHGASSET*), and *ST* is one of the three proxies for short-termism (*PQSPR*, *PESPR*, or *Churn*). The regressions include the following control variables: $1 - R^2$ is stock price nonsynchronicity, *CF* is cash flows, $1/ATQ$ is the inverse of total assets, and *AR* is the abnormal stock return over the next quarter. See Table 1 and Section 2 for details on data screens and variable definitions. Coefficient β_3 is the investment-to-price sensitivity. Coefficient β_1 measures how the investment-to-price sensitivity varies with our short-termism proxies. Panels A, B, and C present the results for the three short-termism proxies *PQSPR*, *PESPR*, and *Churn*, respectively. Fama-MacBeth *t*-statistics with Newey-West corrections are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Intercept estimates are not reported for brevity.

	CAPXRND	*CAPXRND*	*CAPX*	*CAPX*	*CHGASSET*	*CHGASSET*
Panel A: *PQSPR* as short-termism proxy						
PQSPR × *Q*	0.328***	0.228***	0.065***	0.117***	0.427***	0.568***
	(10.91)	(7.27)	(2.70)	(3.81)	(4.35)	(5.10)
PQSPR	−0.294***	−0.380***	−0.137***	−0.136***	−0.715***	−0.729***
	(-8.37)	(-9.73)	(-4.66)	(-4.02)	(-6.52)	(-6.54)
Q	0.713***	0.457***	0.175***	0.090***	2.165***	1.245***
	(18.77)	(9.00)	(5.81)	(4.60)	(22.10)	(7.22)
$(1 - R^2) \times Q$	0.350***	0.758***	0.125*	0.245**	1.652***	1.394***
	(3.51)	(6.14)	(1.66)	(2.59)	(7.47)	(3.12)
$(1 - R^2)$	−0.491***	−0.121	−0.867***	−0.607***	−1.876***	−2.447***
	(-2.84)	(-0.77)	(-6.04)	(-4.19)	(-4.27)	(-4.36)
PQSPR × *CF*		0.237		1.372***		−6.133***
		(0.49)		(4.53)		(-2.74)
CF		15.059***		8.464***		67.612***
		(7.48)		(6.68)		(10.98)
$(1 - R^2) \times CF$		−43.944***		−13.390***		37.370**
		(-10.60)		(-3.82)		(2.52)
$1/ATQ$		0.044***		−0.011***		0.036***
		(5.77)		(-6.84)		(3.73)
AR		−0.229**		−0.223***		0.320
		(-2.40)		(-3.37)		(1.20)
R^2	0.15	0.21	0.03	0.07	0.06	0.11
N	189,170	170,205	189,170	170,205	199,396	179,321
Panel B: *PESPR* as short-termism proxy						
PESPR × *Q*	0.336***	0.211***	0.051**	0.123***	0.395***	0.607***
	(9.82)	(4.34)	(2.04)	(3.61)	(3.46)	(4.44)
PESPR	−0.298***	−0.370***	−0.120***	−0.145***	−0.712***	−0.740***
	(-8.40)	(-8.31)	(-3.99)	(-3.80)	(-5.90)	(-5.24)
Q	0.704***	0.446***	0.182***	0.087***	2.134***	1.194***
	(19.64)	(8.89)	(5.78)	(4.44)	(21.63)	(7.15)
$(1 - R^2) \times Q$	0.383***	0.825***	0.166**	0.275***	1.688***	1.347***
	(3.79)	(7.07)	(2.22)	(3.15)	(8.03)	(3.20)
$(1 - R^2)$	−0.553***	−0.216	−0.935***	−0.656***	−1.931***	−2.568***
	(-3.08)	(-1.37)	(-6.50)	(-4.79)	(-4.41)	(-4.57)
PESPR × *CF*		1.436**		1.938***		−7.693***
		(2.44)		(4.31)		(-3.16)
CF		15.600***		8.422***		68.489***
		(8.28)		(6.76)		(11.18)
$(1 - R^2) \times CF$		−45.496***		−13.362***		40.588***
		(-11.18)		(-3.70)		(2.77)
$1/ATQ$		0.043***		−0.010***		0.038***
		(6.01)		(-7.82)		(3.84)
AR		−0.256***		−0.224***		0.275
		(-2.70)		(-3.38)		(0.99)
R^2	0.14	0.21	0.03	0.07	0.06	0.11
N	183,214	164,903	183,214	164,903	193,429	174,011
Panel C: *Churn* as short-termism proxy						
Churn × *Q*	−1.129***	−1.116***	−0.395**	−0.505**	−0.216	−0.216
	(-4.70)	(-3.60)	(-2.20)	(-1.99)	(-0.22)	(-0.20)
Churn	0.818	1.529*	2.469***	2.291***	11.059***	11.479***
	(1.09)	(1.87)	(6.50)	(5.24)	(5.21)	(5.80)
Q	0.853***	0.555***	0.208***	0.125***	2.269***	1.540***
	(30.39)	(12.98)	(4.88)	(4.54)	(21.23)	(14.09)
$(1 - R^2) \times Q$						

(continued on next page)

Table 3 (*continued*)

	CAPXRND	*CAPXRND*	*CAPX*	*CAPX*	*CHGASSET*	*CHGASSET*
	0.849***	1.242***	0.143*	0.334***	2.318***	2.389***
	(8.07)	(10.70)	(1.71)	(4.61)	(10.59)	(7.20)
$(1-R^2)$	−0.878***	−0.978***	−0.955***	−0.813***	−3.095***	−3.605***
	(-4.92)	(-6.77)	(-6.06)	(-7.35)	(-6.88)	(-6.47)
Churn × *CF*		−18.888*		4.059		−35.111
		(-1.71)		(0.64)		(-1.12)
CF		17.319***		8.462***		63.189***
		(7.98)		(8.06)		(10.60)
$(1-R^2)\times CF$		−40.601***		−8.782**		22.046
		(-8.08)		(-2.24)		(1.37)
1/*ATQ*		0.045***		−0.006***		0.027***
		(10.08)		(-3.30)		(3.45)
AR		−0.238**		−0.224***		0.216
		(-2.43)		(-3.96)		(0.77)
R^2	0.1458	0.2191	0.0382	0.0665	0.0728	0.1260
N	164,385	148,100	164,385	148,100	170,571	153,370

investor horizon (*Turnover* in Panel A and *Churn* in Panel B) vary with the liquidity of the stocks in our sample. In particular, this table shows the average *Turnover* and *Churn* ratio of 3 × 3 portfolios of stocks sorted independently on their previous quarter firm size (quarterly total assets or *ATQ*) and *PESPR*. We independently sort on size and illiquidity because we are interested in the relation between illiquidity and investor horizon after accounting for variation in firm size that may be related to investor horizon for other reasons than illiquidity.

The main finding in Table 2 is that liquid stocks are characterized by a significantly greater *Turnover* as well as *Churn* ratio compared to illiquid stocks within each of the size portfolios. For example, Panel A shows that small and liquid stocks (top left portfolio) have an average quarterly *Turnover* of 110.6% (indicating that the average share changes hands more than four times per year), whereas the average quarterly *Turnover* for small and illiquid stocks is only 33.9%. The difference of 76.7% is highly significant from both an economic and a statistical perspective. The differences in *Turnover* between liquid and illiquid stocks are somewhat smaller for mid-size and big stocks, but, at 48.5% and 21.0%, respectively, still economically sizable and also statistically significant.

We observe similar patterns for *Churn*, which specifically aims to capture the trading horizon of the institutional investors holding a stock. Panel B of Table 2 shows that small and liquid stocks (top left portfolio) have an average quarterly *Churn* ratio of 27.6%, which, following the interpretation on page 1616 of Cella et al. (2013), indicates that the average institutional investor holding the stock has an average holding period across its total portfolio of slightly less than two years, which is more than 50% greater than the average quarterly *Churn* ratio for small and illiquid stocks of 17.9%. Again, the differences between liquid and illiquid stocks are somewhat less pronounced for mid-size and big stocks, but still significant and of considerable magnitude.

We conclude that our basic premise that more liquid stocks tend to attract investors with shorter horizons holds in our sample.

3. Is the investment-to-price sensitivity related to short-termism?

In this section, we present the results of our baseline analyses of the relation between short-termism and the investment-to-price sensitivity. We first examine this relation using cross-sectional regressions (Subsection 3.1), then study how our results relate to those of CGJ (Subsection 3.2), present a number of robustness checks (Subsection 3.3), address the question whether the relation is driven by illiquidity or *Churn* (Subsection 3.4), discuss our results of the DiD analyses (Subsection 3.5), and summarize our overall findings on whether the investment-to-price sensitivity is related to short-termism (Subsection 3.6).

3.1. *Cross-sectional regressions*

We first examine how the investment-to-price sensitivity varies with short-termism by estimating the quarterly cross-sectional regressions in Eq. (1), in which firm-level investment is regressed on lagged *Q*, the interaction of lagged *Q* with our lagged short-termism proxies, and several control variables. The results are in Table 3. In Panels A, B, and C, we use, respectively, *PQSPR*, *PESPR*, and *Churn* as our short-termism proxies. Each panel reports separate regression results (in particular, the average slope co-efficients, as well as their Newey-West corrected time-series *t*-statistics) for our three measures of corporate investment (*CAPXRND*, *CAPX*, and *CHGASSET*), and, for each investment measure, two regression specifications that differ in the number of control variables included.

The results for our illiquidity variables are clear: for both *PQSPR* (Panel A) and *PESPR* (Panel B), for each of the three investment

Table 4

Short-termism, stock price nonsynchronicity, firm size, and the investment-to-price sensitivity. This table reports the average coefficient estimates from quarterly Fama-Macbeth regressions of the investment-to-price sensitivity that are estimated separately for the firms in 3 × 3 portfolios sorted first based on previous quarter stock price nonsynchronicity (Panel A: 1-R^2; in rows) or firm size (Panel B: quarterly total assets or *ATQ*, in rows) and subsequently based on previous quarter illiquidity (*PESPR*; in columns):

$Inv_{i,q} = \delta_{0,q} + \delta_{1,q}Q_{i,q-1} + \upsilon_{i,q},$

where *Inv* is one of the three corporate investment measures (*CAPXRND*, *CAPX*, or *CHGASSET*) and *Q* is Tobin's *Q*. See Table 1 and Section 2 for details on data screens and variable definitions. The table reports the average estimate of coefficient δ_1, which is the investment-to-price sensitivity. Fama-MacBeth *t*-statistics with Newey-West corrections are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Intercept estimates are not reported for brevity.

	CAPXRND			*CAPX*			*CHGASSET*		
	1 (Liq)	2	3 (Illiq)	1 (Liq)	2	3 (Illiq)	1 (Liq)	2	3 (Illiq)
Panel A: Investment-to-price sensitivity for portfolios sorted on 1-R^2 and illiquidity									
1 (Low 1 − R^2)	0.367***	0.586***	0.700***	0.036	0.165***	0.194***	1.057***	1.718***	2.051***
	(11.35)	(16.28)	(15.39)	(1.26)	(4.30)	(5.18)	(14.17)	(13.65)	(15.19)
2	0.566***	0.794***	1.068***	0.177***	0.207***	0.262***	1.707***	2.194***	2.707***
	(17.41)	(16.19)	(15.46)	(5.58)	(4.30)	(3.76)	(13.85)	(15.01)	(10.98)
3 (High 1 − R^2)	0.782***	1.066***	1.375***	0.249***	0.240***	0.429***	2.393***	2.773***	2.975***
	(17.29)	(15.12)	(17.38)	(4.87)	(4.21)	(4.32)	(12.94)	(13.53)	(9.47)
Panel B: Investment-to-price sensitivity for portfolios sorted on firm size and illiquidity									
1 (*Small*)	0.624***	0.901***	1.201***	0.165***	0.209***	0.313***	2.091***	2.224***	2.951***
	(13.49)	(13.40)	(12.61)	(4.08)	(3.63)	(3.79)	(14.13)	(9.95)	(9.21)
2	0.555***	0.754***	1.189***	0.200***	0.317***	0.718***	1.460***	2.085***	3.510***
	(15.02)	(16.27)	(12.04)	(5.18)	(5.57)	(6.40)	(12.64)	(12.70)	(10.47)
3 (*Big*)	0.387***	0.499***	0.991***	0.027	0.169***	0.522***	0.995***	1.488***	2.965***
	(11.63)	(12.13)	(13.67)	(1.32)	(3.37)	(6.47)	(15.65)	(15.02)	(9.08)

measures, and for each regression specification, we find a positive and significant coefficient on the interaction term of lagged *Q* with lagged illiquidity.[7] For our third short-termism proxy (*Churn*, see Panel C), we find that, in line with our conjecture, the coefficient on the interaction term of lagged *Q* with lagged *Churn* is negative in all six regression specifications, and significantly so for the investment measures *CAPXRND* and *CAPX*. For the third investment measure, *CHGASSET*, the interaction coefficient is negative but not significant. We note that *CHGASSET* is arguably the least reliable of our investment measures, since it incorporates any and all changes in the total size of a firm's balance sheet. Overall, the results in Table 3 thus indicate that investment-to-price sensitivity tends to be lower for firms with greater market liquidity and a greater *Churn* ratio. This finding is consistent with our main hypothesis that stocks with greater short-termism are characterized by reduced stock price informativeness, and thus a lower sensitivity of corporate investment to market prices.

In Table 3, the coefficients for the other variables are in line with those reported in the literature. The coefficients on lagged *Q* and on lagged *CF* are consistently positive and significant, supporting the view that managers learn from the stock price in making investment decisions (Bond et al., 2012) and confirming the well-known result that investments depend positively on recent cash flows (Fazzari et al., 1988). The results on the interaction of lagged *CF* with lagged short-termism are mixed, which makes sense since there is no clear reason why short-termism should affect the sensitivity of corporate investment to cash flows. The coefficient on $1/ATQ$ depends on the investment measure: it is positive for *CAPXRND* and *CHGASSET*, and negative for *CAPX*.[8] Consistent with CGJ and with managers' market timing of investment, the coefficient on abnormal future stock returns (*AR*) tends to be negative and significant.[9]

[7] To examine whether the relation between illiquidity and the investment-to-price sensitivity is stable over our sample period, we plot the four-quarter moving average of the quarterly coefficient estimates from the cross-sectional regressions in equation (1) of firm-level investment on the interaction of lagged *Q* with lagged *PESPR* (not reported) and observe that, for all three investment measures, they are positive throughout most of the sample period.

[8] One potential concern about our main results in Table 3 is that liquidity and *Churn* may be correlated with firm size, and firm size may in turn be related to the investment-to-price sensitivity for other reasons. Although our baseline regressions control for the firm's $1/ATQ$ (the inverse of lagged total assets), in unreported tests we replace this variable by the firm's lagged market capitalization – as well as the interaction of lagged market cap with lagged *Q*, and find our main results to be similar. We note that including $1/ATQ$ and market cap side-by-side is not feasible due to collinearity with *Q*. Taken together, these findings suggest that our main results are not driven by firm size.

[9] One difference between the results in Table 3 and those of CGJ is that our table is based on quarterly Fama-MacBeth regressions (FM), while the main tables of CGJ are based on annual panel regressions. Our motivation for using FM is that our main hypothesis is cross-sectional in nature. Our motivation for using quarterly, instead of annual, data is that our illiquidity measures only start with the availability of intraday trade and quote data in 1983 and using annual data may thus give rise to concerns about statistical power. However, in unreported tests, we find that when we use annual panel regressions instead, the sign of the coefficient on the interaction term of lagged *Q* with each of our three short-termism proxies is consistent with our main results, and significantly so in 16 out of the 18 regression specifications. We also obtain similar results when we average *Q* over the past four quarters (instead of using one-quarter lagged *Q* as in Table 3), thereby allowing for a longer response time of corporate investment to market valuations.

To briefly discuss economic significance, we first consider the first model in Panel A of Table 3. In this case, given that the 25th, 50th, and 75th percentile values for *PQSPR* are 0.406, 0.859, and 1.653, respectively (from Table 1), an estimate of 0.328 for the coefficient on the interaction term $PQSPR \times Q$ implies that the investment-to-price sensitivity of a firm with a 25th percentile value of *PQSPR* is equal to 0.5644 [= 0.713 - (0.859–0.406) * 0.328] and that of a firm with a 75th percentile value of *PQSPR* is 0.9734 [= 0.713 + (1.653–0.859) * 0.328]. The latter sensitivity is about 72% higher than the former. Similar calculations yield the result that for the first model in Panel B, the investment-to-price sensitivity at the 75th percentile of *PESPR* is 60% higher than that at the 25th percentile. The corresponding numbers for *Churn* are more modest, but, leaving aside *CHGASSET*, moving from the 25th to the 75th percentile of *Churn* still implies a decrease in investment-to-price sensitivity ranging from 11% to 29% across all cases. Overall, therefore, our results are economically meaningful.

3.2. Relation of investment-to-price sensitivity results with CGJ

Of particular interest in Table 3 is the coefficient on the interaction of lagged 1-R^2 (stock price nonsynchronicity) with lagged *Q*. Following Morck et al. (2000), CGJ argue that greater values of 1-R^2 are an indication of greater stock price informativeness, since less synchronous stock prices contain more stock-specific information. Like CGJ, we find that the coefficient on the interaction of lagged 1-R^2 with lagged *Q* is positive and significant throughout, in line with the notion that the investment-to-price sensitivity is greater for stocks with more informative prices. However, the results in Table 3 indicate that our short-termism variables have an independent effect on the investment-to-price sensitivity that is not subsumed by 1-R^2 and its interaction with lagged *Q*.

As a first step towards understanding how our results relate to those of CGJ, we compute average cross-sectional Pearson correlations of 1-R^2 with *PQSPR* and *PESPR* and find that they are positive and statistically significant, with values ranging from 0.2 to 0.3 (not tabulated). The average correlations of 1-R^2 with *Churn* is −0.17 and also statistically significant. This finding indicates that, indeed, stocks that are more liquid or have higher *Churn* ratios tend to be characterized by more synchronous and thus less informative stock prices.

As a second step, we estimate the investment-to-price sensitivity separately for portfolios of stocks sorted based on their 1-R^2 and their illiquidity. In particular, Panel A of Table 4 reports the investment-to-price sensitivity estimated separately for stocks in 3 × 3 portfolios sorted first based on their 1-R^2 and subsequently based on their *PESPR*. The table reports the average slope coefficient, as well as its time-series Newey-West corrected *t*-statistic, from cross-sectional regressions of each of the three investment measures (*CAPXRND*, *CAPX*, and *CHGASSET*) on lagged *Q*.[10] For almost all portfolios and for almost all investment measures, this slope coefficient (the investment-to-price sensitivity) is positive and significant; the only exception is that the slope coefficient for the liquid, low 1-R^2 is positive but not significant for *CAPX*. We also observe that the investment-to-price sensitivity increases monotonically with illiquidity for all three 1-R^2 portfolios and for all three investment measures (with one exception; for high 1-R^2 stocks and the *CAPX* investment measure, the slope coefficient for the middle liquidity portfolio is slightly smaller than that for the liquid portfolio). Conversely, the investment-to-price sensitivity increases monotonically with 1-R^2 for all three illiquidity portfolios.[11] We interpret these findings as an indication that our analysis of short-termism adds a dimension to our understanding of investment-to-price sensitivity that is not subsumed by the CGJ proxy for stock price informativeness. So our work and CGJ are complementary.

3.3. Robustness of baseline investment-to-price sensitivity results

We next investigate whether our main result is robust to estimating the investment-to-price sensitivity separately for stocks in 3 × 3 portfolios sorted first based on their previous quarter firm size (quarterly total assets or *ATQ*) and subsequently based on their previous quarter *PESPR*.[12] Although we control for a measure of firm size (1/*ATQ*) in the regressions in Table 3, these portfolio sort results add another element to our analysis since they allow us to assess whether our main result that more liquid stocks have a lower investment-to-price sensitivity holds across size portfolios and since they allow for non-linearities in this relation. Panel B of Table 4 shows that the investment-to-price sensitivity increases monotonically with illiquidity for all three size portfolios and for all three investment

[10] We note that the main results in Table 4 are similar when we also include the standard CGJ control variables *CF* (lagged cash flows), 1/*ATQ* (inverse of lagged total assets), and *AR* (lead abnormal stock return) in the regressions to estimate the investment-to-price sensitivity for each portfolio of stocks.

[11] To save table space, we do not report *t*-statistics for the significance of the difference in the slope coefficient between each of the illiquid and liquid portfolios and each of the high 1-R^2 and low 1-R^2 portfolios in Panel A of Table 4. Untabulated Newey-West *t*-statistics show that, out of the 18 differences in the slope coefficients between the extreme portfolios in Panel A, 16 are significant at the 5% level or better.

[12] We note that, in contrast to Table 2, the portfolio sorts for Table 4 are not independent but sequential, because we are unable to estimate the investment-to-price sensitivity for the small liquid portfolio when we use independent sorts.

Table 5

Short-termism and the investment-to-price sensitivity by industry. This table reports the average coefficient estimates from quarterly Fama-Macbeth regressions of the investment-to-price sensitivity that are estimated separately for each of the five Fama-French industries from the website of Ken French:

$Inv_{i,q} = \beta_{0,q} + \beta_{1,q}PESPR_{i,q-1} \times Q_{i,q-1} + \beta_{2,q}PESPR_{i,q-1} + \beta_{3,q}Q_{i,q-1} + \Sigma\beta_q Contr_{i,q-1} + \varepsilon_{i,q}$,

where *Inv* is one of the three corporate investment measures (*CAPXRND*, *CAPX*, or *CHGASSET*), *PESPR* is proportional effective spreads, and Q is Tobin's Q. The regressions are estimated with and without the following control variables (as indicated by the second row of the table): $1 - R^2$ is stock price nonsynchronicity, *CF* is cash flows, $1/ATQ$ is the inverse of total assets, and *AR* is the abnormal stock return over the next quarter. See Table 1 and Section 2 for details on data screens and variable definitions. The table only reports the average estimate of coefficient β_1, which measures how the investment-to-price sensitivity varies with *PESPR*. Fama-MacBeth *t*-statistics with Newey-West corrections are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CAPXRND	*CAPXRND*	*CAPX*	*CAPX*	*CHGASSET*	*CHGASSET*
Controls	No	Yes	No	Yes	No	Yes
Consumer Durables, NonDurables, Wholesale, Retail, and Some Services						
$PESPR_{i,q-1} \times Q_{i,q-1}$	0.492***	0.701**	0.278***	0.609**	0.681**	1.081***
	(5.86)	(2.33)	(4.09)	(2.03)	(2.31)	(3.54)
Manufacturing, Energy, and Utilities						
$PESPR_{i,q-1} \times Q_{i,q-1}$	0.164**	0.159*	0.116**	0.154**	0.498**	0.957***
	(2.41)	(1.79)	(2.25)	(2.08)	(2.08)	(3.64)
Business Equipment, Telephone and Television Transmission						
$PESPR_{i,q-1} \times Q_{i,q-1}$	0.551***	−0.215	0.001	−0.397	1.392***	1.706**
	(4.22)	(-0.43)	(0.01)	(-0.81)	(2.70)	(2.35)
Healthcare, Medical Equipment, and Drugs						
$PESPR_{i,q-1} \times Q_{i,q-1}$	0.454***	−0.607	−0.009	−0.890	1.025**	−1.482
	(4.25)	(-0.64)	(-0.10)	(-0.94)	(2.20)	(-0.81)
Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance						
$PESPR_{i,q-1} \times Q_{i,q-1}$	0.181*	0.219	0.013	0.180	0.626***	0.835***
	(1.77)	(1.27)	(0.16)	(1.09)	(2.82)	(3.34)

measures.[13] These results indicate that our finding that more liquid stocks exhibit a lower sensitivity of corporate investment to market prices obtains for small and big stocks alike and is thus not driven by other aspects of firm size that may be correlated with the investment-to-price sensitivity.[14]

As a further robustness check of our main results, Table 5 presents the results of the quarterly cross-sectional regressions in equation (1) estimated separately for each of the five Fama-French industries (from the website of Ken French). For each of the three investment measures, this table shows the coefficient on the interaction of lagged Q with lagged *PESPR* in regression specifications both with and without control variables. We omit reporting the other coefficients for brevity. We note that the coefficients are likely to be less precisely estimated in the smaller samples within each industry for which we run the cross-sectional regressions. The results in Table 5 indicate that our main finding from Table 3 that the coefficient on the interaction of lagged Q with lagged *PESPR* is positive and significant is reasonably consistent across industries. The coefficient on this interaction term is positive in 24 out of the 30 regressions across industries, and significantly positive in 20 regressions (and never significantly negative). Hence, the results in Table 5 suggest that our result of a negative relation between liquidity and the investment-to-price sensitivity is quite pervasive across different cuts of the sample.

As a final robustness check of our main result, we examine trends in the investment-to-price sensitivity over our sample period. After all, if the investment-to-price sensitivity is inversely related to liquidity, the well-documented long-term downward trend in *PESPR* and other liquidity measures over the 1990s and 2000s (e.g., Chordia et al., 2011) should be accompanied by a gradual decrease in the investment-to-price sensitivity. In unreported plots of the four-quarter moving average of the quarterly coefficient estimates from cross-sectional regressions of firm-level investment on lagged Q (including the standard CGJ control variables *CF*, $1/ATQ$, and *AR*; estimated for all NYSE and NASDAQ stocks that are in the sample for at least 120 quarters in order to limit the degree of time variation in the coefficient estimates that is driven by variation in the sample composition), we see a clear downward trend in the investment-to-price sensitivity based on each of the three investment measures. Each of these three time trends is statistically significant and of nontrivial economic importance. For example, for *CAPXRND*, the coefficient on the linear time trend is -0.0014 (p-value of 0.03). This corresponds to an average decrease in the investment-to-price sensitivity of 0.056 per decade over our sample period spanning more than three decades, which is around 10% of the unconditional average investment-to-price sensitivity based on

[13] Like in Panel A, we do not report *t*-statistics for the significance of the difference in the slope coefficient between the extreme portfolios in Panel B of Table 4, but with the exception of one they are all significant at the 5% level or better.

[14] In unreported tests, we also examine whether the inverse relation between liquidity and the investment-to-price sensitivity could in part be driven by firm complexity. Complex firms with business segments in multiple industries may be characterized by a lower stock price informativeness since informed traders with information on one segment may not be able to trade effectively in the composite firm. To the extent that complexity is also related to liquidity, this relation might influence our estimates of the quarterly cross-sectional regressions in equation (1). However, our main results survive when we additionally include a variable measuring the number of business segments of each firm (obtained from Compustat), as well as its interaction with lagged Q, in these regressions.

Table 6

Short-termism, investor horizon, and the investment-to-price sensitivity. This table reports the average coefficient estimates from the quarterly Fama-Macbeth regressions in equation (1), in which firm-level investment is regressed on lagged Tobin's Q, the interaction of lagged Q with lagged short-termism, and several control variables. We first regress our proxies of illiquidity (*Illiq*) on *Churn* per stock over the whole sample period and then use the fitted value ($\widehat{Illiq}$) and the residual ($Illiq^{\perp}$) separately in the regression.

$$Inv_{i,q} = \beta_{0,q} + \left(\beta_{1,q}\widehat{Illiq}_{i,q-1} + \beta_{1,q}^{\perp}Illiq_{i,q-1}^{\perp}\right) \times Q_{i,q-1} + \beta_{2,q}\widehat{Illiq}_{i,q-1} + \beta_{2,q}^{\perp}Illiq_{i,q-1}^{\perp} + \beta_{3,q}Q_{i,q-1} + \Sigma\beta_q Contr_{i,q-1} + \varepsilon_{i,q},$$

See Tables 1 and 3 for details on variable definitions. Coefficient β_3 is the investment-to-price sensitivity. Coefficient β_1 ($\beta_{1,q}^{\perp}$) measures how the investment-to-price sensitivity varies with our illiquidity measures explained by (orthogonal to) *Churn*. Panels A and B present the results for the illiquidity measures *PQSPR* and *PESPR*, respectively. Fama-MacBeth *t*-statistics with Newey-West corrections are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Intercept estimates are not reported for brevity.

	CAPXRND	*CAPXRND*	*CAPX*	*CAPX*	*CHGASSET*	*CHGASSET*
Panel A: *PQSPR* as illiquidity measure						
$\widehat{PQSPR} \times Q$	0.329***	0.263***	0.087***	0.152***	0.449***	0.600***
	(12.24)	(8.18)	(3.02)	(4.31)	(3.96)	(4.48)
$\widehat{PQSPR}$	−0.321***	−0.404***	−0.159***	−0.170***	−0.702***	−0.685***
	(-9.14)	(-12.14)	(-4.92)	(-4.14)	(-5.31)	(-4.54)
$PQSPR^{\perp} \times Q$	0.283***	0.100*	0.093***	0.080	0.566***	1.022***
	(8.67)	(1.78)	(2.88)	(1.52)	(3.64)	(3.95)
$PQSPR^{\perp}$	−0.214***	−0.112*	−0.180***	−0.086	−0.858***	−1.163***
	(-4.40)	(-1.75)	(-4.75)	(-1.49)	(-4.67)	(-4.42)
Q	0.727***	0.504***	0.192***	0.142***	2.237***	1.363***
	(23.02)	(12.51)	(5.75)	(5.17)	(19.89)	(9.52)
$(1 - R^2) \times Q$	0.286***	0.883***	0.025	0.317***	1.816***	1.585***
	(2.78)	(6.16)	(0.32)	(2.62)	(7.11)	(3.75)
$(1 - R^2)$	−0.513***	−0.109	−0.777***	−0.584***	−2.099***	−2.699***
	(-3.10)	(-0.59)	(-5.34)	(-3.19)	(-4.29)	(-4.69)
$\widehat{PQSPR} \times CF$		−1.199		1.444**		−6.186**
		(-1.45)		(2.46)		(-2.61)
$PQSPR^{\perp} \times CF$		−1.391		−0.625		−15.092***
		(-1.04)		(-1.15)		(-2.91)
CF		15.452***		7.754***		68.103***
		(8.23)		(7.49)		(9.99)
$(1 - R^2) \times CF$		−49.989***		−19.249***		42.065**
		(-9.91)		(-3.65)		(2.48)
$1/ATQ$		0.039***		−0.014***		0.025**
		(6.04)		(-6.83)		(2.41)
AR		−0.234**		−0.251***		−0.083
		(-2.36)		(-3.65)		(-0.29)
R^2	0.1505	0.2230	0.0409	0.0807	0.0732	0.1303
N	159,277	144,337	159,277	144,337	165,371	149,522
Panel B: *PESPR* as illiquidity measure						
$\widehat{PESPR} \times Q$	0.342***	0.213***	0.091***	0.153***	0.533***	0.689***
	(8.95)	(3.30)	(2.72)	(3.48)	(3.30)	(3.77)
$\widehat{PESPR}$	−0.321***	−0.386***	−0.155***	−0.169***	−0.831***	−0.848***
	(-7.44)	(-7.25)	(-4.00)	(-3.12)	(-4.73)	(-4.33)
$PESPR^{\perp} \times Q$	0.328***	0.142*	0.122***	0.145**	0.710***	0.772***
	(8.90)	(1.82)	(3.47)	(2.36)	(4.30)	(4.15)
$PESPR^{\perp}$	−0.261***	−0.189**	−0.208***	−0.169**	−0.969***	−0.970***
	(-4.97)	(-2.57)	(-4.59)	(-2.59)	(-5.01)	(-4.85)
Q	0.739***	0.507***	0.206***	0.151***	2.371***	1.513***
	(24.48)	(12.68)	(5.62)	(5.16)	(15.77)	(10.53)
$(1 - R^2) \times Q$	0.343***	0.845***	0.050	0.259*	2.178***	1.834***
	(3.40)	(5.05)	(0.69)	(1.88)	(6.13)	(4.23)
$(1 - R^2)$	−0.615***	−0.072	−0.825***	−0.480**	−2.476***	−3.003***
	(-3.65)	(-0.31)	(-5.82)	(-2.09)	(-4.54)	(-5.02)
$\widehat{PESPR} \times CF$		1.191		2.906***		−6.761**
		(1.27)		(4.21)		(-2.54)
$PESPR^{\perp} \times CF$		0.118		0.172		−11.370**
		(0.10)		(0.29)		(-2.47)
CF		15.885***		8.084***		66.458***
		(8.55)		(7.29)		(10.22)
$(1 - R^2) \times CF$		−51.358***		−19.782***		31.626*
		(-9.10)		(-3.26)		(1.93)
$1/ATQ$		0.041***		−0.013***		0.038***
		(5.67)		(-6.39)		(3.35)
AR		−0.228**		−0.239***		0.001
		(-2.19)		(-3.14)		(0.00)
R^2	0.1520	0.2293	0.0422	0.0861	0.0779	0.1395
N	157,898	143,383	157,898	143,383	163,851	148,432

Table 7
DiD of exogenous liquidity increase on the investment-to-price sensitivity. This table reports the coefficient estimates from the following fixed-effect panel regressions based on all NYSE-listed firms for which we have valid observations in each of the eight quarters before and after decimalization in 2001:

$$Inv_{i,q} = \sum_i \lambda_i + \sum_q \lambda_q + \lambda_1 Post_{i,q} \times Treat_{i,q} \times Q_{i,q-1} + \lambda_2 Q_{i,q-1} + \\ + \lambda_3 Post_{i,q} \times Q_{i,q-1} + \lambda_4 Treat_{i,q} \times Q_{i,q-1} + \lambda_5 Post_{i,q} \times Treat_{i,q} + \omega_{i,q},$$

where λ_i and λ_q are, respectively, firm fixed effects and quarter fixed effects, *Inv* is one of the three corporate investment measures (*CAPXRND*, *CAPX*, or *CHGASSET*), *Q* is Tobin's *Q*, *Post* is a dummy variable equal to one after decimalization, and *Treat* is a treatment dummy variable equal to one for firms whose stock liquidity improved the most around decimalization (defined as the tercile of stocks with the greatest decrease in average *PQSPR* from the eight quarters before to the eight quarters after decimalization). See Table 1 and Section 2 for details on data screens and variable definitions. Coefficient λ_1 measures the DiD effect of an exogenous increase in stock liquidity on the investment-to-price sensitivity. *t*-statistics clustered by firm are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CAPXRND	*CAPX*	*CHGASSET*
Post × *Treat* × *Q*	−0.253**	−0.277**	−0.888
	(-2.09)	(-2.41)	(-1.42)
Q	0.347***	0.252***	2.662***
	(7.80)	(6.21)	(8.93)
Post × *Q*	0.141***	0.145***	1.760***
	(2.87)	(3.43)	(7.50)
Treat × *Q*	0.056	0.160	0.916
	(0.41)	(1.19)	(1.19)
Post × *Treat*	0.495***	0.537***	2.356**
	(2.60)	(3.01)	(2.49)
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R^2	0.61	0.61	0.14
N	8,704	8,704	10,160

this investment measure. For *CAPX* and *CHGASSET*, the estimated trend coefficients are, respectively, −0.0023 (*p*-value < 0.01) and −0.008 (*p*-value < 0.01), which indicate at least as strong a decrease in the investment-to-price sensitivity relative to its unconditional average. Thus, consistent with our main hypothesis, it appears that the long-term downward trend in the investment-to-price sensitivity over our sample period accords well with the gradual improvement in liquidity over the same period.

3.4. *Are the baseline investment-to-price sensitivity results driven by illiquidity or Churn?*

Thus far, we have considered our three proxies for short-termism (*PQSPR*, *PESPR*, and *Churn*) side-by-side in their relation to the investment-to-price sensitivity. However, an interesting question is how the effect of these individual proxies on the investment-Q sensitivity may be related. In particular, we are interested in whether the effects of our two illiquidity measures (*PQSPR* and *PESPR*) may in part stem from these measures capturing the trading horizon of institutional investors (*Churn*). To answer this question, we first run time-series regressions (estimated by stock over the whole sample period) of our illiquidity measures on *Churn* and then present the results of the quarterly cross-sectional regressions in Eq. (1) with our three investment measures as the dependent variable but then including interactions of lagged *Q* with both the fitted values ($\widehat{Illiq}$) and the residuals ($Illiq^{\perp}$) of lagged illiquidity.

Panels A and B of Table 6 present the estimation results of these cross-sectional regressions for, respectively, *PQSPR* and *PESPR* as liquidity measures. In both Panels A and B, the coefficients on the interaction terms of lagged *Q* with $\widehat{Illiq}$ and with $Illiq^{\perp}$ are all positive, and 23 out of the 24 interaction coefficients across all 12 regression specifications in both panels are statistically significant. There is no clear pattern in the relative importance of $\widehat{Illiq}$ and $Illiq^{\perp}$ in terms of the magnitude of the interaction coefficients or the strength of their statistical significance. These results suggest that higher values of the component of illiquidity that is explained by *Churn* are associated with a greater investment-to-price sensitivity. Part of the reason why illiquidity helps to explain cross-sectional variation in the investment-to-price sensitivity is thus that it to a certain degree captures the variation in the institutional *Churn* ratio, although there are also components of illiquidity independent of *Churn* that are associated with the investment-to-price sensitivity. This may be because liquidity is related to horizons of all investors, whereas *Churn* applies to institutions.

3.5. *DiD analyses of the investment-to-price sensitivity*

As discussed in Subsection 2.4, a potentially important concern about our analyses thus far is the endogeneity of stock market liquidity. We address this concern using the DiD approach outlined in equation (3), which exploits the 2001 decimalization as an exogenous shock to the liquidity of NYSE stocks. Table 7 shows the estimates of fixed-effect panel regressions of the three corporate investment measures on lagged *Q*, as well as lagged *Q* interacted with a *Post* dummy that is equal to one in the eight quarters after decimalization and a *Treat* dummy that is equal to one for stocks whose stock liquidity improved the most around decimalization. The coefficient on the triple interaction of lagged *Q* with both *Post* and *Treat* represents the DiD effect of an exogenous increase in stock

Table 8
Exogenous loss of analyst coverage and the investment-to-price sensitivity. This table reports the average coefficient estimates from quarterly fixed-effect panel regressions, in which firm-level investment is regressed on lagged Tobin's *Q*, the interaction of lagged *Q* with a dummy variable indicating the loss of analyst coverage due to exogenous brokerage closures, and several control variables:
$Inv_{i,q} = \beta_{0,q} + \beta_{1,q} Closure_{i,q} \times Q_{i,q-1} + \beta_{2,q} Closure_{i,q} + \beta_{3,q} Q_{i,q-1} + \Sigma\beta_q Contr_{i,q-1} + \varepsilon_{i,q}$,
where *Inv* is one of the three corporate investment measures (*CAPXRND*, *CAPX*, or *CHGASSET*); and $Closure_{i,q}$ is equal to one if firm *i* lost any analyst coverage in quarter *q* or any of the last three quarters due to an exogenous brokerage closure, and zero otherwise. The regressions include the following control variables: $1 - R^2$ is stock price nonsynchronicity, *CF* is cash flows, $1/ATQ$ is the inverse of total assets, and *AR* is the abnormal stock return over the next quarter. See Table 1 and Section 2 for details on data screens and variable definitions. Coefficient β_3 is the investment-to-price sensitivity. Coefficient β_1 measures how the investment-to-price sensitivity varies with the exogenous loss of analyst coverage. Standard errors are clustered by firm and *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Intercept estimates are not reported for brevity.

	CAPXRND	*CAPXRND*	*CAPX*	*CAPX*	*CHGASSET*	*CHGASSET*
Closure × *Q*	0.108**	0.094**	0.046*	0.048*	1.026***	0.437
	(2.35)	(2.01)	(1.81)	(1.72)	(2.86)	(1.06)
Closure	−0.434***	−0.218**	−0.232***	−0.187***	−2.280***	−0.985
	(-4.42)	(-2.30)	(-3.76)	(-2.87)	(-3.70)	(-1.62)
Q	0.366***	0.285***	0.192***	0.168***	3.984***	3.504***
	(26.28)	(19.90)	(23.35)	(19.78)	(30.74)	(23.08)
$(1 - R^2) \times Q$	0.397***	0.418***	0.165***	0.195***	3.191***	3.081***
	(9.14)	(9.36)	(7.10)	(8.19)	(8.23)	(6.99)
$(1 - R^2)$	−0.813***	−0.499***	−0.782***	−0.655***	−3.952***	−3.418***
	(-7.63)	(-4.77)	(-11.22)	(-9.17)	(-5.39)	(-4.58)
Closure × *CF*		−3.108**		−1.192		12.487
		(-2.32)		(-1.42)		(1.64)
CF		10.172***		3.471***		72.104***
		(20.00)		(15.70)		(27.77)
$(1 - R^2) \times CF$		−17.632***		−6.498***		−15.267
		(-9.07)		(-6.87)		(-1.62)
$1/ATQ$		0.041***		0.007***		0.188***
		(12.59)		(3.86)		(15.22)
AR		−0.081***		−0.126***		−0.067
		(-3.00)		(-7.63)		(-0.35)
R^2	0.59	0.62	0.49	0.51	0.17	0.20
N	206,783	184,334	206,783	184,334	218,945	194,892

liquidity on the investment-to-price sensitivity.

Table 7 shows that the DiD effect of liquidity on the investment-to-price sensitivity is consistently negative, and significantly so for *CAPXRND* and *CAPX*. For *CHGASSET* (arguably the crudest of our investment measures), the *t*-statistic of the coefficient on the triple interaction term is −1.42 and thus not significant at the 10% level. Overall, the results of the DiD analysis confirm the result in Table 3 that the investment-to-price sensitivity is lower for firms with more liquid stocks.

The results in Table 7 also allow for a straightforward assessment of the economic magnitude of this effect. For example, the DiD coefficient in the first column (based on *CAPXRND*) indicates that the investment-to-price sensitivity decreased by 0.253 more around decimalization for stocks whose liquidity improved the most than for stocks whose liquidity improved the least. This effect is large compared to the average investment-to-price sensitivity of stocks in the control group post-decimalization of 0.488 (=0.347 + 0.141 from Table 7) and the average investment-to-price sensitivity of stocks in the treatment group pre-decimalization of 0.403 (=0.347 + 0.056). In light of the considerable impact of decimalization on liquidity documented by Bessembinder (2003)—around a one-third drop in quoted spreads for NYSE stocks on average—it thus appears that the impact of liquidity on the investment-to-price sensitivity is economically significant.

One limitation of the 2001 decimalization event (and thus of the DiD results in Table 7) is that it concerns only one point in time within a sample period of more than 30 years. Inspired by Kelly and Ljungqvist (2012), we therefore also use another exogenous shock to the liquidity of individual stocks: the termination of analyst coverage of a number of stocks due to the closing by 43 U.S. brokerage firms of their research departments between 2000 and 2008. Kelly and Ljungqvist (2012) make the case that the closures of these research departments were unrelated to changes in the prospects of the covered firms, but rather by changes in the economics of producing research, and were thus plausibly exogenous to asymmetric information about the firm. They show empirically that the resulting analyst coverage terminations are indeed correlated with an increase in information asymmetry and illiquidity (as measured by, among others, *PQSPR*) for the affected stocks. Our implicit argument is that the closures reduce public information produced by analysts (Easley et al., 1998), and thus raise information asymmetry and illiquidity, which, in turn adversely impacts the costs of short-termism. Thus, the pathway is that the reduction in public information via analyst coverage raises illiquidity and discourages short-termism, thus encouraging production of long-term private information.

Table 9

DiD of exogenous portfolio disclosure frequency increase on the investment-to-price sensitivity. This table reports the coefficient estimates from the following fixed-effect panel regressions based on all firms in our sample for which we have valid observations for at least 19 out of 20 quarters before and after a market regulation change in 2004 that increased the disclosure frequency of portfolios hold by mutual funds:

$$Inv_{i,q} = \sum_i \lambda_i + \sum_q \lambda_q + \lambda_1 Post_{i,q} \times Treat_{i,q} \times Q_{i,q-1} + \lambda_2 Q_{i,q-1} + $$
$$+\lambda_3 Post_{i,q} \times Q_{i,q-1} + \lambda_4 Treat_{i,q} \times Q_{i,q-1} + \lambda_5 Post_{i,q} \times Treat_{i,q} + \omega_{i,q},$$

where λ_i and λ_q are, respectively, firm fixed effects and quarter fixed effects, *Inv* is one of the three corporate investment measures (*CAPXRND*, *CAPX*, or *CHGASSET*), *Q* is Tobin's *Q*, *Post* is a dummy variable equal to one after 2004, and *Treat* is a treatment dummy variable equal to one for firms with above-median ownership by mutual funds that increased their portfolio disclosure frequency in May 2004 (Agarwal et al., 2018). Observations within the event year (2004) are dropped from the sample. See Table 1 and Section 2 for details on data screens and variable definitions. Coefficient λ_1 measures the DiD effect of an exogenous increase in stock liquidity on the investment-to-price sensitivity. *t*-statistics clustered by firm are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CAPXRND	*CAPX*	*CHGASSET*
Post × *Treat* × *Q*	−0.258**	−0.124**	0.201
	(-2.41)	(-2.10)	(0.24)
Q	0.138**	0.090***	3.841***
	(2.06)	(3.87)	(4.48)
Post × *Q*	0.251**	0.145***	−0.055
	(2.50)	(2.64)	(-0.07)
Treat × *Q*	0.173**	0.072***	−0.557
	(2.45)	(2.65)	(-0.59)
Post × *Treat*	0.358	0.045	−0.727
	(1.36)	(0.29)	(-0.57)
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R^2	0.6008	0.5586	0.1607
N	44,311	44,311	44,311

In unreported tests, we first confirm the result of Kelly and Ljungqvist (2012) that the closures are associated with a statistically and economically significant increase in illiquidity; the mean *PQSPR* of the affected stocks increased from 0.577 to 0.696 (t-stat = 2.83) and the mean *PESPR* increased from 0.522 to 0.636 (t-stat = 3.01) around the closures.[15] Table 8 shows the results of quarterly fixed-effect panel regressions in which firm-level investment is regressed on lagged Tobin's *Q* and the interaction of lagged *Q* with a dummy variable indicating the loss of analyst coverage due to exogenous brokerage closures in the current or any of the prior three quarters. We obtain data on exogenous brokerage closures from Harford et al. (2019). For each of the three investment measures, the table reports the results of two regression specifications that differ in the number of control variables included. The coefficient on the interaction term, which measures how the investment-to-price sensitivity varies with the exogenous loss of analyst coverage, is positive in all six regressions, and significantly so in five of the six regressions. Thus, the exogenous termination of analyst coverage is associated with an increase in the investment-to-price sensitivity. This result is in line with our hypothesis of an indirect effect through a decrease in the liquidity of the affected stocks and thereby a greater sensitivity of corporate investment to market prices. One may consider this result surprising in the sense that we might expect the direct effect of analyst coverage loss on the investment-to-price sensitivity to be negative. But, if closures reduce the transmission of public information that is available outside of the stock price, we would not expect these closures to have a direct impact on investment-price sensitivity as that reflects the content of private information in the stock price.

3.6. Summary of investment-to-price sensitivity results

Taken together, the results in this section support our main hypothesis that stocks with greater liquidity and a greater institutional *Churn* ratio exhibit a lower sensitivity of corporate investment to market prices, even when accounting for the endogeneity of liquidity. This finding suggests that managers learn less from the market prices of stocks characterized by a greater degree of investor short-termism when making real investment decisions.

4. Further analysis of the relation between short-termism and the investment-to-price sensitivity

In this section, we present the results of a number of supplementary tests to better identify and understand the link between our short-termism proxies and the investment-to-price sensitivity. First, we examine whether an exogenous shock to investor myopia affects the investment-to-price sensitivity (Subsection 4.1). We then present evidence on the question whether the managers of firms

[15] An advantage of these brokerage closures as shocks to illiquidity is that they occurred over a longer time period, although they affected considerably fewer stocks than decimalization did.

Table 10

Short-termism, investor horizon, and CAPX forecasts. This table reports the average coefficient estimates from the quarterly Fama-Macbeth regressions, in which an indicator variable for *CAPX* forecasts is regressed on lagged *Churn* and illiquidity:

$Pr(Treat_{i,q} = 1) = \gamma_{0,q} + \gamma_{1,q} Churn_{i,q-1} + \gamma_{2,q} Illiq_{i,q-1} + \Gamma_q Controls_{i,q-1} + \eta_{i,q}$,

where $Treat_{i,q}$ is an indicator variable equal to one if firm *i* issues a CAPX forecast in quarter *q* and zero otherwise, *Churn* is the churn ratio defined in Table 2, *Illiq* is one of the two proxies for illiquidity (*PQSPR* or *PESPR*), and *Controls* is a vector of control variables as in equation (2) of Jayaraman and Wu (2020): an indicator variable equal to one for stock-quarters with an above-median noise-to-signal in the stock price (*NOISE_SIGNAL*); book leverage defined as the ratio of debt scaled by assets (*LEV*); the logarithm of market value of equity (*SIZE*); asset tangibility, defined as the ratio of (net) PP&E to total assets (*TANG*); income before extraordinary items scaled by total assets (*ROA*); whether *ROA* is negative (*ROA_NEG*); and the 8-quarters standard deviation of *ROA* (*ROA_VOL*). See Table 1 and Section 2 for details on data screens and variable definitions. Columns show the results for the three short-termism proxies with and without control variables. Fama-MacBeth *t*-statistics with Newey-West corrections are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Intercept estimates are not reported for brevity.

	(1)	(2)	(3)	(4)
Churn	0.154*	0.352***	0.266**	0.441***
	(1.82)	(4.41)	(2.22)	(4.18)
PQSPR	−0.112***	−0.036***		
	(-13.95)	(-4.18)		
PESPR			−0.111***	−0.030***
			(-10.21)	(-3.24)
NOISE_SIGNAL		0.023***		0.026***
		(4.29)		(5.06)
LEV		0.116***		0.120***
		(7.15)		(7.83)
SIZE		0.039***		0.040***
		(7.18)		(7.24)
TANG		0.360***		0.359***
		(8.17)		(8.20)
ROA		0.238***		0.239***
		(5.09)		(4.93)
ROA_NEG		−0.025***		−0.024***
		(-5.52)		(-5.12)
ROA_VOL		−0.215***		−0.166***
		(-5.31)		(-3.78)
R^2	0.0393	0.1356	0.0367	0.1329
N	107,361	91,350	100,646	87,127

with more liquid stocks and a greater *Churn* ratio are more likely to issue capital expenditure forecasts, in a bid to stimulate informed trading (Subsection 4.2). Subsequently, we study whether our short-termism proxies are related to the earnings response coefficient as an alternative measure of stock price informativeness (Subsection 4.3).

4.1. Investor myopia and the investment-to-price sensitivity

Although we have established a pervasive relation between our short-termism proxies and the investment-to-price sensitivity, our proxies for short-termism arguably predominantly capture the trading horizon of the investors active in a stock. However, short-horizon investors may not necessarily be short-term oriented (or myopic) in the sense that their trading behavior ignores long-term fundamentals. In this subsection, we exploit a regulation introduced in May 2004 that increased the reporting frequency of mutual funds' portfolio holdings, which AVV argue exogenously increased investor myopia. In particular, AVV cite theoretical research that suggests that greater transparency of mutual fund holdings could make mutual fund managers more myopic since the increased monitoring by mutual fund investors may reduce managers' willingness to pursue investments that may create value in the long run, but can appear as poor stock picks in the short run.

We thus follow AVV and run a DiD analysis of the investment-to-price sensitivity around the May 2004 increase in mutual fund disclosure frequency. The set-up of the DiD is comparable to that described in equation (3). Table 9 shows the estimates of fixed-effect panel regressions of the three corporate investment measures on lagged *Q* as well as lagged *Q* interacted with a *Post* dummy that is equal to one after May 2004 and a *Treat* dummy that is equal to one for firms with above-median ownership by mutual funds that increased their portfolio disclosure frequency in 2004.

Table 9 shows that the coefficient on the triple interaction term of lagged *Q* with both *Post* and *Treat* (the DiD effect of an exogenous increase in mutual fund myopia on the investment-to-price sensitivity) is negative and significant for the investment measures *CAPXRND* and *CAPX*, and insignificant for *CHGASSET*. Thus, the two regression specifications with arguably the most direct measures of corporate investment lend support to the notion that the investment-to-price sensitivity is reduced when investor myopia increases.

4.2. Short-termism and capital expenditure forecasts

We now provide more evidence on the channel through which the investment-to-price sensitivity may be affected by short-termism. Specifically, we provide a another test of our conjecture that short-termism is associated with stock prices that are noisier. Here, we

Table 11
Short-termism and the earnings response coefficient. This table reports the average coefficient estimates from the quarterly Fama-Macbeth regressions in equation (2), in which the cumulative abnormal stock returns (*CAR*) around corporate earnings announcements is regressed on standardized unexpected earnings (*SUE*) and the interaction of *SUE* with lagged short-termism:
$CAR_{i,q} = \gamma_{0,q} + \gamma_{1,q}ST_{i,q-1} \times SUE_{i,q} + \gamma_{2,q}ST_{i,q-1} + \gamma_{3,q}SUE_{i,q} + \eta_{i,q}$,
where *CAR* is the cumulative abnormal return in a two- or three-day window around quarterly corporate earnings announcements, *ST* is one of the three proxies for short-termism (*PQSPR*, *PESPR*, or *Churn*), and *SUE* is the standardized unexpected earnings corresponding to the earnings announcement. See Table 1 and Section 2 for details on data screens and variable definitions. Coefficient γ_3 is the earnings response coefficient (ERC). Coefficient γ_1 measures how the ERC varies with our short-termism proxies. Columns show the results for the three short-termism proxies and for three different event windows around the quarterly earnings announcement: *CAR*(-1,0), *CAR*(0,1), and *CAR*(-1,1), where the numbers in parentheses indicate days relative to the announcement date. Fama-MacBeth *t*-statistics with Newey-West corrections are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Intercept estimates are not reported for brevity.

	CAR(-1,0)			CAR(0,1)			CAR(-1,1)		
PQSPR × *SUE*	−0.299***			−0.279***			−0.315***		
	(-5.41)			(-4.93)			(-5.25)		
PESPR × *SUE*		−0.335***			−0.308***			−0.345***	
		(-5.73)			(-5.24)			(-5.64)	
Churn × *SUE*			3.613***			3.318***			3.566***
			(5.59)			(5.53)			(5.18)
PQSPR	−0.001			−0.003***			−0.002***		
	(-1.37)			(-3.80)			(-3.13)		
PESPR		−0.001			−0.004***			−0.003***	
		(-1.29)			(-4.67)			(-3.59)	
Churn			0.060***			0.068***			0.072***
			(9.32)			(7.98)			(9.78)
SUE	1.156***	1.147***	0.303***	1.072***	1.060***	0.307***	1.187***	1.178***	0.339***
	(9.34)	(9.55)	(2.69)	(8.22)	(8.41)	(2.75)	(9.32)	(9.48)	(2.74)
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
N	174,642	181,197	190,094	174,642	181,197	190,094	174,642	181,197	190,094

follow the argument of Jayaraman and Wu (2020) that firms with noisier stock prices are more likely to issue a forecast of capital expenditures to solicit feedback from informed traders. The logic is that a voluntary disclosure attracts informed trading, and this informed trading is more valuable to the manager when the stock is dominated by short-term traders. To test whether our short-termism proxies are related to the probability of firms issuing capital expenditures forecasts, we follow Eq. (2) of Jayaraman and Wu (2020) and estimate a linear probability model in which the dependent variable is an indicator for whether a firm issues a capital expenditures forecast in a certain quarter.[16] The key independent variables are our short-termism proxies, where we combine *Churn* with either *PQSPR* or *PESPR* in the same regression specification. We also estimate these regressions including the same set of control variables as Jayaraman and Wu (2020).

Table 10 presents the regression estimates. In all four regression specifications, the coefficient on *Churn* is significantly positive and the coefficient on illiquidity (*PQSPR* or *PESPR*) is significantly negative. These findings indicate that firms with greater institutional churn and greater liquidity are indeed more likely to issue a capital expenditures forecast, which is suggestive of a lower signal-to-noise ratio in the prices of these firms.

4.3. Short-termism and the earnings response coefficient

In this subsection, we analyze how the earnings response coefficient (ERC) varies with short-termism. We believe that such an analysis is of interest since the ERC has been used as a measure for the degree of information incorporation into the stock price and may thus help to provide insight on the question of whether stocks with greater short-termism indeed have less informative stock prices, as per our main hypothesis. The argument is that stocks which show a stronger price response to corporate earnings surprises exhibit less informed trading before the earnings announcement, and thus less informative stock prices (Brennan et al., 2018).

Edmans et al. (2017b) propose that managers learn from stock prices when they contain information not known by the managers. Although information incorporated into stock prices around earnings announcements may to a considerable extent be known to managers, we believe that ERC is interesting to study as a general proxy for how much (private) information is incorporated into stock prices before earnings announcements. Furthermore, the stock price response to the announcement itself is not only driven by that particular earnings announcement (which is known to managers), but also by the perceived consequences of the earnings surprise for future earnings (about which managers may be uncertain).

Following the literature, we estimate the ERC in cross-sectional regressions of the cumulative abnormal stock returns (*CARs*) around earnings announcements on the standardized unexpected earnings (*SUE*), as reflected in equation (2). To examine how short-termism affects the ERC, we include lagged short-termism (*PQSPR*, *PESPR*, and *Churn*), and lagged frictions interacted with *SUE* in the

[16] As a robustness check, we also estimate probit regressions per quarter and find that the lagged *Churn* ratio is positively related to the probability of firms issuing capital expenditures forecasts in 24 out of 33 quarters, while illiquidity shows a negative relation in 30 out of 33 quarters.

Table 12
DiD of exogenous increase in liquidity and portfolio disclosure frequency on the earnings response coefficient. This table reports the coefficient estimates from the following fixed-effect panel regressions based on all firms for which we have valid observations in each of the eight quarters before and after the event. In Panel A, the event is decimalization in February 2001 (NYSE stocks only). In Panel B, the event is an increase in the disclosure frequency of portfolios held by mutual funds in May 2004.

$$CAR_{i,q} = \sum_i \lambda_i + \sum_q \lambda_q + \lambda_1 Post_{i,q} \times Treat_{i,q} \times SUE_{i,q} + \lambda_2 SUE_{i,q} + \lambda_3 Post_{i,q} \times SUE_{i,q} + \lambda_4 Treat_{i,q} \times SUE_{i,q} + \lambda_5 Post_{i,q} \times Treat_{i,q} + \omega_{i,q},$$

where λ_i and λ_q are, respectively, firm fixed effects and quarter fixed effects, *CAR* is the cumulative abnormal return in a two- or three-day window around quarterly corporate earnings announcements, *SUE* is the standardized unexpected earnings corresponding to the earnings announcement, *Post* is a dummy variable equal to one after the event, and *Treat* is a treatment dummy variable. In Panel A, *Treat* is equal to one for firms whose stock liquidity improved the most around decimalization in February 2001. In Panel B, *Treat* is equal to one for firms with above-median ownership by mutual funds that increased their portfolio disclosure frequency in May 2004 (Agarwal et al., 2018). See Table 1 and Section 2 for details on data screens and variable definitions. In Panels A and B, Coefficient λ_1 measures the DiD effect of, respectively, an exogenous increase in stock liquidity and an exogenous increase the portfolio disclosure frequency of mutual funds on the earnings response coefficient (ERC). Columns show the results for three different event windows around the quarterly earnings announcement: *CAR*(-1,0), *CAR*(0,1), and *CAR*(-1,1), where the numbers in parentheses indicate days relative to the announcement date. *t*-statistics clustered by firm are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Decimalization			Panel B: Disclosure frequency		
	CAR(-1,0)	CAR(0,1)	CAR(-1,1)	CAR(-1,0)	CAR(0,1)	CAR(-1,1)
Post × *Treat* × *SUE*	2.640**	2.806**	3.740***	0.940	1.573**	1.763**
	(2.35)	(2.38)	(3.03)	(1.38)	(2.20)	(2.41)
SUE	2.508***	2.414***	2.669***	0.964***	0.947***	1.091***
	(3.10)	(3.32)	(3.46)	(3.86)	(4.83)	(4.81)
Post × *SUE*	−2.382**	−2.540**	−2.901***	0.947*	0.444	0.313
	(-2.31)	(-2.41)	(-2.64)	(1.83)	(0.88)	(0.58)
Treat × *SUE*	−1.106	−0.938	−1.407	0.002	−0.184	−0.283
	(-1.18)	(-1.07)	(-1.48)	(0.00)	(-0.38)	(-0.57)
Post × *Treat*	−0.005	−0.003	−0.004	0.002	0.001	0.002
	(-1.55)	(-0.82)	(-1.10)	(0.39)	(0.21)	(0.34)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.09	0.09	0.1099	0.1065	0.1052
N	6,688	6,688	6,688	19,427	19,427	19,427

regressions. Table 11 reports the results of these regressions, estimated separately for the three short-termism proxies and for three different event windows around the quarterly earnings announcement: *CAR*(-1,0), *CAR*(0,1), and *CAR*(-1,1), where the numbers in parentheses indicate days relative to the announcement date.

The results in Table 11 indicate that the coefficient on the interaction between *SUE* and lagged *PQSPR* or lagged *PESPR* (respectively, lagged *Churn*) is negative (positive) and significant throughout. These findings are consistent with our conjecture that greater liquidity and greater short-termism are associated with a lesser degree of information incorporation into the stock price, which could at least partially explain why managers rely less on the prices of more liquid stocks when making real investment decisions. Our finding on the relation between our short-termism proxies and the ERC is reminiscent of the findings of Weller (2018), who shows that algorithmic trading (a form of trading that is generally considered to be short-term) is associated with lower price informativeness around earnings announcements.[17]

Again, a limitation of the regression analyses in Table 11 is that short-termism is potentially endogenous to abnormal stock returns. Hence, we use the DiD approach described in equation (3) to assess the effect of the exogenous increase in market liquidity around decimalization on the ERC. Panel A of Table 12 presents the estimation results of fixed effect panel regressions of the *CAR* over the three different event windows on *SUE* as well as *SUE* interacted with the *Post* and *Treat* dummies defined above. Table 12 shows that the coefficient on the triple interaction term (the DiD effect of an exogenous increase in liquidity on the ERC) is positive and significant in all three specifications. In other words, the ERC increased the most for stocks that experienced the greatest increase in liquidity around decimalization. Thus, even when accounting for potential endogeneity, our evidence supports the notion that more liquid stocks are characterized by a lesser degree of information incorporation.

Furthermore, to assess whether the ERC changed in response to an exogenous increase in investor myopia, we follow the analyses in AVV and in Table 9 and estimate fixed-effect panel regressions of *CAR* for on *SUE*,as well as *SUE* interacted with a *Post* dummy that is equal to one after May 2004 and a *Treat* dummy that is equal to one for firms with above-median ownership by mutual funds that increased their portfolio disclosure frequency in 2004. The results are in Panel B of Table 12. We find that the coefficient on the triple interaction term (defined as in Panel A) is positive for all three event windows, and significantly so for two out of the three. Hence,

[17] In unreported results, we also consider whether the component of illiquidity that is explained by *Churn* (that is, $\widehat{Illiq}$) is related to the ERC. We find that the coefficient on the interaction term of *SUE* with $\widehat{Illiq}$ is negative and significant, which suggests that part of the reason why illiquidity helps to explain cross-sectional variation in the ERC is because it captures variation in the institutional *Churn* ratio.

stock prices become less informative when investors become more short-term oriented. Together with our previous results, this adds support for our main hypothesis that short-termism is associated with less informative stock prices and thus an impaired ability for managers to learn from the stock price when making real investment decisions.

5. Conclusions

In this paper, we propose that prices of stocks that attract short-term investors might incorporate less information about long-term fundamentals. Thus, managers may be less (more) likely to rely on the prices of firms with more (less) short-termism when making corporate investment decisions. Confirming this idea, our empirical evidence shows that the investment-to-price sensitivity is lower for stocks with higher levels of two short-termism proxies: liquidity and institutional churn. We show that the relation between the investment-to-price sensitivity and short-termism goes above and beyond its relation to stock price nonsynchronicity as documented by Chen et al. (2007), a finding that is consistent with the idea that while stock price nonsynchronicity is a general proxy for stock price informativeness (both short-term and long-term), less short-termism encourages the incorporation of long-term information that is relevant for corporate investments.

Our main finding is confirmed in two analyses that exploit plausibly exogenous shocks to one of our short-termism proxies, i.e., liquidity: the switch to decimalization in 2001 and the loss of analyst coverage due to the closures of brokerage firms' research departments. In another identification scheme, we consider an event proposed by Agarwal et al. (2018), wherein mutual funds were forced to disclose their holdings at higher frequencies. We show that stocks with higher levels of holdings by affected funds demonstrate a decrease in their investment-to-price sensitivity. This finding is in line with the notion that stocks with greater short-termism exhibit a lesser degree of information incorporation. We also find that short-termism is accompanied by an increase in the earnings response coefficient, suggesting that stock price informativeness about earnings is inversely related to short-termism.

Our study suggests other avenues of research. For example, high liquidity reduces costs of capital as per Amihud and Mendelson (1986), and if short-termism increases liquidity, it might also reduce required returns. This effect operates on the denominator of a firm's present value. We mainly focus on the impact of liquidity on the investment-price sensitivity, and real investment impacts the numerator of value. The net effects of short-termism and liquidity are of considerable policy interest, and this forms an important avenue for future research. We also note that our results speak to the effect of short-termism on the investment-to-price sensitivity, and whether managers are stimulated to collect more information signals beyond the stock price when short-termism is high. Further, markets with excessive short-termism might discourage entrepreneurs with long-term projects from taking their firms public, because accurate indicators of the long-term success may not be available from such markets. Thus, the increased scrutiny and loss of control might not be outweighed by the informational benefits of public stock prices. Finally, while highly liquid markets might encourage short-term investing, they might also allow easier diversification for entrepreneurs and lead to lower costs of capital. Integrated theoretical and empirical analysis of these issues form a promising avenue for future work.

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