Journal of Financial Economics 145 (2022) 217–238

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Ripples into waves: Trade networks, economic activity, and asset prices ☆

Jeffery (Jinfan) Chang[a], Huancheng Du[b,*], Dong Lou[c], Christopher Polk[c]

[a] School of Management and Economics, Chinese University of Hong Kong, Shenzhen, China
[b] School of Finance, Central University of Finance and Economics, Beijing, China
[c] Department of Finance, London School of Economics, UK and CEPR, United Kingdom

ARTICLE INFO

Article history:
Received 25 March 2021
Revised 25 May 2021
Accepted 10 June 2021
Available online 15 August 2021

JEL classification:
G12
G15
F40

Keywords:
Sovereign CDS
Return predictability
Trade networks
Limited attention
Information aggregation

ABSTRACT

We exploit information in sovereign CDS spreads and the international trade network to provide causal evidence of the propagation of global economic shocks. We show that trade links are an important source of shock transmission using the natural experiments of the Japanese tsunami and the COVID-19 lockdown in China. We then confirm more general and gradual information flows along the trade network by showing extensive country-level credit/equity cross-sectional return predictability. News about country fundamentals flows primarily from importers to exporters, depends on both direct and indirect links in the trade network, and is magnified by the exporting country's financial vulnerability.

1. Introduction

A growing number of studies examine the way shocks to individual sectors (Acemoglu et al., 2012) and/or firms (Gabaix, 2011) transmit and consequently aggregate through the corresponding economic network. A key take-away from these studies is that the nature and structure of the network are of great importance. In stark contrast to Lucas (1977), where microeconomic shocks wash out and have negligible effects on aggregate outcomes, the interconnectedness of sectors and firms provides a network-based view of what drives aggregate fluctuations. However, the way in which shocks propagate across countries remains an important research question in an increasingly interconnected world.

We exploit the international trade network to reveal novel facts about the propagation of country-level shocks across the global macro-economy. In other words, our

☆ We thank John Campbell, Vasco Carvalho, Randy Cohen, ML Cooper, Wenxin Du, Andrea Frazzini, Julian di Giovanni, Christian Julliard, Kalina Manova, Stuart McDonald, Veronica Rappoport, Robert Ready, Iván Rodríguez, Alireza Tahbaz-Salehi, Tuomo Vuolteenaho, as well as seminar participants at Aalto University, Arrowstreet Capital, Barclays Capital, Chinese University of Hong Kong (Shenzhen), HEC Paris, London Business School, London School of Economics, New York Federal Reserve, Renmin University, Tsinghua University, UBS, University of British Columbia, University of Geneva, the 2018 Brazilian Finance Association Annual Meeting, the 2018 Finance UC Conference, the 2018 FIRS Conference, and the 2019 American Finance Association Annual Meeting for helpful comments. Jeffery (Jinfan) Chang, a.k.a. Jinfan Zhang, appreciates help from friends and colleagues at the International Monetary Fund (IMF) and acknowledges financial support from the National Natural Science Foundation of China (under Project Number 71,733,004). Lou and Polk are grateful for funding from the Paul Woolley Center at the LSE. All remaining errors are our own. An earlier draft of this paper was circulated under the title "Trade Networks and Asset Prices: Evidence from the SCDS Market."

* Corresponding author.
E-mail addresses: zhangjinfan@cuhk.edu.cn (J. Chang), huancheng.du@gmail.com (H. Du), d.lou@lse.ac.uk (D. Lou), c.polk@lse.ac.uk (C. Polk).

https://doi.org/10.1016/j.jfineco.2021.08.005
0304-405X/

work adds to the growing number of studies that try to differentiate between the transmission of idiosyncratic shocks and the common exposures to global shocks.[1] More specifically, our analysis provides a new perspective on the importance of trade links by exploiting information contained in the sovereign credit default swap (SCDS) contracts on foreign-currency-denominated debt of over 90 developed and developing countries. We argue and show that these relatively liquid assets, compared to sovereign bond markets, provide a useful barometer of a country's well-being.[2] This close link to country fundamentals contrasts with equity markets where only a small proportion of volatility comes from cash-flow news (Shiller, 1981).[3]

We first provide evidence of causal links by studying two natural experiments: the exogenous local shocks of the Japanese tsunami and the COVID-19-driven Wuhan lockdown. On March 11, 2011, a 9.1-magnitude earthquake took place 231 miles northeast of Tokyo. This earthquake was the largest earthquake on record ever to hit Japan and generated a tsunami with waves over 30 feet high, which damaged several nuclear reactors in the area. Conservative estimates indicate nearly 20,000 deaths, 2500 missing persons, and damage from the earthquake/tsunami/radioactivity of over \$300 billion. On January 23, 2020, China imposed a strict lockdown in Wuhan and other cities in the Hubei province in an effort to quarantine the outbreak of COVID-19. At the time of the Wuhan lockdown, there were very few diagnosed COVID-19 cases outside of China. Both the Japanese tsunami and the lockdown in China are events that are initially entirely local/idiosyncratic in nature. We exploit this fact to identify the way country-level shocks propagate.

In particular, we study the weeks and days surrounding these two local events, linking SCDS returns to export-based measures of country exposures. We first note that the SCDS spread of both countries increased significantly on the event day, with Japan's spread increasing from 75 to 125 bps and China's spread increasing from 33 to nearly 40 bps. We then exploit the variation in each country's exports to the shocked country (i.e., Japan or China) as a fraction of its total exports in the prior year. Our results show that information flows from both Japan and China to their upstream countries. In particular, the consequences of the local shock can be seen in the cross-section of SCDS returns with both a contemporaneous and a lagged response. Thus, we provide clear evidence that country-level shocks propagate through the trade network, in contrast to the alternative view that countries comove only because of common exposures to aggregate shocks.

We next turn to a broader study of information flows in these markets, exploiting lead-lag return predictability. Specifically, we construct a time-varying matrix, $Trade$, where each row corresponds to an exporting country and each column corresponds to an importing country. Therefore, each cell contains the fraction of total export accounted for by the importing country. For each country in our sample and in every month, we then calculate the export-weighted average SCDS return of the countries it exports to, namely $Trade_{t-1} \times r_t^{CDS}$, where r_t^{CDS} is the vector of SCDS returns for the countries we study. Thus, our method exploits the time-varying import/export linkages that characterize the international trade network in conjunction with SCDS returns to identify the way in which country-specific information propagates through the global economy.

With this measure, dubbed $ExpRet$, for each month, we sort countries based on their $ExpRet$ signal and examine the subsequent abnormal returns on their own SCDS. We find that our measure of $ExpRet$ has an economically and statistically significant effect on the cross-section of SCDS returns, a fact that is robust to a variety of controls for systematic risk in the SCDS market. For example, the top 20% of countries sorted by $ExpRet$ outperform the bottom 20% by 47 bps per month with an associated t-statistic of 3.69, implying an annualized Sharpe ratio of 1.1.

In addition, we document important heterogeneity in this predictability linked to both a country's position in the network, as well as the vulnerability of the country receiving the shock. We find that our effect is stronger for countries on the periphery of the network and those countries that are financially vulnerable. The former effect is consistent with a limited attention argument. The latter effect is true whether we sort on credit quality, leverage, or our vulnerability index, which combines these two measures.

We further show that the returns on these portfolios are not driven by links in the cross-border capital-flow network and are robust to controls for the gravity model of global trade. Moreover, our findings are robust across a variety of subsamples and subperiods. In particular, our results continue to hold when we exclude China; safe haven countries with low SCDS spreads; the G20, the European Union, or OPEC countries; or the smallest or most illiquid countries from the sample. We also find similar effects in the subperiods before and after the Global Financial Crisis. Thus, the predictability caused by trade-network links is not driven by a particular crisis event or a particular subset of countries; instead, our finding is a pervasive phenomenon. Moreover, these abnormal returns do not revert in the long run, consistent with a striking underreaction phenomenon in this global market.

We then turn to analyzing the information contained in the indirect links between countries in the global trade network. The weights of these indirect links are the row elements of $Trade^2 = Trade \times Trade$. We calculate the export-weighted average SCDS return of a country's indi-

[1] See, for example, di Giovanni et al. (2014,2020), and Kramarz et al. (2020). Unlike these papers, we focus on understanding the country-level trade network.

[2] Credit spreads are volatile throughout our sample period. Longstaff et al. (2011) investigate the extent to which local and global factors can explain variation in credit spreads. We show in Section 5 that a country's SCDS return contains information about subsequent import growth and thus an export-weighted average of the SCDS returns on a country's export destination contains significant information about export and GDP growth.

[3] Shiller (1981)'s excess volatility puzzle has been quantified in terms of return decomposition by a large literature starting with Campbell (1991), who argues that roughly 80% of return volatility is due to discount-rate news. Others, such as Campbell et al. (2018), confirm similar numbers in data including our sample period. Consistent with this view, in Section 5.2 we document that a measure of investor sentiment (Baker and Wurgler, 2006) strongly forecasts aggregate stock market returns but has no ability to forecast future SCDS returns.

rect links as $Trade^2_{t-1} \times r^{CDS}_t$, which we dub *ExpRetInd*. We then ask the question: To what extent does variation in the credit quality of one's trading partners' trading partners matter? In regressions with both *ExpRet* and *ExpRetInd*, the SCDS return predictability associated with indirect trade links is roughly as strong as that from direct links. Furthermore, information concerning the quality of one's indirect trading partners takes longer to show up in realized returns than that concerning the quality of one's direct trading partners. These findings are consistent with fundamental shocks, particularly the indirect ones, taking time to work their way around the globe.

If these patterns reflect information about fundamentals, we should see similar predictability in equity markets, since the stock market must ultimately be driven by cash-flow news. A simple equity strategy that buys the 20% of countries with the lowest *ExpRet* and sells the 20% of countries with the highest *ExpRet* earns roughly 1% per month, with an associated t-statistic of 3.26.[4] After we adjust for market, value, and two different measures of equity momentum, the resulting four-factor alpha increases to 1.05% and the t-statistic to 3.74. Thus, information about a country's export destinations' credit quality also helps describe the cross-section of average equity returns. Interestingly, the reverse is not true; that is, if we use export destinations' equity market returns to compute an otherwise similarly defined *ExpStock*, this alternative measure does not forecast the focal country's sovereign credit returns. In other words, sovereign credit markets incorporate information faster than equity markets.

Finally, we provide evidence that $ExpRet_{c,t}$ indeed contains information about real economic activity that is directly relevant to a country's sovereign credit risk. We start by showing that a country's SCDS return, $OwnRet_{c,t}$, forecasts its own imports; in other words, if a country is performing relatively poorly in terms of credit quality, its future imports are relatively low. Building on this result, we then use a country's $ExpRet_{c,t}$ to forecast its subsequent export growth, GDP growth, and changes in the external-debt-to-GDP ratio, which is more directly related to a country's sovereign credit risk. We show that $ExpRet_{c,t}$ indeed predicts the country's export growth, GDP growth, and changes in the country's external-debt-to-GDP ratio.

In summary, we provide causal evidence of country-level information flows through the trade network in the SCDS market. This information is distinct from other possible network effects. News about one's trading partners affects a country's export activity, GDP growth, external-debt-to-GDP, SCDS spread, and stock market return. As the trade network is continually evolving and the typical country has many trading partners, who in turn have many trading partners, our analysis reveals a novel mechanism by which many small ripples of information turn into a wave of return predictability across countries.[5]

Our primary contribution is to the emerging literature that argues that the network of economic activity is important. Barrot and Sauvagnat (2016) show that the specificity of intermediate inputs allows firm idiosyncratic shocks to propagate in the supply-chain network by exploiting data on supplier-customer relations among US publicly listed firms. For example, disruptions to suppliers caused by natural disasters lead to a two to three percentage point drop in customers' sales growth; this negative shock further spills over to other suppliers of the same customer due to the complementary nature of intermediate inputs. Carvalho et al. (2021) provide evidence of both upstream and downstream shock propagation using Japanese input-output data. They document a 3.6% (2.9%) decline in the sales growth of firms whose suppliers (customers) were hit by the 2011 Japanese earthquake. In aggregate, this natural disaster caused a 0.47% decline in Japan's real GDP in the following year. Unlike these papers that study firm linkages, we focus on understanding the country-level international trade network. In doing so, we provide the first macroeconomic confirmation that uses forward-looking financial variables to show the importance of trade networks to country-level shock propagation in a global setting.

Our work also has a strong connection to the literature on international business cycle fluctuations. These studies argue that countries that trade more with each other have more correlated business cycles (e.g., Frankel and Rose 1998). The mechanisms underlying such correlation is a key question in the empirical macro literature. In particular, researchers ask whether the increased correlation arises from the prevalence of common shocks hitting countries that trade more together and thus increasing business cycle comovement of countries or from the propagation of country-specific shocks through the trade channel (Imbs, 2004). Our two natural-experiment tests show the causal importance of country-specific shocks along the trade network, and our methodology provides a general way to aggregate information in either fundamentals or prices in order to compare the importance of different network links. Moreover, given the fact that stock market cycles and business cycles have only a loose correlation (Fama and French, 1989), our insights regarding the importance of the SCDS market may facilitate progress in the international business cycle literature.

Exploiting financial data to identify the propagation of macroeconomic activity via networks is an additional important contribution of our work to this growing literature. Previous studies that focus on accounting/macro data are hamstrung by the fact that accounting realizations, such as sales or GDP, contain a large predictable component and are the result of activity only over the accounting quarter/year in question (so low frequency). In contrast, our approach allows us to examine the importance of the trade network not only at a higher frequency (which helps with identification) but also by using forward-looking asset prices, which should capitalize news about the value

[4] This estimate implies an annualized Sharpe ratio of 0.95; for reference, the annualized Sharpe ratio of a long position in the US equity market over our sample period is only 0.31.

[5] The top ten destinations for the typical country account for only 75% of the total export activity of the typical country in our sample. Given that we show the importance of indirect links, markets must aggregate information across a wide range of trading partners.

of information contained in these links. Indeed, recognizing these links allows us to describe novel variation in risk and in the average return for the cross-section of country-level equity and credit markets.

This paper also contributes to the growing literature on sovereign credit by illustrating a new information-discovery mechanism in the SCDS market. While Pan and Singleton (2008), Longstaff et al. (2011), Xiao et al. (2021), and Augustin and Tedongap (2016) document the comovement of SCDS prices with global systemic risk factors, others focus on the relation between SCDS prices and country-specific risk. Acharya et al. (2014) illustrate the way the financial strain of the contingent debt burden arising from public bank bailouts may feed into sovereign credit risk. Aizenman et al. (2013) show that country-specific macroeconomic risk also feeds into the SCDS spread. Lee et al. (2016) document that SCDS spreads are related to the degree of property and creditor rights protection and the disclosure requirements. Complementary to these domestic financial, macroeconomic, and institutional factors, we find that the credit quality of a country's export destinations also plays an important role in determining its SCDS spread.

Our paper also sheds light on the way sovereign credit risk spills over across countries. The majority of the existing literature focuses on the sovereign credit risk spillover occurring during the European debt crisis, a time of high volatility and comovement. For example, Beirne and Fratzscher (2013) attribute the cross-country sovereign credit risk spillover during those times to investors' increased sensitivity to country-specific fundamentals. In contrast, our paper shows that sovereign credit risk spillover exists not just in crisis states, but also in normal times, and that spillover comes, at least in part, through the global trade network. Moreover, export destination credit risk can be spread not only through direct trade links but also through indirect trade links.

This paper further contributes to the literature on investors' limited attention and information processing capacity. Our findings provide insight on the extent to which macroeconomic information slowly diffuses in the financial derivative markets, which is complimentary to prior studies on the diffusion of firm information in the stock market (e.g., DellaVigna and Pollet 2007, Cohen and Frazzini 2008, Cohen and Lou 2012, Albuquerque et al. 2015, Xiao et al. 2021 and Wang et al. 2021). Our findings show that even financial derivative markets, often presumed to be more efficient in aggregating information than stock markets (e.g., Easley et al. 1998 and Pan and Poteshman 2006), are subject to investors' limited attention.

Finally, this paper relates to the informational role of derivatives markets. A large literature studies the way information flows across markets. For instance, Black (1975) emphasizes that the embedded leverage in most derivatives allows investors to trade their information more efficiently. Nevertheless, there remains a debate on the direction of information flow between derivative markets and the market for the underlying asset. On the one hand, Acharya and Johnson (2007) find that the corporate CDS market forecasts future negative credit events. Furthermore, Lee et al. (2021) show that information in the corporate CDS market can be used to improve the price momentum strategy of Jegadeesh and Titman (1993). Xiao et al. (2021) find that the SCDS market forecasts stock markets and economic activities across countries with the predictive power coming almost entirely from the global, rather than country-specific, information from the sovereign CDS market. On the other hand, Hilscher et al. (2015) find evidence that information flows from the equity market to the corporate CDS market. Our paper contributes to this debate by providing additional evidence that SCDS contains information about trade that is gradually incorporated into country-level returns.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 examines responses of SCDS spreads to two natural experiments. Section 4 documents slow transmissions of export destination news, and Section 5 discusses the underlying economic mechanisms. We conclude the paper in Section 6.

2. Data

2.1. Sovereign credit default swaps

Our SCDS data are from Markit, which collects daily SCDS quotes from major SCDS dealers and publishes the average SCDS spread following a careful data validation procedure.[6] Our sample covers 88 sovereign countries, from 2001 to 2015. We list when each country enters the sample in Appendix Table A1, Panel A. Our analysis focuses on USD-denominated, five-year maturity contracts with the underlying being senior unsecured debt.[7] We choose this type of SCDS contracts because they are the most actively traded with the smallest trading cost. Table 1 provides the summary statistics of our SCDS data. The average SCDS par spread is 243 bps, with a standard deviation of 597 bps. The monthly average SCDS return is −0.01%, with a standard deviation of 2.61%. On average, a SCDS contract has five dealers providing quotes.

2.1.1. The calculation of SCDS returns

SCDS allows market participants to purchase or sell protection against the risk of default of a sovereign government. During the term of the SCDS contract, the buyer makes quarterly payments based on the CDS coupon/spread to the seller in exchange for the seller's promise of protection. Should a credit event occur, the parties settle the contract to allow the buyers to collect their

[6] Of the various providers of SCDS price data, Markit's quality is deemed to be of the highest quality and is used by the IMF and World Bank to monitor sovereign credit risk. This high quality is in contrast to Bloomberg, whose data can be plagued by stale quotations (Rodriguez et al. 2019).

[7] While corporate CDS are usually traded under ISDA's XR or MMR restructuring clauses, sovereign reference entities typically trade under the CR/CR14 restructuring clause. This clause means that in the event of a restructuring credit event, there is no maturity limitation on deliverable obligations beyond the usual 30 years.

Table 1
Summary statistics.
This table shows summary statistics of the variables used in the paper. Panel A reports the number of trading partners each country has. Panel B provides summary statistics of other key variables used in our analyzes. Our sovereign CDS (SCDS) data cover the period January 2001 to September 2015. The CDS spread is the par spread provided by Markit. Monthly SCDS returns are calculated using the standard CDS P&L model following O'Kane (2011). We compute monthly SCDS returns using SCDS spreads on the 20th of each month to the 19th of the following month. Stock index returns in each country are the monthly US-dollar denominated stock index total returns from Bloomberg. In order to be consistent with the timing of SCDS monthly returns, monthly stock index returns are also from the 20th of each month to the 19th of the next month. The annual international trade data are obtained from the UN Comtrade database. Credit rating and credit outlook data include sovereign credit information from S&P, Fitch, and Moody's, with rating grades converted into numerical values from 1 ("AAA/Aaa") to 22 ("D"). Credit Rating is the monthly average of the numerical credit rating of S&P, Fitch, and Moody's. Inflation is calculated month-over-month using the seasonally-adjusted CPI index.

Panel A: Trade network links

	Mean	Std. Dev.	25%	Median	75%
Number of export destination countries	62.531	3.980	62.281	64.178	64.656
Number of import source countries	63.013	6.962	63.210	65.278	65.948

	Cumulative trade value		
	25%	50%	75%
Number of export destination countries (per importing country)	1.730	4.086	10.016
Number of import source countries (per exporting country)	1.816	4.392	10.677

Panel B: Summary statistics

	No. of Obs.	Mean	Std. Dev.	25%	50%	75%
SCDS spreads (bps)	11,997	242.651	596.924	35.022	116.218	266.588
SCDS returns (%)	11,778	−0.014	2.612	−0.371	−0.005	0.219
Number of dealers	11,997	5.063	2.300	3.000	5.136	7.000
Export-to-GDP ratio (%)	15,441	47.473	32.326	28.108	39.483	57.141
Monthly inflation (%)	15,431	0.391	0.884	0.042	0.262	0.573
Annual GDP growth (%)	15,477	3.658	4.317	1.658	3.607	5.630
Headline PMI	4897	51.325	4.879	49.032	51.671	54.227
Credit rating	12,329	10.062	4.808	6.500	10.000	14.000
Stock index returns (%)	10,814	0.997	7.950	−2.998	1.125	5.162

credit risk protection payment, which is the face value loss of the sovereign debt.[8],[9]

Following standard market practice, the SCDS return is defined as the profit/loss (P&L) of trading a unit of $1 nominal protection over a particular period of time. We calculate the mark-to-market SCDS return using the widely adopted ISDA CDS model, described in detail in O'Kane (2011). The SCDS return increases when the underlying country's creditworthiness deteriorates; that is, a higher SCDS return indicates bad news.

There are two practical issues when applying this approach to our data. First, there are four fixed premium payment dates each year in the SCDS market: March 20, June 20, September 20, and December 20. A five-year contract will mature on the first premium payment date after the contract exists for five years. For instance, a new five-year SCDS launched between March 20, 2015 and June 19, 2015 will mature on June 20, 2020, unless a credit event is triggered before that day. The new SCDS contract traded in the market before the next premium payment date is called the on-the-run contract and has the highest liquidity (our SCDS price data are all on-the-run spreads). Given these institutional features, we compute the monthly SCDS return based on the spreads on the 20th of the current month and the 19th of the next month to ensure that these two spreads are from the same contract.

Second, if the credit event happens during the holding period of the SCDS, the monthly return should be the realized loss on the bond, 1-R. We use the commonly used realized recovery rate $R = 40\%$ to calculate the SCDS return in case of default. There are three sovereign defaults in our sample, all of which are auction-settled: Ecuador in 2009, Greece in 2012, and Argentina in 2014.[10]

2.2. Other data

We obtain our annual US-dollar-denominated bilateral trade data from the United Nations Commodity Trade Statistics Database (UN Comtrade). As can be seen from Table 1, a typical country in our sample exports to 62

[8] Credit Events are determined by the ISDA Determinations Committee and according to the ISDA definitions, include failure to pay, moratorium, obligation acceleration, and restructuring.

[9] In most cases, the parties use cash settlement with an auction process in which the CDS seller makes a cash payment based on an auction-generated market price of certain eligible debt obligations of the sovereign government. An alternative is physical settlement in which the protection buyers tender an eligible bond to the sellers and receive the par value of the bond.

[10] http://www.creditfixings.com/CreditEventAuctions/fixings.jsp is the website providing the detailed information of each CDS credit event and settlement with data coming from the Markit and Creditex.

countries and the total export accounts for 47.5% of a country's GDP. We gather information on bilateral foreign direct investment (FDI) from the United Nations UNCTAD's Bilateral FDI Statistics database and information on bilateral portfolio investment from the IMF Coordinated Portfolio Investment Survey (CPIS) database.

Other macroeconomic data, including the annual GDP growth rate and monthly seasonality-adjusted CPI inflation rate, are collected from the International Monetary Fund's World Economic Outlook (WEO) database. The average GDP growth rate in our sample is 3.7%, with a standard deviation of 4.3%, while the seasonality-adjusted month-over-month inflation rate is 0.39%, with a standard deviation of 0.80%. Information on the purchasing manager index (PMI) is obtained from Markit's Global PMI database. The PMI is a key economic indicator derived from the monthly surveys of private sector companies in six categories: production level, new orders from customers, speed of supplier deliveries, inventories, order backlogs, and employment level. We focus on the headline PMI, which incorporates all sub-indices data. The average headline PMI is 51.3 in our sample, with a standard deviation of 4.9.

We also collect information on sovereign credit ratings/outlook from major credit rating agencies: Moody's, Standard & Poor's, and Fitch. We first convert all ratings into numerical scores: "AAA/Aaa" to 1 and "*D*" to 22. We then calculate for each country the monthly average credit rating across the three agencies as a measure of credit risk. The average credit rating for all countries is 10.1, equivalent to "BBB+."

Finally, we obtain daily USD-denominated returns of stock market indices from Bloomberg. The complete list of countries and their corresponding stock market indices are provided in Appendix Table A1, Panel A. To be consistent with the calculation of SCDS returns, we construct monthly stock index returns from the 20th of each month to the 19th of the subsequent month.

2.3. Summary statistics

Table I provides the summary statistics of our sample. Panel A of Table 1 also contains the basic statistics of the trade network. The first two rows show that a typical country exports to and imports from most other countries in our sample: the average number of export destination countries is 62 and the average number of import source countries is 63. The third and fourth rows report the concentration of export/import relations. For example, the top two export destinations account for more than 25% of a country's total exports, and the top ten destinations account for 75% of the total exports. Taken together, these results indicate that (a) trade is not spread evenly across all trading partners, and (b) our method relies on aggregating information across all trading partners. Panel B reports the summary statistics of the macroeconomic and financial variables. For instance, the average SCDS spread is 2.4%, and the average SCDS return is close to zero. There is, however, substantial volatility in this market, potentially related to news about country fundamentals.

2.4. Measuring export destination news

We use the SCDS returns on a country's export destinations to reflect changes in its export demand. More specifically, we define our measure of the change in export destination credit quality for each country as the weighted average of export destinations' SCDS returns using the bilateral export in the prior calendar year as the appropriate weight,

$$ExpRet_{c,t} = \frac{\sum_{i \neq c} Export^{c}_{i,y-1} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} Export^{c}_{i,y-1}}. \tag{1}$$

$ExpRet_{c,t}$ measures the export destination credit quality of country c at the end of month t, and $Export^{c}_{i,y-1}$ denotes the dollar amount of export from country c to country i in the calendar year before month t. We use the prior calendar year export activity to weight returns to ensure that the export data would have been available to investors when calculating our measure. $Ret_{i,(t-F+1,t)}$ is country i's SCDS return from month t-$F+1$ to t, where F is referred to as the formation period of the proxy. We typically study the information in the past three-month SCDS return ($F = 3$), unless otherwise specified.[11]

The typical country in our sample exports 81% of its total export to countries with traded SCDS, with a standard deviation of 13%. Therefore, we argue that our measure $ExpRet_{c,t}$ reflects news about a significant component of a country's export destinations. Figs. 1 and 2 provide a visual representation of the rich network structure in 2001 (the first year of our sample) and 2015 (the last year), respectively. The time-varying network structure in conjunction with SCDS returns are thus the two components of our $ExpRet_{c,t}$ variable.[12]

3. Two natural experiments

To show that patterns in the SCDS market are consistent with country shocks propagating through the network, we examine two natural experiments in Table 2. Panels A1 and A2 document the ripple effect of the Japanese triple-disasters (earthquake, tsunami, and radioactive fallout) in March 2011 while Panels B1 and B2 document the ripple effect of the Wuhan COVID-19 lockdown in January 2020. In the right side of each panel, we focus on the three weeks surrounding the event. In Panels A1 and A2, we define the event as March 11, 2011 (the day the earthquake hit Japan's east coast), with week W0 being the event week. In Panels B1 and B2, we define the event as January 23, 2020 (the day the central government of China imposed a lockdown in Wuhan and other cities in Hubei

[11] We include all of country c's export destination countries which have traded SCDS. For instance, assume that in 2005, country c exports \$100 billion and \$50 billion to countries x and y, respectively. Denoting $Ret_{x,(t-2,t)}$ and $Ret_{y,(t-2,t)}$ as country x and y's SCDS returns from month t-2 to t, the resulting export destination return $ExpRet_{c,t}$ in month t in 2006 is then $ExpRet_{c,t} = \frac{100 * Ret_{x,(t-2,t)} + 50 * Ret_{y,(t-2,t)}}{150}$.

[12] The Sharpe ratio of our headline result declines by 32% if we ignore the evolution of the trade network over our sample and only use the beginning-of-the-sample trade links when computing Eq. (1).

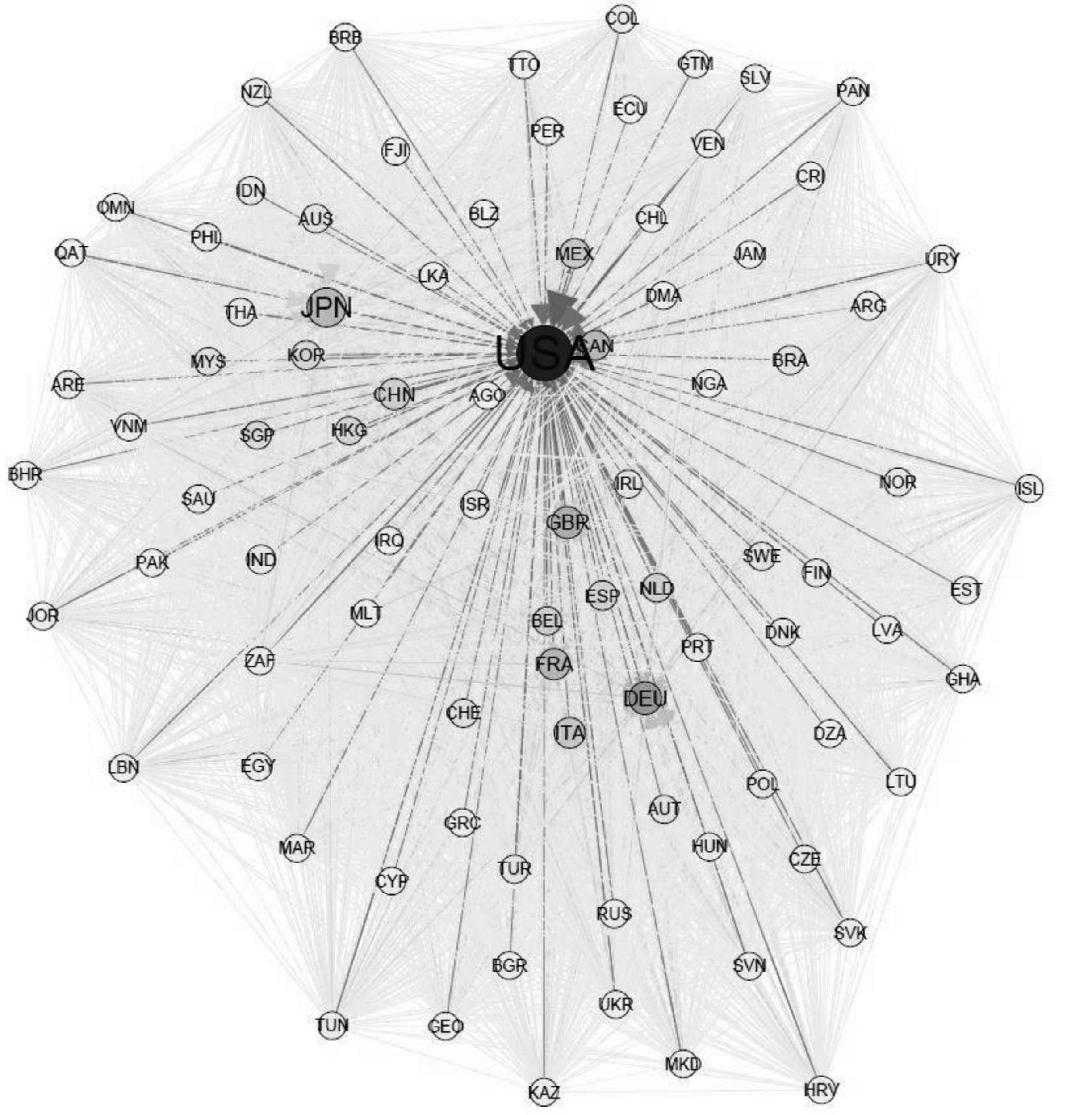

Fig. 1. The global trade network in 2001.
This figure shows the global trade network in 2001. Each circle denotes an individual country. The size of the circle represents the size of the economy which is proportional to countries' GDP. The arrow represents the export direction. The thickness of the arrow is proportional to each country's bilateral export weight, which is measured as the ratio of bilateral export over the country's total export. The degree of darkness inside each circle represents the eigenvector centrality of the country in the trade network.

province to quarantine the initial COVID-19 outbreak). In the left side of the panels, we zoom in on the four days surrounding the event with day T0 being the event day.

For each week or day in our sample, we conduct a cross-sectional regression (with bootstrapped standard errors) of each country's SCDS return on its closeness to Japan (Panels A1 and A2) or China (Panels B1 and B2) in the trade network in terms of export activity to the shocked country. Our main independent variable, *ExpShare*, is the share of a country's export to Japan (Panels A1 and A2) or China (Panels (B1 and B2) as a fraction of the country's aggregate exports measured in 2010. Other control variables include the country's own lagged one-month sovereign CDS return and seasonally adjusted inflation rate. In Panels A1 and B1, we use *ExpShare*, and in Panels A2 and B2, we construct a dummy variable $ExpShare_{DUM}$ that equals one if the country's share of export to Japan (Panel A1) or China (Panel B2) is in the top 20% of the sample,

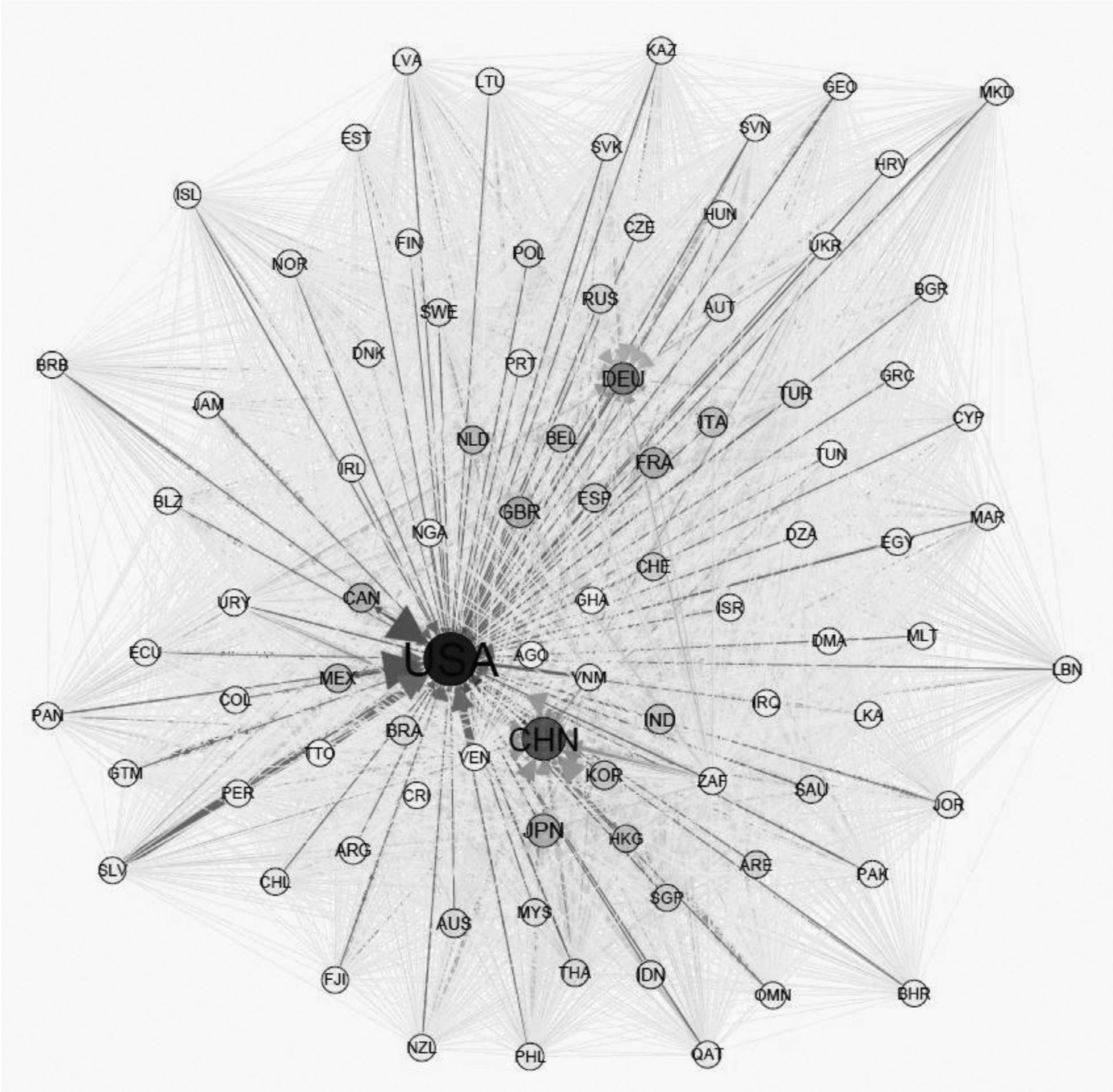

Fig. 2. The global trade network in 2015.
This figure shows the global trade network in 2015. Each circle is an individual country. The size of the circle represents the size of the economy which is proportional to countries' GDP. The arrow represents the export direction. The thickness of the arrow is proportional to each country's bilateral export weight, which is measured as the ratio of bilateral export over the country's total export. The degree of darkness inside each circle represents the eigenvector centrality of the country in the trade network.

and zero otherwise. All of our findings are robust to using either *ExpShare* or $ExpShare_{DUM}$. We focus on the results related to the latter, given its simplicity and ease of interpretation.

On the day of the triple-disaster, the Japanese SCDS spread experienced a large increase, moving from 75 to 125 bps. If this idiosyncratic shock indeed propagates through the trade network, countries that export more to Japan should experience a larger decline in credit quality. Across both the weekly and daily specifications, the coefficients on *ExpShare* and $ExpShare_{DUM}$ are significantly positive. For example, the top 20% of countries in terms of exposure to import activity from Japan experienced an increase in their SCDS returns of 4.81% (t-statistic = 2.98) the week of the Japanese tsunami. We note that in the two weeks following the event week, there is no evidence of any reversal of the week 0 effect. If we move from the weekly to the daily frequency, we find that $ExpShare_{DUM}$ is associated with a return of 2.48% (t-statistic = 2.98) on the event day and 2.85% (t-statistic = 2.56) on the

Table 2
Spillover in the trade network during disaster events.

This table reports the ripple effect in the SCDS market using two exogenous events. The first event is the March 2011 Japanese triple-disasters (earthquake, tsunami, and radioactive fallout). The second event is the January 2020 Wuhan lockdown driven by COVID-19 in China. We conduct event studies both on a daily (columns 1–5) and weekly basis (columns 6–8). *T0/W0* represents the day / week when the event occurred. We focus on the effects during days and weeks following the event. We restrict our sample to countries that export to the country where events take place. For each week (day), we run a cross-sectional regression explaining exporting countries' SCDS returns. Our main independent variable, *ExpShare*, is the total export share of a country's bilateral export to the event country measured in the previous year. $ExpShare_{DUM}$ is a dummy variable that takes the value of 1 if the exporting country's export share falls into the top 20%, and takes the value of 0 otherwise. Other control variables include the country's own lagged sovereign CDS return, the inflation rate measured in previous month, bilateral geographical distance measured as the inverse of the logarithm of distance, and the export-to-GDP ratio measured in the previous year. Panels A1 and A2 report results for the 2011 Japanese tsunami. Panels B1 and B2 report results for the COVID-19 Wuhan lockdown. We report *t*-statistics based on bootstrapped standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Daily returns					Weekly returns		
	T0	*T1*	*T2*	*T3*	*T4*	*W0*	*W1*	*W2*
Panel A1: Japanese tsunami, continuous export share								
ExpShare	0.106**	0.173***	0.041	0.000	−0.012	0.221***	−0.001	−0.012
	(2.03)	(2.64)	(0.91)	(0.01)	(−0.39)	(2.61)	(−0.01)	(−0.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	71	71	71	71	71	71	71	71
Adj. R^2	0.50	0.23	0.30	0.17	0.02	0.08	0.11	0.21
Panel A2: Japanese tsunami, dummy variable								
$ExpShare_{DUM}$	0.025***	0.029***	0.000	−0.001	0.001	0.048***	−0.005	0.010
	(2.98)	(2.56)	(0.02)	(−0.14)	(0.16)	(2.98)	(−0.36)	(0.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	71	71	71	71	71	71	71	71
Adj. R^2	0.54	0.28	0.29	0.17	0.02	0.13	0.11	0.22
Panel B1: COVID-19 Wuhan lockdown, continuous export share								
ExpShare	0.082**	0.079***	0.158***	−0.061	−0.030	0.205***	−0.029	−0.041
	(2.08)	(3.17)	(3.23)	(−1.12)	(−0.91)	(2.73)	(−0.56)	(−1.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	60	60	60	60	60	60	60	60
Adj. R^2	0.01	0.25	0.24	0.24	0.03	0.12	0.08	0.07
Panel B2: COVID-19 Wuhan lockdown, dummy variable								
$ExpShare_{DUM}$	0.022***	0.017***	0.044***	−0.009	−0.012	0.059***	−0.008	−0.008
	(2.67)	(2.59)	(3.36)	(−0.62)	(−1.45)	(3.15)	(−0.58)	(−0.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	60	60	60	60	60	60	60	60
Adj. R^2	0.01	0.16	0.26	0.22	0.07	0.14	0.08	0.06

subsequent day. Thus, our daily regressions further reveal that the negative shock, despite its extreme salience to not just SCDS market participants but economic agents more broadly, still takes more than a day to be fully incorporated into SCDS prices.

On the day of the Wuhan lockdown, the Chinese SCDS spread increased from 33 bps to nearly 40 bps. Despite the difficulty in evaluating the ultimate consequences of the early stages of a pandemic, we continue to find that countries who have China comprising a relatively large share of their export activity have their SCDS strongly react to the news of the Wuhan lockdown. Indeed, the point estimate associated with $ExpShare_{DUM}$ in the event week is larger, 5.85% (*t*-statistic = 3.15), than that found in the Japanese event. Again, no evidence of reversal is present in the two weeks following the event. We also find that the Wuhan lockdown shock takes longer to ripple through the SCDS market, as the effect on China's import source countries remains economically and statistically significant even two days following the event. Specifically, we find that $ExpShare_{DUM}$ is associated with a return of 2.19% (*t*-statistic = 2.67) on the event day, 1.74% (*t*-statistic = 2.59) on the subsequent day, and 4.36% (*t*-statistic = 3.36) on the third day.

Together, our results confirm that information flows from the affected country to its upstream countries. Namely, the aftershock of the Japanese earthquake can also be felt in the global SCDS market, and the initial outbreak of COVID-19 can be traced in the global SCDS market as well. Thus, we confirm that country-level shocks can propagate through the trade network, rather than the alternative view that countries comove only because of exposures to common shocks. We find these well-identified effects both contemporaneously and with a lag.

4. Slow transmission of information: forecasting SCDS returns

Generalizing the results in Table 2, we now show that trade networks cause countries to (ultimately) move together by exploiting the fact that abnormal return predictability can reflect information flow. In particular, if information concerning export destination countries' quality is relevant for exporting countries' CDS prices but is only gradually incorporated into prices, then $ExpRet_{c,t}$ should predict the exporting country's SCDS returns. Given that even the quite salient Japanese tsunami and Wuhan lockdown took two to three days to be fully incorporated into prices, it is reasonable and perhaps quite likely that less salient events (ripples) that aggregate together may ultimately result in slow-moving return waves. Therefore, in this section, we examine the information contained in $ExpRet_{c,t}$ about an exporting country's credit quality using either simple portfolio sorts or Fama-MacBeth regressions.

4.1. Monthly long-short trading strategies

We study the following trading strategy. At the end of each month, we sort countries into five quintiles, P1 (low) to P5 (high), based on $ExpRet_{c,t}$ and study the resulting returns on these portfolios, as well as the difference between P5 and P1. This difference reflects the return to a zero-cost portfolio that buys credit default protection for countries whose export destination countries have seen their credit quality deteriorate and simultaneously writes default protection on countries whose export destination countries have seen their credit quality improve. We report equal-weight portfolio returns over the next H months.

Table 3 Panel A reports the profits of our long/short strategy from January 2001 to September 2015 across various combinations of formation periods, F, and portfolio holding periods, H. The return predictability is robust, as the long/short portfolio returns remain significant across different combination of reasonable formation and holding periods. For instance, for formation period $F = 3$ months and holding period $H = 1$ month, our strategy generates a monthly return of 47 bps (5.76% on an annual basis) with a t-statistic of 3.69 and Sharpe ratio of 1.10. As can be seen in the table, the average returns increase monotonically, consistent with our slow information diffusion interpretation.

Since the efficacy of our strategy declines as F becomes larger than three, the rest of our analysis focuses on that specification. Nevertheless, even for other specifications we have studied, predictability remains economically and statistically significant. For example, if $F = 6$ months and $H = 1$ month, the long/short strategy generates a monthly return of 30 bps (or 3.6% annualized), with a t-statistic of 2.62 and a Sharpe ratio of 0.85.

In Table 3 Panel B, we further examine the robustness of the ability of $ExpRet_{c,t}$ to forecast cross-sectional variation in SCDS by controlling for other potential risk factors. More specifically, we regress the time series of returns to our long/short portfolio strategy (with $F = 3$, $H = 1$) on various risk factors documented in the literature. In the regression for the first row of Panel B, we do not control for any risk factor and report the raw return of the long/short strategy for sake of comparison. In the regression for the second row, we control for a SCDS momentum factor based on a three-month formation period and a one-month holding period as studied in Xiao et al. (2021). In the regression for the third row, the risk factor is a market factor, namely the equal-weighted return of all SCDS in our sample. We include both this market return and the momentum return together in the regression for the fourth row. Finally, in the regressions for the fifth and sixth rows, we additionally control for the global momentum and value factors in Asness et al. (2013), as well as the US market factor. As can be seen, after controlling for all the risk factors, we still obtain a statistically significant risk-adjusted abnormal return as the resulting monthly alpha is 0.23% (t-statistic = 2.86).

Panel B of Table 3 also reports the way our findings vary across different subperiods. Specifically, we study the pre-crisis period from January 2001 to November 2007, as well as the crisis and post-crisis periods from December 2007 to December 2010 and January 2011 to September 2015, respectively. The risk-adjusted abnormal returns are all positive and statistically significant at the 5% level during the pre- and post-crisis periods. The average abnormal return becomes statistically insignificant (but still economically sizable) during the crisis period, likely due to the extreme volatility and comovement of SCDS spreads occurring during that relatively short period of time.

4.1.1. Heterogeneity across countries

As transmission of information is facilitated by investors' attention, one would expect that more central countries in the network, such as Singapore, Hong Kong, China, United States, and the United Kingdom, would experience weaker effects as investors are likely more attentive to trade information for these countries. We measure a country's "centrality" using the most widely used eigen-centrality measure in network analysis (e.g., Allen and Babus 2008 and Acemoglu et al., 2012, 2013). Specifically, eigen-centrality is the corresponding eigenvalue calculated by applying the standard eigenvalue decomposition on the export destination matrix *Trade* in year t in a way similar to Richmond (2019).

Moreover, the SCDS of countries with relatively poor credit quality and/or relatively high external debt are likely more vulnerable to bad news about fundamentals. We measure the extent to which predictability increases with either of these two characteristics or with a composite vulnerability index (the rank average of the export country's credit rating and its external debt to GDP ratio).

Panel C of Table 3 reports the results of double sorts using $ExpRet_{c,t}$ in tandem with either network centrality, credit rating, external debt, or our vulnerability index. In each case, the observed heterogeneity is consistent with our economic story: our effect is stronger for countries on the periphery of the network and those countries that are financially vulnerable. The former effect is consistent with a limited attention argument, which we confirm in Section 5.3. The latter effect is true whether we sort on credit quality, leverage, or our vulnerability index. All effects are strongly statistically significant.

Finally, the information in $ExpRet_{c,t}$ is publicly observable and arguably easy to understand. Therefore, limits to arbitrage likely play an important role in facilitating the return predictability we document. To test this idea, we split our SCDS data into two subsamples based on the number of dealers providing price quotes. At each point in time, cross-sectional variation in the number of dealers likely proxies for cross-sectional variation in SCDS liquidity and thus limits to arbitrage. As shown in the last two rows, the long-short SCDS portfolio sorted by *ExpRet* generates

Table 3
Forecasting SCDS returns.

This table reports calendar-time portfolio returns of SCDS. At the end of each month, SCDS contracts are sorted into five groups (P1–P5) based on *ExpRet*, the weighted average SCDS return on a country's export destinations over the past *F* months, where the weights are proportional to how much the country exported to its export destinations in the prior year. All countries are equally weighted within each quintile and the portfolios are held for *H* months. The long/short strategy is constructed by going long SCDS in quintile P5 and selling short SCDS in quintile P1. Panel A reports the average returns of these quintile portfolios based on different formation and holding periods. In Panel B, we further control for common risk factors in SCDS returns. We fix the formation period $F = 3$ months and the holding period $H = 1$ month. The first row of Panel B reports raw portfolio returns. The second row reports portfolio alpha after controlling for the sovereign CDS momentum factor (constructed based on a three-month formation period and a one-month holding period). The third row reports portfolio alpha after controlling for the equal-weight global SCDS return factor. The fourth row reports portfolio alpha controlling for both the SCDS momentum factor and the global SCDS return factor. Rows five and six add the global momentum and value factors (as in Asness et al. 2013) and the US stock market factor. In Panel C, we examine the returns to the long-short portfolio of SCDS for various subsamples: sorted by each country's eigenvector centrality in the trade network, credit rating, external-debt-to-GDP ratio, the vulnerability index (which is the rank average of each country's (inverse) credit rating and external-debt-to-GDP ratio), and SCDS liquidity measured by the number of SCDS dealers providing price quotes. We report *t*-statistics in parentheses that are based on Newey-West standard errors with a lag parameter of 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calendar-time portfolio returns of SCDS contracts (in%)

	Portfolio returns in the following month					Holding period returns		
	P1	P2	P3	P4	P5	Long/short strategy (P5 – P1) H = 1m	H = 3m	H = 6m
F = 1 m	−0.052	−0.076	−0.018	−0.012	0.148	0.200**	0.242***	0.133**
	(−0.43)	(−0.81)	(−0.25)	(−0.11)	(1.01)	(2.00)	(3.66)	(2.24)
Sharpe Ratio						0.45	0.85	0.77
F = 3 m	−0.242*	−0.019	−0.027	−0.030	0.232*	0.474***	0.296***	0.201**
	(−1.80)	(−0.23)	(−0.29)	(0.38)	(1.69)	(3.69)	(2.84)	(2.11)
Sharpe Ratio						1.10	0.87	0.81
F = 6 m	−0.212	−0.029	−0.046	0.030	0.091	0.303***	0.250**	0.204**
	(−1.34)	(−0.31)	(−0.66)	(0.30)	(0.67)	(2.62)	(2.33)	(2.05)
Sharpe Ratio						0.85	0.82	0.79

Panel B: Controlling for common risk factors (in%)

Quintile portfolio returns					Long/short strategy (P5 – P1)			
P1	P2	P3	P4	P5	Full Sample	Pre-Crisis 01/01–11/07	Crisis 12/07–12/10	Post-Crisis 1/11–9/15
Raw portfolio returns								
−0.242*	−0.019	−0.027	−0.030	0.232*	0.474***	0.627***	0.356**	0.338**
(−1.80)	(−0.23)	(−0.29)	(−0.38)	(1.69)	(3.69)	(2.74)	(2.38)	(2.04)
Controlling for SCDS momentum								
−0.264**	−0.088	−0.120*	−0.108*	0.005	0.269***	0.309**	0.110	0.252**
(−2.42)	(−1.43)	(−1.94)	(−1.75)	(0.07)	(3.16)	(2.27)	(0.82)	(2.54)
Controlling for global SCDS returns								
−0.236***	−0.014	−0.021	−0.025	0.241***	0.477***	0.672***	0.342	0.338**
(−3.08)	(−0.42)	(−0.55)	(−0.60)	(3.38)	(3.56)	(2.85)	(1.42)	(2.06)
Controlling for SCDS momentum + global SCDS returns								
−0.142**	0.006	−0.027	−0.016	0.139***	0.281***	0.324*	0.138	0.254**
(−2.41)	(0.15)	(−0.82)	(−0.49)	(3.28)	(3.08)	(1.92)	(0.89)	(2.48)
Controlling for SCDS momentum + global SCDS, momentum and value								
−0.100*	−0.004	−0.035	−0.034	0.140***	0.240***	0.253**	0.156	0.314***
(−1.87)	(−0.09)	(−1.08)	(−0.86)	(3.38)	(2.90)	(2.10)	(0.97)	(2.78)
Controlling for SCDS momentum + global SCDS, momentum and value + US stock market								
−0.097*	−0.012	−0.025	−0.024	0.133***	0.230***	0.211*	0.156	0.377***
(−1.85)	(−0.29)	(−0.76)	(−0.62)	(3.27)	(2.86)	(1.78)	(0.97)	(4.34)

(*continued on next page*)

Table 3
(*continued*)

Panel C: Double sorts on country characteristics and *ExpRet* (in%)

	Portfolio returns in the month following formation					Portfolio returns
	P1	P2	P3	P4	P5	(P5 – P1)
Sort by centrality						
High	−0.045	−0.054	0.012	−0.068	0.167	0.214
	(−0.38)	(−0.67)	(0.19)	(−0.92)	(1.29)	(1.41)
Low	−0.332*	0.042	−0.147	0.059	0.216	0.592***
	(−1.89)	(0.32)	(−0.92)	(0.53)	(1.33)	(3.42)
Sort by credit ratings						
High	−0.067	−0.013	−0.007	0.012	0.118	0.194**
	(−0.95)	(−0.31)	(−0.20)	(0.25)	(1.56)	(2.41)
Low	−0.334*	−0.009	−0.098	−0.026	0.255	0.590***
	(−1.88)	(−0.05)	(−0.60)	(−0.21)	(1.41)	(3.39)
Sort by external debt						
High	−0.437*	−0.130	−0.233	0.113	0.194	0.635***
	(−1.92)	(−0.34)	(−1.02)	(0.56)	(1.43)	(3.12)
Low	−0.220*	−0.027	−0.010	−0.048	0.185	0.414***
	(−1.89)	(−0.34)	(−0.14)	(−0.71)	(0.96)	(2.74)
Sort by the vulnerability index						
High	−0.312*	−0.080	−0.129	−0.065	0.341	0.682***
	(−1.66)	(−0.39)	(−0.80)	(−0.45)	(1.52)	(2.89)
Low	−0.109	0.010	0.012	−0.005	0.059	0.170***
	(−1.65)	(0.24)	(0.32)	(0.11)	(1.08)	(2.72)
Sort by liquidity						
High	−0.226	−0.112	−0.0001	−0.072	0.148	0.374**
	(−1.38)	(−1.15)	(−0.01)	(−0.85)	(1.03)	(2.34)
Low	−0.201	0.099	−0.128	0.043	0.305*	0.548***
	(−1.48)	(0.89)	(−1.16)	(0.48)	(1.81)	(3.26)

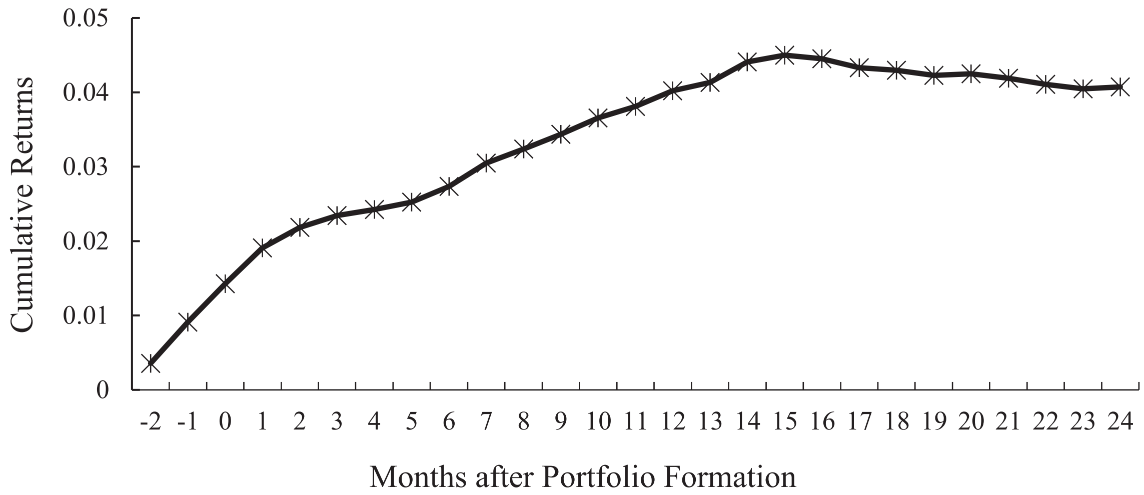

Fig. 3. Buy-and-hold returns to the long-short SCDS portfolio.
This figure shows the cumulative return to the long-short portfolio of SCDS contracts from three months before to twenty-four months after portfolio formation. At the end of month zero, countries are sorted into quintiles based on *ExpRet*, the weighted average SCDS return on a country's export destinations over the past three months, where the weights are proportional to how much the country exported to its export destinations in the prior year.

a monthly alpha of 37 bps for the high liquidity subgroup and 55 bps for the low liquidity subgroup. In other words, the return effect is indeed stronger for less liquid SCDS contracts, consistent with a liquidity-friction view.

4.1.2. Buy-and-hold long-run returns

The ability of $ExpRet_{c,t}$ to forecast cross-sectional variation in average country SCDS returns is consistent with an underreaction interpretation. Investors fail to incorporate the full extent of a country's export destination sovereign credit risk information into the pricing of its own sovereign credit risk in a timely fashion and particularly so for countries on the periphery of the trade network.[13] Of course, an overreaction interpretation is also possible. To differentiate between these two competing interpretations, we calculate the cumulative average return (CAR) of our long/short portfolio starting from 3 months before the formation of the portfolio (with the formation period $F = 3$ months) to 24 months after and plot the results in Fig. 3.

In Fig. 3, the cumulative long/short portfolio return is up 2% at the beginning of the holding period. The long/short portfolio return continues to drift after the initial price response. This drift lasts for about 15 months and generates an additional 2.4% cumulative return. Most importantly, the long/short portfolio return does not show any sign of reversal. These results lend support to our view that SCDS returns underreact to information in a country's export destinations' credit quality.

4.2. Fama-MacBeth regressions

The above results provide evidence of cross-sectional variation in average SCDS returns and support the hypothesis that a country's SCDS price reacts sluggishly to information in the trade network. However, there are at least three alternative explanations of these findings: (1) omitted characteristics, such as own-SCDS momentum, (2) systemic risk factors, and (3) financial links. In this section, we use the Fama-MacBeth regression framework to control for these possible effects and address these concerns (Fama and MacBeth, 1973).

For each month t, we run a cross-sectional regression specified as follows:

$$Ret_{c,t+1} = \alpha + \beta_1 ExpRet_{c,t} + \beta_2 Proxy_{c,t} + X'_{c,t}\gamma + \varepsilon_{c,t}, \quad (2)$$

where $Ret_{c,t+1}$ is country c's SCDS return in month $t+1$. The time-series coefficients in the monthly regressions are averaged following the standard Fama-MacBeth approach, and the standard errors are computed with a Newey-West correction based on 12 lags. $X'_{c,t}$ contains a basic set of macro-variables that control for country characteristics, including GDP growth, inflation, and the export-to-GDP ratio. More importantly, we also control for other alternative interpretations via the inclusion of $Proxy_{c,t}$, variables reflecting other potential explanations of the correlation between $ExpRet_{,}$ and subsequent SCDS returns that we have documented.

4.2.1. Controlling for SCDS momentum

One potential explanation for this return predictability is that our results may instead just reflect a simple momentum phenomenon. Shocks are not slowly propagating from export destination countries to the exporting country but are rather news about the exporting country that is slowly being incorporated into its market price. Simply put, *ExpRet* could be correlated with the exporting country's own past CDS returns. In this section, we provide evidence confirming that *ExpRet*'s predictive power is distinct from an own-country momentum effect. To facilitate comparison with our previous analysis based on quintile sorts, we estimate the effect of the weighted variables in Table 4 after first converting them to quintile dummies.

[13] See Section 5.3 for the complementary evidence of how contemporaneous return links vary with network location.

Table 4
Fama-MacBeth regressions of SCDS returns.

This table reports results of forecasting regressions of monthly sovereign CDS (SCDS) returns. The main independent variable, *ExpRet*, the weighted average SCDS return, is defined in Table 3. The set of controls include the following variables. $ExpStock_t$ ($ExpCurr_t$) is the weighted average stock index (currency) return of a country's export destinations over the past three months. $OwnRet_t$ is the SCDS return for a country over the past three months. $ImpRet_{c,t}$ is the weighted average SCDS return on a country's import sources over the past three months, where the weights are proportional to how much the country imported from its import sources in the prior year. $FDIRet_t^{in}$($FDIRet_t^{out}$) is the weighted average SCDS return on FDI source (destination) countries over the past three months, where weights are proportional to the inward (outward) FDI in the prior year. $PortInvRet_t^{in}$ ($PortInvRet_t^{out}$) is the weighted average SCDS return on inward (outward) portfolio investment countries over the past three months, where the weights are proportional to the inward (outward) bilateral portfolio investment in the prior year. $DistRet_t$ is the weighted average SCDS return over the past three months, where the weights are proportional to the inverse of the logarithm of the geographic distances to countries from the country in question. $ExpGDPGrowth_t$ is the weighted average GDP growth across all export destination countries over the last year, where the weights are proportional to how much the country exported to its export destinations in the prior year. All independent variables are quintile dummies. Other controls that are included in each specification but are not reported include lagged seasonally-adjusted month-over-month inflation, lagged annual GDP growth rate, and the lagged export-to-GDP ratio. We report t-statistics in parentheses that are based on Newey-West standard errors with a lag parameter of 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Forecasting monthly SCDS returns in $(t+1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
$ExpRet_t$	0.083***	0.053**	0.072**	0.091***	0.081**	0.091**
	(4.26)	(2.35)	(2.44)	(2.75)	(2.36)	(2.31)
$ExpStock_t$	0.016	−0.020	−0.024	−0.021	−0.036	−0.042
	(−0.67)	(−0.62)	(−0.70)	(−0.65)	(−1.20)	(−1.43)
$ExpCurr_t$	−0.008	0.017	0.013	0.012	0.003	−0.004
	(−0.24)	(0.60)	(0.46)	(0.40)	(0.12)	(−0.20)
$DistRet_t$		0.011	0.001	0.011	0.016	0.016
		(0.42)	(0.02)	(0.33)	(0.49)	(0.50)
$OwnRet_t$		7.065**	7.594**	7.589**	7.883**	8.003**
		(2.06)	(2.12)	(2.11)	(2.16)	(2.15)
$ImpRet_t$			−0.032	−0.023	−0.031	−0.027*
			(−1.57)	(−1.19)	(−1.61)	(−1.72)
$FDIRet_t^{in}$				−0.021	−0.027	−0.027
				(−0.97)	(−1.31)	(−1.29)
$FDIRet_t^{out}$				−0.014	−0.009	−0.009
				(−0.75)	(−0.60)	(−0.56)
$PortInvRet_t^{in}$					0.017	0.013
					(0.73)	(0.53)
$PortInvRet_t^{out}$					−0.017	−0.014
					(−0.61)	(−0.56)
$ExpGDPGrowth_t$						0.025
						(0.87)
No. of Obs.	173	172	172	172	172	171
Average R^2	0.22	0.25	0.28	0.31	0.34	0.36

In column 1 of Table 4, we only include our export destination news variable, $ExpRet_{c,t}$, in conjunction with the corresponding stock and currency variables, *ExpStock* and *ExpCurr*. In particular, we define

$$ExpStock_{c,t} = \frac{\sum_{i \neq c} Export_{i,y-1}^{c} Ret_{i,\ (t-F+1,t)}^{Stock}}{\sum_{i \neq c} Export_{i,y-1}^{c}}, \tag{3}$$

$$ExpCurr_{c,t} = \frac{\sum_{i \neq c} Export_{i,y-1}^{c} Ret_{i,\ (t-F+1,t)}^{Curr}}{\sum_{i \neq c} Export_{i,y-1}^{c}} \tag{4}$$

where $Ret_{i,\ (t-F+1,t)}^{Stock}$ is country *i*'s US dollar denominated stock index return in the past *F* months and $Ret_{i,\ (t-F+1,t)}^{Curr}$ is country *i*'s US dollar denominated currency return (Menkhoff et al., 2012).

In column 2, we add the past three-month SCDS return *RetOwn* and a variable *DistRet* where, following gravity theory, SCDS returns are weighted by the inverse of log geographic distance. The coefficient on $ExpRet_{c,t}$ in column 2 is 0.0532 (*t*-statistic=2.35), confirming that our finding does not simply reflect either a momentum effect or a simple gravity phenomenon.

4.2.2. Asymmetry between export and import measures

A potential explanation of our findings is that our results may instead reflect other non-trade economic channels. For example, a country's important trading partners may be geopolitically and/or economically similar and thus exposed to a common shock. Therefore, changes in trading partners' sovereign credit quality may simply reflect information about the underlying country's sovereign credit quality. To address this alternative interpretation, we introduce an import-source equivalent of our key variable. Specifically, we measure a weighted average of a country's import source countries' SCDS returns, using the import amount of country *c* as the weight. For country *c*, the change in import source credit quality as of month *t* is calculated as follows:

$$ImpRet_{c,t} = \frac{\sum_{i \neq c} Import_{i,y-1}^{c} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} Import_{i,y-1}^{c}}. \tag{5}$$

$Import_{i,y-1}^{c}$ is country *c*'s import from country *i* in the calendar year before month *t* and $Ret_{i,(t-F+1,t)}$ is the SCDS return of country *i* from month t-*F* + 1 to t, where *F* identifies the formation period similar in the definition of $ExpRet_{c,t}$. As with *ExpRet*, all trade variables are measured in US dollars. We set $F = 3$ for both $ImpRet_{c,t}$ and $ExpRet_{c,t}$ in the following tests.

Since trade is bilateral, a country's export destination countries and the import source countries are usually the same group of countries. Therefore, the main difference between $ImpRet_{c,t}$ and $ExpRet_{c,t}$ is the weight on each trading partner. If a non-trade interpretation is correct, it is not obvious why $ExpRet_{c,t}$ should have stronger predictive power than $ImpRet_{c,t}$. In contrast, our trade network interpretation clearly indicates an asymmetry: $ExpRet_{c,t}$ should have stronger predictive power than $ImpRet_{c,t}$, because a country's sovereign credit risk is affected by changing external demand from its export destination countries, but has little to do with its import source countries' credit risk. We run a horse race between $ExpRet_{c,t}$ and $ImpRet_{c,t}$ to identify which hypothesis better explains the data. As shown in column 3 of Table 4, the coefficient of $ExpRet_{c,t}$ is statistically significant while the coefficient of $ImpRet_{c,t}$ is not. Note that this finding is not due to a multicollinearity issue; the correlation between $ExpRet_{c,t}$ and $ImpRet_{c,t}$ is around 0.5. This asymmetric result lends support to our trade network hypothesis, which makes specific predictions about the direction of the links that matter.

4.2.3. Trading links vs. financial links

We next consider a subtler alternative interpretation based on financial links between countries. The trade links between two countries are often accompanied by financial links. For instance, the US is both China's major export destination country and China's capital inflow source country. A large negative shock to the US economy could affect China through both reduced imports and capital inflows. Bilateral capital flows consist of both FDI, which is long-term direct equity investment, and portfolio investment, which includes both debt and speculative equity investment. To measure FDI flow risk, we define both inward and outward measures, $FDIRet^{in}_{c,t}$ and $FDIRet^{out}_{c,t}$ as follows:

$$FDIRet^{in}_{c,t} = \frac{\sum_{i\neq c} FDI\_inward^{c}_{i,y-1} Ret_{i,(t-F+1,t)}}{\sum_{i\neq c} FDI\_inward^{c}_{i,y-1}} \tag{6}$$

$$FDIRet^{out}_{c,t} = \frac{\sum_{i\neq c} FDI\_outward^{c}_{i,y-1} Ret_{i,(t-F+1,t)}}{\sum_{i\neq c} FDI\_outward^{c}_{i,y-1}}, \tag{7}$$

where $FDI\_inward^{c}_{i,y-1}$ ($FDI\_outward^{c}_{i,y-1}$) is country c's inward (outward) FDI from (to) country i by the end of the calendar year prior to month t.

Similarly, to measure portfolio investment risk, we define an inward portfolio investment risk measure, $PortInvRet^{in}_{c,t}$, and an outward portfolio investment risk measure, $PortInvRet^{out}_{c,t}$, as follows:

$$PortInvRet^{in}_{c,t} = \frac{\sum_{i\neq c} PI\_inward^{c}_{i,y-1} Ret_{i,(t-F+1,t)}}{\sum_{i\neq c} PI\_inward^{c}_{i,y-1}} \tag{8}$$

$$PortInvRet^{out}_{c,t} = \frac{\sum_{i\neq c} PI\_outward^{c}_{i,y-1} Ret_{i,(t-F+1,t)}}{\sum_{i\neq c} PI\_outward^{c}_{i,y-1}}, \tag{9}$$

where $PI\_inward^{c}_{i,y-1}$ ($PI\_outward^{c}_{i,y-1}$) is country c's inward (outward) portfolio investment from (to) country i by the end of the calendar year prior to month t.

We run horse races among $ExpRet_{c,t}$, $FDIRet^{in}_{c,t}$, $FDIRet^{out}_{c,t}$, $PortInvRet^{in}_{c,t}$, and $PortInvRet^{out}_{c,t}$ in a Fama-MacBeth regression setting. As shown in columns 4 and 5 of Table 4, only the coefficient on $ExpRet_{c,t}$ is statistically significant. These results confirm that the return predictability we document stems from trade links rather than from financial links.

4.2.4. Fundamental momentum controls

Another possibility is that SCDS returns are correlated with past fundamental shocks, and it is the latter that predicts future SCDS returns. In column 6, we further control for *ExpGDPGrowth*, the weighted average GDP growth rate across all export destination countries in the past quarter. We construct this variable in a similar fashion to *ExpRet*, except that instead of using past SCDS returns as the proxy for fundamental news, we use past GDP growth. As compared to columns 4 and 5, the coefficient on *ExpRet* is virtually unchanged, while the coefficient on *ExpGDPGrowth* is statistically insignificant. This result emphasizes the usefulness of exploiting a forward-looking price-based measure from the financial markets when identifying the importance of trade networks and the information that these networks propagate.

4.3. SCDS return predictability: robustness

We conduct further robustness checks and present the results in Appendix Table A2. The analyzes are similar to that in Panel B of Table 3 (going long countries with the highest *ExpRet* and short countries with the lowest *ExpRet*). In the regression for all columns, we further control for US market returns, as well as commodity market and carry strategy returns. As can be seen from column 1 of Panel A, including these additional risk factors has virtually no impact on our main results. Column 2 reports portfolio alpha using market-adjusted SCDS returns instead of raw returns when constructing $ExpRet_{c,t}$. Column 3 reports portfolio alpha by scaling the long/short portfolio to have constant volatility following Barroso and Santa Clara (2015). Our results continue to hold. In Panel B of Appendix Table A2, we examine different subsamples. Columns 1–7 show that our key return predictability results continue to hold when we exclude from our sample China (1), safe haven countries (2), G20 countries (3), European Union countries (4), the 10% smallest countries (5), the 10% most illiquid countries (6), and OPEC countries (7).

5. The underlying mechanism

Having established return predictability linked to $ExpRet_{c,t}$, we dig deeper into understanding the mechanisms through which information is incorporated in prices. In this section, we explore whether the predictability in SCDS returns that we document is driven by investors' inattention, whether *ExpRet* also predicts cross-sectional variation in average country-level equity returns, and whether the information in *ExpRet* can be traced back to information about fundamentals. We also examine the extent to which information in trade networks is informative about contemporaneous links among countries.

Table 5
Direct vs. indirect trade links.
This table reports regressions forecasting weekly sovereign CDS (SCDS) returns. The dependent variable is the weekly SCDS return in the following one to eight weeks. The main independent variables are *ExpRet*, the weighted average SCDS return on a country's export destinations over the past three months, where the weights are proportional to how much the country exported to its export destinations in the prior year, and *ExpRetInd*, the square of the import-export matrix multiplied by the vector of SCDS returns. We also include the following control variables (not reported for brevity): exporting countries' own past three-month SCDS returns, lagged seasonally-adjusted inflation (month-over-month), the lagged one-year GDP growth rate, and the lagged one-year export-to-GDP ratio. All independent variables are measured at the end of week *t*. We report *t*-statistics in parentheses that are based on Newey-West standard errors with a lag parameter of 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Forecasting weekly SCDS returns in $(t+k)$							
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$
$ExpRet_t$	0.110***	0.096**	0.060	0.072*	0.025	0.013	0.008	0.014
	(2.66)	(2.00)	(1.48)	(1.92)	(0.60)	(0.36)	(0.24)	(0.38)
$ExpRetInd_t$	0.032	0.076	0.098**	0.141***	0.066	0.089*	0.046	0.009
	(0.70)	(1.55)	(2.00)	(2.65)	(1.30)	(1.77)	(0.89)	(0.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	746	746	746	746	746	746	746	746
Adj. R^2	0.003	0.004	0.004	0.004	0.004	0.004	0.004	0.004

5.1. Indirect trade links

If investors underreact to the information contained in direct trade network information, incorporating news from indirect network links should take longer. For example, China is Australia's major export destination country, while the US is the biggest export destination for China. The 2008 Subprime Crisis resulted in a sovereign credit risk shock to the US and a significant contraction of US imports from China, which dampened China's economic growth. This dampening in turn reduced China's import of raw materials from Australia, reducing Australian sovereign credit quality. Therefore, China provides an indirect link through which US sovereign credit quality shocks should propagate to Australia.

To measure information concerning the credit quality of a country's indirect export destinations, we premultiply *ExpRet* with the *Trade* matrix, and generate the indirect version of our measure, $ExpRetInd_{c,t}$. We measure the incremental information flow occurring through direct and indirect channels by estimating a (Fama and MacBeth, 1973) regression with the following specification:

$$Ret_{c,t+h} = \alpha + \beta_1 ExpRet_{c,t} + \beta_2 ExpRetInd_{c,t} + Controls + \varepsilon_{c,t}. \quad (10)$$

$ExpRet_{c,t}$ and $ExpRetInd_{c,t}$ are calculated using the cumulative SCDS return over the previous 12 weeks and then converted to quintile dummies. The control variables include the country's own CDS returns in the past 12 weeks, lagged monthly inflation, lagged annual GDP growth rate, and lagged export-to-GDP ratio.

The regression results are shown in Table 5. These estimates indicate that in the first and second weeks after the sorting week ($h = 1, 2$), the coefficients on $ExpRet_{c,t}$ are statistically larger than the corresponding coefficients on $ExpRetInd_{c,t}$. Moreover, only the coefficients on $ExpRet_{c,t}$ are statistically significant. However, in the third and fourth weeks, the coefficients on $ExpRetInd_{c,t}$ increase and become statistically significant. The regression results show that investors respond more rapidly to information in direct links than to information in indirect links but that indirect links nevertheless provide incremental information that is relevant for returns. This finding supports the idea that information complexity plays an important role in the speed of information processing.

5.2. Spillover from the SCDS market to the stock market

A natural follow-up question is whether this trade information is relevant for the stock market. To measure cross-market predictability, we create a long-short portfolio in the cross-section of country equity. Specifically, we sort countries into quintiles according to their past three-month export destination credit risk proxy $ExpRet_{c,\ t}$ at the end of each month. We then go long the stock indices of countries in the lowest quintile and sell short stock indices of countries in the highest quintile, holding the resulting portfolio for one month. In the first row of Panel A of Table 6, we report the average return of the stock indices in each quintile and the long-short portfolio P1–P5. As can be seen, the long-short portfolio generates a monthly return of 0.99%, with a *t*-statistic of 3.26 and a Sharpe ratio of 0.95. Moreover, the monthly equity index return declines monotonically from portfolios P1 to P5.

To document the robustness of our finding, we report the average abnormal returns on the long-short portfolio P1–P5 after controlling for various risk factors. In the second row of Panel A of Table 6, we control for an own stock index momentum factor based on a three-month formation period and a one-month holding period. In the third row, we control for the equal-weighted average return of all the stock indices in our sample. We include both the market average return and the momentum return in the fourth row and further control for the global momentum and value factors in the fifth row. Average abnormal returns are statistically significant across all specifications. This finding lends further support to our argument that markets, including not only credit markets but also stock markets, incorporate trade network information in a sluggish fashion.

We investigate whether a trade-weighted measure using stock returns (instead of SCDS returns) can predict cross-sectional variation in average country equity returns. We include both $ExpRet_{c,t}$ and $ExpStock_{c,t}$ in a Fama-

Table 6
Forecasting stock market returns.

In this table, we examine the ability of SCDS returns to forecast future stock market index returns. Panel A reports calendar-time portfolio returns of stock market indices. At the end of each month, stock market indices are sorted into five groups (P1–P5) based on the weighted average SCDS return *ExpRet*, which is defined in Table 3. All countries are equally weighted within a given portfolio, and the portfolios are held for one month. The first row reports raw portfolio returns. The second row reports portfolio alpha after controlling for the stock market index momentum factor. The third row reports portfolio alpha after controlling for the equal-weight global stock market return. The fourth row reports portfolio alpha controlling for both the momentum factor and global stock market factor. Row five further includes the global momentum and value factors (as in Asness et al. 2013). Panel B reports forecasting regressions of monthly stock index returns on lagged SCDS returns. The main independent variable is *ExpRet*. Other control variables include $ExpStock_t$ ($ExpCurr_t$), the weighted average stock index (currency) returns across all export destination countries in the past three months. $DistRet_t$ is the weighted average stock return in the past three months, where the weight is proportional to the inverse of the logarithm of the geographic distance. We further control for the country's previous-month stock market return ($OwnStock_t$), currency return ($OwnCurr_t$), seasonally-adjusted month-over-month inflation, the previous-year GDP growth rate, and the export-to-GDP ratio. We report t-statistics in parentheses that are based on Newey-West standard errors with a lag parameter of 12. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calendar-time stock market portfolio returns (in%)

P1	P2	P3	P4	P5	P1 − P5
Raw portfolio returns					
1.578***	1.310**	0.974*	0.909*	0.585	0.993***
(2.75)	(2.27)	(1.81)	(1.76)	(1.03)	(3.26)
Controlling for stock index momentum (formation period = 3 months, holding period = 1 month)					
1.820***	1.368**	1.063**	1.009**	0.712	1.108***
(3.55)	(2.59)	(2.13)	(2.02)	(1.26)	(3.39)
Controlling for global stock market returns					
0.482**	0.250**	−0.059	−0.143	−0.494***	0.975**
(2.28)	(2.55)	(−0.59)	(−1.12)	(−3.30)	(2.94)
Controlling for SCDS momentum + global stock market returns					
0.633***	0.162**	−0.100	−0.173	−0.492***	1.126***
(2.77)	(2.02)	(−0.95)	(−1.30)	(−2.74)	(2.93)
Controlling for SCDS momentum + global stock market returns, momentum and value					
0.633***	0.187**	−0.129	−0.266*	−0.413***	1.046***
(3.30)	(2.00)	(−1.23)	(−1.77)	(−3.10)	(3.74)

Panel B: Fama-MacBeth regressions of future stock market returns (in%)

	(1)	(2)	(3)	(4)
$ExpRet_t$	−0.196***	−0.177***	−0.169***	−0.101**
	(−4.22)	(−3.74)	(−3.75)	(−2.02)
$ExpStock_t$	0.173***	0.137**	0.117*	0.119**
	(2.75)	(2.26)	(1.95)	(1.98)
$ExpCurr_t$	0.004	0.010	−0.073	−0.0517
	(0.07)	(0.17)	(−1.11)	(−0.89)
$OwnStock_t$		2.697***	3.899***	4.402***
		(3.02)	(4.55)	(5.15)
$OwnCurr_t$			9.654***	9.530***
			(3.59)	(3.55)
$DistRet_t$				0.089*
				(1.75)
$Inflation_t$				1.395
				(0.08)
$GDPGrowth_t$				0.066*
				(1.92)
$ExportToGDP_t$				−0.117
				(−0.73)
No. of Obs.	173	173	173	173
Adj-R^2	0.08	0.12	0.16	0.24

MacBeth regression framework to test which variable is more informative.

The results are reported in the Panel B of Table 6. In the regression for column 1, we run a horse race among $ExpRet_{c,t}$, $ExpStock_{c,t}$ and $ExpCurr_{c,t}$ and find that the coefficient on $ExpRet_{c,t}$ remains negative and statistically significant, although $ExpStock_{c,t}$ does have some predictive power. In the regression for column 2, we add the stock market return over the past three months to control for a country-level stock market momentum effect and find that the coefficient of $ExpRet_{c,t}$ is still negative and statistically significant. In the regression for columns 3 and 4, we further include the currency market return over the past three months to control for a currency momentum effect, as well as macroeconomic variables including inflation, GDP growth, and the export-to-GDP ratio. We find

Table 7
Determinants of comovement in SCDS returns.

This table reports the regression results of pairwise comovement in SCDS returns on bilateral export shares. The dependent variable in both columns 1 and 2 is the correlation in SCDS returns between two countries, measured using monthly returns in each year. The main independent variable of interest, $ExpShare^{AVG}_{i,j,t}$, is the average fraction of country i and j's total exports that are accounted for by their bilateral trade. Other control variables include: *Distance*, the logarithm of the level of geographic distance between the two countries; *Language*, a dummy variable that equals one if the two countries speak a common official language and zero otherwise; *Colony* is a dummy variable that equals one if the two countries had a colonial relationship in the past and zero otherwise. Year and region-pair fixed effect are included in both columns. We report t-statistics based on standard errors double-clustered by both year and country pair in parentheses with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) $Correlation_{i,j,t}$	(2) $Correlation_{i,j,t}$
$ExpShare^{AVG}_{i,j,t}$	0.616***	0.636***
	(2.91)	(2.83)
Distance		−0.004
		(−0.26)
Language		0.004
		(0.26)
Colony		−0.036
		(−1.31)
Double cluster	Yes	Yes
Year fixed effect	Yes	Yes
Region pair fixed effect	Yes	Yes
No. of pairs	3380	3380
No. of years	15	15
Adj-R^2	0.113	0.114

that the coefficients on $ExpRet_{c,t}$ remain negative and statistically significant. For comparison, as shown in Table 4, $ExpStock_{c,t}$ does not forecast the country's future SCDS returns. In other words, the sovereign credit market incorporates information faster than equity markets.

A potential explanation for this finding is that stock returns are noisier because they are much more affected by the sentiment of retail investors, while SCDS, a complex financial derivative, is only traded by large sophisticated financial institutions. In Online Appendix Table A6, we compare the relation between investor sentiment and future returns across these two different markets. As can be seen in columns 1–4, Baker and Wurgler's (2006) well-known sentiment index strongly negatively forecasts US stock market returns 1–12 months in the future. In sharp contrast, as shown in columns 5–8, we are unable to reject the hypothesis that the same sentiment index is uncorrelated with US SCDS returns over comparable forecasting horizons.

5.3. Contemporaneous covariance

In Table 7, we examine the way country SCDS contemporaneous return correlations vary with export activity.[14] In particular, we estimate a regression explaining the pairwise correlation of SCDS returns using $ExpShare^{AVG}_{i,j,t-1}$, the average fraction of country i and j's total exports that are accounted for by their bilateral trade in the previous year.[15] We first focus on explaining the correlation component using $ExpShare^{AVG}_{i,j,t-1}$ in the presence of year and region pair fixed effects (we list these regions in Appendix Table A1, Panel B). The estimate is statistically significant (t-statistic = 2.91).

Column 2 of Table 7 documents that this finding is robust to controlling for distance, language, and colony—pairwise characteristics often used to identify similar countries. In results not reported, if we instead forecast weighted covariances (i.e., the full second term in Online Appendix Eq. (1)), the resulting t-statistic increases to 8.49 and the R^2 nearly triples to 30.8%.

In Section 2 of the Online Appendix, we trace the propagation of shocks reflected in weekly SCDS returns through trade links using the identification through heteroscedasticity (ITH) method of Rigobon (2003). That analysis shows that shock propagation in SCDS returns is strongly related to export links but not to import links.

The analysis in the Online Appendix further connects these results to those in Section 4 by pointing out that whether our findings are increasing or decreasing with network centrality critically depends on whether we measure the response using contemporaneous or lagged returns. Since investors' inattention leads to slow information transmission, countries in the center of the trade network should experience stronger effects when it comes to contemporaneous return links. In other words, high "centrality" countries in the trade network should have weaker SCDS return predictability but stronger contemporaneous links according to our limited-attention hypothesis. In contrast, higher financial vulnerability should result in a large effect both in contemporaneous and future returns. Our results in the Online Appendix confirm that the heterogeneity that we find in SCDS return predictability is also present in contemporaneous links exactly as we have predicted.

5.4. Forecasting country fundamentals

We now provide evidence that $ExpRet_{c,t}$ indeed contains information about real economic activity that is directly relevant to a country's sovereign credit risk. We use a panel regression to measure the information in $ExpRet_{c,t}$ concerning subsequent real economic activity. Specifically, we regress year $t+1$ export growth and GDP growth on $ExpRet_{c,t}$, which is calculated in the December of year t with a formation period $F = 12$. We forecast annual growth so that all countries in our sample are included in the analysis since higher-frequency export or GDP growth is not widely available. Our results are robust to using other formation periods when measuring $ExpRet_{c,t}$.

The results in Panel A of Table 8 first confirm that a country's SCDS return, $OwnRet_{c,t}$, forecasts its own imports. If a country is performing relatively poorly in terms of

[14] We provide additional evidence for the decomposition of the variance-covariance matrix of SCDS returns in Section 1 of the Online Appendix.

[15] We exploit the technique of Anton and Polk (2015), who introduce this methodology to forecast cross-sectional variation in firm-level stock return correlations.

Table 8
SCDS returns forecasting real economic outcomes.

This table reports regression results forecasting real economic outcomes with SCDS returns. The dependent variable in Panel A is the import growth of each country in year $t+1$. The main independent variable of interest is the corresponding country's SCDS return in year t ($OwnRet_t$). Other control variables include the country's equity market return ($OwnStock_t$), currency return ($OwnCurr_t$), as well as import growth and GDP growth, all measured in year t. Panel B reports regression results for forecasting exporting countries' future export growth, GDP growth, and changes in the external debt-to-GDP ratio with the importing countries' SCDS returns. The dependent variable in columns 1 and 2 is an exporting country's export growth rate in year $t+1$, in columns 3 and 4 it is its GDP growth rate in year $t+1$, and in columns 5 and 6, it is the annual growth in the external debt to GDP ratio in year $t+1$. The main independent variable of interest is $ExpRet_t$, the weighted average SCDS return on a country's export destinations over the past one year, where the weights are proportional to how much the country exported to its export destinations in the prior year. Other control variables include similar export-weighted averages of export destinations equity market returns ($ExpStock_t$) and currency returns ($ExpCurr_t$), as well as the exporting country's own SCDS return, $OwnRet_t$, export growth, GDP growth and external debt to GDP ratio. All independent variables are standardized to have a mean of zero and standard deviation of one. Time fixed effects are included in all specifications. We report t-statistics based on standard errors double-clustered by time and country in parentheses with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Forecasting import growth (in%)

	(1)	(2)	(3)	(4)	(5)
$OwnRet_t$	−2.134***	−2.183***	−1.988***	−1.972**	−1.963**
	(−2.83)	(−3.10)	(−2.86)	(−2.49)	(−2.54)
$OwnStock_t$				2.651***	2.501***
				(4.83)	(4.47)
$OwnCurr_t$					−0.543
					(−0.98)
$ImportGrowth_t$		1.837*	−0.209	−0.300	−0.390
		(1.67)	(−0.24)	(−0.32)	(−0.44)
$GDPGrowth_t$			4.299***	3.834***	3.802***
			(5.31)	(4.95)	(4.94)
Time FE	Yes	Yes	Yes	Yes	Yes
No. of Obs.	866	864	864	768	756
Adj. R^2	0.51	0.52	0.54	0.56	0.56

Panel B: Forecasting growth in exports, GDP, and external debt to GDP (in%)

	$ExportGrowth_{t+1}$		$GDPGrowth_{t+1}$		$\Delta ExDebt/GDP_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$ExpRet_t$	−1.598**	−1.645**	−0.406***	−0.340***	1.350**	1.396**
	(−2.16)	(−2.09)	(−4.73)	(−3.89)	(2.31)	(2.31)
$ExpStock_t$	4.159	3.796	2.027***	1.843***	0.721	1.179
	(1.01)	(0.93)	(2.80)	(2.75)	(0.42)	(0.72)
$ExpCurr_t$	0.425	0.065	0.222	0.599*	1.281	1.622
	(0.30)	(0.04)	(0.51)	(1.86)	(1.00)	(1.31)
$OwnRet_t$	−0.510	−0.502	−0.687***	−0.558***	0.865***	0.837***
	(−0.59)	(−0.57)	(−2.81)	(−2.91)	(3.14)	(3.11)
$ExportGrowth_t$		−1.855				
		(−0.76)				
$GDPGrowth_t$				2.502***		
				(8.73)		
$ExDebt/GDP_t$						−1.065**
						(−2.56)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	981	981	980	980	409	409
Adj. R^2	0.62	0.63	0.28	0.53	0.20	0.22

credit quality, its future imports are relatively low. The results in column 1 indicate that the return on a country's SCDS has information about that country's import activity. Subsequent results indicate that this predictive ability is robust to including lagged import growth, lagged GDP growth, $OwnStock_{c,t}$, and $OwnCurr_{c,t}$ in the regressions. Of particular note is the fact that a country's currency movements do not have any incremental ability to forecast important activity.[16] This result continues to hold if we exclude countries in the Euro area, which share a common currency, from the analysis.

We next exploit the trade network to examine the way this information propagates in the global macro-economy. In Panel B of Table 8, column 1,2 report the results of regressions forecasting export growth. In the regression, we control for variation in a country's own lagged annual SCDS return, $OwnRet_{c,t}$, as well as for variation in its lagged annual export growth, $ExportGrowth_{c,t}$. We also include $ExpStock$ and $ExpCurr$, the stock return and currency return counterparts of $ExpRet$ (i.e., instead of SCDS returns, we now aggregate stock market returns and currency returns across export destinations).

A country's export growth is importantly determined by its export destination countries' demand, which is af-

[16] In contrast, Panel A of Table 8 shows that $OwnStock_{c,t}$ does have significant information about a country's subsequent import growth. However, Panel B shows that the ability of $ExpStock_{c,t}$ to forecast a country's export growth is largely subsumed by $ExpRet_{c,t}$.

fected by these countries' sovereign credit risk. Therefore, a high $ExpRet_{c,t}$, which implies a decrease in trading partners' sovereign credit quality, should predict low export growth. Columns 1,2 show that the coefficient on $ExpRet_{c,t}$ is indeed negative and statistically significant. To aid in interpretation, all forecasting variables are normalized to have a unit standard deviation. We find that a one-standard-deviation increase in $ExpRet_{c,t}$ reduces next year's export growth by 1.64% after controlling for information in lagged stock and currency returns, as well as lagged export growth. No other variable is significant in our full specification.

We repeat this analysis using GDP growth. Given the importance of export activity for the typical country in our sample (Table 1 shows that the average export-to-GDP ratio is 47.5%), it is natural to expect that $ExpRet_{c,t}$ should predict GDP growth as well. The regression results in columns 3,4 of Panel B in Table 8 confirm this intuition; the coefficient on *ExpRet* is negative and statistically significant after controlling for lagged stock market and currency returns, as well as the lagged annual GDP growth rate. A one-standard-deviation increase in the export destination risk leads to a decline of 0.34 percentage points in a country's GDP growth in the following year.

For a more precise test of the link between the news about a country's export destinations and its SCDS returns, we examine changes in the export country's external-debt-to-GDP ratio.[17] This ratio directly reflects the sustainability of the debt burden; as a result, variation in this ratio is more closely related to changes in the probability of sovereign default and thus SCDS returns. Columns 5 and 6 in Panel B of Table 8 show that SCDS returns are a strong predictor of $\triangle ExDebt/GDP_{t+1}$. Specifically, we find that the coefficient on $ExpRet_t$ is 1.350 (t-statistic=2.31). Moreover, that coefficient is not only robust to controlling for $ExpStock_t$, $ExpCurr_t$, and $OwnRet_t$, but is also robust to controlling for the lagged external-debt-to-GDP ratio ($ExDebt/GDP_t$).

5.5. The asymmetry between upstream and downstream links

Carvalho et al. (2021) examine the role of individual firms in the supply chain. Specifically, they show that when an individual firm is "removed" from the supply chain (due to, for example, a natural disaster), both its suppliers and customers experience production interruptions in the short run; thus, the effects on upstream and downstream links are symmetric.

This mechanism, however, does not directly apply to our setting. When a country's sovereign credit risk goes up (e.g., because of a depletion of foreign reserves), its ability to import from another country goes down (as the country can no longer pay in foreign currencies). The country's ability to export, however, should not be severely damaged. Indeed, the country now has a stronger incentive to export (to rebuild its foreign reserves) and is also poised to benefit from a weaker currency.

In Online Appendix Table A7, we examine the relation between a country's SCDS returns and its subsequent export growth to confirm that the asymmetry we find in predicting returns is also present in predicting fundamentals. As shown in Panel A of the table, SCDS returns do not forecast the own country's future export growth. This finding is in sharp contrast to the result in Panel A of Table 8, where we show that own SCDS returns are a strong predictor of the country's future import growth.

In Panel B of Online Appendix Table A7, we further analyze whether *ImpRet* (the weighted average SCDS returns of upstream countries) helps forecast downstream countries' import growth. Consistent with the result shown in Panel A, we do not find a significant relation between *ImpRet* and the downstream country's import growth.

5.6. Linking variation in global SCDS returns to macroeconomic quantities

Finally, we conduct a time-series analysis of the relation between global SCDS returns and global macro-economic conditions. Specifically, we define the global SCDS return, $Ret_{g,t}$, as:

$$Ret_{g,t} = \sum_i w_{i,t-1} * Ret_{i,t}, \tag{11}$$

where the weight, $w_{i,t}$, is measured as the share of global exports for country i at time t,

$$w_{i,t} = \frac{export_{i,t}}{export_{g,t}}. \tag{12}$$

We measure $export_{i,t}$ as the total export of country i at time t and $export_{g,t}$ as the aggregate export activity for all 88 countries in our sample at time t. We define the global SCDS spread in a similar fashion.

In the top panel of Fig. 4, we plot quarterly values of the global SCDS spread against global GDP growth.[18] We calculate global GDP as the trade-weighted average of quarterly real GDP growth over the 88 countries in our sample in order to be consistent with the calculation of the global SCDS spread. We find a strong negative correlation (−0.58) between these variables.

In the bottom panel of Fig. 4, we repeat this exercise using trade-weighted PMI. This variable has the benefit of being a monthly measure of economic activity that is available for a large cross-section of countries over a relatively long period of time and that is widely used by investors as a barometer of economic conditions. Fig. 4 shows that monthly variation in the global SCDS spread is strongly negatively correlated (−0.65) with economic conditions measured by PMI.

6. Conclusions

We introduce a novel way of tracing the propagation of country-level shocks in the global trade network.

[17] We focus on debt denominated in foreign currencies here, as debt denominated in local currencies can be "inflated" away. All credit events of SCDS contracts in our sample are triggered by default of external sovereign debts. See http://www.creditfixings.com/CreditEventAuctions/fixings.jsp for detailed information on each SCDS credit event.

[18] See Section 3 of the Online Appendix for additional regression results.

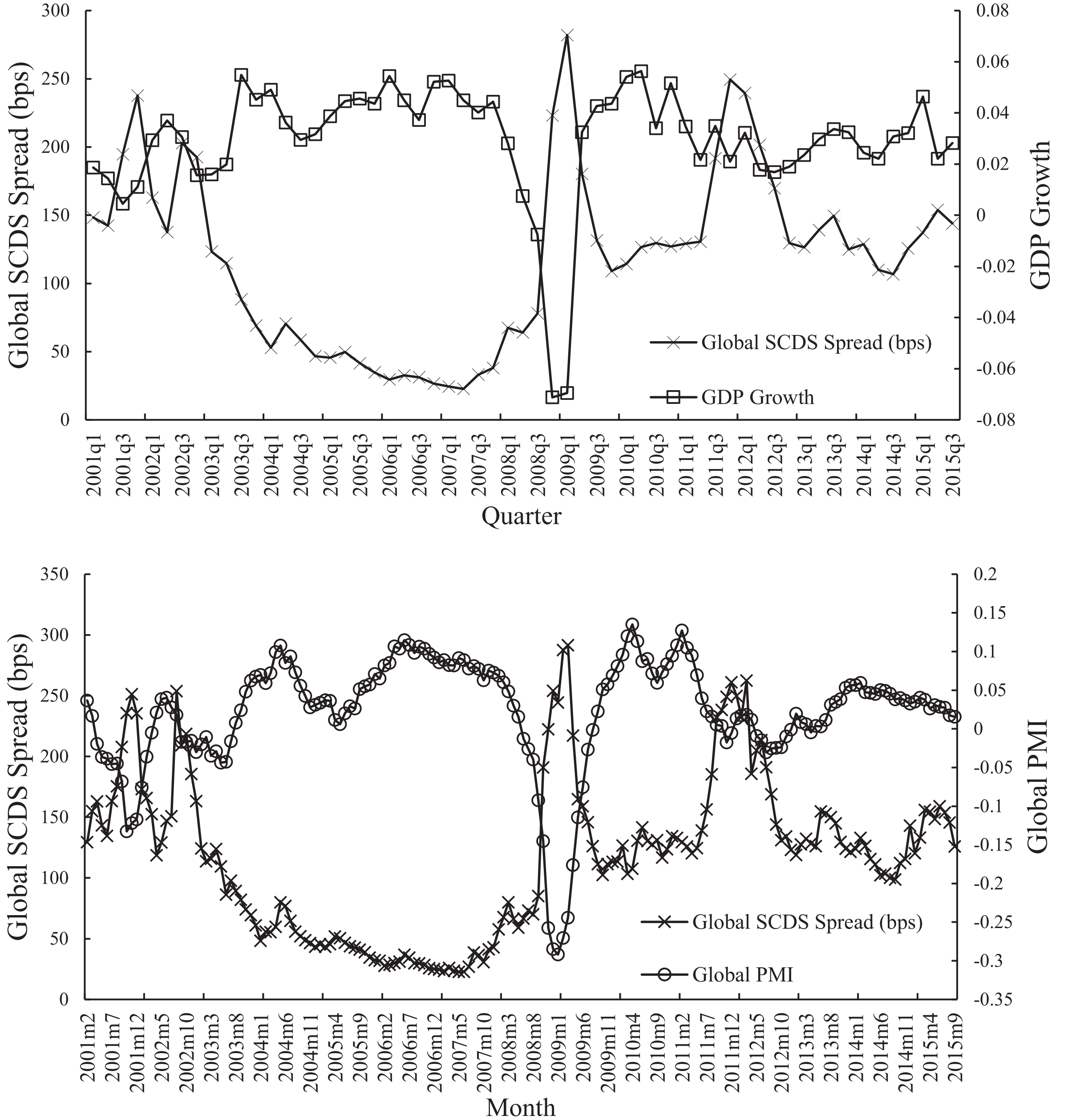

Fig. 4. Global SCDS spreads (bps) and real economic outcomes.
This figure shows the time series of global SCDS spreads vs. real economic outcomes (GDP growth rates and Purchasing Managers' Index) measured contemporaneously. All variables are calculated as the trade-weighted averages across all countries in our sample.

Our analysis provides a new perspective on the importance of trade links by exploiting information contained in sovereign credit default swap (SCDS) contracts. Our novel approach reveals that trade links play a significant role in driving global SCDS returns, with information flowing from importers to exporters.

We first use two natural experiments (the Japanese tsunami and the Wuhan COVID-19 lockdown) to confirm the causal importance of the trade network, with local shocks spreading from these two shocked countries to other countries. We then establish broader return predictability as countries respond, both immediately and with a substantial lag, to news contained in their export destinations countries' SCDS returns. The size of the response depends both on the financial vulnerability of the country in question and its location in the network. In particular, the immediate response is weaker, and the lagged response is stronger for those countries on the periphery of the trade network.

Consistent with the importance of a network understanding of macroeconomic activity, we find that indirect links matter as well: A country's fundamentals depend not only on the quality of the fundamentals of its direct trading partners but also indirectly on the quality of those trading partners' trading partners. Additional analyzes support our narrative; for example, our measure of trade network news not only describes cross-sectional variation in country credit returns but also describes cross-section variation in country equity returns. Our work is the first macroeconomic confirmation of the causal importance of network theories of shock propagation to country-level credit/equity markets using forward-looking financial variables.

References

Acemoglu, D., Carvalho, V., Ozdaglar, A., Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. Econometrica 80, 1977–2016.

Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A., 2013. The network origins of large economic downturns. NBER working paper, 19230 doi:10.3386/w19230.

Acharya, V., Johnson, T., 2007. Insider trading in credit derivatives. J. Financ. Econ. 84, 110–141.

Acharya, V., Drechsler, I., Schnabl, P., 2014. A pyrrhic victory? Bank bailouts and sovereign credit risk. J. Financ. 69, 2689–2739.

Aizenman, J., Hutchison, M., Jinjarak, Y., 2013. What is the risk of European sovereign debt defaults? Fiscal space, CDS spreads and market pricing of risk. J. Int. Money Financ. 34, 37–59.

Albuquerque, R., Ramadorai, T., Watugala, S., 2015. Trade credit and cross–country predictable firm returns. J. Financ. Econ. 115, 592–613.

Allen, F., Babus, A., 2008. Networks in Finance. Wharton Financial Institutions Center Working Paper No. 08-07.

Anton, M., Polk, C., 2015. Connected stocks. J. Financ. 69, 1099–1127.

Asness, C., Tobias, M., Pedersen, L., 2013. Value and momentum everywhere. J. Financ. 68 (3), 929–985.

Augustin, P., Tédongap, R., 2016. Real economic shocks and sovereign credit risk. J. Financ. Quant. Anal. 51, 541–587.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61 (4), 1645–1680.

Barroso, P., Santa-Clara, P., 2015. Momentum has its moments. J. Financ. Econ. 116, 111–120.

Barrot, J., Sauvagnat, J., 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. Q. J. Econ. 131 (3), 1543–1592.

Beirne, J., Fratzscher, M., 2013. The pricing of sovereign risk and contagion during the European sovereign debt crisis. J. Int. Money Financ. 34, 60–82.

Black, F., 1975. Fact and fantasy in the use of options. Financ. Anal. J. 31, 36–72.

Campbell, J., 1991. A variance decomposition for stock returns. Econ. J. 101, 157–179.

Campbell, J., Giglio, S., Polk, C., Turley, R., 2018. An intertemporal CAPM with stochastic volatility. J. Financ. Econ. 128, 207–233.

Carvalho, V., Nirei, M., Saito, Y., Tahbaz-Salehi, A., 2021. Supply chain disruptions: evidence from the great east japan earthquake. Q. J. Econ. 136, 1255–1321.

Cohen, L., Lou, D., 2012. Complicated firms. J Financ. Econ. 104, 383–400.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. J. Financ. 63, 1977–2011.

DellaVigna, S., Pollet, J., 2007. Demographics and industry returns. Am. Econ. Rev. 97, 1667–1702.

di Giovanni, J., Levchenko, A., Medjean, I., 2014. Firms, destinations, and aggregate fluctuations. Econometrica 82, 1303–1340.

di Giovanni, J., Levchenko, A., Mejean, I., 2020. Foreign shocks as granular fluctuations. NBER working paper 28123. doi:10.3386/w28123.

Easley, D., O'Hara, M., Srinivas, P., 1998. Option volume and stock prices: evidence on where informed traders trade. J. Financ. 53.

Fama, E., French, K., 1989. Business conditions and expected returns on stocks and bonds. J. Financ. Econ. 25, 23–49.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. The Journal of Political Economy 81 (3), 607–636.

Frankel, J., Rose, A., 1998. The endogeneity of the optimum currency area criteria. Econ. J. 108, 1009–1025.

Gabaix, X., 2011. The granular origins of aggregate fluctuations. Econometrica 79, 733–772.

Hilscher, J., Pollet, J., Wilson, M., 2015. Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets. J. Financ. Quant. Anal. 50 (3), 543–567.

Imbs, J., 2004. Trade, finance, specialization, and synchronization. Rev. Econ. Stat. 86, 723–734.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Financ. 48 (1), 65–91.

Kramarz, J., Martin, J., Mejean, I., 2020. Volatility in the small and in the large: the lack of diversification in international trade. J. Int. Econ. 122, 1–19.

Lee, J., Narnjo, A., Sirmans, S., et al., 2016. Exodus from sovereign risk: global asset and information networks in the pricing of corporate credit risk. J. Financ. 71 (4), 1813–1856.

Lee, J., Narnjo, A., Sirmans, S., 2021. CDS momentum: slow moving credit ratings and cross-market spillovers. Rev. Asset Pricing Stud. 11, 352–401.

Longstaff, F., Pedersen, L., Pan, J., Singleton, K., 2011. How sovereign is sovereign credit risk. Am. Econ. J. Macroecon. 3 (2), 75–103.

Lucas, R., 1977. Understanding business cycles. Carnegie Rochester Conf. Ser. Public Policy 5, 7–29.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Currency momentum strategies. J. Financ. Econ. 106, 660–684.

O'Kane, D., 2011. Modeling Single-Name and Multi-Name Credit Derivatives. John Wiley & Sons.

Pan, J., Poteshman, A., 2006. The information in option volume for future stock prices. Rev. Financ. Stud. 19, 871–908.

Pan, J., Singleton, K., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. J. Financ. 63, 2345–2384.

Richmond, R., 2019. Trade network centrality and currency risk premia. J. Financ. 74 (3), 1315–1361.

Rigobon, R., 2003. Identification through heteroscedasticity. Rev. Econ. Stat. 85, 777–792.

RodrÍguez, I., Dandapani, K., Lawrence, E., 2019. Measuring sovereign risk: are CDS spreads better than sovereign credit ratings? Financ. Manag. 48, 229–256.

Shiller, R., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? Am. Econ. Rev. 71, 421–436.

Wang, X., Xiao, Y., Yan, H., Zhang, J., 2021. Under reaction in the sovereign CDS market. J. Bank. Financ. 130, 106191.

Xiao, Y., Yan, H., Zhang, J., 2021. A global version of Samuelson's dictum. working paper. doi:10.2139/ssrn.3810241.