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Information flows and the law of one price

Rui Fan [a], Oleksandr Talavera [b,*], Vu Tran [c]

[a] School of Economics and Finance, Xi'an Jiaotong University, Xi'an, 710049, China and School of Management, Swansea University, Fabian Way, Swansea SA1 8EN, UK

[b] Birmingham Business School, University of Birmingham, Edgbaston Park Road, Birmingham B15 2TY, UK

[c] ICMA Centre, Henley Business School, University of Reading, Whiteknights, Reading RG6 6BA, UK

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ABSTRACT

This paper explores the role of information flows for the law of one price in an almost frictionless environment. Specifically, we examine whether the volume and content of social media messages are related to the exchange rate pass-through (ERPT) to prices of dual-listed stocks. Our sample includes 37 million tweets mentioning the name of a stock cross-listed in the United Kingdom (UK) and the United States (US) from 2015 to 2018. Using a high-frequency intraday data sample, we observe a negative (positive) link between the ERPT and volume (agreement) of tweets. The findings suggest that large information flows and a high degree of disagreement add extra frictions for the law of one price. In addition, there is an asymmetric pattern of the pass-through, notwithstanding that there are no import/export or geographically-related frictions. This presents further evidence of the importance of information flows in understanding the law of one price.

1. Introduction

Extensive economic literature investigates whether the law of one price, or its weaker version, the purchasing power parity (PPP), holds in practice and how quickly deviations from the law are eliminated (e.g., Campa & Goldberg, 2005; Rogoff, 1996). There are various reasons why the law of one price seldom holds in the real world. Previous literature shows that deviations from the law of one price are time-varying and heterogeneous across countries, with potential causes being price stickiness (e.g., Campa & Goldberg, 2005), exchange rate regime changes (e.g., Takhtamanova, 2010), or home bias in consumption, noise traders and limits to arbitrage (e.g., Itskhoki & Mukhin, 2021). We aim to investigate whether information flows on social networks are related to exchange rate pass-through in the context of multiple-market traded stocks, this being a close-to-ideal laboratory.

Market frictions and geographical factors are among the causes for the law of one price seldom holding in the real world. However, we exploit stocks listed in multiple markets in which these price-setting frictions are minimized. Investors can access information on stock prices and exchange rates with ease. Arbitrage opportunities can be exploited instantly via online trading tools from anywhere in the world. The cost related to trading stocks is also lower compared to trading goods. Buying and selling stocks mainly involves commissions, while trading products requires additional search and transportation costs. There are no producers, importers, or exporters in stock markets, highlighting legitimate reasons why price discrepancies for goods cannot be applied to stocks. This ideal setting provokes expectations of a perfect exchange rate pass-through. However, our empirical evidence shows that the pass-through for dual-listed stocks is still not perfect, although it is significantly higher than for conventional goods. We also find that significant deviations from the law of one price are strongly linked to the volume of social media information.

This paper mainly contributes to the existing exchange rate pass-through literature. Various lines of research have studied the relationship between exchange rate pass-through and the price of traded goods. For example, Campa and Goldberg (2005) show that exchange rate pass-through can be incomplete and can vary for different countries. Imbs, Mumtaz, Ravn, and Rey (2005, 2010) employ micro-level price data and find that pass-through and the speed of price adjustment are larger for more precisely defined goods, with the half-life decreasing to around one year. Itskhoki and Mukhin (2021) present a theoretical model explaining deviations from the law of one price where noise traders and

* Corresponding author.
E-mail address: o.talavera@bham.ac.uk (O. Talavera).

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limits to arbitrage are the main ingredients. Our paper provides empirical evidence for their propositions. A large number of papers have investigated micro data and the exchange rate pass-through to prices and trade.[1] In addition, exchange rate pass-through is documented to be asymmetric for goods (e.g., Brun-Aguerre, Fuertes, & Greenwood-Nimmo, 2017; Bussiere, 2013; Pollard & Coughlin, 2004). Our empirical results also find asymmetric exchange rate pass-through for financial assets. Prior papers examine the relationship between the exchange rate pass-through and the price of goods, but no study exists in which the exchange rate pass-through of dual-listed stock prices is empirically investigated. To the best of our knowledge, this paper is the first to investigate the relationship between social media information and the exchange rate pass-through of cross-listed stock prices and the underlying economic forces.

The data used in this study cover British stocks cross-listed in the UK and the US exchanges from August 2015 to December 2018. The data are from two sources. First, our unique Twitter dataset contains 37 million tweets containing the names of the sampled companies. Second, the intraday and daily stock prices and exchange rates are from Bloomberg. Following previous literature, we estimate the long-run pass-through to examine whether there is any deviation from the law of one price for cross-listed stock prices.[2] An error correction/cointegration model of stock price differences is used to measure the speed of price adjustment to investigate how fast the (dual-listed stock) price discrepancies are eradicated.

The values of pass-through are high, and the speed of the price adjustment of the GBP/USD exchange rate on the UK-US dual-listed stock prices varies, particularly during the 2-h overlapping trading period. The magnitude of the pass-through varies from 89% to 96%. These figures are significantly higher than those for goods, but are still less than perfect. There is a statistically significant and negative relationship between tweet volume and stock price discrepancies, suggesting that a large volume of information flow is associated with extra frictions. We also find positive associations between the agreement measure of tweets and stock price differences. This evidence indicates that higher uncertainty, proxied by a high level of disagreement among social media users, leads to a reduced exchange rate pass-through to prices of cross-listed stocks. Our findings support the theoretical propositions in Itskhoki and Mukhin (2021). An abnormal amount of social media information is linked to high costs of information processing and increased costs of arbitrage. An abnormal volume of social media posts is also associated with a higher degree of noise trader risk.

In addition, we find an asymmetric effect of GBP/USD exchange rate pass-through on the UK-US cross-listed stock price discrepancies, which is consistent with prior literature. However, there are fewer frictions in stock markets than in the market for goods. Specifically, the depreciation of the British pound against the US dollar combined with a higher level of agreement on social media is passed through more strongly than the appreciation of GBP relative to USD when there is higher uncertainty.

This paper connects several strands of literature on multi-market trading, financial market integration, and social media's relationship with stock markets. First, the literature on multi-market trading highlights the critical role of arbitrage in maintaining financial market efficiency (e.g., Foucault, Kozhan, & Tham, 2017). Arbitrageurs play a critical role in enforcing the law of one price and market efficiency while facing significant costs (e.g., Pontiff, 2006). Gagnon and Karolyi (2010) measure arbitrage opportunities by comparing the intraday prices of American Depositary Receipts (ADRs) with synchronous prices of corresponding home-market shares adjusted by foreign exchange rates. Additionally, several studies document that the prices of ADRs and underlying stocks do not violate the law of one price.[3] In contrast, some works find the opposite: financial markets are not fully efficient.[4] We add to this stream of literature by investigating the role of information flows on social networks for the law of one price for dual-listed stocks.

This study also adds additional evidence to the literature on financial market integration. If the law of one price holds, markets where stocks are listed should be integrated. Certain previous studies show that financial markets are, to some degree, integrated (e.g., Kryzanowski & Zhang, 2002; Lowengrub & Melvin, 2002). However, results presented in other papers indicate that capital markets are segmented (e.g., Froot & Dabora, 1999; Hupperets & Menkveld, 2002; Werner & Kleidon, 1996). Hence, the question of market integration/segmentation remains only partially resolved. We contribute to this body of literature by investigating whether the rapid spread of information on social networks is linked to capital market integration and the law of one price. Specifically, our paper suggests that social networks play an essential role in financial market integration. The fast-moving nature and the sheer volume of social media information widens price discrepancies.

Furthermore, our paper connects to the emerging literature on the linkage between social media and financial markets. Some studies examine the relationship between social media features and stock market characteristics. For example, Renault (2017) constructs a lexicon to deduce investor sentiment from messages posted on the microblogging platform, StockTwits, and shows that this can help when forecasting intraday stock index returns. Giannini, Irvine, and Shu (2019) document that around earnings announcements, the convergence of views across tweets is associated with negative abnormal returns, while the divergence of opinions of Twitter posts is related to positive abnormal returns. Shen, Urquhart, and Wang (2019) use the number of tweets from Twitter as a measure of investor attention and find that it drives next day Bitcoin trading volume and realized volatility. Al-Nasseri, Ali, and Tucker (2021) extract the investor sentiment of Dow Jones 30 stocks based on tweets from StockTwits, and examine its ability to predict stock returns using quantile regression.[5] Other research investigates the use of social networks in forming trading strategies. For instance, Sun, Lachanski, and Fabozzi (2016) propose profitable trading strategies using textual information generated from microblogs to forecast S&P 500 stock returns. Cookson and Niessner (2020) find that a disagreement measure used on messages from StockTwits presents a connection with trading. However, to the best of

[1] For example, Rigobon (2020) discusses what online prices can reveal about exchange rate pass-through. Casas (2020) finds an association between the use of imported inputs and the reaction of prices to movement in F/X rates across manufacturing industries using microdata from Colombia. Giuliano and Luttini (2020) document that the majority of Chilean imports are invoiced in USD, and the changes to the exchange rate against USD can explain most of the exchange rate pass-through to border prices in the short run.

[2] See a survey on the related literature by Goldberg and Knetter (1997).

[3] For example, Kato, Linn, and Schallheim (1990) find no significant price differences between the ADRs and the foreign (the UK, Australia and Japan) stocks on which they are based, which supports the law of one price. Alaganar and Bhar (2001) also show that the ADRs of the underlying Australian stocks are priced efficiently and the law of one price holds.

[4] For instance, Suarez (2005) demonstrates that large deviations from the law of one price are found using high frequency French and American stock price data, and argues that these markets are inefficient. Grossmann, Ozuna, and Simpson (2007) investigate 74 ADRs from nine countries and find that ADRs with higher transaction costs and lower dividend payments exhibit larger price discrepancies from the underlying assets during higher interest rate periods.

[5] In addition, Wu, Tiwari, Gozgor, and Huang (2021) and Aharon, Demir, Lau, and Zaremba (2022) find a causal link between the two Twitter-based economic policy uncertainty measures and the returns of four cryptocurrencies. Chatterjee and French (2021) find that Twitter-based market uncertainty predicts stock market returns during the COVID-19 pandemic. Guindy (2021) also shows that discussions on Twitter about COVID-19 correlate with stock market returns.

our knowledge, there is no prior study which examines the association between social media information and dual-listed stocks and the link to the law of one price and financial market integration.

Finally, some literature illustrates that investors are biased regarding the forms of information disclosure.[6] Prior studies document that there are two main views related to the mechanism via which media information can affect stock markets: the information view highlights that public information can make information acquisition easier and reduce information asymmetry (e.g., Bushee, Core, Guay, & Hamm, 2010; Tetlock, 2010), while the salience view says that media coverage attracts investor attention and increases investment demands (e.g., Da, Engelberg, & Gao, 2011; Solomon, Soltes, & Sosyura, 2014). However, certain types of public news, such as social media, can affect investor behaviour by creating excess information. We contribute to the information disclosure literature by documenting that social media information flows may create distortions in relation to the law of one price.

Our results have several implications. First, it is potentially beneficial for investors to monitor abnormal information flows on social networks to exploit informational frictions and deviations from the law of one price. Second, policymakers should have a regulatory code of practice which they could use to enhance transparency and to verify the credibility of information. This would significantly reduce the amount of noise and informational frictions and would enhance market efficiency. Our paper shows that making social media data available is beneficial for academia and for the public. Social media data related to a broader sample of stocks from a wider range of geographical regions would be useful for future investigations and studies.

This paper is organized as follows. Section 2 describes the data and methodology employed in the study. Section 3 explains the empirical estimation methods. Section 4 discusses the empirical results. Section 5 concludes the paper.

2. Data and methodology

2.1. Data

This paper employs the Twitter Streaming application programming interface (API) to gather the Twitter data. API can be considered a messenger between the users and the system of Twitter servers. The messenger passes the queries from the users to the system, and then sends the replies back to the users. In this paper, we make requests to obtain tweets containing a UK and US cross-listed British firm name and then obtain a sample of tweets with the keywords. Each tweet we obtain includes data of the text of the tweet, username and ID, date, and follower counts. A total of 37 million tweets with the name of a UK and US dual-listed company are collected from the three years between 15th August 2015 and 31st December 2018. We obtain 5-min and daily stock prices and exchange rates from Bloomberg. In particular, we centre on 20 UK and US cross-listed British firms, which have a daily average of >100 tweets.[7]

Tweets are cleaned using three steps following Fan, Talavera, and Tran (2020). First, special characters in tweets, for example, link tokens (starting with 'http', 'https', 'www'), hashtag tokens (starting with '#'), and user identifier tokens (starting with '@') are eliminated from the tweets. Second, we delete all tweets with only links or URLs. Finally, we exclude all non-English tweets.

2.2. Aggregation of tweet information

We acknowledge the importance of the sentiment of news and separate the positive and negative tweets. TextBlob, a text-processing tool in Python, is used to obtain a polarity score of the sampled tweet messages.[8] The polarity score of each tweet ranges from −1 to 1. Tweets with negative (positive) scores are categorised as negative (positive) sentiment tweets, while tweets with zero scores are identified as neutral sentiment tweets. We employ PatternAnalyzer and NaiveBayesAnalyzer in TextBlob to conduct a sentiment analysis and obtain the same sentiment score for each tweet posting.[9]

All tweets are aggregated during interval t to explore the relationship between tweet postings and stock price discrepancies at the end of interval t. The time intervals cover every five minutes during the 2-h overlapping period for the intraday investigation, a measure which is widely employed in prior literature. For the daily analysis, we focus on four different time points during a day, i.e. when the London Stock Exchange (LSE) opens and closes and when the New York Stock Exchange (NYSE)/NASDAQ stock market (NASDAQ) opens and closes. Aggregate measures are based on tweets published just before these points. This is done to mitigate any potential reverse causality issues. Following Antweiler and Frank (2004), Sprenger, Tumasjan, Sandner, and Welpe (2014) and Cookson and Niessner (2020), we define the aggregate tweet measures as follows:

$$Positiveness_t = ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right), \quad (1)$$

$$Agreement_t = 1-\sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}, \quad (2)$$

where $M_t^{positive}$ and $M_t^{negative}$ give the counts of positive and negative tweets on day t. $Positiveness_t$ is a sentiment measure as a fraction of positive tweets. $Agreement_t$conveys the extent to which tweets agree with each other, i.e. whether there is an identical or different number of positive and negative tweets. The agreement measure is one if all tweets are positive or negative. Tweet volume is the natural logarithm of the number of tweets with a UK-US dual-listed firm name on day t.

3. Estimation framework

One method commonly used to capture the properties of price differences of cross-listed stocks by economists is to use two measures: pass-through and the speed of price adjustment. Pass-through describes the degree to which changes in nominal exchange rates are translated into changes in the prices of goods (stocks in our case), while the speed of price adjustment shows how quickly the prices move to the equilibrium levels.[10] Adapting the framework found in the study by Gorodnichenko and Talavera (2017), we define an error correction model as follows:

$$\begin{aligned} log\left(\frac{P_{i,t}^{UK}}{P_{i,t}^{US}}\right) &= \alpha FX_t + \beta_1 Positiveness_{i,t}\times FX_t + \beta_2 Message_{i,t}\times FX_t \\ &\quad + \beta_3 Agreement_{i,t}\times FX_t + \delta C_t + \varepsilon_{i,t}, \end{aligned} \quad (3)$$

[6] For example, Hirshleifer and Teoh (2003) find that information disclosures can influence investors' decisions. Barber and Odean (2008) show that the majority of investors have limited attention and are more likely to purchase stocks that attract their attention.

[7] A list of the 20 firms in the sample can be found in Appendix B.

[8] See Loria (2020) for more information about TextBlob.

[9] Fan et al. (2020) find that the correlation between the sentiment score obtained by TextBlob and Renault (2017)'s social media dictionary is 0.7 for their sampled firms, on the condition that the sentiment is found (one or more words are detected as being either positive or negative).

[10] See Goldberg and Knetter (1997) for a review of a general specification of the exchange rate pass-through in the literature.

$$dlog\left(\frac{P^{UK}_{i,t}}{P^{US}_{i,t}}\right) = \beta\left(log\left(\frac{P^{UK}_{i,t-1}}{P^{US}_{i,t-1}}\right) - \left(\alpha + \gamma_1 \times Positiveness_{i,t} + \gamma_2 \times Message_{i,t} + \gamma_3 \times Agreement_{i,t}\right)FX_{t-1}\right) + \eta dlog\left(\frac{P^{UK}_{i,t-1}}{P^{US}_{i,t-1}}\right) + \theta dFX_{t-1} + \delta C_t + \varepsilon_{i,t}, \tag{4}$$

where i stands for firm and t denotes time, $P_{i,\,t}$ denotes the prices of the UK-US dual-listed stocks in LSE and NYSE/NASDAQ, respectively. FX_t is the natural logarithm of the GBP/USD exchange rate at time t.

The main departure from the methodological frameworks that exist in prior papers is that we add interaction terms between exchange rates and social media variables in eqs. (3) and (4). $Positiveness_{i,\,t}$, $Message_{i,\,t}$, and $Agreement_{i,\,t}$ are aggregate tweet features observed during time windows just before the corresponding points of time and are used to estimate the dependent variables. We understand that there are some concerns related to the endogeneity issue, hence we use lagged explanatory variables to partially address the reverse causality. Concerning omitted variables, we use fixed effects to control for unobserved time-invariant heterogeneity, but we also acknowledge time-variant heterogeneity. With regard to mismeasurement, it is not clear whether our measurement error is correlated with the error term. $Positiveness_{i,\,t}$ examines the relationship between sentiment and stock market features. $Message_{i,\,t}$ is calculated as the natural logarithm of the number of tweets. Given that more tweets will bring more frictions to the markets, we expect a negative coefficient of message in explaining stock price discrepancies. $Agreement_{i,\,t}$ measures the degree to which tweets agree with or are different from each other, i.e. similar or a significantly different number of positive against negative tweets. We anticipate a positive coefficient of agreement in explaining stock price differences, because a higher agreement measure indicates similar beliefs about the information in the markets, suggesting higher pass-through values. C_t is a vector of control variables.

The coefficient α is equal to one if the law of one price holds, but practically it is less than one, which indicates minor deviations from the law of one price. Our experiment with cross-listed stocks is an ideal setup in which α value should be close to one, but the information on social networks may create extra frictions, and hence could cause the value of α to be less than one. An error correction/cointegration model is used, where β captures how fast the deviations from the equilibrium disappear. Given that the error terms in eqs. (1) and (2) may be correlated over time, Driscoll and Kraay (1998)'s standard errors are employed. The more negative the value of β, the quicker the speed of price adjustment. $Positiveness_{i,\,t} \times FX_t$, $Message_{i,\,t} \times FX_t$, and $Agreement_{i,\,t} \times FX_t$ are the interaction terms between positiveness, message, agreement, and the pound dollar exchange rate at time t.

LSE opening hours are between 8:00 and 16:30 London time, while NYSE/NASDAQ opens from 9:30 to 16:00 New York time, hence there are two hours which overlap. We exploit this to investigate how tweets posted during this period are linked to the UK-US dual-listed stocks. Moreover, we also focus on the determinants of price discrepancies between the UK stocks and the corresponding ADRs on the same day by examining the relationship between the stock price differences and the aggregate indicators from tweets at four different time points, i.e. when LSE opens, when NYSE/NASDAQ opens, when LSE closes and when NYSE/NASDAQ closes, using similar regression specifications as before.

4. Empirical results

4.1. Summary statistics

A total of 37 million tweets with the name of a UK-US dual-listed company are collected. Table 1 and Table A1 in Appendix A show the descriptive statistics of the market and tweet indicators. The mean number of daily tweets is 1846, while the standard deviation is around 5590 tweets a day. A large number of tweet postings for each company on each day indicates that our data contains a sound information flow. The mean of log UK-US stock price difference is around −0.31, and the standard deviation is around 0.06. This standard deviation is significantly lower than the standard deviation of 0.22 to 0.27 for online prices of electronic goods (Gorodnichenko & Talavera, 2017), but is in line with the standard deviation of 0.09 to 0.11 for price differences within and across countries (Engel & Rogers, 1996). Although the

Table 1
Descriptive statistics – based on intraday data.

	Mean	SD	Q1	Q2	Q3
Price Difference	−0.3079	0.0645	−0.3556	−0.2911	−0.2601
Log(GBP/USD)	−0.3049	0.0647	−0.3532	−0.2840	−0.2573
Price Difference – Log (GBP/USD)	−0.0029	0.0180	−0.0107	−0.0018	0.0015
Message	2.2928	1.0713	1.3863	2.1972	3.0910
Positiveness	0.5936	0.8855	0.0000	0.6931	1.0986
Agreement	0.5871	0.4452	0.0868	1.0000	1.0000

This table reports the summary statistics of all variables using intraday data. Price difference is the (log) difference between the UK price and the US price. Aggregate tweet measures include Positiveness, Message, and Agreement. Message is calculated as the natural logarithm of the number of tweets, Positiveness is $Positiveness_t = ln\left(\frac{1+M^{positive}_t}{1+M^{negative}_t}\right)$, where $M^{positive}_t$ and $M^{negative}_t$ are the number of positive and negative tweets on day t, and Agreement is defined as $Agreement_t = 1 - \sqrt{1-\left(\frac{M^{positive}_t - M^{negative}_t}{M^{positive}_t + M^{negative}_t}\right)^2}$. Number of observations = 160,514.

Table 2
Correlations – based on intraday data.

	Price Difference	Log(GBP/USD)	Message	Positiveness
Log(GBP/USD)	0.9080***			
Message	−0.0736***	−0.1110***		
Positiveness	−0.0342***	−0.0503***	0.4660***	
Agreement	−0.0047	0.0007	−0.5500***	0.1990***

This table displays the correlations between market and tweet features using intraday data. Market features include price difference and log pound dollar exchange rate. Message is the natural logarithm of the number of tweets, Positiveness is given as $Positiveness_t = ln\left(\frac{1+M^{positive}_t}{1+M^{negative}_t}\right)$, where $M^{positive}_t$ and $M^{negative}_t$ are the counts of positive and negative tweets on day t, and Agreement is $Agreement_t = 1 - \sqrt{1-\left(\frac{M^{positive}_t - M^{negative}_t}{M^{positive}_t + M^{negative}_t}\right)^2}$. *, **, *** denotes correlations that are significantly different from 0 at the 5%, 1%, 0.1% significance level, respectively.

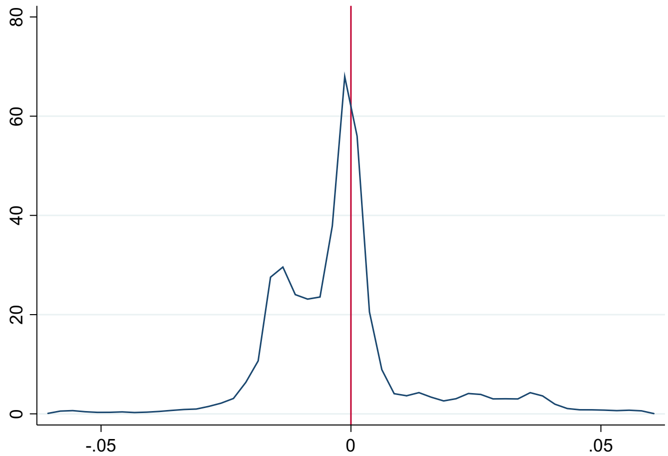

Fig. 1. Kernel density of log price differences.
This figure shows the kernel density of log price differences on the 20 sampled UK-US dual-listed companies from August 2015 to December 2018. The differences between the natural logarithm of UK-US cross-listed stock price discrepancies and log (GBP/USD) exchange rate are close to zero with small deviations.

characteristics of cross-listed stock price discrepancies are, to some extent, similar to those of regular stores and online markets, the scale of the price difference is smaller. This suggests that the frictions in stock markets are smaller, though there are some price discrepancies that cannot be ignored. Correlations between stock market features and tweet features are statistically significant, as shown in Table 2 and Table A2 in Appendix A.

Fig. 1 shows a plot of the kernel density of log price differences on the 20 sampled UK-US cross-listed firms between August 2015 and December 2018. The differences between the natural logarithm of UK-US dual-listed stock price discrepancies and the (log) GBP/USD exchange rate fluctuate around zero. In other words, the raw price discrepancies (i.e. before they are adjusted by exchange rate) are indeed largely driven by exchange rate movement. Interestingly, we find that most quotes are below the median value, suggesting an exchange rate asymmetric effect. When the British pound appreciates against the US dollar, the GBP/USD exchange rate increases. If there is a delayed price-setting process in one of the countries, then we will have negative quotes. Contrastingly, when GBP depreciates against the USD, the pound dollar F/X rate is lower. If there is a large exchange rate pass-through to prices of dual-listed stocks, then there will be positive quotes.

These observations are consistent with prior literature on the asymmetric effect of exchange rate pass-through on goods (e.g., Brun-Aguerre et al., 2017; Bussiere, 2013), which finds that domestic currency depreciation is passed through more strongly than appreciation. The figure suggests that asymmetric exchange rate pass-through exists, although there are fewer frictions in stock markets than in the market for products. Our results are also in line with previous research on market integration. For example, Suarez (2005) studies the price differences between French stocks and their corresponding ADRs using high-frequency data and shows that there are considerable but infrequent deviations from the law of one price. Our paper confirms the conclusions using 5-min UK-US dual-listed stock prices data and finds that these financial markets are segmented and inefficient.

4.2. Twitter and the timeliness of information diffusion

Fixed effects panel regressions for price differences between the UK-US cross-listed stocks in LSE and NYSE/NASDAQ as dependent variables are reported in Table 3. The employed independent variables include the interaction terms between the three tweet features, i.e. the positiveness sentiment measure of tweets, tweet volume, the agreement measure of tweets, and GBP/USD exchange rate. The tweets variables are derived from all tweets with a sampled UK-US dual-listed company name.

We use three different specifications in Table 3, which employ year

Table 3
Pass-through during multiple-trading period.

	(1)	(2)	(3)	(4)
Log(GBP/USD)	0.9605***	0.9640***	0.9648***	0.9647***
	(0.0012)	(0.0016)	(0.0016)	(0.0016)
Log(GBP/USD) x Positiveness		0.0001	0.0001	0.0001
		(0.0003)	(0.0003)	(0.0003)
Log(GBP/USD) x Message		−0.0132***	−0.0131***	−0.0131***
		(0.0004)	(0.0004)	(0.0004)
Log(GBP/USD) x Agreement		0.0050***	0.0051***	0.0051***
		(0.0005)	(0.0005)	(0.0005)
Year Dummies	Yes	Yes	Yes	Yes
Month Dummies	Yes	No	Yes	Yes
Day-of-week Dummies	Yes	No	No	Yes
R^2	0.9245	0.9246	0.9247	0.9247
No. of Obs.	160,514	160,514	160,514	160,514

This table reports the fixed-effects regressions of the UK-US price discrepancies during the multiple-trading period. The dependent variable is (log) price difference $log\left(\frac{P_{i,t}^{UK}}{P_{i,t}^{US}}\right)$ at the end of each 5-min interval. Main independent variables are contemporaneous (log) GBP/USD exchange rate and the interactions between the exchange rate and aggregate tweet measures. Message is calculated as the natural logarithm of the number of tweets, Positiveness is $Positiveness_t = ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day t, and Agreement is defined as $Agreement_t = 1-\sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}$. Tweets are collected during each 5-min interval. Driscoll-Kraay standard errors are in parentheses. *, **, *** denotes 10%, 5%, 1% significance, respectively. The sample uses intraday data of 20 British cross-listed stocks during the period from 15th August 2015 to 31st December 2018.

Table 4
Speed of price adjustment.

	(1)	(2)	(3)	(4)
$\Delta Price_{t-1} - \alpha * Log(GBP/USD)_{t-1}$	−0.0228***			
	(0.0003)			
$\Delta Price_{t-1} - [\alpha+\gamma * Twitter] * Log(GBP/USD)_{t-1}$		−0.0322***	−0.0323***	−0.0323***
		(0.0008)	(0.0008)	(0.0008)
Lagged Return Difference	−0.1548***	−0.1487***	−0.1487***	−0.1487***
	(0.0103)	(0.0108)	(0.0108)	(0.0108)
Lagged ΔLog(GBP/USD)	−0.1003***	−0.0952***	−0.0952***	−0.0952***
	(0.0094)	(0.0097)	(0.0097)	(0.0097)
Year Dummies	Yes	Yes	Yes	Yes
Month Dummies	Yes	No	Yes	Yes
Day-of-week Dummies	Yes	No	No	Yes
R^2	0.0166	0.0159	0.0159	0.0159
No. of Obs.	159,960	159,960	159,960	159,960

This table reports the fixed-effects regressions of the UK-US return difference during the multiple-trading period, i.e. 2-h overlapping period. The dependent variable is the change in price differential at the end of each 5-min interval. Driscoll-Kraay standard errors are in parentheses. *, **, *** denotes 10%, 5%, 1% significance, respectively. The sample uses intraday data of 20 British cross-listed stocks during the period from 15th August 2015 to 31st December 2018.

Table 5
Varying pass-through.

	Price Difference at LSE open		Price Difference at NYSE open		Price Difference at LSE close		Price Difference at NYSE close	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(GBP/USD)	0.8898***	0.8981***	0.9024***	0.9147***	0.9026***	0.9160***	0.8989***	0.9112***
	(0.0091)	(0.0103)	(0.0035)	(0.0060)	(0.0034)	(0.0060)	(0.0088)	(0.0101)
Log(GBP/USD) x Positiveness		0.0003		0.0121		0.0136*		0.0125*
		(0.0018)		(0.0017)		(0.0017)		(0.0016)
Log(GBP/USD) x Message		−0.0246***		−0.0318***		−0.0332***		−0.0314***
		(0.0007)		(0.0006)		(0.0006)		(0.0006)
Log(GBP/USD) x Agreement		0.0321***		0.0198**		0.0175**		0.0195**
		(0.0066)		(0.0066)		(0.0063)		(0.0064)
R^2	0.8068	0.8088	0.8290	0.8308	0.8294	0.8312	0.8227	0.8245
No. of Obs.	14,634	14,634	14,850	14,850	14,899	14,899	15,055	15,055

This table reports the fixed-effects regressions of the UK-US price discrepancies at four different points in time on a trading day. The price difference is measured at LSE open, NYSE open, LSE close, and NYSE close in columns (1) and (2) to (7) and (8), respectively. In columns (1) and (2), the price difference is between the UK price at 8:00 am and the US price at 9:00 pm the previous day, while it is the difference between the UK and US price at 2:30 pm in columns (3) and (4) and at 4:30 pm in columns (5) and (6). In columns (7) and (8), the price difference is between the UK price at 4:30 pm and US price at 9:00 pm. Our time stamp is always the UK local time, which is Greenwich Mean Time (GMT) in the winter and British Summer Time (BST) in the summer. Main independent variables are contemporaneous (log) GBP/USD exchange rate and the interactions between the exchange rate and aggregate tweet measures. Message is calculated as the natural logarithm of the number of tweets, Positiveness is $Positiveness_t = ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day t, and Agreement is defined as $Agreement_t = 1-\sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}$. Tweets are collected before the estimations of the price difference. Year-month-day-of-week effects are controlled for. Driscoll-Kraay standard errors are in parentheses. *, **, *** denotes 10%, 5%, 1% significance, respectively. The sample uses the daily data of 20 British cross-listed stocks during the period from 15th August 2015 to 31st December 2018.

dummies, year and month dummies, and year, month, and day-of-week dummies. All results show that the estimated pass-through value is higher than 96%. These values are much larger than the values (60%–75%) obtained based on prices for goods collected from online markets (Gorodnichenko & Talavera, 2017), and the values (20%–40%) from prices of goods received through regular stores (Campa & Goldberg, 2005). We argue that there may be several potential reasons for the high pass-through values of stocks. First, stock price movement is instantaneous. Second, investors can trade stocks online easily from anywhere in the world. Third, the cost associated with trading is relatively low.

There is a significant positive relationship between the agreement measure and stock price discrepancies. This link suggests that if there is a higher level of agreement about information in the markets, then a larger proportion of the nominal exchange rate movement is translated into stock price difference movement. We also find significant negative correlations of tweet volume with stock price differences. In line with recent evidence (e.g., Cookson & Niessner, 2020), these results support the argument that high levels of tweet traffic and disagreement among social media users motivates trading, this being our conjecture. A large volume of information combined with a high disagreement measure on social networks may create more frictions in the markets. Our results are also similar in nature to Renault (2017), who documents empirical evidence that the messages on investor social media platform, StockTwits, could prompt trading at the intraday level. Our findings are also consistent with prior literature on financial market integration. For example, Froot and Dabora (1999) find discrepancies between stock prices of 'twin' companies listed in different countries' stock exchanges and argue that the frictions in the market could be a potential cause of stock market segmentation. However, they suggest that it is hard to identify the exact source of frictions. While our study demonstrates that information flows on social media could bring the markets more frictions.

The results of estimating the speed of price adjustment using all three different specifications are similar and are reported in Table 4. The obtained β values indicate that the speed of conversion of prices to equilibrium is rapid. Over 3.2% of the gap to the long-term equilibrium is closed during the 5-min interval, which means that deviations from the equilibrium disappear in around 30 intervals or two and a half hours, and this is equivalent to a half-life of around one hour and 15 min. Hence, our estimates of the half-life are much shorter than the half-life of 2.9 quarters for the same goods in regular stores from different countries (Broda & Weinstein, 2008) and shorter than the approximated three to five years for price indexes (Rogoff, 1996). Again, the possible reason for the rapid speed of price adjustment could be that investors can easily compare the prices of dual-listed stocks and can trade instantly from any location.[11]

4.3. Twitter information incorporation when stock markets open/close

The price discrepancies between the UK-US dual-listed British stocks and their corresponding ADRs are examined by checking the correlations between the tweet indicators and the stock price differences at four different times, i.e. when LSE opens and closes and when NYSE/NASDAQ opens and closes. Table 5 reports the regression results for price differences at different time intervals as the dependent variables. As expected, the pass-through values at these times are smaller than during the 2-h overlapping period when both the UK and US stock markets are trading.

There are also some marginal differences across the four periods. Specifically, the pass-through stands at 88.98% before both the UK and US stock markets open and then rises to 90.24% when the UK stock market starts to trade. It increases further to 90.26% when both markets are operating before finally declining to 89.89% when both markets close. These values are all lower than the pass-through value (96.05%) in Table 3, which indicates that the largest amount of exchange rate movement is passed through when information is collected at 5-min intervals during the 2-h overlapping period. The reason for this is that

[11] Moreover, we use the firm-year-month-day clustered standard errors and repeat the regressions of pass-through and the speed of price adjustment. The findings reported in Table A3 and A4 in Appendix A are in line with the main results and support our conclusions.

when both markets open, there is a higher percentage of nominal exchange rate variations incorporated into stock price changes, compared to when one or both countries' markets close.

Consistent with our previous results, the coefficients of the agreement measure are positive and statistically significant, and the coefficients of tweet volume are significantly negative. These findings indicate that a large volume of tweets may be treated as frictions and are associated with lower pass-through. Again, our results are consistent with prior literature in relation to stock trading and social media (e.g., Renault, 2017), in that tweets on social networks may be associated with stock trading. Giannini et al. (2019) also document that agreement in beliefs among social media tweets is associated with lower returns around earnings announcements. This further evidences that the convergence of opinions on social networks is related to stock prices.

4.4. The asymmetric effect of exchange rate

If the market is frictionless and has perfect competition, then the law of one price suggests that all foreign exchange rate changes (appreciation and depreciation) should be incorporated into price changes. However, in the real world, the impact of appreciation and depreciation on pass-through is usually asymmetric. Therefore, we divide our sample into sub-periods, when the pound appreciates and depreciates, and conduct a similar analysis for pass-through.

Specifically, we follow Koutmos and Martin (2003) to separate GBP/USD exchange rates into two parts, i.e. when the pound appreciates against the dollar and when GBP depreciates against USD.[12] We define FX_t^- and FX_t^+ as pound-dollar exchange rates when there are negative and positive changes, respectively, and we denote the following regression:

$$log\left(\frac{P_{i,t}^{UK}}{P_{i,t}^{US}}\right) = \alpha + \zeta^- FX_t^- + \zeta^+ FX_t^+ + \delta C_t + \varepsilon_{i,t}. \quad (5)$$

The null hypothesis says that the effect of exchange rate is symmetric, i.e. $H_0 : \zeta^- = \zeta^+$, while the alternative hypothesis states that the F/X rate exposure is asymmetric and $H_1 : \zeta^- \neq \zeta^+$. Rearranging eq. (5), we get

$$log\left(\frac{P_{i,t}^{UK}}{P_{i,t}^{US}}\right) = \alpha + (\beta_0 + \beta_D D_t) FX_t + \delta C_t + \varepsilon_{i,t}, \quad (6)$$

where $\beta_0 = \zeta^+$ and $\beta_D = \zeta^+ - \zeta^-$. When the pound appreciates against the dollar, i.e. $\Delta FX_t > 0$, dummy $D_t = 0$, and the impact of the exchange rate is β_0. When GBP depreciates against USD, i.e. $\Delta FX_t < 0$, dummy $D_t = 1$, and the effect of F/X rate is equal to $\beta_0 + \beta_D$. Therefore, eq. (6) provides a clearer explanation for the exchange rate asymmetry hypothesis. Equivalently, the hypothesis on asymmetry tests that β_D is statistically significantly different from zero.

There are two theories about the asymmetric effect of exchange rate on pass-through. On the one hand, the capacity constraints theory says that exporter companies often operate at full capacity and cannot manage an increasing demand if the importer country's currency appreciates. Exporters could choose to keep the price and increase their mark-ups to gain more profit, consistent with sticky prices modelling. Depreciation of domestic currency can lead to higher pass-through than appreciation. When a domestic currency depreciates, foreign exporters usually increase the price to keep the margin constant in order to prevent a loss. However, this usually happens when a domestic country is more import-dependent. Exporters have some pricing power, and there is imperfect competition between exporters for the products. On the other hand, the market share theory states that exporter firms reduce the price when the importer country's currency appreciates in order to increase the market share and pass through appreciation (Krugman, 1986).

The empirical evidence on this is mixed. For example, Pollard and Coughlin (2004) find the asymmetric effect of dollar appreciation and depreciation on 30 US industries, but the direction of asymmetry varies. On the contrary, Bussiere (2013) states that domestic currency depreciation is passed through more strongly than appreciation for G7 countries' economies between 1980 and 2006. Brun-Aguerre et al. (2017) also document that home country currency depreciation leads to higher pass-through than appreciation for 33 emerging and developed economies from 1980 to 2010.

However, no obvious producers, importers, or exporters exist in stock markets, thus, some explanations applicable to price discrepancies for products may not work on stocks. Table 6 shows that the estimate of β_D, which stands for the coefficient of pound depreciation against the dollar, is positive and statistically significant. Therefore, we conclude that there is an asymmetric effect of GBP/USD exchange rate pass-through on the UK-US cross-listed stock price differences, despite the fact that stock markets have fewer frictions than the market for goods. Moreover, there is a statistically significant coefficient of the interaction term between pound dollar exchange rate depreciation dummy and agreement. This evidence suggests that the depreciation of GBP against USD when there is a higher agreement measure of tweets is passed through more strongly than the appreciation of the British pound relative to the US dollar combined with lower agreement among tweets.

Table 6
Pass-through when British pound appreciates/depreciates against US dollar.

	(1)	(2)
	Price Difference	Price Difference
Log(GBP/USD)	0.9735***	0.9785***
	(0.0015)	(0.0018)
Log(GBP/USD) Negative	0.0027***	−0.0022
	(0.0003)	(0.0011)
Log(GBP/USD) x Positiveness		0.0011
		(0.0003)
Log(GBP/USD) Negative x Positiveness		−0.0013
		(0.0004)
Log(GBP/USD) x Message		−0.0146***
		(0.0004)
Log(GBP/USD) Negative x Message		0.0033
		(0.0004)
Log(GBP/USD) x Agreement		0.0026**
		(0.0005)
Log(GBP/USD) Negative x Agreement		0.0060***
		(0.0006)
R^2	0.9248	0.9250
No. of Obs.	160,514	160,514

This table reports the fixed-effects regressions of the UK-US price difference during the multiple-trading period, i.e. 2-h overlapping period. The regression equation used is $log\left(\frac{P_{i,t}^{UK}}{P_{i,t}^{US}}\right) = \alpha + (\beta_0 + \beta_D D_t) FX_t + \delta C_t + \varepsilon_{i,t}$. The dependent variable is price difference at the end of each 5-min interval. The main independent variables are (log) exchange rates, dummy for GBP depreciation against USD, and interaction terms with tweets aggregate features. Message is calculated as the natural logarithm of the number of tweets, Positiveness is $Positiveness_t = ln\left(\frac{1 + M_t^{positive}}{1 + M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day t, and Agreement is defined as $Agreement_t = 1 - \sqrt{1 - \left(\frac{M_t^{positive} - M_t^{negative}}{M_t^{positive} + M_t^{negative}}\right)^2}$. Control variables include year, month, day-of-week effects. Driscoll-Kraay standard errors are in parentheses. *, **, *** denotes 10%, 5%, 1% significance, respectively. The sample uses intraday data of 20 British cross-listed stocks during the period from 15th August 2015 to 31st December 2018.

[12] See Jorion (1990) and Choi and Prasad (1995) for the standard way to formulate the regression equation in the literature.

5. Conclusions

Various literature has examined whether the law of one price can hold in the real world and studies have found different types of frictions (e.g., search costs, distributions costs, etc.) that violate the law of one price. Stock markets possess certain characteristics, i.e. lower search and transportation costs compared to the market for goods. This gives us a new mode for examining whether the law of one price can be established in this almost frictionless environment. The recent rise of social media usage has also supplied a new opportunity to investigate its association with stock markets (e.g., Cookson & Niessner, 2020; Renault, 2017). In this study, we explore whether information flows on social media are associated with exchange rate pass-through in the context of multiple-market traded stocks. This unique setting offers a new angle for us to uncover the economic forces behind the influence of Twitter information, dual-listed stocks, and financial market integration.

There is a statistically significant negative association between tweet volume and stock price differences, indicating that a high volume of tweets may be regarded as frictions. There is a positive relationship between the agreement among tweets and stock price discrepancies, which suggests that more uncertainty in the market is linked to a reduced exchange rate pass-through to prices of dual-listed stocks. The values of pass-through and the speed of price adjustment of pound dollar F/X rate on the UK-US cross-listed stock price discrepancies are large, and the estimates of pass-through vary over time when NYSE/NASDAQ opens and closes, and are greater when one or both countries' markets open. There is also the asymmetric effect of GBP/USD exchange rate pass-through on the UK-US dual-listed stock price differences, and the depreciation of GBP against USD is passed through to a greater extent than the appreciation of the British pound relative to the US dollar.

Collectively, our results show that social media information flows are related to exchange-rate pass-through in the context of multiple-market traded stocks, a close-to-ideal environment, and the law of one price does not hold. Our paper provides several important implications. First, attention should be given to informational frictions in future research on the law of one price and its deviations. Second, the study highlights the transparency of information and the potential monitoring role of regulators on social networks. This would significantly reduce the amount of noise and informational frictions. Further to this, policymakers should use these findings to increase the social media literacy of the public in order to mitigate the potential impact of false information on social networks. Additionally, the evidence has practical implications for investors and arbitrageurs who can exploit these deviations by carefully embedding social media information into their investment strategies. Finally, these findings also suggest that social media data should be made publicly available. There will be ample new research opportunities for academics and practitioners stemming from social media networks, which may support policymakers in their decision making and help to bring benefits to the general public.

There are several potential directions for future work. First, further research on investment strategies incorporating this new source of data could be beneficial for investors. Additionally, further research may also cover a wider geographical area and cross-listed stocks from different pairs of countries could be examined. Examples include the US and Canada, New Zealand and Australia, and the UK and other European countries, as the time difference is less and there is a closer geographical relationship between the two countries in the pairs. Finally, further research could also extend to investigate other social network platforms, such as StockTwits and Facebook.

Disclosure statement

We have no interests to disclose in connection with this research.

Appendix A

Table A1
Descriptive statistics – based on daily data

	Mean	SD	Q1	Q2	Q3
Panel A: Daily data at LSE open (No. of observations = 14,634)					
Price Difference	−0.3082	0.0712	−0.3558	−0.2910	−0.2585
Log(GBP/USD)	−0.3033	0.0641	−0.3508	−0.2835	−0.2570
Price Difference – Log(GBPUSD)	−0.0049	0.0324	−0.0123	−0.0028	0.0046
Message	5.4881	2.0123	3.9318	5.3327	7.0926
Positiveness	0.9004	0.9840	0.3610	0.9226	1.4788
Agreement	0.2698	0.3161	0.0501	0.1458	0.3386
Panel B: Daily data at NYSE open (No. of observations = 14,850)					
Price Difference	−0.3084	0.0702	−0.3557	−0.2905	−0.2596
Log(GBP/USD)	−0.3032	0.0639	−0.3510	−0.2830	−0.2574
Price Difference – Log(GBPUSD)	−0.0052	0.0302	−0.0121	−0.0025	0.0015
Message	5.8778	1.9718	4.3438	5.7301	7.4248
Positiveness	0.9510	0.9643	0.4055	0.9808	1.5159
Agreement	0.2415	0.2813	0.0501	0.1411	0.3043
Panel C: Daily data at LSE close (No. of observations = 14,899)					
Price Difference	−0.3084	0.0702	−0.3556	−0.2904	−0.2595
Log(GBP/USD)	−0.3031	0.0639	−0.3511	−0.2830	−0.2571
Price Difference – Log(GBPUSD)	−0.0053	0.0302	−0.0121	−0.0024	0.0014
Message	5.9842	1.9669	4.4543	5.8435	7.5332
Positiveness	0.9595	0.9549	0.4055	0.9901	1.5088
Agreement	0.2341	0.2723	0.0500	0.1391	0.3001
Panel D: Daily data at NYSE close (No. of observations = 15,055)					
Price Difference	−0.3080	0.0707	−0.3561	−0.2905	−0.2587
Log(GBP/USD)	−0.3029	0.0640	−0.3520	−0.2823	−0.2569
Price Difference – Log(GBPUSD)	−0.0051	0.0309	−0.0126	−0.0033	0.0039
Message	5.9821	1.9669	4.4427	5.8435	7.5310
Positiveness	0.9579	0.9545	0.4055	0.9876	1.5044
Agreement	0.2339	0.2724	0.0492	0.1391	0.3001

This table reports the summary statistics of all variables using daily data. Price difference is the (log) difference between the UK price and the US price. Aggregate tweet measures include Positiveness, Message, and Agreement. Message is calculated as the natural logarithm of the number of tweets, Positiveness is $Positiveness_t = ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day t, and Agreement is defined as $Agreement_t = 1-\sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}$.

Table A2
Correlations - based on daily data.

	Price Difference	Log(GBP/USD)	Message	Positiveness
Log(GBP/USD)	0.8970***			
Message	−0.1810***	−0.2240***		
Positiveness	−0.0946***	−0.0941***	0.3480***	
Agreement	−0.0142	0.0304***	−0.3790***	0.5010***

This table displays correlations between market and tweet features using daily data. Market features include price difference and log pound dollar exchange rate. Message is the natural logarithm of the number of tweets, Positiveness is given as $Positiveness_t = ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the counts of positive and negative tweets on day t, and Agreement is $Agreement_t = 1-\sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}$. *, **, *** denotes correlations that are significantly different from 0 at the 5%, 1%, 0.1% significance level, respectively.

Table A3
Pass-through during multiple-trading periods (Firm-year-month-day clustered errors)

	(1)	(2)	(3)	(4)
	Price Difference	Price Difference	Price Difference	Price Difference
Log(GBP/USD)	0.9605***	0.9640***	0.9648***	0.9647***
	(0.0048)	(0.0051)	(0.0051)	(0.0051)
Log(GBP/USD) x Positiveness		0.0001	0.0001	0.0001
		(0.0005)	(0.0005)	(0.0005)
Log(GBP/USD) x Message		−0.0132**	−0.0131**	−0.0131**
		(0.0011)	(0.0011)	(0.0011)
Log(GBP/USD) x Agreement		0.0050***	0.0051***	0.0051***
		(0.0008)	(0.0008)	(0.0007)
Year Dummies	Yes	Yes	Yes	Yes
Month Dummies	Yes	No	Yes	Yes
Day-of-week Dummies	Yes	No	No	Yes
R^2	0.9245	0.9246	0.9247	0.9247
No. of Obs.	160,514	160,514	160,514	160,514

This table reports the fixed-effects regressions of the UK-US price discrepancies during the multiple-trading period. The dependent variable is (log) price difference at the end of each 5-min interval. The main independent variables are contemporaneous (log) GBP/USD exchange rate and the interactions between the exchange rate and aggregate tweet measures. Message is calculated as the natural logarithm of the number of tweets, Positiveness is $Positiveness_t = ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day t, and Agreement is defined as $Agreement_t = 1-\sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}$. Tweets are collected during each 5-min interval. Firm-year-month-day-of-week clustered standard errors are in parentheses. *, **, *** denotes 10%, 5%, 1% significance, respectively. The sample uses intraday data of 20 British cross-listed stocks during the period from 15th August 2015 to 31st December 2018.

Table A4
Speed of price adjustment (Firm-year-month-day clustered errors)

	(1)	(2)	(3)	(4)
	Return Difference	Return Difference	Return Difference	Return Difference
$\Delta Price_{t-1} - \alpha^*Log(GBP/USD)_{t-1}$	−0.0227***			
	(0.0003)			
$\Delta Price_{t-1} - [\alpha+\gamma^*Twitter]^* Log(GBP/USD)_{t-1}$		−0.0322***	−0.0323***	−0.0323***
		(0.0008)	(0.0008)	(0.0008)
Lagged Return Difference	−0.1548***	−0.1487***	−0.1487***	−0.1487***
	(0.0121)	(0.0127)	(0.0127)	(0.0127)
Lagged ΔLog(GBP/USD)	−0.1003***	−0.0952***	−0.0952***	−0.0952***
	(0.0106)	(0.0109)	(0.0109)	(0.0109)
Year Dummies	Yes	Yes	Yes	Yes
Month Dummies	Yes	No	Yes	Yes

(continued on next page)

Table A4 (*continued*)

	(1)	(2)	(3)	(4)
	Return Difference	Return Difference	Return Difference	Return Difference
Day-of-week Dummies	Yes	No	No	Yes
R^2	0.0166	0.0159	0.0159	0.0159
No. of Obs.	159,960	159,960	159,960	159,960

This table reports the fixed-effects regressions of the UK-US return difference during the multiple-trading period, i.e. 2-h overlapping period. The dependent variable is return difference (i.e. the first derivative of price difference) at the end of each 5-min interval. The main independent variable is the lagged difference between the UK-US price difference and a product of (log) GBP/USD exchange rate and its coefficients estimated from eq. (1). Firm-year-month-day-of-week clustered standard errors are in parentheses. *, **, *** denotes 10%, 5%, 1% significance, respectively. The sample uses intraday data of 20 British cross-listed stocks during the period from 15th August 2015 to 31st December 2018.

Appendix B: Sampled companies

This table lists the names of the firms in the sample.

	Firm name		Firm name
1	AstraZeneca	11	Intercontinental Hotels
2	Barclays	12	Lloyds
3	BHP Billiton	13	National Grid
4	British American Tobacco	14	Pearson
5	British Petroleum	15	Prudential
6	BT Group	16	Rio Tinto
7	Carnival	17	Royal Bank of Scotland
8	Diageo	18	Royal Dutch Shell
9	GlaxoSmithKline	19	Unilever
10	HSBC	20	Vodafone

References

Aharon, D. Y., Demir, E., Lau, C. K. M., & Zaremba, A. (2022). Twitter-based uncertainty and cryptocurrency returns. *Research in International Business and Finance, 59*, Article 101546.

Alaganar, V. T., & Bhar, R. (2001). Diversification gains from American depositary receipts and foreign equities: Evidence from Australian stocks. *Journal of International Financial Markets Institutions and Money, 11*(1), 97–113.

Al-Nasseri, A., Ali, F. M., & Tucker, A. (2021). Investor sentiment and the dispersion of stock returns: Evidence based on the social network of investors. *International Review of Financial Analysis, 78*, Article 101910.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance, 59*(3), 1259–1294.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behaviour of individual and institutional investors. *Review of Financial Studies, 21*(2), 785–818.

Broda, C., & Weinstein, D. E. (2008). Understanding international price differences using barcode data. *NBER working paper, 14017*.

Brun-Aguerre, R., Fuertes, A.-M., & Greenwood-Nimmo, M. (2017). Heads I win; tails you lose: Asymmetry in exchange rate pass-through into import prices. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 180*(2), 587–612.

Bushee, B. J., Core, J. E., Guay, W., & Hamm, S. J. W. (2010). The role of the business press as an information intermediary. *Journal of Accounting Research, 48*(1), 1–19.

Bussiere, M. (2013). Exchange rate pass-through to trade prices: The role of nonlinearities and asymmetries. *Oxford Bulletin of Economics and Statistics, 75*(5), 731–758.

Campa, J. M., & Goldberg, L. S. (2005). Exchange rate pass-through into import prices. *Review of Economics and Statistics, 87*(4), 679–690.

Casas, C. (2020). Industry heterogeneity and exchange rate pass-through. *Journal of International Money and Finance, 106*, Article 102182.

Chatterjee, U., & French, J. J. (2021). A note on tweeting and equity markets before and during the Covid-19 pandemic. *Finance Research Letters, 102224*.

Choi, J. J., & Prasad, A. M. (1995). Exchange risk sensitivity and its determinants: A firm and industry analysis of U.S. multinationals. *Financial Management, 24*(3), 77–88.

Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. *Journal of Finance, 75*(1), 173–228.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance, 66*(5), 1461–1499.

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics, 80*(4), 549–560.

Engel, C., & Rogers, J. H. (1996). How wide is the border? *American Economic Review, 86*(5), 1112–1125.

Fan, R., Talavera, O., & Tran, V. (2020). Social media bots and stock markets. *European Financial Management, 26*(3), 753–777.

Foucault, T., Kozhan, R., & Tham, W. W. (2017). Toxic arbitrage. *Review of Financial Studies, 30*(4), 1053–1094.

Froot, K. A., & Dabora, E. M. (1999). How are stock prices affected by the location of trade? *Journal of Financial Economics, 53*(2), 189–216.

Gagnon, L., & Karolyi, G. A. (2010). Multi-market trading and arbitrage. *Journal of Financial Economics, 97*(1), 53–80.

Giannini, R., Irvine, P., & Shu, T. (2019). The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets, 42*, 94–120.

Giuliano, F., & Luttini, E. (2020). Import prices and invoice currency: Evidence from Chile. *Journal of International Money and Finance, 106*, Article 102183.

Goldberg, P. K., & Knetter, M. M. (1997). Goods prices and exchange rates: What have we learned? *Journal of Economic Literature, 35*(3), 1243–1272.

Gorodnichenko, Y., & Talavera, O. (2017). Price setting in online markets: Basic facts, international comparisons, and cross-border integration. *American Economic Review, 107*(1), 249–282.

Grossmann, A., Ozuna, T., & Simpson, M. W. (2007). ADR mispricing: Do costly arbitrage and consumer sentiment explain the price deviation? *Journal of International Financial Markets Institutions and Money, 17*(4), 361–371.

Guindy, M. A. (2021). Fear and hope in financial social networks: Evidence from COVID-19. *Finance Research Letters, 102271*.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics, 36*(1–3), 337–386.

Hupperets, E. C. J., & Menkveld, A. J. (2002). Intraday analysis of market integration: Dutch blue chips traded in Amsterdam and New York. *Journal of Financial Markets, 5*(1), 57–82.

Imbs, J. M., Mumtaz, H., Ravn, M. O., & Rey, H. (2005). PPP strikes back: Aggregation and the real exchange rate. *Quarterly Journal of Economics, 120*(1), 1–43.

Imbs, J. M., Mumtaz, H., Ravn, M. O., & Rey, H. (2010). One TV, one price? *Scandinavian Journal of Economics, 112*(4), 753–781.

Itskhoki, O., & Mukhin, D. (2021). Exchange rate disconnect in general equilibrium. *Journal of Political Economy, 129*(8), 2183–2232.

Jorion, P. (1990). The exchange-rate exposure of U.S. multinationals. *Journal of Business, 63*(3), 331–345.

Kato, K., Linn, S., & Schallheim, J. (1990). Are there arbitrage opportunities in the market for American depositary receipts. *Journal of International Financial Markets Institutions and Money, 1*(1), 73–89.

Koutmos, G., & Martin, A. D. (2003). Asymmetric exchange rate exposure: Theory and evidence. *Journal of International Money and Finance, 22*(3), 365–383.

Krugman, P. (1986). *Pricing to market when the exchange rate changes. NBER working paper 1926*.

Kryzanowski, L., & Zhang, H. (2002). Intraday market price integration for shares cross-listed internationally. *Journal of Financial and Quantitative Analysis, 37*(2), 243–269.

Loria, S. (2020). TextBlob documentation (online) Available at: https://media.readthedocs.org/pdf/textblob/dev/textblob.pdf (Accessed 8 October 2020).

Lowengrub, P., & Melvin, M. (2002). Before and after international cross-listing: An intraday examination of volume and volatility. *Journal of International Financial Markets Institutions and Money, 12*(2), 139–155.

Pollard, P. S., & Coughlin, C. C. (2004). *Size matters: Asymmetric exchange rate pass-through at the industry level. Working paper*,. Federal Reserve Bank of St. Louis.

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics, 42*(1–2), 35–52.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the U.S. stock market. *Journal of Banking and Finance, 84*, 25–40.

Rigobon, R. (2020). What online prices teach us about exchange rate pass-through? *Journal of International Money and Finance, 106*, Article 102179.

Rogoff, K. (1996). The purchasing power parity puzzle. *Journal of Economic Literature, 34* (2), 647–668.

Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict bitcoin? *Economics Letters, 174*, 118–122.

Solomon, D. H., Soltes, E., & Sosyura, D. (2014). Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics, 113*(1), 53–72.

Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. *European Financial Management, 20*(5), 926–957.

Suarez, E. D. (2005). Arbitrage opportunities in the depositary receipts market: Myth or reality? *Journal of International Financial Markets Institutions and Money, 15*(5), 469–480.

Sun, A., Lachanski, M., & Fabozzi, F. J. (2016). Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction. *International Review of Financial Analysis, 48*, 272–281.

Takhtamanova, Y. F. (2010). Understanding changes in exchange rate pass-through. *Journal of Macroeconomics, 32*(4), 1118–1130.

Tetlock, P. C. (2010). Does public financial news resolve asymmetric information? *Review of Financial Studies, 23*(9), 3520–3557.

Werner, I. M., & Kleidon, A. W. (1996). U.K. and U.S. trading of British cross-listed stocks: An intraday analysis of market integration. *Review of Financial Studies, 9*(2), 619–664.

Wu, W., Tiwari, A. K., Gozgor, G., & Huang, L. (2021). Does economic policy uncertainty affect cryptocurrency markets? Evidence from twitter-based uncertainty measures. *Research in International Business and Finance, 58*, Article 101478.