DOI: 10.1111/fima.12354

Financial Management

financial analysts' forecasts (Malloy, 2005), bank lending (Degryse & Ongena, 2005), equity issuance (Loughran, 2008), mergers and acquisitions (Kang & Kim, 2008), and corporate investment (Giroud, 2013).

In this study, we provide evidence regarding the relation between a firm's geographic proximity to the nearest financial center and the informational efficiency of its stock prices. Price efficiency has significant implications for the capital market and real economy. More efficient prices better reflect the fundamentals of firms and help them make more informed investment and financing decisions (Chen et al., 2007). We hypothesize that the informational efficiency of stock prices is higher for firms that are closer to financial centers. Financial institutions are clustered in financial centers, so proximity to financial centers facilitates information dissemination and acquisitions. Accordingly, a short distance to financial centers attenuates information asymmetry between the firm and the financial markets and improves price efficiency.

We test our hypothesis using a sample of Chinese publicly listed firms from 2008 to 2016. China provides an ideal setting to investigate this issue. China covers a vast territory and the geographic distance constitutes a major cost in information acquisition and dissemination. In addition, the Chinese government imposes tight controls on the media and the Internet making some information difficult to acquire online. Moreover, China is experiencing rapid, yet unequal, development, and financial resources are concentrated in several metropolises. Due to these factors, the impact of location on the informational efficiency of stock prices is magnified.

We focus on the high-frequency measure of price efficiency that provides a more reliable estimate than long horizon measures in our context. The Chinese stock market is dominated by retail investors who trade excessively (Bailey et al., 2009) and the average annual turnover rate in China is typically more than twice that in the United States (Pan et al., 2016). Studies (Chordia et al., 2005) find that traders monitor the market closely and price discovery occurs primarily within one trading day. Due to the extreme turnover rate and the speed of price discovery, short-term measures are suitable to capture the relative informational efficiency of prices. Following previous studies (Boehmer & Wu, 2013; Cao et al., 2017), we assume that informationally efficient prices follow a random walk. We use intraday trade data from more than 1500 stocks from 2008 to 2016 to construct our measure as to how far transaction prices deviate from this benchmark. Using the method in Hasbrouck (1993), we separate the variation of a stock's efficient price from the variation of a pricing error by a vector autoregression model. The standard deviation of the pricing error measures the inefficiency of the stock price. We also consider an alternative proxy that is the absolute value of the quote midpoint return autocorrelation (Boehmer & Wu, 2013). A large absolute value of the autocorrelation indicates low price efficiency.

One difficulty in identifying the casual effect of geographic proximity on price efficiency is that firms with certain characteristics may be closer to financial centers and the observed relation can be driven by omitted variables. To establish the casual relation, we explore how shocks to geographic proximity affect price efficiency by studying the cities' connections to their nearest financial centers via the high-speed railway network in China. Construction of the high-speed railway network began in 2007. As of 2014, China had the world's longest and most active high-speed railway with connections among 81 cities and an annual ridership of 857 million. High-speed railway changes travel patterns profoundly, and a connected city usually experiences a significant increase in the number of train passengers (Lin, 2017). The shock to ease of travel affects different city pairs over time and generates cross-sectional variations.

We manually collect information about connections on the first high-speed railway between firm cities and their nearest financial centers and adopt a difference-in-difference research design. In particular, we compare the changes in the price efficiency of firms in cities that experience a shock to their transportation mode with the changes in price efficiency of firms in cities that do not experience a shock around the time when the high-speed railway connections are established. We expect the high-speed railway connection to attenuate the effect of distance and improve price efficiency.

The empirical tests support our hypothesis. We find that stock prices are more informationally efficient for firms that are closer to financial centers. Although geographic distance is time invariant, it generates important cross-sectional differences in the informational efficiency of stocks prices. More important, ease of travel attenuates the negative impact of geographic distance on price efficiency. Stock prices of firms in cities that are connected to the nearest financial center by the high-speed railway network are more informationally efficient than stock prices of firms that are not connected. This finding is not driven by the high-speed railway connection to other nearby important cities that are not financial centers. The results are also robust to the alternative proxy for price efficiency from Bartram & Grinblatt (2018).

The evidence from the high-speed railway connections helps us verify the channel through which location affects price efficiency. A firm's connection to a financial center facilitates information acquisition and dissemination. Because investors and financial analysts are more informed about firms connected to financial centers, their stock prices become more efficient. Next, we examine the effects conditional on the type of cities and further identify the mechanism behind our results.

We hypothesize that our findings are stronger for firms closer to the nearest financial center. For firms that are far from their nearest financial center, the benefits of the high-speed railway connection may be limited as air travel could be a superior transportation mode for long distance travel. To test this hypothesis, we adopt a triple difference type specification andtype whether the local proximity of traders in financial centers to the corporate headquarters of the traded stocks affects traders' performance. The informational advantage related to location extends to other participants in the financial markets. Geographically proximate analysts issue more accurate forecasts and have a greater market impact than other analysts (Bae et al., 2008). Market makers closer to the firm's headquarters make more contributions to price discovery (Anand et al., 2011). Shive (2012) uses power outages as exogenous shocks to trading and examines the role of local investors on market efficiency. Our study complements the literature by demonstrating that the stock prices of firms that are connected to their nearest financial centers by high-speed railway networks are more informationally efficient. Thus, geographically proximate investors not only generate superior returns based on their informational advantage, but their informed trading also improves price efficiency.

Finally, our paper adds to the growing literature on the effect of transportation on financial markets. Herpfer et al. (2018) find that a reduction in travel time affects both new and existing borrowing relationships. The introduction of new airline routes affects venture capitalists' involvement with their portfolio companies (Mao et al., 2014; Bernstein et al., 2016), broadens firms' investor base, lowers their cost of equity (Da et al., 2021), affects mutual fund holdings (Ellis et al., 2020), and leads to an increase in plant-level investment from the headquarters and to total factor productivity (Giroud, 2013). Koudijs (2015, 2016) studies how private information is incorporated into prices and asset price volatility exploiting a natural experiment from the 18th century in which information flows were transmitted by sailing boats that were regularly interrupted by adverse weather conditions. Chen et al. (2021) find that mutual fund managers in China increase their site visits to a city after a direct high-speed railway connection is created. These studies all suggest ease of travel attenuates the effect of geographic distance on communication and information gathering. Our paper provides consistent evidence that access to a high-speed railway network enhances price efficiency resulting in an improvement in information acquisition and dissemination.

The rest of the paper is organized as follows. Section 2 describes the sample and descriptive statistics. Section 3 provides the main empirical analysis. Section 4 examines cross-sectional heterogeneity and the mechanism, and Section 5 provides our conclusions.

2 | DATA AND DESCRIPTIVE STATISTICS

We obtain accounting information, stock returns of publicly traded firms, mutual fund ownership, and financial analyst coverage data from the China Stock Market & Accounting Research (CSMAR) database. The sample period is from 2008 to 2016. We focus on the sample after 2008 for two reasons. First, the Chinese split-share reform was completed in 2007 and represents a major regime change in the development of the Chinese stock market (Liao et al., 2014). In addition, high-speed railways were introduced in 2008 and we rely on this shock to transportation to identify the impact of distance on price efficiency.

2.1 | Proximity to financial centers

Following the literature (Coval & Moskowitz, 1999, 2001; Loughran & Schultz, 2005; Anand et al., 2011), we define firm location as the city of the firm's headquarters. Major corporate decisions are made at their headquarters and they represent the information centers that connect firms with their suppliers, clients, and investors. We manually collect information about headquarter locations from the annual financial reports of companies.

To construct the proximity to financial centers, we consider three major metropolitan cities in China: Beijing in the north, Shanghai in the middle, and Shenzhen in the south. By the end of 2016, the gross domestic products (GDP) of these three cities in USD are \$377.26 billion, \$416.15 billion, and \$295.34 billion making them the second, the first, and the fourth largest cities in China, respectively. They not only play important roles in politics and economics, but also act as financial centers. Beijing is the capital city of China and contains all of the primary regulatory agencies

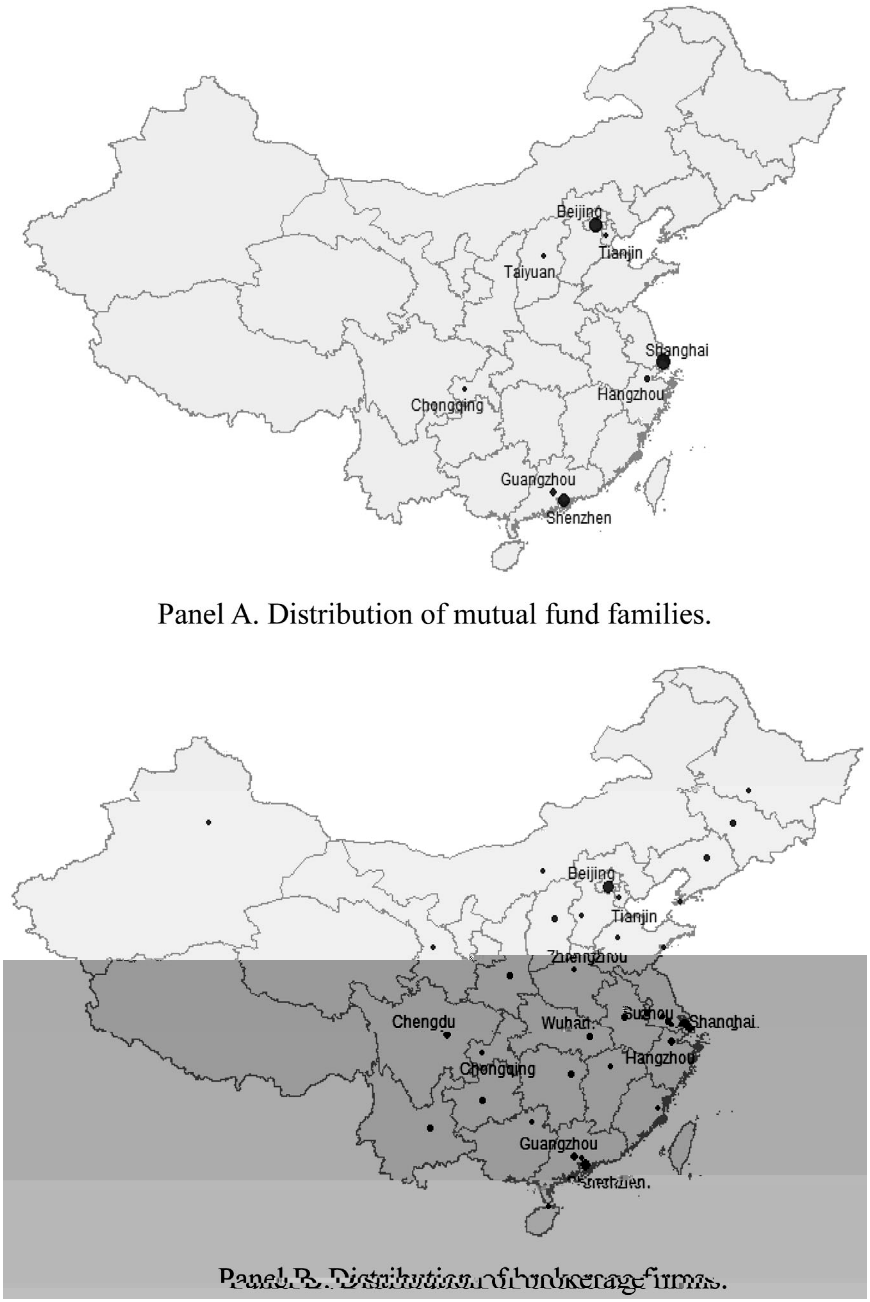

FIGURE 1 Distribution of financial institutions in China
Note: This figure depicts the headquarters locations of the mutual fund families (in Panel A) and brokerage firms (in Panel B) in China at the end of 2016. A larger dot indicates a higher number of mutual fund families or brokerage firms in a city. For figure brevity, the city of Sansha in Hainan Province is omitted

can be serially correlated or correlated with the innovation of efficient prices. Because the expected value of the deviations is zero, the standard deviation of the pricing error, σ_s, represents the magnitude of the deviations from the efficient price and is a measure of price efficiency. Instructions for estimating σ_s are presented in Appendix A. To make comparisons across stocks meaningful, σ_s is scaled by the standard deviation of price to control for cross-sectional differences in the return variance. Standardized PEV reflects the proportion of the deviation from the efficient price in the total variability of the observable transaction price process and is a measure of the informational efficiency of prices. A smaller PEV indicates a more efficient stock price.

Following the literature (Boehmer & Wu, 2013), our second measure of stock price efficiency is the absolute value of the quote midpoint return autocorrelation. The midpoint of the bid and ask price is the best estimate of the true value of the stock at any point in time. Therefore, if the prices are efficient, the midpoint returns should follow a random walk and their autocorrelations in either direction should be small. A large absolute value of the midpoint return autocorrelation indicates a low level of price efficiency. We calculate the return autocorrelation based on a nonoverlapping 20-min interval and use |AR20| to denote its absolute value. Results are similar if we choose a 15- or 30-min interval. For these two measures of price efficiency, we first calculate their daily value for each stock and then take the annual average3-1�-1g0.2(n-)]�TJ�ET�.0005999992�i�60002�92�i�6001�0�0478.9(a)-0.0�I�S�/G

TABLE 1 Descriptive statistics

Variable	Mean	SD	P5	P50	P95	N
PEV	0.09	0.05	0.05	0.08	0.18	13,028
|AR20|	0.23	0.02	0.20	0.23	0.27	13,026
DIS	522.01	469.49	84.76	407.90	1223.47	13,350
VWAP	16.58	13.68	4.59	12.32	44.01	13,028
RES	0.00	0.00	0.00	0.00	0.00	13,028
OIB	0.09	0.03	0.05	0.08	0.15	13,028
MFHD	0.04	0.07	0.00	0.02	0.18	13,355
SHO	0.00	0.00	−0.00	0.00	0.00	11,297
SIZE	7.98	1.17	6.31	7.87	10.18	13,355
ROA	0.06	0.06	−0.03	0.05	0.15	13,355
LEV	0.44	0.24	0.10	0.43	0.80	13,355
Q	2.78	2.15	1.05	2.09	6.86	13,114

Note: This table reports summary statistics for the main variables. The accounting and stock returns data are from the China Stock Market & Accounting Research (CSMAR) database. The intraday price quote data are from RESSET. Firm location information is manually collected. The sample period is from 2008 to 2016. DIS is the distance between a firm and its nearest financial center. Other variable definitions are in Appendix B. This table reports the mean, standard deviation, 5th percentile, 50th percentile, 95th percentile, and number of observations for the full sample.

In the untabulated analysis, we compare the price efficiency measures during the two subperiods of 2008–2012 and 2013–2016 and find that PEV and |AR20| are both smaller in the later sample period than in the earlier period. This holds for both the mean and median and suggests that stocks are more efficiently priced in 2013–2016. Because cities are connected to the high-speed railway network over time, ease of travel attenuates the effects of distance more strongly in the later sample period. Therefore, this pattern of price efficiency over time is consistent with our hypothesis. We also calculate the correlation coefficients for the main variables in the untabulated analysis. Consistent with our hypothesis, a high level of price efficiency is associated with a high trading price (low percentage trading cost), high institutional ownership, and active short selling activity, whereas large bid–ask spreads and one-sided trading pressure reduce price efficiency. It suggests that our measures are correct proxies for the underlying economic variables.

3 | GEOGRAPHIC PROXIMITY TO FINANCIAL CENTERS AND PRICE EFFICIENCY

3.1 | Univariate test

If geographic distance affects information acquisition and dissemination, price efficiency for firms close to financial centers should be higher than for firms far from financial centers. Before presenting the evidence from the multivariate analysis, we first conduct a univariate test to compare the price efficiency between proximate and nonproximate firms. A firm is considered a proximate (nonproximate) firm if the distance between the firm's city and the nearest financial center is within (more than) 300 km. Results are similar if alternative distances of 100, 200, or 400 km are used.

Table 2 presents the results. We find that both PEV and |AR20| are smaller for proximate firms than for nonproximate firms and the differences are statistically significant. This holds for both the average and the median. This result suggests that stocks of proximate firms are more efficiently priced. The difference in PEV and |AR20| in the univariate test also implies the impact of geographic proximity on price efficiency is prominent and an important feature in

TABLE 2 Proximate and nonproximate firms: Univariate test

	Proximate		Nonproximate		Difference	
Variable	Mean	Median	Mean	Median	Mean	Median
PEV	0.09	0.08	0.10	0.08	−0.00***	−0.00***
|AR20|	0.23	0.23	0.23	0.23	−0.00***	−0.00***
VWAP	17.63	13.23	15.84	11.71	1.79***	1.52***
RES	0.00	0.00	0.00	0.00	−0.00***	−0.00***
OIB	0.09	0.08	0.09	0.08	0.00	0.00
MFHD	0.04	0.02	0.05	0.02	−0.00**	−0.00
SHO	0.00	0.00	0.00	0.00	−0.00*	0.00
SIZE	7.89	7.80	8.04	7.92	−0.15***	−0.12***
ROA	0.06	0.06	0.05	0.05	0.01***	0.01***
LEV	0.41	0.39	0.47	0.46	−0.06***	−0.07***
Q	2.84	2.18	2.75	2.03	0.09**	0.15***

Note: This table reports the mean and median of the main variables for proximate and nonproximate firms and their difference between the mean and the median. A firm is defined as proximate (nonproximate) if the distance between the firm city and the nearest financial center is within (more than) 300 km. Variable definitions are in Appendix B. For the difference, ***, **, and * denote two-tailed statistical significance of the mean or median at the 1%, 5%, and 10% levels, respectively.

the data providing strong evidence for our hypothesis. Several firm characteristics are different between the proximate and nonproximate firms. This highlights the importance of controlling for these characteristics and dealing with omitted variables.

3.2 | High-speed railway connections and price efficiency

Although price efficiency is negatively associated with geographic distance as shown in Table 2, it is difficult to infer the casual impact in multivariate regressions. It is possible that firms with specific characteristics are close to financial centers and that omitted variables drive the results. To establish the casual relation, we study how shocks to geographic proximity affect price efficiency by exploiting the rapidly changing mode of transportation that significantly altered ease of travel between Chinse cities: the introduction of the high-speed railway. We consider the introduction of high-speed railway connections between firm cities and their nearest financial centers as shocks to ease of travel, and adopt a difference-in-difference approach to examine the causal impact of distance on price efficiency. Because ease of travel alleviates the geographic distance constraint by reducing the overall cost (time, effort, etc.), the high-speed railway connection facilitates information acquisition and dissemination. For example, Chen et al. (2021) find that mutual fund managers in China increase their site visits to a city after a direct high-speed railway connection is established. Thus, we expect high-speed railway connections to help attenuate the effect of distance and improve price efficiency.

The high-speed railway network in China underwent rapid development during our sample period. The State Council first released the Mid-to-Long Term Railway Development Plan in 2004 and issued a revised Plan in 2008. The Plan set the goal of a national high-speed railway grid composed of four north–south corridors and four east–west corridors with a budget of 4000 billion RMB (or about 571 billion USD). The purpose of this national project is to connect the major cities across provinces with faster transportation. The placement of high-speed railway routes, as well as the choice of cities to receive high-speed train stations, is based on factors including economic development, population, and resource distribution.

TABLE 3 High-speed railway connections to financial centers

Year	(1) Cities	(2) Firms
2008	0	0
2009	0	0
2010	12	247
2011	23	246
2012	21	118
2013	34	333
2014	22	98
2015	15	54
2016	9	70

Note

model:

$$Y_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \text{Controls}_{i,c,t-1} + \gamma_{i,c} + \omega_{c,t} + \varepsilon_{i,c,t}, \tag{2}$$

where i denotes the firm, c denotes the cohort, and t denotes the year. The dependent variable is one of two proxies for pricing efficiency. Treat is equal to 1 if the city of firm i in cohort c is connected to its nearest financial center by high-speed railway and 0 otherwise. Post is equal to 1 if the connection is established after year t in cohort c and 0 otherwise. The control variables include VWAP, RES, OIB, MFHD, SHO, SIZE, ROA, LEV, and Q. We include firm–cohort fixed effects, $\gamma_{i,c}$, to control for any fixed differences between firms, and we include year–cohort fixed effects, $\omega_{c,t}$, to control for any time trends. We allow the firm and year fixed effects to vary by cohort. If the high-speed railway connection facilitates the information acquisition and dissemination, we expect β_1, which captures the average treatment effect across multiple events, to be negative and significant.

Table 4 presents the results. In Column (1), we use PEV as the proxy for price efficiency. We find the interaction term has a negative and significant coefficient. Stock prices of firms in cities that are connected to the nearest financial centers by a high-speed railway network are more informationally efficient than stock prices of firms that are not connected. In particular, the connection results in a 9.7% increase in price efficiency, on average, after controlling for other factors. This suggests that geographic distance has a causal impact on price efficiency. It also helps us identify the channel through which location affects price efficiency as shown in Table 2. A connection to a financial center reduces travel costs and facilitates information acquisition and dissemination. Because investors are more informed about firms that are connected to the network, the stock price becomes more efficient.

The coefficients on the control variables generally have the expected signs. A higher RES indicates higher transaction costs deterring the trading of arbitrageurs and decreasing price efficiency. Stocks with more mutual fund holdings are priced more efficiently and the net shorting flow has a positive effect on price efficiency. These results confirm the previous finding that institutional investors and short sellers make prices informationally efficient.

In Column (1), we consider all firm-year observations of the control group that can be included when constructing a cohort. Although we control for a number of firm characteristics in Equation (2), it is still possible that the results are driven by the differences between the treated and the control firms. To address this concern, we match treated firms to control firms based on a number of firm characteristics including total assets, return on assets, leverage ratio, firm age, and state ownership. We then construct the cohorts using the matched sample. Column (2) reports the estimates from this matched sample with PEV as the proxy for price efficiency. Because of the matching, the sample size is reduced by 50%, but the main finding is largely unchanged. The coefficient on the interaction term is negative and significant and its magnitude is almost the same as in Column (1). Price efficiency is higher after high-speed railway connections were introduced between the firm city and the nearest financial center. In Columns (3) and (4), we use |AR20| as an alternative proxy for price efficiency and find similar and robust evidence.

We next show that the parallel-trend assumption underlying the difference-in-differences estimator is not violated. One concern with the difference-in-difference approach in Equation (2) is that the estimated treatment effect could be due to pretreatment differences in the characteristics of the treated and the control groups. To address this concern, we examine the dynamics of price efficiency around the new high-speed railway connections by adding two leads (before treatment) and two lags (after treatment) of the variable Post in Equation (2). The leads, Treat × Post (–2) and Treat × Post (–1), can control for pretreatment effects, whereas the lags, Treat × Post (+2) and Treat × Post (+1), can trace the treatment effects in the periods after the initial shock.

Table 5 presents the estimates based on this new specification. The dynamics of price efficiency around the high-speed railway connections largely support our hypothesis. We do not find a strong anticipatory effect. The interaction terms are generally not significant prior to the event, especially for the matched sample, so stock prices are not informationally more efficient before the connections. Alternatively, price efficiency is improved right after the connections and the significant effect of the lag interactions suggests the impact of the shock to the ease of travel is long lasting.

TABLE 4 Connections to financial centers and price efficiency

	(1)	(2)	(3)	(4)
	PEV		|AR20|	
	Full	Matched	Full	Matched
Treat × Post	−0.01***	−0.01***	−0.00***	−0.00**
	(−7.35)	(−5.86)	(−4.58)	(−2.54)
VWAP	0.00	0.00	0.00***	0.00***
	(0.95)	(0.97)	(7.45)	(7.64)
RES	14.76***	12.28***	4.74***	2.44***
	(8.42)	(7.48)	(6.36)	(5.08)
OIB	−0.01	−0.01	−0.03	−0.02**
	(−0.39)	(−0.51)	(−1.56)	(−2.15)
MFHD	−0.09***	−0.08***	−0.02**	−0.02
	(−6.23)	(−5.47)	(−2.39)	(−1.54)
SHO	−47.98***	−57.08***	6.07	3.38
	(−3.78)	(−4.43)	(0.87)	(0.69)
SIZE	−0.00	−0.00	−0.00***	−0.01***
	(−1.06)	(−1.30)	(−4.16)	(−8.97)
ROA	−0.07***	−0.08***	−0.01	−0.02**
	(−3.04)	(−4.42)	(−1.68)	(−2.65)
LEV	0.00	−0.00	0.00	0.01
	(0.09)	(−0.71)	(0.22)	(1.30)
Q	−0.00***	−0.00***	−0.00**	−0.00
	(−4.92)	(−3.56)	(−2.54)	(−1.19)
Year × cohort	Yes	Yes	Yes	Yes
Firm × cohort	Yes	Yes	Yes	Yes
N	18,799	9968	18,798	9967
Adj. R^2	0.60	0.60	0.21	0.23

Note: This table presents the results of the regression in Equation (2). The dependent variable is pricing error variance (PEV) in Columns (1) and (2) and |AR20| in Columns (3) and (4). |AR20| is the absolute value of the return autocorrelations calculated from the midpoints of the bid–ask spread quotes at nonoverlapping 20-min intervals (|AR20|). The accounting and stock return data are from the China Stock Market & Accounting Research (CSMAR) database. The intraday price quote data are from RESSET. The sample period is from 2008 to 2016. For each new connection, we construct a cohort of the treated and the control firms using firm-year observations for the 2 years before and the 2 years after the connection. In Columns (1) and (3), we use all firm-year observations of the control group that can be included when constructing a cohort. In Columns (2) and (4), we match treated firms to control firms based on a number of firm characteristics. Treat is equal to 1 if the city of firm in the cohort is connected to its nearest financial center by high-speed railway and 0 otherwise. Post is equal to 1 if the connection is established in a year in the cohort and 0 otherwise. Other variable definitions are in Appendix B. We include year × cohort and firm × cohort fixed effects. Standard errors are clustered at the industry level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

These results do not suggest that the parallel-trend assumption underlying the difference–indifferences estimator is violated.

Overall, the evidence in Tables 4 and 5 indicates that high-speed railway connections between firm cities and their nearest financial center have a significant impact on the informational efficiency of stock prices. The new mode of

TABLE 5 Connections to financial centers and price efficiency: Dynamic effects

	(1)	(2)	(3)	(4)
	PEV		|AR20|	
	Full	Matched	Full	Matched
Treat × Post (−2)	−0.00	0.00	−0.00	−0.00
	(−1.30)	(1.13)	(−1.54)	(−1.15)
Treat × Post (−1)	−0.01**	0.00	−0.00	0.00
	(−2.46)	(0.72)	(−0.54)	(0.61)
Treat × Post (0)	−0.01***	−0.00	−0.00***	−0.00***
	(−5.48)	(−1.39)	(−4.07)	(−3.37)
Treat × Post (+1)	−0.01***	−0.01**	−0.00	−0.00
	(−3.96)	(−2.44)	(−1.40)	(−1.63)
Treat × Post (+2)	−0.02***	−0.01***	−0.00**	−0.00**
	(−4.79)	(−7.04)	(−2.35)	(−2.63)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Firm × cohort	Yes	Yes	Yes	Yes
N	18,799	9968	18,798	9967
Adj. R^2	0.60	0.60	0.21	0.23

Note: This table presents the results of the dynamic tests based on the model in Equation (2). The dependent variable is pricing error variance (PEV) in Columns (1) and (2) and |AR20| in Columns (3) and (4). |AR20| is the absolute value of the return autocorrelations calculated from the midpoints of the bid–ask spread quotes at nonoverlapping 20-min intervals (|AR20|). The accounting and stock return data are from the China Stock Market & Accounting Research (CSMAR) database. The intraday price quote data are from RESSET. The sample period is from 2008 to 2016. For each new connection, we construct a cohort of the treated and the control firms using firm-year observations for the 2 years before and the 2 years after the connection. In Columns (1) and (3), we use all firm-year observations of the control group that can be included when constructing a cohort. In Columns (2) and (4), we match the treated firms to the control firms based on a number of firm characteristics. Treat is equal to 1 if the city of the firm in the cohort is connected to its nearest financial center by a high-speed railway and 0 otherwise. Post (0) is equal to 1 if the connection is established in the event year in the cohort and 0 otherwise. We add two leads (before treatment) and two lags (after treatment) of the variable Post in Equation (2). Other variable definitions are in Appendix B. We include year × cohort and firm × cohort fixed effects. Standard errors are clustered at the industry level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

transportation alleviates the geographic distance constraint and facilitates information dissemination and acquisition leading to an improvement in the price efficiency.

4 | ADDITIONAL TESTS

In this section, we examine the robustness of our main findings and report the cross-sectional differences in the effect of high-speed railway connections on price efficiency to provide further evidence on the underlying mechanisms.

4.1 | Connections to other important cities

Figure 1 indicates financial resources are lopsidedly distributed in Beijing, Shanghai, and Shenzhen, and these three cities are the headquarters for more than 90% of mutual fund families and almost 60% of brokerage firms. It suggests the importance of the connection to financial centers in improving price efficiency. Nonetheless, the geographic proximity to other nearby important cities may also play a role.[4] In this subsection, we further examine whether the high-speed railway connection to other important cities affects the main findings.

We use two methods to define other important cities. First, we follow the plan of the central government on city development. In 2010, the Ministry of Housing and Urban-Rural Development of China issued the "National Urban System Plan" and designated five major cities, Beijing and Tianjin in the Bohai Economic Zone, Shanghai in the Yangtze River Delta Economic Zone, Guangzhou in the Pearl River Delta Economic Zone, and Chongqing in the West Triangle Economic Zone, as the National Central Cities. In 2016, Chengdu, Wuhan, and Zhengzhou were included in the National Central Cities. Therefore, the first definition provides six important cities in addition to the three financial centers. Additionally, we define the important cities based on their total annual GDP by the end of 2016. We consider the top 10 cities with the largest GDP. They include Shanghai, Beijing, Guangzhou, Shenzhen, Tianjin, Suzhou, Hangzhou, Chongqing, Chengdu, and Wuhan. The second method provides seven important cities excluding financial centers.

Next, we construct an indicator variable, *OtherConn*, that is equal to 1 after the firm's city is connected to its nearest important city (excluding the financial centers) and 0 otherwise.[5] To avoid the multicollinearity problem, we exclude

TABLE 6 The impact of connections to other important cities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PEV				|AR20|			
	Full sample		Matched sample		Full sample		Matched sample	
	Central	GDP	Central	GDP	Central	GDP	Central	GDP
Treat × Post	–0.01***	–0.01***	–0.01***	–0.02***	–0.00**	–		

TABLE 7 Connections to financial centers and price efficiency: Alternative proxy

	(1) Full	(2) Matched
Treat × Post	−0.05**	−0.08***
	(−2.32)	(−3.78)
VWAP	0.00	0.00
	(0.76)	(0.06)
RES	5.40	−6.94
	(0.36)	(−0.56)
OIB	0.30	0.54
	(0.46)	(1.34)
MFHD	−0.16	−0.19
	(−0.66)	(−1.11)
SHO	−236.96	−237.67
	(−1.12)	(−1.02)
SIZE	−0.00	−0.03
	(−0.15)	(−0.94)
ROA	−0.82***	−0.60***
	(−7.26)	(−4.87)
LEV	−0.12	−0.00
	(−1.15)	(−0.02)
Q	−0.03**	−0.03***
	(−2.55)	(−4.10)
Year × cohort	Yes	Yes
Firm × cohort	Yes	Yes
N	18,719	9911
Adj. R^2	0.46	0.46

Note: This table presents the results of the regression in Equation (2). The dependent variable is the mispricing measure |Mis| from Bartram & Grinblatt (2018). The accounting and stock return data are from the China Stock Market & Accounting Research (CSMAR) database. The intraday price quote data are from RESSET. The sample period is from 2008 to 2016. For each new connection, we construct a cohort of the treated and the control firms using firm-year observations for the 2 years before and the 2 years after the connection. In Column (1), we use all firm-year observations of the control group that can be included when constructing a cohort. In Column (2), we match the treated firms to the control firms based on a number of firm characteristics. Treat is equal to 1 if the city of the firm in the cohort is connected to its nearest financial center by a high-speed railway and 0 otherwise. Post is equal to 1 if the connection is established in a year in the cohort and 0 otherwise. Other variable definitions are in Appendix B. We include year × cohort and firm × cohort fixed effects. Standard errors are clustered at the industry level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

stocks with negative Mis are undervalued. Because undervaluation or overvaluation represents mispricing, we take the absolute value of Mis as our measure of price efficiency (|Mis|).

We estimate Equation (2) with |Mis| as the dependent variable and report the results in Table 7. In both columns with different samples of cohorts, we find the coefficient of the interaction term is negative and significant. A high-speed railway connection to the nearest financial center significantly improves price efficiency. This finding is consistent with the results in Table 4 and provides further evidence for our main hypothesis.

4.3 | Different types of cities and price efficiency

In this subsection, we conduct tests to determine the city-level cross-sectional differences in the impact of high-speed railway connections on price efficiency and to provide further evidence regarding the underlying mechanisms. Loughran & Schultz (2005) find that urban firms whose headquarters are in the 10 largest metropolitan areas of the United States trade much more, have lower trading costs, are covered by more analysts, and are owned by more institutions than rural firms. This evidence indicates that it could be more difficult to obtain information on firms based in rural locations than on firms based in large metropolitan areas. In a similar spirit, we examine whether the impact of the high-speed railway connections on price efficiency is different across large and small cities and adopt a triple difference type specification as follows:

$$\begin{aligned} Y_{i,c,t} = {} & \beta_0 + \beta_1 \text{Treat}_{i,c} \times \text{Post}_{c,t} \times \text{City}_j + \beta_2 \text{Treat}_{i,c} \times \text{Post}_{c,t} + \beta_3 \text{City}_j \\ & + Controls_{i,c,t-1} + \text{Industry} + \omega_{c,t} + \varepsilon_{i,c,t}, \end{aligned} \tag{4}$$

where City_j denotes certain characteristics of the firm's city *j*, Industry denotes the industry fixed effects, and the other notations follow Equation (2).[7] We create a dummy variable, *Large_City*, that is equal to 1 if the population of a firm's city at the end of 2007 is above 5 million and 0 otherwise.[8] If the impact of the connection is more prominent for large cities, we expect that β_1 will be negative and significant.

Panel A of Table 8 presents the estimates. In all columns, the triple interaction term is negative, but insignificant for both proxies for price efficiency and both the full and matched samples of cohorts. Therefore, the stock price efficiency of firms in large cities is not improved significantly more than that of firms in small cities after high-speed railway connections to the nearest financial center.

The heterogeneity in the geographic proximity of firms to the nearest financial center may generate differential effects of the connections to price efficiency. As shown in Table 1, the average distance between a firm and the nearest financial center is 522.01 km, and it is about six times as long as that of the 5th percentile and less than half of that of the 95th percentile in the sample. For long distances, air travel could be a more convenient transportation mode than a train in terms of travel time. Thus, the impact of high-speed railway connections on price efficiency may be more prominent for firms closer to the nearest financial center.

To test this hypothesis, we estimate Equation (4) and the city characteristic is Proximity, which is a dummy variable that is equal to 1 if the distance between the firm city and its nearest financial center is within 300 km and 0 otherwise.[9] Panel B of Table 8 presents the estimates. In all columns, we find the triple interaction term is negative and significant. The stock price efficiency of firms that are close to their nearest financial center increases significantly more than that of firms that are far from financial centers after the high-speed railway connections. This evidence is consistent with idea that the high-speed train mainly facilitates short distance travel leading to a more prominent improvement in the price efficiency of proximate firms.

4.4 | Different characteristics of firms and price efficiency

Next, we examine the effects conditional on different characteristics of firms. We first explore how firm size affects our main finding. The literature (Grullon et al., 2004) indicates that larger firms tend to have greater investor recognition including a greater number of shareholders and more financial analyst coverage. Better investor recognition can

[7] We use industry fixed effects as firm–cohort fixed effects can subsume the cross-sectional differences among cities.

[8] The average city population at the end of 2007 is about 4.3 million people, and our results are similar if alternative cutoffs (e.g., 4 or 6 million) are used.

[9] Results are similar if we use 400 km to compute the indicator variable or the continuous variable of *–log(1+distance)*.

TABLE 8 Connections to financial centers and price efficiency: Conditional on the type of cities

Panel A. Large cities	(1)	(2)	(3)	(4)
	PEV		|AR20|	
	Full	Matched	Full	Matched
Treat × Post × *Large_City*	−0.00	−0.00	−0.00	−0.00
	(−0.62)	(−1.03)	(−1.49)	(−1.44)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	18,816	9974	18,815	9973
Adj. R^2	0.50	0.50	0.18	0.18
Panel B. Proximate cities	**(1)**	**(2)**	**(3)**	**(4)**
	PEV		**|AR20|**	
	Full	**Matched**	**Full**	**Matched**
Treat × Post × Proximity	−0.00*	−0.01***	−0.00***	−0.00***
	(−1.95)	(−3.11)	(−4.80)	(−5.37)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	18,816	9974	18,815	9973
Adj. R^2	0.50	0.50	0.19	0.19

This table presents the results of the regression in Equation (4). The dependent variable is pricing error variance (PEV) in Columns (1) and (2) and |AR20| in Columns (3) and (4). |AR20| is the absolute value of the return autocorrelations calculated from the midpoints of the bid–ask spread quotes at nonoverlapping 20-min intervals (|AR20|). The accounting and stock return data are from the China Stock Market & Accounting Research (CSMAR) database. The intraday price quote data are from RESSET. The sample period is from 2008 to 2016. In Panel A, *Large_City* is a dummy variable that is equal to 1 if the population of a firm's city at the end of 2007 is above 5 million and 0 otherwise. In Panel B, Proximity is a dummy variable that is equal to 1 if the distance between the firm city and its nearest financial center is within 300 km and 0 otherwise. For each new connection, we construct a cohort of the treated and the control firms using firm-year observations for the 2 years before and the 2 years after the connection. In Columns (1) and (3), we use all firm-year observations of the control group that can be included when constructing a cohort. In Columns (2) and (4), we match the treated firms to the control firms based on a number of firm characteristics. Treat is equal to 1 if the city of the firm in the cohort is connected to its nearest financial center by a high-speed railway and 0 otherwise. Post is equal to 1 if the connection is established in a year in the cohort and 0 otherwise. Other variable definitions are in Appendix B. We include year × cohort and industry fixed effects. Standard errors are clustered at the industry level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

moderate the negative effect of geographic distance. In addition, soft information not included in the financial report could be important for small firms in their price discovery process, and ease of travel could facilitate the acquisition of soft information. Therefore, we expect that our finding should be stronger for small firms. To test this hypothesis, we construct an indicator variable, *Small_Firm*, that is equal to 1 if the firm size is below the sample median in the event year of the connection and 0 otherwise.[10] We use this indicator variable and estimate the following triple difference

[10] The indicator variable does not change within each cohort for a firm. Depending upon the sample distribution in the event years, a firm-year observation could be in a small firm group in one cohort and a large firm group in another cohort. The other indicator variables based on firm characteristics in the later analysis are defined similarly.

model:

$$Y_{i,c,t} = \beta_0 + \beta_1 \text{Treat}_{i,c} \times \text{Post}_{c,t} \times \text{Firm}_{i,c} + \beta_2 \text{Treat}_{i,c} \times \text{Post}_{c,t} + \text{Controls}_{i,c,t-1} + \gamma_{i,c} + \omega_{c,t} + \epsilon_{i,c,t}, \tag{5}$$

where $\text{Firm}_{i,c}$ denotes a certain firm characteristic. In this case, it is the *Small_Firm*.[11]

Panel A of Table 9 presents the results. In all columns, the estimate of the triple interaction term is negative and significant. It suggests the effects of ease of travel are mainly concentrated in small firms. After the firm city is connected to its nearest financial center through the high-speed train, the improvement in price efficiency for small firms is stronger than that of large firms. These results support our hypothesis and are consistent with the underlying mechanism.

Next, we investigate the role of institutional ownership that can lead to the differential effects of high-speed railway connections on price efficiency. Note that institutional ownership can be directly associated with price efficiency. Institutional investors prefer liquid stocks and these stocks have low transaction costs that facilitate arbitrage trading. Institutional investors may also have superior information about the firms and informed trading can increase price efficiency. Therefore, we include mutual fund ownership in Equation (2) as a proxy to control for the effects of institutional ownership. In addition to these direct effects, the shock to geographic distance can change the behavior of institutional investors in our setting. Ellis et al. (2020) find that introducing direct flights between a fund and a metropolitan statistical area leads to an increase in the fund's aggregate investment in firms in the area. Chen et al. (2021) confirm high-speed railway connections between mutual fund and firm cities increase site visits of fund managers to firms. Because

TABLE 9 Connections to financial centers and price efficiency: Conditional on the characteristics of firms

	(1)	(2)	(3)	(4)
	PEV		|AR20|	
Panel A. Firm size	**Full**	**Matched**	**Full**	**Matched**
Treat × Post × *Small_Firm*	−0.02***	−0.02***	−0.00**	−0.00***
	(−3.75)	(−4.00)	(−2.48)	(−3.29)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Firm × cohort	Yes	Yes	Yes	Yes
N	18,799	9968	18,798	9967
Adj. R^2	0.60	0.60	0.21	0.23
	(1)	(2)	(3)	(4)
	PEV		|AR20|	
Panel B. Mutual fund ownership	**Full**	**Matched**	**Full**	**Matched**
Treat × Post × *Low_MFHD*	−0.01**	−0.01**	−0.00	−0.00
	(−2.29)	(−2.55)	(−0.83)	(−0.75)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Firm × cohort	Yes	Yes	Yes	Yes
N	18,799	9968	18,798	9967
Adj. R^2	0.60	0.60	0.21	0.23
	(1)	(2)	(3)	(4)
	PEV		|AR20|	
Panel C. Analyst coverage	**Full**	**Matched**	**Full**	**Matched**
Treat × Post × *Low_Coverage*	−0.01**	−0.01***	−0.00*	−0.00*
	(−2.87)	(−2.96)	(−1.82)	(−1.77)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Firm × cohort	Yes	Yes	Yes	Yes
N	18,799	9968	18,798	9967
Adj. R^2	0.60	0.60	0.21	0.23
	(1)	(2)	(3)	(4)
	PEV		|AR20|	
Panel D. Short sale	**Full**	**Matched**	**Full**	**Matched**
Treat × Post × *Off_Short*	−0.02***	−0.02***	−0.01***	−0.01***
	(−9.76)	(−10.06)	(−5.59)	(−6.38)
Controls	Yes	Yes	Yes	Yes
Year × cohort	Yes	Yes	Yes	Yes
Firm × cohort	Yes	Yes	Yes	Yes
N	18,799	9968	18,798	9967
Adj. R^2	0.60	0.60	0.21	0.23

(Continues)

TABLE 9 (Continued)

Note: This table presents the results from a series of triple difference type regressions in Equation (5). The dependent variable is pricing error variance (PEV) in Columns (1) and (2) and |AR20| in Columns (3) and (4). |AR20| is the absolute value of the return autocorrelations calculated from the midpoints of the bid–ask spread quotes at nonoverlapping 20-min intervals (|AR20|). The accounting and stock return data are from the China Stock Market & Accounting Research (CSMAR) database. The intraday price quote data are from RESSET. The sample period is from 2008 to 2016. In Panel A, *Small_Firm* is a dummy variable that is equal to 1 if the firm size is below the sample median in the event year of the connection and 0 otherwise. In Panel B, *Low_MFHD* is a dummy variable that is equal to 1 if the size- and time-adjusted mutual fund ownership is below the sample median in the event year of the connection and 0 otherwise. We regress the mutual fund ownership of each firm on the firm size and time dummies and take the residual to avoid grouping stocks by a characteristic that is highly correlated with size. We do the same for analyst coverage mentioned below. In Panel C, *Low_Coverage* is a dummy variable that is equal to 1 if the analyst coverage is below the sample median in the event year of the connection and 0 otherwise. In Panel D, *Off_Short* is a dummy variable that is equal to 1 if the stock is not short sales eligible in the event year of the connection and 0 otherwise. For each new connection, we construct a cohort of the treated and the control firms using firm-year observations for the 2 years before and the 2 years after the connection. In Columns (1) and (3), we use all firm-year observations of the control group that can be included when constructing a cohort. In Columns (2) and (4), we match the treated firms to the control firms based on a number of firm characteristics. Treat is equal to 1 if the city of the firm in the cohort is connected to its nearest financial center by a high-speed railway and 0 otherwise. Post is equal to 1 if the connection is established in a year in the cohort and 0 otherwise. Other variable definitions are in Appendix B. We include year × cohort and firm × cohort fixed effects. Standard errors are clustered at the industry level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

(5) with this indicator variable and report the results in Panel C of Table 9. In all columns, the triple interaction term is negative and significant. When firms are not well covered by financial analysts, the connection between the firm city and the nearest financial center largely improves price efficiency. This supports our conjecture that financial analysts are more likely to visit firms in connected cities resulting in greater information acquisition and production.

Finally, we examine the effects of high-speed railway connections on price efficiency for firms with different short selling status. The CSRC initiated a pilot program on March 31, 2010 by removing a short sales ban on a designated list of firms. The number of short sales eligible firms grew from 90 in the pilot program to about 900 by the end of 2016. The SHSE and SZSE established several requirements for firms to be included on the short sales list, and the list is adjusted each year. Beyond the direct effects that short selling activities have on improving price efficiency (Chang et al., 2014), Meng et al. (2020) find that negative media coverage of a firm increases after it is included on the short sales list. This suggests that short sales eligibility encourages information acquisition and mitigates the effect of geographic distance on price efficiency. Thus, we expect the effect of high-speed railway connections on the improvement in price efficiency should be weaker for firms on the short sales list.

We collect information about short sales status from the CSMAR database. We construct an indicator variable, *Off_Short*, that is equal to 1 if the stock is not short sales eligible in the event year of connection and 0 otherwise. We estimate the triple difference model in Equation (5) with this indicator variable and report the results in Panel D of Table 9. As expected, the interaction term is negative and significant across all four columns. The improvement in price efficiency after a high-speed railway connection is significantly higher for firms that cannot be shorted than firms on the short sales list. These findings support our hypothesis and are consistent with those in Panels A–C of Table 9. When a new mode of transportation alleviates the geographic distance constraint, the effects on price efficiency improvement are concentrated in firms that are more informationally opaque. This further corroborates the mechanism behind our main finding.

5 | CONCLUSION

The literature has long recognized the importance of geographic proximity in economics and finance. However, its role in determining the informational efficiency of stock prices has not received much attention. In this study, we examine how geographic proximity of firms to financial centers affects the efficiency of stock prices. Using the high-speed railway connections between firm cities and the nearest financial center in China as exogenous shocks, we find stock prices of connected firms are more efficiently priced than firms that are not connected. Our findings are consistent with the literature demonstrating that geographic proximity alleviates information asymmetry.

Our results are robust to alternative definitions of price efficiency. Consistent with our hypothesis, the effects of ease of travel on price efficiency are stronger for firms that are closer to their nearest financial center, smaller, have less institutional ownership and financial analyst coverage, and are not on the short sales list. Our study not only identifies geographic location as an important determinant of asset price efficiency, but also highlights the unique role of transportation and infrastructure construction in improving financial markets.

ACKNOWLEDGMENTS

The authors thank Bing Han (Editor), the anonymous reviewer, Kewei Hou, Qinghai Wang, Xiaoran Ni, and seminar participants at Tsinghua University and University of International Business and Economics for helpful comments and suggestions. Qu thanks the National Natural Science Foundation of China (grant ID 72003025) and University of International Business and Economics Outstanding Young Scholar Supporting Program (grant ID 20YQ13) for financial support. Shen thanks the Tsinghua University Initiative Scientific Research Program (grant ID 2019THZWJC17) and National Natural Science Foundation of China (grant ID 71603147) for financial support. All errors are of the authors.

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How to cite this article: Gao H, Qu Y, Shen T. Geographic proximity and price efficiency: Evidence from high-speed railway connections between firms and financial centers. *Financial Management*. 2022;*51*:117–141. https://doi.org/10.1111/fima.12354

APPENDIX A: ESTIMATION OF PRICING ERROR VARIANCE

To estimate the pricing error, we estimate the following vector autoregression system with five lags:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \cdots + b_1 \mathbf{x}_{t-1} + b_2 \mathbf{x}_{t-2} + \cdots + v_{1,t}, \\ x_t &= c_1 \mathbf{x}_{t-1} + c_2 \mathbf{x}_{t-2} + \cdots + d_1 r_{t-1} + d_2 r_{t-2} + \cdots + v_{2,t}, \end{aligned} \tag{A1}$$

where r_t is the difference in prices, p_t, and $\mathbf{x}_t$ is a vector of trade-related variables including a trade sign indicator, signed trading volume, and the signed square root of the trading volume to allow for concavity between prices and trades. $v_{1,t}$ and $v_{2,t}$ are zero mean, serially uncorrelated disturbances. The system Equation (A1) can be inverted to obtain its vector moving average representation that expresses the variables in terms of contemporaneous and lagged disturbances:

c

$$\begin{aligned} r_t &= a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} .. + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} \cdots \\ x_t &= c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} .. + d^* \end{aligned}$$

Name	Description	Definition
SIZE	Firm size	Logarithm of total assets.
ROA	Return on assets	Earnings before interest and taxes scaled by total assets.
LEV	Leverage	Total liability scaled by total assets.
Q	Tobin's *Q*	Market equity plus total book liability minus deferred taxes scaled by total assets.
|Mis|	Mispricing	Based on Bartram and Grinblatt (2018). See Section 4.2 for details.