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How Do Shocks Arise and Spread Across Stock Markets? A Microstructure Perspective

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Abstract. We study intraday, market-wide shocks to stock prices, market liquidity, and trading activity on international stock markets and assess the relevance of recent theories on "liquidity dry-ups" in explaining such shocks. Market-wide price shocks are prevalent and large, with rapid spillovers across markets. However, price shocks are predominantly driven by information; they do not revert and are often associated with macroeconomic news. Furthermore, liquidity shocks are typically isolated and transitory. Overall, we find little evidence for liquidity effects fomenting price shocks or non-fundamental contagion, nor for alternative explanations. Market-wide liquidity dry-ups are thus of little concern to international investors.

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Keywords: financial market shocks • liquidity dry-ups • spillovers across international stock markets • information • international diversification

1. Introduction

It is well known that stock markets occasionally exhibit sudden, market-wide price shocks (Jarrow and Rosenfeld 1984) that can also spillover to other markets, even at high frequencies.[1] However, the channels through which such shocks arise and spread across markets are still not well understood. A growing body of theoretical research points at an important role for market liquidity. In classical models (Stoll 1978, Kyle 1985), prices can temporarily deviate from fundamental value because of illiquidity, but these deviations dissipate as information asymmetry is resolved or inventory concerns are relieved.

In contrast, more recent models feature feedback loops in which even small information or liquidity shocks can lead to "sudden market-wide evaporation of liquidity," "liquidity black holes," or "liquidity dry-ups" and result in significant liquidity-driven deviations of prices from fundamentals and spillovers to other markets. Morris and Shin (2004) and Bernardo and Welch (2004) model how such feedback loops can arise because of the loss limits of short-horizon traders, financial market runs, and margin calls. Spillovers to other markets can result when investors hold positions in multiple markets. Cespa and Foucault (2014) show how feedback loops driven by cross-asset learning can lead to non-fundamental contagion across markets. These three papers all cite specific real-life incidences of large, intraday, market-wide stock price shocks to motivate the feedback loops in their models, suggesting that they can arise at high frequencies and can have market-wide effects.

Our purpose is to assess the relevance of theories on liquidity dry-ups in explaining how *sudden intraday market-wide price shocks* arise and spread across international stock markets. We focus on such shocks in particular because both investors and regulators should be concerned about the possibility of sudden liquidity-driven price shocks at the market-level that cannot be diversified and could have systemic effects.

Our main alternative hypothesis to the liquidity dry-up channel is that sudden market-wide price shocks are driven by information and that spillovers across markets reflect economic news that is relevant for multiple markets (King and Wadhwani 1990). The liquidity dry-up and information channels are not mutually exclusive, and other channels may also be at play. Furthermore, liquidity dry-ups are difficult to study empirically because the trading behavior of different market participants is typically not directly observable.

Although our tests of the liquidity dry-up channel are thus indirect, our battery of empirical analyses using detailed microstructure data on international stock markets suggest that the role of liquidity dry-ups in explaining sudden, market-wide price shocks is limited vis-à-vis other channels.

We use global tick-by-tick trade and quote data for individual stocks from the Thomson Reuters Tick History (TRTH) database to construct high-frequency time-series of market-wide stock returns (based on midquotes), liquidity (quoted spreads), and trading activity (order imbalance or *OIB*) for 12 stock markets over 1996–2011. We include both developed and emerging markets in three regions: America (Brazil, Canada, Mexico, United States), Asia (Hong Kong, India, Japan, Malaysia), and Europe/Africa (France, Germany, South Africa, United Kingdom).

To identify sudden intraday market-wide shocks to stock prices, liquidity, and trading activity, we use the jump measure of Barndorff-Nielsen and Shephard (2006), which is a statistical nonparametric method to test for jumps in a time-series. We thus construct time series of market-wide jumps in prices, liquidity, and trading activity for each market over 1996–2011 (using more than 5 billion individual stock transactions and 27 billion quote updates).

Our microstructure perspective involves analyzing how shocks arise and spread across markets at a much higher frequency than prior studies: 5-minute, 15-minute, and 1-hour intervals within the trading day. Most studies to date (see endnote 1) study financial market linkages at daily or even lower frequencies. However, a relatively low-frequency approach could miss shocks and spillovers at higher frequencies (which have become more relevant in today's fast-paced markets) and could fail to uncover intraday patterns in liquidity and/or trading activity that help to explain price shocks within and across markets.

We find that intraday jumps in prices, spreads, and *OIB* are frequent and large in magnitude (around four to seven jump-free standard deviations) in all markets/regions in our sample. We present four broad types of evidence to examine the channels through which sudden intraday market-wide price shocks arise and spread across markets.

First, we find little evidence that jumps in prices are accompanied by jumps in liquidity, which is an initial indication that liquidity dry-ups may not play a central role in how market-wide price jumps arise. We do find that some price jumps are contemporaneously associated with jumps in *OIB*. Such a pattern may reflect mechanical effects in which large market orders, for example, with an informed, speculative motive, eat into the order book and thereby make prices move.

Second, we look into economic news events as a potential source of price jumps, which is challenging given the plethora of potentially relevant news events, the potential anticipation of news, and the difficulty in measuring news. Nonetheless, we find that a substantial fraction of the jumps in prices occur specifically around macro announcements, especially in European markets for which many U.S. macro announcements occur within the opening hours. Although this finding points to news as an important source of price jumps, it does not rule out liquidity feedback effects, which could even be triggered by news.

Third, we therefore study the behavior of prices, liquidity, and trading activity around price jumps. We find that the vast majority of price jumps represent immediate and permanent shocks to prices, which is most consistent with the information channel. Furthermore, around both negative and positive price jumps, spreads tend to increase slightly, followed by subsequent reversal, and there is a clear, once-off spike in *OIB* in the same direction as the price jump. There is little indication of feedback effects in which shocks to prices, liquidity, and trading activity are self-reinforcing (even for the small fraction of price jumps that do exhibit subsequent reversals). Rather, these patterns seem consistent with mechanical effects resulting from slow replenishment of order books, for example, because of a temporary increase in adverse selection costs and/or inventory risk around the arrival of economic news.

Fourth, we test a number of hypotheses on specific channels through which price shocks can arise and spread across markets (detailed in Section 2.1) using intraday and daily logit models to explain the occurrence of negative price jumps in particular. We find that, although negative price jumps can spillover across markets at high frequencies, the link with liquidity jumps is weak at best. Moreover, we find no evidence that shocks in liquidity and *OIB* trigger subsequent shocks in prices. In our daily logits, we include additional proxies to identify potential liquidity feedback channels. We find no evidence that negative price jumps can be explained by funding constraints of liquidity providers, which feature as a key channel for liquidity feedback loops in some recent theories (Brunnermeier and Pedersen 2009). Also, although negative contemporaneous *OIB* jumps do have explanatory power for negative price jumps, proxies for market runs (passive mutual fund flows) and hedging-induced positive feedback trading (at-the-money option volume) do not show up significantly. We do find some indication of a (non–liquidity-related) sentiment channel as measured by salient price boundaries. In all specifications, negative macro announcements as a proxy for the information channel shows up as an important determinant of negative price jumps.

Overall, our results suggest that liquidity dry-ups do not play a major role in explaining how sudden, intraday, market-wide price shocks arise and spread across international stock markets. Although liquidity dry-ups may be relevant at lower frequencies, in other asset classes, or for individual securities, our findings alleviate concerns by investors and regulators about the role of liquidity dry-ups in fomenting sudden intraday market-wide stock market shocks and nonfundamental contagion.

Our study contributes to the literature on financial market contagion cited in endnote 1. Some studies specifically examine the role of investor flows in the international transmission of price shocks at relatively low frequencies (Boyer et al. 2006, Jotikasthira et al. 2012). However, to the best of our knowledge, we are the first to assess the role of liquidity dry-ups in understanding of how *sudden intraday market-wide price shocks* arise and spread across international stock markets and to jointly study intraday shocks to prices, liquidity, and trading activity to this end.

We also add to the literature on jumps in stock prices (Bollerslev et al. 2008, Lee 2012, Boudt and Petitjean 2014). Although several papers study price jumps around news announcements, and some analyze the behavior of liquidity around these announcements, we add to this body of research in several ways. First, these papers neither study liquidity dry-ups nor spillovers across markets. Second, they do not examine what fraction of price jumps are associated with liquidity jumps. Third, we broaden the scope of the analysis by analyzing market-wide shocks (as opposed to shocks to individual securities) in stock markets in 12 countries (as opposed to the United States only).

Furthermore, we contribute to the literature on commonality in liquidity and trading activity (Chordia et al. 2000, Cremers and Mei 2007, Brockman et al. 2009, Karolyi et al. 2012). This literature examines the general degree of comovement in the (daily or weekly) liquidity and trading activity of individual stocks. We add to this literature by investigating whether large, intraday, market-wide shocks to liquidity and trading activity exhibit comovement across stock markets around the world and thus whether investors and regulators should be concerned about the systemic nature of such sudden, potentially disruptive shocks.

2. Hypotheses, Data, and Methods

In our analyses, we aim to distinguish between an information channel and a liquidity feedback channel. However, these channels are hard to identify and disentangle empirically. A complicating factor is that even in the absence of a liquidity feedback channel, large price shocks can be associated with changes in liquidity and *OIB* for purely mechanical reasons. To sharpen our identification of liquidity feedback channels, we therefore develop specific hypotheses in the next section that allow us to differentiate between mechanical effects and liquidity feedback effects.

2.1. Hypotheses

In this section, we explore the different channels through which liquidity and price shocks could be related. We classify such effects into two possible types. The first type involves mechanical effects that arise from the organization of markets, and in particular the use of order books and the existence of demand and supply schedules of liquidity providers. The second type involves feedback loops that can lead to liquidity dry-ups.

Mechanical effects can occur as a result of a shock to *OIB*, for example because of a large order. A large order likely consumes all depth at the best quote level in a limit order book and may even deplete depth at other quote levels. Typically, it takes some time for the order book to replenish. As a result, (midquote) prices promptly move in the direction of the order and quoted spreads increase in a mechanical way. Such effects are contemporaneous, may occur for both informed and uninformed orders, and do not set off any trading triggers by other market participants. Hence, *OIB* is expected to revert quickly and quoted spreads will also revert as the order book replenishes. If the order was uninformed, prices will revert. If the order was informed, the price change is permanent.

Liquidity and price shocks can also be related through (positive) feedback effects. Although these feedback effects can be triggered by news, their defining feature is that they give rise to one-sided markets and that a lack of liquidity is instrumental in inciting such one-sidedness. Importantly, these positive feedback effects lead to persistent order imbalances and price changes with positive serial correlations as the initial orders and their associated (mechanical) price effects trigger additional orders in the same direction.

Recent theories describe how liquidity dry-ups can arise as a result of such feedback loops. For example, traders with short horizons can be induced to sell when they get close to their (daily) loss limits, which leads to downward pressure on asset prices and further selling (Morris and Shin 2004). Alternatively, the fear of future shocks to market liquidity can create the financial market equivalent of a bank run, such that prices and liquidity both rapidly deteriorate (Bernardo and Welch 2004). Such feedback loops can spillover to other markets if investors hold positions in multiple markets (Bernardo and Welch 2004) or through cross-asset learning about correlated fundamentals by liquidity providers (Cespa and Foucault 2014).

Specific real-life examples of situations in which such feedback loops can arise include stop loss strategies, technical analysis (in particular trend following), hedging of short positions in options (Hull 2018, p. 554), portfolio insurance (Leland and Rubinstein 1981), margin calls (Gârleanu and Pedersen 2011), funding liquidity spirals (Brunnermeier and Pedersen 2009), behavioral feedback effects (Bhattacharya et al. 2012), and in general any situation in which "traders face constraints on their behavior that shorten their decision horizons" (Morris and Shin 2004, p. 2).

These various channels may interact in a myriad of ways, so it is not easy to point to the exact source of any particular financial market shock. To shed light on the relative importance of the liquidity feedback channels in explaining how price shocks arise and spread across markets, we assess the following hypotheses:

Hypotheses Consistent with Both Mechanical and Feedback Effects

Hypothesis 1. *Price shocks are contemporaneously related to positive quoted spread shocks and to same-sign OIB shocks.*

Hypothesis 2. *Shocks to prices, spreads, and OIB are related across markets (spillovers because of common information or multimarket runs).*

Hypothesis 3. *Price shocks are associated with economic news events (information channel, but could trigger feedback loops).*

Hypotheses Only Consistent with Mechanical Effects

Hypothesis 4. *Price shocks are immediate and permanent (information channel).*

Hypothesis 5. *Shocks to OIB and quoted spreads around price shocks revert quickly (no positive feedback).*

Hypothesis Only Consistent with Feedback Effects

Hypothesis 6. *Shocks to prices, spreads, and OIB are intertemporally related to themselves and each other (liquidity feedback effects).*

Hypotheses Consistent with Specific Feedback Effects

Hypothesis 7. *Price shocks are associated with poor funding liquidity conditions (funding liquidity spirals).*

Hypothesis 8. *Price shocks are associated with large flows in (passive) mutual funds (market runs).*

Hypothesis 9. *Price shocks are associated with salient price boundaries (behavioral feedback effects).*

Hypothesis 10. *Price shocks are associated with large demands to dynamically delta hedge derivative positions with negative gammas such as short positions in plain-vanilla options (feedback effects because of hedging).*

In the next sections, we proceed to discuss the data, variables, and methods we used to test these hypotheses.

2.2. Sample, Data Sources, and Variable Definitions

We obtain intraday data on trades and quotes (and their respective sizes) from the TRTH database, which includes global tick-by-tick data for trades and best bid-offer quotes stamped to the millisecond.[2] To obtain a sample that is representative of global stock 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 (Brazil, Canada, Mexico, United States), Asia (Hong Kong, India, Japan, Malaysia), and Europe/Africa (France, Germany, South Africa, United Kingdom). We obtain the Reuters Instrumental Codes (RICs) for all common stocks that are traded on the major stock exchange (defined as the exchange that handles the majority of trading volume) in each of these countries from Datastream and then collect the RICs for the subset of these stocks that were part of the main local market index at some point during 1996–2011 from the TRTH Speedguide (see Appendix A.1).[3] Following Rösch et al. (2017), 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). We refer to Online Appendix IA.1 for an overview of the sample and filters.

We first measure variables at the individual stock level and then aggregate to the market level, because we are interested in systemic market shocks. We carry out all of our analyses at the 5-minute, 15-minute, and 1-hour frequencies. Following Chordia et al. (2008), we compute log returns in a particular interval based on midpoints between the quoted bid and ask prices (rather than based on the trade prices or on midquotes matched with the last trade in the interval) of individual stocks. Using midquotes avoids the bid-ask bounce in trade price returns and ensures that returns for every stock are computed over the same interval despite differences in trading frequency across stocks.

We use proportional quoted spreads (*PQSPR*) to measure market liquidity and order imbalance (*OIB*) to measure trading activity.[4] We compute *PQSPR* based on quote data only, for the last best bid-offer (BBO) quote available for a given stock in a particular 5-minute, 15-minute, or 1-hour interval. To compute *OIB*, we need to determine whether a trade is buyer or seller initiated. We use the algorithm of Lee and Ready (1991) 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 interval, scaled by the previous-month market capitalization of the stock (from Datastream).

We aggregate our three main variables to the market-level by taking the value-weighted average (using the previous-month market capitalization of the stock) of the stock-level returns, quoted spreads, and *OIB*.[5]

2.3. Jump Measure (BNS)

There is a plethora of different methods to study financial market shocks.[6] We follow Pukthuanthong and Roll (2015) and use a statistical jump measure to identify a financial market shock. Advantages of this approach are that it adheres closely to the intuitive view of a financial market shock as a discontinuous event in an otherwise continuous time series, that it does not require arbitrary definitions of extreme events, and that it is relatively straightforward 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. Potential disadvantages are that on volatile days 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. To mitigate the latter concern, we analyze jumps at different frequencies within the day.

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 realized (squared) variation and is "by far the most developed and widely applied of the different [jump] methods" to identify intraday jumps (Bollerslev et al. 2008, p. 239) and the best jump measure in the simulations of Pukthuanthong and Roll (2015).[7] For example, for identifying jumps in price, the BNS measure boils down to the ratio of r_t^2 to $|r_t r_{t-1}|$, where r_t is the return over interval t. Intuitively, jumps affect r_t^2, but not $|r_t r_{t-1}|$ (assuming jumps are serially uncorrelated). By contrast, the variance of the continuous part affects both r_t^2 and $|r_t r_{t-1}|$ similarly (up to a scalar multiplication).

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. 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). For the 5-minute frequency, we identify a day as a day with a jump if the BNS measure is below the 0.1% percentile of the standard normal distribution. Subsequently, we follow the sequential jump detection algorithm of Andersen et al. (2010) to infer the exact interval in which the jump occurs on that day. We refer to Appendix B for a detailed discussion of our implementation of the BNS jump statistic at the 5-minute, 15-minute, and 1-hour frequencies.[8]

3. Empirical Results

This section first presents summary statistics of the market-level returns, liquidity (*PQSPR*), and trading activity (*OIB*), as well as of the BNS jump measures for each of these variables (Section 3.1). Then, we present four broad types of evidence to assess the hypotheses outlined in Section 2.1. In Section 3.2, we study how jumps in prices, *PQSPR*, and *OIB* are related both within and across markets. In Section 3.3, we explore whether price jumps are associated with economic news events. In Section 3.4, we examine the behavior of prices, liquidity, and trading activity around price jumps. In Section 3.5, we jointly test multiple hypotheses in a (logit) regression framework.

3.1. Summary Statistics

Table 1 shows the mean and standard deviation of the 5-minute, 15-minute, and 1-hour value-weighted returns, value-weighted proportional quoted spreads (*PQSPR*), and value-weighted order imbalance (*OIB*) for the 12 markets in our sample. To conserve space, we present these summary statistics as the equally weighted average across the markets within each region (America, Asia, Europe/Africa) and across all 12 countries (World). The results for individual countries are available in Online Appendix IA.2.

For all regions, the mean 5-minute, 15-minute, and 1-hour returns are slightly negative, because we include the 2007–2009 global financial crisis and exclude overnight returns (Berkman et al. 2012 show that intraday returns tend to be lower than overnight returns), whereas the median returns are slightly positive. For 5-minute frequency, the mean (median) *PQSPR* across all 12 markets is around 0.32% (0.25%) for all frequencies, with a standard deviation of around 0.22%. The mean (median) *OIB* is also slightly negative (positive) over our sample, with a large standard deviation. The final row of Table 1 shows the number of intervals for which the various variables can be computed for each market. The total number of 5-minute intervals across all markets is 2,846,390 (or on average around 237,000 per market), with proportionally smaller numbers for the lower frequencies.

Panel A of Table 2 shows the total number of 5-minute, 15-minute, and 1-hour intervals with significant jumps across variables and regions. Positive (POS) and negative (NEG) jumps are reported separately. We observe a substantial number of jumps in prices, *PQSPR*, and *OIB*. Aggregated across all 12 markets, there are 2,490 (2,277) positive (negative) 5-minute jumps in prices; 946 (894) positive (negative) 5-minute jumps in *PQSPR*; and 2,824 (2,699) positive (negative) 5-minute jumps in *OIB*. Jumps in these variables occur much more often than under the no jumps assumption for all markets in the sample, also at the lower frequencies.[9]

Panel B of Table 2 presents summary statistics (means and standard deviations) of the magnitudes of the 5-minute, 15-minute, and 1-hour market-wide jumps in prices, *PQSPR*, and *OIB* aggregated by region. As a consistent measure of the magnitude of jumps across the different variables and markets, we use the number of "jump-free standard deviations" or the square root of the scaled bipower variation (which measures the

Table 1. Summary Statistics of Value-Weighted Returns, Liquidity, and Trading Activity

		5-minute				15-minute				1-hour			
	Statistic	America	Asia	Europe/Africa	World	America	Asia	Europe/Africa	World	America	Asia	Europe/Africa	World
RETURN	Mean	−0.01	−0.09	−0.03	−0.04	0.01	−0.26	−0.07	−0.10	0.16	−0.98	−0.51	−0.45
	Median	0.08	0.05	0.07	0.06	0.32	0.01	0.16	0.15	1.14	−0.11	0.46	0.50
	SD	8.12	9.43	7.91	7.65	14.80	17.07	14.66	14.03	30.32	37.90	30.85	30.78
PQSPR	Mean	0.25	0.40	0.28	0.32	0.25	0.41	0.28	0.32	0.25	0.38	0.27	0.31
	Median	0.23	0.36	0.22	0.25	0.24	0.37	0.22	0.26	0.24	0.26	0.21	0.24
	SD	0.11	0.29	0.19	0.22	0.11	0.28	0.20	0.22	0.11	0.31	0.18	0.23
OIB	Mean	0.01	0.01	−0.04	−0.01	0.03	0.02	−0.11	−0.02	0.11	0.04	−0.61	−0.18
	Median	0.01	0.00	−0.01	0.01	0.03	0.01	−0.03	0.02	0.11	0.02	−0.18	0.05
	SD	0.07	0.08	1.73	0.82	0.15	0.17	3.55	1.68	0.38	0.38	9.16	4.76
No. of observations		809,229	701,942	1,335,219	2,846,390	276,396	226,814	437,034	940,244	59,110	31,237	94,145	184,492

Notes. This table shows the full-sample time-series mean, median, and standard deviation (SD) of 5-minute, 15-minute, and 1-hour log-returns (*RETURN*, in bps), proportional quoted spreads (*PQSPR*, in %), and order imbalance (*OIB*, in bps of previous month market capitalization) for 12 equity markets over 1996–2011. The variables are first value-weighted within market (by previous month market capitalization) and then equally weighted within region (America, Asia, Europe/Africa, and World). We refer to Section 2.2 and Appendix A for a detailed description of sample selection, data filters, and variable definitions. For the purpose of computing summary statistics only, we winsorize the time-series of returns, *PQSPR*, and *OIB* by region at 0.5% and 99.5% levels. We use non-winsorized data for the jump estimation. The final row presents the total number of 5-minute, 15-minute, and 1-hour intervals in the sample. We note that the way we construct valid intervals (see Appendix A) can result in somewhat more or somewhat fewer 15-minute intervals than the number of 5-minute intervals divided by three. Data to calculate these variables are from TRTH (trade and quote data) and Datastream (market capitalization data). Only common stocks that were ever part of the major local equity index are included in the computation of value-weighted returns, *PQSPR*, and *OIB* (data on index constituents are from the TRTH Speedguide, while common stocks are identified through Datastream).

variation of the continuous, i.e., non-jump, part of the process only). It is clear from Panel B of Table 2 that the magnitudes of the jumps in prices, *PQSPR*, and *OIB* are large across all markets in the sample. The average jump magnitude for both negative and positive jumps in prices, *PQSPR*, and *OIB* is around four to seven jump-free standard deviations.

Panel C of Table 2 translates the magnitude of jumps from jump-free standard deviations to the actual values in terms of returns, changes in *PQSPR*, and *OIB* for positive and negative jumps, respectively. In particular, average positive (negative) jumps in price correspond to average 5-minute returns of 39.12 (−34.74) basis points (bps). Average positive (negative) jumps in *PQSPR* correspond to average 5-minute changes in spread of 45% (−33%), whereas average positive (negative) jumps in *OIB* correspond to average 5-minute *OIB* of 5.65 (−7.06) bps of previous month market capitalization. We also note that the median jump's size of *OIB* is considerably lower than its average value consistent with the large standard deviation of *OIB* observed in Table 1.

Overall, the results in Table 2 thus indicate that jumps in prices, *PQSPR*, and *OIB* are prevalent and large. In the next section, we examine how jumps in prices, liquidity, and trading activity are related within and across markets.

3.2. Are Jumps in Prices, Liquidity, and Trading Activity Related?

As a first assessment of the relevance of liquidity feedback loops in explaining price shocks, we examine whether price shocks tend to be accompanied by shocks to liquidity and/or trading activity (Hypothesis 1). To that end, we treat a jump in prices as an event and examine whether there are jumps in liquidity and/or trading activity at the same time as the event (i.e., in the same interval), before the event (from the beginning of the same trading day or from the previous price jump on the same day until the event), or after the event (from the event until the end of the same trading day or until the next price jump on the same day). We refer to co-jumps on the same day as coinciding and to co-jumps in the same interval as simultaneous.

Panel A (Panel B) of Table 3 assesses whether price jumps (the event) are accompanied by jumps in *PQSPR* (*OIB*) on the same market on the same day. The first two columns of each panel show the signs of the jumps in the variables under consideration. For example, in Panel A, the first column shows the sign of the price jump events (POS or NEG). The first two rows of Panel A show the number of positive or negative 5-minute, 15-minute, and 1-hour price jumps by region 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

Table 2. Frequency and Magnitude of Jumps in Prices, Liquidity, and Trading Activity

			5-minute				15-minute				1-hour			
	Direction	Statistic	America	Asia	Europe/Africa	World	America	Asia	Europe/Africa	World	America	Asia	Europe/Africa	World
			Panel A: Number of jumps											
PRICE	POS		444	884	1,162	2,490	65	113	258	436	44	13	83	140
	NEG		448	950	879	2,277	89	103	188	380	38	18	66	122
PQSPR	POS		141	532	273	946	43	139	90	272	20	—	36	56
	NEG		83	641	170	894	47	111	39	197	5	1	2	8
OIB	POS		725	879	1,220	2,824	64	131	207	402	16	15	73	104
	NEG		549	811	1,339	2,699	45	123	232	400	7	19	59	85
			Panel B: Absolute magnitude of jumps (in jump-free standard deviations)											
PRICE		Mean	5.05	4.46	6.78	5.52	5.32	4.81	7.14	6.17	4.85	5.28	5.70	5.38
		SD	1.51	1.13	4.52	2.93	1.59	1.31	4.29	3.41	1.01	1.58	1.75	1.56
PQSPR		Mean	6.09	5.45	7.37	5.98	6.38	5.94	7.55	6.46	6.00	4.22	7.33	6.76
		SD	2.86	1.89	3.25	2.51	1.99	2.05	2.87	2.38	2.07	—	2.67	2.50
OIB		Mean	5.80	4.86	6.82	5.97	5.96	4.97	7.42	6.45	5.61	4.70	6.36	5.95
		SD	2.45	1.34	3.62	2.82	1.85	1.47	4.17	3.42	2.25	1.12	2.66	2.40
			Panel C: Magnitude of jumps											
PRICE	POS	Mean	34.03	24.59	51.79	39.12	68.54	48.78	97.16	80.31	132.79	154.77	172.43	155.43
		Median	26.41	20.11	36.94	27.51	56.10	42.76	73.27	61.12	120.21	77.89	156.16	139.45
	NEG	Mean	−35.74	−25.44	−44.34	−34.75	−65.93	−60.06	−79.64	−71.23	−135.76	−147.02	−133.52	−136.65
		Median	−27.73	−21.68	−35.33	−27.56	−54.21	−49.15	−70.24	−59.44	−133.49	−112.82	−122.92	−122.09
PQSPR	POS	Mean	0.66	0.18	0.89	0.45	0.63	0.20	1.12	0.57	0.70		1.36	1.12
		Median	0.56	0.14	0.67	0.25	0.59	0.14	1.14	0.36	0.61		1.37	0.86
	NEG	Mean	−0.63	−0.16	−0.86	−0.33	−0.57	−0.25	−1.08	−0.49	−0.55	−0.50	−2.26	−0.97
		Median	−0.53	−0.14	−0.68	−0.17	−0.48	−0.21	−1.06	−0.32	−0.69	−0.50	−2.26	−0.70
OIB	POS	Mean	0.73	0.29	12.68	5.65	2.35	0.64	20.36	10.75	3.84	0.77	38.70	27.09
		Median	0.30	0.22	3.73	0.41	0.87	0.55	2.00	0.93	1.51	0.72	2.92	2.16
	NEG	Mean	−0.72	−0.28	−13.87	−7.06	−1.27	−0.59	−23.70	−14.01	−3.76	−1.02	−41.42	−29.23
		Median	−0.30	−0.22	−5.23	−0.45	−0.70	−0.55	−4.30	−0.89	−1.29	−0.96	−2.59	−1.96

Notes. Panel A of this table shows the number of 5-minute, 15-minute, and 1-hour intervals with a jump in value-weighted returns (*PRICE*), log-changes in value-weighted proportional quoted spreads (*PQSPR*), and value-weighted order imbalance (*OIB*) for 12 equity markets over 1996–2011 (aggregated by region: America, Asia, Europe/Africa, and World). Panel B shows the corresponding mean and standard deviation (SD) of the absolute magnitude of the jump, measured in terms of jump-free SDs (that is, the square root of the scaled bipower variation). Panel C shows the mean and median of jumps in *PRICE* (in bps), *PQSPR*, and *OIB* (in bps) for positive and negative jumps, respectively. For the purpose of computing summary statistics in in Panels B and C, we winsorize jump sizes by region at 0.5% and 99.5% levels. We note that we use non-winsorized data for jump estimation. 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). The jumps are classified according to their sign: positive (POS) and negative (NEG).

accompanied by a simultaneous positive or negative jump in *PQSPR* in the same interval on the same market. The following four rows show the number of positive or negative price jumps that were preceded by a positive or negative jump in *PQSPR* on the same market on the same day. The final four rows show the number of positive or negative price jumps that were followed by a positive or negative jump in *PQSPR* on the same market on the same day. The structure of Panel B is the same.[10]

Panel A of Table 3 shows no consistent pattern in the coincidence of jumps in prices and jumps in *PQSPR*. Very few price jumps are accompanied by jumps in *PQSPR*, either in the same interval or before or after the price jump on the same trading day. Overall, only 8.1% of all 5-minute price jumps in the sample are accompanied by a jump in *PQSPR* on the same day, and this fraction drops to 1.6% for the same 5-minute interval. Of all *negative* 5-minute price jumps that could be driven by a liquidity dry-up, only 0.7% are accompanied by a simultaneous illiquidity shock as reflected by a positive *PQSPR* jump in the same 5-minute interval. These fractions are even lower at the 15-minute and 1-hour frequencies.

Panel B of Table 3 shows a considerably stronger relation between jumps in prices and jumps in *OIB*. Not only do we observe a greater incidence of coinciding jumps in prices and *OIB*, these coinciding jumps also more often have the same sign as the price shocks. In particular, Panel B shows that positive (negative) jumps in prices are regularly accompanied by positive (negative) jumps in *OIB*, especially when prices and *OIB* jump in the same interval (as indicated by the higher numbers in the first and the last rows of the

Table 3. Coinciding Jumps in Prices, Liquidity, and Trading Activity

	Sign of the jump in		5-minute				15-minute				1-hour			
	PRICE	*PQSPR*	America	Asia	Europe/ Africa	World	America	Asia	Europe/ Africa	World	America	Asia	Europe/ Africa	World
Panel A: Coinciding jumps in prices and *PQSPR*														
Jumps in *PRICE* with no jumps in *PQSPR* on the same day	POS	NA	426	741	1,093	2,260	65	108	251	424	44	13	83	140
	NEG	NA	430	855	838	2,123	88	100	183	371	38	18	65	121
Simultaneous jumps in *PRICE* and *PQSPR*	POS	POS	2	7	9	18	—	—	2	2	—	—	—	—
	POS	NEG	1	15	9	25	—	—	1	1	—	—	—	—
	NEG	POS	5	5	7	17	—	2	—	2	—	—	1	1
	NEG	NEG	2	8	4	14	—	1	—	1	—	—	—	—
Jumps in *PRICE* preceded by jump in *PQSPR* on same day	POS	POS	5	12	10	27	—	2	—	2	—	—	—	—
	POS	NEG	3	48	11	62	—	—	—	—	—	—	—	—
	NEG	POS	2	14	8	24	—	—	—	—	—	—	—	—
	NEG	NEG	2	28	5	35	1	1	—	2	—	—	—	—
Jumps in *PRICE* followed by jump in *PQSPR* on same day	POS	POS	4	23	21	48	—	1	3	4	—	—	—	—
	POS	NEG	5	26	25	56	—	2	3	5	—	—	—	—
	NEG	POS	3	18	10	31	—	—	3	3	—	—	—	—
	NEG	NEG	2	17	7	26	—	—	—	—	—	—	—	—
Panel B: Coinciding jumps in prices and *OIB*														
Jumps in *PRICE* with no jumps in *OIB* on the same day	POS	NA	375	680	831	1,886	62	102	234	398	38	10	77	125
	NEG	NA	379	707	651	1,737	88	88	164	340	38	12	57	107
Simultaneous jumps in *PRICE* and *OIB*	POS	POS	26	80	98	204	2	9	12	23	5	3	4	12
	POS	NEG	1	—	2	3	—	1	—	1	—	—	—	—
	NEG	POS	1	1	—	2	—	—	—	—	—	—	—	—
	NEG	NEG	20	113	83	216	—	11	18	29	—	6	9	15
Jumps in *PRICE* preceded by jump in *OIB* on same day	POS	POS	10	17	35	62	1	—	1	2	—	—	—	—
	POS	NEG	6	11	45	62	—	—	4	4	—	—	—	—
	NEG	POS	16	25	37	78	—	2	—	2	—	—	—	—
	NEG	NEG	2	15	24	41	—	—	3	3	—	—	—	—
Jumps in *PRICE* followed by jump in *OIB* on same day	POS	POS	18	48	76	142	—	—	5	5	—	—	1	1
	POS	NEG	9	31	85	125	—	1	2	3	1	—	1	2
	NEG	POS	21	41	25	87	1	—	1	2	—	—	—	—
	NEG	NEG	12	52	53	117	—	3	2	5	—	—	—	—

Notes. This table shows the number of *PQSPR* jumps (Panel A) and *OIB* jumps (Panel B) that occur on the same day (within/before/after that 5-minute, 15-minute, and 1-hour interval) as price jumps for 12 equity markets over 1996–2011. We treat either a positive or a negative price jump as an event and we count the number of 5-minute/15-minute/1-hour intervals with jumps in either *PQSPR* or *OIB* in the same interval as the event (i.e., simultaneously), before the event (that is, from the beginning of the same trading day or from the previous price jump on the same day until the event) and after the event (that is, from the event till the end of the same trading day or until the next price jump). In each panel, the first two columns show the signs of the jumps in the variables under consideration. For example, the first column shows the sign of the price jumps (POS for positive jumps and NEG for negative jumps). In each panel, the first two rows show the number of positive or negative price jumps that are *not* associated with a jump in either *PQSPR* or *OIB* 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 either *PQSPR* or *OIB* on the same market in the same 5-minute/15-minute/1-hour interval. The following four rows show the number of positive or negative price jumps that were preceded by a positive or negative jump in either *PQSPR* or *OIB* on the same market on the same day. The final four rows show the number of positive or negative price jumps that were followed by a positive or negative jump in either *PQSPR* or *OIB* on the same market on the same day. We refer to the legend of Table 2 and to Appendix B for a detailed description of the jump statistics.

Simultaneous jumps section in Panel B). Across the whole sample, 24.0% of the 5-minute price jumps are accompanied by a jump in *OIB* on the same day. Approximately 9% of all 5-minute price jumps are accompanied by an *OIB* jump in the same 5-minute interval, and almost all of these involve same-sign jumps. These patterns are similar, if somewhat weaker, at the 15-minute and 1-hour frequencies.

Overall, the results in Table 3 provide mixed evidence for Hypothesis 1; there is little evidence of a relation between price jumps and *PQSPR* jumps, although a nontrivial fraction of price jumps are accompanied by same-sign *OIB* jumps within the same interval. The latter relation could be indicative of liquidity feedback effects but could also be consistent with mechanical effects.

To assess Hypothesis 2 (spillovers across markets), we study how jumps in prices, *PQSPR*, and *OIB* are related to jumps *in the same variable* on other markets. To save space, we do not present this analysis in the paper but in Online Appendix IA.3; we study (cross-)correlations in more detail in Section 3.5. We find that most jumps in our sample are confined to individual markets, although there are days on which we observe jumps on multiple markets in the same region. To illustrate, in Europe/Africa, 16.6% (14.0%) of all days with 5-minute price (*OIB*) jumps exhibit same-sign price (*OIB*) jumps in at least two different markets. In contrast, only 0.5% of the days with 5-minute *PQSPR* jumps in Europe/Africa exhibit same-sign *PQSPR* jumps in more than one market. Thus, market-wide liquidity shocks rarely occur on multiple markets on the same day (also not in other regions), suggesting that liquidity dry-ups are mainly local phenomena that do not tend to spillover to other markets.

3.3. Are Price Jumps Related to Economic News Events?

Our main alternative hypothesis to the liquidity dry-up channel is that price jumps are driven by information. To assess whether price jumps are related to information events (Hypothesis 3), we focus on macroeconomic news announcements, because they are relatively straightforward to measure globally and have the potential to lead to market-wide price shocks. We obtain data on macro announcements from all available countries in our sample over the period 2001–2011 from the Econoday database (which includes scheduled announcements regarding gross domestic product, nonfarm payroll employment, producer and consumer price indices, etc.). We manually select similar categories of macro announcements as used in Andersen et al. (2003) and Opschoor et al. (2014).[11] In total, there are 6,691 different macro announcements from Canada, China (included because of its relevance for Hong Kong), the European Monetary Union (EMU), France, Germany, Japan, the United Kingdom, and the United States. We examine how many of the jumps in prices in our sample occur within a short window (we look at the window from 5-minute/15-minute/1-hour before until 1 hour after the event) around the release time of any of the macro announcements. We use a one-hour window after the announcements to allow for some time for the news to be incorporated in prices.[12]

Table 4 presents the results. The first row in the table shows the total number of price jumps in each region over 2001–2011. The table then reports the number of 5-minute, 15-minute, and 1-hour price jumps in each region that occur within the event window around three categories of macro announcements: all macro announcements in our sample around the world (Panel A), macro announcements in countries in our sample within the respective region (Panel B), and U.S. macro announcements (Panel C). Each panel shows the number of price jumps that occur around that category of macro announcements and the *p*-value of a test whether the observed number of jumps in the event window is smaller or equal to the expected number of jumps under the assumption that price jumps and macro announcements are independent.

Panel A of Table 4 shows that for America and Europe/Africa, a considerable fraction of the price jumps occurs within one hour of a macro announcement. For America region, 18%, 25%, and 7% of, respectively, the 5-minute, 15-minute, and 1-hour price jumps are associated with a macro announcement. For Europe/Africa region, the corresponding fractions are 31%, 39%, and 25% of all 5-minute, 15-minute, and 1-hour price jumps. For Asia, the fractions are much lower, but we note that none of the U.S. macro announcements and very few of the macro announcements from China and Japan take place within the opening hours of the Asian markets. In other words, the vast majority of global macro announcements in Panel A for Asia are announcements from Europe, which may be of comparatively little relevance for Asian markets. For America, Europe/Africa, and the World, we reject the null hypothesis that price jumps and macro announcements occur independently at the 5-minute and 15-minute frequencies. The *p*-values of this test are higher at the 1-hour frequency, where the number of jumps is considerably smaller.

In Panels B and C of Table 4, we study whether a certain subcategory of global macro announcements is of particular relevance for different regions. Perhaps not surprisingly, we find that U.S. macro announcements are the most influential, even more so than macro announcements from the same region. For America, of all 124 5-minute price jumps that are associated with a macro announcement, 122 occur around a U.S. announcement. For Europe/Africa, of all 483 price jumps associated with a macro announcement, 387 occur around a U.S. announcement and only 91 around an announcement stemming from the same region. We observe similar patterns for the 15-minute and 1-hour frequencies. The final row of the table shows strong statistical evidence that price jumps are related to U.S. macro announcements for America, Europe/Africa, and the World at all three frequencies.

Overall, Table 4 indicates that a considerable number of price jumps are associated with the arrival of important economic news, consistent with the information channel. Of course, our results do not imply that we can trace each price jump to a news event. However, there are many other news events that could cause sudden shocks to stock prices, so we likely significantly underestimate the fraction of price jumps associated with economic news. Also, Table 4 does not rule out feedback effects, a possibility we examine in the next section.

3.4. Behavior of Prices, Liquidity, and Trading Activity Around Price Jumps

The evidence on Hypotheses 1, 2, and 3 presented so far indicates that price jumps bear little relation with liquidity jumps, regularly coincide with trading activity jumps, and are quite often associated with economic news events. Although these results are suggestive of mechanical effects stemming from an information channel, they do not negate feedback effects stemming from a liquidity channel. In this section, we shed light on Hypotheses 4, 5, and 6 to further distinguish between these channels by studying the behavior of prices, liquidity, and trading activity around price jumps. In particular, if price jumps are the result of mechanical effects stemming from an information channel, we would expect price jumps to be immediate and permanent; *PQSPR* jumps and *OIB* jumps around price jumps to revert quickly; and jumps in prices, *PQSPR*, and *OIB* not be mutually or self-reinforcing.

Figure 1 first presents graphs of the cumulative value-weighted return in 5-minute intervals from one hour before ($t = -12$) until one hour after ($t = +12$) jumps in prices (positive jumps in (a) and negative jumps in (b)), aggregated across all jumps on the 12 markets in our sample and measured in bps.[13] The average price jump in Figure 1 is around 40–50 bps, which signifies an economically substantial market-wide price shock over such a short interval. The graphs show that price jumps are truly sudden: there is a clear discontinuity relative to cumulative returns before the 5-minute interval of the jump. Furthermore, there is little evidence of any reversal following price jumps. In other words, price jumps tend to constitute immediate and permanent price changes, consistent with Hypothesis 4 (information channel) and inconsistent with a "sharp V-shaped pattern in prices around the time of the liquidity black hole" (Morris and Shin 2004, p. 1).

Figure 1 also shows the cumulative change in *PQSPR* ((c) and (d); in %) and the dynamics of *OIB* ((e) and (f); in bps) in the same event window around price jumps. Figure 1, (c) and (d), shows that liquidity does fluctuate around price jumps; quoted spreads

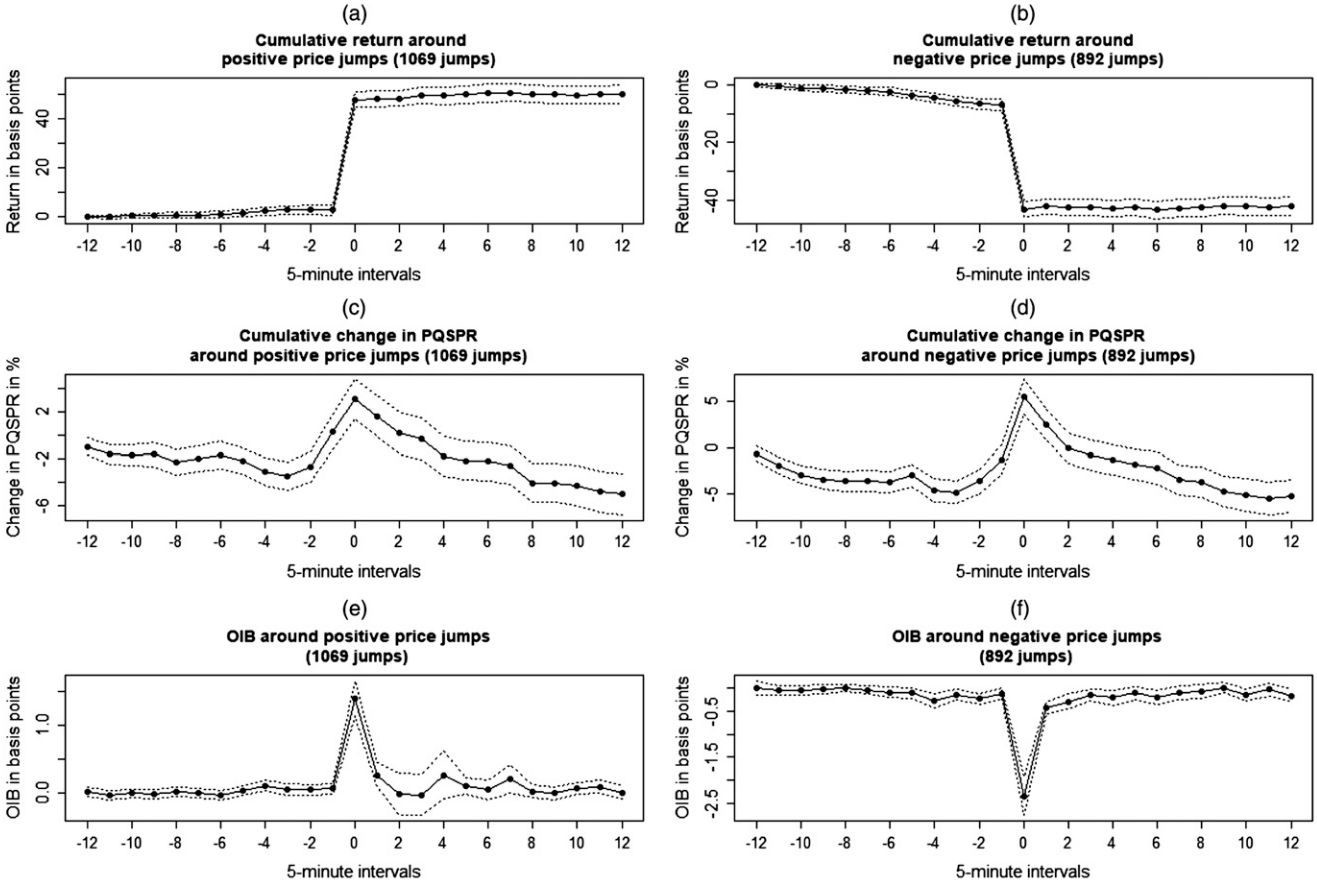
Table 4. Jumps in Prices and Macro Announcements

	5-minute				15-minute				1-hour			
	America	Asia	Europe/ Africa	World	America	Asia	Europe/ Africa	World	America	Asia	Europe/ Africa	World
No. *PRICE* jumps	683	1,416	1,539	3,638	122	177	362	661	71	28	121	220
	Panel A: Global macro announcements											
No. *PRICE* jumps around global macro announcements	124	67	483	674	30	17	141	188	5	1	30	36
p-value (*PRICE* jumps independent of global macro announcements)	0.00***	1.00	0.00***	0.00***	0.00***	0.19	0.00***	0.00***	0.01***	0.66	0.75	0.17
	Panel B: Regional macro announcements											
No. *PRICE* jumps around regional macro announcements	122	6	91	219	30	1	23	54	5	—	9	14
p-value (*PRICE* jumps independent of regional macro announcements)	0.00***	0.90	1.00	0.88	0.00***	0.70	1.00	0.54	0.01***	—	1.00	0.83
	Panel C: U.S. macro announcements											
No. *PRICE* jumps around U.S. macro announcements	122	—	387	509	30	—	119	149	5	—	20	25
p-value (*PRICE* jumps independent of U.S. macro announcements)	0.00***	—	0.00***	0.00***	0.00***	—	0.00***	0.00***	0.01***	—	0.00***	0.00***

Notes. This table presents the number of jumps in 5-minute/15-minute/1-hour value-weighted returns (*PRICE*) within each region (America, Asia, Europe/Africa, and World) that occur within a short event window around macro announcements over 2001–2011. In total, we use data on 6,691 different macro announcements from the American region (Canada, United States), from the Asian region (China, Japan), and from the European region (EMU, France, Germany, United Kingdom). The event window around the macro announcements is [−1,+12]/[−1, +4]/[−1,+1], measured in 5-minute/15-minute/1-hour intervals, respectively. We study global (all) macro announcements (Panel A), regional macro announcements (Panel B), and U.S. macro announcements (Panel C). In addition, we report the *p*-value of a test of the hypothesis that the empirically observed number of jumps in *PRICE* around macro announcements is smaller or equal to the expected number under the assumption that jumps in *PRICE* and macro announcements are independent of each other. We refer to the legend of Table 2 and to Appendix B for a detailed description of the jump statistics. Data on the macro announcements are from the Econoday database.

***, **, and * Statistical significance at 1%, 5%, and 10% levels, respectively.

Figure 1. Behavior of Prices, *PQSPR*, and *OIB* Around Price Jumps



Notes. This figure shows the behavior of prices, *PQSPR*, and *OIB* from one hour before until one hour after either positive or negative 5-minute jumps in prices (averaged across all the price jumps in the 12 stock markets over 1996–2011). (a) and (b) Cumulative average returns around positive and negative price jumps. (c) and (d) Cumulative average changes in *PQSPR* around positive and negative price jumps. (e) and (f) Average *OIB* around positive and negative price jumps. Dashed lines represent 95% confidence intervals. Cumulative returns, cumulative changes in *PQSPR* and *OIB* are plotted for each 5-minute interval in the event window, with the price jump taking place at $t = 0$. We include only jump events without missing observations in the event window. We refer to the legend of Table 2 and Appendix B for a detailed description of the jump statistics.

tend to fall slightly in the hour before a price jump, followed by a small upward blip just before the price jump, and a reversal to pre-event levels after the price jump. Nonetheless, the observed patterns seem hard to square with theories that propose a key role for liquidity dry-ups in how price shocks arise. First, the quoted spread effects are small. The blip in *PQSPR* just before the price jump has a magnitude of 3%–6% relative to pre-event levels, which is much smaller than the average *PQSPR* jump of around 35%–40% (see Online Appendix IA.4 for behavior of prices, *PQSPR* and *OIB* around jumps in *PQSPR*). Second, liquidity tends to improve following a price jump, but Figure 1 shows no evidence of any accompanying price reversal. Third, there is little indication of liquidity spirals in the sense that feedback loops cause liquidity crashes to worsen over time.

Figure 1, (e) and (f), shows a clear, once-off spike in *OIB* in the same direction as the price jump in the same interval. Given the lack of persistence in *OIB* and the absence of price reversals, this pattern in *OIB* around price jumps is more consistent with speculative trading or portfolio rebalancing around the arrival of news than with feedback loops in which initial price drops induce further selling.

Overall, the results in this section seem to agree well with mechanical links among prices, *OIB* and liquidity around large price shocks as laid out in Hypotheses 4 and 5 and inconsistent with liquidity feedback effects as laid out in Hypothesis 6.[14]

3.5. Joint Tests of Specific Hypotheses on Mechanical vs. Feedback Effects

In this section, we present several encompassing analyses to jointly test various of the hypotheses formulated in Section 2.1. In particular, we estimate a number of logit models to explain the occurrence of negative price jumps. We focus on negative price jumps in particular because our main interest concerns the question whether liquidity dry-ups can explain such adverse market-wide

Table 5. Intraday Firthlogit Models to Explain Negative Jumps in Prices

	Panel A: Contemporaneous firthlogit				Panel B: Lagged firthlogit	
	5-minute	15-minute	1-hour		5-minute	15-minute
				Lagged negative jump in PRICE i	0.000	0.001
					(−1.39)	(0.61)
Positive jump in PQSPR i	0.007***	0.005	0.001	*Lagged positive jump in PQSPR i*	0.001	0.002
	(3.24)	(1.40)	(0.25)		(0.62)	(0.58)
Negative jump in OIB i	0.021***	0.011***	0.014	*Lagged negative jump in OIB i*	0.000	0.001
	(9.04)	(3.09)	(1.61)		(0.27)	(0.61)
Negative jumps in PRICE not i	0.022***	0.041***	0.054***	*Lagged negative jumps in PRICE not i*	0.000	0.000
	(9.54)	(4.99)	(2.86)		(−0.23)	(0.42)
Positive jumps in PQSPR not i	−0.001***	0.001	0.005	*Lagged positive jumps in PQSPR not i*	0.001	0.001
	(−3.07)	(0.52)	(0.64)		(0.58)	(0.51)
Negative jumps in OIB not i	0.004***	0.001***	0.002	*Lagged negative jumps in OIB not i*	0.000	0.000
	(5.86)	(2.41)	(1.40)		(−0.60)	(0.36)
Negative Macro	0.000**	0.001***	0.001	*Negative Macro*	0.001***	0.001***
	(2.29)	(2.48)	(0.75)		(7.68)	(4.39)
PQSPR	0.002***	0.001***	−0.002	*Lagged PQSPR*	0.001***	0.000
	(13.82)	(5.55)	(−1.36)		(8.95)	(1.01)
OIB	0.000***	0.000***	0.000***	*Lagged OIB*	0.000*	0.000
	(−15.35)	(−6.19)	(−3.68)		(−1.91)	(−0.12)
Country FE	Yes	Yes	Yes	Country FE	Yes	Yes
Tjur R^2	3.35%	5.48%	11.74%	Tjur R^2	0.04%	0.03%
No. of observations	1,965,635	557,123	86,591	No. of observations	1,938,682	533,178

Notes. This table shows marginal effects of intraday firthlogit models to explain the occurrence of jumps in 5-minute/15-minute/1-hour value-weighted returns (*PRICE*) in our sample over 1996–2011. As dependent variable, we use an indicator variable of whether there was a negative price jump in a particular market *i* in a particular 5-minute/15-minute/1-hour interval. As independent variables, we use an indicator variable of same-sign jumps in value-weighted order imbalance (*OIB*) in market *i* in the same interval, an indicator variable of positive jumps in value-weighted proportional quoted spreads (*PQSPR*) in market *i* in the same interval, indicator variables of whether at least one other market in the same region (labeled "not *i*") has a same-sign (positive) jump in *PRICE* or in *OIB* (*PQSPR*) in the same interval, and an indicator variable for the window [−1,+12] / [−1,+4] / [−1,+1] surrounding negative macro announcements at the 5-minute/15-minute/1-hour frequency, respectively. Negative macro announcements are defined as macro announcements that occur on days with negative close-to-close returns in the respective market. We also control for *PQSPR* and *OIB* in a particular 5-minute/15-minute/1-hour interval. Panel A shows the results of firthlogit models with contemporaneous independent variables, and Panel B shows the results of firthlogit models with one-interval lagged independent variables except indicator variable for macro announcements (due to the rare nature of 1-hour jumps, it is not possible to estimate the lagged model at this frequency). All firthlogit models include country fixed effects. Continuous variables are winsorized at 0.5% and 99.5% levels, but we note that non-winsorized regressions produce equivalent results. We refer to the legend of Table 2 and Appendix B for a detailed description of the jump statistics. Data on the macro announcements are from the Econoday database.

***, **, and * Statistical significance at 1%, 5%, and 10% levels, respectively.

financial shocks. We first estimate intraday logit models to relate the likelihood of 5-minute, 15-minute, and 1-hour price jumps to lagged and contemporaneous variables from the same and from other markets. We then estimate daily logit models that include a number of further explanatory variables, which we can only measure at the daily frequency, that are related to a variety of specific feedback channels.

Table 5 presents the results of the intraday logit models. As dependent variable, we use an indicator variable of whether there was a negative price jump in a particular market *i* in a particular 5-minute, 15-minute, or 1-hour interval. As independent variables, we use indicator variables of positive *PQSPR* jumps and negative *OIB* jumps in market *i* in the same interval, indicator variables of whether at least one other market in the same region (labeled "not *i*" in Table 5) has a negative jump in prices or in *OIB* or a positive jump in *PQSPR* in the same interval, an indicator variable for the period from 5-minute/15-minute/1-hour before until one hour after negative macro announcements (i.e., macro announcements that occur on the days with a negative close-to-close return in the respective market),[15] and the variables *PQSPR* and *OIB* separately. Because of estimation issues with regular logit models when explaining rare events, we follow the recommendation of Heinze and Schemper (2002) and estimate firthlogit models instead.[16]

Table 5 presents the marginal effects of these firthlogit models, with contemporaneous independent variables in Panel A and one-interval lagged independent variables in Panel B, to study feedback effects reflected in serial (cross-)correlations in the main variables of interest. We cannot estimate the lagged firthlogits at the 1-hour frequency because of the extremely rare nature of negative 1-hour price jumps. Regarding Hypothesis 1, Panel A indicates that a positive 5-minute *PQSPR* jump is associated with a statistically significant but economically small increase in the probability of a negative price jump in the same 5-minute interval of 0.7% (consistent with Table 3). However, this effect dissipates at the 15-minute and 1-hour frequencies, suggesting that the relation between liquidity jumps and price jumps is of a transient and mechanical nature. Also consistent with Table 3, negative *OIB* jumps increase the probability of a negative price jump in the same interval (by 2.1% at the 5-minute frequency), and again this effect is weaker at the lower frequencies.

Regarding Hypothesis 2 (spillovers), Panel A of Table 5 confirms the result in Section 3.2 that price shocks can rapidly spillover across markets within the same region. The coefficient on "Negative jumps in *PRICE* not *i*" is positive and statistically significant at all three frequencies. It is also economically substantial; for example, a negative 1-hour price jump in another market in the same region increases the probability of a negative price jump in market *i* in the same hour by 5.4%. In contrast, positive *PQSPR* jumps in other markets within the region do not increase the probability of a negative price jump in market *i* in the same interval. There is some evidence that negative *OIB* jumps in other markets are associated with a greater probability of a negative price jump in market *i*.

Regarding Hypothesis 3 (information events), Panel A of Table 5 reports a positive and significant coefficient on the indicator variable for negative macro announcements at the 5-minute and 15-minute frequencies (consistent with Table 4). Thus, price jumps are more likely around macro announcements. The economic magnitude of the coefficients is limited, indicating that these announcements cannot account for all negative price jumps in the sample. We further include *PQSPR* and *OIB* as control variables and find that negative price jumps are more likely when markets are less liquid and *OIB* is more negative.

Panel B of Table 5 shows that most of the effects in Panel A disappear when the independent variables are lagged by one interval (except for the macro announcements variable), indicating that shocks to liquidity and trading activity and spillover effects only influence price jumps contemporaneously, suggesting mechanical rather than feedback effects (contradicting Hypothesis 6). Panel B also shows that there is no persistence in price jumps themselves, in line with Hypothesis 4 and contradicting Hypothesis 6. In sum, the Table 5 results are most consistent with the information channel and provide little evidence of liquidity feedback effects.

In Table 6, we present the results of regular logit models estimated at the daily frequency designed to include a number of additional variables that proxy for various specific hypotheses on feedback effects for which we can only obtain daily data. Thus, the dependent variable is now an indicator variable of whether there was a 5-minute, 15-minute, or 1-hour price jump in a particular market *i* during a particular day. We include the same independent variables as in Table 5 (redefined at the daily frequency) and the following additional variables to assess Hypotheses 7–10: two proxies for funding liquidity (Hypothesis 7: T-Bill and EuroDollar (TED) spread from Federal Reserve Economic Data (FRED), following Brunnermeier and Pedersen 2009, and stock returns of the local banking sector index from Datastream orthogonalized with respect to local market index, following Hameed et al. 2010), a proxy for market runs (Hypothesis 8: flows into and out of all regional passive mutual funds from Morningstar Direct),[17] a proxy for behavioral feedback effects (Hypothesis 9: indicator variable of whether the local stock market index crossed a salient price boundary during the same day),[18] and a proxy for feedback effects because of dynamic hedging demands (Hypothesis 10: total volume of at-the-money put and call options on the local stock market index from Datastream).[19]

Table 6 shows no relation between the occurrence of negative price jumps on a day and same-day positive *PQSPR* jumps, neither in the same market nor in other markets within the region. Negative price jumps are positively and significantly related to negative *OIB* jumps in both the same and in other markets and to negative price jumps in other markets, as in Table 5. The coefficients on the control variables *PQSPR* and *OIB* are also largely in line with Table 5.

We once again find corroborating evidence for Hypothesis 3 (information events), as the coefficient on the negative macro announcements variable is positive and significant at the 5-minute, 15-minute, and 1-hour frequencies (consistent with Table 4). There is little evidence that variables that are meant to capture potential funding liquidity spirals help to explain the occurrence of price jumps in our sample. If anything, the coefficient on the TED spread is negative, opposite of the expected sign under Hypothesis 7 of liquidity dry-ups because of funding liquidity effects. The coefficient on local bank returns is not significant, with the exception of a marginally significantly negative effect at the 1-hour frequency. Table 6 also shows no other indication that market runs as proxied by regional flows into and out of passive funds (Hypothesis 8) have a significant effect on price jumps at any of the frequencies under consideration.

We do find that our indicator variable for salient price boundaries (a proxy for Hypothesis 9: behavioral feedback effects) has a positive and significant coefficient at the 5-minute and 1-hour frequencies. This finding suggests that behavioral effects may be at play around some of the price jumps, although the statistical and economic significance of this variable are weaker than for our macro announcements variable and there is no indication of associated liquidity effects. In the final specification to explain negative 5-minute price jumps, we add the total volume in at-the-money options on the local stock market index (a proxy for Hypothesis 10: feedback effects

Table 6. Daily Logit Models to Explain Negative Jumps in Prices

	5-minute								15-minute	1-hour
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Positive jump in PQSPR i	0.012	0.014	0.011	0.012	0.014	0.012	−0.018	0.015	0.008	—
	(1.06)	(1.19)	(0.85)	(0.96)	(1.15)	(0.93)	(−0.97)	(1.09)	(1.08)	—
Negative jump in OIB i	0.077***	0.073***	0.077***	0.075***	0.077***	0.076***	0.124***	0.074***	0.041**	0.030*
	(3.11)	(3.12)	(3.17)	(3.01)	(3.02)	(2.99)	(2.92)	(3.03)	(2.51)	(1.67)
Negative jumps in PRICE not i	0.032**	0.036**	0.032**	0.036**	0.031**	0.035**	0.081***	0.037**	0.046***	0.034***
	(2.09)	(2.14)	(2.14)	(2.22)	(1.99)	(2.18)	(3.17)	(2.08)	(3.76)	(3.23)
Positive jumps in PQSPR not i	0.002	0.004	0.002	0.001	0.001	0.001	−0.013	0.003	0.002	0.003
	(0.64)	(0.67)	(0.45)	(0.19)	(0.32)	(0.18)	(−1.55)	(0.42)	(0.52)	(0.38)
Negative jumps in OIB not i	0.015***	0.016***	0.016***	0.015***	0.014***	0.015***	0.029**	0.016***	0.019***	0.023***
	(3.80)	(3.00)	(4.00)	(4.04)	(3.70)	(3.61)	(1.97)	(3.31)	(3.04)	(3.16)
Average PQSPR	0.036***	0.036	0.041***	0.034***	0.035***	0.036***	0.117	0.042	0.014	−0.002
	(3.10)	(1.35)	(3.35)	(3.01)	(3.01)	(3.14)	(0.57)	(1.56)	(1.36)	(−0.23)
Average OIB	−0.014***	−0.011***	−0.013***	−0.014***	−0.013***	−0.014***	−0.014	−0.012***	−0.002***	−0.000***
	(−5.22)	(−4.35)	(−5.56)	(−4.96)	(−5.38)	(−5.37)	(−1.47)	(−4.49)	(−5.63)	(−6.82)
Negative Macro		0.017***						0.017***	0.008***	0.006***
		(4.82)						(5.93)	(3.69)	(2.64)
TED			−0.022***					−0.028***	−0.004	−0.005***
			(−3.90)					(−4.15)	(−0.93)	(−3.32)
Orthogonal BankReturn				−0.047				−0.148	0.020	−0.053*
				(−0.43)				(−1.00)	(0.33)	(−1.71)
Regional Passive Fund Flows					0.676			0.550	−0.012	−0.014
					(1.35)			(1.07)	(−0.08)	(−0.11)
Salient Price Boundaries						−0.001		0.005*	0.003	0.004***
						(−0.48)		(1.73)	(1.35)	(2.63)
Option volume							−0.000			
							(−1.14)			
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	5.0%	6.2%	5.2%	5.0%	5.0%	5.0%	10.8%	6.5%	11.1%	19.2%
No. of observations	39,950	28,398	38,294	37,590	38,437	38,097	3,899	25,186	22,574	17,421

Notes. This table shows marginal effects of daily logit models to explain the occurrence of days with negative jumps in 5-minute/15-minute/1-hour value-weighted returns (*PRICE*) in our sample over 1996–2011. As dependent variable, we use an indicator variable of whether there was a 5-minute/15-minute/1-hour price jump in a particular market *i* on a particular day. As independent variables, we use an indicator variable of positive 5-minute/15-minute/1-hour jumps in value-weighted proportional quoted spreads (*PQSPR*) in market *i* during the same day, an indicator variable of negative 5-minute/15-minute/1-hour jumps in value-weighted order imbalance (*OIB*) in market *i* on the same day, indicator variables of whether at least one other market in the same region (labeled "not *i*") has a negative (positive) jump in *PRICE* or in *OIB* (*PQSPR*) on the same day, the average *PQSPR* and *OIB* on the same day, an indicator variable for a negative macro announcement on the same day (negative macro announcements are defined as announcements that occur on days with negative close-to-close returns in the respective market), the T-Bill and EuroDollar (TED) spread, the stock return of the local banking sector (orthogonalized with respect to the local market index under consideration), aggregate regional flows into and out of passive mutual funds (divided by the previous-year market capitalization of the region), an indicator variable whether the local stock market index crossed salient price boundary during the same day, and the exponentially-weighted moving average volume of at-the-money put and call options on the local market index (including contemporaneous volume and with an exponential weighting factor 0.5). All logit models include country and year fixed effects. Standard errors are clustered by country. Continuous variables are winsorized at 0.5% and 99.5% levels, but we note that non-winsorized regressions produce equivalent results. We refer to the legend of Table 2 and Appendix B for a detailed description of the jump statistics. Data are from TRTH (trade and quote data), Federal Reserve Economic Data (TED spread), Datastream (option volumes and stock return of the local banking sector), Econoday (macro announcements), Morningstar Direct (passive fund flows), and World Bank (country market capitalization).

***, **, and *Statistical significance at 1%, 5%, and 10% levels, respectively.

because of dynamic hedging demand). We note that the number of observations drops dramatically because these data only start in 2009, and we cannot estimate this specification at the 15-minute and 1-hour frequencies. The coefficient on this variable is not significant.

Taken together, the results in Tables 5 and 6 are largely supportive of information as the predominant channel through which price shocks arise and spread across markets and provide little support for feedback effects that could lead to liquidity dry-ups fomenting sudden adverse intraday market-wide price shocks and spillovers across markets.

4. Conclusion

We study how intraday market-wide shocks arise and spread across 12 stock markets around the world over 1996–2011, with a particular focus not only on shocks to prices but also on shocks to liquidity and trading activity. Our main purpose is to assess the relevance of the liquidity and information channels in explaining how sudden market-wide shocks arise and spread across stock markets. Our findings can be summarized as follows. First, jumps in prices, quoted spreads, and order imbalance are prevalent and large. Second, we document a significant association of price jumps with jumps in order imbalance but not with jumps in spreads. Third, jumps in prices and order imbalance exhibit significant spillover effects across markets (even at high frequencies), but spillovers of jumps in spreads to other markets are rare. Fourth, we test a number of specific hypotheses to distinguish between the liquidity and information channels. We find that price jumps are immediate and permanent and are often associated with macro announcements. Shocks to spreads and order imbalance around price jumps revert quickly and we find little evidence of feedback loops, neither by examining the behavior of prices, spreads, and order imbalance around price jumps nor by examining proxies for funding liquidity spirals, market runs, and other feedback effects.

We believe that our finding that liquidity dry-ups do not play more than a minor role in explaining how sudden intraday market-wide price shocks arise and spread across international stock markets should be of interest to investors and regulators alike. Our analysis does not rule out that theories on liquidity dry-ups are relevant in other markets, in other asset classes, at (much) higher or lower frequencies, and for shocks to individual securities rather than to the market as a whole. However, our results do suggest that investors can effectively reduce their exposure to intraday stock market liquidity dry-ups through international diversification. Regulators may find comfort in our finding that liquidity dry-ups seem to play a less central role in how sudden, market-wide price shocks arise and spread across stock markets than perhaps previously thought.

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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 TRTH. From the former, we obtain RICs for all common stocks that are traded on 12 exchanges around the world. Then, we identify stocks that were ever part of the major local market index for each of these exchanges from 1996 until 2011 through the TRTH Speedguide. Subsequently, we follow Boehmer et al. (2020) and use the exchanges that they identify as primary trading venues for each country. We select common stocks that are traded in local currency, are identified as the major security type for each firm and have their primary quote from the primary trading venue (to exclude cross-listings). In a final step, we merge the data on major index constituents from the TRTH Speedguide with those on common stocks and market capitalization from Datastream.

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 exchange and the equity index used are in parentheses): Brazil (exchange: Bolsa de Valores, Mercadorias and Futuros de São Paulo; index: BOVESPA), Canada (exchange: Toronto Stock Exchange; index: TSX COMPOSITE), Mexico (exchange: Bolsa Mexicana de Valores; index: IPC), United States (exchange: New York Stock Exchange, index: S&P100). The Asian region includes Hong Kong (exchange: Stock Exchange of Hong Kong; index: HSI), India (exchange: National Stock Exchange of India; index NIFTY50), Japan (exchange: Tokyo Stock Exchange; index: NIKKEI225), Malaysia (exchange: Bursa Malaysia; index: KLCI). The European/African region includes France (exchange: Paris Euronext; index: CAC40), Germany (exchange: Xetra; index: DAX), South Africa (exchange: Johannesburg Stock Exchange; index: JALSH), United Kingdom (exchange: London Stock Exchange; index: 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 2006.

We obtain the historical opening hours for each of the exchanges from several sources: the TRTH Speedguide, Skeete (2004), exchanges' websites, and the Federation of European Securities Exchanges. We cross-check these opening hours by examining the trading activity patterns observed in the data and select the shortest opening hours when in doubt. Because we cannot clearly distinguish between auctions and continuous trading sessions, we disregard the first and the last 15 minutes of each trading day. We also discard overnight changes. We also take into account the daylight saving time (DST) for all markets under consideration. We refer to Online Appendix IA.1 for a summary of the sample selection, information on the exchanges' opening hours, time zone, and GMT offset with and without DST.

A.2. Data Screens

We filter the data following Rösch et al. (2017). 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, when the trade price is not positive, when the trade size is more than 10,000 shares (to exclude block trades from our sample), or when 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, when the bid and ask prices are not positive, when the bid price is higher than the ask price, when the bid or ask price differs from the bid or ask price of the 10 surrounding ticks by more than 10%, and when the proportional bid-ask spread exceeds 25%. To reduce the impact of stock-level noise and to secure a certain level of representativeness, we discard 5-minute, 15-minute, and 1-hour intervals for a given market when there are fewer than ten stocks with a trade (indicating very low trading activity that could be due to breaks, public holidays, or trading halts that we are unable to identify in a consistent manner). To optimize the use of our data, we processed it such that omitting a 5-minute interval does not necessarily mean omitting the associated 15-minute interval. We use all available 5-minute intervals to construct the 15-minute interval: sum the log-returns, take the last value of the proportional quoted spread, and sum the order imbalance. If at least during one of the 5-minute intervals the number of stocks with trades was greater than 10, the whole 15-minute interval is valid. We refer to Online Appendix IA.1 for a summary of stock-level and market-level filters.

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, we do not have access to historical index constituents. We believe that these limitations are not severe due to the value-weighting averaging of the stock-level variables, which results in a small weight for small and illiquid stocks that may not have been part of the index in the time interval under consideration. Finally, we cross-checked our market-wide returns by verifying that their means and standard deviations are close to those of the corresponding indices for the respective markets and that the market-wide returns displayed a high correlation with the corresponding index returns.

Appendix B. BNS Jump Measure

This appendix describes the BNS jump measure of Barndorff-Nielsen and Shephard (2006) and the algorithm of Andersen et al. (2010) that we use to determine the exact interval in which a jump occurs. A jump measure is a statistical non-parametric test statistic for jumps in a time-series. In this paper, we follow Andersen et al. (2010) and use the logarithmic BNS measure:

$$Z_t = \frac{\sqrt{T}(\ln BV_t - \ln RV_t)}{\sqrt{\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)TQ_t BV_t^{-2})}},$$

$$RV_t = \sum\nolimits_{k=2}^{T} (V_{k,t})^2,$$

$$BV_t = \mu_1^{-2} \sum\nolimits_{k=2}^{T} |V_{k,t}||V_{k-1,t}|,$$

$$TQ_t = \frac{1}{T}\mu_{4/3}^{-3} \sum\nolimits_{k=3}^{T} |V_{k,t}|^{4/3} |V_{k-1,t}|^{4/3} |V_{k-2,t}|^{4/3},$$

$$\mu_1 = \sqrt{2/\pi},$$

$$\mu_{4/3} = 2^{2/3}\Gamma(7/6)/\Gamma(1/2),$$

where Z_t is the logarithmic BNS measure in period t, RV_t is the squared variation (realized variation) in period t, BV_t is the bipower variation for period t, TQ_t is the "realized tripower 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 *PQSPR*, or *OIB*) in the k-th interval during period t, and T is the total number of valid intervals within period t. Under the null hypothesis of no jumps, Z_t follows a standard normal distribution. We construct Z_t at a daily, weekly, and monthly frequency, for which we use 5-minute, 15-minute and 1-hour intervals, respectively.

The BNS jump statistic is based on the assumption that V_{kt} follows a Brownian motion with zero drift plus a Poisson jump process. The bipower variation aims to measure 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. The bipower variation is estimated as the sum of the products of the current and lagged absolute values of the variable during the period, and thus the impact of a large jump on the bipower variation is small. In contrast, the squared variation is estimated as the sum of the products of the current absolute value of the variable with itself, and thus a large jump blows up the squared variation compared with the bipower variation. Hence, if there is a jump, the squared variation exceeds the bipower variation and the ratio of these two variables gives an indication of whether a jump occurred. If period t features a jump, then Z_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 volatility is constant over the period over which we test for a jump. We know that volatility exhibits intraday patterns and alleviate this concern by discarding the first and last 15 minutes of each day, since intraday volatility is high at the beginning and end of the trading session (Andersen and Bollerslev 1997). Second, we assume that T is large enough ($T \approx T-1 \approx T-3$). We reject the null hypothesis of no jumps if the BNS statistic is below the 0.1% percentile of the standard normal distribution (one-sided test).

The BNS test statistic indicates whether there was a jump for a given period but does not pinpoint the exact interval when the jump occurs. To determine the exact time of the jump, we use the algorithm of Andersen et al. (2010). We first compute Z_t for any period with *at least* 25 valid intervals available. Then, we check whether we can reject the null hypothesis of no jumps (based the 0.1% percentile of the standard normal distribution). If the null hypothesis is rejected, we search for the most influential interval within period t. In other words, we identify the interval that has the maximum effect on the realized variation (squared variation). We mark this interval as a jump. We repeat the procedure (replacing this observation by the average of the remaining squared observations in the realized variance computation) 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.[20]

Endnotes

[1] See Eun and Shim (1989), Roll (1989), and Hamao et al. (1990) for early research; Forbes and Rigobon (2002), Bae et al. (2003), and Hartmann et al. (2004) for studies on contagion; Karolyi (2003) for a literature review; and Longstaff (2010) and Bekaert et al. (2014) for analyses of the global financial crisis.

[2] Recent papers that use the TRTH database include Lau et al. (2012), Marshall et al. (2012), Boehmer et al. (2019), Frino et al. (2014), Lai et al. (2014), Boehmer et al. (2020), Fong et al. (2017), and Rösch et al. (2017).

[3] For robustness purpose, we conducted all our analysis for the 1996–2006 and 2006–2011 subperiods (see Online Appendix IA.5). Our main findings are robust across subperiods.

[4] Data requirements preclude meaningful price impact estimates at high frequencies. In unreported tests, we also examine effective spreads (*PESPR*, defined as the difference between the trade price and the prevailing midquote) and turnover as measures of liquidity and trading activity, but detect very few jumps in either. A potential explanation is that *PESPR* can only be measured when a trade occurs and rational investors observing a jump in quoted spreads could abandon the market and return when liquidity improves.

[5] We use round intervals to aggregate variables from the 5-minute frequency to lower frequencies. For the 15-minute frequency, we use intervals 0–15, 15–30, 30–45, and 45–60; for the 1-hour frequency, we use interval 0–60. We require that the full hour is available for an hourly observation to be included. This means that if the data start at 9:30 the period from 9:30 to 10:00 is dropped. The reason is that we want to compare intervals with homogeneous horizons.

[6] Examples include coincidences of extreme returns (Bae et al. 2003), extreme value theory (Hartmann et al. 2004), dynamic conditional correlations (Chiang et al. 2007), and copulas (Rodriguez 2007).

[7] Other jump measures include those devised by Jiang and Oomen (2008), Lee and Mykland (2008), Jacod and Todorov (2009), and Caporin et al. (2017).

[8] Our estimation of the BNS measure assumes that volatility is constant within the trading day. Although it is well known that volatility exhibits intraday patterns, this concern is attenuated in our setting because we discard the first and last 15 minutes of the trading session (Andersen and Bollerslev 1997).

[9] To illustrate, we reject the null hypothesis of no 5-minute jumps if the BNS statistic for a particular *day* is below the 0.1% percentile of the standard normal distribution. 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 (i.e., *not* 0.1% of the total number of 5-minute intervals). Put differently, over the entire 1996–2011 sample period, we would expect to see four days per market being classified as days with jumps under the null hypothesis of no jumps. However, the actual numbers of days with detected jumps in prices, *PQSPR*, and *OIB* are much higher.

[10] We note that the sum of the numbers of price jumps in the columns of Panel A of Table 4 sometimes slightly exceeds the total number of price jumps for the respective market reported in Table 2 in case some price jumps are accompanied by more than one jump in *PQSPR* on the same day. The fractions of coinciding jumps reported in this section are corrected for any such double counting.

[11] We are grateful to Michel van der Wel for providing the data on U.S. macro announcements over 2004–2009, as used in Opschoor et al. (2014), and for his advice on data filters. We note that the Econoday database starts in 2001. For some countries, coverage starts even later and some of the other countries in our sample are not covered at all during our sample period. We aggregate multiple macro announcements with the same release time to one event, so the numbers of announcements reported in the text and in Table 4 refer to the number of unique release times.

[12] A one-hour window may seem long for capturing the response of U.S. markets to U.S. macro announcements in recent years. However, for other markets, for the earlier years in our sample, and for news from other countries/regions, it may take more than a few minutes for the news to be fully incorporated into local prices. As a comparison, Lee (2012) uses a 30-minute post-announcement window in her analysis of jumps in market-wide and firm-specific U.S. stock prices around U.S. macro announcements over 1993–2008.

[13] We include only jump events without missing observations in the event window. We also obtain similar graphs at the 15-minute and 1-hour frequencies (see Online Appendix IA.4).

[14] The results in Figure 1 do not imply that all price jumps are permanent. In the Online Appendix, we follow the definition of Brogaard et al. (2018) of shocks that revert by less than one third (more than two thirds) as permanent (transitory). Around 18% of all price jumps are classified as transitory (V-shaped) based on the one-hour window after the jump. Even for these transitory price jumps, the behavior of *PQSPR* also does not accord well with the description of liquidity black holes by Morris and Shin (2004) that "Rather like a tropical storm, they appear to gather more energy as they develop." Furthermore, there are only two transitory negative price jumps that coincide with positive jumps in *PQSPR* (of 186 negative transitory price jumps in total). The Online Appendix also presents graphs of the behavior of prices, *PQSPR*, and *OIB* around (i) price jumps that coincide with *OIB* jumps and (ii) price jumps that are not related to macro announcements. The overall patterns are similar.

[15] Unfortunately, we do not have data on surprises that particular macro announcements entail. Therefore, we cannot directly define negative news and have to rely on this indirect proxy.

[16] Estimating regular logit models as in Bae et al. (2003) is problematic because of separation problems in the estimation that often arise when explaining rare events. If one of the independent variables could almost perfectly explain jumps in prices in market i, then numerically we observe fitted probabilities equal to either 0 or 1, which results in unreliable model estimation. For instance, if negative jumps in prices in market i never coincide during the same 5-minute interval with positive jumps in *PQSPR* from another region, then having an indicator variable for positive jumps in *PQSPR* from another region equal to 1 guarantees no negative jumps in prices in market i during that interval. Heinze and Schemper (2002) recommend using Firth (1993) penalized likelihood estimation to overcome these separation problems. Our daily analyses in Table 6 do not have these separation problems and are thus carried out using regular logit models.

[17] We only use equity mutual funds that at the end of our sample period invest at least 20% in a country under consideration and have data available. We aggregate passive fund flows (in USD) by

region (as many funds have regional rather than country specialization) and divide by the regional market capitalization of the previous year (available from World Bank). Passive fund flows are measured in bps.

[18] We define a cross of the salient price boundary if on a particular day we observe (i) a change in tenth if index price is below 1,000 units of local currency: for example, from 280 to 293 and (ii) a change in hundreds if index price is above 1,000 units in local currency: for example, from 1,280 to 1,301 (in the spirit of Bhattacharya et al. 2012).

[19] We use the "Volume" data item of the Datastream 100% moneyness volatility surface of the respective local index. We use an exponentially weighted moving average which includes contemporaneous volume with a weighting factor 0.5.

[20] The BNS jump statistic is based on the assumption that the variable of interest follows a Brownian motion plus a Poisson jump process. Jump statistics are commonly applied to prices, but we argue that our time-series of bid-ask spreads and trading activity can be modeled in a similar way. If prices follow a continuous process, so do bid-ask spreads because they are based on bid and ask prices. Because prices and trading activity are jointly determined in many theoretical models, it is natural to assume that trading activity follows a continuous process as well. We transform the stock variable *PQSPR* to a flow variable by taking log-changes (in line with Pukthuanthong and Roll 2015, who compute shocks to prices based on the return series).

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