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COVID-19 pandemic and liquidity commonality

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ABSTRACT

This paper shows how the US, UK, Germany and China are financially connected through their stock market liquidity in the COVID-19 pandemic. Using high frequency data on transaction costs, we identify a decrease in stock market liquidity and an increase in liquidity commonality amongst these countries after the World Health Organisation (WHO) declared the global pandemic. Furthermore, there is increased transmission of liquidity shocks from the country with higher COVID new cases and COVID-related death cases, indicating that markets are more connected with increased outbreak severity. Our results suggest that COVID-19 intensifies liquidity risk and worsens the vulnerability of individual stock market’s liquidity to aggregate liquidity shocks in financial markets.

1. Introduction

The downward spiral of market liquidity during a financial crisis is well-documented in the literature. Brunnermeier and Pedersen (2009) explain this occurrence by associating an asset’s market liquidity with the traders’ funding liquidity. As traders’ assets diminish in value, the probability of margin calls increases, forcing traders to sell part of their portfolio and putting further downward pressure on asset prices. This process can explain liquidity commonality across securities and the flight-to-quality. While this phenomenon is commonly observed within a financial market, little is known about how liquidity commonality occurs across bear markets induced by a pandemic. Market stability and risk depend on the co-movement in liquidity of stocks within and across markets; investors are averse to stocks that are illiquid and need to be compensated with a return premium as the market becomes illiquid (Acharya and Pedersen, 2005).\footnote{The seminal work of Amihud and Mendelson (1986), followed by Brennan, Chordia and Subrahmanyam (1998), Jacoby, Fowler, and Gottesman (2000), and Amihud (2002), documented the role of liquidity as a determinant of expected returns. In addition, Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) relate liquidity risk to expected stock returns.}

Furthermore, the level of systemic risk can increase as greater shocks transmission occurs with liquidity co-movement, increasing the cost of capital and impacting the real economy through the level of investment. Thus, it is important to examine how market liquidity and its spillover to other markets unfold in a pandemic.

This paper examines the market liquidity spillover and the spillover responses to severe outbreaks amongst selected countries in the COVID-19 pandemic. Unlike a financial crisis, this global pandemic created significant uncertainty in financial markets through its effects on the economy brought about by the risk of infection and death, the economic turmoil and uncertainty, and the ongoing challenges countries face to contain the spread of the virus. To date, countries have continued to face challenges through government-enforced measures like lockdowns, border closures, and social distancing to prevent ongoing outbreaks. Against this background, we
examine financial connectedness amongst COVID-19 affected countries through market liquidity spillover as the virus ricochets in these countries.

Different from the extensive literature on financial connectedness, which focuses on asset returns and volatility (Diebold and Yilmaz, 2009, 2012, 2014) and low frequency liquidity proxies (Inekwe, 2020), our analysis centers on transaction costs which are regarded as liquidity benchmarks (Marshall et al. 2013, 2018), rather than proxies. Moshirian et al. (2017) adopts high frequency liquidity benchmarks to examine global commonality and considers the benchmark superior to other low-frequency liquidity proxies. As indicated in the market microstructure literature, transaction cost, measured by effective bid-ask spread, comprises the order-processing cost and the adverse selection cost (Glosten and Harris, 1988). The adverse selection cost captures the information asymmetry that traders face in the market. Given the extensive market uncertainty during the pandemic, we focus on the adverse selection cost to investigate liquidity spillover in COVID-19 affected countries. Following the declaration of the COVID-19 pandemic, margin requirements increase sharply in global equity markets. Foley et al. (2021) argues that market makers, who heavily rely on leverage for liquidity provision, are more likely to withdraw from market as margin requirement increases. Thus, we also use effective spread, the profits required by market makers, as a measure of liquidity. Finally, we measure pandemic severity with COVID cases and deaths and examine how the severity affects the liquidity spillover across global financial markets.

Conventional wisdom suggests market liquidity varies with the state of the economy. The spread between liquid and illiquid assets tends to vary over the business cycle. Liquidity crises also coincide with economic downturns. Eisfeldt (2004) develops a model to explain how the productivity of the real sector endogenously determines liquidity. When productivity is high, the relative return on risky investment is high, so investors initiate larger scale risky projects, increasing their incomes’ riskiness. The outcome of risky projects has a larger impact on investors’ income. More claims to high-quality projects are sold to supplement current income for use in consumption and new investment. Consequently, the claims price, and hence market liquidity, increases. In a pandemic, this process is reversed as investors are reluctant to initiate larger scale risky projects, which reduce the riskiness of their incomes. As incomes become less risky, there are fewer claims sales to high-quality projects leading to a fall in liquidity. It is possible in a pandemic that adverse selection causes markets to be illiquid because claims sold are likely to be of low quality.

We select four dominant economies that are substantially affected by the initial pandemic outbreak during the most turbulent days, similar to Kinateder et al. (2021) and study the liquidity spillover in these financial markets. Our results indicate that after a lockdown in Wuhan and other cities in China, the liquidity shocks transmitted from China to other markets appear to increase. The US was a net transmitter of shocks during the first pandemic wave, following the declaration of a global pandemic by the WHO (i.e., March – June 2020). During the second pandemic wave (i.e., July – September 2020), COVID-19 infection numbers in Germany increased to their peak levels in April 2020, making the country a net transmitter of liquidity shocks during this period. The regression results of liquidity spillover and relative COVID-19 severity in paired countries suggest that the outbreak’s severity in one country intensifies the liquidity spillover to another country. This result is consistent with the financial contagion literature in which financial connectedness between countries tends to increase as the financial crisis unfolds in one country. Our study provides new evidence on the financial market linkages other than through returns and volatility spillovers which are commonly examined by the vast literature concerning the stock market effects of the pandemic. Importantly, our results provide an alternative mechanism in explaining why non-economic events like the COVID-19 pandemic is regarded by Iwanicz-Drozdowska et al. (2021) as the most widespread source of contagion.

We make three important contributions to the existing literature on financial connectedness through market liquidity. First, our dynamic connectedness approach identifies both the transmitters and recipients of liquidity shocks across countries and the spillovers between country pairs, with close attention paid to outbreaks when liquidity is needed the most. Second, we are one of the first studies that provide evidence on the relationship between liquidity spillovers and the severity of the pandemic occurring in each country in our sample. We establish the link between liquidity spillovers to the relative severity of the pandemic between countries. Finally, from the COVID-19 and financial market literature, this paper explores an important aspect of the financial market – market liquidity – which has rarely been examined in the voluminous research published on the pandemic.

The rest of the paper is structured as follows. Section 2 presents the literature review and the hypotheses development. Section 3 presents the data and describes the methodology. Section 4 reports the empirical findings and their implications. Robustness test results are also presented in this section. Section 5 concludes.

2. Literature review and hypotheses development

Financial connectedness in market liquidity is synonymous with liquidity commonality within and across markets. The commonality in liquidity within a market refers to how the liquidity of individual securities co-moves with market-wide liquidity (Chordia, et al. 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001). Investors can trade stocks in large quantities in a liquid market and incur low transaction costs (Huberman & Halka, 2001). The possibility that liquidity might disappear from a market and be unavailable when needed is a significant source of risk to an investor. Several studies have investigated the relationship between market

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2 The systematic time-varying component of liquidity is documented in Chordia, Roll, and Subrahmanyam (2001), Huberman and Halka (2001), and Longstaff (2004). Additionally, Pulvino (1998) and Eisfeldt and Rampini (2006) show that real assets are less liquid in recessions.

3 Eisfeldt (2004) refers to “liquidity” as the cost of transferring the value of expected future payoffs from long-term assets into current income. Here, the claims price is increasing in the fraction of high-quality claims traded thus the market is more liquid when there is less adverse selection. The sellers of high-quality assets in Eisfeldt (2004) model are synonymous to the liquidity traders of the microstructure literature. They bear the cost of the asymmetric information and their trades improve liquidity.
liquidity and expected returns and provided evidence that liquidity is priced into financial markets (Acharya & Pedersen, 2005; Lee, 2011). Liquidity risk arising from liquidity commonality is also a priced factor across global stock markets as investors dislike stock markets that become illiquid when the global liquidity dries up, as was most evident during a time of crisis (Rösch and Kaserer, 2014; Moshirian et al., 2017).

Empirical evidence of commonality in illiquidity was first documented in the US market (Chordia et al., 2000) and was later identified in several different international markets with varying market structures (Brockman & Chung, 2002; Fabre & Frino, 2004) and a range of asset classes (Cao & Wei, 2010; Mancini et al., 2013; Frino et al., 2014; Sensoy et al., 2021). As capital markets become increasingly globalised due to low costs of information technology and a tendency towards free trade and deregulation, it is necessary to understand the co-movements of capital and liquidity across countries. Brockman et al. (2009) investigate the extent to which commonality is a global versus local phenomenon and identify the sources of commonality both within and across countries. The determinants of global liquidity commonality have important implications for international asset pricing (Chordia et al., 2000; 2011). Karolyi et al. (2012) analyse a wide range of market-level factors affecting liquidity commonality and categorise them into demand-side and supply-side components. Their study provides a comprehensive view of the inter-market determinants across time and countries. Financial markets have transformed over the last decade due to technology advancements, and co-movements in liquidity have increased following the introduction of high frequency trading (Malceniece et al., 2019) and the consolidation of trading venues (Klein and Song, 2021).

The Global Financial Crisis of 2007–2009 (GFC) suggests that market conditions can be severe, and liquidity can decline or disappear. Moreover, such illiquidity can spread to other markets if the liquidity shocks are systemic. The systematic nature of shocks in illiquidity across markets is due to: a) financial constraints affecting liquidity providers in different securities/markets simultaneously (Comerton-Forde et al., 2010); or b) a decline in the capital available to financial intermediaries active in multiple securities that trigger an increase in risk aversion, impairing the supply of liquidity in these securities/markets (Kyle & Xiong, 2001). Either way, this suggests that a study of liquidity dynamics is essential to policymakers and institutional and retail investors.

A recent study conducted by Batten et al. (2022) indicates that the negative effect of COVID-19 on the financial market is more substantial than in the GFC period. During the recent economic slowdown and the rise in global corporate defaults in 2020, the widespread increase in stock illiquidity is expected to dampen the overall stock market liquidity. Moreover, investors’ massive flight to liquidity could initiate funding illiquidity, leading both trading and funding illiquidity to mutually reinforce and potentially triggering a liquidity spiral (Brunnermeier & Pedersen, 2009). In the same vein, it is critical to understand the response of stock market liquidity during this pandemic for both market practitioners and policymakers to implement appropriate financial interventions.

A small but growing body of literature has explored liquidity spillovers during times of crisis. Rösch & Kaserer (2014) examine the drivers of market liquidity during the GFC period using a unique high-frequency liquidity measure. The study reveals that liquidity commonality increases during market downturns and peaks at significant crisis events. Xu et al. (2018) document increased volatility and illiquidity shocks in eight developed equity markets during the 2008 financial crisis. Illiquidity is a more important channel than volatility in propagating the shocks in equity markets. Both studies suggest that understanding the dynamics of liquidity spillover is vital in crisis scenarios as market liquidity can be a driving force for financial contagion experienced during a market downturn.

Based on the literature that there are liquidity spillovers during a crisis, we conjecture the following hypothesis:

H1: There is an increase in liquidity commonality across stock markets resulting from liquidity spillover from the country that experiences a COVID-19 outbreak to the other countries.

Following the start of the COVID-19 pandemic, there is a growing body of research quantifying the severity of the pandemic crisis and examining the impact of the crisis on economies and financial markets. Zhang et al. (2020) study the general patterns of country-specific and systemic risks in the global financial markets during the COVID-19 pandemic. Their results show that individual stock market reactions to the pandemic are linked to the severity of the outbreak in each country. Baek et al. (2020) construct various COVID-19 proxies to capture the effect of changes in the spread of COVID-19 on the US stock market. They find that changes in volatility are more sensitive to changes in COVID-19 proxies than economic indicators. They also compare the impact of different COVID-19 proxies on stock market volatility and find that COVID deaths are twice as impactful as COVID recoveries. Ding et al. (2021) use data on over 6,000 firms across 56 economies during the first quarter of 2020 and evaluate the connection between corporate characteristics and stock price reactions to COVID-19 cases. Specifically, they adopt the growth rate of weekly COVID cases to measure changes in an economy’s exposure to the COVID-19 pandemic. They find that the pandemic-induced drop in stock prices was milder among firms with (a) stronger pre-2020 finances (more cash, less debt, and larger profits), (b) less exposure to COVID-19 through global supply chains and customer locations, (c) more CSR activities, and (d) less entrenched executives. While this study covers many countries, the short period of the data sample involving non-intraday daily data, may not fully capture each country’s market microstructure liquidity dynamics. More importantly, unlike the focus of this study, they do not examine the extent of liquidity commonality between countries and the link between the severity of the pandemic and liquidity spillover across financial markets.

While we do not provide an exhaustive list of citations of other related works, suffice to say, the scale and depth of this pandemic has a forceful impact on the US stock market and possibly worldwide compared to previous pandemics including the Spanish flu (Baker et al., 2020). Based on the predictions and findings of past studies, we conjecture the following hypothesis:

H2: There is an increase in liquidity spillover from a country with a more severe COVID-19 outbreak proxied by new COVID cases and COVID-related deaths relative to another country.
3. Data and methodology

3.1. Data

This paper uses stock transaction and quotation data for the constituents of four major stock indexes over the sample period from the 2nd of September 2019 to the 30th of September 2020, sourced from Refinitiv Tick History (RTH) database. We focus on this sample period because we are particularly interested in the financial markets’ responses to the initial unfolding of the pandemic. The data obtained from RTH comprise (1) the best bid price prevailing each trade, (2) the best ask price prevailing each trade, (3) trade price, and (4) volume of trade. The end-of-data includes (1) adjusted close price, (2) open price, (3) the highest trade price, and (4) the lowest trade price for each stock on each trading day. The sample data includes the day trading sessions only. Not all index constituents have a night-time trading session. As opening and closing mechanisms differ across exchanges, we identified all opening and closing sessions. We removed the data during these periods to ensure market liquidity is only captured during continuous trading.

The sample includes emerging and developed markets and covers influential markets in three regions defined by MSCI. The four stock indexes are Germany DAX, China SSE180, UK FTSE 100, and US S&P 500. The three MSCI regions are Europe (Developed Markets in Europe), Americas (Developed Markets), and Pacific (Emerging Market).

We compute the effective spread and adverse selection cost for each trade using transaction and quotation data. We then averaged the effective spread and adverse selection cost to form the daily time-series data for each stock. Next, volatility variables are calculated based on the high-low range and realised volatility estimators to control stock trading activity. The high-low measure is the log difference between the highest and the lowest prices for each stock each day (Parkinson, 1980). The realised volatility measure is defined as the squared percentage log-returns based on open to close prices for each stock day (Andersen and Todorov, 2010).

The following outliers are filtered from the sample. We deleted observations associated with zero or negative bid-ask spread or with the spread that is smaller than the local tick size. All liquidity and control variables are winsorised at the 99.9% and 0.01% levels before aggregation to generate market-level measures. Our final sample consists of 214,710 stock-day observations across the four markets (131,500 for the US, 27,500 for the UK, 8,190 for Germany, and 47,520 for China). We then averaged the stock-day observations to construct the daily measures for each market. The spillover analysis is conducted on consolidated daily data over 281 trading days across the four markets.

3.2. Methodology

This section presents the methodology for (1) computing liquidity for each of the four stock markets (China, Germany, the US, and the UK); (2) calculating liquidity spillover across the four markets; (3) evaluating the severity of the pandemic crisis in each of the four countries and the relative severity for each country pair, and investigating the effect of COVID severity on liquidity spillover across the four markets.

3.2.1. Measures of liquidity

Following Chordia et al. (2001), the effective bid-ask spread is adopted as our measure for liquidity. It is defined as the difference between the execution price and the mid-point of the prevailing best bid and ask prices. Thus, it proxies the total price impact as it measures the ability of market participants to trade immediately and the associated market impact or transaction cost. The effective spread is calculated based on the transaction and quotation data. The benefit of using the effective spread as a liquidity measure is that it considers orders that walk down or up the limit order book.

The effective spread of a trade is measured as follows:

\[
\text{EffectiveSpread} = 100^\text{*D}^\text{*}(\text{Price} - \text{MQBefore})/\text{MQBefore}
\]  

Following Eleswarapu, et al. (2004) and Hendershott, et al. (2011), we adopt adverse selection cost as our liquidity measure that reflects information asymmetry:

\[
\text{AdverseSelectionCost} = 100^\text{*D}^\text{*}(\text{MQAfter} - \text{MQBefore})/\text{MQBefore}
\]  

where MQBefore is the prevailing mid-quote at the time of the trade, and MQAfter is the mid-quote price five minutes after the trade is executed. Price is the transaction price. D is a binary variable that equals 1 for buyer-initiated orders and −1 for seller-initiated orders. Consistent with the extant literature, we applied the Lee and Ready’s (1991) method to partition transactions into buyer or seller-initiated trades.

Adverse selection cost quantifies the cost of trading with informed investors, thus reflecting the extent of private information in the market, i.e. the informational component of the effective spread. Rational informed traders utilise their private information to exploit market mispricing and establish a new equilibrium price level. Thus, the private information creates a permanent price impact in the

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4 CSI300 is the major stock index in China and it represents the largest 300 stocks from two major stock exchanges, namely Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). In this paper, we only source data on the largest 180 SSE stocks as SZSE does not provide high frequency trade and quote data to Thomson Reuters.

5 We rescale the high-low measure as (high-low)^2×10000 to make it comparable with the squared return measure.
3.2.2. Measure of liquidity spillover

We estimate liquidity spillover using a multivariate time-series approach introduced by Diebold & Yilmaz (2012). We start with setting up a generalised vector autoregressive (VAR) model as defined by Sims (1980) and then decompose the forecast error variance of the VAR model.

Consider a covariance stationary N-variable VAR (p):

\[ y_t = \sum_{i=1}^{N} \theta_i y_{t-1} + \epsilon_t \]

where \( y_t = (y_{1t}, y_{2t}, \ldots, y_{Nt}) \) and \( \theta_i \) is an N \times N matrix of autoregressive coefficient. \( \epsilon_t \) represents a vector of disturbances and is assumed to be independently and identically distributed with mean 0 and covariance \( \Omega \). As the VAR is covariance stationary, we can derive the moving average (MA) of the VAR process as

\[ y_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i} \]

where \( A_i \) is the covariance matrix of the error term \( \epsilon_t \), and \( \epsilon_t \) is a selection vector with a value of 1 for the \( i \)th element and 0 otherwise. The spillover index comprises an N \times N matrix of \( \hat{\theta}(H) \) where each element \( \hat{\theta}_{ij}(H) \) represents the contribution of variable \( j \) to the forecast error variance of variable \( i \). The variance decomposition separates forecast error variance into own variance shares and cross variance shares where the own variance share is the fraction of H-step ahead error variance in forecasting \( y_i \) due to shocks to \( y_i \) and the cross variance share is the fraction of error variance in forecasting \( y_i \) due to shocks to \( y_j \), for \( j \neq i \).

Under the generalised variance decomposition approach, the own and cross variance shares do not sum to 1. Therefore, we normalise each element of the N \times N matrix \( \hat{\theta}(H) \) by its row sum, as follows:

\[ \bar{\theta}_{ij}(H) = \frac{\hat{\theta}_{ij}(H)}{\sum_{j=1}^{N} \hat{\theta}_{ij}(H)} \]  \hspace{1cm} (5)

so that \( \sum_{j=1}^{N} \bar{\theta}_{ij}(H) = 1 \) and \( \sum_{i=1}^{N} \bar{\theta}_{ij}(H) = N \).

The total spillover (TS) measures the contribution of spillover of shocks across all variables to the total forecast error variance, which is defined as:

\[ TS(H) = \frac{\sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \bar{\theta}_{ij}(H)}{\sum_{i=1}^{N} \bar{\theta}_{ii}(H)} \times 100 \]  \hspace{1cm} (6)

The directional spillover (DS) received by variable \( i \) FROM all other variables \( j \) is defined as:

\[ DS_{ij}(H) = \frac{\sum_{j=1, j \neq i}^{N} \bar{\theta}_{ij}(H)}{\sum_{j=1}^{N} \bar{\theta}_{ij}(H)} \times 100 \]  \hspace{1cm} (7)

The directional spillover (DS) transmitted from variable \( i \) TO all other variables \( j \) is defined as:

\[ DS_{ij}(H) = \frac{\sum_{i=1}^{N} \bar{\theta}_{ij}(H)}{\sum_{j=1}^{N} \bar{\theta}_{ij}(H)} \times 100 \]  \hspace{1cm} (8)

The net spillover (NS) measures the difference between the gross shocks of market \( i \) transmitted to others (“from \( i \) TO others”) and those received from others (“FROM others to \( i \”). It is defined as:

\[ NS_i(H) = DS_{ij}(H) - DS_{ij}(H). \]  \hspace{1cm} (9)

The net pairwise spillover (NPS) between variable \( i \) and \( j \) measures the difference between the gross shocks transmitted from variable \( i \) to variable \( j \) and those transmitted from \( j \) to \( i \). It is defined as:

\[ NPS_{ij}(H) = \left( \frac{\bar{\theta}_{ij}(H) - \bar{\theta}_{ji}(H)}{N} \right) \times 100 \]  \hspace{1cm} (10)

3.2.3. The effects of COVID-19 severity on liquidity spillover

To examine whether the liquidity spillover from one country to another is affected by the relative COVID-19 severity between these countries, we calculate the cross variance shares of the forecast error variance as given below. The generalised variance decomposition approach removes any dependence of results on the ordering of variables.

\[ \bar{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \]

where \( \sigma_j \) is the standard deviation of the error term of the \( j \)th equation, \( \Omega \) is the covariance matrix of the error term \( \epsilon_t \), and \( \epsilon_t \) is a selection vector with a value of 1 for the \( i \)th element and 0 otherwise. The spillover index comprises an N \times N matrix of \( \hat{\theta}(H) \) where each element \( \hat{\theta}_{ij}(H) \) represents the contribution of variable \( j \) to the forecast error variance of variable \( i \). The variance decomposition separates forecast error variance into own variance shares and cross variance shares where the own variance share is the fraction of H-step ahead error variance in forecasting \( y_i \) due to shocks to \( y_i \) and the cross variance share is the fraction of error variance in forecasting \( y_i \) due to shocks to \( y_j \), for \( j \neq i \).

Under the generalised variance decomposition approach, the own and cross variance shares do not sum to 1. Therefore, we normalise each element of the N \times N matrix \( \hat{\theta}(H) \) by its row sum, as follows:

\[ \bar{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \]

so that \( \sum_{j=1}^{N} \bar{\theta}_{ij}(H) = 1 \) and \( \sum_{i=1}^{N} \bar{\theta}_{ij}(H) = N \).

The total spillover (TS) measures the contribution of spillover of shocks across all variables to the total forecast error variance, which is defined as:

\[ TS(H) = \frac{\sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \bar{\theta}_{ij}(H)}{\sum_{i=1}^{N} \bar{\theta}_{ii}(H)} \times 100 \]

The directional spillover (DS) received by variable \( i \) FROM all other variables \( j \) is defined as:

\[ DS_{ij}(H) = \frac{\sum_{j=1, j \neq i}^{N} \bar{\theta}_{ij}(H)}{\sum_{j=1}^{N} \bar{\theta}_{ij}(H)} \times 100 \]

The directional spillover (DS) transmitted from variable \( i \) TO all other variables \( j \) is defined as:

\[ DS_{ij}(H) = \frac{\sum_{i=1}^{N} \bar{\theta}_{ij}(H)}{\sum_{j=1}^{N} \bar{\theta}_{ij}(H)} \times 100 \]

The net spillover (NS) measures the difference between the gross shocks of market \( i \) transmitted to others (“from \( i \) TO others”) and those received from others (“FROM others to \( i \”). It is defined as:

\[ NS_i(H) = DS_{ij}(H) - DS_{ij}(H). \]

The net pairwise spillover (NPS) between variable \( i \) and \( j \) measures the difference between the gross shocks transmitted from variable \( i \) to variable \( j \) and those transmitted from \( j \) to \( i \). It is defined as:

\[ NPS_{ij}(H) = \left( \frac{\bar{\theta}_{ij}(H) - \bar{\theta}_{ji}(H)}{N} \right) \times 100 \]
paired countries, we employ the following panel regression model:

\[ \Delta \text{NPS}_{ij,t} = \alpha + \beta COVID\text{SeverityRatio}_{ij,t} + \gamma Controls_{ij,t} + \mu_{ij,t} + \varepsilon_{ij,t} \]  

(11)

where \( \Delta \text{NPS}_{ij,t} \) is the change in the 75-day moving average net spillover of adverse selection cost from country \( i \) to country \( j \) on day \( t \) relative to day \( t-1 \). COVIDSeverityRatio\(_{ij,t}\) are variables measuring the COVID severity in country \( i \) relative to country \( j \) based on cases and deaths reports on day \( t \). Controls\(_{ij,t}\) are volatility ratio and turnover ratio of country \( i \) relative to country \( j \) on day \( t \). \( \mu_{ij,t} \) is the country-pair fixed effect.

Here, we construct several relative COVID severity measures based on Baek et al. (2020) and Ding et al. (2021), defined as follows:

\[ \text{Covidnewcaseratio}_{ij,t} = \frac{\text{Newcases}_{ij,t} + 1}{\text{Newcases}_{ij,t} + 1} \]  

(12)

\[ \text{Covid7dayMAnewcaseratio}_{ij,t} = \frac{7\text{dayMAnewcases}_{ij,t} + 1}{7\text{dayMAnewcases}_{ij,t} + 1} \]  

(13)

\[ \text{Coviddeathto7dayMAnewcaseratio}_{ij,t} = \frac{(\text{Deaths}_{ij,t} + 1)/(7\text{dayMAscases}_{ij,t} + 1)}{(\text{Deaths}_{ij,t} + 1)/(7\text{dayMAscases}_{ij,t} + 1)} \]  

(14)

The control variable, turnover ratio, is the ratio of turnover in country \( i \) over country \( j \) in logarithms. The volatility ratio is the ratio of the range-based volatility of country \( i \) over country \( j \). The range-based volatility is measured as follows according to Parkinson (1980):

\[ \text{High-Low Vol}_{ij,t} = \sqrt{\frac{(\ln(\text{high}_{ij,t}) - \ln(\text{low}_{ij,t}))^2}{4\ln(2)}} \]  

(15)

where \( \text{high}_{ij,t} \) and \( \text{low}_{ij,t} \) are the highest and lowest observed stock transaction prices for index stock \( i \) on day \( t \). According to Alizadeh et al. (2002), a range-based estimator of volatility is not only a highly efficient volatility estimator but also robust to microstructure noise, as, for example, bid–ask price bounces.

We perform Levin-Lin-Chu unit-root test for our panel data, and the results are presented in Appendix A. The results show that we cannot reject a unit root for NPS\(_{ij,t}\). Thus, we take the first difference in NPS\(_{ij,t}\) and \( \Delta \text{NPS}_{ij,t} \) is stationary. We also check the stationarity of our COVID severity variables, and the results show that Covidnewcaseratio\(_{ij,t}\) and Covid7dayMAnewcaseratio\(_{ij,t}\) are not stationary. We take the first difference of these two measures to circumvent the non-stationarity property of the series. In addition, all liquidity spillover, COVID severity variables and control variables are winsorised at the 99.9% and 0.01% levels to address extreme outlier problems.

4. Results

In this section, we present our empirical results. We first report descriptive statistics on liquidity measures of the four stock markets. Then, we present results on static liquidity spillover, followed by results on time-varying liquidity spillover. Last, we document the effect of relative COVID severity on the pairwise liquidity spillover.
4.1. Descriptive statistics

The descriptive statistics are presented based on data from the 2nd of September 2019 to the 30th of September 2020. Our primary motivation is to examine the dynamic connectedness across global markets during the recent pandemic. Thus we include dominant developed and emerging markets in the global economy that have been heavily affected by the crisis.

Table 1 reports information on the four stock markets, including benchmark stock indexes, number of constituent stocks, liquidity and volatility measures. Our sample markets include the US, the U.K., Germany and China, and the corresponding stock indexes are S&P 500, FTSE 100, DAX and SSE 180. To compare market variables between the period before and during the pandemic, we divide our sample period into two sub-periods: the pre-pandemic period (the 2nd of September 2019 to the 10th of March) and the pandemic (the 11th of March 2020 to the 30th of September 2020), using the official date that WHO declares COVID-19 as a global pandemic.

Panel A reports summary statistics computed over the pre-pandemic period, while Panel B reports statistics computed over the pandemic period. Effective spread (ES) measures the total transaction costs incurred by market participants. During the pre-pandemic period, the average cost of trading ranges from 1.338 bps for US stocks to 6.955 bps for Chinese stocks. The average cost of trading across all markets is 3.095 bps, indicating that the US is the most liquid while China is the least liquid stock market. Adverse selection cost is our primary liquidity measure as it extracts informational component from total transaction costs, filtering the effects from real friction costs. The average adverse selection cost ranges from 1.230 bps for US stocks to 4.127 bps for Chinese stocks during the pre-pandemic period. The average adverse selection cost across all markets is 2.438 bps. We find that Germany is the least volatile market for both volatility measures while China is the most volatile market during the pre-pandemic period.

Comparing Panel B with Panel A, we find that liquidity and volatility measures increase dramatically in the crisis period, indicating that liquidity worsens, transaction cost rises, and volatility heightens during the pandemic. During this period, as reported in Panel B,
Fig. 1. Total liquidity spillovers. This figure plots the variations in total liquidity spillovers across the four stock markets over time. Each spillover statistic is estimated using a 75-day rolling window over the sample period from the 2nd of September 2019 to the 30th of September 2020, with the first rolling window ends on the 17th of December 2019. The dotted line represents spillover of effective spread, which measures total transaction cost faced by investors. The solid line represents spillover of adverse selection cost, which measures the information component of total transaction cost. On the 20th of March 2020, WHO declared the coronavirus (COVID-19) outbreak as a pandemic, which marks the official start of the pandemic.

Fig. 2. Directional liquidity spillovers TO all other markets. This figure plots the variation in directional liquidity spillovers to all other stock markets over time. The spillover statistic measures the power of market i in influencing all other three markets, and it is estimated using a 75-day rolling window over the sample period from the 2nd of September 2019 to the 30th of September 2020.
we find that the US is the most liquid market while China is the least liquid market, consistent with findings from the pre-pandemic period. Turning to volatility measures, it is worth noting that China is the least volatile market. At the same time, the UK is the most volatile market, possibly because the COVID-19 outbreak started at a much earlier date in China than the official pandemic date announced by the WHO. Thus, the Chinese financial market response to COVID-19 is not reflected in our defined pandemic period.

Table 2 Panel A reports the mean, median (the 50th percentile), maximum (the 99.9th percentile), minimum (the 0.01th percentile), standard deviation (Std), skewness, and kurtosis values of our adverse selection cost measure, which is the primary liquidity proxy for the spillover analysis. We find that the UK exhibits the highest adverse selection cost of trading with informed traders for the entire sample period while the US exhibits the lowest. The skewness and kurtosis values indicate that adverse selection cost is highly positively skewed and leptokurtic in the US, the UK and Germany, indicating extreme events occurred during the sample period. UK stocks experience the highest skewness and kurtosis among the four markets, while Chinese stocks experience the lowest skewness and kurtosis during the full sample period.

The correlation coefficients across the four markets are reported in Table 2 Panel B. The US and the UK exhibit the highest correlation (0.886), and the UK and China present the lowest correlation (0.253) across all country pairs. By and large, the US market is more correlated with the other markets, while the Chinese market is less correlated with the other markets.

4.2. Static liquidity spillover

This section assesses the static liquidity spillover across the US, U.K., Germany and China by decomposing the 10-step ahead forecasting error variance of a four-variable second-order VAR model. Table 3 reports pairwise, directional, and net directional spillovers of adverse selection cost across the four markets for the sample period from the 2nd of September 2019 to the 30th of September 2020.

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The choice of predictive horizon is consistent with Diebold and Yilmaz (2012). Akaike information criterion (AIC) is used in this paper to determine the most optimal lag length and the order of the VAR model.
September 2020\textsuperscript{7}. As shown in Table 3, the total connectedness of the four markets is 28.928%, indicating that 28.928% of total forecast error variance can be explained by spillovers of liquidity shocks across the four markets. TO measures the directional liquidity spillovers transmitted by market $i$ to the other three markets. We find that the US is the most influential market, contributing to 82.758% of total forecast error variations in the system. On the other hand, China is the least influential market, contributing to 3.81% of total variations in the system. FROM measures the directional liquidity spillovers received by market $i$ from the other three markets. Our results show that the UK is highly influenced by liquidity shocks within the system of countries based on our sample. About 61.734% of liquidity variations in the UK are attributed to shocks from other markets. This is followed by 39.917% for Germany, 9.538% for the US and 4.524% for China, making China the most exogenous market in the system. Net spillover of market $i$ is the difference between the gross liquidity shocks of market $i$ transmitted to others ("from $i$ to others") and those received from others ("from other to $i$"). The results further demonstrate that the US is a net transmitter of liquidity shocks while the U.K., Germany and China are the net recipients of liquidity shocks.

4.3. Dynamic liquidity spillover

Global stock markets have experienced tremendous turbulence since the start of the COVID-19 pandemic. It is widely recognised that the connectivity between financial markets typically increases and peaks during significant crisis events such as the global financial crisis (Rösch & Kaserer, 2014, Xu et al., 2018). This section examines how global liquidity spillovers vary over time in the pandemic. By constructing dynamic spillover indexes over 75-day rolling windows, we can assess the evolution of financial connectedness between markets.

Fig. 1 presents total liquidity spillovers using effective spread (dotted line) and adverse selection cost (solid line) measures and

\textsuperscript{7} As our primary interest is to explore the informational component of liquidity cost and how information co-moves across markets during a unique sample period, we report all spillover statistics using adverse selection cost measure. We also test liquidity spillover with the effective spread measure and find quantitatively similar results, see robustness checks.
Fig. 5. Net pairwise liquidity spillovers. This figure plots the variations in net pairwise liquidity spillovers between each of the two markets over time. The net pairwise spillover \((i-j)\) measures the directional spillover of adverse selection cost from market \(i\) to market \(j\). The statistic is estimated using a 75-day rolling window over the sample period from the 2nd of September 2019 to the 30th of September 2020. The statistic is positive when market \(i\) is a net transmitter of liquidity shocks to market \(j\). It is negative when market \(i\) is a net recipient of liquidity shocks from market \(j\).

Table 4
The effects of relative COVID-19 severity on net pairwise liquidity spillover.

This table reports the panel regression results in equation (11) using adverse selection cost:

\[
\Delta NPS_{i,j,t} = \alpha + \beta \cdot \text{COVIDSeverityRatio}_{i,j,t} + \gamma \cdot \text{Controls}_{i,j,t} + \mu_{i,j} + \epsilon_{i,j,t}
\]

The dependent variable, \(\Delta NPS_{i,j,t}\), is the change in the 75-day moving average net spillover of adverse selection cost from country \(i\) to country \(j\) on day \(t\) relative to day \(t-1\). \(\text{COVIDSeverityRatio}_{i,j,t}\) are variables measuring the COVID severity in country \(i\) relative to country \(j\) based on cases and deaths reports on day \(t\). \(\text{Controls}_{i,j,t}\) are volatility ratio and turnover ratio of country \(i\) relative to country \(j\) on day \(t\). \(\mu_{i,j}\) is the country-pair fixed effect. The standard errors, reported in parentheses, are clustered at the country pair level. Statistical significance at the 1%, 5% and 10% levels are indicated by ***, ** and *, respectively.

| Variable                        | \(\Delta NPS\) | \(\Delta NPS\) | \(\Delta NPS\) |
|--------------------------------|----------------|----------------|----------------|
| **Diff COVID new cases ratio** | 0.006***       | (0.002)        |                |
| **Diff COVID 7 day MA new cases ratio** | 0.102***       | (0.033)        |                |
| **COVID death to 7 day MA new cases ratio** | 0.266**        | (0.122)        |                |
| Control variables              |                |                |                |
| Volatility ratio               | 0.020          | 0.020          | 0.022*         |
| (0.013)                        | (0.013)        | (0.014)        |                |
| Trading volume ratio           | -0.338         | -0.327         | -0.368         |
| (0.892)                        | (0.893)        | (0.902)        |                |
| Country pair FE                | Yes            | Yes            | Yes            |
| N                              | 1230           | 1230           | 1230           |
reveals dramatic patterns surrounding the pandemic outbreak. On the 11th of March 2020, the WHO characterised the coronavirus (COVID-19) as a pandemic, marking the official start of a global pandemic. As shown in Fig. 1, the total spillovers of adverse selection costs rose sharply from 26% to 43% following the WHO announcement. The spillovers of effective spread also rose dramatically from 20% to 50%, but the increase came two weeks earlier.

Furthermore, while the total spillovers of adverse selection cost spiked in the rolling window starting on the 11th of March 2020 and ending on the 23rd of June 2020, it adjusted downwards rapidly on subsequent windows before returning to the pre-pandemic level in the window ending on the 1st of July 2020. The total spillovers of effective spread reveal similar patterns and return to the pre-pandemic level on the 1st of July 2020. Results in Fig. 1 provide support for H1.

Fig. 2 depicts directional spillovers of adverse selection cost from market i TO all other markets. It outlines the power of market i in influencing others. Comparing directional spillovers across markets, we find that the US liquidity shocks contribute most to the overall system shocks and are the major transmitter of liquidity shocks to other markets. This result is consistent with findings from the static spillover. Furthermore, the US market liquidity spillover dominates the other markets spillover during the pandemic. We also identify an increase in directional spillover for China in February 2020. On the 23rd of January 2020, the Chinese government announced a lockdown in Wuhan and other cities in Hubei province to contain the spread of COVID-19. Following this lockdown, the transmission of liquidity shock from China to the different markets appears to increase. This finding suggests that the COVID-19 outbreak in China could have influenced other global markets via the transmission of liquidity shocks.

Fig. 3 illustrates directional spillovers of adverse selection cost FROM all other markets to market i. It represents the degree of market i being affected by liquidity shocks coming from other markets. Comparing directional spillovers across markets, we discover that the UK market is the primary recipient of liquidity shocks from other markets, followed by Germany. Both markets experienced the highest level of liquidity shocks from the other markets during the pandemic.

Fig. 4 illustrates the net spillovers of adverse selection costs for the four markets. It sets out the difference between “transmitted from i to others” and “received from others to i” (i.e., TO-FROM). Comparing the net liquidity spillovers across markets, the US was a net transmitter of shocks during the first wave of the pandemic, which is the 3-month following the declaration of a global pandemic by the WHO (i.e., March – June 2020). The U.K. and Germany were net recipients of liquidity shocks during the pandemic as they were heavily affected by the US market. During July – September 2020, COVID-19 infection numbers in Germany had returned to the peak levels in April 2020, marking a second pandemic wave. Germany became a net transmitter of shocks during this period, much like China was a net transmitter of shocks during the Wuhan lockdown (February 2020). China was a net recipient of shocks in June 2020 during the second wave of the COVID-19 outbreak in Europe.

Fig. 5 shows net pairwise spillovers of adverse selection cost for each market pair. The net pairwise spillover (i-j) measures liquidity shocks transmitted from market i to market j. The statistic measure is positive when market i is a net transmitter of liquidity shocks to market j and becomes negative when market i is a net recipient of liquidity shocks from market j. Comparing net pairwise spillovers across country pairs, we observe that liquidity shocks spilled over from the US to the UK and from the US to Germany during the global outbreak of the pandemic (March – June 2020). During the Wuhan lockdown (i.e., February 2020) period, liquidity shocks in China spilled over to the US, UK and Germany. During the second wave of the pandemic in Europe (i.e., July – September 2020), liquidity shocks in Germany spilled over to China, while liquidity shocks in the UK spilled over to the US.

4.4. Liquidity spillover and COVID-19 severity

We estimate the panel regression outlined in equation (11) using fixed effects model with Least Square Dummy Variable (LSDV) method to investigate the impact of relative COVID severity of paired countries on the net pairwise liquidity spillover between the paired countries. Three measures, defined in equations (12), (13) and (14), are employed to quantify the relative COVID severity in each country pair. The standard errors are clustered at the country pair level, following the procedure of Petersen (2009); thus, our finding is not affected by country-specific characteristics.

As presented in Table 4, the relative COVID severity has a positive impact on the net pairwise spillovers of adverse selection cost from country i to country j at the 1% or 5% significant level for all three severity measures, indicating that liquidity spillover increases in the country with more severe COVID situation relative to the paired country. Turning to the control variables, we find weak evidence that liquidity spillover increases in the country with higher volatility relative to the paired country. Table 4 presents results that support H2. One policy implication of our findings is that governments in COVID-stricken countries should undertake measures to prevent further escalation in the severity of the COVID cases and deaths to ameliorate the effect of liquidity flights to other countries.

Although the government stringency index can determine its association with liquidity spillover, we have not proceeded with this analysis for several reasons. Appendix 2 provides a plot of two measures for the severity of COVID outbreak in our sample countries, which are proxied by the 7-day moving average of confirmed COVID cases and the government stringency index. There are concerns with using the government stringency index over new COVID cases and COVID-related deaths to proxy relative COVID severity. While the stringency index tracks closely with the cumulative COVID cases, in the U.S., when cumulative cases have yet to increase.

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8. See news announcement at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen.
9. See news announcement at: https://www.xinhuanet.com/english/2020-01/23/c_138729430.htm.
10. See news article at: https://www.dw.com/en/coronavirus-germany-measures-angela-merkel/a-54680167.
11. This is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest). The data are available from https://ourworldindata.org/hashtag/covid-stringency-index.
dramatically, we observe that the stringency index has kicked in very early at the onset of the spread. The index does not appropriately capture the state of the COVID severity because of its pre-emptive nature. The stringency index is calculated using strict preventive measures to curb the COVID spread, and hence they kick in very early at the onset of the outbreak. The stringency index is also a deterrent measure to prevent future outbreaks. Accordingly, the stringency index remains high in countries even after the cumulative cases have fallen. While the stringency index may suggest that these preventive measures are put in place, the reality is that people are not following these measures hence using these measures may not truly reflect the severity of the COVID cases occurring in the country. As a result, the new COVID cases and death numbers are more accurate measures of COVID severity. Finally, by and large, the stringency index displays lesser variability than the COVID cases, which can pose concerns for estimation precision.

5. Conclusion

This study examines dynamic liquidity spillover across globally dominant stock markets during the recent COVID-19 pandemic. Using transaction and quotation data for stock index constitutes listed in the US, the U.K., Germany and China during the period from the 2nd of September 2019 to the 30th of September 2020, we find that liquidity spillover increased significantly in March 2020 following the declaration of a global pandemic by WHO. During the period of Wuhan lockdown (February 2020), China was a net transmitter of liquidity shocks to the US, UK and Germany. During the first pandemic wave (March – June 2020), the US market was a net transmitter of liquidity shocks; shocks spilled over from the US to the UK and Germany. During the second pandemic wave in Europe (July – September 2020), Germany and UK contributed significantly to liquidity variations in the system. Specifically, liquidity shocks in Germany spilled over to China, and liquidity shocks in the UK spilled over to the US.

We find that liquidity spillover increases from the country with more acute COVID situation, suggesting that markets become more connected for countries with increased COVID severity locally. Our result is consistent with the increased financial connectedness view showcased by greater volatility and returns spillover in a financial crisis. As liquidity spillover is regarded as a source of systematic risk, our finding has practical implications for pricing global market liquidity risk, particularly amongst developed economies. Moreover, since liquidity spillover rises with the severity of COVID stricken countries, the systemic stability of these dominant markets can be at risk. Hence, measures to curb the deterioration of COVID in many countries could alleviate the destabilising effect of the pandemic on financial markets stability. Findings from this research will provide a framework for stock exchanges and policymakers to understand linkages between pandemic severity and financial market spillover and develop effective procedures to monitor liquidity shocks in other markets during a pandemic.

CRediT authorship contribution statement

**Sandy Suardi:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Caihong Xu:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – review & editing. **Zeyang Ivy Zhou:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A1. Robustness tests

Our results have shown that the US market is the only net transmitter of liquidity shocks, and UK is the largest net recipient of liquidity shocks in the system during the COVID period. We have also demonstrated that spillovers increase from the country with a relatively more severe COVID situation. In this section, we undertake spillovers analysis with effective spread measures to assess previous results’ robustness.
Table A1 reports static spillovers of effective spread, and the results show that the total connectedness of the four markets is 33.478%, which is much larger than spillovers of adverse selection cost (28.928%). Net spillovers measure the net directional liquidity spillovers transmitted by market $i$ to the other three markets. Our results show that the US is a net transmitter of liquidity shocks while the U.K., Germany and China are the net recipients of liquidity shocks, with the UK being the largest one among the three. In general, the finding is consistent with the spillovers of adverse selection cost; however, the leading role of the US is much weaker with the effective spread measure, evidenced by the smaller net spillovers for the US in Table A1.

Table A1
Static spillover of effective spread.

| i       | US  | UK   | Germany | China | Directional FROM Others |
|---------|-----|------|---------|-------|-------------------------|
| US      | 65.216 | 21.257 | 10.152  | 3.375  | 34.784 |
| UK      | 37.009 | 47.465 | 13.238  | 2.288  | 52.535 |
| Germany | 15.454 | 12.359 | 66.463  | 5.724  | 33.537 |
| China   | 4.272  | 5.395  | 3.390   | 86.943 | 13.057 |
| Directional TO Others | 56.735 | 39.011 | 26.780  | 11.387 | Total Spillover |
| NET Spillovers (TO-FROM) | 21.952 | -13.524 | -6.757  | -1.670  | 33.478% |

Fig. A1 shows net pairwise spillovers of effective spread for each market pair. The measure is positive when market $i$ is a net transmitter of liquidity shocks to market $j$ and negative when market $i$ is a net recipient of liquidity shocks from market $j$. comparing net pairwise spillovers between effective spread and adverse selection cost measures, we observe similar, but weaker variations in the pairwise spillovers of effective spread, indicating that trading friction cost from different market microstructures might reduce the connectedness between country pairs. During the second wave of the pandemic in Europe (i.e., July – September 2020), liquidity shocks in the UK no longer spilled over to the US with the effective spread measure, possibly due to the more minor effects of the second COVID outbreak.

Fig. A1. Net pairwise spillover of effective spread.
Table A2 reports the relative COVID severity of paired countries on the net pairwise liquidity spillover between the paired countries using effective spread measures. The results reveal similar evidence of COVID severity effects on the spillovers of effective spread. All three severity measures are positive, consistent with the adverse selection cost measure, two out of three measures are significant at 1% level.

Table A2
The effects of relative COVID-19 severity on net pairwise liquidity spillover.

This table reports the panel regression results in equation (11) using effective spread liquidity measure:

\[
\Delta NPS_{i,j,t} = \alpha + \beta \times \text{COVIDSeverityRatio}_{i,j,t} + \gamma \times \text{Controls}_{i,j,t} + \mu_{i,j} + \epsilon_{i,j,t}.
\]

The dependent variable, \(\Delta NPS_{i,j,t}\), is the change in the 75-day moving average net spillover of effective spread from country \(i\) to country \(j\) on day \(t\) relative to day \(t-1\). COVIDSeverityRatio\(_{i,j,t}\) are variables measuring the COVID severity in country \(i\) relative to country \(j\) based on cases and deaths reports on day \(t\). Controls\(_{i,j,t}\) are volatility ratio and turnover ratio of country \(i\) relative to country \(j\) on day \(t\). \(\mu_{i,j}\) is the country-pair fixed effect. The standard errors, reported in parentheses, are clustered at the country pair level. Statistical significance at the 1%, 5% and 10% levels are indicated by ***, ** and *, respectively.

| Variables                        | \(\Delta NPS\) | \(\Delta NPS\) | \(\Delta NPS\) |
|----------------------------------|----------------|----------------|----------------|
| Diff_COVID new cases ratio       | 0.011***       | 0.011***       | 0.011***       |
| 0.002                            | (0.002)        | (0.002)        | (0.002)        |
| COVID 7_day MA new cases ratio   | 1.812***       | 1.812***       | 1.812***       |
| (0.095)                          | (0.095)        | (0.095)        | (0.095)        |
| COVID death to 7_day MA new cases ratio | 0.266         | 0.266          | 0.266          |
|                                   | (0.425)        | (0.425)        | (0.425)        |
| Control variables                |                |                |                |
| Volatility ratio                 | 0.095***       | 0.096***       | 0.097***       |
| (0.025)                          | (0.025)        | (0.025)        | (0.025)        |
| Trading volume ratio             | -3.196**       | -3.307**       | -3.217**       |
| (1.119)                          | (1.185)        | (1.105)        | (1.105)        |
| Country pair FE                  | Yes            | Yes            | Yes            |
| N                                | 1230           | 1230           | 1230           |

A2. Unit root tests

See Table A3

Table A3
Levin-Lin-Chu unit-root test for Table 4 & Table A2.

| Variables                                 | Average ADF lag length (AIC) | Adjusted t | P-value |
|-------------------------------------------|------------------------------|------------|---------|
| Net Pairwise Spillover (Adverse Selection Cost) | 3                            | -0.074     | 0.471   |
| Net Pairwise Spillover (Effective Spread)  | 4                            | -0.579     | 0.281   |
| COVID new case_ratio                      | 7                            | 0.899      | 0.816   |
| COVID 7 day MA new case ratio             | 7                            | -1.359     | 0.087   |
| COVID death to 7 day MA new case ratio    | 3                            | -2.014     | 0.022   |

A3. Government stringency index

Panel A, B, C, D of Fig. A2 compare COVID cases and stringency index in the US, UK, Germany and China, respectively, from the beginning of 2020 to the 30th of September 2020. The dotted line represents the 7-day moving average of confirmed cases in each country, while the solid line represents the government stringency index in each country.
Fig. A2. Comparison of COVID-19 cases and the government stringency index.
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