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

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

November 2014

Abstract

We study the high-frequency propagation of shocks across international equity markets. We identify shocks to stock prices, liquidity (quoted and effective spreads), and trading activity (turnover and order imbalance) for 12 equity markets around the world based on non-parametric jump statistics at the 5-minute frequency from 1996 to 2011. Jumps in prices, quoted spreads, and order imbalance are prevalent and large, while jumps in effective spreads and turnover are rare. Within a market, jumps in prices are regularly accompanied by jumps in order imbalance, but are independent of jumps in liquidity. Jumps in prices and co-jumps in prices and order imbalance are primarily driven by information rather than liquidity, since there is no subsequent price reversal and since they often occur around U.S. macroeconomic news announcements. We also present evidence that jumps in prices and order imbalance (but not liquidity) spillover across markets within the same 5-minute interval. Overall, we find that order imbalances help explain why shocks to stock prices occur and spread across markets, while shocks to liquidity tend to be isolated events.

---

*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. Corresponding author: Darya Yuferova. We are grateful to Torben Andersen, Francis Longstaff, seminar participants at Erasmus University, and conference participants at the 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 within and across regions (see, e.g., Eun and Shim, 1989; Roll, 1989; Hamao, Masulis, and Ng, 1990; Lin, Engle, and Ito, 1994, for early research on these questions). 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 (e.g., Reinhart and Calvo, 1996; Forbes and Rigobon, 2002; Bae, Karolyi, and Stulz, 2003; Hartmann, Straetmans, and De Vries, 2004; see Karolyi, 2003 for a review). The recent global financial crisis has highlighted how shocks to certain financial markets (e.g., the U.S. mortgage-backed security market) can rapidly spread to markets for other asset classes (e.g., Longstaff, 2010) and to markets in other countries (e.g., Bekaert, Ehrmann, Fratzscher, and Mehl, 2011).

But we still know relatively little about *how* shocks to equity prices propagate across markets. Prior work attempts to link coincidences of extreme returns on different markets to financial and macroeconomic variables, with limited success. In this paper, we take a different approach by offering a microstructure perspective on the propagation of shocks across international financial markets. In particular, we aim to improve our understanding of why shocks to equity prices occur and spread across markets by investigating their relation with shocks to market liquidity and/or trading activity. After all, the literature on market microstructure and asset pricing suggests that studying liquidity and trading activity is important for understanding the price formation process on financial markets. Moreover, it is widely accepted that market liquidity dry-ups played a crucial role during the recent global financial crisis (e.g., Brunnermeier, 2008). To the best of our knowledge, we are the first to study cross-market linkages between stock prices jointly with liquidity and trading activity.[1]

[1] 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 comovement 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.

We also add to prior work by analyzing the propagation of shocks across markets at a much higher frequency: 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; Pukthuanthong and Roll, 2012). This approach could possibly miss interdependence at a higher frequency 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.[2]

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, liquidity (quoted and effective spreads), and trading activity (turnover and order imbalance) for 12 equity markets around the world 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 (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 sample period.

Our results can be summarized as follows. First, we analyze the time-series of jumps within each market. 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

[2]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.

markets. The magnitudes of typical jumps in prices, quoted spreads and order imbalance are large, at around 4-6 jump-free standard deviations.

Second, we study what happens to liquidity and trading activity around jumps in prices. Within a market, our evidence indicates that jumps in prices do not occur independently from jumps in trading activity, as measured by order imbalance. On average, around 8% of the jumps in prices 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.[3] Many of the coinciding jumps in prices and order imbalance happen within the same 5-minute interval, and in almost all cases they involve jumps in prices and order imbalance of the same sign. In contrast, 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 occurrence of price jumps.

Third, we examine the potential channels through which price jumps and simultaneous jumps in prices and order imbalance arise. They could be either liquidity-driven (that is, large uninformed order flow results in temporary price pressure due to low market resiliency) or information-driven (that is, new information arriving on the market results in a large one-directional order flow and a permanent price reaction). We carry out two tests to distinguish these explanations. Specifically, we investigate whether there are reversals after jumps in prices (and simultaneous jumps in order imbalance) and whether jumps in prices (and simultaneous jumps in order imbalance) occur around U.S. macro news announcements. We find little evidence that jumps in prices subsequently exhibit reversals, and we find that 40% of the jumps in prices and 50% of the simultaneous jumps in prices and order imbalance on developed equity markets in Europe happen within one hour after U.S. macro news announcements. Both pieces of evidence are most consistent with the information channel.

Fourth, we explore within-region and across-region spillover effects of jumps in prices, quoted spreads, and order imbalance. We document significant spillover effects at the 5-

[3]At the same time, we note that this finding implies that more than 90% of the price jumps are not accompanied by jumps in order imbalance.

minute frequency for jumps in prices and trading activity, based on spearman correlations of the time-series of jumps in prices and order imbalance, adjusted for the magnitude of the jump. These correlations are especially strong within the European/African region and between developed Europe and the U.S. Remarkably, jumps in quoted spreads are not correlated across different markets, which suggests that "liquidity black holes" (Morris and Shin, 2004) are mainly local phenomena. We then 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 spearman 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 shows that the time-series of market-wide equity prices, quoted spreads, and order imbalance measured over 5-minute intervals within the trading day are characterized by frequent jumps of substantial magnitude. Although many of these jumps are stand-alone events, a significant fraction of the jumps in prices coincide with jumps in order imbalance of the same sign in the same 5-minute interval, both within and across markets – plausibly because new information arrives on the market that results in one-sided trading and a permanent effect on prices. Counter to what seems to be conventional wisdom, our results are not supportive of an important role for market liquidity in the propagation of shocks across different markets. Jumps in effective spreads are sporadic, and although jumps in quoted spreads occur frequently, they tend to be isolated events that are not associated with jumps in prices (neither on the same nor on other markets) or with jumps in quoted spreads on other markets.

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 method

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.[4]

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, Asia, and Europe/Africa.[5] 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 then obtain 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 RICs for all 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 (2014), 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).

[4]Recent papers that use the TRTH database include Fong, Holden, and Trzcinka (2011), Boehmer, Fong, and Wu (2012a), Boehmer, Fong, and Wu (2012b), Marshall, Nguyen, and Visaltanachoti (2012), Marshall, Nguyen, and Visaltanachoti (2013a), Marshall, Nguyen, and Visaltanachoti (2013b), Rösch, Subrahmanyam, and van Dijk (2014), and Frino, Mollica, and Zhou (2014).

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

2.1. Variable definitions

Our primary goal is to provide a microstructure perspective on the propagation of shocks across international equity 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 detect the intraday propagation of shocks 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 equity markets in our sample). 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.

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 on the trade prices or 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. 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 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 these five 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 (2012) and use a statistical jump measure to identify a shock.[6] 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 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 on 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).

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 the best jump measure in the simulations of Pukthuanthong and Roll (2012). 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. In case of a (discontinuous) shock in 5-minute interval t, the squared observation on that day will be significantly larger than the corresponding absolute product of the observations in 5-minute intervals t and $t-1$. Hence, 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.

The underlying idea of the BNS measure is illustrated in Figure 1. Panel A of Figure 1 shows the actual time-series of 5-minute midquote returns for the London Stock Exchange on February 9th, 2011, which clearly exhibits a discontinuous negative shock at 10:45 GMT.

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

Panel B of Figure 1 plots the same time-series but with the return observation in this 5-minute interval replaced by a zero return. The ratio of scaled bipower variation to squared variation is close to one in the Panel B (ratio is equal to 0.94), while the bipower variation is significantly smaller than the squared variation in Panel A (ratio is equal to 0.24).

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) and thus reject the null hypothesis of no jumps on a day if the BNS measure is below -3.09 (the 0.1% percentile of the standard normal distribution, one-sided test). Our time-series based on 5-minute intraday intervals over 1996-2011 contain sufficient observations (around 230,000) to still have the potential to detect a substantial number of jumps based on this strict statistical criterion.

In the example of Figure 1, the BNS statistic based on the series in Panel A is -10.90 and thus leads to the rejection of the null hypothesis of no jumps on that day (p-value$<$0.001). For the series in Panel B, the BNS statistic is -0.86 and hence the null-hypothesis of no jumps cannot be rejected (p-value=0.2). For each day in the sample period, we compute the BNS measure for the market-wide returns, market-wide quoted and effective spreads, and market-wide turnover and order imbalance based on the 5-minute observations for those variables within the day.

For each day, we can thus identify whether there was a jump in any of these series 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 develop 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 such an observation. Afterwards, 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. A more detailed description of this algorithm is contained in Appendix B.[7]

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 (Sections 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).

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 of the inclusion of the recent crisis in our sample period and potentially because we exclude

[7] We thank Torben Andersen for suggesting this approach.

overnight returns from our sample. 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 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 higher over the period 1996-2000 and that our number is equally-weighted instead of value-weighted. 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 two rows of Table 1 show the number of 5-minute intervals for which the various variables can be computed per each market; this number varies according to the opening hours of the exchange as well as the intensity of trading activity on the exchange (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 230,886 for returns and 236,775 for the other variables. We note that the number of 5-minute return observations is lower than that of the other variables because computing returns requires two valid consecutive 5-minute observations, while for the other variables one interval suffices.

Since we want to analyze the propagation of shocks across variables and markets, we transform the stock variables $PQSPR$ and $PESPR$ to a flow variable by taking 5-minute log-changes (following Pukthuanthong and Roll (2012), 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 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 of jumps in prices, liquidity, and trading activity

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 price; 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 jump 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 price, $PQSPR$, and OIB are much higher. For example, in Germany there are 205 5-minute intervals with a negative jump in price, which occur on 178 different days (compared to four days under the null hypothesis) or approximately 4.7% (compared to 0.1% under the null hypothesis) of all trading days from 1996 to 2011. The finding that jumps in prices, $PQSPR$, and OIB occur much more frequently than under the no jump assumption is obtained for all markets in the sample, although there is considerable cross-market variation in the number of jumps in these variables. 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. There are two potential explanations for the low number of jumps in $PESPR$ as compared to jumps in $PQSPR$. First, $PESPR$ can only be measured when a trade occurs. Rational investors observing a jump in quoted spread could abandon the market and return when liquidity improves. A second, alternative interpretation of the joint finding of relatively frequent jumps in $PQSPR$ and no jumps in $PESPR$ is that investors face relatively low execution risk. Based on the results in Table 2, we exclude the time-series of jumps in $PESPR$ and turnover from the remainder of our analyses.

Although these overall empirical patterns of jumps in the different variables are quite similar across markets, there also is considerable cross-country 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.

The jumps documented in 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 Table 3 we present summary statistics for 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, 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 Table 3 that the magnitude of the jumps in prices, $PQSPR$, and OIB we detect using the BNS approach is large for all markets in the sample. The average jump magnitude for both negative and positive jumps in price, $PQSPR$, and OIB is around five jump-free standard deviations with a range in absolute terms from 3.85 (negative $PQSPR$ jumps in Hong Kong) to 7.61 (negative $PQSPR$ jumps in France) jump-free standard deviations.

For jumps in prices, five jump-free standard deviations correspond to a market return of around 40 basis points, which 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 quoted spread change of 42%, which is 83 times greater than the absolute value of the average 5-minute change in market-wide quoted spreads.

The theoretical probability of observing a five standard deviations 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.

Another important aspect of the empirical patterns of jumps in prices, liquidity, and trading activity is whether these jumps tend to cluster during a trading day. In our approach, this tends not to be the case. Jumps generally occur at most once per day. 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 only 2% have three or more price jumps.

In the next section, 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

We are interested in whether the occurrence and propagation of shocks to aggregate equity prices occur in the same time frame as shocks to liquidity and trading activity. Accounts of the development of the recent global financial crisis (e.g., Brunnermeier, 2008) often attribute the sharp declines of various markets to a sudden evaporation of liquidity, or, more specially, to liquidity spirals that can arise as the result of the interaction between funding liquidity and market liquidity (Brunnermeier and Pedersen, 2009). Thus, it is worthwhile to investigate whether jumps in equity prices tend to be accompanied by "liquidity black holes" (i.e., jumps in market liquidity) or sudden shifts in trading activity.

We start by documenting the links among jumps in the different variables within each market. For example, on days with a price jump, are there jumps in other variables as well? We treat a jump in equity prices (or in one of the other variables) as an event and examine whether there are jumps in liquidity and/or trading activity before the event (that is, 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 (that is, from the event until the end of the same trading day – or until the next price jump on the same day).

The results are in Table 4. The table contains three panels. Panels A and B discloses whether price jumps (the event) are accompanied by jumps in, respectively, $PQSPR$ and OIB on the same market on the same day. Panel C discloses 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" for positive price jumps and "NEG" for negative price jumps). 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 positive or negative jump in $PQSPR$ on the same market in the same 5-minute interval.[8] The following four rows show the number of positive or negative price jumps that were preceded by positive or negative jumps 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 positive or negative jumps in $PQSPR$ on the same market on the same day. The structure of Panels B and C is the same.

Panel A of Table 4 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.[9] 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

[8] We refer to co-jumps on the same day as "coinciding" and to co-jumps in the same 5-minute interval as "simultaneous".

[9] We note that the sum of the numbers of price jumps in each column of Panel A of Table 4 can exceed the total number of price jumps for the respective country reported in Table 2 in case some price jumps are accompanied by more than one jump in $PQSPR$ on the same day.

jump in the same 5-minute interval are of positive sign (in line with our expectation that a sudden deterioration in liquidity is associated with a price decline), we also observe that, unexpectedly, 13 of the 16 $PQSPR$ jumps in Japan that accompany a positive price jump in the same 5-minute interval are positive. Panel B of Table 4 shows a stronger relation between jumps in prices and jumps in OIB. Not only do we observe a greater incidence of coinciding jumps in price and OIB (especially within the same 5-minute interval, with the exception of South Africa), these coinciding jumps also more often have the expected sign. That is, negative (positive) jumps in prices tend to be associated with negative (positive) jumps in OIB, as indicated by the higher numbers in the first and the last rows in simultaneous jumps section in Panel B. In general, this pattern is stronger for markets in Asia and Europe/Africa than for markets in America.

Within each region, developed markets tend to show a more consistent pattern than emerging markets. For example, in South Africa, jumps in prices and OIB coincide in the same 5-minute interval with the same sign only once, while the average number of simultaneous price and OIB jumps of the same sign within developed Europe (France, Germany, and the U.K.) is 54. Similarly, developed markets in Asia (Hong Kong and Japan) on average experience 72 simultaneous price and OIB jumps of the same sign over our sample period, while emerging markets in Asia (India and Malaysia) have only 13 such cases on average. In the American region, Canada and the U.S. exhibit on average 14 simultaneous jumps of the same sign in price and OIB, while Brazil and Mexico have three such cases on average.

Panel C of Table 4 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 associated with jumps in $PQSPR$ on the same day.

Overall, the results in Table 4 indicate that a notable 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 whether these simultaneous jumps are frequent enough compared to the total number of jumps in prices and OIB. For 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 negative jumps in prices on the German equity market are accompanied by simultaneous negative jumps 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 of the same sign in prices and OIB and 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 of the empirical probability being greater than the theoretical probability.

Table 5 shows the number of simultaneous jumps in prices and OIB of the same sign in the same 5-minute interval by market, as well as the 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. As an example, for Germany the empirical probability of a jump in prices equals 9.18 basis points and of a jump in OIB equals 11.8 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 is 0.01 basis points (9.18 basis points $\times$ 11.8 basis points). However, Table 4 shows that simultaneous jumps in prices and OIB are observed in 59 5-minute intervals, which corresponds to an empirical probability of simultaneous jumps equal to 1.48 basis points. The final row of Table 5 shows that the p-value of the test that the empirical probability of simultaneous jumps (1.48 basis points) is equal to the theoretical probability (0.01 basis points) is <0.001, which implies a 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. 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 jumps in OIB, which suggests that studying such co-jumps can help us to understand why price jumps occur.

In the subsequent section, we examine the potential channels through which shocks to prices occur and are related to shocks to OIB.

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

We distinguish between two broad, competing explanations for why price jumps occur and why they occur simultaneously with jumps in order imbalance. First, 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. Second, 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 large-scale portfolio rebalancing. (We note that given 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 tests to distinguish between these liquidity-based and information-based channels. First, we investigate whether prices exhibit a reversal after a price jump and after a simultaneous jump in prices and OIB. The liquidity-based hypothesis predicts that price pressure is temporary and price should revert, while the information-based hypothesis predicts that price adjustments are permanent and no reversal should be observed.

Figure 2 presents graphs of the cumulative market return from one hour before until one hour after jumps 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 jumps in Panel C and negative jumps in Panel D), averaged across the 12 markets in our sample and measured in basis points. 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. 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 price across all markets from Table 2). The total number of jumps underlying Panels C and D is 184 and 185, respectively (obtained by aggregating the number of positive and negative simultaneous jumps in price and OIB across all markets from Table 4). As discussed above, the average price jump is around 40-50 basis points, which is a substantial 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 2 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.

More importantly from the perspective of distinguishing the liquidity and information channels, there is little consistent evidence of any reversal following either price jumps or simultaneous jumps in prices and OIB. In other words, price jumps 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.

The second test of the liquidity vs. the information channel is aimed to examine more directly whether price jumps and simultaneous jumps in prices and OIB are related to information events. In particular, we investigate the relation between jumps in prices and OIB and 25 categories of U.S. macroeconomic news announcements over the period 2004-2009, obtained from the Econoday database (the data on macroeconomic news announcements includes announcements regarding GDP, nonfarm payroll employment, producer and consumer price indices, etc.).[10] We follow Andersen, Bollerslev, Diebold, and Vega (2003) and Opschoor, Van der Wel, Van Dijk, and Taylor (2014) and use the same classification of U.S. macroeconomic news announcements. In total, we have data on 2,798 different macroeconomic news announcements, out of which 653 (around 23%) occur within U.S. trading hours and out of which around 2,500 (90%) occur within the opening hours of European markets. We exclude the Asian region from this analysis since none of the Asian markets is open during any of the announcements.

Table 6 presents evidence on the frequency with which price jumps and simultaneous jumps in prices and OIB occur around U.S. macroeconomic news announcements. The four lines in the table show the number of price jumps on each American and European/African market over the period 2004-2009, the number of price jumps that occur within a short window around the release time of the macroeconomic news announcements (from five minutes before till one hour after the event), the number of simultaneous jumps in prices and OIB on each market over the period 2004-2009, and the number of simultaneous in prices and OIB that occur within the window around one of the news announcements.

Since most of the macroeconomic news announcements occur outside the opening hours of the American exchanges in our sample, it is not surprising that these exchanges exhibit few price jumps or simultaneous jumps in prices and OIB that occur in the event window. However, for Europe, we find strong evidence that price jumps or simultaneous jumps in prices and OIB are related to U.S. macroeconomic news announcements. For example, for Germany, we document 181 5-minute intervals with price jumps over 2004-2009, of which 73 (or 40%) occur around a U.S. macroeconomic news announcement. Over the same period, we observe 29 5-minute intervals with simultaneous jumps in prices and OIB of the same sign in Germany, of which 19 (or 66%) are in the event window surrounding one of the announcements. On average across the three European markets in our sample, 40% of the

[10]We are grateful to Michel van der Wel for providing the data on U.S. macroeconomic news announcements for this period, as used in Opschoor, Van der Wel, Van Dijk, and Taylor (2014).

price jumps and 50% of the simultaneous jumps in prices and OIB occur within one hour after a U.S. macroeconomic news announcement. In an unreported analysis, we also examine whether jumps in prices and simultaneous jumps in prices and OIB 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 simultaneous jumps in prices and OIB.

To sum up, the evidence based on return reversals surrounding jumps in prices (and OIB) and based on the occurrence of jumps in prices (and OIB) around U.S. macroeconomic news announcements indicates that the information channel is an important explanation for the occurrence of price jumps and of simultaneous jumps in prices and OIB.

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 simultaneous jumps in different variables within one market, and on the main source of (co-)jumps in prices (and OIB). We now turn to one of the main goals of the paper: to analyze the role of microstructure effects 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 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. Co-jumps in prices, liquidity, and trading activity across markets

Table 7 reports the number of days on which one, two, or three or more markets within the same region exhibit a positive/negative jump in price, $PQSPR$, 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 price, $PQSPR$, or OIB during a particular day in a particular region, but there are also a substantial number of cases of two or more countries having a jump in the same variable in the same direction 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 both prices and OIB in Asia. Co-jumps in the same variable in the same direction on different markets within a region are much less likely in America. Furthermore, we find very few occasions of co-jumps in $PQSPR$ on different markets within the same region, which suggests that shocks to liquidity do not tend to occur on multiple markets in the same time frame.

Overall, the results in Table 7 suggest 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 across multiple markets on the same day 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 8, we extend the analysis in Table 7 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 8 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 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. Bold correlations are significant at the 10% 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 13.08%. The correlations between price jumps on developed markets in Europe and South Africa are considerably smaller (around 1.5%) 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%), but also with Brazil, Canada, and Mexico (correlations in the range of 1-5%). 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 2%). 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 23 out of the 46 market-pairs in our sample exhibit statistically significant 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 important spillover effects across equity markets around the world.

In contrast, Panel B of Table 8 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 Germany and the U.K., which are both statistically significant, but they are considerably smaller than the corresponding numbers for correlations of the price jumps in Panel A (correlation coefficients are around 1%). These results again suggest that "liquidity black holes" tend to be local phenomena that do not tend to spillover to other markets within or across regions.

The correlations between jumps in OIB across different markets presented in Panel C of Table 8 show a similar pattern as the price jump correlations in Panel A, though perhaps a bit weaker. 17 out of the 46 market-pairs in our sample show significant correlations of the expected sign. Jumps in OIB are strongly 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. Co-jumps in prices, liquidity, and trading activity across markets and variables

We now build upon the analyses in Tables 7 and 8 by not only studying co-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 extreme events are propagated from one market to another, with a specific focus on microstructure variables.

We adopt the method first 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 9. 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. Naturally, the time-series of 5-minute negative and positive price jumps for each market can only be constructed during the opening hours of the respective market.

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 9) 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. 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 as well as 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 spillover of price jumps, we exclude $PQSPR$ jumps from the analyses in Table 9.

Table 9 presents the marginal effects (in %) of the logit models (estimated over the whole sample period) organized by region (Panel A: America; Panel B: Asia; Panel C: Europe/Africa) and by the sign of the price jumps within each panel. 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 second and third models also include independent variables from one of 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 model is substantially reduced relative to the first model. We generally estimate two models for markets in America and Asia and three models for markets in Europe/Africa, but have to discard some models for individual markets in case there is a separation problem in the estimation.[11]

[11]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 price in market i never coincide during the same 5-minute interval with positive jumps in OIB from another region, then having an indicator variable for positive jumps in OIB from another region equal to 1 guarantees no jumps in price on market i during that interval.

We expect 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 9 are all expected to be positive.

The results of the logit models in Table 9 are consistent with our findings in Table 4 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 10 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 country), especially for markets in Asia and Europe/Africa. The significant marginal effects for jumps in OIB for market i in Asian region vary from 6.51% (positive jumps in price on Hong Kong market) to 41.26% (negative jumps in price on Japanese market) and from 0.57% (negative jumps in price on the U.K. market) to 3.17% (positive jumps in price on the U.K. market) in developed Europe. In only one case (South Africa) do we observe a significantly negative marginal effect of OIB jumps on the same market, but, at -0.03%, its economic magnitude is small.

Table 9 also confirms the results of the correlation analysis in Table 8. In particular, jumps in prices on other markets in the same region significantly increase the probability of a price jump on market i in 14 out of the 24 cases (based on the first logit model for each country). These effects are observed in all regions. For instance, jumps in price on the other markets within the Europe/Africa region have positive and significant marginal effects varying from 1.78% to 3.17%. Only in three cases (Brazil, Mexico, and Japan) we observe significantly negative marginal effects of jumps in price on the other markets within the same region, but their economic magnitude is relatively small.

The results on spillovers of jumps in OIB on other markets in the same region to price jumps in 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. However, the marginal effects are small. 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, ranging from 0.22% to 0.54%.

The second and third logit models for each market in Table 9 assess cross-region spillovers of jumps in prices and OIB. Perhaps not surprisingly, the evidence for cross-region spillovers 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-a-vis the European/African region (marginal effect of 0.66%, see Panel A), for positive price jumps in the U.K. vis-a-vis the American region (0.73%, Panel C), and for 27 negative price jumps in Germany vis-a-vis the American region (0.75%, Panel C).

Furthermore, we also examine whether jumps in OIB in other regions are related to price jumps in market i. In most cases, the effect is not significant either in statistical or in economic terms, except price jumps in Canada and the U.S. vis-a-vis OIB jumps in Europe/Africa region (marginal effect between 0.80% and 1.77%, see Panel A) and price jumps in France vis-a-vis OIB jumps in America (effect of 0.73%, Panel C). Some of the marginal effects in Table 9 are not in line with expectations. For example, the marginal effect of the OIB jump indicator variable for Asia on the likelihood of price jumps in Germany is -0.04% (Panel C). Although some of these exceptions are statistically significant, the economic magnitude of the decrease in probability is relatively small.

In sum, the results in Table 9 highlight that shocks to prices and trading activity 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.

4. Conclusion

The recent financial crisis has emphasized 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). In other words, we aim to provide a microstructure perspective on the relation between shocks to prices, liquidity, and trading activity as well as on spillover effects across international equity markets.

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, proportional quoted spreads, and order imbalance occur much more often than jumps in proportional effective spreads and turnover. Second, we document a close relation between jumps in prices and in order imbalance, while jumps in proportional 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 strong 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 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, investors and policy makers should not neglect microstructure effects related to the propagation of shocks to prices. In particular, shocks to prices should not be viewed independently from shocks to trading activity. Shocks to liquidity, however, perhaps play a less central role in the 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 that 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, the Handbook of World Stock, Derivatives and Commodity Exchanges (2004), exchanges' websites, and the Federation of European Securities Exchanges. We crosscheck 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 (2014). 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 (2012), 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.

References

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review 93*(1), 36–62.

Bae, K.-H., G. A. Karolyi, and R. M. Stulz (2003). A new approach to measuring financial contagion. *Review of Financial Studies 16*(3), 717–763.

Barndorff-Nielsen, O. E. and N. Shephard (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics 4*(1), 1–30.

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. J. Mehl (2011). Global crises and equity market contagion. *Working paper*.

Boehmer, E., K. Fong, and J. Wu (2012a). International evidence on algorithmic trading. *Working paper*.

Boehmer, E., K. Y. Fong, and J. Wu (2012b). Algorithmic trading and changes in firms' equity capital. *Working paper*.

Brockman, P., D. Y. Chung, and C. Pérignon (2009). Commonality in liquidity: A global perspective. *Journal of Financial and Quantitative Analysis 44*(04), 851–882.

Brunnermeier, M. K. (2008). Deciphering the liquidity and credit crunch 2007-08. *Journal of Economic Perspectives 23*(1), 77–100.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Chiang, T. C., B. N. Jeon, and H. Li (2007). Dynamic correlation analysis of financial contagion: Evidence from asian markets. *Journal of International Money and Finance 26*(7), 1206–1228.

Chordia, T., R. Roll, and A. Subrahmanyam (2000). Commonality in liquidity. *Journal of Financial Economics 56*(1), 3–28.

Connolly, R. A. and F. A. Wang (2003). International equity market comovements: Economic fundamentals or contagion? *Pacific-Basin Finance Journal 11*(1), 23–43.

Cremers, K. M. and J. Mei (2007). Turning over turnover. *Review of Financial Studies 20*(6), 1749–1782.

Eun, C. S. and S. Shim (1989). International transmission of stock market movements. *Journal of Financial and Quantitative Analysis 24*(02), 241–256.

Fong, K., C. Holden, and C. Trzcinka (2011). What are the best liquidity proxies for global research? *Working paper*.

Forbes, K. J. and R. Rigobon (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance 57*(5), 2223–2261.

Frino, A., V. Mollica, and Z. Zhou (2014). Commonality in liquidity across international borders: Evidence from futures markets. *Journal of Futures Markets 34*(8), 807–818.

Hamao, Y., R. W. Masulis, and V. Ng (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies 3*(2), 281–307.

Hartmann, P., S. Straetmans, and C. G. De Vries (2004). Asset market linkages in crisis periods. *Review of Economics and Statistics 86*(1), 313–326.

Jacod, J. and V. Todorov (2009). Testing for common arrivals of jumps for discretely observed multidimensional processes. *The Annals of Statistics*, 1792–1838.

Jiang, G. J. and R. C. Oomen (2008). Testing for jumps when asset prices are observed with noise a swap variance approach. *Journal of Econometrics 144*(2), 352–370.

Karolyi, G. A. (2003). Does international financial contagion really exist? *International Finance 6*(2), 179–199.

Karolyi, G. A., K.-H. Lee, and M. A. Van Dijk (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics 105*(1), 82–112.

King, M. A. and S. Wadhwani (1990). Transmission of volatility between stock markets. *Review of Financial studies 3*(1), 5–33.

Lee, S. S. and P. A. Mykland (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies 21*(6), 2535–2563.

Lin, W.-L., R. F. Engle, and T. Ito (1994). Do bulls and bears move across borders? international transmission of stock returns and volatility. *Review of Financial Studies 7*(3), 507–538.

Lo, A. W. and J. Wang (2000). Trading volume: Definitions, data analysis, and implications of portfolio theory. *Review of Financial Studies 13*(2), 257–300.

Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics 97*(3), 436–450.

Marshall, B. R., N. H. Nguyen, and N. Visaltanachoti (2012). Commodity liquidity measurement and transaction costs. *Review of Financial Studies 25*(2), 599–638.

Marshall, B. R., N. H. Nguyen, and N. Visaltanachoti (2013a). Liquidity commonality in commodities. *Journal of Banking & Finance 37*(1), 11–20.

Marshall, B. R., N. H. Nguyen, and N. Visaltanachoti (2013b). Liquidity measurement in frontier markets. *Journal of International Financial Markets, Institutions and Money 27*, 1–12.

Opschoor, A., M. Van der Wel, D. Van Dijk, and N. Taylor (2014). Order flow and volatility:an empirical investigation. *Working paper*.

Pukthuanthong, K. and R. Roll (2012). Internationally correlated jumps. *Working paper*.

Ramchand, L. and R. Susmel (1998). Volatility and cross correlation across major stock markets. *Journal of Empirical Finance 5*(4), 397–416.

Reinhart, C. and S. Calvo (1996). Capital flows to Latin America: Is there evidence of contagion effects? *Working paper*.

Rodriguez, J. C. (2007). Measuring financial contagion: A copula approach. *Journal of Empirical Finance 14*(3), 401–423.

Roll, R. (1989). Price volatility, international market links, and their implications for regulatory policies. *Journal of Financial Services Research 3*, 211–246.

Rösch, D. M., A. Subrahmanyam, and M. A. van Dijk (2014). An empirical analysis of co-movements in high-and low-frequency metrics for financial market efficiency. *Working paper*.

Susmel, R. and R. F. Engle (1994). Hourly volatility spillovers between international equity markets. *Journal of International Money and Finance 13*(1), 3–25.

Zhang, Z., J. Cai, and Y. L. Cheung (2009). Explaining country and cross-border liquidity commonality in international equity markets. *Journal of Futures Markets 29*(7), 630–652.

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 stock 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 two rows present the total number of valid 5-minute intervals in the sample for market returns and for the other variables (at least ten companies should be traded in each particular interval to be included in the sample). Countries 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.
Returns	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. for *Returns*		108,792	280,498	132,995	278,899	131,377	151,764	158,348	226,344	362,324	313,523	257,530	368,249
# Obs. for all other variables		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 of jumps in prices, liquidity, and trading activity (12 equity markets, 1996-2011)

This table shows the number of 5-minute intervals that have a jump in 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 stock markets over 1996-2011. 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 for this variable. 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). Countries 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).

		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 3: Summary statistics of the magnitude of jumps in prices, liquidity, and trading activity (12 equity markets, 1996-2011)

This table presents the time-series mean and standard deviation of the magnitude of the 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 the aggregate market capitalization (OIB) for 12 stock markets over 1996-2011. 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 for this variable. Subsequently, we follow an algorithm that allows us to pinpoint the exact 5-minute interval in which the jump occurs. The magnitude of the jumps is measured in terms of jump-free standard deviations (that is, the square root of the scaled bipower variation). The jumps are classified according to their sign: positive (POS) and negative (NEG). Countries 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 spreads, and order imbalance (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.
$PRICE$	POS	# jumps	33	132	109	140	433	19	500	244	201	162	148	227
		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	# jumps	39	127	88	160	439	68	637	187	225	205	134	212
		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	# jumps	6	189	110	38	35	38	191	167	27	107	222	278
		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	# jumps	7	63	107	21	42	16	82	154	13	47	131	92
		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	# jumps	304	383	54	129	324	77	205	232	590	246	410	115
		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	# jumps	254	296	25	79	266	182	143	242	560	224	493	139
		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 4: 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 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 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). The first column indicates the sign of the jump in variable 1 (the event): NA=no jump, POS=positive, NEG=negative. The second column indicates the sign of the jump in variable 2. The first two rows (No Jumps in variable 1) show the number of positive and negative jumps in variable 1 that occur during a day with no jumps in variable 2. The next four rows (Simultaneous jumps) show the number of positive or negative jumps in variable 2 that occur during the same 5-minute interval as a positive or negative jump in variable 1. The following four rows (Before jump in variable 1) show the number of positive or negative jumps in variable 2 that occur before a positive or negative jump in variable 1. The final four rows (After jump in variable 1) show the number of positive or negative jumps in variable 2 that occur after a positive or negative jump in variable 1. 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. Countries 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 $PQSPR$ before jump in $PRICE$	POS	POS	0	2	7	1	3	0	4	4	5	3	7	21
	POS	NEG	0	2	5	1	2	0	4	4	1	1	4	6
	NEG	POS	1	6	2	3	3	1	4	4	0	5	4	7
	NEG	NEG	0	5	2	3	6	0	9	14	0	1	0	1
Jumps in $PQSPR$ after jump in $PRICE$	POS	POS	0	2	4	1	0	0	8	8	2	1	0	13
	POS	NEG	0	4	5	1	0	1	2	0	3	2	5	3
	NEG	POS	1	1	8	1	1	0	10	11	1	2	7	7
	NEG	NEG	2	1	10	2	0	0	1	6	3	0	4	1

Table 4: 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 OIB before jump in $PRICE$	POS	POS	3	4	0	6	20	0	11	5	15	6	6	1
	POS	NEG	4	3	0	2	10	2	4	1	11	7	9	5
	NEG	POS	2	4	0	6	13	2	12	0	19	10	2	1
	NEG	NEG	1	7	0	2	17	9	15	5	18	6	5	5
Jumps in OIB after jump in $PRICE$	POS	POS	3	6	1	4	22	2	36	6	30	16	14	17
	POS	NEG	5	7	0	0	10	0	8	5	19	5	19	11
	NEG	POS	3	6	1	1	18	1	34	1	11	7	19	8
	NEG	NEG	2	7	1	3	41	7	37	6	35	12	10	7

Panel B: 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 $PQSPR$ before jump in OIB	POS	POS	1	17	1	0	2	1	2	3	2	10	11	3
	POS	NEG	1	5	2	0	2	2	2	4	1	5	15	3
	NEG	POS	0	21	0	3	0	4	3	3	3	3	15	13
	NEG	NEG	0	3	0	1	2	0	1	5	0	2	7	2
Jumps in $PQSPR$ after jump in OIB	POS	POS	2	9	0	1	0	0	4	5	7	5	16	1
	POS	NEG	1	5	1	0	0	0	0	0	1	3	4	0
	NEG	POS	1	4	0	1	1	2	1	4	2	4	24	4
	NEG	NEG	0	3	0	1	0	1	0	2	2	2	6	0

Table 5: 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 of the same sign 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 of the same sign, 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 final 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 0.1% level or better (one-sided test). Countries 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	44	19	100	7	77	59	1	27
Prob(simultaneous jumps) empirical	0.09	0.37	0.10	0.60	2.89	1.02	5.71	0.28	2.02	1.48	0.03	0.69
Prob(simultaneous jumps) theoretical, under independence assumption	0.00	0.02	0.00	0.01	0.22	0.01	0.13	0.03	0.03	0.01	0.02	0.01
p-value (one-sided test)	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	0.51	**<0.001**

Table 6: Simultaneous jumps in prices and order imbalance within a market and U.S. macroeconomic news announcements (8 markets, 2004-2009)

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 happen around the U.S. macroeconomic news announcements for 8 of the 12 equity markets in our sample over 2004-2009. The event window around macroeconomic news announcements is [-1,+12], measured in 5-minute intervals. We exclude the Asian markets from this table since none of the Asian markets is open during any of the announcements. Countries 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. Data on the U.S. macroeconomic news announcements are from the Econoday database.

	America				Europe/Africa			
	Brazil	Canada	Mexico	U.S.	Germany	France	U.K.	South Africa
# of jumps in $PRICE$	36	72	144	126	181	154	131	101
# of jumps in $PRICE$ in the window [-1,+12] around macro announcements	8	20	12	24	73	61	53	10
# of simultaneous jumps in $PRICE$ and OIB	1	5	0	7	29	31	18	0
# of simultaneous jumps in $PRICE$ and OIB in the window [-1,+12] around macro announcements	1	0	0	1	19	17	11	0

Table 7: 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 jumps 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), based on 12 stock 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 countries that have a jump of the same sign in the same variable on the same day, and distinguish between three cases: only one country has a jump in that variable on a certain day, two countries have a jump in that variable of the same-sign on the same day, and three or more countries 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 8: 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 stock 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 10% level or better. Countries 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		**2.03%**	0.00%	0.00%					**3.11%**	**3.13%**	0.00%	**4.72%**
	Canada			0.00%	**1.80%**					**1.62%**	-0.76%	0.00%	**0.87%**
	Mexico				**0.42%**					**0.94%**	**1.75%**	0.00%	**1.04%**
	U.S.									**7.34%**	**6.90%**	0.01%	**7.12%**
Asia	Hong Kong						0.00%	0.02%	**9.74%**	0.01%	0.00%	0.00%	0.02%
	India							-0.01%	**1.39%**	**3.07%**	-0.01%	0.00%	-0.01%
	Japan								0.01%				
	Malaysia									0.01%	0.00%	0.00%	0.00%
Europe/Africa	France										**16.16%**	**1.57%**	**13.05%**
	Germany											**1.97%**	**13.08%**
	South Africa												**1.86%**
	U.K.												

Table 8: 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%	0.00%
	Canada			0.00%	**0.81%**					-0.01%	-0.02%	-0.05%	-0.02%
	Mexico				0.00%					0.00%	0.00%	0.04%	0.00%
	U.S.									0.00%	0.00%	0.01%	0.00%
Asia	Hong Kong						0.00%	0.01%	0.00%	-0.01%	-0.03%	-0.03%	0.00%
	India							-0.05%	0.00%	0.00%	-0.01%	0.00%	-0.01%
	Japan								0.04%				
	Malaysia									-0.04%	-0.05%	-0.02%	-0.08%
Europe/Africa	France										0.00%	0.00%	**0.94%**
	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%	0.00%	**1.04%**					**0.95%**	**0.51%**	-0.54%	**1.75%**
	Canada			**0.88%**	**0.80%**					**0.81%**	0.58%	**-1.69%**	0.00%
	Mexico				0.00%					0.00%	0.00%	0.00%	0.00%
	U.S.									**5.34%**	**3.32%**	-0.01%	**1.26%**
Asia	Hong Kong						0.01%	**1.80%**	-0.27%	**-2.38%**	-0.01%	0.01%	0.00%
	India							0.00%	0.00%	0.60%	0.00%	0.00%	0.00%
	Japan								**3.09%**				
	Malaysia									0.00%	0.00%	0.00%	0.00%
Europe/Africa	France										**7.49%**	**0.35%**	**3.97%**
	Germany											**0.71%**	**5.90%**
	South Africa												0.26%
	U.K.												

Table 9: 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 time overlap between the trading hours of the American and Asian markets. 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 countries 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) and positive price jumps (Part II). Countries 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.	
$OIB\ POS\ i$	0.12	0.02	0.03	0.02	0.25	0.14	0.09	**-0.05**
$PRICE\ POS\ not\ i$	0.34	**-0.01**	**1.80**	0.40	3.46	9.17	**10.50**	**5.09**
$OIB\ POS\ not\ i$	0.10	0.05	0.39	1.46	**-0.04**	**-0.07**	0.31	0.29
$PRICE\ POS\ Europe/Africa$		0.73		0.10		0.65		0.77
$OIB\ POS\ Europe/Africa$		0.04		**1.03**		0.23		**0.80**
# Obs.	279,000	75,294	300,000	75,294	298,000	73,434	300,000	75,294

Part II: Negative jumps in $PRICE$

Market i	Brazil		Canada		Mexico		U.S.	
$OIB\ NEG\ i$	0.24		0.80	2.26	4.10		1.93	0.69
$PRICE\ NEG\ not\ i$	0.13		**1.72**	1.49	**-0.03**		**1.42**	0.97
$OIB\ NEG\ not\ i$	0.10		0.33	0.38			0.13	0.15
$PRICE\ NEG\ Europe/Africa$				0.34				**0.66**
$OIB\ NEG\ Europe/Africa$				0.02				**1.77**
# Obs.	279,000		300,000	75,294	298,000		300,000	75,294

Table 9: 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	
$OIB\ POS\ i$	**6.51**	5.89	4.91	**17.50**	1.77	3.25
$PRICE\ POS\ not\ i$	**4.00**	3.68	0.20	**-0.36**	**2.71**	1.97
$OIB\ POS\ not\ i$	**-0.26**	-0.15	**-0.01**	**-0.37**	**-0.10**	-0.06
$PRICE\ POS\ Europe/Africa$		-0.16				-0.06
# Obs.	152,000	28,428	117,000	86,298	209,000	64,596

Part II: Negative jumps in $PRICE$

Market i	Hong Kong		India	Japan	Malaysia	
$OIB\ NEG\ i$	**7.44**	4.63	4.69	**41.26**	1.22	
$PRICE\ NEG\ not\ i$	**7.23**	6.35		1.10	**4.50**	
$OIB\ NEG\ not\ i$	-0.15	-0.15	**-0.03**	0.57	-0.04	
$OIB\ NEG\ Europe/Africa$		-0.15				
# Obs.	152,000	28,428	117,000	86,298	209,000	

Table 9: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.		
$OIB\ POS\ i$	**2.12**	**1.34**	2.52	**1.89**	1.40	6.95		0.39	**3.17**	2.82	-0.07
$PRICE\ POS\ not\ i$	**2.38**	**1.61**	0.27	**1.78**	1.66	0.69	0.36	0.28	**2.71**	**1.83**	0.29
$OIB\ POS\ not\ i$	**0.54**	**0.85**	**-0.04**	**0.22**	0.22	0.18	0.02	0.19	**0.52**	**0.24**	1.36
$PRICE\ POS\ America$		0.13			0.22					**0.73**	
$OIB\ POS\ America$		**0.73**			**-0.04**			**-0.04**		0.07	
$PRICE\ POS\ Asia$			1.58								-0.07
$OIB\ POS\ Asia$			0.18			**-0.04**					**-0.07**
# Obs.	381,000	114,000	81,132	396,198	115,000	92,832	338,000	56,202	384,000	115,000	82,410

Part II: Negative jumps in $PRICE$

Market i	France			Germany			South Africa		U.K.		
$OIB\ NEG\ i$	**1.18**	**1.42**	1.56	**1.61**	**1.57**	2.01	**-0.03**		**0.57**	**1.13**	2.88
$PRICE\ NEG\ not\ i$	**2.25**	**2.54**	0.68	**2.83**	**3.23**	1.70	0.59		**2.30**	**2.51**	0.68
$OIB\ NEG\ not\ i$	**0.42**	**0.47**	0.87	**0.52**	**0.85**	0.36	0.20		**0.51**	**0.19**	0.85
$PRICE\ NEG\ America$		0.05			**0.75**					0.19	
$OIB\ NEG\ America$		**-0.05**			0.03					-0.03	
$PRICE\ NEG\ Asia$											**-0.08**
$OIB\ NEG\ Asia$			**-0.06**			**-0.04**					0.74
# Obs.	381,000	114,000	81,132	396,000	115,000	92,832	338,000		384,000	115,000	82,410

Figure 1: Illustration of the BNS jump measure

This figure illustrates the intuition underlying the jump measure (a statistical non-parametric way to test for jumps in a time-series) proposed by Barndorff-Nielsen and Shephard (2006, BNS), which is based on the ratio of the scaled bipower (continuous) variation to the squared variation. 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. Panel A shows the actual time-series of 5-minute market returns for the London Stock Exchange on February 9th, 2011, which clearly exhibits a discontinuous negative shock at 10:45 GMT. Panel B of Figure 1 plots the same time-series but with the return observation in this 5-minute interval replaced by a zero return. Both graphs show the scaled bipower variation, the squared variation, the ratio of scaled bipower to squared variation, the BNS statistic, and the p-value of the one-sided test that the BNS statistic follows a standard normal distribution. We refer to the caption of Table 2 and to Appendix B for a detailed description of the jump statistics. Data are from TRTH and Datastream.

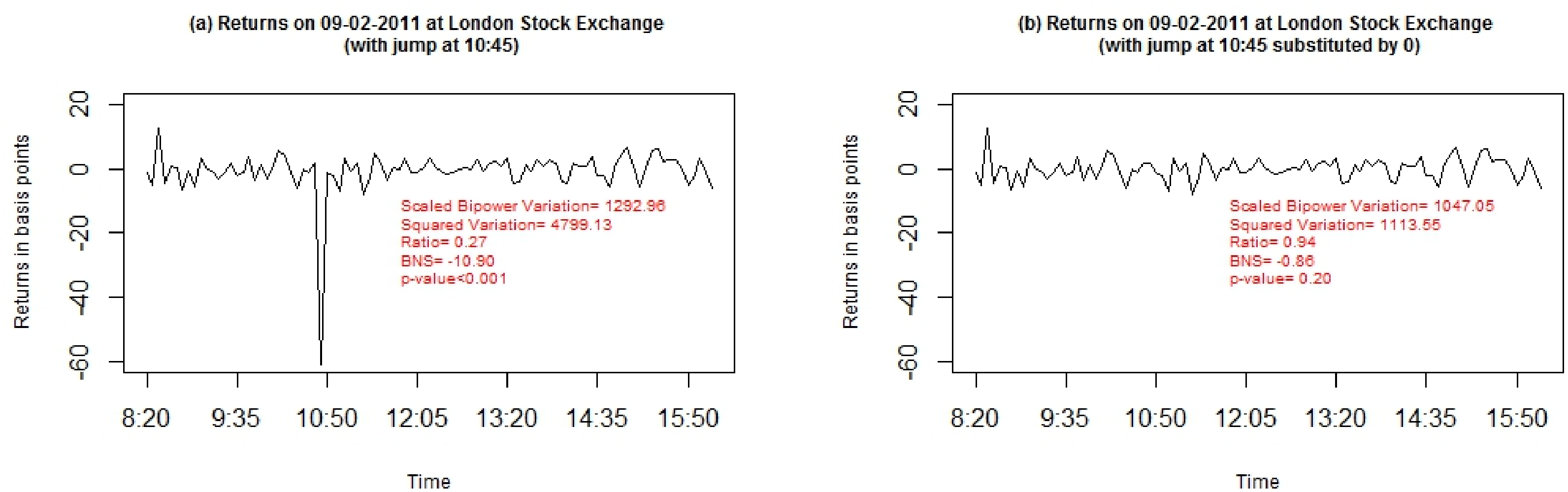

Figure 2: Average cumulative return around jumps in price (across 12 equity markets, 1996-2011)

This figure shows the cumulative 5-minute market-wide equally-weighted returns in basis points (averaged across all 12 equity markets in our sample) 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. 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.