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Full Length Article

Information shocks and the cross section of expected returns

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Abstract

This paper examines the risk premium associated with information shocks in equity markets. For all stocks traded on Borsa Istanbul between March 2005 and December 2020, we calculate information shocks as unanticipated information asymmetry by focusing on changes in the proportion of the effective spread attributable to adverse selection. Our results indicate a significant return premium for an information shock strategy. Specifically, the return premium associated with the zero-investment information shock portfolios is 72 basis points. After controlling for several factors, we then document a significant predictive relationship between information shocks and future returns. The predictive power and the return premium associated with the information shock strategy are stronger after the initiation of the BISTECH trading system, which enables heterogeneity across investors vis-à-vis trade execution latency. These results suggest that, after the introduction of fast trading, the risks associated with information shocks become systemically important in the cost of equity.

JEL classification: G11; G12; G14

Keywords: Asset pricing; Information asymmetry; Transaction costs

1. Introduction

Theoretical asset-pricing models assume that the transaction costs in financial markets are negligible (Lintner, 1965a; 1965b; Ross, 1976; Sharpe, 1964). On the contrary, transaction costs play a crucial role in the decision-making process of individual and institutional investors during portfolio formation. The role of transaction costs in financial markets is mainly emphasized in market microstructure literature, in which both theoretical and empirical studies document that liquidity providers adjust transaction costs when faced with the risk of adverse selection (Copeland & Galai, 1983; Easley and O'Hara, 1987; Glosten & Milgrom, 1985; Kyle, 1985). These studies also provide a framework for the incorporation of information in the order flow into the prices. The seminal work by Glosten and Milgrom (1985) shows that, when uninformed liquidity providers observe a buy (sell) order, they revise their expectation for the stock upward (downward), and these revisions are directly reflected in the transaction costs and, subsequently, in the equilibrium prices.

More specifically, the standard theoretical models of trading under information asymmetry indicate that uninformed liquidity providers increase the transaction costs to compensate for the adverse selection risk that they undertake when they trade against informed traders. On the empirical side, the standard asymmetry information models decompose price changes into two components: a transitory component related to order-processing costs and an adverse selection component associated with permanent price change and informed trading (Glosten & Harris, 1988; Huang & Stoll, 1997; Madhavan et al., 1997).

The existing literature shows some tension over whether adverse selection risk, due to information asymmetry between informed and uninformed investors, systemically affects securities returns. On the one hand, the rational expectations model of Easley and O'Hara (2004) indicates that uninformed investors are slow at updating their portfolios in response to the

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new information arriving in the market. Therefore, according to Easley and O'Hara (2004), information asymmetry systemically influences securities returns, and the adverse selection risk is not diversifiable because, holding everything else constant, investors demand a premium for investing in stocks with high levels of information asymmetry. On the other hand, Hughes et al. (2007) suggest that, in a market with a sufficiently large number of assets, aggregate information asymmetry is the only driver of securities returns. Therefore, according to their model, firm-specific information is idiosyncratic and fully diversifiable after other systemic asset-pricing factors are controlled for.

We contribute to the existing debate by examining systemic risk associated with adverse selection risk in an emerging stock market, Borsa Istanbul (BIST). BIST, a vibrant stock market in an emerging economy, also provides a natural experiment for examining the impact of changes in the market design on the systemic relationship between adverse selection risk and equity returns. Specifically, in November 2015, BIST introduced NASDAQ's Genium INET trading engine (also known as the BISTECH trading system), enabling collocation services that establish differences in order submission and trade execution latency among investors. Ekinci and Ersan (2022) highlight the negative externalities related to the involvement of high-frequency traders (HFTs, or fast traders) in BIST. In particular, they document that, even though the HFT involvement is relatively low (on average, 5%) compared to other equity markets, it significantly reduces the liquidity provision by non-HFTs, highlighting a potential crowding-out effect in BIST. Next, they argue that HFTs consistently outperform the market; that is, the excess returns are positive (negative) when HFTs are on the buy (sell) side. These results align with the broader literature that argues that HFTs contribute to the price discovery process more than non-HFTs through different channels (Brogaard et al., 2010; 2014) and might suggest that HFTs in BIST are better informed (or at least better at reacting to news arriving in the market). Therefore, investors in BIST might be at a disadvantage when trading directly against HFTs. This would further imply higher adverse selection risk for slow traders in BIST (Biais et al., 2015; Brogaard et al., 2014). We complement this literature by documenting that, after the introduction of fast trading, risks associated with adverse selection can be amplified and systemically increase the cost of equity.

Our primary focus is change in the level of information asymmetry, measured by the proportion of the adverse selection component of the spread. An earlier paper by Tiniç and Salih (2020) documents that the level of the probability of informed trading is not systemically important in BIST. However, we investigate the impact of information asymmetry that is unanticipated by investors (i.e., information shocks) by examining the effects of changes in the proportion of the adverse selection component of the spread on future returns to better capture investment behavior in response to news arriving in the market. We employ the seminal model by Glosten and Harris (1988) to estimate the proportion of the effective spread that is attributable to adverse selection. We first document a significant adverse selection component of the spread for 491 out of 505 stocks traded on BIST between 2005 and 2020. We show that, on average, 14 percent of the estimated spread is attributable to adverse selection risk. Therefore, we argue that the adverse selection component of the spread is significant not only statistically but also economically for stocks traded on BIST.

Next, we examine the relationship between information shocks, proxied by changes in the proportion of the adverse selection component of the spread, and the cross section of expected returns on BIST. Univariate portfolios based on firm-specific information shock measures indicate that investors on BIST demand a premium for holding stocks with a sudden increase in transaction costs due to information asymmetry. Specifically, the value-weighted return differential between high- and low-quintile portfolios based on information shocks is around 77 basis points (bps). The return premium on the value-weighted difference is around 72 bps and is statistically significant at the 1 percent level, even after controlling for market risk, size, value (Fama & French, 1993), and momentum factors (Carhart, 1997). Furthermore, we document that the return premium due to information shocks is robust to multivariate portfolio settings in which we control for firm size, return reversal, idiosyncratic volatility, lottery stock characteristics, and trading volume, which are significantly correlated with the information shock measure.

Moreover, we test the predictive relationship between information shocks and future returns via firm-level cross-sectional regressions. We observe that a 1 percent increase in our information shock measure is associated with an increase of 30 bps in one-month-ahead returns even after controlling for the variation in firm-specific characteristics, such as firm size, market risk, the book-to-market ratio, liquidity, recent return performance measured by return reversal and momentum, lottery stock characteristics, trading volume, and idiosyncratic volatility.

Finally, our results indicate that both the return premium and the predictive power associated with the information shock strategy became more prominent after the introduction of the BISTECH trading system, which introduced heterogeneity across investors vis-à-vis order submission and trade execution latency. More specifically, the results of our subsample analysis indicate that the value-weighted average return differential between high- and low-information shock portfolios is around 67 bps in the pre-BISTECH period (March 2005–November 2015). This difference increases to one percentage point in the post-BISTECH period (December 2015–December 2020). We observe that the predictive relationship between information shocks and future returns is not statistically significant after controlling for the variation in other firm-specific measures in the pre-BISTECH period. However, we document a statistically significant predictive relationship between information shock measures and future returns in the post-BISTECH period. In particular, a 1 percent increase in information shock measures is associated with an increase in future returns of 76 bps in the post-BISTECH period, even after controlling for the variation in all other firm-specific characteristics.

Overall, these results support the theoretical expectations of Easley and O'Hara (2004), which suggest that uninformed investors demand a premium for holding stocks that face information shocks, as they are slow in updating their portfolios with respect to news arriving in the market. We contribute to the current debate on the role of HFTs in BIST by documenting that the systemic risk associated with adverse selection is mainly prominent during the subsample period, which has heterogeneity across investors concerning the speed of order submission and trade execution. Our results suggest that adverse selection risk, which would otherwise be diversifiable, can systemically influence the cross section of expected returns under fast trading.

This paper is organized as follows. Section 2 introduces the data. Section 3 discusses the methodology. Section 4 presents the results. Section 5 concludes.

2. Data

We obtain intraday trade and quote data for all stocks traded on BIST between March 2005 and December 2020 from the BIST Datastore.[1] We divided our sample into two subsamples, pre-BISTECH and post-BISTECH, in November 2015. BISTECH introduced heterogeneity among investors vis-à-vis order submission and trade execution latency. The BISTECH platform also enabled BIST to integrate the national equity market with the derivatives market under a single operating system. Borsa Istanbul (2015) documents that it introduced new order types, such as market orders, market-to-limit orders, and imbalance orders, along with order types that depend on a particular condition (price, quantity, or time) and midpoint orders. Moreover, a new circuit-breaking rule began to be implemented with the BISTECH system. There were small changes in the continuous trading hours after November 2015, along with specific changes in the regulation of price increments during continuous trade. The algorithm that determines the opening prices for the continuous trade session was also updated. BIST also introduced market-making activity for a limited number of small and illiquid stocks.

Our sample comprises 505 different stocks.[2] Each order entry contains information regarding the date, time, ticker, order ID, order type, quantity, and price in our quote dataset. The order type enables us to identify whether the order is a buy or a sell order. Each entry has the date, time, ticker, quantity, and price stamps in our trade dataset.

Furthermore, each trade entry has an order ID on both the buy and sell sides. We also rely on a trade classification flag that enables us to objectively identify the active side of the trade. To that end, we do not rely on any trade classification algorithms, which are shown to create bias in estimations (Aktas & Kryzanowski, 2014).

[1] Intraday quote and trade data for all stocks traded on BIST are available at datastore.borsaistanbul.com. Because all intraday data are denominated in the local currency, Turkish lira (TL), all firm-specific measures are denominated in TL. As a robustness check, we also repeat the analysis using variables denominated in the US dollar (USD) to account for any potential impact of macroeconomic conditions, such as inflation; the main findings remain robust to this change.

[2] After controlling for ticker changes and excluding stocks with special voting rights.

2.1. Calculating firm-specific measures

For all stocks traded on BIST, we obtain firm-specific accounting measures, daily price levels, along with daily benchmark index levels (BIST100 Index) from the Bloomberg terminal. For each stock i in each month m, we calculate the firm size (SIZE) as the natural logarithm of the end-of-the-month market value. We take the book-to-market (BTM) ratio as the ratio between the firm's book value of equity in the last quarter prior to month m and its market value at the end of month m. We calculate the market risk of firm i in month m (BETA) as the estimate for the slope coefficient of the market model as follows:

$$R_{i,d} = \alpha_i + \beta_i R_d^{mkt} + \varepsilon_{i,d} \quad d = 1, \ldots, D_m. \tag{1}$$

where D_m represents the number of trading days in month m. Moreover, $R_{i,d}$ and R_d^{mkt} represent the daily returns of firm i and the BIST100 Index on a given day d, respectively. We set the idiosyncratic volatility for firm i in month m as the standard deviation of the residuals in Equation (1). We use the natural logarithm of the Turkish lira–denominated monthly trading volume (VOL) as the total trading volume for firm i in month m. Atilgan et al. (2016) document that liquidity systemically influences the equity prices on BIST. To control for variation in (il)liquidity (ILLIQ) of firm i in a given month m, we use the Amihud illiquidity measure (Amihud, 2002), which is calculated as follows:

$$ILLIQ_{i,m} = \frac{1}{D_m}\sum_{d=1}^{D_m}\frac{|R_{i,d}|}{VOL_{i,d}} * 100. \tag{2}$$

We calculate the return momentum (MOM) for firm i in month m as the cumulative percentage return over the prior six months. That is,

$$MOM_{i,m} = \frac{P_{i,m} - P_{i,m-7}}{P_{i,m-7}}. \tag{3}$$

where $P_{i,m}$ is the closing price of stock i at the end of month m. In line with Jegadeesh (1990), we define return reversal for each stock i in month m (REV) as the return on the stock over the prior month. Finally, we calculate the lottery characteristics (MAX) of firm i in month m, which is shown to systemically influence stock prices on BIST (Alkan & Guner, 2018). In line with Bali et al. (2011), we use MAX as the maximum daily return of firm i in a given month m, as follows:

$$MAX_{i,m} = max(R_{i,d}), d = 1, \ldots, D_m. \tag{4}$$

For each stock i in each month m, we also calculate the percentage of the effective spread attributable to adverse selection risk (λ) using the seminal model of Glosten and Harris (1988) [GH]. Glosten and Harris decompose the spread into two components: (1) an adverse selection component related to permanent price change and informed trading and (2) a transitory component attributed to temporary price change and liquidity trading. We discuss the GH model extensively in Section 3. To measure information shocks, for stock i in month m, we calculate the changes in the proportion of the spread attributable to adverse selection risk:

Table 1
Descriptive statistics.

Variable	Obs.	Mean	St.Dev.	Minimum	25th Percentile	75th Percentile	Maximum
RETURN	54,924	0.009	0.147	−1.840	−0.060	0.076	2.289
SIZE	54,924	19.300	1.970	13.970	17.860	20.560	26.420
BTM	54,924	1.095	0.975	0.000	0.482	1.407	17.430
BETA	54,924	0.658	0.572	−8.742	0.333	0.983	10.910
REV	54,924	0.009	0.146	−1.840	−0.061	0.076	2.289
MOM	54,924	0.133	0.598	−0.930	−0.135	0.265	32.580
VOL	54,924	17.340	1.990	8.770	15.960	18.600	25.320
ILLIQ	54,924	0.010	0.875	0.000	0.000	0.000	189.900
IVOL	54,924	0.022	0.014	0.001	0.013	0.026	0.392
MAX	54,924	0.057	0.040	−0.008	0.030	0.073	1.782
λ	54,924	0.156	0.136	0.000	0.041	0.244	0.983
Δλ	54,924	0.000	0.069	−0.862	−0.025	0.025	0.924

Notes: This table presents the descriptive statistics for monthly firm-specific factors calculated for all stocks traded on the Borsa Istanbul between March 2005 and December 2020. RETURN represents the monthly log returns. SIZE is the logarithm of end-of-the-month market capitalization. BTM is the book-to-market ratio. BETA is the systemic risk factor. REV is the return reversal. MOM is the momentum variable. ILLIQ is the Amihud (2002) illiquidity measure. VOL is the natural logarithm of the total trading volume. IVOL presents idiosyncratic volatility. MAX is the maximum daily return within a month. λ and Δλ respectively denote the proportion of the spread attributable to adverse selection and the changes in the proportion of adverse selection component of the spread using the Glosten and Harris (1988) framework. The first column denotes the variable names. The second column presents the number of observations in our sample. Columns (3)–(7) respectively document the sample mean, standard deviation, minimum, 25th percentile, 75th percentile, and maximum values for a given measure.

Table 2
Pairwise correlations.

	RETURN	SIZE	BTM	BETA	REV	MOM	ILLIQ	IVOL	MAX	λ	Δλ
SIZE	0.07***										
BTM	−0.09***	−0.21***									
BETA	−0.14***	0.16***	0.03***								
REV	0.02***	0.07***	−0.10***	−0.02***							
MOM	0.00	0.10***	−0.17***	0.01	0.35***						
ILLIQ	0.00	−0.02***	0.00	0.00	0.00	0.00***					
IVOL	0.17***	−0.18***	−0.02***	0.06***	0.12***	0.22***	0.03***				
MAX	0.35***	−0.13***	−0.03***	0.13***	0.04***	0.12***	0.02***	0.83***			
λ	−0.04***	−0.07***	−0.19***	−0.13***	0.01***	0.05***	0.01	−0.03***	−0.03***		
Δλ	−0.09***	0.00	−0.01	0.07***	0.10***	0.03***	−0.01***	−0.05***	−0.03***	0.25***	
VOL	0.14***	0.66***	−0.13***	0.29***	0.12***	0.16	−0.03***	0.13***	0.16***	−0.44***	−0.06***

Notes: In this table, we present the pairwise correlations among monthly firm-specific variables that are calculated for all stocks traded on the Borsa Istanbul between March 2005 and December 2020. RETURN represents the monthly log returns. SIZE is the logarithm of end-of-the-month market capitalization. BTM is the book-to-market ratio. BETA is the systemic risk factor. REV is the return reversal. MOM is the momentum variable. ILLIQ is the Amihud (2002) illiquidity measure. VOL is the natural logarithm of the total trading volume. IVOL presents idiosyncratic volatility. MAX is the maximum daily return within a month. λ and Δλ respectively denote the proportion of the spread attributable to adverse selection and the changes in the proportion of adverse selection component of the spread using the Glosten and Harris (1988) framework. The first column denotes the variable names. The second column presents the number of observations in our sample. ***, **, and * indicate statistical significance at 1%, 5%. and 10%, respectively.

$$\Delta\lambda_{i,m} = \lambda_{i,m} - \lambda_{i,m-1} \quad (5)$$

Table 1 presents the descriptive statistics of monthly firm-specific variables.[3] In Table 1, we observe that, on average, one-sixth of the effective spread is attributable to risks due to information asymmetry. The sample minimum for the proportion of the adverse selection component of the spread is around 0 percent. The sample maximum is around 98 percent, indicating significant informed trading levels for some stocks in some months (Tiniç & Salih, 2020). Moreover, the sample minimum and the sample maximum for the information shock measure are respectively around −86 percent and 90 percent, implying sudden decreases and increases in transaction costs due to adverse selection risk.

In Table 2, we document the pairwise correlations among firm-specific variables. We observe that the pairwise correlation between information shock measure ($\Delta\lambda$) and monthly logarithmic returns is negative and statistically significant. In line with our expectations, we observe that the pairwise correlation between $\Delta\lambda$ and BETA (VOL) is positive (negative) and statistically significant. To that end, we expect that stocks facing sudden increases in transaction costs due to information asymmetry will have higher market risk and low trading volume and vice versa. Finally, we observe that the pairwise correlations between the information shock measure and measures of recent return performance (REV, MOM) are

[3] Because values for the effective spread cannot be negative, we remove an observation from our monthly sample if the proportion of the spread attributable to adverse selection is less than zero or greater than one (Glosten & Harris, 1988; Huang & Stoll, 1997; Madhavan et al., 1997). We also remove an observation if for a given month and stock, BTM is negative (Fama & French, 1993).

negative, whereas the correlations of information shock measure with IVOL and MAX are positive and statistically significant.

3. Methodology

3.1. Adverse selection component of the spread

To measure the adverse selection component of the spread, we make use of the seminal framework introduced in Glosten and Harris (1988). The GH trade indicator model splits the price changes into two components, an adverse selection component related to informed trading activity and permanent price change and a transitory component related to liquidity trading levels and temporary price change.

In line with the GH model, we denote m_t as the (unobserved) true value of a stock conditional on the information available at time t. m_t changes with the information arriving in the market with new trades as follows:

$$m_t = m_{t-1} + Z_t Q_t + \varepsilon_t \tag{6}$$

where Q_t is the direction of trade, that is, $Q_t = 1$ ($Q_t = -1$) if the trade is buyer (seller) initiated. The trade contains information about the true value of the underlying stock and permanently changes the true value by Z_t, which is defined as the adverse selection component of the spread.

Traders observe (noisy) transaction prices, instead of the true value. The observed price process is modeled as follows:

$$P_t = m_t + Q_t C_t. \tag{7}$$

Observed prices also change with new trade, but this change is temporary. Therefore, C_t is labeled as the transitory component of the spread, which only affects observed prices but does not affect the true value of the underlying stock. To that end, the transitory component of the spread is associated with the changes in the order-processing costs and liquidity trading.

Following the GH model, V_t denotes the trade size. Then, we can model the transitory and adverse selection components of the spread, respectively, as follows:

$$C_t = c_0 + c_1 V_t. \tag{8}$$

$$Z_t = z_0 + z_1 V_t. \tag{9}$$

We cannot solve the systems of Equations (7)–(9) and estimate Z_t and C_t, since we do not observe m_t. However, we get the following equation from the first difference in prices ($\Delta P_t = P_t - P_{t-1}$):

$$\Delta P_t = z_0 + z_1 Q_t V_t + c_0(\Delta Q_t) + c_1(\Delta Q_t V_t) + \varepsilon_t. \tag{10}$$

where the estimate for the adverse selection component of the spread from the GH model is given as ASC $= 2\times\ \widehat{Z} = 2\times(\widehat{z}_0 + \widehat{z}_1\overline{V})$, where $\overline{V}$ is the average trade size at time t. Similarly, the estimate for the transitory component of the spread from the GH model is given as TC $= 2\times\ \widehat{C} = 2\times(\widehat{c}_0 + \widehat{c}_1\overline{V})$. Therefore, the estimated total spread can be calculated as $TOTS = ASC + TC$. To standardize the level of information asymmetry for each stock in our sample, we examine the percentage of the total spread attributable to adverse selection, that is, $\lambda = \frac{ASC}{TOTS}$.[4] Standardizing the level of information asymmetry enables us to avoid spurious results due to heterogeneous tick size levels and changes in tick sizes during our sample period.

3.2. Information shocks and the cross section of expected returns

There are conflicting theoretical expectations about the relationship between adverse selection risk and securities returns. Adverse selection risk arises for uninformed investors when trading against traders with private information. On the one hand, in a rational expectations model with information asymmetry, Easley and O'Hara (2004) demonstrate that uninformed investors cannot adjust their portfolios quickly when new information arrives in the market, that is, when an information shock to the underlying value of the stock occurs. In turn, holding everything else constant, uninformed investors are expected to demand a premium due to adverse selection risks for holding stocks that face information shocks. On the other hand, Hughes et al. (2007) argue that in an economy with a sufficiently large number of assets, aggregate information asymmetry drives securities returns. Therefore, according to Hughes et al. (2007), the adverse selection risk that arises from firm-specific information shocks can be eliminated through portfolio diversification.

To examine the relationship between information shocks and the cross section of expected returns, we employ univariate and multivariate portfolio analyses along with firm-level cross-sectional regressions. To proxy for information shocks, we calculate the change in the proportion of spread attributable to adverse selection for each stock in each month. Let $\lambda_{i,m}$ be the proportion of the effective spread attributable to adverse selection at firm i in month m. We capture the information asymmetry that is unanticipated by investors by calculating the information shock for firm i in month m as $\Delta\lambda_{i,m} = \lambda_{i,m} - \lambda_{i,m-1}$.

3.2.1. Univariate portfolio analysis

To examine the relationship between information shocks and the cross section of expected returns on BIST, we perform portfolio analyses in which we form quintile portfolios by sorting stocks based on changes in the proportion of spread attributable to adverse selection risk, $\Delta\lambda$, and group them into five different (quintile) portfolios. Specifically, at the beginning of each month, we sort stocks with respect to their $\Delta\lambda$ estimates

[4] When estimating Equation (10), we require at least 30 trades for a given stock in a given month. We remove an observation from our sample if the estimate for the proportion of adverse selection component of the spread is not between 0 and 1 (Glosten & Harris, 1988; Huang & Stoll, 1997; Madhavan et al., 1997). When testing the statistical significance for estimates of adverse selection costs, we use Newey-West standard errors to control for potential heteroskedasticity and autocorrelation in the trade arrival process (Newey & West, 1987).

for the previous month. The lowest $\Delta\lambda$ quintile consists of stocks that have the largest drop in information asymmetry in the previous month, whereas the largest $\Delta\lambda$ quintile consists of stocks with the largest increase in information asymmetry. Let R^l and R^h respectively represent the returns of the lowest and highest quintile in the subsequent month. We mimic the portfolio of an investor who has consistently held a long position in stocks with the largest increase in transaction costs due to alleviating information asymmetry and a short position of equal size in stocks, with the largest decrease in transaction costs attributable to the reduction in overall information asymmetry.

We then test whether investors in BIST obtain a premium from the information shock strategy as follows:

Hypothesis 1.

$H_0 : R^h - R^l = 0$

$H_A : R^h - R^l > 0$

We test H1 with a simple *t*-test in which we adjust standard errors for potential heteroskedasticity and autocorrelation using the Newey-West procedure (Newey & West, 1987).

Next, we measure the return premium associated with the information shock strategy, in which we control for classical asset-pricing factors, such as the market risk, size (SMB), and value (HML) factors of Fama and French (1993) and the momentum factor (UMD) of Carhart (1997) as follows[5]

$$\left(R^h - R^l\right) = \alpha + \beta^m R^{mkt} + \beta^s SMB + \beta^h HML + \beta^u UMD + \varepsilon. \quad (11)$$

The constant, α, gives the return premium associated with the information shock strategy. We expect a positive risk premium associated with the information shock strategy. Therefore, we propose our second hypothesis as follows:

Hypothesis 2.

$H_0 : \widehat{\alpha} = 0$

$H_A : \widehat{\alpha} > 0$

We test our second hypothesis with a simple *t*-test in which we adjust standard errors for potential heteroskedasticity and autocorrelation using the Newey-West procedure.

3.2.2. Multivariate portfolio analysis

In Table 2, we observe a significant pairwise correlation between the information shock measure ($\Delta\lambda$) and several firm-specific characteristics, such as firm size (SIZE), return reversal (REV), idiosyncratic volatility (IVOL), lottery stock characteristics (MAX), and trading volume (VOL). To isolate the impact of information shocks on equity returns, we control for the impact of these five firm-specific characteristics one by one in a multivariate portfolio setting. At the end of each month, we sort stocks into quintiles based on a control characteristic. Then, we divide each quintile portfolio into five different groups based on end-of-the-month $\Delta\lambda$ estimates. This procedure yields 25 different portfolios. We then follow the returns of these portfolios in the subsequent month. We form zero-investment portfolios $R_p (p = 1, \ldots, 5)$ by subtracting the returns on portfolios with stocks that face sudden increases in transaction costs due to alleviating adverse selection risk (R_p^h) from the returns of portfolios with stocks that face sudden decreases in transaction costs due to a reduction in adverse selection risk (R_p^l). The returns of zero-investment portfolios in a multivariate setting enable us to observe the systemic impact of information shocks on securities returns, controlling for other firm characteristics. Hence, we propose our third hypothesis as follows:

Hypothesis 3.

$H_0 : R_p = 0$

$H_A : R_p > 0$

We test H3 with a simple *t*-test in which we adjust our standard errors with respect to potential heteroskedasticity and autocorrelation using the Newey-West procedure.

We then examine the return premiums associated with our multivariate portfolios by employing factor tests in which we control for other systemic asset-pricing factors. We present the structure of the factor tests as follows:

$$R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p \quad p = 1, \ldots, 5. \quad (12)$$

To assess whether the information shock strategy yields statistically significant return premiums under different multivariate settings and after controlling for other asset pricing factors, we test the hypothesis that the intercept terms $\alpha_p = \{\alpha_1, \ldots, \alpha_5\}$ are jointly equal to zero, that is,

Hypothesis 4.

$H_0 : \widehat{\alpha_p} = 0$

$H_A : \widehat{\alpha_p} > 0$

To test H4, we use the Gibbons-Ross-Shanken (GRS) test statistic (Gibbons et al., 1989).

3.2.3. Firm-level cross-sectional regressions

One drawback of this multivariate portfolio analysis is that we can only control for the impact of other firm-specific characteristics one at a time. Therefore, we employ firm-level cross-sectional regressions to control for multiple firm-specific characteristics at once when examining the predictive relationship between information shocks and future returns. For each month in our sample, we regress future returns on the information shock measures along with all firm-specific characteristics:

[5] Specifically, we construct SMB and HML as monthly univariate portfolios based on SIZE and BTM, respectively. Similarly, we use UMD as a univariate portfolio based on REV (one-month lagged returns).

$$R_{i,m+1} = \gamma_{0,m} + \gamma_{1,m}\Delta\lambda_{i,m} + \gamma_{2,m}SIZE_{i,m} + \gamma_{3,m}BETA_{i,m} + \gamma'_{4,m}X_{i,m} + \varepsilon_{i,m}. \quad (13)$$

where $R_{i,m+1}$ is the return on stock i in month m+1. $\Delta\lambda_{i,m}$ is the information shock measure for stock i in month m. The matrix $X_{i,m}$ includes all firm-specific factors other than SIZE and BETA for stock i in month m. All firm-specific variables that we employ in our analyses are defined in Section 2.1. In their rational expectations model with information asymmetry, Easley and O'Hara (2004) expect a positive relationship between information asymmetry and future returns. Therefore, we write our fifth hypothesis as follows:

Hypothesis 5.

$H_0 : \overline{\gamma_1} = 0$

$H_A : \overline{\gamma_1} > 0$

We again test H5 with a t-test in which we adjust standard errors for potential heteroskedasticity and autocorrelation using Newey-West adjustment.

4. Results

4.1. Do liquidity providers on BIST charge a significant adverse selection component of the spread?

We start our empirical analysis by investigating whether investors face a statistically and economically significant adverse selection component of the spread when trading on BIST. To that end, we estimate the Glosten and Harris (1988) model presented in Equation (10) using intraday trades for all stocks traded on BIST between March 2005 and December 2020. Table 3 presents the cross-sectional distribution of our full sample estimates. Out of the 505 stocks in our sample, only one has a negative estimate for the adverse selection component of the spread, and 13 have negative estimates for the transitory component of the spread. Therefore, we observe that, for 97 percent of our sample (491 stocks), both the transitory and the adverse selection components of the spread are positive and significant. We document that the average transitory component of the spread (TC) is around 2.2 percentage points, whereas the average adverse selection component of the spread (ASC) is about 50 bps, indicating that both the ASC and the TC are not only statistically significant but also economically significant. Our results also show that, on an average stock, the proportion attributable to the adverse selection component of the effective spread, λ, is around 14 percent. The sample minimum and maximum for the estimates of λ are 0 percent and 49 percent, respectively. This result is in line with the previous findings by Tiniç and Salih (2020), who also document that informed trading levels can significantly differ across stocks on BIST.

Table 3
Cross-sectional distribution of the full sample estimates.

	ASC	TC	TOTS	λ
Minimum	0.0000	0.0050	0.0065	0.39%
25th Percentile	0.0006	0.0082	0.009	6.34%
Mean	0.0047	0.0227	0.0274	13.60%
Median	0.0014	0.0094	0.0105	12.29%
75th Percentile	0.0035	0.0142	0.0171	20.02%
Maximum	0.1254	0.5258	0.6512	49.87%
#Positive	491	491	491	491
#Significant	491	491	491	491

Notes: This table provides the cross-sectional distribution of the parameter estimates obtained from the following model: $\Delta P_t = z_0 + z_1 Q_t V_t + c_0(Qt) + c_1(\Delta Q_t V_t) + \varepsilon$ where ΔPt is the first difference in price, Q_t is the direction of the trade, that is, $Q_t = 1(Q_t = -1)$ if the trade is buyer- (seller-) initiated. V_t is the trade size. The Glosten and Harris (1988) model decomposes the spread into two components: an adverse selection component associated with informed trading activity and the permanent price impact; and a transitory component associated with the liquidity trading activity and temporary price impact. $ASC = 2 \times (\hat{z_0} + \hat{z_1}\ \overline{V})$ denotes the adverse selection component of the spread. $TSC = 2 \times (\hat{c_0} + \hat{c_1}\ \overline{V})$ denotes the transitory component of the spread. TOTS is the total estimated spread. λ corresponds to the proportion of the spread attributable to adverse selection, that is, $\lambda = ASC/TOTS$. The rows respectively present the values for the cross-sectional distribution of the corresponding estimates. The last two rows respectively present the number of positive estimates and the number of estimates that are statistically significant at the 1% level for a given measure.

4.2. Univariate portfolio analysis

We employ univariate portfolio analysis in which we sort stocks into quintile portfolios based on the previous month's information shock measures at the beginning of each month. We form equally and value-weighted portfolios for each quintile and follow the returns of these portfolios for the subsequent month. In that regard, we can construct a mimicking portfolio in which we replicate the information shock strategy—that is, taking a long position in stocks with the largest increase in the proportion of adverse selection component of the spread and a short position of equal size in stocks with the largest drop in the proportion of adverse selection component of the spread. Hence, we can investigate whether investors in BIST demand a premium for holding stocks that face a sudden shock to information asymmetry, which is reflected in the transaction costs attributable to adverse selection risks.

In Fig. 1, we illustrate the performance of zero-investment portfolios based on the information shock strategy. Specifically, we plot the cumulative returns for equally and value-weighted zero-investment portfolios along with the cumulative returns of the benchmark index (BIST100). Our results suggest that a strategy based on information shocks significantly outperforms the benchmark index during our sample period. Interestingly, we observe that the return performance of the information shock strategy is more dominant in the period after November 2015 (emphasized by the dashed vertical line),

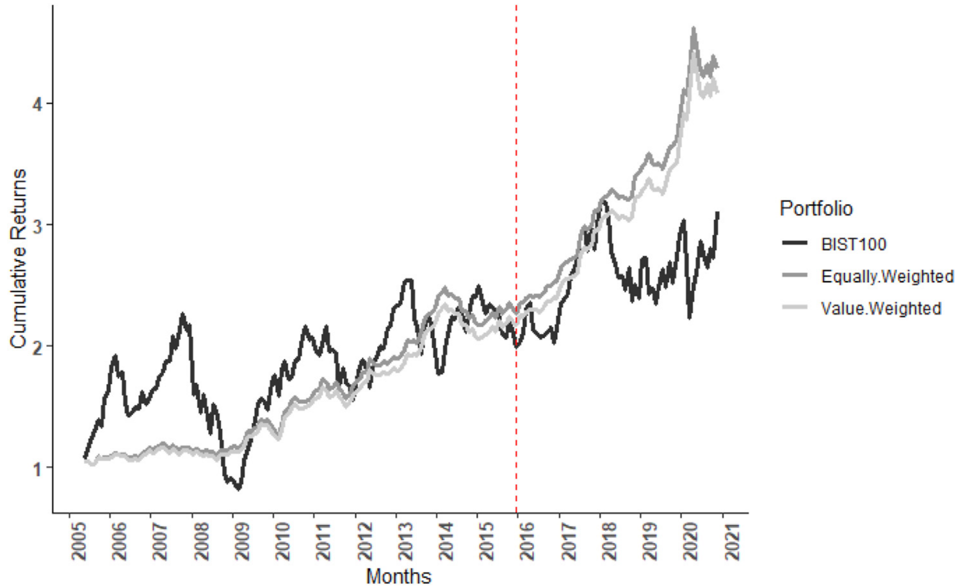

Fig. 1. Cumulative monthly returns for zero-cost information shock portfolio
Notes: This figure presents the cumulative monthly returns for equally and value-weighted zero-cost portfolios based on the information shock strategy. The information shock strategy mimics the portfolio of an investor with a long position in stocks that face sudden increases in the proportion of spread attributable to adverse selection risks and a short position of equal size in stocks that face sudden decreases in the proportion of spread attributable to adverse selection risks. For all stocks traded on the Borsa Istanbul between March 2005 and December 2020, we estimate the adverse selection component of the spread using the Glosten and Harris (1988) framework. We employ changes in the adverse selection component of the spread to capture the impact of information asymmetry that is unanticipated by investors (information shocks) on equity returns. The dashed vertical line represents the introduction of the BISTECH trading system (NASDAQ's Genium INET trading engine) in November 2015. High-frequency traders were introduced to BIST after November 2015 through the BISTECH system, which enabled collocation services.

which coincides with the introduction of NASDAQ's Genium trading engine (also known as the BISTECH trading system), which enables a difference in order submission/trade execution latency between traders. More specifically, the BISTECH system introduced significant speed advantages in BIST for HFTs.

The average portfolio characteristics for quintile portfolios are presented in Table 4. In particular, we present the results for our analyses of the full sample, the pre-BISTECH period (March 2005–November 2015), and the post-BISTECH period (December 2015–December 2020) in Panels A, B, and C of Table 4, respectively. In Panel A, we observe a monotonic increase in the information shock measure, $\Delta\lambda$, as we move from the Low to High quintile, in line with the portfolio construction methodology. Next, we observe in our full sample that the mean returns are higher for stocks that face sudden increases in transaction costs attributable to adverse selection risk, on average, than for stocks that face sudden decreases in the transaction costs related to adverse selection risk. The average equally and value-weighted monthly return differential between High and Low portfolios based on information shock strategy is, respectively, 80 and 77 bps, indicating that the difference is significant not only statistically but also economically. We further examine whether the variations in the standard asset-pricing factors account for the average return differential between High and Low portfolios. Specifically, we employ the standard four-factor setting presented in Equation (11), which incorporates the market return (R^{mkt}) along with size (SMB), value (HML) (Fama & French, 1993), and momentum (UMD) factors (Carhart, 1997). In Panel A, we also present the estimates of the constants for equally ($\alpha - EW$) and value-weighted ($\alpha -$VW) average return premiums obtained from the four-factor model for each quintile. The estimates provide us with the abnormal returns for each quintile. $\alpha - EW$ increases as we move from the lowest to highest information shock quintile, as expected. The average equally weighted return premium for the lowest information shock quintile is around 6 bps, whereas the highest information shock quintile has an $\alpha - EW$ of about 80 bps. Therefore, the average equally weighted return premium for the zero-investment portfolio constructed from the information shock strategy is around 74 bps after controlling for other systemic risk factors. We observe similar results for the value-weighted return premiums ($\alpha -$VW) for which the difference in return premium for the highest and the lowest quintile is around 72 bps.

In Panel A, we further document that the high $\Delta\lambda$ quintile, on average, contains stocks with higher market capitalization, compared to the low $\Delta\lambda$ group, even though the increase in market capitalization is not monotonic. We also observe a nonmonotonic relationship across information shock quintiles in examining the return reversal (REV), idiosyncratic volatility (IVOL), lottery stock characteristics (MAX), and trading volume (VOL). On average, the difference in REV between the High and Low quintiles is around 3 percent, with a statistically significant difference at the 1 percent level. Average IVOL levels are mostly flat across quintiles, but the difference between the High and Low quintiles is -30 bps, statistically significant at the 1 percent level. We observe a similar

Table 4
Results of the univariate portfolio analysis.

Panel A: Full Sample

	Low	2	3	4	High	High-Low	t(HML)
Δλ	−0.080	−0.019	0.001	0.020	0.078	0.1573***	54.02
RETURN-EW	0.007	0.011	0.012	0.012	0.015	0.0080***	4.38
RETURN-VW	0.007	0.011	0.012	0.012	0.015	0.0077***	4.19
α -EW	0.001	0.003	0.005	0.005	0.008	0.0074***	3.62
α -VW	0.000	0.003	0.004	0.004	0.008	0.0072***	3.53
BETA	0.570	0.701	0.739	0.712	0.598	0.0282	0.45
SIZE	19.09	19.32	19.45	19.39	19.10	0.0144***	3.55
BTM	0.970	1.146	1.224	1.141	0.966	−0.0044	−0.34
MOM	0.183	0.119	0.100	0.131	0.184	0.0017	0.15
REV	0.003	0.001	0.005	0.013	0.031	0.0283***	11.07
ILLIQ	0.029	0.004	0.000	0.001	0.013	−0.0156	−0.84
IVOL	0.024	0.022	0.021	0.021	0.022	−0.0025***	−8.19
MAX	0.061	0.057	0.056	0.057	0.056	−0.0054***	−6.44
VOL	16.95	17.67	17.92	17.63	16.62	−0.3272***	−7.19

Panel B: pre-BISTECH (March 2005–November 2015)

	Low	2	3	4	High	High-Low	t(HML)
Δλ	−0.083	−0.020	0.001	0.022	0.080	0.1623***	43.67
RETURN-EW	0.002	0.006	0.006	0.005	0.009	0.0071***	3.2
RETURN-VW	0.002	0.006	0.006	0.005	0.009	0.0067***	3.03
α -EW	−0.004	−0.001	−0.001	−0.002	0.003	0.0072***	2.76
α -VW	−0.004	−0.001	−0.002	−0.002	0.003	0.0070***	2.68
BETA	0.551	0.665	0.700	0.689	0.580	0.0293	−0.09
SIZE	18.75	19.00	19.18	19.13	18.74	−0.0039***	3.16
BTM	1.004	1.127	1.180	1.122	1.000	−0.0039	−0.26
MOM	0.141	0.082	0.076	0.087	0.127	−0.014	−1.46
REV	0.000	−0.006	−0.001	0.006	0.022	0.0218***	8.01
ILLIQ	0.002	0.001	0.000	0.000	0.001	−0.0001	−0.29
IVOL	0.024	0.021	0.021	0.021	0.021	−0.0032***	−10.43
MAX	0.062	0.057	0.055	0.056	0.055	−0.0071***	−7.73
VOL	16.61	17.22	17.50	17.26	16.22	−0.3906***	−6.33

Panel C: post-BISTECH (Dec. 2015–Dec. 2020)

	Low	2	3	4	High	High-Low	t(HML)
Δλ	−0.074	−0.017	0.000	0.017	0.072	0.1460***	37.13
RETURN-EW	0.018	0.021	0.026	0.026	0.028	0.0104***	3.38
RETURN-VW	0.017	0.021	0.025	0.026	0.027	0.0104***	3.26
α -EW	0.006	0.010	0.015	0.014	0.014	0.0080**	2.11
α -VW	0.006	0.010	0.014	0.013	0.014	0.0078**	2.04
BETA	0.612	0.777	0.821	0.763	0.637	0.0244	1.2
SIZE	19.79	19.97	20.01	19.94	19.84	0.0534	1.64
BTM	0.902	1.192	1.320	1.184	0.894	−0.0079	−0.31
MOM	0.262	0.187	0.144	0.214	0.291	0.0289	1.05
REV	0.008	0.013	0.015	0.028	0.050	0.0412***	8.62
ILLIQ	0.083	0.009	0.001	0.001	0.026	−0.0568	−1.03
IVOL	0.024	0.022	0.022	0.023	0.023	−0.0012*	−1.86
MAX	0.061	0.058	0.058	0.059	0.059	−0.002	−1.33
VOL	17.66	18.49	18.79	18.39	17.47	−0.1893***	−4.02

Notes: This table presents average portfolio characteristics for quintile portfolios based on the information shock strategy on the Borsa Istanbul between March 2005 and December 2020. At the end of each month, we sort our stocks into quintile portfolios based on information shock measures and follow the returns for the subsequent month. Low represents the portfolio consisting of stocks with the lowest information shock measures. High represents the portfolio consisting of stocks with the highest information shock measures. HML is the zero-investment information shock portfolio that mimics an investor's portfolio with a long position in High and a short position of equal size in Low. The last column denotes the *t*-statistics for the zero-investment portfolio. Test statistics are obtained from the heteroskedasticity- and autocorrelation-corrected standard errors (Newey-West, 1987). Δλ is the information shock measure. $RETURN–EW(RETURN–VW)$ is the equally (value-) weighted returns of a corresponding quintile portfolio. $\alpha –EW(\alpha –V\ W)$ is the Fama-French four-factor return premium associated with the equally (value-) weighted returns of a corresponding quintile portfolio. SIZE is the logarithm of end-of-the-month market capitalization. BTM is the book-to-market ratio. BETA is the systemic risk factor. REV is the return reversal. MOM is the momentum variable. ILLIQ is the Amihud (2002) illiquidity measure. VOL is the natural logarithm of the total trading volume. IVOL presents idiosyncratic volatility. MAX is the maximum daily return within a month. ***, **, and * indicate statistical significance at 1%, 5% and 10%, respectively.

relationship for lottery stock characteristics in which the average difference in MAX is around −50 bps and statistically significant at the 1% level. Finally, we document that stocks in the fifth information shock quintile, on average, have lower trading volumes than stocks in the first information shock quintile. The differential in market risk (BETA), book-to-market (BTM) ratio, return momentum (MOM), and Amihud illiquidity measures (ILLIQ) between high and low information shock quintiles are not statistically significant.

Table 4, Panel B, documents the results for the pre-BISTECH period, in which no heterogeneity is found among investors in terms of order submission/trade execution latency. In particular, information shock measures monotonically increase from the first to the fifth quintile. As with the findings for the full sample, we observe that average equally and value-weighted return differentials are positive and statistically significant at the 1 percent level. More specifically, the average equally (value-) weighted return of the zero-investment portfolio based on the information shock strategy is 71 bps (67 bps), indicating that the monthly excess return attributed to information shocks is statistically and economically significant. Likewise, the monthly return premium associated with an equally (value-) weighted zero-investment portfolio is 72 bps (70 bps), emphasizing that the information shock strategy in BIST provides significant return premiums even after controlling for market risk along with size, value, and momentum factors. In Panel B, we also observe that, on average, the highest information shock quintile contains companies with less market capitalization than the first quintile. The difference in average market capitalization is significant at the 1 percent level. In line with the results for the full sample, the stocks in the fifth information shock quintile have, on average, lower levels of IVOL, MAX, and VOL and higher average values for BETA and REV than stocks in the first quintile. The differences are statistically significant at the 1 percent level.

Finally, in Panel C, we present the results for the post-BISTECH period, where collocation opportunities created differences in latency for order submission and trade execution across investors. In this subsample, we again observe that information shock measures monotonically increase from the first quintile to the fifth quintile. Furthermore, we observe that the average return differentials are more evident in this subsample. In particular, the economic significance is more dominant, as the differentials for equally weighted and the value-weighted returns in the post-BISTECH subsample are both around 100 bps. The increased economic significance of average return differentials is also reflected in the return premiums. More specifically, we observe that the average return premium associated with an equally (value-) weighted zero-cost information shock portfolio is 80 bps (78 bps). We also observe that the average difference between the fifth and the first $\Delta\lambda$ quintiles is not statistically significant for some firm-specific variables, such as SIZE, BETA, and MAX, which were significantly different across quintiles in the pre-BISTECH period. In the post-BISTECH sample, we observe significant differences only for REV, IVOL, and VOL across the $\Delta\lambda$ quintiles. In particular, we show that REV levels monotonically increase from the first quintile to the fifth quintile. The average difference is around 410 and is significant at the 1 percent level. Similarly, we observe that the average IVOL is lower for stocks in the fifth quintile than for those in the first quintile, even though the IVOL levels are mostly flat across different quintiles. The difference in IVOL between the highest and the lowest $\Delta\lambda$ quintiles is around 12 bps and is statistically significant at the 10 percent level. As with our findings in Panels A and B of Table 4, we show that the average trading volume is lower for stocks in the fifth information shock quintile than in the first quintile.

Overall, these results support the theoretical expectations of Easley and O'Hara (2004), which suggest that uninformed investors demand a premium for holding stocks with higher information asymmetry because they cannot react promptly to news arriving in the market and update their portfolios. We show that investors in BIST demand a premium for holding stocks that face sudden increases in the proportion of the effective spread attributable to adverse selection. We further document that the return premium due to information shocks cannot be explained away by common risk factors, such as the market risk, size, value, and momentum. Finally, the information shock premium seems to be more evident after November 2015, when BIST introduced the BISTECH trading system, which generated heterogeneity among investors regarding order submission/trade execution latency. We observe significant variation across information shock quintiles with respect to other firm-specific variables, such as SIZE, REV, IVOL, MAX, and VOL. Using multivariate portfolio analyses, we test whether variations in these variables have a significant effect in explaining away the information shock premium.

4.3. Multivariate portfolio analysis

This section investigates whether different firm-specific factors—such as firm size (SIZE), return reversal (REV), idiosyncratic volatility (IVOL), lottery stock characteristics (MAX), and trading volume (VOL)—diminish the economic or statistical significance of the return premium attributable to information shock strategy. Specifically, we aim to isolate the impact of sudden increases in the proportion of the spread due to adverse selection on the cross section of expected returns via multivariate portfolio analyses. For example, to examine whether the variations in firm size have significant power in explaining excess returns attributable to information shock strategy, we sort stocks into quintiles based on end-of-the-month market capitalization (SIZE). Then, we further sort stocks in each SIZE quintile into five groups based on changes in the proportion of the adverse selection component of the spread ($\Delta\lambda$). Therefore, this procedure yields 25 different portfolios. Finally, within each SIZE quantile, we form zero-investment information shock portfolios by subtracting the average returns of the stocks in the low information shock quintile from the average returns of the stocks in the high

Table 5
Results of the multivariate portfolio analysis: 5 × 5 portfolios on SIZE and Δλ

Panel A: Full Sample

	Low SIZE	2	3	4	High SIZE
Low Δλ	0.012	0.004	0.006	0.005	0.002
2	0.015	0.009	0.009	0.012	0.008
3	0.014	0.011	0.011	0.006	0.010
4	0.019	0.007	0.012	0.011	0.007
High Δλ	0.018	0.019	0.013	0.010	0.006
High-Low	0.006*	0.015***	0.007	0.005*	0.004
t(HML)	(1.780)	(4.030)	(1.610)	(1.810)	(1.180)

Panel B: pre-BISTECH (March–Nov. 2005)

	Low SIZE	2	3	4	High SIZE
LowΔλ	0.003	−0.001	0.001	0.002	0.005
2	0.007	0.001	0.001	0.008	0.007
3	0.006	0.000	0.007	0.003	0.006
4	0.01	0.000	0.004	0.005	0.006
High Δλ	0.009	0.012	0.008	0.006	0.006
High-Low	0.006	0.013**	0.007	0.004	0.001
t(HML)	(1.510)	(2.550)	(1.600)	(0.990)	(0.430)

Panel C: post-BISTECH (Dec. 2015-Dec. 2020)

	Low SIZE	2	3	4	High SIZE
Low Δλ	0.029	0.012	0.018	0.009	−0.002
2	0.028	0.023	0.025	0.022	0.010
3	0.030	0.034	0.020	0.013	0.018
4	0.039	0.023	0.027	0.022	0.007
High Δλ	0.036	0.035	0.022	0.020	0.006
High-Low	0.007	0.023***	0.004	0.011*	0.008
t(HML)	(1.220)	(3.750)	(0.490)	(1.820)	(1.370)

Notes: This table presents the equally weighted return characteristics of multivariate portfolios based on information shock proxies and firm size. At the beginning of each month, we divide our sample into SIZE quintiles based on the log market capitalization of the previous month. We further divide each SIZE quintile into five groups based on the previous month's information shock measures. Panel A presents the equally weighted average return characteristics for each portfolio for the full sample. Panels B and C respectively present the equally weighted average returns for each portfolio for the pre-BISTECH and post-BISTECH periods. High − Low is the difference between High and Low Δλ portfolios for each SIZE quintile. For each zero-investment portfolio, the corresponding *t*-statistics are obtained from Newey-West standard errors, presented in parentheses. ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% confidence levels.

information shock quintile. Overall, by following this procedure, we can account for the role of any firm-specific measure on the relationship between information shocks and future returns.

Table 5 lists the equally weighted returns of 5 × 5 multivariate portfolios constructed using SIZE and $\Delta\lambda$, along with the equally weighted returns of the zero-investment portfolio for each size quintile. Panels A, B, and C, respectively, document the results for the full sample (March 2005–December 2020), pre-BISTECH period (March 2005–November 2015), and post-BISTECH period (December 2015–December 2020). In Table 5, Panel A, we observe that the zero-investment portfolios constructed for the first, second, and fourth SIZE quintiles have positive and significant returns in the full sample. Specifically, the average equally weighted return of zero-cost information shock portfolios constructed in the first, second, and fourth SIZE quintiles are 60 bps, 150 bps, and 50 bps, respectively. The statistical significance of the zero-investment information shock portfolio constructed in the first SIZE quintile disappears in both subsamples. Moreover, in Table 5, Panel B, we document that the average equally weighted returns of zero-investment information shock portfolios are statistically significant only for the second SIZE quintile for the pre-BISTECH period, in which the coefficient is 130 bps. The statistical and economic significance are larger for the zero-investment information shock portfolios constructed in the post-BISTECH period. Specifically, in the post-BISTECH period, the average return differential between the high and low information shock portfolios for the second SIZE quintile rises to 230 bps. In addition, the average return of the zero-investment information shock portfolio for the fourth SIZE quintile is 110 bps and statistically significant at the 5 percent level.

Table 6 presents the results of the factor analysis for the full, pre-BISTECH, and the post-BISTECH samples separately. In Panel A, we observe that the return premium associated with the zero-investment portfolios varies between 36 bps and 142 bps for the full sample. The return premiums are statistically significant for the second, fourth, and fifth SIZE quintiles. In turn, we reject the null hypothesis that the estimates for the intercept terms from the four-factor model presented in Equation (12) are both zero. To that end, for the full sample, we observe that the return premium due to the information shock strategy is robust even after controlling for the variation in firm size. In Panel B of Table 6, we again reject the null hypothesis that the intercept terms of the four-factor model are zero, indicating a significant return premium due to the information shock strategy in the pre-BISTECH period. Unlike the results presented for the average returns, in Panel C, the statistical significance of the return premiums associated with the information shock strategy largely disappears after controlling for the variation in firm size. Specifically, for the post-BISTECH period, we fail to reject the null hypothesis that the return premium associated with zero-investment SIZE – $\Delta\lambda$ portfolios are zero, even though the return premium associated with the second SIZE quintile is around 190 bps and is statistically significant at the 1 percent level.

In Table 7, we present equally weighted returns of 5 × 5 multivariate portfolios constructed using REV and $\Delta\lambda$, along with the return characteristics of the zero-investment portfolios for each REV quintile. Panels A, B, and C provide the full, pre-BISTECH, and post-BISTECH sample results, respectively. In Panel A, we document that the zero-investment portfolios constructed in all REV quintiles except the third quintile have positive average returns in the full sample. The information shock strategy provides statistically significant returns in the first, fourth, and fifth REV quintiles. The coefficients vary between 60 bps and 120 bps, indicating that the average return difference due to the information shock strategy is also economically significant. In Panels B and C of Table 7, we compare the average return differential due to the information shock strategy for pre- and post-BISTECH samples, respectively. Similar to our previous findings, our results indicate that the average returns associated with the information shock strategy are higher in the post-BISTECH sample. Specifically,

Table 6
Results of the factor analysis: 5 × 5 portfolios on SIZE and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	−0.0212 -(0.0478)	0.0150 (0.0726)	0.0138 (0.0543)	0.0919* (0.0510)	−0.0460 (0.0424)
$\widehat{\beta_p^s}$	−0.0306 (0.1267)	−0.0510 (0.1281)	0.0579 (0.1282)	0.1796 (0.1384)	0.2286** (0.1066)
$\widehat{\beta_p^h}$	0.2080 (0.1481)	0.1350 (0.1875)	−0.0186 (0.1737)	−0.1870* (0.1130)	−0.2004* (0.1208)
$\widehat{\beta_p^u}$	0.3278** (0.1411)	−0.0224 (0.1508)	−0.1168 (0.1591)	−0.1068 (0.1362)	−0.3122** (0.1376)
$\widehat{\alpha_p}$	0.0036 (0.0046)	0.0142*** (0.0042)	0.0064 (0.0042)	0.0081** (0.0039)	0.0072* (0.0041)
Observations	187	187	187	187	187
R^2	0.0366	0.0066	0.0057	0.0389	0.0826
GRS ($\widehat{\alpha}$)	3.759				
p(GRS)	0.003				

Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	−0.0020 (0.0512)	−0.0150 (0.0902)	0.0876* (0.0491)	0.0904* (0.0546)	−0.0568 (0.0454)
$\widehat{\beta_p^s}$	0.1260 (0.1790)	−0.1968 (0.1662)	0.1866 (0.1541)	−0.1201 (0.1275)	0.2034 (0.1336)
$\widehat{\beta_p^h}$	−0.0267 (0.1553)	0.2677 (0.2649)	−0.1931 (0.2183)	−0.1623 (0.1207)	−0.1703 (0.1407)
$\widehat{\beta_p^u}$	0.2338 (0.1824)	0.2593 (0.1716)	−0.2297 (0.1796)	−0.2387* (0.1278)	−0.2078 (0.1469)
$\widehat{\alpha_p}$	0.0072 (0.0051)	0.0082 (0.0054)	0.0104** (0.0046)	0.0059 (0.0045)	0.0054 (0.0052)
Observations	127	127	127	127	127
R^2	0.0212	0.0332	0.0430	0.0432	0.0547
GRS ($\widehat{\alpha}$)	2.063				
p(GRS)	0.075				

Panel C: post-BISTECH (Dec. 2015-Dec. 2020)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	−0.0769 (0.1122)	0.1775** (0.0745)	−0.2546* (0.1546)	0.1057 (0.1382)	0.0032 (0.1122)
$\widehat{\beta_p^s}$	−0.2141 (0.2104)	0.0736 (0.2341)	−0.0932 (0.2035)	0.6559*** (0.2001)	0.2149 (0.1793)
$\widehat{\beta_p^h}$	0.4824* (0.2551)	0.1243 (0.1812)	0.2598 (0.2658)	−0.1592 (0.2388)	−0.2222 (0.2451)
$\widehat{\beta_p^u}$	0.4412* (0.2330)	−0.5414** (0.2375)	0.1572 (0.2757)	0.1354 (0.2387)	−0.4984* (0.2759)
$\widehat{\alpha_p}$	0.0028 (0.0080)	0.0190*** (0.0064)	0.0026 (0.0087)	0.0049 (0.0082)	0.0101 (0.0080)
Observations	60	60	60	60	60
R^2	0.1490	0.1613	0.0866	0.2028	0.1315
GRS ($\widehat{\alpha}$)	1.398				
p(GRS)	0.241				

Notes: We run the following regression on the time series of monthly returns of five zero-cost SIZE-Δλ portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$. The sample period is March 2005–December 2020. Panel A provides the results for the full sample. Panel B provides the results for the pre-BISTECH period. Panel C provides the results for the post-BISTECH period. We provide the estimate for the coefficients and the respective Newey and West (1987) adjusted standard errors in parentheses. For goodness of fit, we provide R^2 measures. The last two rows in each panel respectively provide the Gibbons et al. (1989) test statistics for the null hypothesis that $\widehat{\alpha} = 0$. ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively.

in Panel C, the average returns on the zero-investment portfolios are positive and statistically significant for the lowest and highest (the first and the fifth) REV quintiles, with corresponding coefficients of 130 bps and 210 bps.

The return premiums associated with zero-investment REV – $\Delta\lambda$ portfolios are presented in Table 8. Panels A, B, and C, respectively, again document the return premiums for the corresponding portfolios for the full sample, pre-BISTECH, and post-BISTECH periods. As with the average returns, the return premiums associated with the first, fourth, and fifth REV quintiles are statistically significant. We reject the null hypothesis that the intercept terms of the four-factor model are all zero. The corresponding coefficients for the return premiums associated with the first, fourth, and fifth REV quintiles are 80 bps, 103 bps, and 145 bps, respectively. This indicates that the return premium associated with the information shock strategy is both statistically and economically significant even after controlling for the variation in return reversal during portfolio formation. The statistical significance of the return premiums associated with the information shock strategy is evident only in the post-BISTECH period. Specifically, in Panel B of Table 8, we fail to reject the null hypothesis that the return premiums are all zero, as the corresponding GRS test statistic is 1.28. By contrast, we observe a statistically significant return premium associated with the information shock strategy in the post-BISTECH period, especially for stocks in the highest REV quintile. Overall, the results presented in Tables 7 and 8 align with the information hypothesis. To the extent that extreme

Table 7
Results of the multivariate portfolio analysis: 5 × 5 portfolios on REV and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)

	Low REV	2	3	4	High REV
Low Δλ	0.005	0.009	0.012	0.006	0.000
2	0.007	0.013	0.015	0.010	0.004
3	0.004	0.014	0.016	0.008	0.012
4	0.006	0.009	0.011	0.016	0.008
High Δλ	0.013	0.015	0.011	0.014	0.012
High-Low	0.008**	0.006	−0.001	0.008***	0.012***
t(HML)	(2.008)	(1.392)	(-0.060)	(2.621)	(2.928)

Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)

	Low REV	2	3	4	High REV
Low Δλ	0.002	0.004	0.009	0.001	−0.003
2	0.002	0.007	0.007	0.006	−0.001
3	−0.004	0.007	0.010	0.004	0.006
4	0.003	0.005	0.002	0.009	0.004
High Δλ	0.007	0.008	0.007	0.011	0.006
High-Low	0.005	0.004	−0.002	0.010**	0.009
t(HML)	(1.126)	(1.155)	(-0.366)	(2.009)	(1.565)

Panel C: post-BISTECH (Dec. 2015-Dec. 2020)

	Low REV	2	3	4	High REV
Low Δλ	0.011	0.021	0.019	0.016	0.006
2	0.017	0.026	0.030	0.018	0.012
3	0.021	0.028	0.027	0.016	0.027
4	0.013	0.017	0.030	0.031	0.016
High Δλ	0.024	0.029	0.021	0.021	0.027
High-Low	0.013**	0.008	0.002	0.005	0.021***
t(HML)	(2.181)	(0.813)	(0.368)	(1.425)	(3.340)

Notes: This table presents the equally weighted return characteristics of multivariate portfolios based on information shock proxies and return reversal. At the beginning of each month, we divide our sample into quintiles based on return reversal measures (REV). We further divide each REV quintile into five groups based on the previous month's information shock measures. Panel A presents the equally weighted average return characteristics for each portfolio for the full sample. Panels B and C respectively present the equally weighted average returns for each portfolio for the pre-BISTECH and post-BISTECH periods. High - Low is the difference between High and Low Δλ portfolios for each REV quintile. For each zero-investment portfolio, the corresponding *t*-statistics are obtained from Newey-West standard errors, presented in parentheses. ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% confidence levels.

return reversals are associated with low latency trading activity, these results might also suggest that the return premium due to the information shock strategy could result from the tendency by investors to demand compensation for holding stocks for which they are at a disadvantage against HFTs.

Next, we provide the average returns of the multivariate portfolios constructed using IVOL and $\Delta\lambda$ in Table 9. We observe that the average returns associated with the zero-investment portfolios are statistically significant only for the highest IVOL quintile. Therefore, in terms of statistical significance, the information shock strategy is more dominant, with stocks that have high idiosyncratic volatility captured by the standard deviation of the error terms obtained from the market model. In Panels B and C of Table 9, the zero-investment portfolio for the highest IVOL quintile provides an average return of around 200 bps, irrespective of the subsample.

We obtain similar results for the return premiums associated with the information shock strategy with multivariate IVOL – $\Delta\lambda$ portfolios. In particular, in Table 10, Panel A, the return premiums related to the zero-investment portfolios are positive for all IVOL quintiles; however, only the premiums associated with the fourth and fifth IVOL quintiles are statistically significant. Specifically, the estimates for intercept coefficients from the four-factor model are around 63 bps and 183 bps, respectively, for the fourth and the fifth IVOL quintiles. Nonetheless, we reject the null hypothesis that the intercept terms for all quintile portfolios are all zero, with a GRS test statistic of 2.183. Hence, the information shock strategy yields significant return premiums for our full sample, even after controlling for the variation in idiosyncratic volatility. For both the pre- and post-BISTECH period, we fail to reject the null hypothesis that the return premiums associated with the information shock strategy are statistically significant after controlling for the variation in idiosyncratic volatility. More specifically, in Panel B (C), the GRS test statistic is 1.390 (0.937), indicating that the return premiums of the multivariate IVOL – $\Delta\lambda$ portfolios are statistically indistinguishable from zero in both subsamples.

Another firm-specific measure that is highly correlated with $\Delta\lambda$ is the MAX factor, which proxies the lottery stock characteristics (Bali et al., 2011). Alkan and Guner (2018) present evidence of the MAX anomaly in BIST, highlighting the negative relationship between MAX and future returns. The results of our univariate portfolio analysis show that return premiums due to the information shock strategy may arise from the variation in the MAX factor as the average difference in MAX levels between high and low $\Delta\lambda$ portfolios is statistically significant. To isolate the impact of the information shock strategy on the cross section of expected returns, we control for the variation in MAX levels by forming multivariate MAX – $\Delta\lambda$ portfolios.

Table 11 presents the average return characteristics of the MAX – $\Delta\lambda$ portfolios. As in the previous tables, Panels A, B, and C of Table 11, respectively, show the results for the full, pre-BISTECH, and post-BISTECH subsamples. In Panel A, the average returns for the zero-investment MAX – $\Delta\lambda$ portfolios are positive for all MAX quintiles. The average returns vary between 0 bps and 120 bps, and all quintiles except the third MAX quintile are statistically significant. The average returns for the zero-investment portfolios are larger in magnitude for all MAX quintiles in the post-BISTECH sample. On the one hand, the average returns of the zero-investment portfolios in the pre-BISTECH period vary between 0 bps and 120 bps. On the other hand, the average returns are between 0 bps and 160 bps in the post-BISTECH period, indicating the more dominant impact of the information shock strategy. The average returns for the fourth and fifth MAX quintiles are statistically significant in the pre-BISTECH period, whereas, in the post-BISTECH period, the average returns associated with the second, fourth, and fifth quintiles are statistically significant.

Table 8
Results of the factor analysis: 5 × 5 portfolios on REV and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)

	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0663 (0.0499)	−0.0061 (0.0659)	0.1115** (0.0499)	0.0364 (0.0513)	−0.0009 (0.0585)
$\widehat{\beta_p^s}$	0.1809 (0.1236)	−0.0116 (0.1301)	−0.0483 (0.1221)	0.0953 (0.1001)	0.0255 (0.1577)
$\widehat{\beta_p^h}$	−0.0984 (0.1475)	0.3061* (0.1650)	0.0215 (0.1195)	−0.1018 (0.1282)	−0.0967 (0.1764)
$\widehat{\beta_p^u}$	−0.1462 (0.1329)	−0.1439 (0.1457)	−0.1086 (0.1313)	0.0750 (0.1211)	0.1126 (0.1648)
$\widehat{\alpha_p}$	0.0079* (0.0042)	0.0007 (0.0047)	−0.0012 (0.0042)	0.0103** (0.0043)	0.0145*** (0.0052)
Observations	186	186	186	186	186
R^2	0.0285	0.0400	0.0349	0.0127	0.0057
GRS ($\widehat{\alpha}$)	3.013				
p(GRS)	0.012				

Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)

	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0662 (0.0607)	0.0275 (0.0759)	0.1132* (0.0591)	0.0933 (0.0568)	0.0109 (0.0731)
$\widehat{\beta_p^s}$	0.1534 (0.1837)	0.2782** (0.1290)	−0.0765 (0.1326)	0.0746 (0.1402)	−0.2985* (0.1725)
$\widehat{\beta_p^h}$	−0.3060 (0.1926)	0.1536 (0.1380)	−0.0138 (0.1422)	−0.0466 (0.1565)	0.0774 (0.2089)
$\widehat{\beta_p^u}$	−0.0407 (0.1697)	−0.1618 (0.1467)	−0.0226 (0.1462)	0.0205 (0.1388)	0.0141 (0.1784)
$\widehat{\alpha_p}$	0.0096* (0.0050)	0.0027 (0.0046)	−0.0023 (0.0052)	0.0092 (0.0056)	0.0072 (0.0066)
Observations	126	126	126	126	126
R^2	0.0342	0.0669	0.0379	0.0245	0.0218
GRS ($\widehat{\alpha}$)	1.288				
p(GRS)	0.274				

Panel C: post-BISTECH (Dec. 2015-Dec. 2020)

	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.1016 (0.0799)	−0.0998 (0.1484)	0.1312 (0.0885)	−0.1625* (0.0868)	−0.0491 (0.1233)
$\widehat{\beta_p^s}$	0.2146 (0.1557)	−0.4652** (0.2081)	−0.0287 (0.2454)	0.1461 (0.1389)	0.4185** (0.1961)
$\widehat{\beta_p^h}$	0.3890* (0.2292)	0.4557 (0.3301)	0.1526 (0.2317)	−0.1749 (0.2248)	−0.4442* (0.2619)
$\widehat{\beta_p^u}$	−0.3665** (0.1646)	−0.1655 (0.3228)	−0.2445 (0.2713)	0.2777 (0.2069)	0.4270 (0.3230)
$\widehat{\alpha_p}$	0.0021 (0.0080)	0.0064 (0.0109)	−0.0011 (0.0066)	0.0102 (0.0071)	0.0264*** (0.0077)
Observations	60	60	60	60	60
R^2	0.1653	0.1371	0.0592	0.1120	0.1428
GRS ($\widehat{\alpha}$)	2.080				
p(GRS)	0.083				

Notes: We run the following regression on the time series of monthly returns of five zero-investment REV- Δλ portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$. The sample period is March 2005–December 2020. Panel A provides the results for the full sample. Panel B provides the results for the pre-BISTECH period. Panel C provides the results for the post-BISTECH period. We provide the estimate for the coefficients and the respective Newey and West (1987) adjusted standard errors in parentheses. For goodness of fit, we provide R^2 measures. The last two rows in each panel respectively provide the Gibbons et al. (1989) test statistics for the null hypothesis that $\widehat{a} = 0$. ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively.

We then demonstrate the return premium associated with the equally weighted zero-investment MAX – $\Delta\lambda$ portfolios in Table 12. The estimates obtained from the four-factor model for the full, pre-BISTECH, and post-BISTECH samples, along with the GRS test statistics, are presented in Panels A, B, and C. In Panel A, the return premium associated with the information shock strategy varies between 6 bps and 146 bps. The return premium associated only with the fourth quintile is statistically significant at the 1 percent level. However, we reject the null hypothesis that the intercept terms for the four-factor models are equal for all MAX quintiles with a GRS statistic of 3.140. We see a statistically significant return premium for the information shock strategy during our sample period, even after controlling for the variation in lottery stock characteristics. The statistical significance of the return premiums associated with the MAX – $\Delta\lambda$ portfolios is again evident in the post-BISTECH period. Specifically, in Panel B, we fail to reject the null hypothesis that the intercept terms are zero for the zero-investment MAX – $\Delta\lambda$ portfolios. The corresponding GRS test statistic is 1.430, even though the return premiums for the fourth and fifth MAX quintiles are statistically significant. On the contrary, we reject the null hypothesis that the return premiums associated with the MAX – $\Delta\lambda$ portfolios are zero in the post-BISTECH period. The GRS

Table 9
Results of the multivariate portfolio analysis: 5 × 5 portfolios on IVOL and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)					
	Low IVOL	2	3	4	High IVOL
Low Δλ	0.013	0.012	0.013	0.013	−0.014
2	0.011	0.014	0.011	0.017	−0.005
3	0.01	0.013	0.015	0.012	0.001
4	0.012	0.016	0.011	0.015	0.000
High Δλ	0.016	0.014	0.013	0.017	0.006
High-Low	0.003	0.002	−0.000	0.004	0.020***
t(HML)	(1.074)	(0.398)	(-0.037)	(1.031)	(4.349)
Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)					
	Low IVOL	2	3	4	High IVOL
Low Δλ	0.011	0.010	0.011	0.009	−0.020
2	0.006	0.010	0.007	0.012	−0.012
3	0.007	0.006	0.008	0.003	−0.008
4	0.009	0.011	0.006	0.009	−0.008
High Δλ	0.012	0.008	0.008	0.010	0.000
High-Low	0.001	−0.002	−0.003	0.001	0.020***
t(HML)	(0.421)	(-0.737)	(-0.661)	(0.431)	(3.373)
Panel C: post-BISTECH (Dec. 2015-Dec. 2020)					
	Low IVOL	2	3	4	High IVOL
Low Δλ	0.016	0.017	0.019	0.023	0.000
2	0.021	0.022	0.019	0.027	0.007
3	0.016	0.029	0.031	0.030	0.019
4	0.018	0.026	0.023	0.025	0.017
High Δλ	0.022	0.028	0.023	0.030	0.016
High-Low	0.006	0.011	0.004	0.007	0.016***
t(HML)	(1.275)	(1.574)	(0.908)	(1.369)	(2.839)

Notes: This table presents the equally weighted return characteristics of multivariate portfolios based on information shock proxies and idiosyncratic volatility. At the beginning of each month, we divide our sample into IVOL quintiles based on the idiosyncratic volatility measures for the previous month. We further divide each IVOL quintile into five groups based on the previous month's information shock measures. Panel A presents the equally weighted average return characteristics for each portfolio for the full sample. Panels B and C respectively present the equally weighted average returns for each portfolio for the pre-BISTECH and post-BISTECH periods. High - Low is the difference between High and Low Δλ portfolios for each IVOL quintile. For each zero-investment portfolio, the corresponding *t*-statistics are obtained from Newey-West standard errors, presented in parentheses. ***, **, and * respectively indicate statistical significance at the 1%, 5% and 10% confidence levels.

statistic is 2.879, indicating that the return premium associated with the information shock strategy is statistically significant even after accounting for the MAX variation.

Finally, we construct 5 × 5 multivariate portfolios using VOL and $\Delta\lambda$ to assess whether variations in trading volume explain the excess return attributable to the information shock strategy. Table 13 presents the equally weighted returns of the zero-investment portfolios for each VOL quintile. Panels A, B, and C of Table 13, respectively, list the average returns obtained in the full, pre-BISTECH, and post-BISTECH subsamples. Table 13, Panel A, shows that the average returns for zero-investment portfolios constructed for the first, third, and fourth VOL quintiles have positive and significant returns in the full sample. In particular, the average equally weighted return of zero-investment information shock portfolios constructed in the first, third, and fourth VOL quintiles are 60 bps, 120 bps, and 160 bps, respectively. In Panel B of Table 13, the statistical significance of the average equally weighted returns of the zero-investment portfolio constructed in the first VOL quintile disappears in the pre-BISTECH sample. Moreover, the average equally weighted returns of the zero-investment information shock portfolios constructed for the third and fourth VOL quintiles are below the values observed for the full sample. Hence, the statistical and economic significance of the information shock strategy are both more prominent in the post-BISTECH period. Specifically, in Panel C of Table 13, the average equally weighted returns for the first, third, fourth, and fifth VOL quintiles are statistically significant. The corresponding coefficients vary between 140 bps and 230 bps, indicating that the economic impact of the information shock strategy is significantly more potent in the post-BISTECH period, even after accounting for the variation in trading volume.

We present the return premium associated with the zero-investment VOL – $\Delta\lambda$ portfolios in Table 14. Panels A, B, and C respectively, document the return premiums associated with each portfolio for the full, pre-BISTECH, and post-BISTECH samples. In Panel A, the return premium obtained from the four-factor model is positive for all zero-investment portfolios except the second VOL quintile. The return premiums associated with the first and fourth quintile are 91 bps and 240 bps, respectively, and are statistically significant. Thus, we reject the null hypothesis that the return premiums associated with zero-

Table 10
Results of the factor analysis: 5 × 5 portfolios on IVOL and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)

	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0417 (0.0398)	0.0689 (0.0505)	−0.0214 (0.0431)	0.0127 (0.0424)	0.0590 (0.0767)
$\widehat{\beta_p^s}$	0.1834** (0.0730)	0.2157** (0.1028)	−0.0822 (0.1040)	−0.0577 (0.1045)	0.1258 (0.1752)
$\widehat{\beta_p^h}$	0.0768 (0.1011)	−0.1451 (0.1330)	−0.0450 (0.1101)	−0.1537 (0.1167)	0.1005 (0.1878)
$\widehat{\beta_p^u}$	0.0485 (0.0913)	−0.0038 (0.1092)	−0.0551 (0.1398)	−0.2768** (0.1409)	0.1336 (0.1694)
$\widehat{\alpha_p}$	0.0003 (0.0032)	0.0021 (0.0037)	0.0012 (0.0037)	0.0063* (0.0037)	0.0183*** (0.0055)
Observations	187	187	187	187	187
R^2	0.0436	0.0465	0.0075	0.0338	0.0135
GRS ($\widehat{\alpha}$)	2.183				
p(GRS)	0.058				

Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)

	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0429 (0.0463)	0.0953* (0.0527)	−0.0047 (0.0520)	0.0178 (0.0431)	0.0470 (0.0910)
$\widehat{\beta_p^s}$	0.2456** (0.0955)	0.2038* (0.1083)	−0.2374** (0.1107)	0.1072 (0.1118)	−0.0483 (0.2128)
$\widehat{\beta_p^h}$	0.1234 (0.1066)	−0.3662*** (0.1371)	−0.0027 (0.1461)	−0.2487* (0.1424)	0.1009 (0.2490)
$\widehat{\beta_p^u}$	0.0096 (0.1360)	−0.0724 (0.1083)	0.0181 (0.1304)	−0.1728 (0.1376)	0.1120 (0.2470)
$\widehat{\alpha_p}$	−0.0007 (0.0037)	0.0024 (0.0038)	−0.0029 (0.0048)	0.0058 (0.0048)	0.0189** (0.0074)
Observations	127	127	127	127	127
R^2	0.0683	0.1043	0.0262	0.0305	0.0058
GRS ($\widehat{\alpha}$)	1.393				
p(GRS)	0.232				

Panel C: post-BISTECH (Dec. 2015-Dec. 2020)

	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0097 (0.0764)	0.0045 (0.1172)	−0.0656 (0.0873)	0.0478 (0.1196)	0.0969 (0.1444)
$\widehat{\beta_p^s}$	0.0817 (0.1221)	0.1977 (0.1775)	0.0641 (0.2186)	−0.3580* (0.1853)	0.4290* (0.2572)
$\widehat{\beta_p^h}$	−0.0176 (0.2082)	0.2913 (0.2329)	−0.0449 (0.1629)	0.0469 (0.2561)	0.1129 (0.2565)
$\widehat{\beta_p^u}$	0.1296 (0.1090)	0.0783 (0.2162)	−0.1025 (0.2795)	−0.5199* (0.2895)	0.0956 (0.2322)
$\widehat{\alpha_p}$	0.0044 (0.0067)	0.0023 (0.0088)	0.0052 (0.0061)	0.0123** (0.0062)	0.0106 (0.0079)
Observations	60	60	60	60	60
R^2	0.0235	0.0488	0.0275	0.1489	0.0895
GRS ($\widehat{\alpha}$)	0.937				
p(GRS)	0.465				

Notes: We run the following regression on the time series of monthly returns of five zero-investment IVOL-Δλ portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$. The sample period is March 2005–December 2020. Panel A provides the results for the full sample. Panel B provides the results for the pre-BISTECH period. Panel C provides the results for the post-BISTECH period. We provide the estimate for the coefficients and the respective Newey and West (1987) adjusted standard errors in parentheses. For goodness of fit, we provide R^2 measures. The last two rows in each panel respectively provide the Gibbons et al. (1989) test statistics for the null hypothesis that $\widehat{a} = 0$. ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively.

investment VOL – $\Delta\lambda$ portfolios are zero with a corresponding GRS test statistic of 4.189. This result indicates that the premium associated with the information shock strategy is robust to the variation in trading volume for the full sample. In Panel B, we fail to reject the null hypothesis that the return premiums associated with zero-investment VOL – $\Delta\lambda$ portfolios are zero for the pre-BISTECH period (GRS = 1.854), even though the premium associated with the fourth quintile is statistically significant. On the contrary, in Panel C, the return premium associated with the first and fourth VOL quintiles is positive (corresponding coefficients of 239 bps and 276 bps, respectively) and statistically significant. Contrary to our expectations, the return premium estimate of the zero-investment portfolio constructed for the second VOL quintile is negative (−150 bps) and statistically significant. Nonetheless, we reject the null hypothesis that the return premiums associated with the zero-investment VOL– $\Delta\lambda$ are zero for the post-BISTECH period. These results indicate that, as with the findings for other multivariate portfolios, the information shock strategy is more dominant in the post-BISTECH period, even after controlling for the variation in trading volume.

Overall, the results of the multivariate portfolio analyses show that investors demand a premium for holding stocks that face sudden increases in information shocks measured by the

Table 11
Results of the multivariate portfolio analysis: 5 × 5 portfolios on MAX and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)					
	Low MAX	2	3	4	High MAX
Low Δλ	0.011	0.012	0.012	0.006	−0.008
2	0.010	0.014	0.012	0.011	0.001
3	0.015	0.012	0.015	0.012	0.001
4	0.014	0.016	0.012	0.008	−0.001
High Δλ	0.016	0.018	0.012	0.016	0.004
High-Low	0.005*	0.006*	0.000	0.010**	0.012***
t(HML)	(1.659)	(1.892)	(0.19)	(2.491)	(2.63)
Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)					
	Low MAX	2	3	4	High MAX
Low Δλ	0.009	0.012	0.007	0.001	−0.013
2	0.006	0.011	0.008	0.005	−0.007
3	0.011	0.006	0.007	0.007	−0.005
4	0.009	0.010	0.005	0.004	−0.011
High Δλ	0.012	0.014	0.007	0.010	−0.001
High-Low	0.003	0.002	0.000	0.009*	0.012**
t(HML)	(1.03)	(0.388)	(0.124)	(1.963)	(2.167)
Panel C: post-BISTECH (Dec. 2015-Dec. 2020)					
	Low MAX	2	3	4	High MAX
Low Δλ	0.017	0.012	0.023	0.016	0.003
2	0.019	0.022	0.020	0.025	0.017
3	0.024	0.026	0.031	0.024	0.016
4	0.023	0.026	0.027	0.018	0.018
High Δλ	0.024	0.028	0.023	0.030	0.017
High-Low	0.007	0.016***	0.000	0.014*	0.014*
t(HML)	(1.369)	(2.923)	(0.207)	(1.848)	(1.779)

Notes: This table presents the equally weighted return characteristics of multivariate portfolios based on information shock proxies and lottery stock characteristics. At the beginning of each month, we divide our sample into MAX quintiles based on the maximum daily return for the previous month. We further divide each MAX quintile into five groups based on the previous month's information shock measures. Panel A presents the equally weighted average return characteristics for each portfolio for the full sample. Panels B and C respectively present the equally weighted average returns for each portfolio for the pre-BISTECH and post-BISTECH periods. High - Low is the difference between High and Low Δλ portfolios for each MAX quintile. For each zero-investment portfolio, the corresponding *t*-statistics are obtained from Newey-West standard errors, presented in parentheses. ***, **, and * respectively indicate statistical significance at the 1%, 5% and 10% confidence levels.

change in the proportion of the spread attributable to adverse selection risk, even after controlling for the variation in firm size, return reversal, idiosyncratic volatility, lottery stock characteristics, and trading volume. In line with the results presented in the previous section, we document that the statistical significance of the return premium associated with multivariate information shock portfolios is more substantial in the post-BISTECH period. Specifically, we show that the return premium associated with the information shock strategy loses its statistical significance in the pre-BISTECH period when we account for the variation in all five firm-specific measures except firm size. By contrast, the statistical significance of the return premiums under a multivariate setting is not evident in the post-BISTECH period, when we control for the variation in firm size and idiosyncratic volatility.

4.4. Firm-level cross-sectional regressions

This section examines the predictive relationship between information shocks and future returns with firm-level cross-sectional regressions. Unlike with multivariate portfolio analyses, cross-sectional regressions simultaneously account for the variation in multiple firm-specific factors, such as firm size (SIZE), market risk (BETA), book-to-market (BTM) ratio, (il)liquidity (ILLIQ), recent return performance (REV) and momentum (MOM), lottery stock characteristics (MAX), idiosyncratic volatility (IVOL), and trading volume (VOL).

Table 15 lists the time-series averages of the coefficients obtained from the cross-sectional regressions presented in Equation (13). Panels A, B, and C, respectively, show the results for the full sample (March 2005–December 2020), the pre-BISTECH sample (March 2005–November 2015), and the post-BISTECH sample (December 2015–December 2020). In Panel A, column 1 presents the univariate relationship between $\Delta\lambda$ and future returns. The average coefficient is around 0.045 and is significant at the 1 percent level. The interpretation of the economic significance of information shocks on future returns is in line with the findings documented earlier. Specifically, in Table 4, the average difference in $\Delta\lambda$ for the zero-investment information shock portfolio is around 0.1573. Multiplying this difference by the corresponding coefficient of $\Delta\lambda$ in the cross-sectional regression indicates that a 1 percent

Table 12
Results of the factor analysis: 5 × 5 portfolios on MAX and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0869** (0.0424)	−0.0312 (0.0436)	0.0816 (0.0538)	0.0887* (0.0517)	−0.0271 (0.0862)
$\widehat{\beta_p^s}$	0.0537 (0.0782)	0.0698 (0.0950)	−0.0027 (0.1261)	−0.1664 (0.1156)	0.2190 (0.1627)
$\widehat{\beta_p^h}$	−0.0542 (0.1056)	0.0271 (0.0979)	−0.0293 (0.1289)	−0.3008* (0.1575)	0.1845 (0.1960)
$\widehat{\beta_p^u}$	−0.0335 (0.1139)	−0.0367 (0.1095)	−0.2023 (0.1523)	−0.2743* (0.1568)	0.0830 (0.1618)
$\widehat{\alpha_p}$	0.0043 (0.0031)	0.0053 (0.0033)	0.0006 (0.0043)	0.0146*** (0.0043)	0.0095 (0.0062)
Observations	187	187	187	187	187
R^2	0.0332	0.0084	0.0257	0.0492	0.0168
GRS ($\widehat{\alpha}$)	3.140				
p(GRS)	0.010				
Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0995** (0.0490)	−0.0266 (0.0458)	0.1329** (0.0546)	0.0418 (0.0552)	−0.0249 (0.0964)
$\widehat{\beta_p^s}$	0.1154 (0.0886)	−0.0767 (0.1121)	−0.0131 (0.1162)	−0.1661 (0.1485)	0.1360 (0.1984)
$\widehat{\beta_p^h}$	0.0240 (0.1052)	−0.0069 (0.1195)	−0.1738 (0.1309)	−0.0114 (0.1631)	−0.2020 (0.2215)
$\widehat{\beta_p^u}$	−0.1578 (0.1423)	0.0463 (0.1307)	−0.3284** (0.1619)	−0.0505 (0.1727)	0.0886 (0.2237)
$\widehat{\alpha_p}$	0.0024 (0.0037)	0.0016 (0.0036)	0.0024 (0.0049)	0.0087* (0.0053)	0.0157** (0.0073)
Observations	127	127	127	127	127
R^2	0.0760	0.0085	0.0726	0.0137	0.0125
GRS ($\widehat{\alpha}$)	1.430				
p(GRS)	0.218				
Panel C: post-BISTECH (Dec. 2015-Dec. 2020)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0139 (0.0751)	−0.0228 (0.1094)	−0.0909 (0.1412)	0.2490** (0.1223)	0.0130 (0.1956)
$\widehat{\beta_p^s}$	−0.0727 (0.1343)	0.2016 (0.1436)	0.0407 (0.2276)	−0.2851 (0.2196)	0.4594 (0.2861)
$\widehat{\beta_p^h}$	−0.2684 (0.2362)	0.1732 (0.1761)	0.2427 (0.2641)	−0.7657*** (0.2591)	0.9824*** (0.2848)
$\widehat{\beta_p^u}$	0.2343 (0.1656)	−0.1668 (0.1824)	0.0569 (0.2882)	−0.6250** (0.2973)	−0.0564 (0.2864)
$\widehat{\alpha_p}$	0.0123** (0.0060)	0.0096 (0.0072)	−0.0026 (0.0076)	0.0280*** (0.0076)	−0.0071 (0.0118)
Observations	60	60	60	60	60
R^2	0.1022	0.0670	0.0271	0.2170	0.1848
GRS ($\widehat{\alpha}$)	2.879				
p(GRS)	0.023				

Notes: We run the following regression on the time series of monthly returns of five zero-investment MAX- Δλ portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$ The sample period is March 2005–December 2020. Panel A provides the results for the full sample. Panel B provides the results for the pre-BISTECH period. Panel C provides the results for the post-BISTECH period. We provide the estimate for the coefficients and the respective Newey and West (1987) adjusted standard errors in parentheses. For goodness of fit, we provide R^2 measures. The last two rows in each panel respectively provide the Gibbons et al. (1989) test statistics for the null hypothesis that $\widehat{\alpha} = 0$. ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively.

increase in information shocks increases future returns by approximately 70 bps. In Panel A, the impact of $\Delta\lambda$ on future returns is robust even after controlling for all other firm-specific factors. We document that a 1 percent increase in information shocks is associated with a 30 bps increase in future returns.

As in our previous findings, both the statistical significance and the economic significance of the predictive relationship between information shocks and future returns are more evident in the post-BISTECH period. In particular, in Panel B, column 1 shows that the univariate relationship between information shock measures and future returns is statistically significant in the pre-BISTECH period. More specifically, a 1 percent increase in $\Delta\lambda$ is associated with a 55 bps increase in one-month-ahead returns. However, the statistical significance of this relationship disappears after controlling for the variation in other firm-specific factors. In Panel C of Table 15, the univariate predictive relationship between $\Delta\lambda$ and future returns is also statistically significant in the post-BISTECH period. In particular, a 1 percent increase in $\Delta\lambda$ results in an average increase of about one percentage point in one-month-ahead returns, which suggests that the predictive power of information shocks is also economically significant. The predictive power of $\Delta\lambda$ remains statistically and economically significant, even after controlling for all other firm-specific measures in the post-BISTECH period. The results presented

Table 13
Results of the multivariate portfolio analysis: 5 × 5 portfolios on VOL and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)					
	Low VOL	2	3	4	High VOL
Low Δλ	0.017	0.013	−0.002	−0.004	−0.003
2	0.025	0.018	0.008	0.001	−0.001
3	0.022	0.020	0.013	0.007	0.007
4	0.023	0.015	0.008	0.007	0.004
High Δλ	0.023	0.011	0.010	0.011	0.003
High-Low	0.006*	−0.002	0.012***	0.015***	0.006
t(HML)	(1.976)	(-0.632)	(2.946)	(3.516)	(1.628)
Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)					
	Low VOL	2	3	4	High VOL
Low Δλ	0.013	0.007	−0.005	−0.007	−0.004
2	0.018	0.012	0.000	−0.002	0.000
3	0.014	0.009	0.003	−0.001	0.005
4	0.015	0.011	0.000	0.003	0.003
High Δλ	0.016	0.008	0.004	0.005	−0.002
High-Low	0.003	0.001	0.009*	0.012**	0.002
t(HML)	(0.987)	(0.211)	(1.874)	(2.438)	(0.445)
Panel C: post-BISTECH (Dec. 2015-Dec. 2020)					
	Low VOL	2	3	4	High VOL
Low Δλ	0.026	0.027	0.004	0.002	−0.002
2	0.037	0.030	0.028	0.007	−0.002
3	0.039	0.039	0.032	0.023	0.012
4	0.039	0.025	0.023	0.017	0.007
High Δλ	0.038	0.016	0.022	0.023	0.014
High-Low	0.014**	−0.009	0.018**	0.021**	0.016*
t(HML)	(2.203)	(-1.627)	(2.434)	(2.798)	(1.994)

Notes: This table presents the equally weighted return characteristics of multivariate portfolios based on information shock proxies and overall trading volume. At the beginning of each month, we divide our sample into VOL quintiles based on the logarithm of the total trading volume in the previous month. We further divide each VOL quintile into five groups based on the previous month's information shock measures. Panel A presents the equally weighted average return characteristics for each portfolio for the full sample. Panels B and C respectively present the equally weighted average returns for each portfolio for the pre-BISTECH and post-BISTECH periods. High - Low is the difference between High and Low Δλ portfolios for each VOL quintile. For each zero-investment portfolio, the corresponding *t*-statistics are obtained from Newey-West standard errors, presented in parentheses. ***, **, and * respectively indicate statistical significance at the 1%, 5% and 10% confidence levels.

in column 10 of Panel C indicate that a 1 percent increase in information shock measures is associated, on average, with a 76 bps increase in one-month-ahead returns.

5. Conclusion

Conflicting theoretical expectations have been expressed about the systemic impact of adverse selection risk on cost equity. On the one hand, in a rational expectations model with information asymmetry, Easley and O'Hara (2004) examine the systemic pricing of adverse selection risk in equity markets. They argue that the expected returns should be higher in stocks with high adverse selection risk for uninformed investors who cannot react to firm-specific news that quickly arrives in the market. Therefore, investors demand compensation for holding stocks that face information shocks. On the other hand, Hughes et al. (2007) indicate that aggregate information asymmetry drives securities returns, and the risks associated with firm-specific information shocks are diversifiable in a market with a large number of assets.

In this paper, we contribute to the ongoing debate by examining the systemic pricing of information shocks on BIST with a series of univariate and multivariate portfolio analyses along with firm-level cross-sectional regressions. BIST provides a unique setting for investigating the pricing risk associated with information shocks due to an exogenous transformation in its market design. Collocation services introduced by the NASDAQ's Genium INET trading engine (BISTECH trading system) enabled differences in order submission and trade execution latency among investors after November 2015. Even though the market participation of the HFTs in BIST is relatively low, by documenting the superior performance of the fast traders on both the buy and the sell sides of trade, recent studies suggest that fast traders contribute more to the price discovery process than slow traders (Ekinci & Ersan, 2022). These results may suggest that BIST achieves more rapid diffusion of information and efficient price discovery through high-frequency trading. However, heterogeneity across investors in terms of the speed of order submission or trade execution can alleviate adverse selection risk for slow

Table 14
Results of the factor analysis: 5 × 5 portfolios on VOL and Δλ

Panel A: Full Sample (March 2005–Dec. 2020)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.1495*** (0.0439)	−0.0100 (0.0424)	−0.0530 (0.0630)	0.1544** (0.0623)	0.0470 (0.0794)
$\widehat{\beta_p^s}$	0.0166 (0.1100)	0.1058 (0.1300)	0.1351 (0.1253)	−0.1834 (0.1620)	0.3684*** (0.1241)
$\widehat{\beta_p^h}$	−0.2476** (0.1253)	0.0607 (0.1279)	0.4596*** (0.1478)	−0.3043* (0.1703)	0.1390 (0.1689)
$\widehat{\beta_p^u}$	−0.3100** (0.1258)	0.0561 (0.1336)	0.1070 (0.1428)	−0.4693** (0.2004)	0.1766 (0.1581)
$\widehat{\alpha_p}$	0.0091** (0.0039)	−0.0035 (0.0041)	0.0042 (0.0045)	0.0204*** (0.0051)	0.0024 (0.0040)
Observations	187	187	187	187	187
R^2	0.0827	0.0075	0.0520	0.0740	0.0621
GRS ($\widehat{\alpha}$)	4.189				
p(GRS)	0.001				
Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.0811* (0.0426)	0.0230 (0.0482)	−0.0596 (0.0727)	0.2259*** (0.0604)	0.1393** (0.0678)
$\widehat{\beta_p^s}$	0.1858 (0.1188)	0.1312 (0.1349)	0.0859 (0.1671)	−0.3081* (0.1785)	0.2778** (0.1350)
$\widehat{\beta_p^h}$	−0.1456 (0.1002)	−0.0205 (0.1425)	0.4622** (0.1929)	−0.3875* (0.2023)	0.0322 (0.1847)
$\widehat{\beta_p^u}$	−0.2064** (0.0936)	0.1215 (0.1605)	0.0993 (0.1674)	−0.3785* (0.2012)	0.2129 (0.1602)
$\widehat{\alpha_p}$	0.0054 (0.0039)	0.0010 (0.0050)	0.0026 (0.0054)	0.0168*** (0.0061)	0.0002 (0.0051)
Observations	127	127	127	127	127
R^2	0.0704	0.0138	0.0466	0.1326	0.0939
GRS ($\widehat{\alpha}$)	1.854				
p(GRS)	0.108				
Panel C: post-BISTECH (Dec. 2015-Dec. 2020)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta_p^m}$	0.3352*** (0.1172)	−0.0862 (0.0864)	0.0078 (0.1309)	−0.0779 (0.1847)	−0.2347 (0.2226)
$\widehat{\beta_p^s}$	−0.3342 (0.2059)	0.1739 (0.2882)	0.1863 (0.1981)	−0.1367 (0.2990)	0.4182* (0.2386)
$\widehat{\beta_p^h}$	−0.4553 (0.2853)	0.2458 (0.2638)	0.5465** (0.2450)	−0.1068 (0.2812)	0.3905 (0.3220)
$\widehat{\beta_p^u}$	−0.5557** (0.2703)	−0.0410 (0.2601)	0.0168 (0.2561)	−0.4651 (0.3917)	0.2509 (0.3430)
$\widehat{\alpha_p}$	0.0239** (0.0099)	−0.0150** (0.0072)	0.0041 (0.0085)	0.0276** (0.0118)	0.0060 (0.0089)
Observations	60	60	60	60	60
R^2	0.1997	0.0571	0.0870	0.0653	0.1114
GRS ($\widehat{\alpha}$)	2.715				
p(GRS)	0.030				

Notes: We run the following regression on the time series of monthly returns of five zero-investment VOL-Δλ portfolios: $R_p = \alpha_p + \beta_p^m R^{mkt} + \beta_p^s SMB + \beta_p^h HML + \beta_p^u UMD + \varepsilon_p$. The sample period is March 2005–December 2020. Panel A provides the results for the full sample. Panel B provides the results for the pre-BISTECH period. Panel C provides the results for the post-BISTECH period. We provide the estimate for the coefficients and the respective Newey and West (1987) adjusted standard errors in parentheses. For goodness of fit, we provide R^2 measures. The last two rows in each panel respectively provide the Gibbons et al. (1989) test statistics for the null hypothesis that $\widehat{a} = 0$. ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively.

traders because they are less able to react to news that arrives in the market. In line with this expectation, for example, Ekinci and Ersan (2022) argue that fast trading activity significantly reduces the liquidity provision by slow traders, highlighting a potential crowding-out effect related to fast trading. Our results complement these findings by suggesting that adverse selection risk may have become systemically important in equity markets since the introduction of fast trading.

We examine the impact of information asymmetry that is unexpected by investors (information shocks) by focusing on changes in the information asymmetry levels, proxied by the proportion of effective spread that is attributable to adverse selection risk. We employ the seminal framework by Glosten and Harris (1988) to decompose the effective spread into two parts: an adverse selection part associated with the permanent price impact and informed trading and a transitory part related to the temporary price impact and liquidity trading. We first observe a statistically significant adverse selection component of the spread for 97 percent of the stocks traded on BIST between 2005 and 2020. Our results also suggest that, on average, the proportion of the effective spread attributable to adverse selection risk is around 14 percent, indicating an economically

Table 15
Results of the firm-level cross-sectional regressions.

Panel A: Full Sample (March 2005–Dec. 2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INTERCEPT	0.011*	0.045***	0.043***	0.023	0.055***	0.066***	0.064***	0.069***	0.072***	0.079***
p(INTERCEPT)	(0.07)	(0.01)	(0.01)	(0.19)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δλ	0.045***	0.043***	0.041***	0.042***	0.032***	0.028***	0.026***	0.02*	0.024**	0.019*
p(Δλ)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.08)	(0.04)	(0.10)
SIZE		−0.002**	−0.002**	−0.001	0.002**	0.001	0.001	0.001	0.001	0.000
p(SIZE)		(0.02)	(0.02)	(0.17)	(0.02)	(0.33)	(0.33)	(0.40)	(0.44)	(0.96)
BETA			0.003	0.002	0.006***	0.007***	0.006***	0.006***	0.006***	0.004*
p(BETA)			(0.20)	(0.44)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
BTM				0.006***	0.007***	0.006***	0.006***	0.005***	0.005***	0.005***
p(BTM)				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VOL					−0.005***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
p(VOL)					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MAX						−0.150***	−0.148***	−0.159***	−0.154***	0.033
p(MAX)						(0.00)	(0.00)	(0.00)	(0.00)	(0.49)
MOM							−0.009**	−0.008*	−0.008**	−0.006
p(MOM)							(0.03)	(0.08)	(0.05)	(0.18)
REV								0.014	0.013	0.013
p(REV)								(0.21)	(0.24)	(0.24)
ILLIQ									−1.02	−0.652
p(ILLIQ)									(0.84)	(0.89)
IVOL										−0.345**
p(IVOL)										(0.03)

Panel B: pre-BISTECH (Mar. 2005-Nov. 2015)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
INTERCEPT	0.006	0.008	0.005	−0.017	0.016	0.029	0.027	0.034**	0.033*	0.041**
p(INTERCEPT)	(0.46)	(0.62)	(0.78)	(0.32)	(0.32)	(0.09)	(0.13)	(0.05)	(0.08)	(0.03)
Δλ	0.034***	0.031**	0.031**	0.031**	0.022*	0.015	0.013	0.008	0.009	0.003
p(Δλ)	(0.00)	(0.02)	(0.02)	(0.02)	(0.10)	(0.24)	(0.32)	(0.58)	(0.53)	(0.84)
SIZE		0.000	0.000	0.001	0.004***	0.003***	0.002***	0.002**	0.002**	0.001*
p(SIZE)		(0.85)	(0.93)	(0.33)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.10)
BETA			0.002	0.000	0.005*	0.007**	0.006**	0.006***	0.006***	0.003
p(BETA)			(0.55)	(0.90)	(0.06)	(0.02)	(0.05)	(0.01)	(0.01)	(0.16)
BTM				0.007***	0.007***	0.006***	0.006***	0.006***	0.005***	0.005***
p(BTM)				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VOL					−0.006***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
p(VOL)					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MAX						−0.166***	−0.176***	−0.200***	−0.199***	−0.001
p(MAX)						(0.00)	(0.00)	(0.00)	(0.00)	(0.99)
MOM							−0.009*	−0.008	−0.009	−0.006
p(MOM)							(0.08)	(0.16)	(0.11)	(0.27)
REV								0.024	0.024	0.024
p(REV)								(0.11)	(0.12)	(0.12)
ILLIQ									−2.45	−0.693
p(ILLIQ)									(0.75)	(0.92)

IVOL										−1.521***
p(IVOL)										(0.00)

Panel C: post-BISTECH (Dec. 2015-Dec. 2020)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
INTERCEPT	0.023***	0.121***	0.123***	0.106***	0.135***	0.142***	0.138***	0.138***	0.148***	0.154***
p(INTERCEPT)	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δλ	0.069***	0.066***	0.062***	0.065***	0.055***	0.054***	0.052**	0.045**	0.053***	0.052***
p(Δλ)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.01)
SIZE		−0.005***	−0.005***	−0.005***	−0.002	−0.003*	−0.002	−0.002	−0.002	−0.003**
p(SIZE)		(0.00)	(0.00)	(0.00)	(0.24)	(0.09)	(0.12)	(0.13)	(0.12)	(0.04)
BETA			0.005*	0.004	0.007**	0.008***	0.007**	0.005*	0.005*	0.004
p(BETA)			(0.09)	(0.13)	(0.02)	(0.01)	(0.02)	(0.07)	(0.06)	(0.23)
BTM				0.005***	0.006***	0.006***	0.005***	0.005***	0.005***	0.005***
p(BTM)				(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VOL					−0.005***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
p(VOL)					(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
MAX						−0.116***	−0.094***	−0.077	−0.065	0.099
p(MAX)						(0.01)	(0.02)	(0.12)	(0.21)	(0.19)
MOM							−0.008	−0.006	−0.007	−0.005
p(MOM)							(0.24)	(0.69)	(0.28)	(0.45)
REV								−0.007	−0.008	−0.008
p(REV)								(0.29)	(0.60)	(0.60)
ILLIQ									1.817	−0.571
p(ILLIQ)									(0.38)	(0.79)
IVOL										1.987***
p(IVOL)										(0.00)

Notes: This table presents the results of firm-level cross-sectional regressions: $R_{i,m+1} = \gamma_{0,m} + \gamma_{1,m}\Delta\lambda_{i,m} + \gamma_{2,m}SIZE_{i,m} + \gamma_{3,m}BETA_{i,m} + \acute{\gamma}_{4,m}x_{i,m} + \varepsilon_{i,m}$. Each month, we regress the monthly stock returns to the previous month's estimates for the information shock measures (Δλ) along with the firm-specific controls, SIZE, BETA, BTM, MOM, REV, IVOL, MAX, ILLIQ, and VOL. Entries in the table are the time-series averages of the coefficients obtained from the cross-sectional regressions. Values in parentheses are the *p*-values of the corresponding *t*-statistics calculated using Newey and West (1987) standard errors. Panels A, B, and C present the results for the full sample, pre-BISTECH, and post-BISTECH periods, respectively. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

significant impact of adverse selection risk on average transaction costs on BIST.

Next, we examine the systemic impact of information shocks on securities returns through univariate and multivariate portfolio analyses along with firm-level cross-sectional regressions. Monthly univariate portfolios based on information shock measures suggest a statistically significant value-weighted return differential of about 80 bps between stocks in the highest and lowest information shock quintiles. The average return premium due to the information shock strategy is around 74 bps, even after controlling for the variation in market risk, size, value (Fama & French, 1993), and momentum factors (Carhart, 1997). These results suggest that investors in BIST demand a premium for holding stocks that face an increase in transaction costs due to mitigating information asymmetry. Univariate portfolio analyses also show significant variations across firm size, return reversal, idiosyncratic volatility, lottery stock characteristics, and trading volume across information shock quintiles. Therefore, we further control for variations in these firm-specific measures one by one under multivariate portfolio settings to isolate the impact of information shocks. Under the multivariate setting, we strongly reject the hypothesis that the return premiums associated with zero-investment information shock portfolios are zero for all alternative firm-specific controls. Therefore, we argue that the return premium associated with the information shock strategy is robust to variations in these firm-specific measures.

In addition, we test the predictive relationship between information shocks and one-month-ahead returns through firm-level cross-sectional regressions. We document that a 1 percent increase in information shock measures results, on average, in a 30 bps increase in the following month's returns, even after controlling for different firm-specific factors, such as firm size, market risk, book-to-market ratio, liquidity, recent return performance measured by return reversal and momentum, lottery stock characteristics, trading volume, and idiosyncratic volatility.

Finally, we highlight that the return premium associated with the information shock strategy and the predictive power of the information shock measures are both more dominant after the introduction of the BISTECH trading system. In particular, we show that the difference in the value-weighted return between the high and low information shock portfolios is 67 bps in the pre-BISTECH period (March 2005–November 2015). This differential increases to one percentage point in the post-BISTECH period (December 2015–December 2020). Under the multivariate setting, the premium associated with the information shock strategy loses its statistical and economic significance after controlling for variations in return reversal, idiosyncratic volatility, lottery stock characteristics, and trading volume. Furthermore, we highlight that the predictive relationship between information shocks and future returns is not statistically significant in the pre-BISTECH period. However, our results suggest that the predictive relationship is statistically and economically meaningful in the post-BISTECH period. Specifically, a 1 percent increase in information shocks results in a 76 bps increase in the next month's returns, on average, even after controlling for all other firm-specific characteristics in the post-BISTECH period.

Overall, these findings are in line with the theoretical predictions of Easley and O'Hara (2004), who indicate that the cost of equity is higher for stocks with high adverse selection risk. In addition, we complement the existing literature by showing that superior information diffusion and more efficient price discovery, achieved by the introduction of HFTs, may have unintended consequences. Specifically, the mitigated adverse selection by slow traders due to HFT activity (Biais et al., 2015; Brogaard et al., 2014) can make information risk, which would otherwise be idiosyncratic, systemically important, especially in emerging markets where the majority of the trading activity is performed by slow traders. Therefore, in emerging markets, in their effort to improve the governance of trading platforms, regulators should consider the value of the benefits of fast traders, such as efficient diffusion of information and faster price discovery, along with the potential systemic impact of fast trading on the cost of equity.

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