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CALIFORNIA INSTITUTE OF TECHNOLOGY

PASADENA, CALIFORNIA 91125

The Propagation of Shocks Across International Equity Markets: A Microstructure Perspective

Richard Roll
California Institute of Technology

Dion Bongaerts, Dominik Rösch, Mathijs van Dijk, Darya Yuferova
Erasmus University

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Dion Bongaerts, Richard Roll, Dominik Rösch, Mathijs van Dijk, and Darya Yuferova*

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Abstract

We study the high-frequency propagation of shocks across international equity markets. We identify intraday shocks to stock prices, liquidity, and trading activity for 12 equity markets around the world based on non-parametric jump statistics at the 5-minute frequency from 1996 to 2011. Shocks to prices are prevalent and large, with regular spillovers across markets – even within the same 5-minute interval. We find that price shocks are predominantly driven by information rather than liquidity. Consistent with the information channel, price shocks do not revert and often occur around macroeconomic news announcements. Liquidity shocks tend to be isolated events that are neither associated with price shocks nor with liquidity shocks on other markets. Our results challenge the widespread view that liquidity plays an important role in the origination and propagation of financial market shocks.

*Bongaerts, Rösch, van Dijk, and Yuferova are at the Rotterdam School of Management, Erasmus University; Roll is at the California Institute of Technology. E-mail addresses: dbongaerts@rsm.nl, rroll@caltech.edu, drosch@rsm.nl, madijk@rsm.nl, and dyuferova@rsm.nl. We are grateful to Yakov Amihud, Torben Andersen, Joachim Grammig, Charles-Albert Lehalle, Francis Longstaff, Albert Menkveld, Asani Sarkar, Ramabhadran Thirumalai, Michel van der Wel, Christian Voight, Avi Wohl, seminar participants at Erasmus University, and conference participants at the 5th Emerging Markets Finance Conference in Bombay, the 2014 Extreme Events in Finance conference in Royaumont, the 8th Financial Risks International Forum in Paris, the 2014 German Finance Association meeting in Karlsruhe, and the 2014 INFER workshop in Bordeaux for helpful comments. We thank Michel van der Wel for sharing the U.S. macro news announcements data. Van Dijk gratefully acknowledges financial support from the Vereniging Trustfonds Erasmus Universiteit Rotterdam and from the Netherlands Organisation for Scientific Research through a "Vidi" grant. This work was carried out on the National e-infrastructure with the support of SURF Foundation. We thank OneMarket Data for the use of their OneTick software.

1. Introduction

Since at least the stock market crash of October 1987, investors, policy makers, and researchers have been interested in whether and how shocks to one financial market spread to other markets. The Mexican, Asian, and LTCM crises in the 1990s were accompanied by the emergence of a large literature on international financial market linkages and financial contagion. The recent global financial crisis has further highlighted how shocks to certain financial markets can rapidly spread to markets for other asset classes and to markets in other countries. Yet, the channels through which financial market shocks originate and propagate across markets are not well understood.[1]

A growing body of theoretical research points at an important role for market liquidity. In particular, recent theories feature "sudden liquidity dry-ups," "liquidity crashes," or "liquidity black holes" that arise through channels related to the supply of and/or demand for liquidity; in turn, these liquidity shocks induce shocks to security prices and spillovers to other markets.[2] Prominent accounts of the recent crisis (e.g., Brunnermeier, 2008; Brunnermeier, Crockett, Goodhart, Persaud, and Shin, 2009; Gorton, 2009a,b) emphasize the importance of these liquidity channels, but direct empirical evidence is limited.

In this paper, we aim to test the relevance of the liquidity channel for the origination and propagation of financial market shocks by taking a microstructure perspective. Specifically, we analyze why shocks to equity prices occur and whether and how they spread across markets by investigating their relation with shocks to market liquidity and trading activity, using microstructure data for 12 developed and emerging equity markets around the world over the period 1996-2011. To the best of our knowledge, we are the first to study cross-market

[1]See, among others, Eun and Shim (1989), Roll (1989), Hamao, Masulis, and Ng (1990), and Lin, Engle, and Ito (1994) for early research on the propagation of financial market shocks; Reinhart and Calvo (1996), Forbes and Rigobon (2002), Bae, Karolyi, and Stulz (2003), and Hartmann, Straetmans, and de Vries (2004) for studies on contagion; Karolyi (2003) for a literature review; and Longstaff (2010) and Bekaert, Ehrmann, Fratzscher, and Mehl (2014) for analyses of the propagation of shocks across, respectively, markets for different asset classes and international equity markets during the recent crisis.

[2]Recent theoretical studies on such liquidity channels include Kyle and Xiong (2001), Gromb and Vayanos (2002), Kodres and Pritsker (2002), Bernardo and Welch (2004), Morris and Shin (2004), Yuan (2005); Gârleanu and Pedersen (2007), Pasquariello (2007), Andrade, Chang, and Seasholes (2008), Brunnermeier and Pedersen (2009), Huang and Wang (2009), and Cespa and Foucault (2014).

linkages of stock prices jointly with liquidity and trading activity.[3] Our main alternative hypothesis to the liquidity explanation is that shocks are driven by information; i.e., shocks to prices may reflect economic news that could also be relevant for securities traded on other markets (e.g., King and Wadhwani, 1990).

Our microstructure perspective also involves analyzing the origination and propagation of shocks at a much higher frequency than prior work: 5-minute intervals within the trading day. Most studies to date study the interconnectedness of financial markets at the daily or even lower frequency (e.g., Bae, Karolyi, and Stulz, 2003; Hartmann, Straetmans, and de Vries, 2004; Longstaff, 2010; Bekaert, Ehrmann, Fratzscher, and Mehl, 2014; Pukthuanthong and Roll, 2015). However, a relatively low-frequency approach could miss spillovers at higher frequencies and fail to uncover patterns in liquidity and/or trading activity that could help to explain the occurrence and propagation of shocks to prices within and across markets.[4] We note that for developed markets in recent years, the 5-minute frequency might no longer be perceived as high-frequency. But for emerging markets and for our full sample period 1996-2011, this seems a reasonable frequency to ensure sufficient trading in each interval as well as sufficient time for shocks to propagate to other markets.

Using global tick-by-tick trade and quote data from the Thomson Reuters Tick History (TRTH) database, we construct time-series at the 5-minute frequency of market-wide stock returns (based on midquotes), liquidity (quoted and effective spreads), and trading activity (turnover and order imbalance) for 12 equity markets over the period 1996-2011. We include both developed and emerging equity markets within three regions: America (Brazil, Canada, Mexico, and the U.S.), Asia (Hong Kong, India, Japan, and Malaysia), and Europe/Africa

[3]Several papers examine co-movement in liquidity within and across equity markets (e.g., Chordia, Roll, and Subrahmanyam, 2000; Brockman, Chung, and Pérignon, 2009; Zhang, Cai, and Cheung, 2009; Karolyi, Lee, and van Dijk, 2012) and co-movement in the turnover of individual U.S. stocks (e.g., Lo and Wang, 2000 and Cremers and Mei, 2007), but none of these papers also studies stock price linkages.

[4]Some prior work does study intraday spillover effects of returns and/or volatility across markets (e.g., Hamao, Masulis, and Ng, 1990; King and Wadhwani, 1990; Lin, Engle, and Ito, 1994; Susmel and Engle, 1994; Ramchand and Susmel, 1998; Connolly and Wang, 2003), but these studies generally measure returns and/or volatility over intervals of 15 minutes or one hour, look at a more limited sample of markets, and do not consider these variables jointly with liquidity and/or trading activity.

(France, Germany, South Africa, and the U.K.).

We identify shocks to prices, liquidity, and trading activity in each country using the jump measure of Barndorff-Nielsen and Shephard (2006), which is a statistical non-parametric method to test for jumps in a time-series. We propose a refinement of their method so that we are not only able to infer whether a jump occurred on a certain day, but also in which exact 5-minute interval. This approach allows us to create time-series of jumps in prices, liquidity, and trading activity at the 5-minute frequency for each equity market over the period 1996-2011 (based on data on over 5 billion transactions in total).

We first study the origination of shocks on the 12 equity markets in our sample. We find that 5-minute jumps in prices, quoted spreads, and order imbalance are frequent, while jumps in effective spreads and turnover are rare for most markets. The magnitudes of typical jumps in prices, quoted spreads, and order imbalance are large, at around 4 to 6 jump-free standard deviations.

We find little evidence that jumps in prices are accompanied by jumps in liquidity, as measured by quoted spreads. This constitutes initial evidence that liquidity may not play a central role in the origination of price jumps. We do find a relation between jumps in prices and jumps in trading activity, as measured by order imbalance. Around 20% of the jumps in prices in our sample are accompanied by jumps in order imbalance on the same day, which is far more than expected if jumps in prices and order imbalance were independent. Close to 8% of price jumps happen simultaneously with order imbalance jumps in the same 5-minute interval, and almost all of these involve jumps in prices and order imbalance of the same sign. This finding could be an indication that at least some of the price jumps are driven by temporary price pressure effects (i.e., a liquidity demand channel), but could also be consistent with speculative trading around or portfolio rebalancing in response to the arrival of news (i.e., an information channel).

We carry out two specific tests to distinguish the liquidity and information hypotheses. First, we investigate whether there are reversals after jumps in prices (and after simultaneous jumps in prices and order imbalance). We find that, whether accompanied by jumps in order imbalance or not, price jumps represent sudden and permanent shocks to prices; there is no evidence of subsequent price reversals. Second, we examine whether jumps in prices (and simultaneous jumps in prices and order imbalance) occur around macroeconomic news announcements stemming from one of the countries in our sample. We find that a substantial fraction of the jumps in prices (and of the simultaneous jumps in prices and order imbalance) occur around such announcements. For example, in developed Europe, almost 40% of the jumps in prices and around 50% of the simultaneous jumps in prices and order imbalance happen within one hour after a macroeconomic news announcement.[5] The evidence that price jumps do not revert and often occur around macroeconomic news announcements is most consistent with the information channel.

We then investigate within-region and across-region spillover effects of jumps in prices, quoted spreads, and order imbalance. We document significant spillover effects at the 5-minute frequency for jumps in prices as well as for jumps in trading activity, based on correlations of the time-series of jumps in prices and order imbalance, taking into account the magnitude of the jump. These correlations are especially strong within Europe and between Europe and the U.S. However, jumps in quoted spreads are not correlated across different markets, which suggests that liquidity shocks do not propagate across markets and "sudden liquidity dry-ups" are mainly local phenomena.

We further estimate logit regressions with the jumps in prices on a particular market as the dependent variable to distinguish between same-country, within-region, and across-region spillover effects of jumps in prices and order imbalance. This analysis confirms our findings based on the correlations and furthermore provides evidence of the existence of spillover effects between jumps in prices and order imbalance not only within the same country but also within and across regions.

Overall, this paper finds little empirical support for theories in which liquidity plays a key role in the origination and propagation of financial market shocks. Jumps in equity

[5]These fractions are lower for other countries, primarily because U.S. macroeconomic news announcements yield the strongest results, and the most important U.S. announcements (e.g., GDP, nonfarm payroll employment) fall outside of the opening hours of the American and Asian markets.

prices are prevalent and large, and regularly coincide with jumps in order imbalance and with price jumps in other markets. However, price jumps do not revert and often happen around macroeconomic news announcements. Jumps in quoted spreads tend to be isolated events that are neither associated with jumps in prices nor with jumps in quoted spreads on other markets.

Of course, there are limitations to our analysis. Our focus is on the high-frequency origination and propagation of financial market shocks, so we may miss lower-frequency shocks to prices, liquidity, and trading activity. Nevertheless, our results also hold at the 15-minute and 1-hour frequencies (instead of the 5-minute frequency). Our evidence based on intraday data seems to at least challenge the widely held view that financial market liquidity can suddenly evaporate and thereby cause precipitous price drops and spillover effects to other markets. In fact, by analyzing shocks at relatively high frequencies, we stack the cards in favor of finding supportive evidence of a liquidity channel, since our approach allows us to identify price jumps that revert within the day, which lower frequency analyses might miss. Notwithstanding, our results indicate that sudden price shocks are predominantly driven by information.

Also, our liquidity measures are limited to quoted and effective spreads, which may not cover all relevant aspects of market liquidity. However, price impact measures estimated at the 5-minute frequency are extremely noisy and may be mechanically related to price changes. We do obtain similar results using a liquidity measure based on the number of stocks trading in an interval. In separate tests, we also find little evidence that shocks to a variety of proxies for funding liquidity (a potential liquidity supply channel) are associated with a relatively greater prevalence of jumps in prices, liquidity, or trading activity. Furthermore, it is hard to imagine that a true liquidity crash would not show up in quoted spreads.

Our primary contribution is to the literature on international financial market linkages and financial contagion. We add to this line of research by analyzing such linkages across international equity markets at the 5-minute frequency, and by offering a detailed analysis of the dynamics of liquidity and trading activity around shocks to equity prices. We thereby investigate the prediction of a number of recent theoretical studies that channels related to the supply of and/or demand for market liquidity play an important role in the propagation of financial market shocks. Moreover, we contribute to the literature on commonality in liquidity and trading activity by studying the degree of cross-market co-movement in large, sudden changes in liquidity and trading activity.

We believe that our paper sheds new light on a number of important issues. In today's complex, dynamic, and interconnected global financial system, it is important for investors, exchanges, and regulators to understand whether and how shocks are propagated from one financial market to another at high speed, what the role of liquidity and trading activity is in the occurrence and propagation of shocks to prices, and how strong cross-market linkages are within and across different regions. Our results may help investors to make better decisions regarding optimal portfolio diversification, financial institutions to develop better risk management policies, and exchange officials and regulators to develop better policies to reduce international financial fragility.

2. Data and methods

This section describes the data, variable definitions, and methods used in the paper. We obtain intraday data on trades and quotes (and their respective sizes) from the Thomson Reuters Tick History (TRTH) database. TRTH is provided by Securities Industry Research Centre of Asia-Pacific (SIRCA) and includes tick-by-tick data for trades and best bid-offer quotes stamped to the millisecond. The database is organized by Reuters Instrumental Codes (RICs), spans different asset classes, and covers more than 400 exchanges since 1996.[6]

To obtain a sample that is representative of global equity markets but still manageable in light of the vast size of the global tick-by-tick data, we pick four countries (with different levels of development) from each of three regions classified based on their time zone: America,

[6] Recent papers that use the TRTH database include Boehmer, Fong, and Wu (2012), Lau, Ng, and Zhang (2012), Marshall, Nguyen, and Visaltanachoti (2012), Marshall, Nguyen, and Visaltanachoti (2013a,b), Boehmer, Fong, and Wu (2014), Fong, Holden, and Trzcinka (2014), Frino, Mollica, and Zhou (2014), Lai, Ng, and Zhang (2014), and Rösch, Subrahmanyam, and van Dijk (2015).

Asia, and Europe/Africa.[7] In particular, we select Brazil, Canada, Mexico, and the U.S. from the American region; Hong Kong, India, Japan, and Malaysia from the Asian region; and France, Germany, South Africa, and the U.K. from the European/African region. We obtain the RICs for all common stocks that are traded on the major stock exchange (defined as the exchange that handles the majority of trading volume) in each of these countries from Datastream and then collect the RICs for all of these stocks that were part of the main local market index at some point during the sample period from 1996 till 2011 from the TRTH Speedguide (see Appendix A.1). Following Rösch, Subrahmanyam, and van Dijk (2015), we apply extensive data filters to deal with outliers and trades and quotes outside of the daily trading hours (details are in Appendix A.2).

2.1. Variable definitions

Our primary goal is to provide a microstructure perspective on the propagation of shocks across international equity markets and to test the liquidity vs. information explanations for why such shocks occur and spillover to other markets. Therefore, we focus on intraday data for returns, liquidity, and trading activity at the market-level. Specifically, we choose 5-minute intervals as our unit of observation, which seems to be a reasonable compromise between intervals that are sufficiently fine-grained to study the high-frequency propagation of price shocks and their relation to liquidity and trading activity on the one hand, and intervals that have enough trades to adequately measure trading activity and effective spreads (especially in the beginning of our sample period and for the emerging markets in our sample) and that are long enough to capture spillovers to other markets on the other hand. Our choice of 5-minute intervals is also motivated by Tauchen and Zhou (2011), who use the same frequency to analyze jumps in the S&P500 index (1986-2005), 10-year Treasury bonds (1991-2005) and the dollar/yen exchange rate (1997-2004). We discard overnight changes in prices, liquidity, and trading activity. In supplementary tests, we rerun all of our analyses at the 15-minute and 1-hour frequencies.

[7] We note that even within these regions there are small differences in time zones and trading hours.

We first measure variables at the individual stock-level and then aggregate to the market-level. Following Chordia, Roll, and Subrahmanyam (2008), log returns are computed over 5-minute intervals based on midpoints between the quoted bid and ask prices (rather than based on the trade prices or on midquotes matched with the last trade in the interval) of individual stocks. Using midquote returns has two advantages. First, it avoids the bid-ask bounce problem that is inherent in returns based on trade prices. Second, it ensures that returns for every stock are computed over the same 5-minute interval despite differences in trading frequency across stocks.

We use proportional quoted spreads and proportional effective spreads ($PQSPR$ and $PESPR$) as measures of liquidity. While the former measures transaction costs only if the trade does not exceed the depth at the best bid-offer (BBO), the latter measures the actual transaction costs when a trade takes place. We compute $PQSPR$ based on quote data only, for the last BBO available for a given stock in a particular 5-minute interval. For $PESPR$, we first match trade and quote data and then compute the effective spread based on the last trade within a particular 5-minute interval as the difference between the trade price and the prevailing midquote. $PESPR$ is thus only available for 5-minute intervals with at least one trade. This restriction is not very onerous as in total there are more than 5 billion trades in our sample. We stay away from estimating price impact measures at the 5-minute frequency, since they tend to be very noisy and may be mechanically related to price changes. As a further test, we redo all of our analyses based on the number of stocks trading in a specific interval as an alternative market-wide liquidity measure. Motivated by the emerging literature on the link between market liquidity and funding liquidity (e.g., Brunnermeier and Pedersen, 2009), we also examine whether shocks to various measures of funding liquidity are associated with shocks to prices, liquidity, and trading activity.

We use turnover and order imbalance (OIB) to measure trading activity. We compute turnover as the total trading volume (in local currency) of a stock during the 5-minute interval, and scale this number by the aggregate market capitalization at the end of the previous year. To compute OIB, we need to determine whether a trade is buyer- or seller-initiated. We use the Lee and Ready (1991) algorithm to sign trades. We then compute the OIB of a given stock as the difference between buyer- and seller-initiated trading volume (in local currency) during the 5-minute interval, scaled by the aggregate market capitalization at the end of the previous year. We obtain data on aggregate market capitalization (in USD) and exchange rates from the World Bank website.

We aggregate our five main variables (returns, quoted and effective spreads, turnover, and order imbalance) to the market-level by taking an equally-weighted average of the stock-level variables for returns and spreads, and by summing up the scaled stock-level variables for turnover and order imbalance. To reduce the impact of stock-level noise and to secure a certain level of representativeness, we discard 5-minute intervals for a given market when there are fewer than ten stocks with a trade.

2.2. Jump measure (BNS)

There is a vast literature that studies spillover effects from one market to another as well as a plethora of different methods. For example, Bae, Karolyi, and Stulz (2003) define "coexceedances" as the simultaneous incidence of extreme returns (identified as those in the top or bottom 5% of the return distribution by country over the whole sample period) and model the determinants of such coexceedances using multinomial logit models. Hartmann, Straetmans, and de Vries (2004) use extreme value theory to show that the actual probability of a simultaneous crash on two markets is much higher than the expected probability under the assumption that extreme events are independent across markets. Chiang, Jeon, and Li (2007) use a dynamic conditional correlation (DCC) model, while Rodriguez (2007) employs a switching copula approach to document spillover effects.

In this paper, we follow Pukthuanthong and Roll (2015) and use a statistical jump measure to identify a shock.[8] Advantages of this method are that it adheres closely to the intuitive view of a shock to financial markets as a discontinuous event in an otherwise continuous time-series, that it does not require arbitrary definitions of extreme events, and that it is easy to compute

[8]Various jump measures include those devised by Barndorff-Nielsen and Shephard (2006), Jiang and Oomen (2008), Lee and Mykland (2008), and Jacod and Todorov (2009).

and does not require the estimation of a large number of parameters. Furthermore, it can pinpoint the particular interval when the shock occurs and it can detect both country-specific shocks and shocks that are transmitted to other markets, without a need to make assumptions regarding the joint distribution of variables across multiple markets. Potential disadvantages are that on days with many observations in the tail of the full-sample distribution, it may not classify observations as jumps that could be regarded as extreme under different methods and, similarly, it may not identify "clumps" (series of changes in the variables of interest that may accumulate to a large change but do not constitute discontinuous jumps). To mitigate the latter concern, we also measure jumps at the 15-minute and 1-hour frequencies.

In this paper, we use the jump measure proposed by Barndorff-Nielsen and Shephard (2006) [BNS] which is based on the ratio of scaled bipower (continuous) variation to squared variation and which is "by far the most developed and widely applied of the different [jump] methods" (Bollerslev, Law, and Tauchen, 2008, p. 239) and the best jump measure in the simulations of Pukthuanthong and Roll (2015). The squared variation is obtained by summing up the squared 5-minute observations during a day, while the bipower variation is based on the scaled summation of the products of the absolute values of the current and lagged 5-minute observations. The bipower and squared variations on a particular day are similar in the absence of jumps, while the bipower variation is significantly smaller than the squared variation if the time-series has a jump on that day.

Under the null hypothesis of no jumps, the BNS measure follows a standard normal distribution, so statistical significance can be determined based on standard normal critical values. Since the time-series of jumps in prices, liquidity, and trading activity form the inputs of our subsequent analyses, the usual tradeoff between type I and type II errors is especially relevant in our setting. In particular, we are concerned about incorrectly classifying "normal" observations as jumps. To limit the type I error, we use a 0.1% significance level (instead of the common 10%, 5%, or 1% thresholds). Our time-series based on 5-minute intraday intervals over 1996-2011 contain sufficient observations (up to around 370,000) to still have the potential to detect a substantial number of jumps based on this strict statistical criterion.

For each day, we can thus identify whether there was a jump in any of these variables on any market. A drawback of the standard application of the BNS method is that it cannot pinpoint the exact 5-minute interval when the jump occurs. We thus propose a refinement of the BNS approach in the form of an algorithm that allows us to infer the exact interval in which the jump occurs. In short, for each day with a significant jump statistic for a certain variable, we identify the 5-minute return interval with the observation that has the greatest effect on the jump statistic and is greater in absolute terms than 1.96 jump-free standard deviations (i.e., the square root of the scaled bipower variation for that variable on that day). We classify such observations as jumps. It turns out that on all days in our sample for which the BNS statistic is significant, there is at least one such observation. Subsequently, we remove it from the time-series of that variable on that day and again test for the occurrence of a jump on that day, repeating the procedure until no further jumps are detected. Appendix B presents a more detailed description of this algorithm.[9]

3. Empirical results

This section first presents summary statistics for the returns, liquidity, and trading activity at the market-level (Section 3.1), followed by summary statistics of the BNS jump measures for each of these variables (Section 3.2). Subsequently, we investigate the link between jumps in prices, liquidity, and trading activity within each market (Section 3.3) and whether any such link is driven by liquidity or information (Section 3.4). Then, we study the propagation of shocks to prices, liquidity, and trading activity across equity markets within the same region and also across regions, for the same variable and across different variables (Section 3.5). We conclude this section with a discussion of a number of supplementary tests (Section 3.6).

[9]We thank Torben Andersen for his advice on this approach.

3.1. Summary statistics

Table 1 shows the mean and the standard deviation of the 5-minute equally-weighted market returns, equally-weighted proportional quoted spreads ($PQSPR$) and effective spreads ($PESPR$), aggregate market turnover, and aggregate market order imbalance scaled by aggregate market capitalization (OIB) for each of the 12 markets.

Averaged across the 12 markets in our sample, the mean 5-minute return equals -0.1 basis points per 5-minute interval, with an average standard deviation of around 10 basis points. Average returns are slightly negative for 9 out of 12 countries, primarily because we include the recent crisis in our sample period and exclude overnight returns (Berkman, Koch, Tuttle, and Zhang (2012) show that intraday returns tend to be lower than overnight returns). The average mean $PQSPR$ ($PESPR$) across markets is equal to 0.49% (0.36%), with an average standard deviation of 0.34% (0.24%). As a comparison, Chordia, Roll, and Subrahmanyam (2011) report an average $PESPR$ of 0.0223% for NYSE stocks over 2001-2008, which is of roughly the same order of magnitude as the number of 0.088% reported for the U.S. in Table 1, especially when taking into account that spreads were considerably higher over the period 1996-2000. Averaged across markets, scaled turnover (OIB) is equal to 0.19 (0.003) basis points, with a standard deviation of 0.17 (0.08) basis points.

The final row of Table 1 shows the number of 5-minute intervals for which the various variables can be computed for each market; this number varies across markets according to the sample period available in TRTH, the opening hours, and the intensity of trading activity (since we discard 5-minute intervals during which fewer than ten stocks are traded). The average number of 5-minute intervals across all markets is 236,775. We transform the stock variables $PQSPR$ and $PESPR$ to a flow variable by taking 5-minute log-changes (in line with Pukthuanthong and Roll (2015), who compute shocks to prices based on the return series). We also take log-changes of turnover to construct a variable with a mean close to zero. We then compute the daily BNS jump measure for the five key variables of interest and use the algorithm described in Appendix B to identify the exact 5-minute interval when a jump occurs in case the daily BNS statistic is statistically significant.

3.2. Frequency and magnitude of jumps in prices, liquidity, and trading activity

Panel A of Table 2 shows the total number of 5-minute intervals with jumps across variables and markets. Positive ("POS") and negative ("NEG") jumps are reported separately. We observe a substantial number of jumps in prices, $PQSPR$, and OIB. Averaged across all 12 markets, there are 196 (210) positive (negative) jumps in prices; 117 (65) positive (negative) jumps in $PQSPR$; and 256 (242) positive (negative) jumps in OIB. Jumps in these variables occur much more often than under the no jumps assumption. We reject the null hypothesis of no jumps if the BNS statistic for a particular day is below the 0.1% percentile of the standard normal distribution (one-sided test). Thus, the type I error (erroneously rejecting the null hypothesis of no jumps) is 0.1% of the total number of days in our sample. Put differently, over the entire 1996-2011 sample period we would expect to see four days being classified as days with jumps under the null hypothesis of no jumps. However, the numbers of jumps in prices, $PQSPR$, and OIB are much higher. For example, in Germany there are 205 5-minute intervals with a negative jump in prices, which occur on 178 different days (compared to four days under the null hypothesis) or approximately 5.1% (compared to 0.1% under the null hypothesis) of all 3,523 trading days from 1999 to 2011 for which jumps could be estimated for Germany. The finding that jumps in prices, $PQSPR$, and OIB occur much more frequently than under the no jumps assumption is obtained for all markets in the sample. While positive and negative jumps in prices and order imbalance are equally likely, we identify almost twice as many positive as negative jumps in $PQSPR$. Intuitively, sudden evaporations of liquidity are more common than sudden liquidity improvements.

Jumps in $PESPR$ and turnover are considerably less prevalent than jumps in prices, $PQSPR$, and OIB. In fact, $PESPR$ (11 positive and 7 negative jumps on average across markets) and turnover (14 positive and 19 negative jumps on average across markets) almost never jump. With the notable exceptions of $PESPR$ for Japan and turnover for India, the number of days on which we identify jumps in $PESPR$ and turnover is only slightly greater than the type I error of our test. A potential explanation for the low number of jumps in $PESPR$ (as compared to jumps in $PQSPR$) is that $PESPR$ can only be measured when a trade occurs; rational investors observing a jump in quoted spreads could abandon the market and return when liquidity improves. Based on the results in Panel A of Table 2, we exclude the time-series of jumps in $PESPR$ and turnover from the remainder of our analyses.

Although these empirical patterns of jumps in the different variables are overall quite similar across markets, there is also considerable cross-market variation in the number of jumps for individual variables. For example, the number of positive (negative) 5-minute jumps in prices varies from 19 to 500 (from 39 to 637) across different markets; the number of positive (negative) jumps in $PQSPR$ varies from 6 to 278 (from 7 to 154); and the number of positive (negative) jumps in OIB varies from 54 to 590 (from 25 to 560). There is no clear pattern across developed and emerging markets. In unreported analyses (available from the authors), we also study the time-series development of the number of jumps by country and by variable and find little evidence of consistent patterns (e.g., trends or clustering).[10]

The jumps documented in Panel A of Table 2 are all statistically significant at a very high confidence level. However, market participants not only care about the frequency and statistical significance of shocks to financial markets, but also about their economic magnitude. Therefore, in Panel B of Table 2, we present summary statistics (means and standard deviations) of the magnitudes of the 5-minute market-wide jumps in prices, $PQSPR$, and OIB. To obtain a consistent measure of the magnitude of jumps across the different variables and markets, we assess the magnitude in terms of the number of "jump-free standard deviations" or the square root of the scaled bipower variation (since the bipower variation measures the variation of the continuous, i.e., non-jump, part of the process only).

It is clear from Panel B of Table 2 that the magnitudes of the jumps in prices, $PQSPR$, and OIB we detect using the BNS approach are large for all markets in the sample. The average jump magnitude for both negative and positive jumps in prices, $PQSPR$, and OIB is around five jump-free standard deviations, with a range in absolute terms from 3.85 (neg-

[10]We also find only limited evidence that jumps in prices, liquidity, and trading activity cluster during a trading day on a specific market. For example, averaged across the 12 markets, 89% of the days with a significant BNS statistic for the time-series of aggregate equity prices have only one price jump, 9% have two price jumps, and 2% have three or more price jumps.

ative $PQSPR$ jumps in Hong Kong) to 7.61 (negative $PQSPR$ jumps in France) jump-free standard deviations.[11]

For jumps in prices, five jump-free standard deviations correspond to a 5-minute market-wide shock to equity prices of around 40 basis points, which signifies an economically large market-wide price shock over such a short interval (40 basis points is 400 times greater than the absolute value of the average 5-minute market return across markets). Jumps in $PQSPR$ of five jump-free standard deviations amount to a market-wide shock to quoted spreads of 42%, which is 83 times greater than the absolute value of the average 5-minute change in market-wide quoted spreads.

The results in Table 2 thus indicate that jumps in prices, $PQSPR$, and OIB are prevalent and large. In the next subsection, we examine the relation between jumps in prices, liquidity, and trading activity within each market.

3.3. Coinciding jumps in prices, liquidity, and trading activity within a market

Recent theoretical studies (referenced in footnote 2) suggest an important role for channels related to the supply of and/or demand for liquidity in the origination and propagation of price shocks. A common thread in these theories is that shocks to prices are accompanied by shocks to liquidity and/or trading activity. For example, price shocks can arise because financial intermediaries reduce the supply of liquidity in the face of funding constraints (e.g., Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009) or because of a surge in the demand for liquidity when wealth effects, loss limits, or hedging desires induce traders to sell (e.g., Kyle and Xiong, 2001; Morris and Shin, 2004; Andrade, Chang, and Seasholes, 2008). In several of these models, feedback loops (e.g., “liquidity black holes” or “liquidity spirals”) can arise in which deteriorating market liquidity, tightening funding constraints, and selling reinforce each other, causing the decline in liquidity and prices to worsen over time.

[11] The theoretical probability of observing a five standard deviation shock to a normally distributed variable is 0.006 basis points. This probability corresponds to one 5-minute interval out of 1,744,277, or one 5-minute interval every 96 years (assuming six-hour trading days and 252 trading days per year). In other words, the observed frequency of such substantial shocks is much higher than the expected frequency under the assumption of normally distributed variables.

As a first assessment of the importance of the liquidity channel for the origination and propagation of price shocks, we are therefore interested in whether price shocks tend to be accompanied by shocks to liquidity and/or trading activity.

We start by documenting the links among jumps in the different variables within each market. To that end, we treat a jump in prices (or in one of the other variables) as an event and examine whether there are jumps in liquidity and/or trading activity at the same time as the event (i.e., in the same 5-minute interval), before the event (from the beginning of the same trading day – or from the previous price jump on the same day – until the event), or after the event (from the event until the end of the same trading day – or until the next price jump on the same day). We refer to co-jumps on the same day as "coinciding" and to co-jumps in the same 5-minute interval as "simultaneous."

The results are in Table 3. Panels A and B assess whether price jumps (the event) are accompanied by jumps in, respectively, $PQSPR$ and OIB on the same market on the same day. Panel C assesses whether OIB jumps (the event) are accompanied by jumps in $PQSPR$ on the same market on the same day. The first two columns of each panel show the signs of the jumps in the variables under consideration. For example, in Panel A, the first column shows the sign of the price jump events ("POS" or "NEG"). The first two rows of Panel A show the number of positive or negative price jumps that are *not* associated with a jump in $PQSPR$ on the same market on the same day. The next four rows show the number of positive or negative price jumps that are accompanied by a "simultaneous" positive or negative jump in $PQSPR$ on the same market. The following four rows show the number of positive or negative price jumps that were preceded by a positive or negative jump in $PQSPR$ on the same market on the same day. The final four rows show the number of positive or negative price jumps that were followed by a positive or negative jump in $PQSPR$ on the same market on the same day. The structure of Panels B and C is the same.[12]

[12]We note that the sum of the numbers of price jumps in the columns of Panel A of Table 3 sometimes slightly exceeds the total number of price jumps for the respective market reported in Table 2 in case some price jumps are accompanied by more than one jump in $PQSPR$ on the same day. The fractions of coinciding jumps reported in this subsection are corrected for any such double counting.

Panel A of Table 3 shows no consistent pattern in the coincidence of jumps in prices and jumps in $PQSPR$. Very few price jumps are accompanied by jumps in $PQSPR$, either in the same 5-minute interval or before or after the price jump on the same trading day. And even for markets for which prices and proportional quoted spreads regularly jump on the same day (such as Japan), there is no consistent pattern in the direction of the jumps. As an example, although all of the 19 $PQSPR$ jumps in Japan that accompany a negative price jump in the same 5-minute interval are of positive sign (in line with the prediction of the liquidity hypothesis that a price decline is associated with a sudden deterioration in liquidity), we also observe that 13 of the 16 $PQSPR$ jumps in Japan that accompany a positive price jump in the same 5-minute interval are positive, which is hard to reconcile with a liquidity story. Only 6.9% of all price jumps in the sample are accompanied by a jump in $PQSPR$ on the same day, and this fraction drops to 2.2% for the same 5-minute interval. Moreover, only about half of the coinciding jumps in prices and $PQSPR$ are of opposite sign, as predicted by the liquidity hypothesis.[13]

Panel B of Table 3 shows a considerably stronger relation between jumps in prices and jumps in OIB. Not only do we observe a greater incidence of coinciding jumps in prices and OIB, these coinciding jumps also more often have the sign predicted by price pressure effects (a liquidity demand channel). In particular, Panel B shows that positive (negative) jumps in prices are regularly associated with positive (negative) jumps in OIB, especially when prices and OIB jump in the same 5-minute interval (as indicated by the higher numbers in the first and the last rows of the "Simultaneous jumps" section in Panel B). Across the whole sample, 19.3% of the jumps in prices are accompanied by a jump in OIB on the same day. Approximately 8% of all price jumps in the sample are accompanied by an OIB jump in the same 5-minute interval, and almost all of these involve same-sign jumps. The finding of regular co-jumps in prices and OIB of the same sign is consistent with the view that prices jump in part because of sudden shifts in the demand for liquidity, but it could also arise as

[13]This finding contrasts the results of Jiang, Lo, and Verdelhan (2011), who show that market liquidity shocks have significant predictive power for jumps in U.S. Treasury-bond prices.

a result of speculative trading around or portfolio rebalancing in response to the arrival of new information.

Panel C of Table 3 shows that the pattern of coincidences of jumps in $PQSPR$ and jumps in OIB is about as weak as in Panel A. In short, there is little evidence that jumps in OIB are related to jumps in $PQSPR$. Only 5.1% (0.28%) of the OIB jumps are accompanied by a $PQSPR$ jump on the same day (in the same 5-minute interval).

Overall, the results in Table 3 indicate that a non-trivial fraction of the 5-minute jumps in prices are accompanied by same-sign jumps in order imbalance, even within the same 5-minute interval. We find little evidence of such links between jumps in prices and jumps in $PQSPR$ and between jumps in $PQSPR$ and jumps in OIB.

To fully understand the strength of the relation between jumps in prices and jumps in OIB, we need to examine how likely simultaneous jumps in these variables are given the total number of jumps in prices and OIB. As an example, in Germany 28 out of the 205 negative price jumps are accompanied by jumps in OIB of the same sign in the same 5-minute interval. Put differently, approximately 14% of the negative jumps in prices on the German equity market are accompanied by a simultaneous negative jump in OIB. We need a metric to judge whether 14% is abnormally high relative to the benchmark where jumps in prices and jumps in OIB are completely independent. To construct such a metric, we conduct a statistical test to compare the empirically observed frequency of simultaneous jumps in prices and OIB to the theoretical frequency that we would observe if jumps in prices and OIB were independent. The test is based on the comparison of two binomial distributions. The first distribution has a probability of success equal to the empirically observed frequency of simultaneous jumps in prices and OIB. The second distribution has a probability of success equal to the theoretical frequency of such simultaneous jumps under the assumption of independence. We test whether these two probabilities are the same, against the alternative hypothesis that the empirical probability is greater than the theoretical probability.

Table 4 shows the number of simultaneous jumps in prices and OIB in the same 5-minute interval by market, as well as the associated empirical probability of simultaneous jumps, the theoretical probability of simultaneous jumps under the independence assumption, and a one-sided p-value of the binomial test described above. For example, for Germany the empirical probability of a jump in prices equals 11.36 basis points and of a jump in OIB equals 14.55 basis points (based on Table 2). Thus, under the assumption that jumps in prices and OIB are independent, the probability of observing a simultaneous jump in prices and OIB in the same 5-minute interval is 0.02 basis points (11.36 basis points $\times$ 14.55 basis points). However, Table 3 shows that simultaneous jumps in prices and OIB are observed in 59 5-minute intervals, which corresponds to an empirical probability of simultaneous jumps of 1.83 basis points. The final row of Table 4 shows that the p-value of the test that the empirical probability of simultaneous jumps (1.83 basis points) is equal to the theoretical probability (0.02 basis points) is <0.001, which implies a clear rejection of the null hypothesis that jumps in prices and OIB on the German equity market are independent.

For all countries except South Africa, we reject the null hypotheses that jumps in prices occur independently from jumps in OIB at the 1% level or better. On some markets (Brazil and Mexico), the number of simultaneous jumps in prices and OIB is quite small, but on many other markets we document frequent simultaneous jumps in prices and OIB in the same 5-minute interval (most notably Japan, with 100 such cases). In other words, a significant fraction of price jumps is associated with simultaneous jumps in OIB, which suggests that studying such co-jumps can help us to understand why price jumps occur.

The evidence in this subsection suggests that price jumps occur independently of $PQSPR$ jumps, but not of OIB jumps. Although we thus find little support for the main prediction of the liquidity hypothesis that shocks to prices are accompanied by shocks to liquidity, the finding that a subset (around 8%) of price jumps occur simultaneously with OIB jumps could be consistent with a liquidity demand channel at least for this subset of price jumps. In the next subsection, we present two specific tests of the predictions of the liquidity and information hypotheses.

3.4. Jumps in prices and OIB: Liquidity vs. information

The liquidity and information hypotheses offer competing explanations for why price jumps occur, and why they occur simultaneously with jumps in order imbalance. On the one hand, jumps in prices can occur as the result of the price pressure associated with large one-directional uninformed order flow when markets are less than perfectly resilient. On the other hand, a sudden and permanent price adjustment can occur as a result of new information arriving on the market that may also give rise to market-wide order imbalances – for example due to speculative trading or large-scale portfolio rebalancing. (We note that given the fact that many co-jumps in prices and OIB occur within the same 5-minute interval, it is hard to pin down causality or the exact sequence of these jump events.)

We conduct two empirical tests to distinguish between these hypotheses. First, we investigate whether prices exhibit a reversal after a price jump (and after a simultaneous jump in prices and OIB) in Section 3.4.1. The liquidity hypothesis predicts that price pressure is temporary and prices should revert, while the information hypothesis predicts that price adjustments are permanent and no reversal should be observed. Then, we examine whether jumps in prices (and OIB) are associated with macroeconomic news announcements, which represent the arrival of important information on the market (Section 3.4.2).

3.4.1. Price reversals after jumps in prices (and OIB)

Figure 1 presents graphs of the cumulative market return in 5-minute intervals from one hour before ($t = -12$) until one hour after jumps ($t = +12$) in prices (positive jumps in Panel A and negative jumps in Panel B) and jumps in prices that are accompanied by jumps in OIB of the same sign in the same 5-minute interval (positive co-jumps in Panel C and negative co-jumps in Panel D), aggregated across all jumps on the 12 markets in our sample and measured in basis points.[14] The total number of jumps underlying Panels A and B is 2,348 and 2,521, respectively (obtained by aggregating the number of positive and negative jumps in prices across all markets from Table 2). The total number of jumps underlying

[14]We substitute missing data with zeroes in case of jumps for which we do not have data for the complete period from one hour before to one hour after the jump.

Panels C and D is 184 and 185, respectively (obtained by aggregating the number of positive and negative simultaneous jumps in prices and OIB across all markets from Table 3). As also shown in Table 2, Figure 1 indicates that the average price jump is around 40-50 basis points, which is a substantial market-wide return over a 5-minute interval. Negative price jumps tend to be slightly larger than positive price jumps, but there is little indication that price jumps that are accompanied by same-sign jumps in OIB are of a different magnitude than price jumps in isolation.

The graphs in the four panels of Figure 1 also show that price jumps are truly sudden: there is a clear discontinuity relative to cumulative returns before the 5-minute interval of the jump – although there is some indication of a slight run-up in the same direction in the hour before the jump (the run-up is statistically significant at the 5% level or better starting at $t = -8$, possibly suggesting a slight amount of information leakage). These patterns indicate that our identification of price jumps is quite clean; unreported results show that jumps in $PQSPR$ and in OIB represent similarly sudden and discontinuous changes in the variable of interest.

More importantly from the perspective of distinguishing the liquidity and information channels, there is little evidence of any reversal following either price jumps or simultaneous jumps in prices and OIB. If anything, there is some slight return continuation, especially after positive price jumps. In other words, price jumps tend to constitute permanent price changes, consistent with the hypothesis that price jumps (as well as simultaneous jumps in prices and OIB) occur due to the arrival of new information on the market rather than due to price pressure effects or other liquidity channels.

3.4.2. Macroeconomic news announcements and jumps in prices (and OIB)

The second test of the liquidity vs. information hypotheses aims to examine more directly whether price jumps (and simultaneous jumps in prices and OIB) are related to information events. In particular, we investigate whether jumps in prices (and OIB) are associated with macroeconomic news announcements from a number of different countries in our sample over the period 2001-2011, obtained from the Econoday database (the data on macroeconomic news announcements includes scheduled announcements regarding GDP, nonfarm payroll employment, producer and consumer price indices, etc.).[15] We manually select similar categories of macroeconomic news announcements as used in Andersen, Bollerslev, Diebold, and Vega (2003) and Opschoor, Taylor, Van der Wel, and van Dijk (2014) based on the description of the announcement. We only include announcements that fall within the opening hours of at least one of the markets in our sample. In total, we analyze 6,037 different macroeconomic news announcements from Canada, China, the European Monetary Union (EMU), France, Germany, Japan, the U.K., and the U.S., out of which 1,921 occur within the opening hours of the American markets, 2,304 occur within the opening hours of the Asian markets, and 4,751 occur within the opening hours of the European/African markets in our sample.[16]

We examine how many of the jumps in prices (and OIB) in our sample occur within a short window (from five minutes before till one hour after the event) around the release time of any of the macroeconomic news announcements we collected. We use a one-hour window after the announcements to allow for some time for the news to be incorporated in prices. One hour may seem like a long period of time to capture the response of U.S. markets to U.S. macroeconomic news announcements in recent years. However, for other markets, for the earlier years in our sample, and for news from other countries/regions, it may take more than a few minutes for the news to be fully incorporated into local prices. As a comparison, Lee (2012) uses a 30-minute post-announcement window in her analysis of jumps in market-wide and firm-specific U.S. equity prices around U.S. macroeconomic news announcements in the period 1993-2008.

[15]We are grateful to Michel van der Wel for providing the data on U.S. macroeconomic news announcements over 2004-2009, as used in Opschoor, Taylor, Van der Wel, and van Dijk (2014), and for his advice on obtaining and filtering the data for the other years and for several of the other countries in our sample. We note that the Econoday database does not cover our full sample period 1996-2011, but starts in 2001. For some countries, coverage starts even later (for example, coverage of macroeconomic news announcements in China – which we include because of their relevance for Hong Kong – starts in 2007) and some of the other countries in our sample are not covered at all during our sample period.

[16]We aggregate multiple macroeconomic announcements with the same release time to one event, so the numbers of announcements reported in the text and in Table 5 refer to the number of unique release times.

Table 5 presents the results. The first line in the table shows the total number of macroeconomic news announcements we collected from around the globe that occurred within the opening hours of each of the 12 markets in our sample. The other four lines in the table show the total number of price jumps on each market over the period 2001-2011, the number of price jumps that occur within the event window around the macroeconomic news announcements, the total number of simultaneous jumps in prices and OIB on each market over the period 2001-2011, and the number of simultaneous jumps in prices and OIB that occur within the event window around the news announcements.

For all of the markets in our sample except Japan, our sample includes at least 500 news announcements from different countries that occur within the market's opening hours over the period 2001-2011. For most markets, a considerable fraction of the price jumps (and simultaneous jumps in prices and OIB) occur within one hour of a macroeconomic news announcement. Around 17% of the price jumps (and 31% of the simultaneous jumps in prices and OIB) on the American markets are associated with a macroeconomic news announcement. These news announcements are mainly European and U.S. announcements, though we note that the most important U.S. announcements (e.g., nonfarm payroll, employment, producer and consumer price indices) fall outside the opening hours of the American markets. For Asia, we find that 6% of the price jumps (and 7% of the simultaneous jumps in prices and OIB) occur within the event window. However, none of the U.S. macroeconomic news announcements and very few of the news announcements from China and Japan take place within the opening hours of the Asian markets. In other words, the vast majority of the macroeconomic news announcements reported in Table 5 for markets in Asia are announcements from Europe, which may be of comparatively little relevance for Asian markets.

For European markets, we find strong evidence that jumps in prices (and OIB) are related to macroeconomic news announcements. For example, for Germany, we document 303 5-minute intervals with price jumps over 2001-2011, of which 119 (or 40%) occur around one of the news announcements in our sample. Over the same period, we observe 54 5-minute intervals with simultaneous jumps in prices and OIB in Germany, of which 29 (or 54%) are in the event window surrounding one of the announcements. Across the three European markets in our sample, 37% of the price jumps and 52% of the simultaneous jumps in prices and OIB occur around an announcement. The relative strength of the results for European markets is likely driven by the fact that many of the U.S. macroeconomic news announcements – arguably the most influential in the world – fall within the opening hours of the European markets.[17]

Across all 12 markets in the sample, 15% of the price jumps (and 30% of the simultaneous jumps in prices and OIB) are associated with a macroeconomic news announcement. We interpret this as evidence that a considerable fraction of the jumps in prices (and OIB) in our sample are associated with the arrival of important economic news, consistent with the information hypothesis. Of course, our results do not imply that we can trace each price jump to one of the many macroeconomic news announcements in our sample. However, we would like to point out that these announcements often involve relatively minor news events or news that was anticipated, and that many of the most important (notably U.S.) announcements do not occur within the trading hours of most markets in our sample. For European markets, which do tend to be open during U.S. macroeconomic news announcements, we find a much stronger association between price jumps and economic news. Furthermore, there is a host of other news events (e.g., unscheduled news announcements, policy speeches, industry news, local or global political news, acts of terrorism, natural or nuclear disasters) that could cause sudden shocks to equity prices but that are hard to measure in a consistent way. Our estimates are therefore likely to heavily underestimate the fraction of price jumps associated with news events.

Nonetheless, to examine whether there is stronger evidence in favor of the liquidity hypothesis for the jumps in prices (and OIB) that we are unable to relate to macroeconomic news, we repeat the price reversal analysis from Section 3.4.1 for the subsets of jumps in

[17] In an unreported analysis, we examine whether jumps in prices (and simultaneous jumps in prices and OIB) in Europe tend to occur around particular categories of U.S. macroeconomic news announcements. We find that especially nonfarm payroll employment, producer and consumer price indices, and initial unemployment claims announcements are often accompanied by jumps in prices (and OIB) in Europe.

prices (and OIB) that do and that do not occur within the event window around one of the macroeconomic news announcements over 2001-2011. The results, which are unreported but available from the authors, show that the graphs of the cumulative market return from one hour before until one hour after price jumps are very similar for jumps in prices (and OIB) that are and that are not associated with macroeconomic news; there is no evidence of price reversals in either case. This finding suggests that even price jumps outside of the event window around the macroeconomic news announcements in our sample are mainly driven by information rather than liquidity.

Taken together, the evidence in this subsection based on return reversals surrounding price jumps (and simultaneous jumps in prices and OIB) and based on the occurrence of jumps in prices (and OIB) around macroeconomic news announcements is most consistent with the information hypothesis. In the next subsection, we assess whether and why jumps in prices, liquidity, and trading activity spill over across markets.

3.5. Spillovers in jumps in prices, liquidity, and trading activity across markets

So far, we have provided evidence on the prevalence of jumps in prices, liquidity, and trading activity, on coinciding jumps in different variables within one market, and on the main channel through which jumps in prices (and OIB) arise. We now turn to one of the main further goals of the paper: to analyze the role of liquidity and trading activity in the within-region and across-region propagation of shocks to financial markets. To the best of our knowledge, our paper is the first to study high-frequency spillover effects of shocks to liquidity and trading activity across equity markets, and to link these to spillovers of price shocks.

We start with presenting summary statistics for coinciding jumps in price, $PQSPR$, and OIB across markets within each of the three regions, followed by an examination of spillover effects within and across regions for each of the variables separately (Section 3.5.1). In Section 3.5.2, we aim to explain price jumps on one market based on variables from the same market, the same region, and other regions.

3.5.1. Coinciding jumps in prices, liquidity, and trading activity across markets

Table 6 reports the number of days on which one, two, or three or more markets within the same region exhibit a positive/negative jump in prices, $PQSPR$, or OIB. Here, we only analyze co-jumps by region since, for example, there is no overlap in trading hours between markets in America and in Asia and we exclude overnight changes in our variables.

In most instances, there is at most one market that has a jump in prices, $PQSPR$, or OIB during a particular day in a particular region, but there are also a considerable number of cases of two or more countries having a jump in the same variable of the same sign on the same day. For example, in the European/African region, we observe 566 days over our sample period on which at least one of the four markets in that region experiences a negative price jump. Out of those 566 days, 489 (86.4%) are days on which only one of the four markets faces a negative price jump, on 56 days (9.9%) two markets face a negative price jump, and on 21 days (3.7%) at least 3 markets face a negative price jump.

Similar results are obtained for positive price jumps and for negative and positive OIB jumps in Europe/Africa and for negative and positive jumps in prices and in OIB in Asia. Co-jumps in the same variable of the same sign on different markets within a region are much less likely in America. Across all 12 markets in the sample, 11.3% (8.7%) of all days with price (OIB) jumps exhibit same-sign price (OIB) jumps in at least two different markets within the same region. In contrast, we find very few occasions of co-jumps in $PQSPR$ on different markets within the same region. Across all markets, only 2.0% of the days with $PQSPR$ jumps exhibit same-sign $PQSPR$ jumps in more than one market. This finding suggests that shocks to liquidity do not tend to occur on multiple markets in the same time frame.

Overall, the results in Table 6 indicate that although the majority of jumps in prices, $PQSPR$, or OIB are market-specific, we regularly observe co-jumps in prices and OIB of the same sign on the same day across multiple markets in the Asian and European/African regions. However, jumps in $PQSPR$ on a given day are almost always contained to a single market.

In Table 7, we extend the analysis in Table 6 by presenting correlations of jumps in prices, $PQSPR$, and OIB at the 5-minute (instead of daily) frequency and not only across individual markets within each region, but also across markets in different regions. Table 7 shows contemporaneous spearman rank correlations for the 5-minute time-series of jumps in prices (Panel A), $PQSPR$ (Panel B), and OIB (Panel C) across different markets (during overlapping trading hours only). We take into account the sign, magnitude, and significance of the jumps by setting our jump variables equal to zero in 5-minute intervals without a significant jump in the respective variable, and to the signed magnitude of the jump (measured in jump-free standard deviations) in 5-minute intervals with a jump. Bold correlations are significant at the 1% level or better. We do not report 5-minute correlations across markets in America and Asia since trading hours do not overlap.

The table shows that the time-series of signed price jumps are significantly correlated at the 5-minute frequency within the European/African region, and in particular within developed Europe. For example, the correlation between price jumps in Germany and the U.K. is equal to 15.71%. The correlations between price jumps on developed markets in Europe and South Africa are considerably smaller (around 2%) but still statistically significant. We note that since the vast majority of the observations of the 5-minute time-series of jumps are zero, high correlations are not to be expected and even very small correlations can be viewed as economically meaningful.

Price jumps on European markets are also significantly correlated with price jumps on American markets, especially with the U.S. (correlations around 7.5%), but also with Brazil, Canada, and Mexico (correlations in the range of 1-7%). Within the American region, we also observe several significant correlations in price jumps across different markets, though the economic magnitude of the correlations is more modest (up to 4%). Co-jumps in prices across markets in Asia are not a prominent phenomenon, with the notable exception of Hong Kong and Malaysia, which exhibit a significant correlation in price jumps of almost 10%. There is little evidence of co-jumps in prices across markets in Europe and Asia.

All in all, we find that 21 out of the 46 market-pairs in our sample exhibit significantly (at the 1% level) positive correlations in price jumps at the 5-minute frequency. We view this as evidence that, even at a very high-frequency, shocks to prices show economically meaningful spillover effects across equity markets around the world.

In contrast, Panel B of Table 7 shows almost no significant correlations in 5-minute jumps in $PQSPR$ across individual markets within and across regions. The exceptions are the correlations between $PQSPR$ jumps in Canada and the U.S. and between $PQSPR$ jumps in France and the U.K.. Both of these correlations are statistically significant, but at around 1% they are considerably smaller than the price jumps correlations in Panel A. These results confirm the conclusion from Table 6 that "sudden liquidity dry-ups" or "liquidity black holes" are mainly local phenomena that do not tend to spill over to other markets within or across regions.

The correlations between jumps in OIB across different markets presented in Panel C of Table 7 show a similar pattern as the price jump correlations in Panel A, although both economic and statistical significance are somewhat weaker. 14 out of the 46 market-pairs in our sample show significantly positive correlations. Jumps in OIB are significantly correlated within the European/African region and between developed Europe and the U.S., while – like price jumps – OIB jumps are only weakly correlated within the Asian region and across Europe/Africa and Asia. Although prior studies have identified links between shocks to prices on different equity markets, we believe we are the first to document that shocks to order imbalance can also be propagated across international equity markets at a high-frequency.

3.5.2. Coinciding jumps in prices, liquidity, and trading activity across markets and variables

We now build upon the analyses in Tables 6 and 7 by not only studying coinciding jumps in the same variable within and across regions, but also examining whether the likelihood of a price jump on a particular market can be explained by jumps in other variables on the same market and on different markets in the same region as well as in other regions. In other words, we attempt to answer the question of how price shocks are propagated from one market to another, with a specific focus on microstructure variables.

We adopt the method proposed by Bae, Karolyi, and Stulz (2003) and estimate logit models to explain the occurrence of price jumps on each individual market at the 5- minute frequency. The results are in Table 8. As dependent variable, we use an indicator variable of whether there was a price jump on a particular market i in a particular 5-minute interval. All of our logits are estimated separately for negative and positive price jumps, to allow for asymmetric effects depending on the sign of the jumps. As independent variables, we use an indicator variable of same-sign OIB jumps on market i in the same 5-minute interval, indicator variables of whether at least one other market in the same region (labeled "not i" in Table 8) has a same-sign jump in prices or in OIB in the same 5-minute interval, and indicator variables of whether at least one market in a different region has a same-sign jump in prices or in OIB in the same 5-minute interval. Since the independent variables based on different markets than market i are only defined during overlapping trading hours, we only include indicator variables of jumps in prices and OIB in Europe/Africa in the logits explaining price jumps on American markets and on Asian markets, while jumps in prices and OIB in both America and Asia serve as independent variables in the logits for price jumps on European markets. Since our results so far indicate little role for liquidity in the occurrence and spillovers of price jumps, we exclude $PQSPR$ jumps from the logit models.[18]

Table 8 presents the marginal effects (in %) of the logit models, organized by region (Panel A: America; Panel B: Asia; Panel C: Europe/Africa) and by the sign of the price jumps within each panel (Part I: positive; Part II: negative). Bold numbers are significant at the 10% level or better. For each market in each region, we estimate one, two, or three logit models, depending on the number of regions with overlapping trading hours with that market. The first model includes only independent variables from the same region. The

[18]In reported tests, we do include $PQSPR$ jumps in the logit models, but find that they can often not be estimated because of "separation problems" in the estimation. Put differently, if one of the independent variables could almost perfectly explain jumps in prices on market i, then numerically we observe fitted probabilities equal to either 0 or 1, which results in unreliable model estimation. For instance, if positive jumps in prices on market i never coincide during the same 5-minute interval with positive jumps in $PQSPR$ from another region, then having an indicator variable for positive jumps in $PQSPR$ from another region equal to 1 guarantees no positive jumps in prices on market i during that interval.

second and third models also include independent variables from one or two other regions – if there is any overlap in the trading hours. We note that the number of observations available for the estimation of the second and third models is substantially reduced relative to the first model.[19]

We hypothesize that the probability of negative (positive) price jumps on market i increases with negative (positive) jumps in OIB on the same market and with negative (positive) jumps in prices and OIB on other markets in the same and in other regions. In other words, the marginal effects in Table 8 are all expected to be positive.

The results of the logit models in Table 8 are consistent with our findings in Table 3 that price jumps on a particular market are linked to OIB jumps of the same sign on the same market in the same 5-minute interval. For 12 out of the 24 cases (negative and positive price jumps on 12 markets), we find a positive and significant marginal effect of OIB jumps on market i (based on the first logit model for each market). These effects are often economically substantial, especially for markets in Asia and Europe: they vary from 6.10% (positive price jumps in Hong Kong) to 41.64% (negative price jumps in Japan) in Asia and from 0.53% (negative price jumps in the U.K.) to 3.10% (positive price jumps in the U.K.) in Europe. In only two cases (Brazil and South Africa) do we observe significantly negative marginal effects of OIB jumps on the same market, but, at -0.03% and -0.04%, their economic magnitude is small.

Table 8 also confirms the results of the correlation analysis in Table 7. In particular, price jumps on other markets in the same region significantly increase the probability of a price jump on market i in 11 out of the 24 cases (based on the first logit model for each country). These effects are observed in all regions. For instance, price jumps on the other markets within the Europe/Africa region have positive and significant marginal effects on price jumps on market i varying from 2.25% to 3.58%. Only in two cases (Mexico and Japan) do we observe significantly negative marginal effects of jumps in prices on the other

[19]We generally estimate two models for markets in America, one model for markets in Asia, and three models for markets in Europe/Africa, but have to discard some individual models for individual markets in case there is a separation problem in the estimation.

markets within the same region, but their economic magnitude is relatively small.

The results on the effect of OIB jumps on other markets in the same region on price jumps on market i are mixed for America and Asia. If anything, the significant marginal effects for this variable in Panels A and B suggest that price jumps on a particular market are associated with OIB jumps of the opposite sign on other markets in the same region. In contrast, for the three European markets in our sample, there is consistent evidence that the probability of price jumps on one market is positively related to same-sign OIB jumps on other markets in the same 5-minute interval. These marginal effects are all positive and significant within developed Europe, but are relatively modest, ranging from 0.29% to 0.60%.

The second and third logit models for each market in Table 8 assess cross-region spillovers of jumps in prices and OIB. Perhaps not surprisingly, the evidence for cross-region spillovers of price jumps is weaker and less consistent than for within-region spillovers. The marginal effect of price jumps in other regions is positive and significant only in few cases: for negative price jumps in the U.S. vis-à-vis the European/African region (marginal effect of 0.63%, see Panel A), for positive price jumps in the U.K. vis-à-vis the American region (0.81%, Panel C), and for negative price jumps in Germany vis-à-vis the American region (0.95%, Panel C). Similarly, in most cases, the effect of OIB jumps in other regions on price jumps on market i is not significant either in statistical or in economic terms, except for price jumps in Canada and the U.S. vis-à-vis OIB jumps in the European/African region (marginal effect between 0.82% and 1.84%, see Panel A) and for positive price jumps in France vis-à-vis OIB jumps in America (effect of 0.82%, Panel C). Some of the marginal effects in Table 8 are not in line with expectations. For example, the marginal effect of OIB jumps in Asia on the likelihood of positive price jumps in Germany is -0.05% (Panel C). Although some of these exceptions are statistically significant, their economic magnitude is small.

In sum, the results in Table 8 highlight that shocks to prices can be propagated from one market to another within a 5-minute horizon. Such propagation is especially strong across markets within the same region, although some cross-region effects are also observed. Furthermore, price jumps are regularly linked to same-sign OIB jumps on the same market, and, for Europe, also to same-sign OIB jumps on other markets in the same region.

To address the question whether the high-frequency propagation of shocks to equity prices across markets is driven by liquidity or by information, we repeat the price reversal analysis from Section 3.4.1 for the subsets of jumps in prices that only occur on one market and that occur simultaneously on at least two of the markets in our sample. Of the 2348 (2521) positive (negative) price jumps in our sample, 200 (253) occur simultaneously with a price jump on at least one other market. Unreported results show that the price reversal graphs are very similar for both subsets of price jumps. In other words, there is no evidence that price jumps that occur simultaneously in multiple markets exhibit reversals, consistent with the hypothesis that these jumps are primarily driven by information rather than liquidity.

3.6. Supplementary tests

Our analyses so far suggest that shocks to equity prices are prevalent and large, are linked to shocks to order imbalance, exhibit regular high-frequency spillovers across international markets, and are mainly driven by information rather than liquidity. In this section, we discuss the results of a number of supplementary tests that we carried out to evaluate the robustness of these conclusions.

3.6.1. Alternative frequencies

One potential limitation of our study is that we measure jumps in prices, liquidity, and trading activity at a relatively high frequency: 5-minute intervals within the trading day. Our choice for this frequency was motivated by our aim of a detailed, intraday analysis of the dynamics of liquidity and trading activity around financial market shocks and by issues concerning non-overlapping trading hours, overnight returns, and special features of the opening session that arise in analyses of cross-market spillovers at the daily frequency. Nonetheless, we repeat all of our analyses at the 15-minute and 1-hour frequencies to assess whether we may have missed lower-frequency shocks, or lower-frequency relations between shocks to prices, liquidity, and trading activity (results available from the authors). At these lower frequencies, the number of jumps is naturally smaller, but we still find quite frequent jumps in prices, quoted spreads, and order imbalance, while jumps in effective spreads are rare; we do now also observe regular jumps in turnover. The economic magnitudes of the jumps are still around five jump-free standard deviations. Similar to Table 3, we find virtually no evidence that price jumps are associated with $PQSPR$ jumps (nor with turnover jumps). In contrast to Table 3, we no longer observe a significant relation between price jumps and same-sign OIB jumps in the same interval at the 15-minute and 1-hour frequencies, which underlines the value of using a relatively high frequency to study the role of liquidity and trading activity around financial market shocks. Similar to Figure 1 and Table 5, we find that price jumps are not followed by reversals, and that a substantial fraction of price jumps occur around macroeconomic news announcements. Both pieces of evidence suggest that 15-minute and 1-hour price jumps are also primarily driven by information rather than liquidity. These price jumps also regularly spill over across markets, consistent with Tables 6 and 7. There is no evidence of spillovers in $PQSPR$ jumps to other markets, but both jumps in OIB and in turnover exhibit significant correlations across markets, especially for Europe. In short, we conclude that our inferences are not materially affected by redoing our analyses at a lower frequency within the trading day.

3.6.2. The dynamics of liquidity and trading activity around price jumps

Table 3 shows that price jumps are regularly associated with same-sign jumps in OIB in the same 5-minute interval, but not with $PQSPR$ jumps. However, it is possible that this result is affected by our approach to identify shocks to liquidity and order imbalance as discontinuous jumps. To obtain a broader picture of the behavior of liquidity and trading activity around price jumps, Figure 2 shows the cumulative change in $PQSPR$ (Panels A and B; in %) as well as the dynamics of OIB (Panels C and D; in basis points) from one hour before until one hour after positive and negative jumps in prices, aggregated across all jumps on the 12 markets in our sample. Panels A and B show that liquidity does fluctuate around price jumps; quoted spreads tend to fall slightly in the hour before a price jump, followed by a small upward blip in the 5-10 minutes before the price jump, and a more pronounced decline after the price jump. Nonetheless, the observed patterns seem hard to square with theories that propose a key role for liquidity in the origination of price shocks. First, the quoted spread effects are small. The blip in $PQSPR$ just before the price jump has a magnitude of 4-5 percentage points, which is much smaller than the average $PQSPR$ jump of around 42%. Second, liquidity tends to improve following a price jump, but Figure 1 shows no evidence of any accompanying price reversal. Third, the liquidity patterns around price jumps are very similar for positive and negative price jumps. Fourth, there is little indication of "liquidity black holes" or "liquidity spirals" in the sense that feedback effects cause liquidity crashes to worsen over time. Rather, the observed patterns in quoted spreads in Figure 2 seem to accord well with an increase in adverse selection costs just before the arrival of economic news, and the resolution of asymmetric information following the news arrival.[20] Panels C and D of Figure 2 show a clear, once-off spike in OIB in the same direction as the price jump, in the same interval. Given the absence of reversals after price jumps, this pattern seems more consistent with speculative trading or portfolio rebalancing around the arrival of news than with temporary price pressure effects or with feedback loops in which initial price drops induce further selling.

3.6.3. Alternative liquidity measures

Liquidity is a multi-faceted concept and the liquidity measures used in this paper ($PQSPR$ and $PESPR$) may not cover all relevant aspects of liquidity. However, we would expect significant shocks to liquidity to also be reflected in quoted or effective spreads. Moreover, price impact measures suffer from large estimation errors at high frequencies and could be mechanically linked to price changes. In unreported analyses, we redo all of our analyses with an alternative liquidity measure based on the number of different stocks that traded on a specific market in a specific interval. This trade-based liquidity measure builds on the

[20]To the extent that the $PQSPR$ patterns in Panels A and B of Figure 2 are driven by macroeconomic news announcements, one might wonder about the scope for asymmetric information around such announcements. However, we note that Boudt and Petitjean (2014) document significant increases in trading costs and the demand for immediacy around macroeconomic news releases and price jumps in Dow Jones stocks. And Jiang, Lo, and Valente (2014) find that high-frequency trading adversely affects liquidity around macroeconomic news announcements. Alternatively, the blip in quoted spreads in Figure 2 could be due to concerns about inventory risk instead of adverse selection.

premise that stocks may not trade in a certain interval in part because of high trading costs. The trade-based measure should thus be positively associated with the level of market liquidity. Indeed, this measure is highly, but not perfectly, correlated with the illiquidity measures $PQSPR$ and $PESPR$; for most markets, these correlations roughly range from -0.4 to -0.7. On average, jumps in the trade-based measures are about as frequent as $PQSPR$ jumps, and are also of similar magnitude. Similar to Table 3, we find little evidence that price jumps coincide with jumps in the trade-based liquidity measure. Similar to Tables 6 and 7, jumps in the trade-based measure are almost always isolated events that do not spillover to other markets. Our conclusion that liquidity does not play more than a minor role the origination and propagation of prices shocks is thus not sensitive to the use of this alternative liquidity measure.

Several studies that model liquidity supply channels for the origination and propagation of financial market shocks feature an important role of funding liquidity. For example, in Brunnermeier and Pedersen (2009), "liquidity spirals" arise when financial intermediaries reduce the supply of liquidity in response to worsening funding liquidity (e.g., increasing margins) and when funding liquidity, in turn, is decreasing in market illiquidity. To more specifically test the implications of these liquidity supply channels, in Table 9, we examine whether shocks to prices, liquidity, and trading activity are associated with shocks to funding liquidity. This table assesses whether jumps in prices, $PQSPR$, and OIB are more likely to occur on days with a jump in the TED spread (the difference between the 3-month LIBOR and the 3-month T-bill rate, obtained from the Federal Reserve Bank of St. Louis), which is a common proxy for funding liquidity.[21] TED spread jumps are measured at the daily frequency, since funding liquidity may not be likely to exhibit sudden intraday changes, since one component of the TED spread (the LIBOR) is determined only once per day, and since we lack intraday data on the other component (the T-bill).

[21]We obtain similar results when, instead of the TED spread, we use the U.S. default spread (Baa-Aaa), the LIBOR, country-specific short-term interest rates, or country-specific banking industry index returns as proxies for funding liquidity.

Panels A and B of Table 9 document the number and empirical frequency of days with negative price jumps, positive $PQSPR$ jumps, negative OIB jumps, and positive TED spread jumps for each of the 12 markets. We focus on jumps with these signs since theories on funding liquidity primarily associate a drop in funding liquidity with a drop in prices, a worsening of liquidity, and securities sales. The TED spread exhibits a positive jump on only 9 days over the entire sample period 1996-2011. We note that the number of TED spread jumps reported in the table differs across countries because not all of these jumps occur within the available sample period for all countries, as the TRTH data coverage for some countries starts later than 1996 (see Appendix A.1). Panel C shows that negative price jumps, positive $PQSPR$ jumps, and negative OIB jumps almost never coincide with positive TED spread jumps on the same day. Panel D presents the results of a test of whether the empirical probability of such coinciding jumps is greater than the theoretical probability under the assumption that the jumps in the individual variables are independent (similar to Table 4). The results in this panel indicate very little evidence that shocks to prices, liquidity, and trading activity are associated with shocks to funding liquidity.

4. Conclusion

The recent financial crisis has highlighted the importance of global systemic risk in the current environment of globally integrated financial markets and fast trading technology. We conduct a study of the intraday propagation of shocks across 12 equity markets around the world at the 5-minute frequency over 1996-2011 – with a particular focus not only on shocks to prices, but also on shocks to liquidity (quoted and effective spreads) and trading activity (turnover and order imbalance). Our main purpose is to test the liquidity vs. information channels for the origination and propagation of financial market shocks.

Our findings are based on jump statistics in these five variables at the 5-minute frequency and can be summarized as follows. First, jumps in prices, quoted spreads, and order imbalance are large and occur much more often than jumps in effective spreads and turnover. Second, we document a significant association between jumps in prices and in order imbalance, while jumps in quoted spreads are independent from jumps in the other variables. Third, we show that jumps in prices and simultaneous jumps in prices and order imbalance are primarily driven by information rather than liquidity. Fourth, jumps in prices and order imbalance exhibit significant spillover effects across markets (even in the same 5-minute interval and especially for markets in Europe and the U.S.), but spillovers of jumps in quoted spreads to other markets are rare.

To sum up, our study provides evidence that the propagation speed of shocks across international equity markets is very high. In designing optimal financial regulation and risk management, policy makers and investors should not neglect microstructure effects related to the occurrence of price shocks. In particular, price shocks should not be viewed independently from shocks to trading activity. Shocks to liquidity, however, seem to play a less central role in the origination and propagation of price shocks than previously thought.

We leave further analyses of the speed and mechanism of the propagation of price shocks across markets for future research. In particular, recent advances in trading technology suggest that, in the later years of our sample period, the propagation of shocks across markets may take place at an even higher frequency than the one studied in this paper. Moving to a higher frequency of analysis would also allow for the estimation of daily vector autoregressions to get a better handle on causality, but will likely limit the sample to developed markets in recent years in order to construct meaningful measures of trading activity over such ultra-short horizons. Another potential extension would be to broaden the scope of the analysis beyond the 12 markets in our sample, which would enable an analysis of the determinants of the speed and the strength of the propagation of stocks across different (pairs of) markets.

Appendix A: Sample selection and data screens

This appendix describes the sample and data filters used in the paper. We start with a detailed description of the data sources and sample selection, subsequently discuss our data screens, and conclude with a discussion of potential limitations in our sample construction.

A.1. Data sources and sample selection

We use two databases to build our sample: Datastream and Thomson Reuters Tick History (TRTH). From the former, we obtain Reuters Instrument Codes (RICs) for all common stocks that are traded on 12 exchanges around the world. Then, we identify common stocks that were ever part of the major local equity index for each of these exchanges from 1996 till 2011 through the TRTH Speedguide. We obtain tick-by-tick data on trades and quotes for these stocks from TRTH. The exchanges in our sample can be classified into three regions based on time zones: America, Asia, and Europe/Africa. The American region includes the following countries (the major equity index used is in parentheses): Brazil (BOVESPA), Canada (TSX COMPOSITE), Mexico (IPC), and the U.S. (S&P100). The Asian region includes Hong Kong (HSI), India (NIFTY50), Japan (NIKKEI225), and Malaysia (KLCI). The European/African region includes France (CAC40), Germany (DAX), South Africa (JALSH), and the U.K. (FTSE100). Data for these exchanges are generally available over 1996-2011, with a few exceptions. In particular, data availability for Germany and South Africa starts in 1997, for Mexico in 1998, for India in 2000, and for Brazil in 2004.

We obtain the historical opening hours for each of the exchanges from several sources: the TRTH Speedguide, Skeete (2004), exchanges' websites, and the Federation of European Securities Exchanges. We cross-check these opening hours by examining the trading activity patterns observed in the data and select the shortest opening hours when in doubt. Since we cannot clearly distinguish between auctions and continuous trading sessions, we disregard the first and the last 15 minutes of each trading day.

A.2. Data screens

We filter the data following Rösch, Subrahmanyam, and van Dijk (2015). We use two sets of screens: one set for trade data and another set for quote data. We discard trades when they occur outside the opening hours of the exchange; the trade price is not positive; the trade size is more than 10,000 shares (to exclude block trades from our sample); the trade price differs from the prices of the 10 surrounding ticks by more than 10% since these are likely to be erroneous entries. We discard quotes when quotes occur outside the opening hours of the exchange; the bid and ask prices are not positive; the bid price is higher than the ask price; the bid or ask price differs from the bid or ask price of the 10 surrounding ticks by more than 10% since these are likely to be erroneous entries; the proportional bid-ask spread exceeds 25%. In addition, we discard stock-days if a stock is traded fewer than ten 5-minute intervals per day. When aggregating stock level data to the market-level, we discard 5-minute intervals in which fewer than 10 stocks are traded.

A.3. Sample construction limitations

There are several potential limitations in our sample construction. First, we use RICs that ever refer to the stock that was part of the index during our sample period (1996-2011). However, RICs can change through time and TRTH does not provide information on re-used RICs. Therefore, some of the data in our sample could stem from different stocks than the index constituents. Second, for the same reason linking TRTH data to data on the market capitalization of individual stocks (for example, from Datastream) is challenging. All of our analyses are therefore based on equally-weighted averages of the variables across stocks only. We believe that these limitations are not severe due to the trading activity filters we apply: stocks should trade at least ten 5-minute intervals per day. Hereby, we avoid many small and illiquid stocks that could definitely not be part of the index in the time interval under consideration. Because the stocks in our sample are relatively large and liquid, analyzing equally-weighted averages seems an appropriate choice. Using an equally-weighted average also reduces the problem of one stock dominating the whole market (e.g., Nokia in Finland).

Appendix B: Jump measure (BNS)

This appendix describes the BNS jump measure (Barndorff-Nielsen and Shephard, 2006) computation together with the algorithm that we use to determine the exact 5-minute interval during which a jump occurs. Following Pukthuanthong and Roll (2015), we use jump measures to identify extreme events on financial markets. A jump measure is a statistical non-parametric way to test for jumps in a time-series. In this paper, we use the BNS ratio measure:

$$H_t = \frac{\sqrt{T}\left(\frac{\pi}{2}\frac{B_t}{S_t} - 1\right)}{\sqrt{\upsilon \frac{Q_t}{B_t^2}}}$$

$$S_t = \Sigma_{k=2}^{T}(V_{k,t})^2$$

$$B_t = \Sigma_{k=2}^{T}|V_{k,t}||V_{k-1,t}|$$

$$Q_t = T \cdot \Sigma_{k=4}^{T}|V_{k,t}||V_{k-1,t}||V_{k-2,t}||V_{k-3,t}|$$

$$\upsilon = \left(\frac{\pi}{2}\right)^2 + \pi - 5$$

where H_t is the BNS ratio measure on day t, S_t is the squared variation on day t based on 5-minute observations within the day, B_t is the bipower variation on day t based on 5-minute observations within the day, Q_t is the "quarticity" of the process (which is part of the scaling factor for statistics to follow a standard normal distribution), V_{kt} is the variable of interest (returns, changes in proportional quoted or effective spreads, turnover, or order imbalance) at k-th 5-minute interval during day t, T is the total number of valid 5-minute intervals within day t. Under the null hypothesis of no jumps, H_t follows a standard normal distribution.

The BNS jump statistic is based on the assumption that V_{kt} follows a Brownian motion with zero drift and some diffusion plus a Poisson jump process. The bipower variation is the variation of the continuous part of process (the Brownian motion itself) that is free of any jumps, while the squared variation is the variation of the process including the jumps.

Thus, without jumps, the squared variation should be approximately the same as the scaled bipower variation. But in case there is a jump, the squared variation exceeds the bipower variation. Hence, the ratio of these two variables gives an indication of whether a jump occurred. If there is a jump on day t, then H_t should be negative and large in absolute terms. In addition to the assumption that our variables follow a Brownian motion with zero drift plus a Poisson jump process, there are several other important assumptions underlying the formulas above. First, we assume that variation is constant over day t. We acknowledge that volatility exhibits intraday patterns, but we circumvent this issue to a large extent by discarding the first and last 15 minutes of the trading session. Second, we also assume that T is large enough ($T \sim T - 1 \sim T - 3$).

The BNS measure indicates whether there was a jump on a given trading day, but does not pinpoint the exact 5-minute interval when the jump occurs. To determine the exact time of the jump, we propose the following algorithm. We first compute H_t for any day with at least 25 5-minute observations within the day. Then, we check whether we can reject the null hypothesis of no jumps (based on a threshold of the 0.1% percentile of the standard normal distribution). If the null hypothesis is rejected, we search for the most influential observation within day t. In other words, we identify the observation that has the maximum effect on the jump measure and is greater in absolute terms than 1.96 jump-free standard deviations (that is, the square root of the scaled bipower variation). We mark this 5-minute interval as a jump interval. We repeat the procedure (temporarily discarding 5-minute intervals that have been identified as jump observations) until we no longer reject the null hypothesis of no jumps or until there are fewer than 10 observations left. In our sample, the latter of these two conditions never becomes binding.

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Table 1: Summary statistics of market returns, liquidity, and trading activity (12 equity markets, 1996-2011)

This table shows the whole sample time-series mean and standard deviation of the 5-minute equally-weighted market returns in basis points, the 5-minute equally-weighted proportional quoted spreads ($PQSPR$) and effective spreads ($PESPR$) in percentage, the 5-minute market aggregate turnover in basis points, and the 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) in basis points for 12 equity markets over 1996-2011. We refer to Section 2 and Appendix A for a detailed description of sample selection, data filters, and variable definitions. The final row presents the total number of valid 5-minute intervals in the sample (at least ten stocks should be traded in each particular interval to be included in the sample). Markets are grouped by region and are listed in alphabetical order within each region. Data to calculate these variables are from TRTH (trade and quote data) and the World Bank website (aggregate market capitalization and exchange rates). Only common stocks that were ever part of the major local equity index are included in the computation of market returns, quoted and effective spreads, order imbalance, and turnover (data on index constituents are from the TRTH Speedguide, while common stocks are identified through Datastream).

		America				Asia				Europe/Africa			
		Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
$PRICE$	Mean	-0.160	-0.047	0.085	0.015	-0.153	-0.385	-0.160	-0.229	-0.062	-0.113	0.055	-0.031
	St.Dev.	14.000	5.346	9.279	10.710	13.752	11.860	11.867	8.992	10.804	10.216	6.062	7.671
$PQSPR$	Mean	0.487	0.751	0.652	0.149	0.476	0.265	0.416	0.941	0.195	0.218	0.819	0.499
	St.Dev.	0.331	0.307	0.378	0.120	0.185	0.144	0.149	0.306	0.113	0.158	0.300	0.348
$PESPR$	Mean	0.358	0.471	0.414	0.088	0.428	0.232	0.350	0.749	0.179	0.159	0.505	0.336
	St.Dev.	0.243	0.215	0.253	0.066	0.186	0.118	0.112	0.177	0.110	0.108	0.248	0.294
$Turnover$	Mean	0.117	0.131	0.102	0.083	0.219	0.306	0.295	0.070	0.516	0.228	0.088	0.156
	St.Dev.	0.187	0.087	0.060	0.038	0.159	0.205	0.198	0.061	0.724	0.172	0.065	0.125
OIB	Mean	0.002	0.004	0.004	0.005	0.005	0.000	0.013	-0.001	0.003	0.000	0.000	-0.001
	St.Dev.	0.119	0.035	0.037	0.016	0.071	0.068	0.090	0.030	0.386	0.064	0.030	0.031
# Obs.		111,302	284,549	148,337	282,881	135,083	154,554	162,314	230,355	366,396	323,607	269,618	372,300

Table 2: The frequency and magnitude of jumps in prices, liquidity, and trading activity (12 equity markets, 1996-2011)

Panel A of this table shows the number of 5-minute intervals with a jump in the 5-minute equally-weighted market returns ($PRICE$), 5-minute log-changes in equally-weighted proportional quoted spreads ($PQSPR$) and effective spreads ($PESPR$), 5-minute log-changes in the market aggregate turnover ($TURNOVER$), and 5-minute market aggregate order imbalance scaled by the aggregate market capitalization (OIB) for 12 equity markets over 1996-2011. Panel B of this table shows the corresponding mean and standard deviation of the magnitude of the jump measured in terms of jump-free standard deviations (that is, the square root of the scaled bipower variation). The total number of 5-minute observations for each variable is shown in Table 1. Jumps are identified using the BNS jump statistic that is based on the ratio of the bipower (continuous) variation to the squared variation of the intraday observations for each variable (see Appendix B for details). We classify a day as a day with a jump in a particular variable if the BNS measure is below the 0.1% percentile of the standard normal distribution. Subsequently, we follow an algorithm that allows us to pinpoint the exact 5-minute interval in which the jump occurs. The jumps are classified according to their sign: positive (POS) and negative (NEG). Markets are grouped by region and listed in alphabetical order within each region. Data to calculate these variables are from TRTH (trade and quote data) and the World Bank website (aggregate market capitalization and exchange rates). Only common stocks that were ever part of the major local equity index are included in the computation of market returns, quoted and effective spreads, order imbalance, and turnover (data on index constituents are from the TRTH Speedguide, while common stocks are identified through Datastream).

Panel A: Number of 5-minute intervals with a jump

		America				Asia				Europe/Africa			
		Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
$PRICE$	POS	33	132	109	140	433	19	500	244	201	162	148	227
	NEG	39	127	88	160	439	68	637	187	225	205	134	212
$PQSPR$	POS	6	189	110	38	35	38	191	167	27	107	222	278
	NEG	7	63	107	21	42	16	82	154	13	47	131	92
$PESPR$	POS	1	4	9	4	7	2	70	5	11	2	3	14
	NEG	1	3	2	6	7	1	11	15	25	2	0	12
$Turnover$	POS	5	10	4	11	30	36	29	4	17	11	0	15
	NEG	0	6	9	9	5	153	9	0	14	12	1	11
OIB	POS	304	383	54	129	324	77	205	232	590	246	410	115
	NEG	254	296	25	79	266	182	143	242	560	224	493	139

Table 2: The frequency and magnitude of jumps in prices, liquidity, and trading activity (continued)

Panel B: Magnitude of the jump (in jump-free standard deviations)

			America				Asia				Europe/Africa			
			Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
PRICE	POS	Mean	5.27	4.65	4.80	4.50	5.82	4.39	5.44	6.35	5.90	4.98	5.06	5.08
		St.Dev.	2.32	1.50	1.81	1.77	2.10	1.41	2.15	2.26	2.31	1.70	1.95	2.01
	NEG	Mean	-4.99	-4.54	-4.65	-4.36	-6.20	-4.50	-5.65	-6.98	-5.40	-5.27	-4.75	-5.42
		St.Dev.	1.57	1.92	1.61	1.39	2.37	1.39	2.17	2.95	2.26	1.90	1.80	2.13
PQSPR	POS	Mean	4.80	5.23	4.47	5.20	4.29	5.20	5.33	5.12	6.05	5.07	4.73	6.63
		St.Dev.	2.98	1.78	1.17	1.74	1.36	1.94	1.78	1.63	4.40	1.75	1.48	2.70
	NEG	Mean	-4.60	-3.90	-4.11	-5.32	-3.85	-4.19	-4.25	-4.17	-7.61	-4.17	-4.01	-5.05
		St.Dev.	2.20	1.16	1.32	2.08	1.25	1.24	1.11	1.32	6.87	1.25	1.10	2.24
OIB	POS	Mean	4.55	5.89	5.08	4.83	4.50	4.17	4.16	4.71	6.71	5.51	6.34	4.91
		St.Dev.	2.43	3.20	1.46	2.46	1.62	1.36	1.34	1.57	4.09	2.14	6.09	1.85
	NEG	Mean	-4.75	-5.88	-4.95	-5.04	-4.68	-4.53	-4.30	-4.67	-7.38	-5.36	-6.46	-4.97
		St.Dev.	3.09	2.75	1.55	2.00	1.63	1.67	1.31	1.60	4.48	2.17	4.06	1.78

Table 3: Coinciding jumps in prices, liquidity, and trading activity within a market (12 equity markets, 1996-2011)

This table shows the number of jumps in variable 1 and variable 2 (where variable 1 and variable 2 refer to either $PRICE$, $PQSPR$, or OIB) that occur on the same trading day (within/before/after the same 5-minute interval) for each of the 12 equity markets in our sample over 1996-2011. We treat either a positive or a negative jump in variable 1 as an event and we count the number of 5-minute intervals with jumps in variable 2 in the same interval as the event (i.e., simultaneously), before the event (that is, from the beginning of the same trading day – or from the previous jump in variable 1 on the same day – till the event) and after the event (that is, from the event till the end of the same trading day – or till the next jump in variable 1 on the same day). In each panel, the first two columns show the signs of the jumps in the variables under consideration. The first column shows the sign of the jumps in variable 1 (POS for positive price jumps and NEG for negative jumps in variable 1). In each panel, the first two rows show the number of positive or negative jumps in variable 1 that are not associated with a jump in variable 2 on the same market on the same day. The next four rows show the number of positive or negative jumps in variable 1 that are accompanied by a positive or negative jump in variable 2 on the same market in the same 5-minute interval. The following four rows show the number of positive or negative jumps in variable 1 that were preceded by a positive or negative jump in variable 2 on the same market on the same day. The final four rows show the number of positive or negative jumps in variable 1 that were followed by a positive or negative jump in variable 2 on the same market on the same day. In Panel A, jumps in variable 1 and variable 2 correspond to jumps in 5-minute equally-weighted market returns ($PRICE$) and 5-minute log-changes in equally-weighted proportional quoted spreads ($PQSPR$), respectively; in Panel B, jumps in variable 1 and variable 2 correspond to jumps in 5-minute equally-weighted market returns ($PRICE$) and 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB), respectively; in Panel C, jumps in variable 1 and variable 2 correspond to jumps in 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) and 5-minute log-changes in equally-weighted proportional quoted spreads ($PQSPR$), respectively. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Markets are grouped by region and listed in alphabetical order within each region. Data are from TRTH, the World Bank website, and Datastream.

Panel A: Coinciding jumps in prices and $PQSPR$

	Sign of the jump in		America				Asia				Europe/Africa			
	$PRICE$	$PQSPR$	Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
Jumps in $PRICE$ with no jumps in $PQSPR$ on the same day	POS	NA	33	120	87	137	428	18	469	227	190	156	128	190
	NEG	NA	37	114	65	150	430	67	596	157	221	199	123	193
Simultaneous jumps in $PRICE$ and $PQSPR$	POS	POS	0	1	2	0	0	0	13	2	1	0	7	4
	POS	NEG	0	1	8	0	0	0	3	1	0	0	3	6
	NEG	POS	0	1	9	2	2	0	19	7	0	0	1	4
	NEG	NEG	0	0	4	0	0	0	0	3	0	1	0	1
Jumps in $PRICE$ preceded by jump in $PQSPR$ on same day	POS	POS	0	1	6	1	3	0	4	4	5	3	7	21
	POS	NEG	0	2	3	1	2	0	4	4	1	0	4	4
	NEG	POS	1	6	2	3	3	1	2	4	0	4	3	6
	NEG	NEG	0	4	2	2	6	0	9	13	0	1	0	1
Jumps in $PRICE$ followed by jump in $PQSPR$ on same day	POS	POS	0	2	1	1	0	0	4	6	2	1	0	13
	POS	NEG	0	4	5	1	0	1	2	0	3	2	4	1
	NEG	POS	1	1	5	0	1	0	7	11	1	2	7	4
	NEG	NEG	2	1	7	2	0	0	1	6	2	0	3	1

Table 3: Coinciding jumps in prices, liquidity, and trading activity within a market (continued)

Panel B: Coinciding jumps in prices and OIB

	Sign of the jump in		America				Asia				Europe/Africa			
	$PRICE$	OIB	Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
Jumps in $PRICE$ with no jumps in OIB on the same day	POS	NA	25	109	106	120	369	12	419	226	118	104	104	190
	NEG	NA	33	106	85	149	359	42	510	173	137	147	109	179
Simultaneous jumps in $PRICE$ and OIB	POS	POS	1	8	2	15	22	2	42	4	43	31	1	13
	POS	NEG	0	0	0	0	1	0	0	0	0	0	0	0
	NEG	POS	0	0	0	0	1	0	1	0	0	0	2	0
	NEG	NEG	2	3	1	3	22	17	58	3	34	28	0	14
Jumps in $PRICE$ preceded by jump in OIB on same day	POS	POS	2	4	0	3	20	0	8	5	15	4	6	0
	POS	NEG	4	3	0	1	10	2	2	1	9	5	9	4
	NEG	POS	2	4	0	3	13	1	8	0	16	10	2	1
	NEG	NEG	1	7	0	2	16	8	6	5	15	4	5	3
Jumps in $PRICE$ followed by jump in OIB on same day	POS	POS	3	5	1	0	19	2	21	5	26	13	13	13
	POS	NEG	5	7	0	0	8	0	5	4	17	4	18	9
	NEG	POS	3	5	1	0	16	1	27	1	9	5	19	7
	NEG	NEG	2	5	1	3	36	3	24	6	21	6	10	5

Panel C: Coinciding jumps in OIB and $PQSPR$

	Sign of the jump in		America				Asia				Europe/Africa			
	OIB	$PQSPR$	Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
Jumps in OIB with no jumps in $PQSPR$ on the same day	POS	NA	301	352	50	128	319	75	195	222	576	236	366	108
	NEG	NA	253	259	25	74	263	174	136	221	552	216	451	116
Simultaneous jumps in OIB and $PQSPR$	POS	POS	0	1	0	0	0	0	3	1	1	0	0	0
	POS	NEG	0	0	0	0	0	0	0	0	1	0	1	0
	NEG	POS	0	1	0	0	0	0	2	4	0	1	0	1
	NEG	NEG	0	0	0	0	0	0	0	0	0	0	0	0
Jumps in OIB preceded by jump in $PQSPR$ on same day	POS	POS	1	17	1	0	2	1	2	3	2	9	11	3
	POS	NEG	1	5	2	0	2	2	2	4	1	5	15	3
	NEG	POS	0	20	0	3	0	4	2	3	2	3	15	13
	NEG	NEG	0	3	0	1	2	0	1	5	0	2	7	2
Jumps in OIB followed by jump in $PQSPR$ on same day	POS	POS	2	7	0	1	0	0	4	5	4	3	14	1
	POS	NEG	1	5	1	0	0	0	0	0	1	2	4	0
	NEG	POS	0	4	0	0	1	2	0	3	2	3	17	4
	NEG	NEG	0	3	0	1	0	1	0	2	1	1	6	0

Table 4: The likelihood of simultaneous jumps in prices and order imbalance within a market (12 equity markets, 1996-2011)

This table assesses whether the empirical frequency of simultaneous (that is, same 5-minute interval) jumps in 5-minute equally-weighted market returns ($PRICE$) and 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) exceeds the theoretical frequency under the assumption that jumps in prices are independent from jumps in OIB, for each of the 12 equity markets in our sample over 1996-2011. The table shows the number of simultaneous jumps in prices and OIB, the empirically observed frequency of such simultaneous jumps (that is, relative to the total number of 5-minute intervals for each market), and the theoretical probability of such simultaneous jumps under the assumption that jumps in prices and OIB occur independently (these probabilities are given in basis points). The next row of the table presents the p-value of a statistical test on the equality of the empirically observed frequency and the theoretical probability. The null hypothesis is that the empirical and theoretical probabilities are equal (in other words, jumps between variables are independent), while the alternative is that the empirical probability is greater than the theoretical probability. Numbers in bold font indicate statistical significance at the 1% level or better (one-sided test). The final row indicates number of 5-minute intervals over which jumps could be computed (at least ten stocks should be traded in each particular interval to be included in the sample and at least 25 intervals should be valid during a particular day to start jumps computation). Markets are grouped by region and listed in alphabetical order within each region. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World Bank website, and Datastream.

	America				Asia				Europe/Africa			
	Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
# simultaneous jumps	3	11	3	18	46	19	101	7	77	59	3	27
Prob(simultaneous jumps) empirical (in bp)	0.27	0.39	0.22	0.64	3.42	1.23	6.25	0.30	2.10	1.83	0.11	0.73
Prob(simultaneous jumps) theoretical, under independence assumption (in bp)	0.03	0.02	0.01	0.01	0.29	0.01	0.15	0.04	0.04	0.02	0.04	0.01
p-value (one-sided test)	**0.006**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	0.072	**<0.001**
# Obs.	110,651	284,365	138,545	282,718	134,326	154,511	161,707	230,193	366,342	322,923	267,093	372,216

Table 5: Simultaneous jumps in prices and order imbalance within a market and macroeconomic news announcements (12 markets, 2001-2011)

This table presents the number of jumps in 5-minute equally-weighted market returns ($PRICE$) and the number of simultaneous jumps in $PRICE$ and 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) that occur within a short event window around macroeconomic news announcements over 2001-2011. In total, we use data on 6,037 different macroeconomic news announcements from the American region (Canada and the U.S.), from the Asian region (China and Japan), and from the European region (EMU, France, Germany, and the U.K.). The event window around the macroeconomic news announcements is [-1,+12], measured in 5-minute intervals. The first row indicates the number of unique release times of macroeconomic news announcements that occur within the opening hours of the market. Markets are grouped by region and listed in alphabetical order within each region. Data are from TRTH, the World Bank website, and Datastream. Data on the macroeconomic news announcements are from the Econoday database.

	America				Asia				Europe/Africa			
	Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
# of macroeconomic news announcements within trading hours	1,871	1,212	1,164	1,212	618	2,183	118	1,280	4,524	4,524	4,337	4,524
# of jumps in $PRICE$	72	154	195	193	714	85	745	341	257	303	197	250
# of jumps in $PRICE$ in the window [-1,+12] around macro announcements	23	15	23	44	60	14	7	25	87	119	29	95
# of simultaneous jumps in $PRICE$ and OIB	3	11	3	12	42	18	62	5	55	54	0	26
# of simultaneous jumps in $PRICE$ and OIB in the window [-1,+12] around macro announcements	2	1	1	5	2	4	3	0	30	29	0	11

Table 6: Co-jumps in prices, liquidity, and trading activity across markets on the same day (12 equity markets, 1996-2011)

This table presents the number of days on which one, two, or three markets within each region (America, Asia, and Europe/Africa) exhibit a jump in 5-minute equally-weighted market returns ($PRICE$), 5-minute log-changes in equally-weighted proportional quoted spreads ($PQSPR$), or 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB), for 12 equity markets over 1996-2011. First, we use the BNS jump measure to identify days with jumps in each variable for each market. Then, we count the number of markets that have a jump of the same sign in the same variable on the same day, and distinguish between three cases: only one market has a jump in that variable on a certain day, two markets have a jump in that variable of the same-sign on the same day, and three or more markets have a jump in that variable of the same-sign on the same day. Jumps are classified according to their sign: positive (POS) and negative (NEG). We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World Bank website, and Datastream.

	America						Asia						Europe/Africa					
	$PRICE$		$PQSPR$		OIB		$PRICE$		$PQSPR$		OIB		$PRICE$		$PQSPR$		OIB	
	POS	NEG	POS	NEG	POS	NEG	POS	NEG	POS	NEG	POS	NEG	POS	NEG	POS	NEG	POS	NEG
=1	339	330	307	166	592	481	856	908	390	259	593	569	452	489	491	241	849	921
=2	9	15	4	3	16	11	102	135	8	1	39	57	71	56	20	2	117	116
>=3	0	1	0	0	1	0	5	6	0	0	2	3	15	21	0	0	9	11

Table 7: Correlations of 5-minute jumps in prices, $PQSPR$, and OIB within and across regions (12 equity markets, 1996-2011)

This table presents contemporaneous Spearman rank correlations between jumps in 5-minute equally-weighted market returns ($PRICE$), 5-minute log-changes in equally-weighted proportional quoted spreads ($PQSPR$), and 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) across 12 equity markets over 1996-2011. Panel A shows Spearman correlations of 5-minute jumps in prices across markets, Panel B shows Spearman correlations of 5-minute jumps in $PQSPR$ across markets, and Panel C shows Spearman correlations of 5-minute jumps in OIB across markets. Correlations are computed based on overlapping trading hours only. We take into account the sign and the magnitude of the jumps by setting our jump variables equal to zero in 5-minute intervals without a jump in the respective variable, and to the signed magnitude of the jump (measured in jump-free standard deviations) in 5-minute intervals with a jump. Numbers in bold font indicate statistical significance at the 1% level or better. Markets are grouped by region and listed in alphabetical order within each region. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World Bank website, and Datastream.

Panel A: Spearman correlations of 5-minute jumps in $PRICE$

		America				Asia				Europe/Africa			
		Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
America	Brazil		**3.97%**	0.00%	0.00%					**5.11%**	**5.08%**	0.00%	**7.28%**
	Canada			0.00%	**1.87%**					**1.66%**	-0.87%	0.00%	0.91%
	Mexico				0.65%					**1.40%**	**2.46%**	0.00%	**1.57%**
	U.S.									**7.61%**	**7.65%**	0.01%	**7.64%**
Asia	Hong Kong						0.00%	0.02%	**10.47%**	0.01%	0.00%	0.00%	0.03%
	India							-0.01%	**1.58%**	**3.19%**	-0.01%	0.00%	-0.01%
	Japan								0.01%				
	Malaysia									0.01%	0.00%	0.00%	0.00%
Europe/Africa	France										**18.78%**	**1.86%**	**13.44%**
	Germany											**2.13%**	**15.71%**
	South Africa												**2.36%**
	U.K.												

Table 7: Correlations of 5-minute jumps in prices, $PQSPR$, and OIB within and across regions (continued)

Panel B: Spearman correlations of 5-minute jumps in $PQSPR$

		America				Asia				Europe/Africa			
		Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
America	Brazil		0.00%	0.00%	0.00%						0.00%	0.00%	0.00%
	Canada			0.00%	**0.85%**					-0.02%	-0.02%	-0.05%	-0.03%
	Mexico				0.00%					0.00%	0.00%	0.04%	0.01%
	U.S.									0.00%	0.00%	0.01%	0.00%
Asia	Hong Kong						0.00%	0.01%	0.00%	-0.02%	-0.03%	-0.05%	-0.01%
	India							-0.02%	0.00%	0.00%	0.00%	0.00%	0.00%
	Japan								0.05%				
	Malaysia									-0.04%	-0.07%	-0.03%	-0.10%
Europe/Africa	France										0.00%	0.00%	**1.00%**
	Germany											-0.01%	-0.01%
	South Africa												-0.01%
	U.K.												

Panel C: Spearman correlations of 5-minute jumps in OIB

		America				Asia				Europe/Africa			
		Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
America	Brazil		0.00%	-0.01%	**1.34%**					**1.91%**	0.77%	-0.99%	**2.65%**
	Canada			**2.02%**	**0.84%**					0.84%	0.71%	**-1.84%**	0.00%
	Mexico				0.00%					0.00%	0.00%	-0.01%	0.00%
	U.S.									**5.48%**	**3.62%**	-0.01%	**1.30%**
Asia	Hong Kong						0.01%	**1.92%**	-0.30%	**-2.45%**	-0.01%	0.02%	0.00%
	India							0.00%	0.00%	0.63%	0.01%	0.00%	0.00%
	Japan								**3.23%**				
	Malaysia									0.00%	0.00%	0.00%	0.00%
Europe/Africa	France										**8.88%**	0.43%	**4.08%**
	Germany											**0.76%**	**6.55%**
	South Africa												0.30%
	U.K.												

Table 8: Logit models to explain 5-minute jumps in prices (12 equity markets, 1996−2011)

This table shows marginal effects (in %) of logit models to explain the occurrence of jumps in 5-minute equally-weighted market returns ($PRICE$) for each of the 12 equity markets in our sample over 1996-2011. As dependent variable, we use an indicator variable of whether there was a price jump on a particular market i in a particular 5-minute interval. As independent variables, we use an indicator variable of same-sign jumps in 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) on market i in the same 5-minute interval, indicator variables of whether at least one other market in the same region (labeled "not i") has a same-sign jump in $PRICE$ or in OIB in the same 5-minute interval, and indicator variables of whether at least one market in a different region has a same-sign jump in price or in OIB in the same 5-minute interval. Independent variables are defined only when at least one of the markets in region has overlapping opening hours with market i. We cannot include American and Asian markets in the same model since there is no overlap in trading hours. Some of the independent variables are omitted from the model specification due to a separation problem in the estimation. Numbers in bold font indicate statistical significance at 10% level and less. The markets are grouped by region: Panel A presents the results for the American markets, Panel B for the Asian markets, and Panel C for the European markets. All logits are estimated separately for negative price jumps (Part I of each panel) and positive price jumps (Part II of each panel). Markets are listed in alphabetical order. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World Bank website, and Datastream.

Panel A: Logit models to explain 5-minute price jumps on American markets

Part I: Positive jumps in $PRICE$

Market i:	Brazil		Canada		Mexico		U.S.	
Model:	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
OIB POS i	0.34	**-0.03**	**1.86**	0.41	3.38	8.85	**10.89**	**5.36**
PRICE POS not i	0.26	0.04	0.02	0.02	0.60	0.37	0.09	**-0.05**
OIB POS not i	0.28	0.05	0.41	1.49	**-0.08**	**-0.16**	0.31	0.30
PRICE POS Europe/Africa		2.05		0.10		1.28		0.75
OIB POS Europe/Africa		0.09		**1.11**		0.43		**0.82**
# Obs.	97,109	26,446	279,646	69,864	137,766	31,579	279,291	69,778

Part II: Negative jumps in $PRICE$

Market i:	Brazil	Canada		Mexico	U.S.	
Model:	(1)	(1)	(2)	(1)	(1)	(2)
OIB NEG i	0.23	0.83	2.35	4.07	1.97	0.63
PRICE NEG not i	0.28	**1.79**	1.57	**-0.06**	**1.48**	0.97
OIB NEG not i	0.32	0.36	0.44		0.13	0.14
PRICE NEG Europe/Africa			0.31			**0.63**
OIB NEG Europe/Africa			0.03			**1.84**
# Obs.	97,109	279,646	69,864	137,766	279,291	69,778

Table 8: Logit models to explain 5-minute jumps in prices (continued)

Panel B: Logit models to explain 5-minute price jumps on Asian markets

Part I: Positive jumps in *PRICE*

Market *i*:	Hong Kong	India	Japan	Malaysia
Model:	(1)	(1)	(1)	(1)
OIB POS i	**6.10**	2.71	**18.85**	1.48
PRICE POS not i	**4.51**	0.25	**-0.43**	2.81
OIB POS not i	**-0.30**	**-0.01**	**-0.43**	**-0.11**
# Obs.	128,250	90,743	71,776	179,525

Part II: Negative jumps in *PRICE*

Market *i*:	Hong Kong	India	Japan	Malaysia
Model:	(1)	(1)	(1)	(1)
OIB NEG i	**7.69**	3.20	**41.64**	0.84
PRICE NEG not i	**7.67**		1.15	**4.73**
OIB NEG not i	-0.17	**-0.03**	0.63	-0.04
# Obs.	128,250	90,743	71,776	179,525

Table 8: Logit models to explain 5-minute jumps in prices (continued)

Panel C: Logit models to explain 5-minute price jumps on European/African markets

Part I: Positive jumps in $PRICE$

Market i:	France			Germany			South Africa	U.K.		
Model:	(1)	(2)		(1)	(2)	(3)	(1)	(1)	(2)	(3)
$OIB\ POS\ i$	**2.16**	**0.80**		**1.74**	2.21	7.74	0.16	**3.10**	3.12	**-0.04**
$PRICE\ POS\ not\ i$	**2.42**	**2.03**		**2.45**	2.61	0.34	0.53	**2.58**	**2.37**	0.30
$OIB\ POS\ not\ i$	**0.55**	**0.71**		**0.29**	0.35	0.24	0.03	**0.48**	0.18	1.06
$PRICE\ POS\ America$		0.17			0.19				**0.81**	
$OIB\ POS\ America$		**0.82**			**-0.06**				0.07	
$PRICE\ POS\ Asia$										**-0.04**
$OIB\ POS\ Asia$						**-0.05**				
# Obs.	364,975	78,574		320,337	72,869	72,582	25,1708	361,716	78,455	71,791

Part II: Negative jumps in $PRICE$

Market i:	France			Germany			South Africa	U.K.		
Model:	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(1)	(2)	(3)
$OIB\ NEG\ i$	**1.19**	**1.92**	1.61	**1.60**	0.60	2.22	**-0.04**	**0.53**	0.60	2.98
$PRICE\ NEG\ not\ i$	**2.32**	**2.74**	0.69	**3.58**	**5.44**	1.96	0.74	**2.25**	**3.27**	0.66
$OIB\ NEG\ not\ i$	**0.44**	0.41	0.96	**0.60**	**0.67**	0.40	0.24	**0.50**	0.22	0.91
$PRICE\ NEG\ America$		0.04			**0.95**				0.17	
$OIB\ NEG\ America$		**-0.05**			0.08				**-0.04**	
$PRICE\ NEG\ Asia$			2.62							**-0.07**
$OIB\ NEG\ Asia$			**-0.07**			**-0.05**				0.77
# Obs.	364,975	78,574	73,007	32,0337	72,869	72,582	251,708	361,716	78,455	71,791

Table 9: Jumps in the TED spread and jumps in prices, $PQSPR$, and OIB (12 equity markets, 1996-2011)

This table shows the number of days with the jumps (Panel A), the probability of observing a day with a jump (Panel B), the number of days with coinciding jumps (Panel C), and the p-values of the test of whether the empirical probability is greater than the theoretical probability (Panel D) for negative jumps in $PRICE$, positive jumps in $PQSPR$, negative jumps in OIB, and positive jumps in the TED spread. Jumps in $PRICE$, $PQSPR$, and OIB are computed at the 5-minute frequency on a daily basis, while jumps in the TED spread are computed at the daily frequency on a yearly basis. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World Bank website, Datastream, and Federal Reserve Bank of St. Louis.

	America				Asia				Europe/Africa			
	Brazil	Canada	Mexico	U.S.	Hong Kong	India	Japan	Malaysia	France	Germany	South Africa	U.K.
Panel A: Number of days with jumps												
$PRICE < 0$	37	107	69	139	411	56	552	177	186	172	115	181
$PQSPR > 0$	6	175	97	37	34	36	181	155	24	76	196	235
$OIB < 0$	153	256	18	71	222	154	121	195	473	192	384	126
$TED > 0$	6	9	6	9	9	3	9	9	9	9	9	9
# Obs.	1,441	3,967	1,960	3,952	3,665	2,560	3,856	3,892	4,011	3,401	3,176	3,990
Panel B: Probability of jumps in percentage												
$PRICE < 0$	2.57	2.70	3.52	3.52	11.21	2.19	14.32	4.55	4.64	5.06	3.62	4.54
$PQSPR > 0$	0.42	4.41	4.95	0.94	0.93	1.41	4.69	3.98	0.60	2.23	6.17	5.89
$OIB < 0$	10.62	6.45	0.92	1.80	6.06	6.02	3.14	5.01	11.79	5.65	12.09	3.16
$TED > 0$	0.42	0.23	0.31	0.23	0.25	0.12	0.23	0.23	0.22	0.26	0.28	0.23
Panel C: Coinciding jumps in the TED spread and either PRICE, PQSPR or OIB												
$PRICE < 0$; $TED > 0$	0	0	0	0	1	0	1	0	1	0	0	0
$PQSPR > 0$; $TED > 0$	0	0	1	0	0	0	0	2	0	1	0	1
$OIB < 0$; $TED > 0$	1	0	0	1	0	0	1	0	0	0	0	0
Panel D: P-value (empirical probability of coinciding jumps > theoretical probability under independence assumption)												
$PRICE < 0$; $TED > 0$	1.00	1.00	1.00	1.00	0.64	1.00	0.72	1.00	0.34	1.00	1.00	1.00
$PQSPR > 0$; $TED > 0$	1.00	1.00	0.26	1.00	1.00	1.00	1.00	**0.05**	1.00	0.18	1.00	0.41
$OIB < 0$; $TED > 0$	0.47	1.00	1.00	0.15	1.00	1.00	0.25	1.00	1.00	1.00	1.00	1.00

Figure 1: Behavior of prices around price jumps and simultaneous price and OIB jumps (across 12 equity markets, 1996-2011)

This figure shows the cumulative 5-minute market-wide equally-weighted returns in basis points (averaged across all the price jumps in the 12 equity markets) from one hour before till one hour after either positive or negative jumps in price over 1996-2011. Panel A and Panel B present cumulative average returns around all price jumps in our sample, while Panel C and Panel D present cumulative average returns around jumps in price that coincide with jumps in OIB of the same sign in the same 5-minute interval. Cumulative returns are plotted for each 5-minute interval in the event window, with the price jump taking place at $t = 0$. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World bank website, and Datastream.

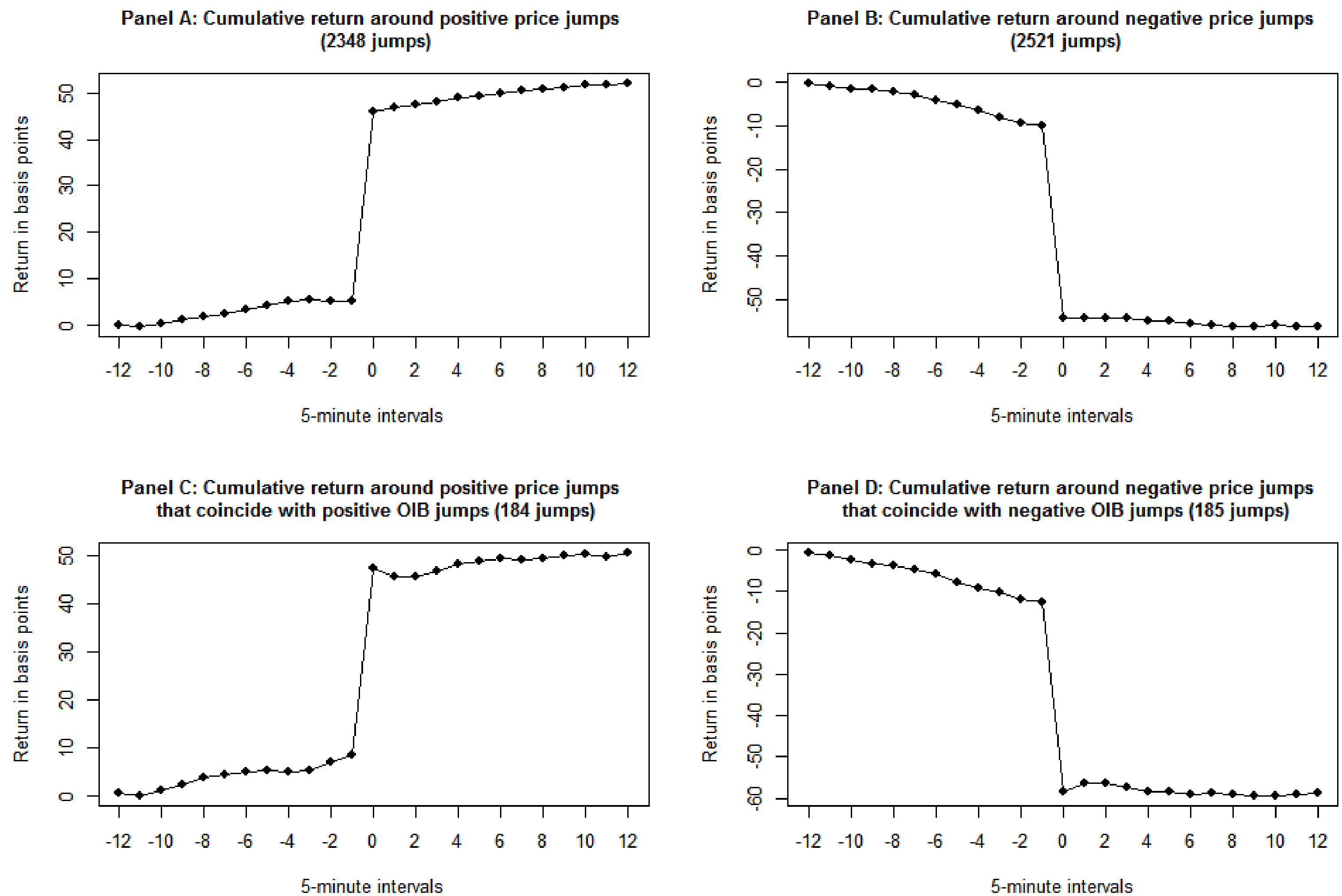

Figure 2: Behavior of $PQSPR$ and OIB around price jumps (across 12 equity markets, 1996-2011)

This figure shows the cumulative changes in 5-minute equally-weighted proportional quoted spreads ($PQSPR$), and 5-minute market aggregate order imbalance scaled by aggregate market capitalization (OIB) (averaged across all the price jumps in the 12 equity markets) from one hour before till one hour after either positive or negative jumps in price over 1996-2011, respectively. Panel A and Panel B present average cumulative changes in $PQSPR$ around positive and negative price jumps in our sample, while Panel C and Panel D present average OIB around positive and negative price jumps in our sample. Cumulative changes in $PQSPR$, OIB are plotted for each 5-minute interval in the event window. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH, the World bank website, and Datastream.