Trade Networks and Asset Prices: Evidence from the SCDS Market*

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Abstract

We exploit the information in sovereign credit default swap (SCDS) prices and the international trade network to reveal novel facts about the propagation of shocks in the global macroeconomy. We show that country fundamentals depend on both direct and indirect links in the trade network. Recognizing these links reveals novel variation in average return for the cross-section of country-level equity and credit, which we argue reflects an underreaction phenomenon occurring on a global scale. Specifically, a portfolio that goes long SCDS with the largest increase in export destinations' credit risk and sells short SCDS with the largest decrease generates an average return of nearly 6% per year with a Sharpe ratio of 1.1. This transmission of value-relevant information across countries is even slower for indirect trade links. We exploit a natural experiment to confirm causality and a variance decomposition exercise to link a significant proportion of global volatility to the trade network.

JEL Classification Number: G12.

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I. Introduction

A growing literature studies the microeconomic foundations of macroeconomic shocks. A crucial aspect of this approach is understanding how shocks to sectors (Acemoglu et al., 2012) or firms (Gabaix, 2011) aggregate up through the corresponding economic network. A key takeaway from this work is that the nature of the network matters. In stark contrast to Lucas (1977), where microeconomic shocks wash out and have negligible effect on aggregate outcomes, the interconnectedness of sectors and firms provides a network-based view of what drives aggregate fluctuations.

We exploit the evolution of trade networks at the country level to reveal novel facts about the propagation of shocks in the global macroeconomy. We document that 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. Thus, our work adds to the growing literature that tries to differentiate between the transmission of idiosyncratic shocks versus exposure to common global shocks (for example, di Giovanni, Levchenko, and Mejean, 2017). Unlike these other papers, our focus is on understanding the country-level international trade network.

Our analysis provides a new perspective on these trade links by exploiting information contained in the sovereign credit default swap (SCDS) contracts on foreign currency denominated debt of over 80 developed and developing countries. These relatively liquid assets, compared to sovereign bond markets, may provide a useful barometer of a country's well-being.[1] This close link to country fundamentals contrasts with equity markets where only a small proportion of the variation is because of cash-flow news (Shiller 1981).[2] Thus, one of our contributions to the literature is the use of financial

[1] Longstaff et al. (2011) investigate the extent to which local and global factors can explain variation in credit spreads.

[2] Shiller'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 because of

data to study the transmission role of networks. This aspect of our approach allows us to examine the importance of the trade network not only at a higher frequency but also using forward-looking asset prices, which should capitalize the value of information contained in these links. Recognizing these links allows us to describe novel variation in risk and average return for the cross-section of country equity and credit.

To motivate our analysis, we document the links between a country's CDS returns and the exporting country's underlying fundamentals. We first confirm that a country's CDS returns forecast its own imports: If a country is performing relatively poorly in terms of credit quality, its future imports are relatively low.

What might be the specific mechanism? Not only does poorer sovereign credit quality reflect the general health of the country in question, sovereign ratings are an effective ceiling on firm credit ratings within the country. Indeed, Almeida et al. (2017) show that investment and reliance on credit markets are both adversely affected by a sovereign ratings downgrade. Of course, if a country's imports are relatively low, it then follows that the exports of the countries it does business with must be relatively low as well, all else equal.

As a consequence, we introduce a novel way of quantifying trade-based information contained in the trade network and asset markets. In particular, we measure the time-varying matrix, $Trade$, where each row corresponds to an exporting country and each column an importing country; so, each cell contains the fraction of total export accounted for by the importing country. With this information, for each country in our sample and in every month, we then calculate the export-weighted SCDS returns of the countries it exports to, namely $Trade_{t-1} r_{t-1}^{CDS}$ where r_{t-1}^{CDS} is a vector of SCDS returns for the countries we study. Thus, our method exploits the time-varying import/export linkages that

discount-rate news. Others, e.g. Campbell, Giglio, Polk, and Turley (2018), have confirmed similar numbers in data including our sample period.

characterize the international trade network to identify how this country-specific information propagates through the global economy.

With this measure, dubbed $ExpRet$, in hand, we forecast key fundamentals of the exporting countries in question, both their subsequent exporting activity and GDP growth. We show that $ExpRet$'s ability to forecast fundamentals is robust to including otherwise similar measures based on stock and currency returns, $ExpStock$ and $ExpCurr$, and is the most consistent source of information about future fundamentals among the three variables studied.

We then show that $ExpRet$ contains information about subsequent patterns in the cross-section of average credit returns. Using a simple portfolio approach, we first measure the importance of direct links between trading partners. Specifically, in each month, we sort countries based on $ExpRet$ and examine the subsequent abnormal returns on their own SCDS. We find that our novel measure of a country's exporting strength has an economically and statistically significant effect on the cross section of average SCDS returns, a fact that is robust to a variety of controls for systematic risk in the SCDS market. In particular, the top 20% of countries that have relatively strong export-weighted SCDS returns of their trading partners outperform the bottom 20% by 47 basis points per month with an associated t-statistic of 3.69, implying an annualized Sharpe Ratio of 1.1. We further show that long-horizon returns on these portfolios do not revert, consistent with an underreaction phenomenon in this market.

Though these empirical findings are all consistent with the importance of the trade network for the propagation of macroeconomic shocks, we dig deeper to confirm our economic interpretation. We do so in four ways. We first show that import-weighted versions of these measures are essentially uninformative. Finding such an asymmetry is key evidence in favor of our network interpretation of the findings since the type of macroeconomic link clearly matters in how we aggregate information from the cross-section of SCDS returns. Indeed, we show that our effects do not reflect other sorts of links, as we control for news about the credit quality of FDI partners as well as news about the credit quality of portfolio-investment partners. Moreover, measures that weight past SCDS returns using the inverse of log geographic distance do not subsume the information in $ExpRet$.

We then turn to study the information contained in the indirect links between firms in the global trade network. The weights of these indirect links are the row elements of $Trade_{t-1}^{2}{=}Trade_{t-1} * Trade_{t-1}$. With these weights, we then calculate the export-weighted SCDS returns of a country's indirect links, $Trade_{t-1}^{2} r_{t-1}^{CDS}$, which we dub $ExpRetInd$. In other words, we ask the following question: To what extent is variation in the quality of one's trading partners' trading partners important? We estimate regressions which contain both $ExpRet$ and $ExpRetInd$ to find significant variation in subsequent abnormal SCDS returns linked to indirect versions of our weighted SCDS measure, predictability that is roughly as strong as the predictability found using the direct links.

Furthermore, we show that the information in the quality of one's indirect trading partners takes longer to show up in realized returns than that found in the quality of one's direct trading partners. These findings are consistent with shocks, particularly the indirect ones, taking their time to work their way through the system.

Third, we exploit the exogenous shock of the Japanese tsunami to confirm the causal interpretation our analysis suggests. On March 11, 2011 a 9.1-magnitude earthquake took place 231 miles northeast of Tokyo. This earthquake was the largest earthquake to ever hit Japan and generated a tsunami with waves over 30 feet high that damaged several nuclear reactors in the area. Conservative estimates indicate nearly 20,000 deaths, 2,500 missing persons, and damage from the earthquake/tsunami/radioactivity over $300B. We study the weeks and days surrounding the time-T event, linking SCDS returns to the following measures of exposure. We first note that Japanese SCDS increased dramatically on the day in question. We then study $ExpShare$, the share of a country s exports to Japan as a fraction of total exports in the prior year, as well as $ExpShare_{DUM}$, a dummy variable if $ExpShare$ is in the top quintile. Our results clearly show that information flows from Japan to its import source destinations; in other words, the aftershock of the Japanese earthquake is also felt in SCDS. Thus, we provide strong evidence that country-level shocks propagate through the trade network, in stark contrast to the alternative view that countries may simply have differential exposures to an aggregate shock.

Our final analysis estimates a variance decomposition to determine the extent to which national shocks contribute to global variance. Following Gabaix (2011), global variance will be affected if country weights in the trade network follow a right-skewed distribution. Alternatively, Acemoglu et al. (2012) argue that asymmetric trade links drive covariations between countries that contributes to global variance. We test both predictions following di Giovanni et al. (2017) and first find that 92% of the global variance is contributed by the second term. We then report evidence confirming each theory's main predictions. Consistent with Gabaix (2011), the Herfindahl index of a region's export activity is positively associated with its contribution to global variance. Consistent with Acemoglu et al. (2012), variation in the contribution of the covariance terms is positively related to the average fraction of a country pair's total exports that are accounted for by their bilateral trade. Thus, both types of terms can be explained by trade links. By linking global volatility to the trade network in this way, not only do we have a potentially better way to forecast the country-level variance-covariance matrix, we provide a specific mechanism to go from national shocks to global fluctuations.

Several additional tests confirm and extend our results. If these patterns reflect information about fundamentals, we should see similar predictability in equity markets, at least in the long run, the stock market is ultimately driven by cash-flow news. Of course, in the short run, stock markets may be driven by other factors as well (Shiller 1981).

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. If 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 increases to 3.74. Thus, information about export destination credit quality describes the cross-section of average equity returns.

As our analysis exploits underreaction in SCDS returns, specific country characteristics should plausibly matter. In particular, countries with relatively poor credit quality or relatively high external debt are likely more sensitive to news about their trading partners credit quality, a conjecture we confirm in the data Furthermore, the underreaction we document should be stronger for countries that have relatively less attention paid to their trade links. Consistent with interpretation, countries on the periphery of the trade network have stronger return predictability based on the trade network. Finally, examining how our results vary across various subsamples also allows us to confirm the robustness of our findings. We show that our main return predictability results continue to hold if we either safe-haven countries or the G20.

This paper contributes to the literature by illustrating a new pricing mechanism in the SCDS market. While Pan and Singleton (2008), Longstaff, Pedersen, Pan and Singleton (2011) and Augustin and Tedongap (2014) document the comovement of SCDS prices with global systemic risk factors, others focus on the relationship between SCDS prices and country-specific risk. Acharya et al. (2014) illustrate how the financial strain of contingent debt burden 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 and disclosure requirement. Complementary to these domestic financial, macroeconomic and institutional factors, we find that export destination countries' credit quality also plays an important role in determining the SCDS spread.

Our paper also sheds light on how sovereign credit risk spills over across countries. The existing literature focuses on 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 to investors' increase in their sensitivity to country-specific fundamentals. In contrast, our paper shows that the 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, the 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 shed light on the extent to which macroeconomic information slowly diffuses in the financial derivative markets, which is complimentary to prior literature on the diffusion of firm information in the stock market (e.g. Cohen and Frazzini 2008; Cohen and Lou 2012; Hou 2007). Our findings show that even financial derivative markets, often presumed to be more efficient in aggregating information than stock markets (e.g., Easley, O'Hara and Srinivas, 1998 and Pan and Poteshman, 2006), are subject to investors' limited attention.

Finally, this paper relates to the informational role of derivatives market. A large body of studies has been dedicated to the understanding of how information flows across markets. For instance, Black (1975) emphasizes that the embedded leverage in most derivatives allows investors to trade their information more efficiently. Novertheless, 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 CDS market forecasts future negative credit events. Furthermore, Lee, Naranjo, and Sirmans (2014) show that information in the corporate CDS market can be used to improve the price momentum strategy of Jegadeesh and Titman (1993). On the other hand, Hilscher, Pollet and Wilson (2014) 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.

II. Data and Methodology

II.A Data

II.A.1 Sovereign Credit Default Swaps

Our SCDS data comes directly from Markit which collects daily SCDS quotation data from the major SCDS dealers and publishes the average SCDS spread following a rigorous data validation procedure. Our sample covers 91 sovereign countries, from January 2001 to September 2015. The detailed country list and the starting time of each country's are listed in the appendix. The number of countries with an actively-traded SCDS contract traded was 29 in 2001; this number has grown to 91 by the end of our sample. Our analysis focuses on USD-denominated, five-year maturity contracts with the default underlying tier being senior unsecured debt and that are traded under the restructure clause CR/CR14.[3] We choose this type of SCDS contract because they are the most actively traded and have the highest market liquidity. Table 1 provides summary statistics of our SCDS data. The average SCDS par spread is 241 bps, with a standard deviation of 556 bps. The monthly average SCDS return is -0.02%, with a standard deviation of 2.59%. On average, a SCDS contract has about 5.9 dealers providing price quotations with a standard deviation of 3.2.

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

II.A.2 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, 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 credit risk protection payment, which is the face value loss of the sovereign debt.[4,5]

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 period of time. We calculate the mark-to-market SCDS return using the widely-used ISDA CDS model, described in detail in O'Kane (2008). The SCDS return increases when the underlying country's creditworthiness deteriorates; that is, a higher SCDS return indicates bad news

In applying this approach to our data, there are two practical issues. First, there are four fixed premium payment dates each year in the SCDS market: March 20, June 20, September 20 and December 20. A 5-year contract will mature in the first premium payment date after the contract exists for 5 years. For instance, a new 5-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 best liquidity (our SCDS price data are all on-the-run spreads). Given these institutional features, we compute the monthly CDS return based on the spreads as of the 20$^{\text{th}}$ of the

[4] The credit event is determined by the ISDA "Determinations Committee", and according to the ISDA definitions includes: failure to pay, moratorium, obligation acceleration, and restructuring.

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

current month and the 19th of the subsequent month to ensure that these two spreads are from the same CDS contract.

Second, if the credit event happens during the holding period of the SCDS, the monthly return should be the realized loss of the bond, 1-R. We use the realized recovery rate R provided by the Creditex Group to calculate the SCDS return in case of default.[6] There have been three sovereign defaults from Jan. 2001 to Sep. 2015 which effectively triggered a SCDS credit event and were subsequently auction-settled: Ecuador in 2009, Greece in 2012 and Argentina in 2014. Among them, the Greece settlement implied a recovery rate R=21.5%, the Argentina settlement implied R=39.5%, and the Ecuador settlement implied R=31.6%. We use those auction results to determine the implied SCDS return in the corresponding default months.

II.A.3. Other data

Our bilateral trade data comes from the United Nations Commodity Trade Statistics Database (UN-Comtrade), which has collected country-level US-dollar-denominated annual bilateral trade data through 2015. Table I shows that from 2001 to 2015, on average, a country exports to 78 countries and that exports accounts for 47.5% of a country's GDP in our sample. These numbers indicate the importance export activity plays in determining a country's economic growth and, as a consequence, sovereign credit risk. We also use the United Nation UNCTAD s Bilateral FDI Statistics database to collect bilateral FDI data and the IMF Coordinated Portfolio Investment Survey (CPIS) database to collect bilateral portfolio investment data. Both the FDI and the portfolio investment data cover a period from 2001 to 2012.

[6] http://www.creditfixings.com/CreditEventAuctions/AuctionByYear.jsp?year=2013 is the web address of the Creditex Group.

Other macroeconomic data, including yearly GDP growth, monthly seasonality-adjusted CPI inflation, and the export-to-GDP ratio are all collected from the International Monetary Fund World Economic Outlook (WEO) database. In our sample period, the average yearly GDP growth rate was 3.7% with a standard deviation of 4.3%, while the seasonality-adjusted month-over-month inflation rate was 0.37% with a standard deviation of 0.8%.

We collect sovereign credit rating/outlook data from the major credit rating agencies, including Moody's, Standard & Poor, and Fitch. We first convert the rating into a numerical score in which "AAA/Aaa" corresponds to 1, "AA+/Aa1" corresponds to 2, fi, and "D" corresponds to 22. Then, for each country, the monthly average credit rating is calculated as our measure of a country's credit risk. The sample average rating for all countries is 10.1, which is equivalent to a "BBB+" rating.

For each country, we further obtain the daily U.S.-dollar-denominated total return of its major stock market index from Bloomberg (dividends included). For instance, we collect the return on the S&P 500 Index for the US, the return on the Tokyo Stock Price Index for Japan, and the return on the FTSE 100 Index for the United Kingdom. The complete list of countries and their corresponding stock market indices are provided in the appendix. As that Table shows, the total number of stock indices reaches 75 by 2015. To be consistent with the SCDS return data, we construct the monthly stock index return as the return from the 20th of the current month to the 19th of the subsequent month. Table I demonstrates that the average monthly stock index return is 1% with a standard deviation of 7.95%.

II.B Summary statistics

Table I present summary statistics of our basic data. In Panel A, we describe the country coverage. The first two rows indicate that the typical country exports and imports from most other countries, at least to some degree. The average number of export destination countries is 78 while the average number of important source countries is 76. The third and fourth rows in Table I Panel document the number of links that are necessary, beginning with the most important trading partner, to make up a particular percentage of a country's trade. On average, more than 25% of a country's exports are to two countries, more than 50% are to five countries, and more than 75% are to 10 countries. These statistics indicate that though trade is certainly not spread evenly across all export destination countries, our method relies on aggregating information across a range of countries and not just one or two trading partners.

Panel B reports summary statistics for the macroeconomic and financial data we use. The first row reports that the average CDS spread is 2.4%, thus the typical country is viewed as being risky. The second row indicates that though CDS returns are on average quite close to zero, there is significant volatility in this market, potentially related to news about fundamentals. The fourth row shows that the average countries export-to-GDP ratio is close to 50%. As a consequence, understanding export activity is critical to understanding GDP.

II.C Measuring export destination news

In this section, we use a country's export destination countries' SCDS return to proxy for changes in the underlying country's export demand. More specifically, we define our measure of the change in export destination quality for each country as the weighted average of the export destination countries' CDS returns using the bilateral export in the prior calendar year as the appropriate weight,

$$ExpRet_{c,t} = \frac{\sum_{i \neq c} Export_{i,t^*(t)}^{c} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} Export_{i,t^*(t)}^{c}}, \qquad (1)$$

where $ExpRet_{c,t}$ denotes the export destination credit quality of country c at the end of month t, and $Export_{i,t^*(t)}^{c}$ denotes the dollar amount of export from country c to country i in the prior calendar year before month t. We use the prior calendar year export amount as the weight to make sure that the export data is accessible to investors at the time they need to calculate our proxy and adjust their portfolio accordingly. $Ret_{i,(t-F+1,t)}$ 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. We include all country *c*'s export destination countries which have SCDS traded. For instance, assume that country *c* exports to country *x* and *y* 100 billion dollars and 50 billion dollars in 2005 respectively. We calculate the export destination risk $ExpRet_{c,t}$ in month *t* in 2006 as

$$ExpRet_{c,t} = \frac{100 * Ret_{x,(t-2,t)} + 50 * Ret_{y,(t-2,t)}}{150}$$

where $Ret_{x,(t-2,t)}$ and $Ret_{y,(t-2,t)}$ are country *x* and *y*'s SCDS returns from month *t-2* to *t*. The typical country in our sample exports on average 81% (median value of 82%) of their total export activity to countries with traded SCDS, with a standard deviation of 13%. As a consequence, we argue that our measure $ExpRet_{c,t}$ provides information on a significant component of the demand for a country's exports.

Our proxy measures the overall increase in the sovereign credit risk among a country's export destination countries. When a country's sovereign credit risk increases, its CDS spread will increase leading to a positive CDS return. Therefore, a high $ExpRet_{c,t}$ implies a significant increase in sovereign credit risk among country c's export destination countries at time *t*.

III. Slow transmission of information

If information concerning export destination countries' quality is relevant for exporting countries' CDS prices but only gradually incorporated into prices, then $ExpRet_{c,t}$ should be able to predict the exporting country's CDS returns. In this section, we implement a simple portfolio approach to examine the information contained in $ExpRet_{c,t}$ about an exporting country's credit quality.

III.A Forecasting fundamentals

We first provide evidence that $ExpRet_{c,t}$ indeed contains information about real economic activity that is directly relevant to a country's sovereign credit risk. In this section, we use a panel data regression framework to measure the information in $ExpRet_{c,t}$ concerning subsequent real economic activity. Since export and GDP growth are both crucial in determining a country's ability to serve its external debt, if our export destination risk proxy can predict these two variables, it would imply that the proxy $ExpRet_{c,t}$ indeed contains information relevant to a country's sovereign credit risk. 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 focus on annual frequency data in this analysis in order to include all the countries in our sample as most do not have export growth or GDP growth data at a higher frequency. Note however that our results are robust to using other formation periods when measuring $ExpRet_{c,t}$.

Table II Panel A first confirms that a country's CDS returns forecast its own imports: If a country is performing relatively poorly in terms of credit quality, its future imports are relatively low. The first regression in this panel indicates that the return on a country's SCDS has information about that country's import activity. Subsequent regressions indicate that this predictive ability is robust to including lagged import growth, lagged GDP growth, $OwnStock_{c,t}$, and $OwnCurr_{c,t}$. Of particular note is the fact that a country's currency movements do not have any incremental ability to forecast important activity. This result continues to hold if we exclude countries in the Euro area, which share a common currency, from the analysis. In contrast, Table I Panel A shows that $OwnStock_{c,t}$ has significant information about a country's subsequent import growth.

Columns (1)-(3) of Table II Panel B report the results of regressions forecasting export growth. The regressions control for a country's own lagged annual SCDS return,

$OwnRet_{c,t}$ as well as lagged annual export growth $Export\ Growth_{c,t}$, $ExpStock$, and $ExpCurr$. A country's export growth is largely determined by its export destination countries' demand, which is affected 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) - (3) show that the coefficients on $ExpRet_{c,t}$ are indeed negative and statistically significant. To aid in interpretation, all forecasting variables are normalized to have unit standard deviation. We find that a one standard deviation increase in $ExpRet_{c,t}$ reduces next year's export growth by 1.65 percent after controlling for information in $ExpStock$, $ExpCurr$, lagged SCDS return, and lagged export growth. Therefore, the predictability linked to $ExpRet_{c,t}$ is not only statistically significant but also economically important. 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, it is natural to expect that $ExpRet_{c,t}$ should predict GDP growth as well. The regression results in columns (4)-(6) of Table II Panel B confirms this intuition; the coefficient on $ExpRet_{c,t}$ is negative and statistically significant even after controlling for $ExpStock$, $ExpCurr$, $OwnRet_{c,t}$, and lagged annual GDP growth rate, $GDPGrowth_{c,t}$. A one standard deviation increase in the export destination risk leads to about 0.33 percent decline in a country's GDP growth in the following year. As a consequence, given these fundamental links documented in the table, it is natural to expect $ExpRisk_{c,t}$ to provide information that should ultimately be incorporated in predict SCDS returns. We also find that, among all of the variables in the full specification, the coefficient on normalized $ExpStock$ is the largest.

III.B Forecasting returns

III.B.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. In particular, this difference reflects the return on 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 III 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, 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 still 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 III 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 on our long/short portfolio strategy (with F=3, H=1) on various risk factors documented in the literature. In 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 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, Yan, and Zhang (2017). In the third row, the risk factor is a market factor, namely the equal-weight return of all SCDS in our sample. We include both this market return and the momentum return together in the fourth row. Finally, in the fifth row, we control for not only the market and momentum factors but also the global momentum and value factors documented in Asness, Moskowitz and Pedersen (2013). As can be seen, after controlling for all four risk factors, in the fifth row, we still obtain economically and statistically significant risk-adjusted abnormal return as the resulting monthly alpha is 0.24%, with a *t*-statistic of 2.90.

Table III Panel B also reports how our findings vary across different subperiods, specifically focusing on the subprime crisis subperiod, as defined by the NBER. 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 during that time period. Indeed, as Figure 1 shows, exports temporarily become a much smaller component of GDP growth.

III.B.2 Long-horizon Returns

The ability of $ExpRet_{c,t}$ to forecast cross-sectional variation in average country SCDS returns is consistent with an underreaction interpretation where investors fail to incorporate a country's export destination sovereign credit risk information into the pricing of its own sovereign credit risk in a timely fashion. Of course, an overreaction interpretation is also possible.[7] 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 Figure 2.

In Figure 2, 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 reversal pattern. These results lend support to our view that the SCDS prices underreact to the export destination risk information.

III.C 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) own-SCDS momentum, (2) systemic risk factors, (3) financial links. In this section, we use the Fama-MacBeth regression framework to control for these possible effects and address these concerns.

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

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

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.

[7] For instance, Da, Engelberg and Gao (2001) find that higher searching volume in Google can predict a higher abnormal return of a stock in the next couple of weeks, but the return reverses back completely over a longer horizon.

$X'_{c,t}$ contains a basic set of macro-variables that control for country characteristics, including GDP growth, inflation and export-to-GDP ratio. More importantly, we also controls for other alternative interpretations via $Proxy_{c,t}$, which might explain the correlation between $ExpRet_t$ and subsequent monthly SCDS returns.

III.C.1 Controlling for SCDS Momentum

One competing interpretation of the return predictability is that information flow is not from the export destination countries to the exporting country as argued in our interpretation, but is rather in the opposite direction, from the exporting country to its export destination due to some other reason. Simply put, $ExpRet_t$ could be correlated with the exporting country's own past CDS return. As Xiao, Yan and Zhang (2017) document a momentum effect in SCDS returns, we might be simply repackaging their result. Note that we have already partially addressed this concern in the prior section by showing that we continue to find statistically-significant average abnormal returns on our long/short portfolio strategy after controlling for a SCDS momentum factor. In this section, we provide additional evidence that *ExpRet*'s predictive power is distinct from a own-stock momentum effect using the Fama-MacBeth regression framework. To aid in comparison with our previous results, we estimate the effect of all of the weighted variables in Table IV using quintile dummies.

Column (1) only includes the export destination risk proxy, $ExpRet_{c,t}$, the comparable stock and currency variables, $ExpStock$ and $ExpCurr$, along with the basic set of control variables. Column (2) adds the past 3-month SCDS return $RetOwn_{c,t}$ and a variable $DistRet$ where, following gravity theory, SCDS returns are weighted by the inverse of log geographic distance. Both $ExpRet_{c,t}$ and $RetOwn_{c,t}$ are grouped into quintiles in the regression. As can be seen, the coefficients of the $ExpRet_{c,t}$ is still positive and statistically significant after controlling for the momentum effect. The coefficient on

$ExpRet_{c,t}$ in Column (2) is 0.0532 with a *t*-statistic of 2.34; the magnitude of the coefficient remains economically important after controlling for past SCDS return $OwnRet_{c,t}$. This result confirms that information in $ExpRet_{c,t}$ about future returns does not simply reflect a momentum effect.

III.C.2 Asymmetry between Export and Import Measures

Another potential explanation of our findings is that it instead reflects some other non-trade economic channel. For example, a country's important trading partners may have close geopolitical/economic similarities with the underlying country or be exposed to similar types of shock. Therefore, changes in the trading partners' sovereign credit quality may simply reflect information about the underlying country's sovereign credit quality. To eliminate this interpretation, we introduce an import source version of our key variable. Specifically, we measure the weighted average of a country's import source countries' CDS return, using the bilateral import amount (in dollar) of country *c* as the weight. Specifically, for country c, the change in import source credit quality as of month *t* is calculated as follows.

$$ImpRet_{c,t} = \frac{\sum_{i \neq c} Import^{c}_{i,t^*(t)} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} Import^{c}_{i,t^*(t)}}$$

where $Import^{c}_{i,t^*(t)}$ is country *c*'s import (in dollar) 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* is referred to as the forming period similar in the definition of $ExprEt_{c,t}$. 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 only difference between $ImpRet_{c,t}$ and $ExpRet_{c,t}$ is the weight on each trading partner country's CDS return. If the non-trade interpretation is correct, it is not obvious why the export destination version $ExpRet_{c,t}$ should have better predictive power than the import source version $ImpRet_{c,t}$. In sharp contrast to this implication, our trade network interpretation clearly indicates the predictability asymmetry between $ExpRet_{c,t}$ and $ImpRet_{c,t}$. According to our hypothesis, $ExpRet_{c,t}$ should have much stronger predictive power than $ImpRet_{c,t}$, because a country's sovereign credit risk change is caused by changing external demand from its export destination countries, but has little to do with its importing source countries' credit risk. We run a horse race test between $ExPRet_{c,t}$ and $ImpRet_{c,t}$ in the Fama-MacBeth regression framework to identify which hypothesis can better explain the observation. In the regression, both $ExpRet_{c,t}$ and $ImpRet_{c,t}$ are grouped into quintiles. (The original continuous variables generate similar results). As shown in Table IV Column 3, the coefficient of $ExpRet_{c,t}$ is statistically significant while the coefficient of $ImpRet_{c,t}$is not. Moreover, the magnitude of $ExpRet_{c,t}$'s coefficient is 0.0719%, which is not only much bigger but also has the correct sign when compared to $ImpRet_{c,t}$'s coefficient of -0.0316%. This asymmetric result lends support to our trade network hypothesis, which makes specific predictions about the direction of the links that matter.

III.C.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 major negative shock to the US economy could affect China through both reduced imports and capital inflows. Therefore, the observed return predictability linked to $ExpRet_{c,t}$ could be driven by capital flow through financial links rather than by export activities through trade links. More specifically, bilateral capital flow is composed of both FDI, which is long-term 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, $FDIRet_{c,t}^{in}$ and $FDIRet_{c,t}^{out}$ as follows:

$$FDIRet_{c,t}^{in} = \frac{\sum_{i \neq c} FDI\_inward_{i,t^*(t)}^{c} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} FDI\_inward_{i,t^*(t)}^{c}}$$

$$FDIRet_{c,t}^{out} = \frac{\sum_{i \neq c} FDI\_outward_{i,t^*(t)}^{c} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} FDI\_outward_{i,t^*(t)}^{c}}$$

where $Ret_{i,(t-F+1,t)}$ is country *i*'s SCDS return from month *t-F+1 to t* and $FDI\_inward_{i,t^*(t)}^{c}$ ($FDI\_outward_{i,t^*(t)}^{c}$) 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 $PortInvRet_{c,t}^{in}$ and an outward portfolio investment risk measure $PortInvRet_{c,t}^{out}$ as follows:

$$PortInvRet_{c,t}^{in} = \frac{\sum_{i \neq c} PI\_inward_{i,t^*(t)}^{c} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} PI\_inward_{i,t^*(t)}^{c}}$$

$$PortInvRet_{c,t}^{out} = \frac{\sum_{i \neq c} PI\_outward_{i,t^*(t)}^{c} Ret_{i,(t-F+1,t)}}{\sum_{i \neq c} PI\_outward_{i,t^*(t)}^{c}}$$

where $Ret_{i,(t-F+1,t)}$is country *i*'s SCDS return from month *t-F+1 to t* and $PI\_inward_{i,t^*(t)}^{c}$ ($PI\_outward_{i,t^*(t)}^{c}$) is country *c*'s inward(outward) portfolio investment from (to) country *i* by the end of the calendar year prior to month *t.*

The definitions of inward/outward FDI risk and inward/outward portfolio investment risk are quite similar to the definition of export/import risk proxies $ExpRet_t$ and $ImpRet_t$, except for using FDI or portfolio investment rather than trade volume as weight. We run horse races among $ExpRet_{c,t}$, $FDIRet_{c,t}^{in}$, $FDIRet_{c,t}^{out}$, $PortInvRet_{c,t}^{in}$, and $PortInvRet_{c,t}^{out}$ in a Fama-MacBeth regression framework. All the above variables are transformed into quintile dummies. In the regressions in columns (4) and (5), we find that only the coefficient on $ExpRet_{c,t}$ is statistically significant. These results confirm that the return predictability we are documenting comes from trade links rather than from financial links.

IV. Underlying Mechanism

Having established return predictability linked to $ExpRet_{c,t}$, we further explore the mechanism through which information is incorporated in prices. In this section, we explore whether the predictability in returns is driven by investors' inattention. We link factors affecting the speed at which that information is incorporated to the magnitude of the return predictability we document.

IV.A. Indirect Trade Links

If investors have limited attention to information related to the trade network and hence absorb this information with a delay, it would be even more difficult for investors to recognize information related to indirect links in the network and to response to it quickly. For example, China is Australia's major export destination country, while the U.S. is the biggest export destination for China. A sovereign credit risk shock in U.S., such as the 2008 Subprime Crisis, caused a significant contraction of US imports from China, which dampened China's economic growth and reduced China's import of raw materials from Australia, reducing the sovereign credit quality ofAustralia. Therefore, China provides a channel through which US sovereign credit quality shocks spread to Australia.

To measure information concerning the credit quality of a country's indirect export destinations, we first construct a direct export matrix *Trade*, with the term in row i and column j, $Trade_{i,j}$, being the ratio of country i's export to country j over country i's total export to all the countries in the sample. The summation of all the terms in a row is therefore equal to 1. By multiplying the direct export destination matrix *Trade* with the SCDS return vector (where the ith term is country i's past three months SCDS return), we generate the export destination risk vector with the *c*'s term being country *c*'s export destination risk proxy $ExpRet_{c,t}$. By iterating, i.e. further premultiplying $ExpRet$ with the *Trade* matrix, we generate the indirect version of our measure, $ExpRetInd_{c,t}$.

To capture the dynamics of information incorporation through direct and indirect channels, we estimate a Fama-MacBeth regression with the following specification:

$$Ret_{c,t+h} = \alpha + \beta_1 ExpRet_{c,t} + \beta_2 ExpRetInd_{c,t} + Controls + \varepsilon_{c,t}$$

The dependent variable is the weekly SCDS return in week $t+h$, where t is the sorting week and the $Ret_{c,t+h}$ is country *c*'s h weeks ahead SCDS weekly return. $ExpRet_{c,t}$ and $ExpRetInd_{c,t}$ are calculated by using the past 12 weeks cumulative SCDS returns and are measured using quintile dummies. The control variables include countries' own CDS return in the past 12 weeks, lagged monthly inflation, lagged annual GDP growth rate, and the lagged export-to-GDP ratio.

The regression results are shown in Table V. These estimates indicate that in the first and second weeks after the sorting week (h=1,2), the coefficients on $ExpRet_{c,t}$ are larger in magnitude than the corresponding coefficients on $ExpRetInd_{c,t}$. Moreover, only the coefficients on $ExpRet_{c,t}$ are statistically significant. In addition, the difference between the coefficient of $ExpRet_{c,t}$ and $ExpRetInd_{c,t}$ is statistically significant. 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. This finding lends support to the idea that the complexity of the information plays an important role in the speed of investors' information processing.

IV.B. Natural Experiment

One potential concern is that we are finding that countries simply have differential exposure to an aggregate shock. To show that patterns in the SCDS market are consistent with country shocks propagating through the network, Table VI documents the ripple effect of the Japanese triple-disasters (Earthquake, Tsunami, and Radioactive fallout) in March 2011. We focus on the four weeks surrounding March 11, 2011 (the day the Earthquake hit Japan's east coast), with week T being the event week. On the right side of the graph, we zoom into the the four days surrounding the event. For each week or day in our sample, we conduct a cross-sectional regression of each country's SCDS return on its closeness to Japan in the trade network. Our main independent variable, $ExpShare$, is the share of a country's export to Japan as a fraction of the country's aggregate exports measured in year 2010. Other control variables include the country's own lagged one-month sovereign CDS return, and lagged one-month seasonally adjusted inflation rate. In Panel A, $ExpShare$, is simply the fraction; in Panel B, we construct a dummy variable, $ExpShare_{DUM}$ that equals one if the country's share of export to Japan is in top 20% of the sample, and zero otherwise.

Our results clearly show that information flows from Japan to its export destinations; an aftershock of the fundamental impact of the Japanese earthquake can also be felt in SCDS. Thus, country-level shocks do propagate through the network rather than countries instead having differential exposure to an aggregate shock.

V. Variance Decomposition

We follow di Giovanni et al. (2017) and decompose the variance of global SCDS returns to differentiate between Gabaix (2011) and Acemoglu et al. (2012). In particular, we treat our SCDS returns as their firm-specific shocks. We measure the variance of our SCDS returns for our 88 countries over 15 years (2001-2015) at a monthly frequency.

V.A. Defining the global SCDS return

First, we conceptually define the global SCDS return as

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

where

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

$export_{g,t}$ is the aggregate export activity for all 88 countries in our sample at time t. $export_{i,t}$ is the total export for country *i* at time *t*. Therefore, $w_{i,t}$ measures the export share of country *i* at time *t*. $R_{g,t}$ is then our global SCDS return, which is a weighted average of each country's SCDS returns, $R_{i,t}$, with weights being each country's export share relative to the global aggregate exports.

V.B. Variance Decomposition

Let $\sigma^2_{g,\tau}$ denote the volatility (variance) of $R_{g,\tau}$, note that notation τ represents the time index at which we fix the weight and treat it constant over time. Mathematically,

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

Thus, $R_{g,\tau}$ is an estimate of the true value of $R_{g,t}$ by treating the weights fixed at time τ. The reason to fix the weight is because this way, the variance of $R_{g,\tau}$, $\sigma^2_{g,\tau}$ will not capture the volatility caused by weight changes over time.

Following Carvalho and Gabaix (2013), we decompose the variance as the following:

$$\sigma^2_{g,\tau} = \underbrace{\textstyle\sum_i \ w^2_{i,\tau-1} * Var\left(Ret_{i,t}\right)}_{DIRECT_\tau} + \underbrace{\textstyle\sum_{i \neq j} \sum_{j \neq i} w_{i,\tau-1} w_{j,\tau-1} Cov\left(Ret_{i,t}, Ret_{j,t}\right)}_{LINK_\tau} \qquad (2)$$

As shown in the above equation, at each time τ, the variance of $R_{g,\tau}$ can be decomposed into two components: $DIRECT_\tau$ and $LINK_\tau$, where $DIRECT_\tau$ captures the volatility of country SCDS return itself and $LINK_\tau$ captures the co-movement or linkages of cross-country SCDS returns.

V.C. Implementation

These two components can be computed directly using our trade data and SCDS return data. We first compute the variance of SCDS return for each country to obtain $Var(Ret_{i,t})$. Then we compute the covariance of SCDS return for any given pair of countries to obtain $Cov(Ret_{i,t}, Ret_{j,t})$. Lastly, we compute the weight as the ratio of country export to aggregate exports of the 88 countries in our sample. This allows us to compute both $DIRECT_\tau$ and $LINK_\tau$. Thus, the contribution of the DIRECT component to the overall volatility is simply measured as $\sqrt{average(DIRECT_\tau)} \big/ \sigma_{g,\tau}$ and the contribution of the LINK component to the overall volatility is measured as the time average of $\sqrt{average(LINK_\tau)} \big/ \sigma_{g,\tau}$

V.D. Regional DIRECT component

Following similar logic, we can compute the regional DIRECT component denoted as: $DIRECT_{R,\tau}$ where R is region index. The regional DIRECT component can be computed as follows:

$$DIRECT_{R,\tau} = \sum_{i \in R} w_{i,\tau-1}^2 * Var(Ret_{i,t})$$

Therefore, the regional share of DIRECT component is simply the square root of average $DIRECT_{R,\tau}$ divided by the square root of average $DIRECT_\tau$, $\sqrt{average(DIRECT_{R,\tau})} \big/ \sqrt{average(DIRECT_\tau)}$

V.E. Decomposition Results

We first find in unreported results that 92% of the global variance is contributed by the second term in equation (2). Thus, the arguments of Acemoglu et al. (2012) seem much more important in this context. We then turn to understanding the economic drivers of cross-sectional variation in each of those two terms. Figure 3 first examines the variance terms at the regional level, linking the regional share of the first set of terms on the right-hand side of equation (2) to the Herfindahl Index of the export weights in each region. We find that weight concentration in a region is positively associated with its contribution to global variance. The adjusted R^2 is over 60%.

Table VII then examines the covariance terms using the method of Anton and Polk (2014). We explain not only cross-sectional variation in country-pair SCDS return correlation but also the LINK terms that make up the second set of terms on the right-hand side of equation (2). We find that $ExpShare_{i,j}^{AVG}$, the average fraction of country i and j's total exports that are accounted for by their bilateral trade, is strongly positively correlated with both LINK and correlation. This relationship continues to hold if we control for both distance and language. Thus, pairwise covariances are strongly associated with bilateral trade links.

VI. Additional Tests

We test additional aspects of our story by linking our results across markets as well as exploiting heterogeneity in the effect predicted by our economic story.

VI.A. Spillover from SCDS market to the stock market

An important remaining question is whether this trade information is relevant for the stock market. Since the stock market has more investors than the SCDS market, especially more domestic investors, it is possible that the stock market responds more quickly to the relevant trade information.

To test the 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 risk proxy $ExpRet_{c,t}$ at the end of each month. We then go long the stock indices of countries in the P1 quintile that contains the lowest $ExpRet_{c,t}$ countries and sell short stock indices of countries in the P5 quintile that contains the highest $ExpRet_{c,t}$ countries, holding the resulting portfolio for one month. In the first row of Table VIII Panel A, we report the average return of the stock indices in each quintile and the long-short portfolio P1-P5. As can been 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 stock index return declines monotonically from portfolio P1 to P5.

To test the robustness of our finding, we further report the average abnormal returns of the portfolio P1 to P5 and the long-short portfolio P1-P5 after controlling for various risk factors. In the second row of Table VIII panel A, 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 combine the market average return and the momentum return together in the fourth row and further control for the global momentum and value factors documented by Asness, Moskowitz and Pedersen (2013) in the fifth row. Average abnormal returns are statistically significant across all specifications. For instance, we estimate an average abnormal return of 1.05% after controlling for all four risk factors, with a *t*-statistic equal to 3.74. This result lends further support to our argument that markets, including stock markets, incorporate trade network information in a sluggish fashion.

Another question we explore is whether a trade-weighted measure based on stock returns can predict cross-sectional variation in average country equity returns. Given the fact that stock markets aggregate information concerning country-specific economic performance, it is conceivable that such a measure could perform better than our SCDS-based variable. Following the construction of $ExpRet_{c,t}$, we study the variable,

$$ExpRet_{c,t}^{Stock} = \frac{\sum_{i \neq c} Export_{i,\,t^*(t)}^{c} Ret_{i,(t-F+1,t)}^{Stock}}{\sum_{i \neq c} Export_{i,\,t^*(t)}^{c}}$$

where $Ret_{i,(t-F+1,t)}^{Stock}$ is country *i*'s stock index return in the past *F* months from *t*-*F*+1 to *t* and $Export_{i,\,t^*(t)}^{c}$ is the export from country *c* to country *i* in the calendar year before the month *t*. We include both $ExpRet_{c,t}$ and $ExpRet_{c,t}^{Stock}$ in a Fama-MacBeth regression framework to test whether the stock-market-return-based proxy is more informative. In this regression, we use the quintile grouping of $ExpRet_{c,t}^{Stock}$ and $ExpRet_{c,t}$ as before.

The results are reported in the Panel B of Table VIII Panel B. In column (1), we confirm that $ExpRet_{c,t}$ describes cross-sectional variation in average country returns. In column (2), we run a horse race test between $ExpRet_{c,t}^{Stock}$ and $ExpRet_{c,t}$ and find that the coefficient of $ExpRet_{c,t}$ is still negative and statistically significant, while the coefficient of $ExpRet_{c,t}^{Stock}$ is only marginally statistically significant. In columns (3) and (4), we further include the past three months stock market cumulative return to control for a country-level stock market momentum effect as well as macroeconomic variables including inflation, GDP growth, and the export-to-GDP ratio to test the robustness of the result. In these two regressions, the coefficients on $ExpRet_{c,t}$ remain negative and statistically significant, while the coefficients on $ExpRet_{c,t}^{Stock}$ remain statistically insignificant.

VI.B. Heterogeneity related to SCDS

Countries with relatively poor credit quality and/or relatively high external debt are likely more vulnerable to bad news about fundamentals. Similarly, as slow transmission of information is facilitated by investors' attention, one would expect that countries on the periphery of the network would experience stronger effects. In contrast, countries which are more central in the global trade network, such as Singapore, Hongkong, China, United States, and the United Kingdom are more likely to draw investors' attention concerning trade information. In other words, high "centrality" countries in the trade network should have weaker CDS return predictability according to our limited-attention hypothesis.

As a consequence, we measure a country's "centrality" using the most widely-used eigen-centrality measure in network analysis, e.g. Allen and Babus (2008), Acemoglu, Ozdaglar and Tahbaz-Salehi (2010, 2013). Specifically, the eigen-centrality measure, $Centrality_{c,t}$, for country c and month t, is the corresponding eigenvalue calculated by applying the standard eigenvalue decomposition on the export destination matrix $Trade_t$ in month t similar to Richmond (2016).

Table IX Panels A, B, and C reports the results of double sort on $ExpRet_{c,t}$ and credit ratings, external debt, or with $Centrality_{c,t}$. In each case, the observed heterogeneity is consistent with our economic story. Our effect is stronger for poor-quality countries, levered countries, and countries on the periphery of the network. The differences are jointly statistically significant.

VI.D. Robustness

Table IX Panel D shows that our key return predictability results when we exclude safe haven countries while Table IX Panel E documents that our results continue to hold if we remove G20 countries from the sample.

VII. Conclusions

We provide a novel way of extracting country-level fundamental news from the trade network. Specifically, we show that SCDS returns provide value-relevant information that slowly propagates through credit markets reflecting underreaction on a global scale. We document that countries are linked through trade networks and that export links, not import links, are the important direction of information flow, consistent with the nature of the trade relationship. These links are distinct from either the FDI or portfolio investment network.

Consistent with the network view and our underreaction interpretation, indirect links matter as well, and our findings are stronger among peripheral, poor-quality, or leveraged countries. Additional analyses support our story as a natural experiment confirms the causal importance of the trade network, and the same variable that forecasts cross-sectional variation in credit also forecasts cross-section variation in average country equity returns. A variance decomposition reveals that trade links play a significant role in understanding global SCDS return volatility.

Reference

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "TheNetwork Origins of Aggregate Fluctuations," *Econometrica* 80 1977–2016.

Acemoglu, Daron, Asuman Ozdaglar and Alireza Tahbaz-Salehi, 2010, Cascades in Networks and Aggregate Volatility," NBER working paper

Acemoglu, Daron, Asuman Ozdaglar and Alireza Tahbaz-Salehi, 2013, "The Network Origins of Large Economic Downturns," NBER working paper

Acharya, V. V., Drechsler, I. and Schnabl, P. ,2014, "A pyrrhic victory? - bank bailouts and sovereign credit risk," *Journal of Finance* 69 2689-2739.

Aizenman, J., M. M. Hutchison, and Y. Jinjarak, 2013, "What is the risk of European sovereign debt defaults? Fiscal space, CDS spreads and market pricing of risk," *Journal of International Money & Finance*, 34:37–59

Allen, Franklin and Ana Babus, 2011, "Networks in Finance," Wharton Financial Institutions Center Working Paper No. 08-07

Anton, Miguel and Christopher Polk, 2015. "Connected Stocks," *Journal of Finance* 69, 1099-1127.

Black, Fisher, 1975, "Fact and Fantasy in the Use of Options," *Financial Analysts Journal*, 31, 36-72.

Beirne, J. and M. Fratzscher, 2013, "The pricing of sovereign risk and contagion during the European sovereign debt crisis," *Journal of International Money and Finance*, 34:60–82

Campbell, John, 1991, "A variance decomposition for stock returns," *Economic Journal* 101:157-179.

Campbell, John, Stefano Giglio, Christopher Polk, and Robert Turley, 2018, An Intertemporal CAPM with Stochastic Volatility, *Journal of Financial Economics* 128, 207-233.

Cohen, Lauren, and Dong Lou, 2012, "Complicated firms," *Journal of Financial Economics* 104 383-400.

Cohen, Lauren, and Frazzini, Andria, 2008, "Economic links and predictable returns," *Journal of Finance* 63 1977-2011.

Da, Zhi, Xing Huang and Laurence Jin, 2017, "Extrapolative Beliefs in the Cross-section: What Can We Learn from the Crowds?" Working Paper

di Giovanni, Julian, Andrei A. Levchenko, and Isabelle Medjean, 2014, "Firms, Destinations, and Aggregate Fluctuations." *Econometrica* 82 1303–40.

Easley, David, Maureen O'Hara and P.S.Srinivas, 1998, Option Volume and Stock Prices: Evidence on Where Informed Traders Trade, *Journal of Finance* 53

Gabaix, Xavier. 2011. "The Granular Origins of Aggregate Fluctuations." *Econometrica* 79 733–72.

Hou, Kewei, 2007, "Industry information diffusion and the lead-lag effect in stock returns," *Review of Financial Studies* 20, 1113-1138.

Hull, John, Mirela Predescu and Alan White, 2004, The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of Banking & Finance*, 28(11), pp.2789-2811

Lee, Jongsub, Andy Narnjo, and Stace Sirmans, 2016, "Exodus from sovereign risk: Global asset and information networks in the pricing of corporate credit risk," *Journal of Finance*, 71(4): 1813-1856.

Lee, Jongsub, Andy Narnjo, and Stace Sirmans, 2014, "CDS Momentum: Slow Moving Credit Ratings and Cross-Market Spillovers," working paper.

Longstaff, Francis, Lasse Pedersen Jun Pan, and Kenneth Singleton, 2011, "How sovereign is sovereign credit risk?" *American Economic Journal: Macroeconomics*, 3(2): 75–103

Lucas, Robert E, 1977, "Understanding Business Cycles," Carnegie–Rochester Conference Series on Public Policy 5 7–29.

Pan, Jun and Allen Poteshman, 2006, "The Information in Option Volume for Future Stock Prices," *Review of Financial Studies* 19, 871-908.

Pan, Jun and Kenneth Singleton, 2008, "Default and recovery implicit in the term structure of SCDS spreads," *Journal of Finance* 63 2345–2384.

Qiu, Jianping and Fan Yu, 2012, "Endogenous liquidity in credit derivatives," *Journal of Financial Economics* 103 611-631.

Richmond, Robert, 2016, "Trade Network Centrality and Currency Risk Premia," Working Paper

Shen, Ji, Hongjun Yan and Jinfan Zhang, 2014, "Collateral-Motivated Financial Innovation," *Review of Financial Studies* 27 2961-2997

Shiller, Robert J., 1981, "Do Stock Prices Move Too Much to be Justified by Susequnet Changes in Dividends?", *American Economic Review* 71 421-436.

Soroka, Stuart, 2006, "Good News and Bad News: Asymmetric Responses to Economic Information," *Journal of Politics*, 68 372–385

Xiao, Yaqing, Hongjun Yan, Jinfan Zhang, 2017, "The Macro-Informational Role of Derivatives: Evidence from the SCDS Market," Working Paper

Table I: Summary Statistics

This table provides summary statistics for key variables used in the analysis. Panel A reports the number of total trading partners for the typical country as well as the number of trading partners (ordered from most important to least important) needed to achieve 25%, 50%, and 75% of the typical country's exports. Panel B summarizes other key variables used in our analyses. Our sovereign CDS (SDCS) data cover the period of January 2001 to September 2015. The CDS spread is the par spread provided by Markit Inc. Monthly SCDS returns are calculated using the standard CDS P&L model following O'Kane (2008). We compute monthly SCDS returns using SCDS spreads on the 20th of a month to the 19th of the following month. Stock index returns in each country are calculated as the monthly US-dollar denominated stock index total return from Bloomberg. In order to be consistent with the calculation of SCDS monthly returns, monthly stock index returns are also from the 20th of a month to the 19th of the next month. The annual international trade data are obtained from UN-COMTRADE database for the period of 2000 to 2015. Credit rating and credit outlook data contain all the sovereign credit rating information from S&P, Fitch and Moody's. The rating letter grades are converted to numerical values ranging from 1 to 22 corresponding to AAA/Aaa to D. Credit Rating is the monthly average of the numerical credit rating of S&P, Fitch, and Moody's. Monthly inflation is calculated month over month using the seasonally-adjusted CPI index.

Panel A: Country Coverage					
	Mean	Std. Dev.	Min	Median	Max
Number of Export Destination Countries	77.87	14.08	9	84	88
Number of Import Source Countries	75.51	13.27	9	80	88
			25%	50%	75%
Number of Export Destination Countries (per importing country)			1.73	4.09	10.02
Number of Import Source Countries (per exporting country)			1.82	4.39	10.68

Panel B: Summary Statistics					
	Mean	Std. Dev.	25%	50%	75%
CDS spreads (bps)	240.4	556.7	36.4	118.8	276.2
CDS returns (%)	-0.02	2.59	-0.37	-0.01	0.22
Number of Dealers	5.9	3.2	3.1	5.4	7.9
Export to GDP ratio (%)	47.5	32.3	28.1	39.5	57.1
Monthly Inflation (%)	0.37	0.8	0.045	0.259	0.553
Annual GDP Growth (%)	3.66	4.32	1.66	3.61	5.63
Credit Rating	10.06	4.81	6.5	10	14
Stock index return (%)	1.00	7.95	-3.00	1.12	5.16

Table II: Forecasting Real Variables

This table reports results of forecasting regressions of real economic outcomes on $OwnRet_{c,t}$ is the SCDS return of the exporting country in the previous year and/or on $ExpRet$, the export-weighted SCDS return on that country's export destinations over the past three months. The regressions also include stock and currency versions of these variables. In Panel A, the dependent variable is annual import growth while in Panel B, the dependent variable is the annual growth rate of either exports or GDP. The regressions include lagged values of the dependent variables. All independent variables are standardized using their respective standard deviations. Time fixed effects are included in all columns. T-statistics based on standard errors double-clustered by time and country are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Import Growth (in %)					
$OwnCDS_t$	-2.13***	-2.18***	-1.99***	-1.97**	-1.96**
	(-2.83)	(-3.10)	(-2.86)	(-2.49)	(-2.54)
$OwnStock_t$				2.65***	2.50***
				(4.83)	(4.47)
$OwnCurr_t$					-0.548
					(-0.98)
$ImportGrowth_t$		1.84*	-0.209	-0.300	-0.390
		(1.67)	(-0.24)	(-0.32)	(-0.44)
$GDPGrowth_t$			4.30***	3.83***	3.80***
			(5.31)	(4.95)	(4.94)
Time FE	Yes	Yes	Yes	Yes	Yes
No. Obs.	866	864	864	768	756
Adj. R2	0.51	0.52	0.54	0.56	0.56

Panel B: Export and GDP Growth (in %)						
	$ExportGrowth_{t+1}$			$GDPGrowth_{t+1}$		
$ExpRet_t$	-1.73**	-1.60**	-1.64**	-0.551**	-0.406***	-0.340***
	(-1.96)	(-2.16)	(-2.09)	(-3.25)	(-4.73)	(-3.89)
$ExpStock_t$	6.88*	4.16	3.80	2.073***	2.027***	1.843***
	(1.81)	(1.01)	(0.93)	(5.21)	(2.80)	(2.75)
$ExpCurr_t$	1.35	0.425	0.0653	0.303	0.222	0.599*
	(1.03)	(0.30)	(0.04)	(0.65)	(0.51)	(1.86)
$OwnRet_t$		-0.510	-0.502		-0.687***	-0.578***
		(-0.59)	(-0.57)		(-2.81)	(-2.91)
$ExportGrowth_t$			-1.86			
			(-0.76)			
$GDPGrowth_t$						2.502***
						(8.73)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	1,223	981	981	1,231	980	980
Adj. R2	0.52	0.62	0.63	0.20	0.28	0.53

Table III: Forecasting Monthly Sovereign CDS Returns

This table reports calendar-time portfolio returns of sovereign CDS (SDCS) contracts. At the end of each month, SCDS contracts are sorted into five quintiles (P1 to P5) based on their export destination countries' average SCDS returns, $ExpRet$. Specifically, $ExpRet$ is the weighted average SCDS returns across all export destination countries in the past F months, where the weight is proportional to the prior year's bilateral export. All countries are equally weighted within a given portfolio and the portfolios are held for H months. The long/short strategy is constructed by going long countries in quintile P5 and selling short countries in quintile P1. Panel A reports equal-weighted returns of each portfolio as well as the long/short strategy. The Sharpe ratio is computed as the mean return divided by the standard deviation of returns. Panel B further controls for common risk factors in SDCS returns. We fix the formation period F=3m and the holding period H=1m. The same analysis is then repeated by dividing the whole sample into the Pre-Crisis (Jan 2001-Nov 2007), Crisis (Dec 2007-Dec 2010) and post-Crisis (Jan 2011-Sep 2015) periods using the NBER definition. 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 3-month forming period and a 1-month holding period). The third row reports portfolio alpha after controlling for the equal-weighted average return of all sovereign CDS. The fourth row reports portfolio alpha controlling for both the SDCS momentum factor and global SCDS factor. Row five further includes the global momentum and value factors (as in Asness, Moskowitz and Pedersen, 2013). T-statistics based on standard errors with Newey-West adjustments of up to 12 lags are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calendar Time Portfolio of Sovereign CDS								
	Portfolio returns in the month following formation					Holding Period Returns		
	P1	P2	P3	P4	P5	Long/Short Strategy (P5 – P1)		
						H=1m	H=3m	H=6m
F=1m	-0.0005	-0.0008	-0.0002	-0.0001	0.0015	0.0020**	0.0024***	0.0013**
	(-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=3m	-0.0024*	-0.0002	-0.0003	0.0003	0.0023*	0.0047***	0.0030***	0.0020**
	(-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=6m	-0.0021	-0.0003	-0.0005	0.0003	0.0009	0.0030***	0.0025**	0.0019*
	(-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 Risk Factors								
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
-0.0024*	-0.0002	-0.0003	-0.0003	0.0023*	0.0047***	0.0063***	0.0036**	0.0034**
(-1.80)	(-0.23)	(-0.29)	(-0.38)	(1.69)	(3.69)	(2.74)	(2.38)	(2.04)
-0.0026**	-0.0009	-0.0012*	-0.0011*	0.0001	0.0027***	0.0031**	0.0011	0.0025**
(-2.42)	(-1.43)	(-1.94)	(-1.75)	(0.07)	(3.16)	(2.27)	(0.71)	(2.54)
-0.0024***	-0.0001	-0.0002	-0.0003	0.0024***	0.0048***	0.0067***	0.0034	0.0034**
(-3.08)	(-0.42)	(-0.55)	(-0.60)	(3.38)	(3.56)	(2.85)	(1.42)	(2.06)
-0.0014**	0.0001	-0.0003	-0.0002	0.0014***	0.0028***	0.0032*	0.0014	0.0025**
(-2.41)	(0.15)	(-0.82)	(-0.49)	(3.28)	(3.08)	(1.92)	(0.89)	(2.48)
-0.0010*	-0.0000	-0.0003	-0.0003	0.0014***	0.0024***	0.0025**	0.0016	0.0031***
(-1.87)	(-0.09)	(-1.08)	(-0.86)	(3.38)	(2.90)	(2.10)	(0.97)	(2.78)

Table IV: Fama-MacBeth Regressions of SCDS Returns

This table reports results of forecasting regressions of monthly Sovereign CDS (SCDS) returns. The main independent variable, $ExpRet$, is the weighted average SCDS returns across all export destination countries in the past three months, where the weight is proportional to the prior year's bilateral export. We also include stock and currency versions of this variable as well as a version where we weight SCDS returns by the inverse of the log geographic distance. The set of controls include $OwnRet_{c,t}$, the country's lagged SCDS return; $DistRet_{c,t}$ and $ImpRet_{c,t}$, the weighted average SCDS returns across all importing countries in the past three months, where the weight is proportional to the prior year's bilateral import. $FDIRet_t^{in}$($FDIRet_t^{out}$) is the weighted average SCDS return in the past three months of FDI source (destination) countries, where the weight is proportional to the inward (outward) FDI in the prior year. $PortInvRet_t^{in}$ ($PortInvRet_t^{out}$) is the weighted average SCDS return in the past three months of inward (outward) portfolio investment countries, where the weight is proportional to the inward (outward) bilateral portfolio investment in the prior year. For ease of interpretation, all of the export-weighted independent variables are transformed to quintile dummies. Other controls that are included in each specification but are not reported include: the lagged seasonally-adjusted month over month inflation, lagged annual GDP growth rate, and the lagged annual export to GDP ratio. *T*-statistics based on Newey-West standard errors (12 lags) are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monthly Sovereign CDS returns Ret_{t+1} (in %)				
	(1)	(2)	(3)	(4)	(5)
$ExpRet_t$	0.0828***	0.0532**	0.0719**	0.1204**	0.1110**
	[4.26]	[2.35]	[2.44]	[2.25]	[2.05]
$ExpStock_t$	0.0163	-0.0202	-0.0236	-0.0127	-0.0275
	[-0.67]	[-0.62]	[-0.70]	[-0.45]	[-1.08]
$ExpCurr_t$	-0.0077	0.0169	0.0127	0.0057	-0.0026
	[-0.24]	[0.60]	[0.46]	[0.18]	[-0.08]
$DistRet_t$		0.0114	0.0007	0.0072	0.0126
		[0.42]	[0.02]	[0.21]	[2.50]
$OwnRet_t$		7.065**	7.5938**	7.7049**	7.9956**
		[2.06]	[2.12]	[2.15]	[2.20]
$ImpRet_t$			-0.0316	-0.0387	-0.0472
			[-1.57]	[-1.32]	[-1.60]
$FDIRet_t^{in}$				-0.0212	-0.0266
				[-0.97]	[-1.31]
$FDIRet_t^{out}$				-0.0134	-0.0089
				[-0.75]	[-0.60]
$PortInvRet_t^{in}$					0.0168
					[1.36]
$PortInvRet_t^{out}$					-0.0165
					[-0.61]
Controls	YES	YES	YES	YES	YES
No. Obs.	173	172	172	172	172
Adj. R^2	0.0018	0.0237	0.0307	0.0307	0.0308

Table V: Direct vs. Indirect Trade Links

This table reports results of forecasting regressions of weekly sovereign CDS returns. The main independent variable, $ExpRet$, is the weighted average SCDS returns across all export destination countries in the past three months, where the weight is proportional to the prior year's bilateral export. We also include in the regression, $ExpRetInd$, which is the average SCDS returns across destinations that a country indirectly exports to. More specifically, we construct an import-export matrix, and then multiple the square of this matrix by SCDS returns. Other control variables include: exporting countries' own past three-months sovereign CDS returns, lagged seasonally-adjusted inflation (month over month), lagged one-year GDP growth rate, and lagged one-year export-to-GDP ratio. We fix all independent variables at the end of week t, and vary the dependent variable from week t+1 to t+8. T-statistics based on Newey-West standard errors (12 lags) are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Weekly Sovereign CDS Returns Ret_{t+k}							
	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
$ExpRet_t$	0.1099***	0.0959**	0.0601	0.0718*	0.0254	0.0126	0.0083	0.0137
	[2.66]	[2.00]	[1.48]	[1.92]	[0.60]	[0.36]	[0.24]	[0.38]
$ExpRetInd_t$	0.0317	0.0759	0.0982**	0.1406***	0.0658	0.0890*	0.0459	0.0087
	[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

Table VI: An Event Study – Japanese Tsunami

This table reports the ripple effect of the Japanese triple-disasters (Earthquake, Tsunami, and Radioactive fallout) in March 2011. We focus on the four weeks surrounding March 11, 2011 (the day the Earthquake hit Japan's east coast), with week T being the event week. For each week in our sample, we conduct a cross-section regression of each country's SCDS return on its closeness to Japan in the import-export network. Our main independent variable, $ExpShare$, is the share of a country's export to Japan as a fraction of the country's aggregate exports measured in year 2010. Other control variables include: the country's own lagged one-month sovereign CDS return, and lagged one-month seasonally adjusted inflation rate. In Panel A, $ExpShare$ is simply the fraction; in Panel B we construct a dummy variable, $ExpShare_{DUM}$ that equals one if the country's share of export to Japan is in top 20% of the sample, and zero otherwise. T-statistics based on bootstrapped standard errors are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Weekly Sovereign CDS Returns Ret_{t+k}								
	Weekly Returns				Daily Returns			
	T-1	T	$T+1$	$T+2$	T-1	T	$T+1$	$T+2$
$ExpShare$	-0.0639	0.2255***	0.0258	-0.0272	0.0401	0.131**	0.201***	-0.011
	[-0.66]	[2.87]	[0.32]	[-0.51]	[0.69]	[2.07]	[2.66]	[-0.17]
$OwnRet$	0.0517	0.0620	-0.1166**	0.2482***	-1.013*	-0.659	0.067	-0.037
	[0.59]	[0.59]	[-2.09]	[3.85]	[-1.87]	[-1.31]	[0.48]	[-0.28]
No. Obs.	72	72	72	72	72	72	72	72
Adj. R^2	0.01	0.03	0.04	0.10	0.28	0.38	0.17	0.003

Panel B: Weekly Sovereign SCDS Returns Ret_{t+k}								
	Weekly Returns				Daily Returns			
	T-1	T	$T+1$	$T+2$	T-1	T	$T+1$	$T+2$
$ExpShare_{DUM}$	-0.0123	0.0509***	-0.0035	0.0065	0.0007	0.0291***	0.0335***	-0.0045
	[-0.98]	[3.36]	[-0.30]	[0.70]	[0.09]	[3.09]	[3.47]	[-0.46]
$OwnRet$	0.0531	0.0557	-0.1078*	0.2378***	-1.031*	-0.656	0.015	-0.016
	[0.63]	[0.58]	[-1.94]	[3.85]	[-1.87]	[-1.38]	[0.12]	[-0.10]
No. Obs.	72	72	72	72	72	72	72	72
Adj. R^2	0.02	0.10	0.04	0.11	0.26	0.41	0.21	0.007

Table VII: Covariances of SCDS Returns

This table shows evidence of the relation between bilateral export share and co-movement of SCDS returns of a given pair of countries. We use two measures of return co-movement. The dependent variable in Columns 1 and 2, $LINK$, is computed following Giovanni, Levchenko and Mejean (2014): $LINK_{i,j} = w_{i,\tau} * w_{j,\tau} * Cov\left(Ret_{i,t}, Ret_{j,t}\right)$, where $w_{i,\tau}$ is country i's share of the aggregate global trade at time τ (which in this table is the beginning of our sample period), and $Cov\left(Ret_{i,t}, Ret_{j,t}\right)$ is the covariance of the SCDS returns between countries i and j measured over the whole sample period. The dependent variable in Columns 3 and 4 is the correlation in SCDS returns between the two countries, again measured over the whole sample period. Our main independent variable of interest is $ExpShare_{i,j}^{AVG}$, which is the average fraction of country i and j's total exports that are accounted for by their bilateral trade. T-statistics based on standard errors clustered at the country level are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) LINK	(2) LINK	(3) Correlation	(4) Correlation
$ExpShare_{i,j}^{AVG}$	5.344***	5.943***	0.386**	0.417**
	(5.42)	(5.26)	(2.19)	(2.18)
distance		0.296**		-0.0174
		(2.15)		(-0.26)
language		-0.211***		-0.0159
		(-6.00)		(-1.01)
colony		0.0850		-0.0324
		(1.08)		(-1.31)
No. Obs.	3380	3380	3793	3793
Adj. R^2	0.092	0.112	0.001	0.001

Table VIII: Forecasting Stock Market 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 quintiles (P1 to P5) based on their corresponding export destination countries' average SCDS returns, $ExpRet$. Specifically, $ExpRet$ is the weighted average SCDS returns across all export destination countries in the past three months, where the weight is proportional to the prior year's bilateral export. 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 (constructed based on a three-month forming period and a one-month holding period). The third row reports portfolio alpha after controlling for the equal-weighted average return of all stock markets. The forth row reports portfolio alpha controlling for both the momentum factor and global market factor. Row five further includes the global momentum and value factors (as in Asness, Moskowitz and Pedersen, 2013). Panel B reports results of forecasting regressions of monthly stock index returns. The main independent variable is $ExpRet$. Other controls include: $ExpRet^{stock}$, the weighted average stock market returns across all export destination countries in the past three months, where the weight is proportional to the prior year's bilateral export, the country's lagged stock market return, lagged seasonally-adjusted month over month Inflation, lagged annual GDP growth rate and lagged annual export to GDP ratio. T-statistics based on standard errors with Newey-West adjustments of up to 12 lags are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calendar Time Stock Market Portfolios

P1	P2	P3	P4	P5	P1 – P5
1.58***	1.31**	0.97*	0.91*	0.59	0.99***
(2.75)	(2.27)	(1.81)	(1.76)	(1.03)	(3.26)
1.82***	1.38**	1.06**	1.01**	0.71	1.11***
(3.55)	(2.59)	(2.13)	(2.02)	(1.26)	(3.39)
0.48**	0.25**	-0.06	-0.14	-0.49***	0.98**
(2.28)	(2.55)	(-0.59)	(-1.12)	(-3.30)	(2.94)
0.63***	0.16**	-0.10	-0.17	-0.49***	1.13***
(2.77)	(2.02)	(-0.95)	(-1.30)	(-2.74)	(2.93)
0.63***	0.19**	-0.13	-0.27*	-0.41***	1.05***
(3.30)	(2.00)	(-1.23)	(-1.77)	(-3.10)	(3.74)

Panel B: Fama-MacBeth Regressions (expressed in %)				
	(1)	(2)	(3)	(4)
$ExpRet_t$	-0.196***	-0.177***	-0.169***	-0.102**
	[-4.22]	[-3.74]	[-3.75]	[-2.01]
$ExpStock_t$	0.173***	0.137**	0.117*	0.125*
	[2.75]	[2.26]	[1.95]	[1.94]
$ExpCurr_t$	0.00436	0.00957	-0.0731	-0.0665
	[0.07]	[0.17]	[-1.11]	[-1.11]
$OwnStock_t$		0.270***	0.390***	0.377***
		[3.02]	[4.55]	[5.07]
$OwnCurr_t$			0.965***	0.938***
			[3.59]	[3.48]
$Inflation_t$				0.197
				[0.11]
$GDPGrowth_t$				0.0650*
				[1.85]
$ExportToGDP_t$				-0.0850
				[-0.54]
No. Obs.	173	173	173	173
Adj. R^2	0.0024	0.0211	0.0213	0.0216

Table IX: Double Sorts on Country Characteristics and Robustness

This table reports calendar-time portfolio returns of sovereign CDS (SDCS) contracts. At the end of each month, SCDS contracts are sorted into five quintiles (P1 to P5) based on their export destination countries' average SCDS returns, $ExpRet$. Specifically, $ExpRet$ is the weighted average SCDS returns across all export destination countries in the past three months, where the weight is proportional to the prior year's bilateral export. All countries are equally weighted within a given portfolio and the portfolios are held for one month. The long/short strategy is constructed by going long countries in quintile P5 and selling short countries in quintile P1. We examine the returns to this long-short portfolio for various subsamples based on each country's credit rating (Panel A), external debt to GDP ratio (Panel B), or eigen centrality (Panel C). Panels D and E repeat the analysis of Table III Panel B excluding safe-haven countries and the G20 respectively. T-statistics based on standard errors with Newey-West adjustments of up to 12 lags are shown in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Double Sort on Country Characteristics and $ExpRet$						
	Portfolio returns in the month following formation					Portfolio Return
	P1	P2	P3	P4	P5	(P5 – P1)
Panel A: Sort by Credit Ratings						
High	-0.0007	-0.0001	-0.0001	0.0001	0.0012	0.0019**
	(-0.95)	(-0.31)	(-0.20)	(0.25)	(1.56)	(2.41)
Low	-0.0033*	-0.0001	-0.0010	-0.0003	0.0026	0.0059***
	(-1.88)	(-0.05)	(-0.60)	(-0.21)	(1.41)	(3.39)
Panel B: Sort by External Debt						
High	-0.0044*	-0.0013	-0.0023	0.0011	0.0019	0.0063***
	(-1.92)	(-0.34)	(-1.02)	(0.56)	(0.96)	(3.12)
Low	-0.0022*	-0.0003	-0.0001	-0.0005	0.0019	0.0041***
	(-1.89)	(-0.34)	(-0.14)	(-0.71)	(1.43)	(2.74)
Panel C: Sort by Centrality						
High	-0.0004	-0.0005	0.0001	-0.0007	0.0017	0.0021
	(-0.38)	(-0.67)	(0.19)	(-0.92)	(1.29)	(1.41)
Low	-0.0033*	0.0004	-0.0015	0.0006	0.0022	0.0059***
	(-1.89)	(0.32)	(-0.92)	(0.53)	(1.33)	(3.42)

Panel D: Controlling for Risk Factors without Safe Haven Countries								
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
-0.0024*	-0.0002	-0.0003	-0.0003	0.0024*	0.0048***	0.0063***	0.0033**	0.0038**
(-1.79)	(-0.20)	(-0.34)	(-0.33)	(1.68)	(3.76)	(2.78)	(2.31)	(2.13)
-0.0027**	-0.0008	-0.0012*	-0.0012*	0.0002	0.0029***	0.0032**	0.0011	0.0029**
(-2.40)	(-1.18)	(-1.87)	(-1.87)	(0.27)	(3.28)	(2.38)	(0.77)	(2.60)
-0.0024***	-0.0001	-0.0003	-0.0002	0.0024***	0.0048***	0.0067***	0.0032	0.0038**
(-3.12)	(-0.35)	(-0.67)	(-0.50)	(3.39)	(3.63)	(2.87)	(1.35)	(2.15)
-0.0015**	0.0001	-0.0003	-0.0002	0.0015***	0.0030***	0.0034**	0.0014	0.0029**
(-2.50)	(0.31)	(-0.86)	(-0.63)	(3.37)	(3.23)	(2.02)	(0.84)	(2.56)
-0.0011*	-0.0000	-0.0004	-0.0004	0.0016***	0.0026***	0.0027**	0.0015	0.0036***
(-1.91)	(-0.09)	(-1.11)	(-1.00)	(3.47)	(3.00)	(2.23)	(0.87)	(2.76)

Panel E: Controlling for Risk Factors without G20								
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
-0.0025*	-0.0002	-0.0003	0.0000	0.0023*	0.0048***	0.0053***	0.0016	0.0063***
(-1.91)	(-0.18)	(-0.25)	(0.00)	(1.74)	(4.06)	(2.92)	(1.34)	(3.22)
-0.0025**	-0.0008	-0.0011	-0.0008	0.0008	0.0033***	0.0040***	0.0003	0.0038***
(-2.42)	(-0.94)	(-1.51)	(-1.24)	(0.83)	(3.52)	(2.69)	(0.18)	(3.48)
-0.0025***	-0.0002	-0.0002	0.0000	0.0023***	0.0048***	0.0057***	0.0014	0.0063***
(-4.08)	(-0.38)	(-0.51)	(0.05)	(3.13)	(3.90)	(2.84)	(0.69)	(3.23)
-0.0016***	-0.0000	-0.0003	-0.0001	0.0017***	0.0034***	0.0043**	0.0005	0.0038***
(-3.22)	(-0.03)	(-0.72)	(-0.24)	(2.98)	(3.50)	(2.54)	(0.27)	(3.20)
-0.0014***	-0.0003	-0.0004	-0.0001	0.0016***	0.0031***	0.0040**	0.0004	0.0046***
(-2.77)	(-0.68)	(-0.77)	(-0.24)	(2.91)	(3.21)	(2.11)	(0.23)	(3.18)

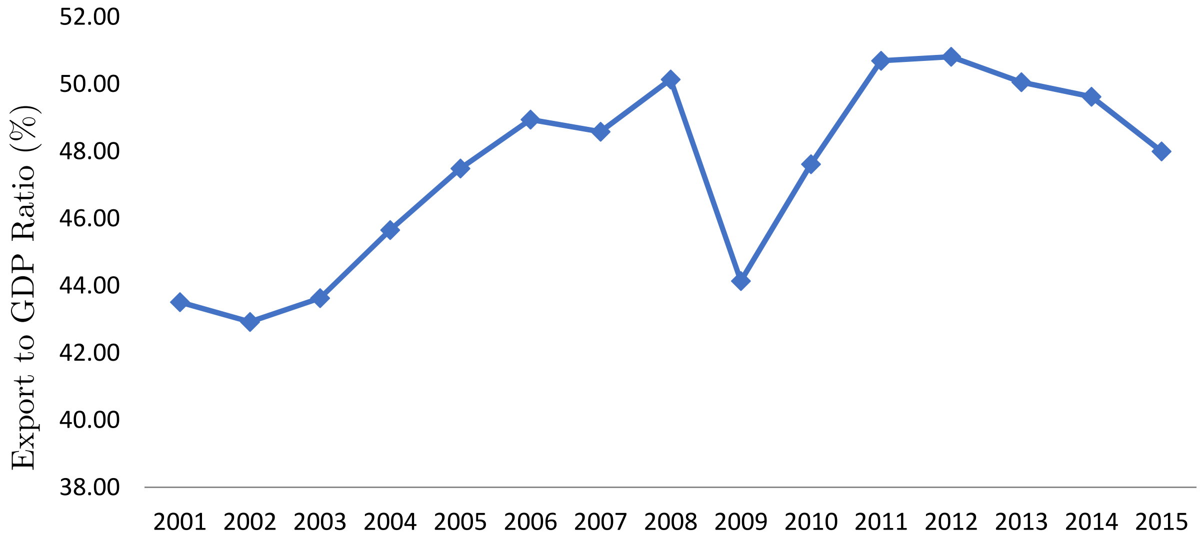

Figure 1: This figure shows the average Export-to-GDP Ratio across all nations in our sample for the period 2001-2015.

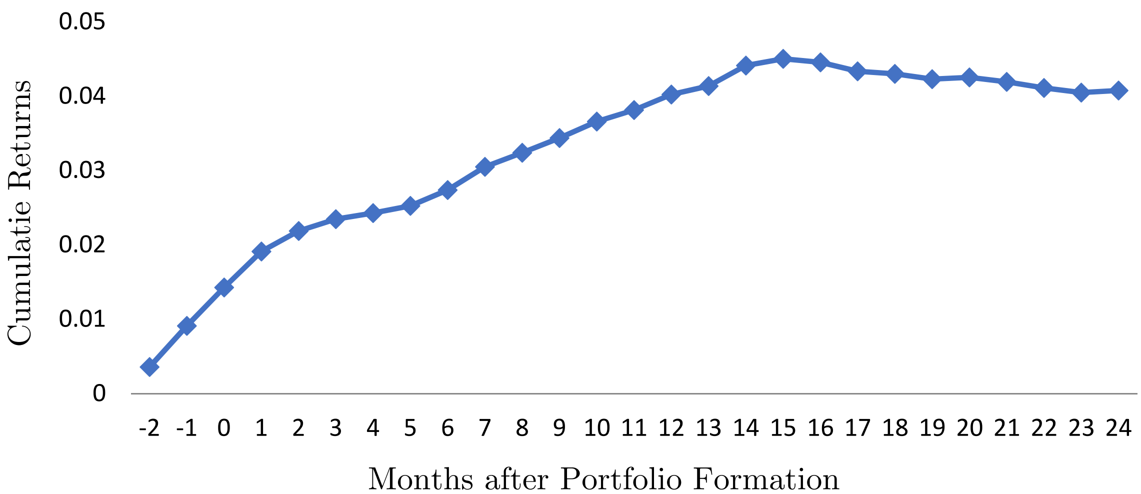

Figure 2: This figure shows the cumulative returns of the long-short portfolio from three months before to twenty-four months after portfolio formation. At the end of month zero, countries are sorted into quintiles based on the weighted average sovereign CDS return across all export destination countries in the past three months, where the weight is proportional to the prior year's bilateral export.

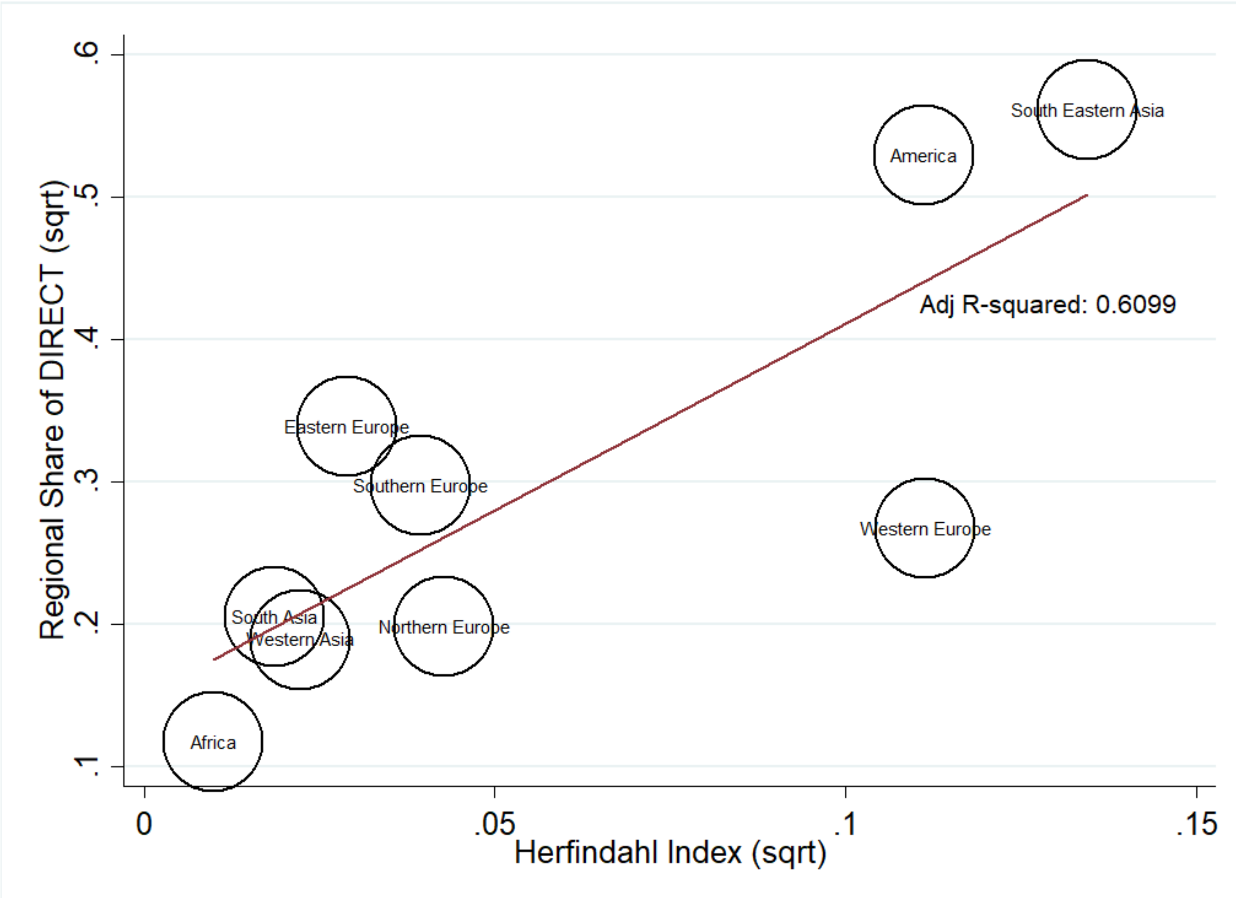

Figure 3: This figure shows the relation between regional export concentration and the region's contribution to the global SCDS volatility. The vertical axis is the share of regional contribution to the $DIRECT$ component of the global SCDS volatility. The decomposition of global SCDS volatility into the $DIRECT$ and $LINK$ components follows Giovanni, Levchenko and Mejean (2014):

$$\sigma_{g,\tau}^2 = \underbrace{\sum_i w_{i,\tau-1}^2 Var\left(Ret_{i,t}\right)}_{DIRECT_\tau} + \underbrace{\sum_i \sum_j w_{i,\tau-1} * w_{j,\tau-1} * Cov\left(Ret_{i,t}, Ret_{j,t}\right)}_{LINK_\tau}.$$

The horizontal axis is the Herfindahl index of each country's share of the global export in each region. We also fit a regression line through these observations, obtaining an R^2 of 0.61.

Appendix Table A1: List of Countries with Sovereign CDS data

Country	SCDS Starting Date	Stock Index	Stock index Starting Date
Algeria	Sep-2008		
Angola	Oct-2009		
Argentina	Apr-2001	MERVAL	Apr-2001
Austria	Jul-2001	ATX	Jul-2001
Australia	Oct-2003	AS51	Oct-2003
Barbados	Jul-2006		
Belgium	Mar-2001	BEL20	Mar-2001
Bulgaria	May-2001	SOFIX	May-2001
Bahrain	Aug-2004	BHSEASI	Aug-2004
Belize	Jan-2010		
Brazil	Feb-2001	IBOV	Feb-2001
Tunisia	Dec-2003	TUSISE	Dec-2003
Canada	Oct-2003	SPTSX	Oct-2003
Chile	Mar-2002	IGPA	Mar-2002
China	Feb-2001	SHSZ300	Feb-2001
Hong Kong	Sep-2004	HSCI	Sep-2004
Colombia	Apr-2001	COLCAP	Apr-2001
Costa Rica	Sep-2003	CRSMBCT	Sep-2003
Croatia	Feb-2001	CRO	Feb-2001
Cyprus	Aug-2002	CYSMMAPA	Aug-2002
Czech	Apr-2001	PX	Apr-2001
Germany	Nov-2002	DAX	Nov-2002
Denmark	Dec-2002	KFX	Dec-2002
Dominica	Aug-2003		
Ecuador	Jul-2003		
Egypt	Apr-2002	HERMES	Apr-2002
El Salvador	Jul-2003		
Estonia	Jul-2004	TALSE	Jul-2004
Fiji	Jul-2007		
Finland	Aug-2002	HEX	Aug-2002
France	May-2002	CAC	May-2002
Greece	Feb-2001	ASE	Feb-2001
Guatemala	Sep-2003		
Iceland	Apr-2004		
India	Aug-2003	SENSEX	Aug-2003
Indonesia	Jan-2002	JCI	Jan-2002
Iraq	Mar-2006		
Ireland	Feb-2003	ISEQ	Feb-2003

Israel	May-2001	TA-25	May-2001
Italy	Mar-2001	FTSEMIB	Mar-2001
Jamaica	Oct-2003	JMSMX	Oct-2003
Japan	Feb-2001	TPX	Feb-2001
Jordan	Oct-2003	JOSMGNFF	Oct-2003
Kazakhstan	Feb-2004	KZKAK	Feb-2004
South Korea	May-2001	KRX100	May-2001
Latvia	Sep-2004	RIGSE	Sep-2004
Lebanon	Apr-2003	BLOM	Apr-2003
Lithuania	May-2002	VILSE	May-2002
Malaysia	May-2001	FBMKLCI	May-2001
Malta	Aug-2004	MALTEX	Aug-2004
Macedonia	Oct-2011	MCTSTAT	Oct-2011
Mexico	Feb-2001	MEXBOL	Feb-2001
Morocco	May-2001	MCSINDEX	May-2001
Netherlands	Sep-2003	AEX	Sep-2003
Nigeria	Jan-2007	NGSEINDX	Jan-2007
Norway	Nov-2003	OBX	Nov-2003
New Zealand	Jan-2004	NZSE50FG	Jan-2004
Oman	Dec-2008	MSM30	Dec-2008
Pakistan	Aug-2004	KSE100	Aug-2004
Panama	Mar-2002	BVPSBVPS	Mar-2002
Peru	Mar-2002	SPBLPGPT	Mar-2002
Philippines	Apr-2001	PCOMP	Apr-2001
Poland	Feb-2001	WIG	Feb-2001
Portugal	Mar-2002	BVLX	Mar-2002
Qatar	Oct-2001	DSM	Oct-2001
Hungary	Apr-2001	BUX	Apr-2001
Georgia	Jul-2015		
Romania	Apr-2002	BET	Apr-2002
Ghana	Jun-2008	GGSECI	Jun-2008
Russia	Oct-2001	INDEXCF	Oct-2001
Saudi Arabia	Mar-2007	SASEIDX	Mar-2007
Singapore	Aug-2003	STI	Aug-2003
Slovakia	Jun-2001	SKSM	Jun-2001
Slovenia	Mar-2002		
South Africa	Feb-2001	TOP40	Feb-2001
Spain	Mar-2001	IBEX	Mar-2001
Serbia	Jul-2006	BELEXLN	Jul-2006
Sri Lanka	Jan-2008	CSEALL	Jan-2008
Sweden	Jul-2001	OMX	Jul-2001

Switzerland	Jul-2007	SMI	Jul-2007
Taiwan	Sep-2006	TWSE	Sep-2006
Thailand	Apr-2001	SET	Apr-2001
Trinidad and Tobago	Dec-2004		
Turkey	Feb-2001	XU100	Feb-2001
UAE	Mar-2007	DFMGI	Mar-2007
United Kingdom	Apr-2006	UKX	Apr-2006
Ukraine	Oct-2002	UX	Oct-2002
Uruguay	Jun-2002		
US	Jan-2004	SPX	Jan-2004
Venezuela	Mar-2001		
Vietnam	Sep-2002	VNINDEX	Sep-2002