

Limited Investment Capital and Credit Spreads*

Online Appendix

Emil N. Siriwardane[†]

Abstract

This appendix provides additional evidence supporting the analysis in the main text, as well as details of all data used in the study.

*The views expressed in this paper are those of the author's and do not reflect the position of the Depository Trust & Clearing Corporation (DTCC) or the Office of Financial Research (OFR). DTCC data is confidential and this paper does not reveal any confidential information.

[†]Affiliation: Harvard Business School and the Office of Financial Research, U.S. Department of Treasury. E-mail: esiriwardane@hbs.edu.

1 Additional Discussion

1.1 Concentration and Barriers to Entry in the CDS Market

Intuitively, concentration develops naturally in any market with high fixed entry costs. CDS markets are costly to enter for a few reasons. First, trading CDS requires back-office processing of trades and risk management to manage existing positions. To this point, many smaller hedge funds will pay their dealer an additional fee in return for the dealer handling the oversight of trades. Moreover, establishing a CDS desk requires substantial information acquisition (Merton (1987)), not only in terms of hiring traders and managers with expertise in credit risk, but also specifically in credit derivatives. He and Xiong (2013) also show that segmentation may arise endogenously when agency considerations mean that it is optimal to give traders a limited investment mandate. Second, CDS trading is similar to banking in the sense that relationships are “sticky” (Chodorow-Reich (2014)). For example, the average non-dealer in my sample trades with only three counterparties. In lieu of the costs of building new trading relationships, it is no surprise that trading activity in all over-the-counter markets is dominated by a handful of dealers who can use their existing relationships from many lines of business. Third, operating a CDS desk is costly from a funding standpoint. Since the 2007-09 crisis, it has been common practice for CDS positions to be marked-to-market every day. Consequently, CDS desks need a stable source of funding in order to survive daily fluctuations in mark-to-market values. There are large economies to scale in terms of funding, and as a result, large dealers and hedge funds naturally emerge as key players in the market.

Of course, there are a multitude of additional reasons why CDS markets are concentrated. The purpose of this paper is not to answer this question, but rather to understand how limited capital in the market ultimately affects pricing in CDS. Nonetheless, my findings do shed some light on the question of concentration. For instance, because I find that asset managers have become a dominant seller of CDS protection, it is unlikely that relationships play a first order role in concentration; if relationships were primarily driving concentration, dealers would always be the largest net buyers and sellers. On the other hand, the fact that limited capital does seem to impact prices suggests that funding frictions may be important for explaining the concentration of the CDS market. While concentration is certainly an interesting and important topic, further inquiry is outside of the scope of this paper.

2 Main Text: Supplementary Analysis

This section provides some complimentary evidence to support the analysis in Section 4 and 5 of the main text.

2.1 Composition of Sellers and Buyers Across Firms in the Same Industry

In the main text, the regression that delivers the strongest identification of the impact of capital shocks on spreads is as follows:

$$\Delta cds_{f,t} = a_f + a_{i,t} + \Delta cds_{f,t-1} + \beta_1' \Delta \mathbf{Z}_{f,t} + \zeta_s SC_{f,t} + \zeta_b BC_{f,t} \quad (1)$$

where $SC_{f,t}$ is my proxy for seller capital shocks, $BC_{f,t}$ is my proxy for buyer capital shocks, and $a_{i,t}$ is an industry-by-time fixed effect. I classify firms into an industry based on the definition provided by Markit. Table A1 shows the distribution of industries across firms in the study. The two most represented industries are Financials and Consumer Goods, and the two least represented industries are Telecom and Technology. For the most part though, firms are pretty evenly spread out across the ten Markit industries, as the maximum percentage of any one industry is under 17%.

The industry-by-time fixed effect is key to this regression because it absorbs any unobservable characteristics common to the cross section of CDS spreads for firms within each industry at each point in time. Hence, the exclusion restriction for identifying ζ_s would be violated only if $SC_{f,t}$ captures some factor that drives f 's CDS spread, but in a way that is: (i) not common to all firms in f 's industry, as ruled out by the industry-by-time fixed effect; and (ii) not correlated with f 's firm specific covariates $\mathbf{Z}_{f,t}$ (e.g. f 's own equity price). The same logic applies to unbiased estimation of ζ_b . The exclusion restriction in the regression is made even more palatable by the fact that both $SC_{f,t}$ and $BC_{f,t}$ are computed by excluding positions written on firms in f 's industry.

In order for this identification strategy to work, there must be ample variation of $SC_{f,t}$ and $BC_{f,t}$ across firms in the same industry. To see why, consider a knife-edge case where there is a single seller for all firms in f 's industry. In this case, $SC_{f,t}$ will be the same for all firms in the industry, rendering identification of ζ_s impossible. More generally, the power of the regression depends critically on there being ample variation in the identities of sellers and buyers across firms in the same industry. Figures A1 and A2 show that this is indeed the case. In Figure A1, I plot: (i) the average percent of sellers in common for each pair of firms in an industry; and (ii) the average percent of notional sold by common sellers for each pair of firms in an industry. For example, for firms a and b in industry i , I compute the percent of sellers who are common to both a and b , as well as the percent of their total net notional outstanding that is sold by common sellers. I repeat this process for all pairs of firms in industry i and at each point in time. The graph plots the average over all pairs and time periods. Figure A2 displays the same exercise for buyers.

Figure A1 indicates that firms have a fairly degree of overlap in terms of their sellers. In terms of counts, for a given pair of firms in an industry, about 15% of their sellers are in common by count, and 40% by notional. From Figure A2, we can see that buyers have less commonality than sellers. In terms of estimating regression (1), neither buyer or seller overlap pose any issues because both are far from 100%.

2.2 What Explains CDS Spreads? Full Results

Table A2 summarizes the results from the following regression:

$$\Delta cds_{f,t} = a_f + \Delta cds_{f,t-1} + \beta'_1 \Delta \mathbf{Z}_{f,t} + \beta'_2 \Delta \mathbf{X}_t$$

where $\mathbf{Z}_{f,t}$ is a vector of firm-specific controls and \mathbf{X}_t is a vector of macroeconomic controls. See the table for a full list of all of the variables considered. a_f is a firm fixed effect. The purpose of this regression is to establish a baseline for the explanatory power of variables that are theoretically supposed to explain changes in credit spreads (e.g. from structural models of credit) or those that have previously been documented to explain credit spread movements. In terms of the important dependent variables and the overall R^2 , these results echo previous studies that examine the determinants of credit spread changes (Collin-Dufresne, Goldstein, and Martin (2001); Tang and Yan (2017)).

2.3 Alternative Capital Measures

Alternative Measures of CDS-Desk Capital Shocks

In the main text, for a given firm f , I compute capital shocks at the CDS desks of f 's sellers using the dollar change in the mark-to-market value of their CDS portfolio, excluding all firms in f 's industry. Capital shocks for f 's buyers are computed in an analogous fashion. The headline result of the paper is that these capital shocks — more specifically seller shocks — lead to changes in f 's CDS spreads. In this subsection, I conduct some robustness tests of this finding using alternative ways to define capital shocks. For sellers of f , these alternatives are: (i) returns to sellers' CDS portfolios, excluding positions in f 's industry; (ii) the dollar change in the mark-to-market value of sellers' CDS portfolios, excluding positions written on f itself; and (iii) returns to sellers' CDS portfolios, excluding positions written on f itself. The same alternative capital shock measures are computed for f 's buyers. Section 5.3 of this appendix contains details of how I compute CDS portfolio returns for buyers and sellers.

Table A4 shows basic summary statistics for these alternative capital measures. The summary statistics in Table A4 highlight an important caveat when interpreting any results using the return-based capital shock measures. To see why, notice that the standard deviation of weekly seller returns (excluding positions in f 's industry) is 0.128%, which translates to an annual portfolio volatility of about 1%. This is very small for a levered derivative portfolio, which indicates that the method through which I compute portfolio returns is extremely conservative in terms of leverage.¹ I have virtually no information on allowable leverage, so a better alternative to computing

¹I loosely base my return calculations on FINRA's margin requirements. However, a critical step in computing initial margins (e.g. leverage) requires one to make an assumption about how collateral netting occurs between counterparties. I have very little information on this at the counterparty level, so I make a simplifying assumption that initial margins are computed based on the net position between any two counterparties. See Section 5.3 for a complete discussion.

portfolio margins is at best ad-hoc. I therefore interpret the results using the return-based capital shocks with some caution.

Table A5 uses these alternative capital measures in regressions of the form:

$$\Delta \log(CDS_{f,t}) = c + \beta_S \times SC_{f,t} + \beta_B \times BC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t}$$

The table reports the estimates for β_S and β_B . $\mathbf{Z}_{f,t}$ is a vector of the following firm-level controls: the lagged log-change in CDS spread, each firm's own equity return, the log-change in Moody's expected default frequency (EDF), the log-change in loss-given-default (LGD) from Markit, and the change in Markit depth. When included, the option-based controls are: the log-change in option-implied CDS spreads (computed according to Carr and Wu (2011)) and the change in ATM volatility from option prices. All regression specifications include a firm fixed effect, and reported R^2 are computed within each firm-group. Some regressions also include an industry-by-time fixed effect.

In Columns 1-3, $SC_{f,t}$ measures the percent return to the CDS portfolio of f 's net sellers, excluding all positions written on firms in the same industry as f . In Columns 4-6, $SC_{f,t}$ measures the dollar change (in \$ bn) in the mark-to-market value of f 's net sellers, excluding all positions written on f . In columns (7)-(9), $SC_{f,t}$ measures the percent return to the CDS portfolio of f 's net sellers, excluding all positions written on f . In all cases, $BC_{f,t}$ mimics the same construction, but for f 's net buyers of protection.

A few features of the table are worth noting. When moving from Column 1 to Column 2, the estimated coefficient on seller capital shocks shrinks by a factor of almost two in absolute value. Column 2 adds an industry-by-time fixed effect to the regression in Column 1. The same pattern occurs for all the alternative capital measures (e.g. Column 4 to 5, or Column 7 to 8). The fact that β_S decreases in absolute value therefore indicates that seller capital shocks are partly absorbed by the industry-by-time effect. This result is not particularly surprising because it is likely that the capital shocks of sellers in the CDS market are at least partially driven by a common set of factors.

The bigger takeaway of Table A5 is that, regardless of how capital is measured, there is a robust relationship between firm f 's CDS spread changes and shocks at f 's protection sellers. Across all specifications, the coefficient on β_S is negative and statistically significant. In terms of economic magnitude, the coefficient when using the dollar-based capital measure in Column 4-6 resembles the effect found in the main text. The coefficient on both return-based capital shock measures indicates a smaller response of CDS spreads to seller shocks, but this is likely driven by the way I compute portfolio returns (see the discussion above).

When using either of the return-based measures in Columns 1-3 or 7-9, capital shocks to buyers $BC_{f,t}$ have a positive and statistically significant coefficient. A positive value for β_B means that CDS spreads rise when buyers of CDS experience a positive shock to their CDS portfolio. As discussed in the main text, one explanation for this finding is that buyers are partially hedging a corporate bond position with CDS. When their CDS portfolio makes money, their corporate bond portfolio loses money. Thus, a positive CDS shock translates to a negative wealth shock overall. In turn, a negative wealth shock increases the effective risk aversion of buyers, thereby making

them willing to pay a higher premium to purchase credit protection. Put differently, if buyers have increased risk aversion, they require a higher premium for holding corporate bonds going forward. Importantly though, the economic magnitude of β_B when using the return-based measures is quite small. From Table A4, we see that a one standard deviation return shock to buyers translates to only about a 0.4% increase in firm f 's CDS spread.² Moreover, when using the dollar-based capital shock measure that excludes positions on f , the coefficient on buyer capital is no longer statistically significant. Echoing the conclusion in the main text, this exercise does not provide robust evidence of a link between credit spreads and shocks at the CDS desks of protection buyers.

2.4 Institution-Wide and CDS-Desk Specific Capital Constraints

To develop a better sense of the relationship between institution-wide capital constraints and CDS-specific shocks, I run the following regression:

$$\begin{aligned} \Delta cds_{r,t} = & a_r + a_{i,t} + \Delta cds_{r,t-1} + \beta_1' \Delta \mathbf{Z}_{rt} + \zeta_b BC_{r,t} \\ & + \zeta_{LL} SC_{r,t} \times 1_{LSL} \times 1_{LSCL} + \zeta_{LH} SC_{r,t} \times 1_{LSL} \times 1_{HSCL} \\ & + \zeta_{HL} SC_{r,t} \times 1_{HSL} \times 1_{LSCL} + \zeta_{HH} SC_{r,t} \times 1_{HSL} \times 1_{HSCL} \end{aligned} \quad (2)$$

This regression interacts my proxy for seller capital shocks at the CDS desk with two different indicator variables. The first is meant to capture the financial health of the CDS desk, whereas the second measures constraints that apply to the whole institution.³ The indicator variable 1_{HSCL} equals one if the pooled CDS portfolio for f 's net sellers has experienced “high” levels of losses in the previous four weeks (e.g. from $t - 5$ to $t - 1$). The previous month's cumulative CDS portfolio losses are considered high if they are in their lower 10% tail. The indicator variable $1_{LSCL} = 1 - 1_{HSCL}$ indicates when seller losses have been low. In a similar spirit, 1_{HSL} and 1_{LSL} are indicators for if seller leverage is high or low at time $t - 1$. I define f 's net sellers as having high leverage if their average *level* of leverage is in its upper 10% tail.

Regression (2) allows for the interaction between spreads and capital shocks to depend on other factors that may influence sellers' risk taking appetite. For instance, the coefficient ζ_{HH} in equation (2) provides an answer to following question: how does a seller capital shock transmit to the CDS market when sellers are not only highly leveraged at an institution level, but have also experienced large CDS portfolio losses in the preceding month? The point estimates in Column 1 of Table A6 reveal an intuitive answer to this question.

The fact that the estimated $|\zeta_{LH}| > |\zeta_{LL}|$ and $|\zeta_{HH}| > |\zeta_{HL}|$ shows that, regardless of their leverage, negative seller shocks raise spreads more when the CDS desk has experienced losses over the previous month. This finding accords with the idea that specialized divisions or desks

²A one-standard deviation negative return shock to sellers translates to about 1.6% increase in spreads, so almost four times the impact of a buyer shock.

³Though not listed in Equation (2), I also all individual indicator variables and their relevant interactions in the regression.

within financial institutions are preallocated a pool of capital to finance trading activity. However, when this capital gets depleted by prolonged losses, additional negative shocks lead to a sharper increase in the marginal value of wealth for CDS sellers. The increase in effective risk aversion translates to higher CDS spreads for the firms that these traders sell protection on.

Column 1 also indicates that, regardless of past losses, negative desk-specific shocks increase spreads more when sellers are more leveraged as an institution. This conclusion follows naturally from the fact that $|\zeta_{HL}| > |\zeta_{LL}|$ and $|\zeta_{HH}| > |\zeta_{LH}|$. Intuitively, if sellers are constrained at the institution level, they may not have any additional capital to allocate towards their CDS traders. In addition, it is reasonable to think any within-institution agency problems only worsen when sellers are highly leveraged. The worst scenario in terms of how seller capital shocks impact spreads is unsurprisingly when sellers have experienced past CDS losses and they are also very levered. In this case, a negative billion dollar seller capital shock causes an increase in spreads of 2.51 percent. Keep in mind that all of these regressions have an industry-by-time fixed effect, meaning that the magnitude of this effect is likely understated.

Subsample of Dealers Column 2 of Table A6 repeats the analysis contained in Column 1, but only for the subsample of firms where dealers are the majority net seller. I focus on this set of firms in these robustness tests because institution-wide measures of leverage are only available for dealers. Thus, one might be concerned that the inclusion of asset managers in the preceding analysis somehow confounds the results. Column 2 largely corroborates the conclusions drawn from Column 1, but the point estimates on the various interactions with $SC_{f,t}$ are all moderately lower. I interpret this finding to mean that negative shocks to the CDS desks of dealers have a somewhat muted effect on spreads compared to the entire sample that includes sellers who are not dealers. A logical implication of these results is that internal capital market frictions at dealers are smaller than at asset managers.

2.5 Subsample Analysis

In this subsection, I explore whether the link between seller capital shocks and CDS spreads is present in different subsamples of firms. As a baseline, Column (1) of Table A7 repeats the results of running regression (1) for my main sample of firms.

Column (2) reports the findings when looking only at firms that are in the on-the-run (OTR) CDX Investment Grade (IG) index.⁴ As discussed in the main text, the link between seller capital shocks and CDS spreads is nonexistent for this subset of firms. My interpretation of this fact is that firms in the on-the-run IG index have more integrated and competitive CDS markets, which is why seller capital shocks do not translate to meaningful price movements. Indeed, a fairly common strategy in the CDS market is to trade on the relative pricing of an index against the basket of its constituents. Nonetheless, the reason that the CDS markets for these firms are subject

⁴i.e. Column 3 of Table 5 in the main text.

to less frictions could also be because these firms have high credit quality, as opposed to the fact that they are a part of the index. To check this hypothesis, Column (3) runs the regression for IG firms that are not in the on-the-run index. In this case, the point estimate on seller capital is statistically significant and comparable to the baseline results in Column (1), thereby favoring the index inclusion story. Furthermore, Column (4) shows that my main finding is present in high yield firms, though the magnitude of the effect is slightly weaker.

A related concern might be that OTR IG firms dominate my sample, which would be problematic because my main pricing effect does not show up for this subset. In terms of pure counts, OTR IG firms are relatively small in terms of number of firms (25%), though these firms do account for about 60% of the total net notional outstanding in my sample. This latter fact is perhaps not surprising given that the investment grade index is by far the most liquid and actively traded product in the CDS market. Nevertheless, my main effect is present for 40% of my sample in notional terms and 75% of my sample in terms of number of firms. It thus seems fair to say that seller losses lead to higher spreads for a non-trivial portion of the CDS market.

One might also wonder whether the frictions I document in the paper are present for large and small firms. For example, it seems reasonable to think that information is more difficult to obtain for smaller firms, which could then act as an additional reason why seller capital is slow to flow into CDS market for these firms. Columns (5) and (6) of Table A7 runs regression (1) for small firms and large firms, where small firms are defined as those above the median market value of equity in my sample. The most important takeaway from these results is that the link between seller capital and spreads is rather robust across the size classifications, which reinforces my main conclusions. Still, in terms of statistical precision, one can't reject the null that the point estimate on seller capital is the same for small and large firms. With that said, my measure of size is pretty coarse, and I leave it to future research to pursue this potential channel further.

As a final robustness check, Column (7) of Table A7 presents the results of regression (1), but excludes dealers when computing seller capital shocks of a given firm. This approach should alleviate any concern that dealers are driving my main pricing relationship, which could potentially be an issue if the complex organizational structure of dealers renders my measure of capital less suitable for them.⁵ In Column (7), the absolute value of the point estimate on seller capital actually increases when excluding dealers, and remains statistically significant at conventional levels. In addition, as shown in Figure 7 of the main text, the impact of a \$1 bn seller capital loss on spreads becomes stronger later in the sample. This provides some additional relief that dealers are not driving all of my results because asset managers also become the primary net sellers of protection later in the sample (see Figure 4 of the main text).

⁵I thank an anonymous referee for raising this possibility.

2.6 Entry and Exit into the CDS Market

In Section 4 of the main text, I evaluate some potential explanations for why CDS spreads increase immediately after sellers of protection experience negative capital shocks, eventually returning to their original levels after about 8-10 weeks. One such explanation for this mean reversion is that new, better-capitalized sellers enter the CDS market and are willing to provide protection at a lower price. To address this possibility in the data, Table A8 studies entry and exit into the CDS market for firm f after capital shocks to f 's buyers and sellers. Specifically, I run the following regression:

$$NNS_{f,t-1 \rightarrow t-1+k} = a_{i,t} + \Delta SCAP_{f,t-1 \rightarrow t} \quad (3)$$

where $NNS_{f,t-1 \rightarrow t-1+k}$ is the net number of new sellers of f that enter the market between time $t-1$ and $t-1+k$. $\Delta SCAP_{f,t-1 \rightarrow t}$ is one of two proxies for capital shocks to f 's sellers at time t . When computing $\Delta SCAP_{f,t-1 \rightarrow t}$ for time t , I use the set of net sellers on f at time $t-1$. The first proxy for capital shocks is just the dollar change in the mark-to-market value of all of f 's net sellers. The second is just the total CDS portfolio return of all of f 's net sellers (i.e. pooled across the entire set). Because there are not reverse causality issues inherent to this regression, I include all positions when constructing both proxies. I estimate regression (3) for $k = 1, \dots, 5$. Columns 1-5 of Table A8, Panel A contain the results when using the dollar proxy, and the same columns of Panel B contain the results when using the return proxy. Across all the various capital proxies and time horizons, there does not appear to be robust evidence that new sellers enter the market after losses at incumbents. The consistently negative coefficient on seller capital shocks does indicate that, on net, new sellers enter the market following losses at incumbent sellers; however, the point estimate is not reliably significant across specifications and is very small in magnitude. For instance, Column 5 of Panel A shows that a one billion dollar loss at incumbent sellers forecasts only 0.33 sellers to enter the market in the 4 weeks following the loss. As documented heavily in the main text, these same losses lead to a rise in CDS spreads for firm f , followed by a fairly fast spread reversion in the weeks following the loss. Combined with that fact, the current analysis therefore suggest that the reason spreads rise and then fall after losses has little to do with incumbent sellers being replaced by new sellers entering the market. Instead, it appears that after a loss, incumbent sellers increase their reservation price for selling additional protection, which subsequently falls as internal capital market frictions at these sellers thaw and their effective risk aversion returns to its original level.

Table A8 also contains the same analysis for new buyers. Specifically, to study how buyers behave following losses, I run the following regression:

$$NNB_{f,t-1 \rightarrow t-1+k} = a_{i,t} + \Delta BCAP_{f,t-1 \rightarrow t} \quad (4)$$

where NNB measures the net number of new buyers who enter the market and $\Delta BCAP$ proxies for buyer capital shocks. Columns 6-10 in Panels A and B of A8 contain the results of this regression using both capital shock proxies (e.g. dollars and returns). In both cases, there does not appear to be much evidence of a compositional shift in the identities of buyers of firm f 's protection following shocks to incumbent buyers.

3 Japanese Tsunami

This section contains supportive analysis and additional background information on the 2011 Japanese tsunami.

3.1 Background on 2011 Japanese Tsunami

On March 11, 2011, a magnitude 9.0 earthquake hit off the coast of Tohoku and was the most powerful earthquake ever recorded in Japanese history. The earthquake in turn triggered a tsunami that devastated the entire country, resulting in hundreds of billions of dollars in damages. One year after the event, the Japanese government estimated material damages could cost as much as \$300 billion.⁶

A simple way to visualize the aggregate effects of the natural disaster is through the CDS spread of the entire country of Japan, which I henceforth denote by JPN. Figure A3 plots this series from March 4, 2011 to March 17, 2011. Prior to the tsunami, JPN's CDS spread was low, hovering around 80 basis points. The tsunami occurred on a Friday, and the CDS spread increased by nearly 50% on the following Monday to just over 115 basis points.

Figure A4 shows that U.S. traders had fairly large and heterogenous CDS exposure to Japan. To compute the exposure of a given counterparty to Japanese firms, I simply sum their net position in any reference entity who is registered in the country.⁷ In the figure, the largest buyers and their associated positions are found on the left. The largest sellers and the size of their positions are on the right.

At the time of the tsunami, the largest seller of protection had an outstanding exposure of over \$4 bn to Japanese firms. Conversely, the largest buyer of protection had bought over \$1b in credit protection. Furthermore, these exposures represent a nontrivial portion of each counterparty's overall portfolio. To roughly quantify this statement, I compute the ratio of the net sold on Japanese firms to the absolute value of all net sold positions in each counterparty's portfolio. For the largest sellers of Japanese firms, this ratio ranges anywhere from 4 to 106 percent.⁸ Similarly, for the largest five buyers of CDS on Japanese firms, this ratio is between -2 to -90 percent. Clearly, the absolute and relative size of these positions are not insignificant, and we would therefore expect a negative shock to Japan to have a nontrivial impact on the overall portfolios of these counterparties.

3.2 Data Description

Before proceeding further, let me briefly describe the data I use for the remainder of this section. On March 11, 2011, I determine the largest 500 firms in the U.S. CDS market as measured by

⁶Source: <http://www.cnn.com/2012/02/26/world/asia/rebuilding-japan-overview/>

⁷I use the country designations provided by Markit.

⁸The ratio can exceed 1 in absolute value because the counterparty may, for instance, sell a lot on Japan and then be a buyer of protection in other names.

net notional outstanding. I then obtain a time-series of 5-year CDS spreads for each reference entity from Markit. In particular, the CDS spreads I examine are for senior unsecured debt, with a “MR” restructuring clause. I then match each reference entity to Moody’s EDF database and CRSP, resulting in slightly less than 300 firms with a full set of variables.

In order to keep this appendix relatively self-contained, I now summarize my approach to testing how the shock of the tsunami gets transmitted to CDS markets via protection sellers and buyers. First, I construct measures of how exposed a U.S. firm f was to the tsunami through its sellers and buyers:

$$\begin{aligned}\Gamma_{S,f} &:= \sum_{f \in \mathcal{S}_f} \left[\frac{NS_{c,f}}{NO_f} \right] \times NS_{c,JPN} \\ \Gamma_{B,f} &:= \sum_{f \in \mathcal{B}_f} \left[\frac{|NS_{c,f}|}{NO_f} \right] \times NS_{c,JPN}\end{aligned}\quad (5)$$

Here, $NS_{c,JPN}$ is the net amount sold by counterparty c on Japanese firms. \mathcal{S}_f and \mathcal{B}_f are the set of sellers and buyers, respectively, of firm f . $\Gamma_{S,f}$ is the weighted average exposure of f ’s sellers to Japan. The term in brackets is the weight, and is the proportion of total net outstanding for f that is sold by c . $\Gamma_{B,f}$ carries the same intuition for buyers, and is the weighted average exposure of f ’s buyers to Japan. The absolute value in the definition of $\Gamma_{B,f}$ is just to make sure the weights are positive and sum to 1. All of my measures are computed as of March 11, 2011, so I also omit time dependencies for brevity.

In the main text, I estimate variants of the following cross-sectional regression:

$$\Delta \log(CDS_{f,1}) = a + \phi_1 \Gamma_{S,f} + \phi_2 \Gamma_{B,f} + \beta' \mathbf{Z}_f + \varepsilon_f \quad (6)$$

where \mathbf{Z}_f is a vector of observable reference entity characteristics that I will discuss shortly. $\Delta \log(CDS_{f,1})$ is the log-change in f ’s CDS spread in the week following the tsunami. To iterate, I consider only U.S. firms.

\mathbf{Z}_f controls for changes in observable firm fundamentals following the tsunami, I use the change in Moody’s 5-year EDF, the change in Markit’s LGD, and the equity return of the firm. Including the equity return of the firm is compelling from the perspective of structural models of credit, where any shock to credit spreads is the same as a shock to equity. In many ways, including the equity return of each firm allows me to dramatically reduce the number of necessary control variables, since any residual changes in CDS spreads must be driven by something independent of equity market movements. Because certain industries may have been more exposed to Japanese firms, \mathbf{Z}_f also contains a fixed effect corresponding to each firm’s NAICS code. I also include level of CDS spreads for each reference entity on 3/11/2011 to allow for the possibility that Γ captures sellers/buyers who specialize in riskier credits. Finally, I include the 90-day running volatility of each reference entity’s CDS spread (in log-changes); this allows for the possibility that reference entities who experienced large spread movements post-tsunami are those that have larger volatility.

I now turn to addressing potential identification issues with attributing changes in CDS spreads after the tsunami with high levels of Γ , as the regression (6) would suggest.

3.3 Potential Identification Issues

To develop the identification challenge I face, suppose the change in U.S. spreads following the tsunami takes a linear form:⁹

$$\Delta \log(CDS_{f,1}) = a + \phi_1 \Gamma_{S,f} + \phi_2 \Gamma_{B,f} + \beta' \mathbf{Z}_f + \gamma U_f + \varepsilon_f \quad (7)$$

where $\Delta \log(CDS_{f,1})$ is the log-change in the CDS spread for firm f following the tsunami. By convention, I take $t = 0$ to be the day of the tsunami, and $t = 1$ to be the week following the tsunami. Again, \mathbf{Z}_f is a vector of observable characteristics for firm f . U_f is a vector of unobserved characteristics that are orthogonal to \mathbf{Z}_f , and ε_f is an error term independent of all variables in the model. Because U_f is unobservable, we can collapse it into the error term, defined by a tilde:

$$\tilde{\varepsilon}_f = \gamma U_f + \varepsilon_f$$

If we estimate the regression in (7), consistent estimation requires $\text{corr}(\Gamma_{S,f}, U_f) = 0$, or $\gamma = 0$. Put differently, it must be the case that f 's weighted-average seller exposure to Japan is uncorrelated with unobservable characteristics that caused spread movements. The effectiveness of my identification therefore rests with my ability to argue that any possible omitted characteristics that cause spread movements are uncorrelated with the included covariates.

With that in mind, a natural objection to my identification strategy is firms with high $\Gamma_{S,f}$ are those more correlated with Japan. For instance, it could be that U.S. sellers of CDS protection specialize in U.S. firms who are fundamentally correlated with the state of the Japanese economy. To alleviate this concern, Figure A5 displays the average correlation between JPN's CDS spread and each U.S. firm in my sample, after splitting reference entities into deciles based on $\Gamma_{S,f}$ or $\Gamma_{B,f}$. Each pairwise correlation between f and Japan is computed using log-changes in CDS spreads in the 90 days prior to the tsunami. The top plot in the left panel displays the average $\Gamma_{S,f}$ within each decile of $\Gamma_{S,f}$, and the bottom plot of the same panel shows the average correlation with Japan in that decile. The right panel of the figure repeats the exercise, but splits firms into deciles based on $\Gamma_{B,f}$.

Figure A5 provides visual evidence against the ‘‘specialization hypothesis’’. That is, sellers who have large exposures to Japan also have exposures to U.S. firms whose fundamentals are linked to Japan. Regardless of whether firms are grouped by $\Gamma_{S,f}$ or $\Gamma_{B,f}$, there is no observable pattern in terms of correlation with Japan. Moreover, the average correlation with Japan within any percentile is relatively low, and never reaches above 18%. Of course, these patterns in simple correlations are only suggestive that sellers of Japanese CDS do not specialize in U.S. firms that are fundamentally

⁹The following exposition could be easily generalized to more general response functions and GMM arguments.

correlated with Japan. In the regression tests contained in the main text, I explicitly include each firms' own equity return (in the week after the tsunami) as a control in regression (7), which is a more direct way to account for any potential fundamental links between U.S. firms and Japan.

3.4 Isolating Concentration

$\Gamma_{S,f}$ and $\Gamma_{B,f}$ are useful because they simultaneously capture if a firm's major sellers were also faced with a capital shock from the tsunami. For this reason, though, they do not allow us to separate the importance of concentration versus total capital losses for a firm's spread movements. A simple example illustrates the distinction. Consider two firms, f_A and f_B , who have the same two sellers S_1 and S_2 . S_1 's share of selling in firm f_A is 90 percent, which means that S_2 's share is 10 percent. Conversely, S_1 and S_2 have an equal share of selling in f_B . Finally, suppose S_1 had net exposure of 100 to Japanese firms and S_2 had exposure of 10. In this example, the total exposure of f_A and f_B 's sellers is the same because they have the same two sellers. Still, we might expect that f_A will be more sensitive to the shock of the tsunami because its primary seller had large exposure to Japanese firms.

I flesh this thought experiment out in the data in two ways. To start, I construct alternative versions of $\Gamma_{S,f}$ ($\Gamma_{B,f}$) by taking simple averages of seller (buyer) exposures to Japan:

$$\begin{aligned}\Gamma_{S,f}^{avg} &:= \sum_{c \in \mathcal{S}(f)} \left[\frac{1}{\|\mathcal{S}(f)\|} \right] \times NS(c, Japan) \\ \Gamma_{B,f}^{avg} &:= \sum_{c \in \mathcal{B}(f)} \left[\frac{1}{\|\mathcal{B}(f)\|} \right] \times NS(c, Japan)\end{aligned}$$

where the $\|\cdot\|$ operator denotes the size of a set. $\Gamma_{S,f}^{avg}$ ignores any possible concentration and allows me to compare two firms that were, on average, similarly exposed to Japan through their sellers.

Column 1 in Table A9 suggests that firms whose sellers had higher average exposure to Japan did indeed see their spreads rise very slightly, but the standard error of the point estimate on $\Gamma_{S,f}^{avg}$ is relatively large. Column 2 includes all Γ variables, both equal and share-weighted versions, in the regression. Even after controlling for the average exposure of each firm's sellers to Japan, the point estimate on $\Gamma_{S,f}$ is still economically large and statistically significant. These results highlight that it is critical to consider the combined effect of concentration and capital losses when explaining spread dynamics.

As a second way to reinforce the importance of concentration, I take advantage of the fact that there was one seller in particular who had an extremely large exposure to Japanese firms just prior to the tsunami. I denote this seller by the index J . The regression I estimate is then:

$$\Delta \log(CDS_{f,1}) = a + \eta_J \omega_{J,f} + \beta' X_f$$

where $\omega_{J,f}$ is the share of J in the net selling of f and X_f is the same set of controls used throughout this section. Fixing the seller and only varying J 's share across firms allows me to focus on how

concentration interacts with pricing. In addition, in Section 3.5 I verify that $\omega_{J,f}$ is once again not just a proxy for firms with high fundamental exposure to the Japanese economy.

Column 3 of Table A9 displays the results of this regression. As these results show, firms where J had a larger share of selling also experienced larger spread increases after the tsunami hit. To give an economic sense of magnitude, I compare firms where J had a high share (90th percentile of $\omega_{J,f}$) to firms where J had a low share (10th percentile of $\omega_{J,f}$). High $\omega_{J,f}$ firms saw their CDS spread levels increase by 2 percent following the tsunami, relative to low $\omega_{J,f}$ firms. These results further highlight why the distribution of exposures – in addition to the level — is important for price dynamics

3.5 Does seller J just specialize?

In the previous subsection, I explained CDS spread movements after the tsunami using seller J 's share in each firm, denoted by $\omega_{J,f}$. The logic of this approach was to isolate the importance of concentrated selling, since seller J had a very large exposure to Japanese firms prior to the tsunami striking. Like with my use of the Γ variables in the main text, a reasonable objection to this approach is that seller J specializes in U.S. firms who are fundamentally connected. I rule this out in the same way as before. I group U.S. firms into deciles based on $\omega_{J,f}$ and then compute the average correlation with Japan's CDS spread within each decile. Figure A6 displays the output of this exercise.

At first glance, there does not appear to be a pattern across the deciles of $\omega_{J,f}$. There is a slight increase in correlation with Japan when moving from the 40th to the 50th percentile. However, the absolute magnitude of the correlation difference is small, 10 percent versus 16 percent. To be safe, I have estimated my regressions only using firms in the 50th percentile and higher. None of my main conclusions are affected. I therefore conclude that seller J is not simply specializing in U.S. firms with fundamental correlation to Japan.

3.6 How Long Does the Effect Last?

If limited capital of sellers is really driving the pricing effects induced by the tsunami, we should observe the impact of the shock dissipate as capital flows into the CDS market. To study the time signature of the tsunami shock, I take a simple graphical approach. Of the 288 firms I analyze, I divide firms into two sets. Firms in the “low Γ_S ” set are those reference entities whose sellers are below the 30-percentile of Γ_S . Firms in the “high Γ_S ” set are those reference entities whose sellers were most exposed to Japan (above the 70-percentile Γ_S). Within each set, I then compute an average CDS spread.

Figure A7 plots the difference in the time series of each set's average CDS spread. The magnitude of this difference is fairly small, though as seen in the more formal regression analysis, this masks considerable heterogeneity within each bucket. Roughly speaking, the spread difference between the two groups of firms returns to normal on about ten days or so after the tsunami. This

pattern of a shock, a price effect, and a reversal is consistent with the results from Section 4 of the main text and, more generally, asset pricing theories with limited capital.

In addition, the ten day window is economically sensible when considering the steps taken by the Japanese government in the aftermath of the tsunami. In particular, the Fukushima Daiichi nuclear disaster was a major catastrophe caused by the tsunami. In the days following the initial shock, it was unclear whether a full-fledged meltdown of the nuclear power plant would ensue. Before Japanese officials were able to stabilize the plant, many experts opined that a full meltdown would be akin to dropping a nuclear bomb on the site. It is easy to imagine the potential for this outcome played a major role in the heightened effective risk aversion for U.S. sellers who were exposed to Japanese firms. By March 25, the Fukushima plant had been relatively stabilized, and the likelihood of a full meltdown dropped sharply. This resulted in a rebound of risk appetite, which was accompanied by the spread difference between high Γ_S and low Γ_S firms returning to its usual level.

The length and magnitude of the effect should also be interpreted in conjunction with the size of Japanese firm exposure to the overall exposures of the largest sellers in the market. Loosely speaking, for the largest sellers of U.S. CDS, Japanese exposures were roughly 4 to 6 percent of their overall portfolio. While this certainly not trivial, one would also not expect the shock of the tsunami to have an enormous effect on their overall risk bearing appetite. Put differently, the primary emphasis of this exercise is not magnitudes, but rather to observe that a shock to risk bearing capacity impacts spreads in a cleanly identified setting.

4 A Discussion of Prime-Brokerage Services

A potential complication to my conclusion is the prime-brokerage services that parent companies of dealers provide to their clients. Examples of prime-brokerage services include centralized margining, basic custodial services, and risk management advisory services. Whether prime-brokerage activities confound the results of the paper rests crucially on how brokerage services play out in CDS markets. Suppose Dealer A is also the prime-broker for Hedge Fund X, and Hedge Fund X wants to sell \$100 of protection on GE. Moreover, Dealer A has found a second Hedge Fund Y who wants to buy \$100 of protection.

Prime-Brokers Trade With Clients If prime-brokers trade with clients, then it means they contractually take the other side of client trades. In this example, this means that I observe two transactions. In the first, Dealer A buys \$100 of protection from Hedge Fund X. In the second, Dealer A sells \$100 of protection to Hedge Fund Y. The credit risk is passed from Hedge Fund Y to Hedge Fund X, and Dealer A correctly appears to have zero exposure.

According to the DTCC, this is the primary way in which prime-brokerage services operate in

CDS markets.¹⁰ The legal agreement between the prime-broker and the client is typically called a “give-up” agreement. Normally, a client has an agreement with their prime-broker that the client can execute trades with a preset group of other dealers. The give-up arrangement means that, upon a trade being executed between the client and the dealer (not the prime-broker), the client will give-up the trade to their prime broker. Legally, two transactions occur, with the prime-broker trading with the dealer and the prime-broker trading with their client.

The net position of the prime-broker in this case is zero. The client is keen to have these give-up arrangements in place because they centralize trade processing with their prime broker, and they have the ability to face multiple dealers. The prime broker is properly incentivised because they earn fees from their clients for providing this service. Finally, the other dealers happily accept this legal arrangement because they get volume from the client; from a counterparty risk standpoint, they also only face the prime broker, who is usually less risky than smaller clients (e.g. hedge funds).

Importantly, this means that all net positions I observe in my database are true economic exposures. That is, it is not the case that I observe a prime broker trading on *behalf* of their client, so that it appears that the prime broker is taking a position, but in reality the position is fully backed by a “hidden” client.

5 Data Appendix

5.1 Data Construction: CDS Positions from the DTCC’s TIW

5.1.1 Background and Data Description

The main data source for this paper comes from the Depository Trust & Clearing Corporation (DTCC). The DTCC provides trade processing and registration services for all major dealers in CDS markets. After a trade is registered with the DTCC, it is recorded into a Trade Information Warehouse (TIW). The data sample provided to the Office of Financial Research (OFR) is a subset of the TIW, and includes trades that 1) involve a U.S. registered firm, or 2) involves at least one U.S. registered counterparty. A simple example of the types of trades not contained in the OFR’s version of the TIW illustrates the scope of the data: if a bank in Paris enters into a credit default swap with a bank in Germany on Portuguese sovereign debt, then I am not able to see this transaction. At a minimum, I can therefore make definitive statements about the nature of the U.S. Corporate CDS markets.

The DTCC provides two types of data from the TIW: transactions and positions. Transactions are a flow variable and positions are a stock variable. The DTCC uses an internal algorithm to compute the position stock from the transaction flows. I rely primary on the positional database. This section documents how I process the positional database.

¹⁰Thank you to Chris Mullen of the DTCC for a very helpful discussion on these issues.

Defining a Reference Entity Throughout this study I call the underlying entity on which a CDS contract covers a “firm”. Traders often refer to the underlying firm in a CDS as the “reference entity”, and I use these two terms interchangeably. Depending on the context in the paper, I define a reference entity in one of two ways. The first way — and the predominant way — defines a reference entity simply by its Markit RedID[®], which I refer to henceforth as its RedID. Defining a reference entity by its RedID is useful for a broad understanding of credit risk. The second way refines the definition, and uses the RedID and the maturity of the swap. Specifically, I assign each swap into a “maturity bucket” based on its remaining term. The maturity buckets I consider are: 0-2 years, 2-4 years, 4-6 years, 6-8 years, 8-10 years, and 10+ years. A reference entity is then defined by its RedID and maturity bucket. This second way of defining a reference entity is useful for a more granular understanding of credit risk. When determining the overall size of the CDS market in the main text, I use the more granular definition since it is analogous to different maturity bonds on the same underlying firm. For all other computations in the main text, I collapse the term in order to make the computations more tractable. Additionally, for the remainder of this appendix, I refer to the underlying reference entity in CDS as the “reference entity” or the “firm”.

5.1.2 Disaggregating Index Positions

There are three types of credit default swap products in the DTCC: single name CDS, index CDS, and CDS written on index tranches. In this paper, I focus on only single name and index CDS, since these are by far the largest types of products traded in the market. Of the nearly 900 million positions in the DTCC database, 98% are either single name or index CDS. Index or single name swaps account for 90% of the total gross notional in the dataset.

A CDS index swap is just a basket of single name swaps. For example, suppose a trader sells \$100 of notional on an index swap that contains 100 different single names. Like a single name swap, if one of the names defaults, the trader must pay out up to \$1 in notional to the buyer of the index swap, depending on the recovery rate of the underlying bond. After this payment, there are 99 names in the index remaining. Writing \$100 in protection via an index is therefore equivalent to writing 100 different single name swaps, each worth \$1 in notional.

Thus, in order to ascertain who ultimately bears corporate credit risk, I must disaggregate each index position into the individual single name positions that are implied by the index exposure. In turn, once an index swap has been disaggregated into its components, it can be properly netted against any single name positions to obtain an accurate measure of net risk exposure. Moreover, disaggregating indexes is necessary to compute the pricing of index positions. This is because Markit provides index price information for a limited number of maturities (e.g. 5 and 10 year), whereas they provide a much more complete term structure for single names.

To obtain a list of the single name constituents (and weights) of given index, I use the Markit RED database. The Markit RED database contains additional information on the index like its annex date, which is when the index became active. Furthermore, the database provides important contractual information on *each* of the constituents such as the “doc clause” that specifies what a

default event actually is, the REDID, and the ISIN.¹¹ I obtain information from Markit RED on all of the following index families: CDX North America, ITRAXX Asia, ITRAXX Europe, and ITRAXX SOVX. In addition, there are some index swaps that do not have a RedID in the DTCC database. To address this case, I manually go through the set of swaps with missing RedIDs and use the field “Reference_Entity_Name_Unscrub” to try to infer what the correct Index RedID should be.

For a given date t and an index i , I then proceed as follows:

1. In order to ensure I use the correct weights for each constituent in the index on each date, I first have to check if there has been a credit event on index i in between the beginning of the transaction and date t . To check if there has been a credit event for i , I take the following steps:
 - (a) Find the last version of the index whose annex date is before date t . The annex date for an index indicates which date its characteristics were made public on Markit’s website. Using the latest annex ensures that all credit events that have happened up to date t are accounted for. Call the index matching this criteria i^* .
 - (b) If a reference entity has defaulted, then its weight in i^* is zero, so this is how I infer defaulted constituents. Based on this inference from i^* , I set the weights of any defaulted names in i equal to zero. I apply the original weights in i to the non-defaulted constituents. I do so because the DTCC does not update the outstanding notional on index contracts after default events.¹²
 - (c) If there has not been a credit event, then I use the original weights provided by Markit to create the single name exposures generated by i
 - (d) I also use i^* to obtain the underlying documentation clause (what defines the default event) and the ISINs of the non-defaulted constituents. I use the latest version of the index (i^*) for the ISIN information because when a bond retires, the CDS contracts on the bond issuer must be updated so that they point to a bond issue that is still outstanding. The information i^* ensures I am thus using the latest information on ISINs for each single name constituent.
2. Using the weights and the aforementioned information, I then create the set of “synthetic” single name positions that comprise the index. Naturally, the maturity of each synthetic name is the same as the original index, and I adjust the notional of each synthetic single name position using the weights. These synthetic single name are then combined with the

¹¹ISINs refer to a bond issue by a corporation. A 6-digit REDID identifies the corporation itself, and might be associated with multiple ISINs. The ISIN is useful for pricing because it indicates which tier of debt the CDS contract is written on. The REDID, tier, doc clause, and currency in the CDS position allow me to merge the DTCC data with pricing data from Markit.

¹²This is according to formal conversations with the DTCC.

raw set of single name positions in the DTCC database. In this larger set of swaps, I keep track of positions that came as a result of disaggregation (i.e. from an index) or from an actual single name contract in the original raw DTCC position database.

3. Finally, for indices that do not have a RedID or do not have a match in Markit RED, I simply do not disaggregate.

5.1.3 Defining U.S. Reference Entities

My analysis in the main text reports basic statistics on the size and concentration of the CDS market. In order to precisely define these statistics, I must be certain that I see the entire CDS market for a particular reference entity, which is why I restrict my analysis to only U.S. reference entities. For single name positions, the jurisdiction of the underlying reference entity is reported by DTCC. For swaps that arise from disaggregating index positions, I must determine the underlying jurisdiction myself. This subsection describes how I go about that process.

Consider an index with 100 constituents. After the disaggregation process, I effectively have 100 “synthetic” single name positions. For each of these newly created synthetic single name positions, I first check via RedID whether there exists a (real) single name position in the DTCC positional database. If so, I use this actual single name position to assign the reference entity jurisdiction to the synthetic single name position. For instance, suppose the RedID of the synthetic position is ABC and there is an actual single name position written on ABC in the DTCC positional database with jurisdiction equal to U.S. I then assign the synthetic single name position as being a U.S. reference entity as well.

If there is no match in the actual DTCC single name position, I then use the reference entity jurisdiction provided by Markit. Again, I match the synthetic single name position to Markit using RedIDs. If there is no match in Markit, I do not assign a reference entity jurisdiction and do not include this reference entity in any subsequent analysis.

Residential Mortgage Backed Securities I observe a reasonable amount of credit default swaps written on mortgage backed securities. For each swap I observe, there is a field titled “subproduct”, which, if populated, is how I can tell the swap is written on an MBS. In addition, starting in 2012, the “Reference Entity Scrubbed Name” gives an indication that these swaps are MBS, as the names often include words like “residential trust”, etc. Because CDS written on MBS are unique for a number of reasons, I do not include them in the analysis. The most pertinent reason is that each bank or dealer often packages their a variety of MBS into a unique trusts, and then passes the credit risk onto other banks or end-users via the CDS. Thus, the number of unique CDS written on MBS is almost 2000.¹³ Filtering out MBS is not a straightforward task, as the DTCC actually did not start providing detailed information on these swaps until 2012. For example, prior to 2012 I might

¹³The total outstanding net notional on MBS is small compared to the entire market, as the average total size is under \$20 billion.

observe a CDS between Goldman and Bank of America, written on an MBS and originated in 2008. However, the “scrubbed” name and the “subproduct” for this swap are missing prior to 2012. After 2012, the relevant information for the *same* swap appears in the database. The most consistent commonality that I find between all swaps written on MBS is that their “unscrubbed” name is “THEISSUEROFTHEREFERENCEOBLIGATION”, which I can only assume is an accounting standard kept at the DTCC. I have verified that all of observed swaps with this unscrubbed name are in fact written on MBS.¹⁴ Thus, I filter CDS written on MBS by excluding swaps with this unscrubbed name.

5.1.4 Marking Positions to Market

At each point in time, I compute the market value of each swap in the master dataset of single name positions and disaggregate indices. This process is typically referred to as marking to market. For a given swap, I obtain pricing information for the entire term structure of the underlying reference entity’s CDS from Markit. Because I observe the fixed coupon paid in each swap, I can use current information on the default likelihood of the underlying reference entity to compute the net present value of the future premiums and the future potential default payout by the seller. As is standard in the industry, I use the ISDA pricing model to mark to market.¹⁵ When the underlying reference entity of a swap does not have an associated price quote in Markit, I do not mark it to market on that day. Marking a position also requires a term structure of riskless interest rates in the currency that the position is written. I only mark positions that are denominated in USD, EUR, and JPY because these represent over 99.9% of the notional in the dataset. For each of these currencies, I obtain risk-free term structures using swap rates from Bloomberg. Across all dates and positions in the master dataset of single name and disaggregated index positions, I am able to successfully mark 88.2% of the positions by count and 87.6% of the positions by notional.

5.2 Other Data

CDS Spreads and Loss-Given-Default For the analysis contained in Section 4 and 5 of the main text, I obtain a weekly time series of 5-year CDS spreads and expected loss-given-default (LGD) from Markit for as many reference entities that are in my positional data set from January 2010 to May 2014. I focus on CDS written on senior unsecured debt in U.S. dollars, and use swaps that have a “modified restructuring” clause in their definition of what triggers default in the CDS contract. In the Markit database, this corresponds to a restructuring clause of “MR”. I choose this restructuring clause for two reasons. The first is that it is among the more abundant contracts over the course of my sample period. The second is that I will eventually compare CDS spreads to

¹⁴To be precise, this includes CMBS, RMBS, ECMBS, AND ERMBS, and excludes entries where the subproduct type is unlisted.

¹⁵<http://www.cdsmodel.com/cdsmodel/>

Moody's EDF metric. Based on the definition of default in Moody's computations, the modified restructuring clause in CDS contracts is comparable.¹⁶

Moody's EDF I obtain the 5-year annualized EDF series from Moody's. To match RedIDs from Markit to Moody's, I use the 6 digit CUSIP.

The CDS-Bond Basis As Duffie (1999) argues, a credit default swap can be replicated by a combination of a par floating rate note issued by the reference entity and a default-free floating rate note. The reference entity's floating rate note has payments that are a fixed spread S over the default-free floating rate note. With some simplifying assumptions, buying CDS protection is equivalent to shorting the reference entity floating rate note and buying the default-free floating rate note.

In practice, though, a standard corporate bond is a fixed coupon instrument. To compare its price to a credit default swap, one must first convert the fixed payments to floating payments by appropriately layering the bond with an interest rate swap. Asset swaps are the conventional way of doing so, and the asset swap spread refers to the par spread over a benchmark (typically LIBOR) that the fixed rate payer in the asset swap receives. A closely related concept is the "Z-spread" which uses observable bond prices and the zero-coupon yield curve in valuing the asset swap. The difference between the asset swap spread and the Z-spread is often small, and the nuances of the two are beyond the scope of this paper. To compute a reference entity's "CDS-Bond" basis, I compare the CDS spread of a reference entity with its Z-spread. I obtain the CDS-Bond basis for each firm directly from Bloomberg based on each reference entity's ticker, as reported by Markit.¹⁷

It is important to recognize that Z-spreads are a generally a noisy proxy for bond spreads. Bloomberg computes Z-spreads as the spread over zero-coupon Treasuries that would be needed to match the market price of a bond. High-frequency bond prices can be noisy due to liquidity reasons, and may even be inferred using CDS spreads themselves. In addition, the term-structure of Z-spreads is interpolated to match the maturity of the relevant CDS, which adds another layer of potential measurement error.

5.3 Computing CDS Portfolio Returns

To translate a given counterparty's capital gains in dollars to returns requires one to take a stance on how capital each counterparty commits to a position. For example, suppose when I sell \$1 of protection I have to post \$0.10 of initial margin to the buyer of the swap. Any capital gain I experience on the position is then applied to a capital base of \$0.10. From my perspective, I

¹⁶See: <http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/2012/2012-28-06-Public-EDF-Methodology.ashx>

¹⁷Bloomberg interpolates the CDS curve to determine the CDS spread to match the firm's Z-spread nearest to five years in maturity. I specifically use the Bloomberg data field "BLP_CDS_BASIS_MID".

obtain 10-to-1 leverage on the position. Aggregating this logic to the portfolio level then requires an estimate of the total initial margin posted in order to support a given portfolio.

Define the total net amount of protection sold by counterparty i to j on firm f with maturity bucket u as $NS(i, j, f, u)$. In my empirical implementation, I group positions between i and j on f based on their maturities. For instance, all positions with a maturity of less than 1 year would be in the $u = 1$ bucket, etc. I also omit time arguments for expositional purposes, but this computation is done at each point in time. I define the initial margin posted by i to j for this net position as:

$$IM_{i,j,f,u} = \begin{cases} m_{s,f,u} \times |NS(i, j, f, u)| & \text{if } NS(i, j, f, u) > 0 \\ m_{b,f,u} \times |NS(i, j, f, u)| & \text{else} \end{cases}$$

This construction allows the initial margin posted by i to j to vary depending on if i sells to j , the underlying firm f , and the maturity bucket of the exposure u . I use FINRA's margin requirements to guide how I parametrize $m_{s,f,u}$ and $m_{b,f,u}$.¹⁸ For instance, $m_{s,f,u} > m_{b,f,u} \quad \forall f, m$ reflects the large potential future liability that sellers incur from providing protection. In addition, both $m_{s,f,u}$ and $m_{b,f,u}$ are increasing in the credit risk of f and maturity of the position. Table A10 contains the specific parameterization that I use for $m_{s,f,u}$. Following FINRA, I also assume that $m_{b,f,u} = m_{s,f,u}/2$. Furthermore, I adopt the convention in Duffie, Scheicher, and Vuillemeys (2015) by assuming that dealers do not post any initial margin to non-dealers, but do post margin to other dealers and the central clearing party (CCP). Conversely, non-dealers post initial margin to all counterparties. Finally, I assume the CCP does not post any initial margin.

The total initial margin posted by counterparty i is computed simply by summing across all of its counterparty-firm-maturity bucket pairs:

$$IM_i = \sum_{j,f,u} IM_{i,j,f,u}$$

The return on i 's CDS portfolio is just the dollar change over a given period, divided by the total initial margin posted plus the NPV of the portfolio at the beginning of the period. The same logic extends to computing the pooled-return of a set of counterparties. I simply sum up the total dollar change in portfolio value across a set of counterparties, and then scale by the total initial margin posted by those same counterparties (as well as their beginning of period portfolio NPV).

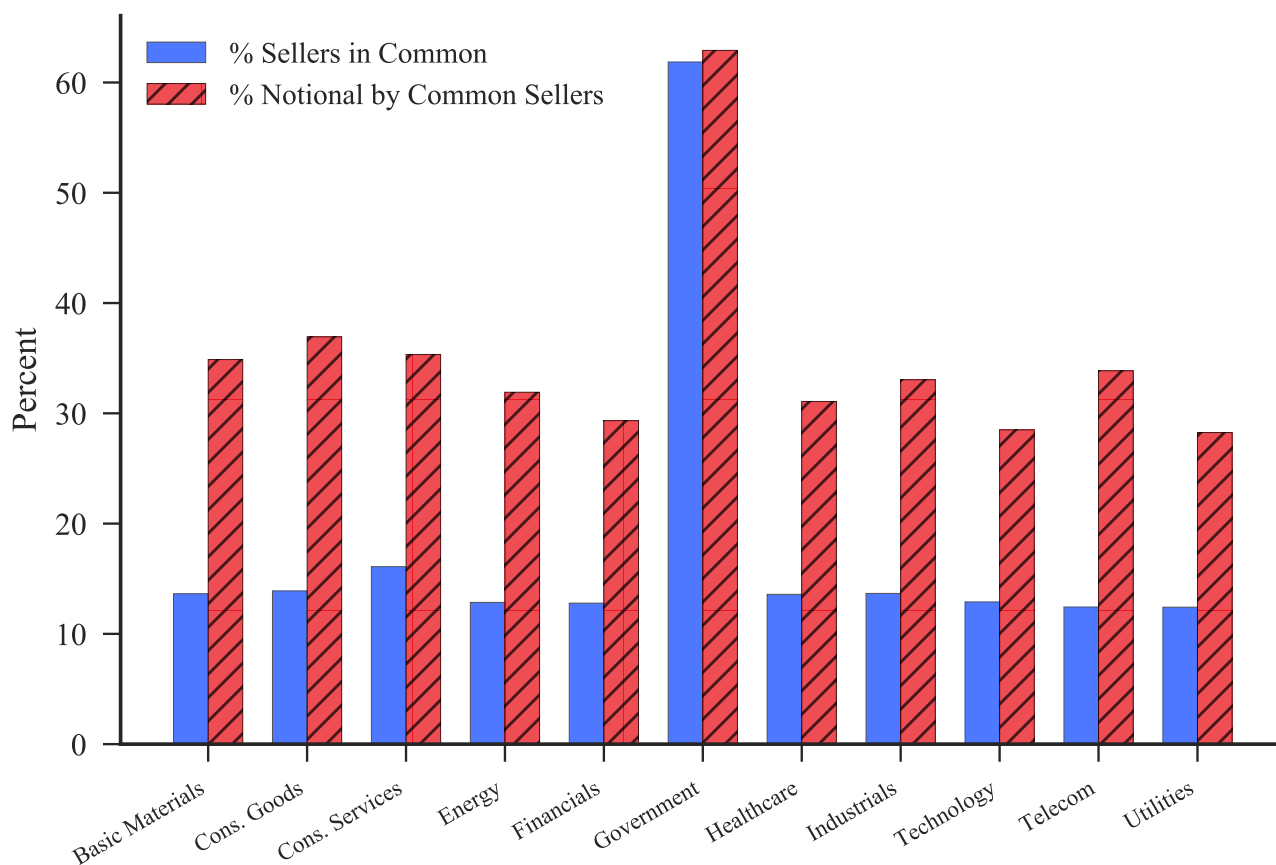
My approach to computing initial margins (and thus returns) is very conservative. This is because I am only allowing netting to occur within an (i, j) - f - u pair. In practice, the initial margin between two counterparties is typically set using the entire bilateral portfolio between those two counterparties, potentially across asset classes. It is difficult for me to conduct this type of margin computation without more data. Furthermore, I also ignore any potential double-counting when pooling counterparties together to compute portfolio returns. That is, if I sum the *total* initial margin posted by counterparties i and j , I ignore the fact that some of their margin may be posted

¹⁸http://finra.complinet.com/en/display/display_main.html?rbid=2403&element_id=8412

to one another. For all of these reasons, I am cautious in interpreting the robustness tests that use capital shock proxies deriving from portfolio returns.

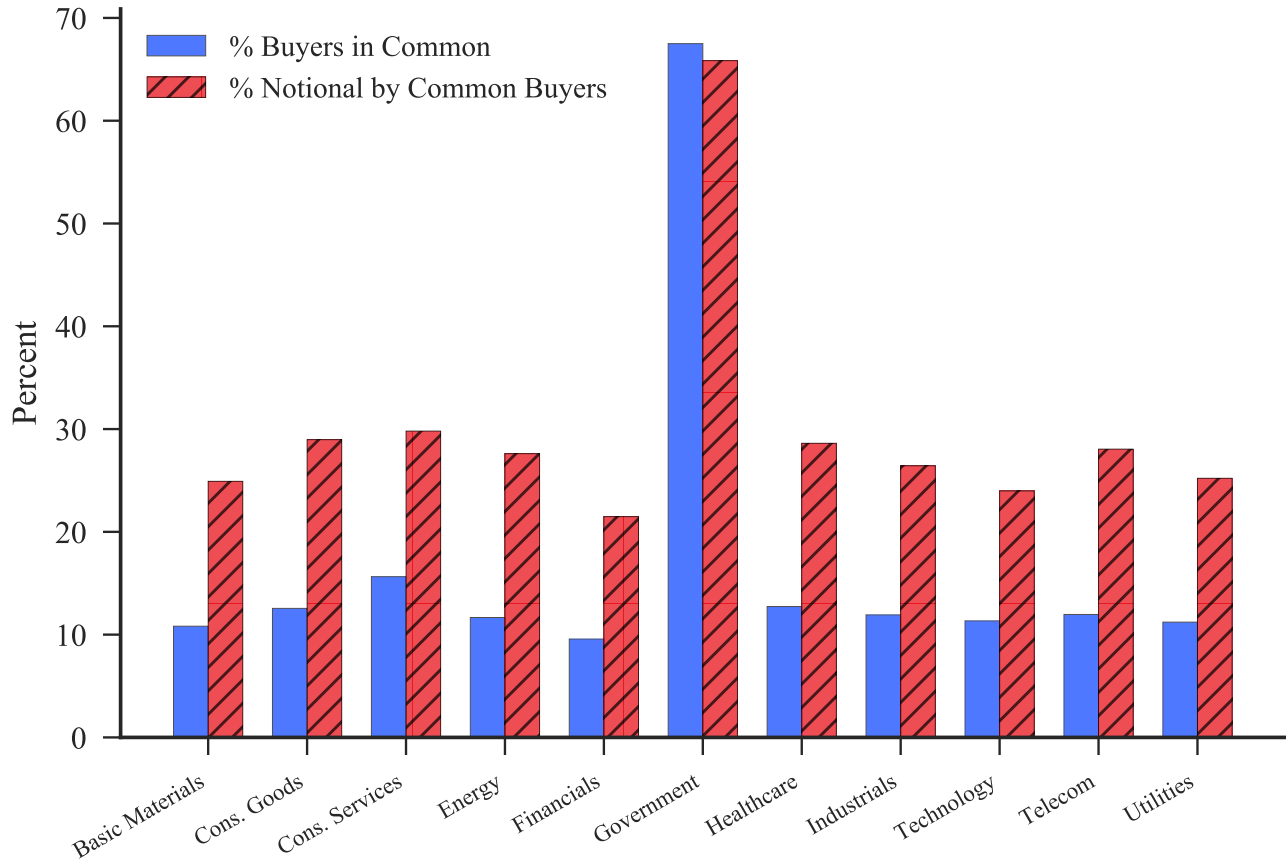
FIGURES

Figure A1: Seller Overlap Within Each Market Industry



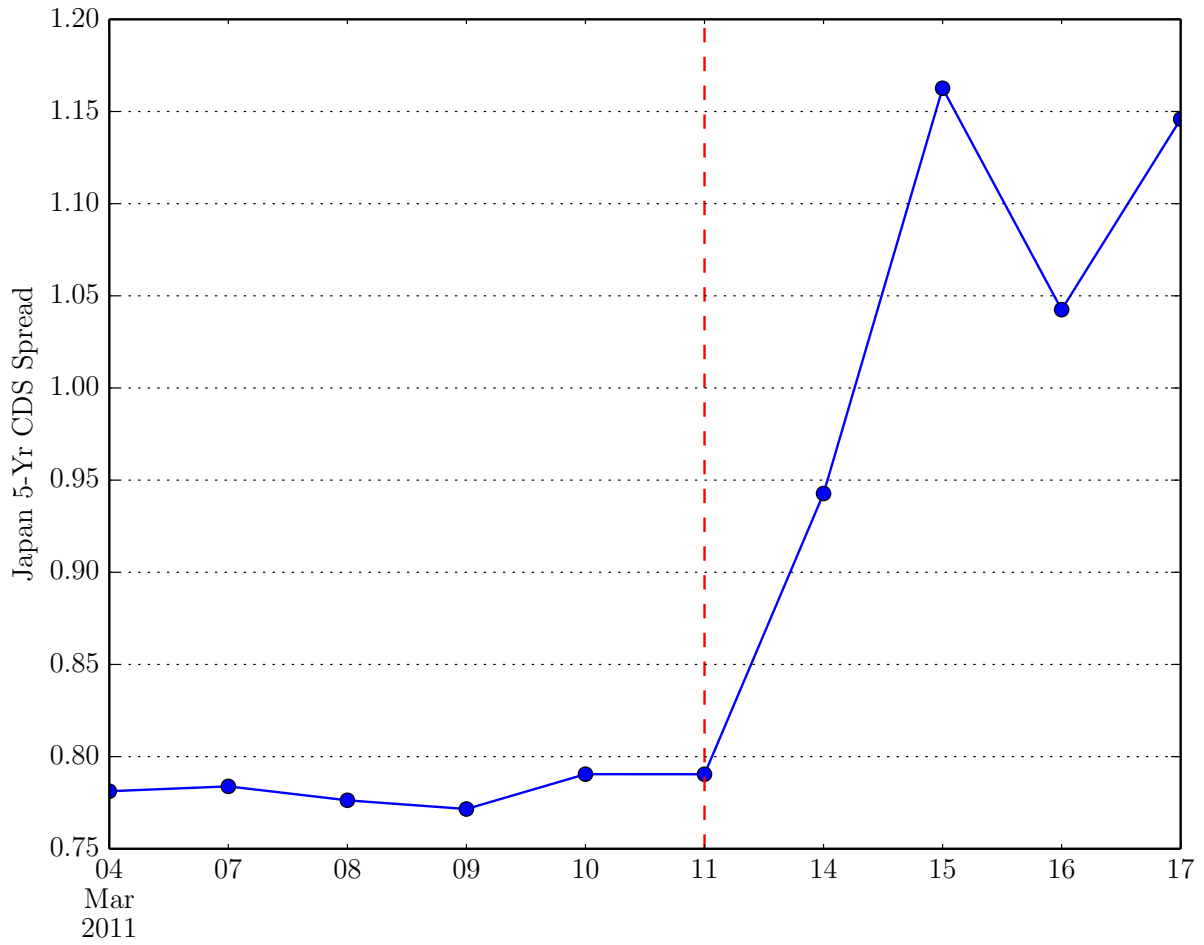
Notes: This figure plots the average percent of sellers in common for each pair of firms in an industry (blue) or the average percent of net notional sold by common sellers for each pair for firms in an industry (red). Industries are defined by Markit. To compute the net amount sold by a counterparty c on f , I disaggregate index positions and net them against any single name positions. See the Online Appendix for complete details. Data is weekly and spans 2/19/2010 to 10/7/2016.

Figure A2: Buyer Overlap Within Each Markit Industry



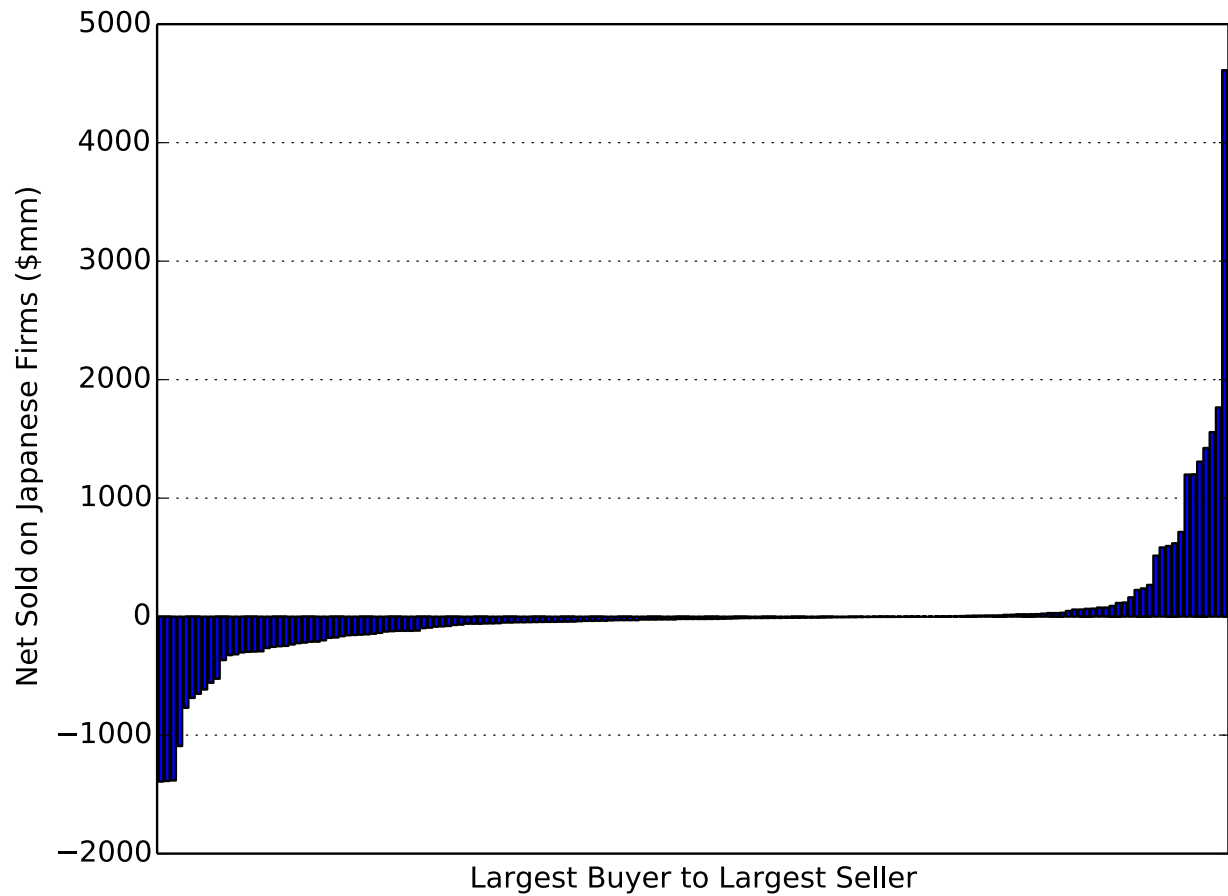
Notes: This figure plots the average percent of buyers in common for each pair of firms in an industry (blue) or the average percent of net notional sold by common buyers for each pair for firms in an industry (red). Industries are defined by Markit. To compute the net amount sold by a counterparty c on f , I disaggregate index positions and net them against any single name positions. See the Online Appendix for complete details. Data is weekly and spans 2/19/2010 to 10/7/2016.

Figure A3: Five Year CDS Spread of Japan



Notes: This figure plots the 5 year CDS spread for Japan from March 4, 2011 - March 17, 2011. The documentation clause for the CDS spread is "CR", applies to senior unsecured debt, and is denominated in dollars.

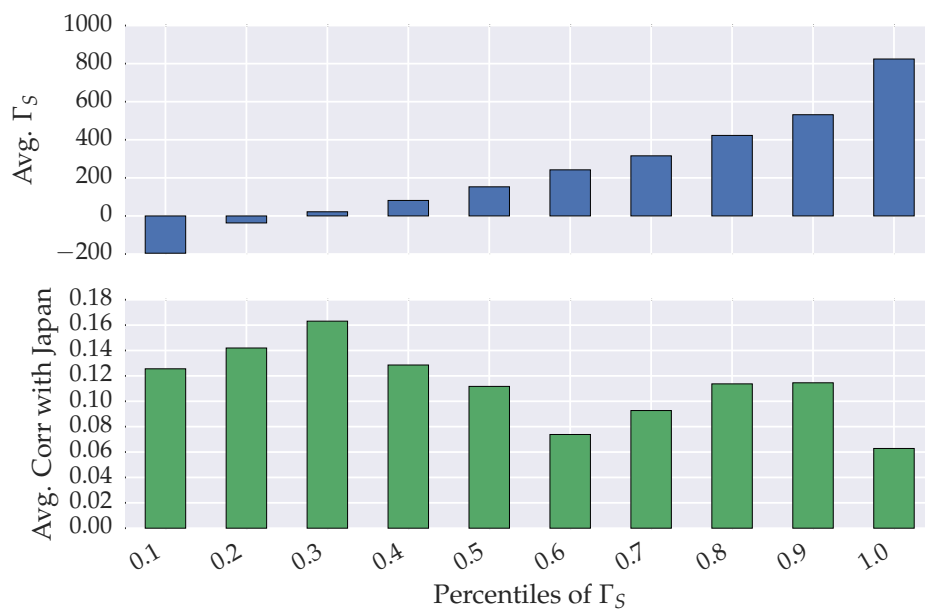
Figure A4: Exposures of U.S. Counterparties to Japanese Firms on 3/11/2011



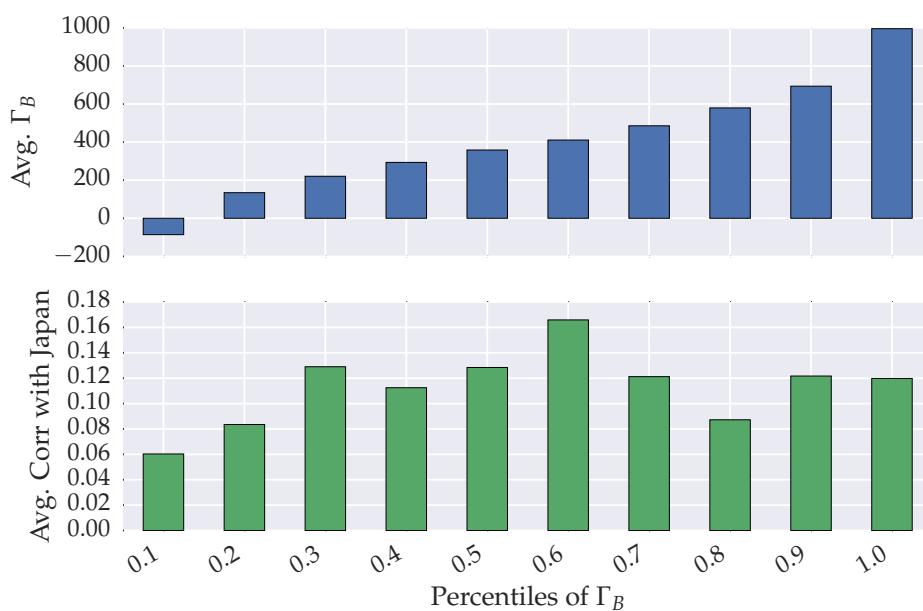
Notes: This figure shows the exposure of U.S. counterparties to Japanese firms. For each counterparty in the U.S., I compute the net amount sold as of 3/11/2011 on any firm whose country jurisdiction is in Japan, as classified by Markit. Positive values indicate a net seller overall, negative values indicate a net buyer.

Figure A5: Do Sellers and Buyers Specialize in Japanese Firms?

Panel A (Sellers):



Panel B (Buyers):

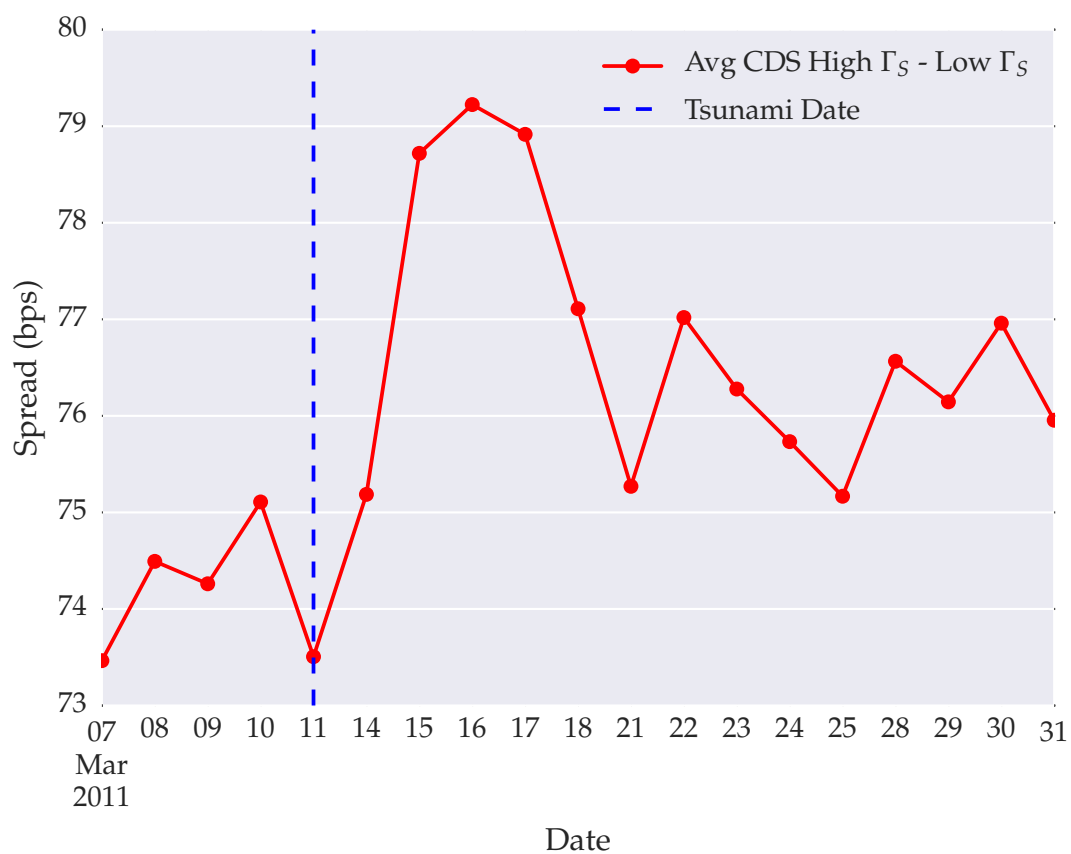


Notes: The top panel in this figure shows the correlation between U.S. firm's CDS spreads and the country of Japan's (JPN) CDS spread, averaged within deciles of $\Gamma_{S,f}$. $\Gamma_{S,f}$ is the share-weighted average CDS exposure of f 's net sellers to Japanese firms. The bottom panel is the same computation, but firms are grouped by deciles of $\Gamma_{B,f}$, which is the share-weighted average CDS exposure of f 's net buyers to Japanese firms. Correlations are computed using log-changes in CDS spreads in the 90 days prior to the Japanese tsunami on March 11, 2011.

Figure A6: Does Seller J Specialize in Japanese Firms?

Notes: This figure shows the correlation between U.S. firm's CDS spreads and the country of Japan's (JPN) CDS spread, averaged within deciles of $\omega_{J,f}$. $\omega_{J,f}$ is the share of net selling by j in firm f . Correlations are computed using log-changes in CDS spreads in the 90 days prior to the Japanese tsunami on March 11, 2011.

Figure A7: How Long Did the Shock of the Tsunami Last?



Notes: This figure shows the difference between the average CDS spread of high $\Gamma_{S,f}$ firms and low $\Gamma_{S,f}$ firms. High (low) $\Gamma_{S,f}$ firms are those whose sellers were in the top (bottom) 30 percent of $\Gamma_{S,f}$, which measures how exposed a firm's sellers were to Japanese firms. See Section 3 of the Online Appendix for additional details. The tsunami hit on March 11, 2011.

TABLES

Table A1: Breakdown of Firms by Industry

Markit Sector	Frequency	Percentage of Total
Basic Materials	10,027	7.82
Consumer Goods	19,960	15.56
Consumer Services	18,021	14.05
Energy	12,811	9.99
Financials	21,391	16.68
Healthcare	8,885	6.93
Industrials	19,362	15.1
Technology	7,457	5.81
Telecommunications Services	2,478	1.93
Utilities	7,851	6.12
Total	128,243	100

Notes: This table reports the distribution of firms used in the main results (Section 4 and 5 of main text) by industry. Industries are defined by Markit. I apply the following filters to the data: (i) the underlying firm must be registered in the United States; (ii) each firm must have at least 162 observations, which is the 5th percentile in terms of observations per firm; (iii) the firm must have a non-zero net notional outstanding; and (iv) the CDS spread must be less than 5000 bps. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A2: How Much Do Firm and Macroeconomic Variables Explain CDS Spread Dynamics?

Dep. Variable	$\Delta \log(CDS_{f,t})$			
	(1)	(2)	(3)	(4)
$\Delta \log(CDS_{f,t-1})$	0.03 (-0.03)	0.03 (-0.03)	0.05** (-0.02)	0.05* (-0.02)
$\Delta \log(EDF_{f,t})$	0.08* (-0.05)	0.02 (-0.03)	0.08** (-0.02)	0.07** (-0.03)
$Ret_{f,t}^{Equity}$	-0.29** (-0.06)	-0.35** (-0.04)	-0.12** (-0.03)	-0.16** (-0.03)
$\Delta \log(LGD_{f,t})$	0.04 (-0.03)	0.01 (-0.05)	0.05 (-0.03)	0.01 (-0.05)
$\Delta Depth_{f,t}$	0.25** (-0.06)	0.24** (-0.07)	0.24** (-0.05)	0.24** (-0.06)
$\Delta \log(OCDS_{f,t})$		0.02** (0.00)		0.01** (0.00)
$\Delta ATM_{f,t}$		9.30** (-1.83)		2.10** (-0.99)
Ret_t^{CRSPVW}			-0.55** (-0.12)	-0.60** (-0.14)
Ret_t^{HML}			-0.48** (-0.14)	-0.54** (-0.16)
Ret_t^{SMB}			-0.15 (-0.13)	-0.16 (-0.15)
$\Delta 10Y2Y_t$			-2.16 (-2.72)	-2.02 (-3.21)
$\Delta 10Y_t$			1.99 (-2.00)	2.17 (-2.44)
ΔVIX_t			0.09 (-0.08)	0.10 (-0.09)
ΔTED_t			10.89** (-4.96)	11.59** (-5.60)
Within- R^2	0.10	0.15	0.18	0.22
N	128,243	59,578	118,956	58,460

Notes: This table reports results from regressing log-changes in CDS spreads on a number of potential explanatory variables. Firm-level variables include the lagged log-change in CDS spread, log-change in expected default (EDF), equity return of the underlying firm, log-change in loss-given-default (LGD), Markit depth, option-implied CDS spread ($OCDS$), and at-the-money volatility from options. The option-implied CDS is computed using the method of Carr and Wu (2011). Macroeconomic variables are the return of the three Fama-French factors, plus the the change in the 10-year minus 2-year Treasury spread ($10Y2Y$), 10-year treasury spread ($10Y$), VIX, and TED spread. Log-changes in CDS spreads are winsorized at the 1% level and are reported in percentage terms (scaled by 100). CDS spreads come from Markit, have a 5-year maturity, are denominated in USD, and cover senior unsecured debt with documentation clause MR. I apply the following filters to the data: (i) the underlying firm f must be registered in the United States; (ii) each firm must have at least 162 observations, which is the 5th percentile in terms of observations per firm; (iii) the firm must have a non-zero net notional outstanding; and (iv) the CDS spread must be less than 5000 bps. All regressions contain a firm fixed effect. All standard errors are double clustered by firm and time, and listed below point estimates in parenthesis. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A3: Summary Statistics of Alternative Institution-Wide Capital Measures

	Sellers					Buyers						
	CDS (bps)	Δ CDS (bps)	SRISK(\$mm)	Δ SRISK (\$mm)	CDS (bps)	Δ CDS (bps)	SRISK(\$mm)	Δ SRISK (\$mm)	CDS (bps)	Δ CDS (bps)	SRISK (\$mm)	Δ SRISK (\$mm)
Mean	141.13	-0.12	59,735	-58	136.30	-0.07	55,530	-58	136.30	-0.07	55,530	-58
Std. Dev.	71.60	13.39	15,848	2,361	64.83	12.90	17,901	2,136	64.83	12.90	17,901	2,136
p10	73.33	-12.25	41,322	-2,619	71.50	-12.17	34,369	-2,345	71.50	-12.17	34,369	-2,345
p25	84.43	-5.50	49,250	-1,099	85.07	-5.25	43,072	-981	85.07	-5.25	43,072	-981
p50	123.25	-0.50	58,496	-40	122.00	-0.36	53,582	-16	122.00	-0.36	53,582	-16
p75	166.13	4.83	69,101	1,136	160.50	5.00	66,718	1,015	160.50	5.00	66,718	1,015
p90	258.00	12.40	80,282	2,464	241.50	12.00	78,675	2,176	241.50	12.00	78,675	2,176
Min	45.33	-136.00	-19,152	-50,964	42.00	-123.00	-60,622	-32,247	42.00	-123.00	-60,622	-32,247
Max	520.50	110.00	161,730	26,004	706.00	139.00	155,109	23,281	706.00	139.00	155,109	23,281
<i>N</i>	127,364	126,976	123,786	120,156	127,283	126,886	123,699	120,056	127,283	126,886	123,699	120,056

Notes: This table reports summary statistics for alternative capital measures used to explain changes in credit spreads. Capital measures are computed in each week for net sellers and net buyers of protection for each firm. The capital measures listed in this table are computed at the institution-wide level, as opposed to proxying for capital at the CDS desks of buyers and sellers. The column CDS is the average CDS spread for net sellers (or buyers) of protection on firm f . The column Δ CDS is the average change from date $t - 1$ to t in CDS spreads for net sellers (or buyers) of protection on firm f , where sellers and buyers are as of date $t - 1$. SRISK is a measure of systemic risk based on Brownlees and Engle (2017). Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A4: Summary Statistics of Alternative CDS-Based Capital Measures

	Sellers (SC)			Buyers (BC)		
	Returns ex-ind	Dollars ex- f	Returns ex- f	Returns ex-ind	Dollars ex- f	Returns ex- f
Mean	-0.002	-5.06	-0.002	-0.002	-7.90	-0.002
Std. Dev.	0.128	755.20	0.143	0.099	510.26	0.110
p10	-0.147	-762.33	-0.164	-0.109	-518.17	-0.123
p25	-0.059	-271.49	-0.066	-0.050	-217.34	-0.056
p50	0.000	-0.81	0.000	-0.003	-10.73	-0.003
p75	0.062	292.48	0.069	0.045	191.97	0.050
p90	0.142	748.80	0.159	0.107	507.36	0.120
Min	-0.427	-6661.84	-0.473	-0.308	-6195.59	-0.342
Max	0.383	4367.68	0.420	0.332	4549.24	0.367
N	128,243	128,243	128,243	128,243	128,243	128,243

Notes: This table reports summary statistics for various capital measures used to explain changes in credit spreads. Capital measures are computed in each week for net sellers (SC) and net buyers (BC) of protection for each firm f . Returns ex-ind measures the percentage return of the CDS portfolio, excluding positions written on firms in the same industry as f . Dollars ex- f is the same variable, but measures the dollar change in the mark-to-market value of the CDS portfolio, excluding positions written on f itself. Returns ex- f measures the percentage return of the CDS portfolio, excluding positions written on f itself. For example, consider firm f in industry i . Returns ex-ind for f 's net sellers in a given week would be computed by: (i) aggregating the CDS portfolio of all of f 's net sellers, excluding positions on firms in industry i ; and (ii) computing the weekly return of this portfolio. All dollar-based capital measures are reported in \$mm and all return-based capital measures are in percentages. In addition, return-based capital measures are winsorized at the 1% level. To compute returns, I assume initial margin requirements for each CDS position that mimic FINRA's margin requirements. See the Section 5.3 of the Online Appendix for a complete description of how initial margins are set. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A5: Credit Spread Dynamics and Alternative CDS-Based Capital Measures

Dep. Variable	$\Delta \log(CDS_{f,t})$								
	Returns, Ex-Industry			Dollars, Ex- f			Returns, Ex- f		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SC_{f,t}$	-11.89**	-5.65**	-4.67**	-2.50**	-1.85**	-1.60**	-10.91**	-5.09**	-4.11**
	(1.16)	(0.70)	(0.74)	(0.24)	(0.21)	(0.27)	(1.05)	(0.63)	(0.68)
$BC_{f,t}$	2.82**	2.91**	3.64**	0.19	-0.01	0.03	2.85**	2.86**	3.67**
	(0.82)	(0.57)	(0.70)	(0.29)	(0.18)	(0.23)	(0.74)	(0.53)	(0.65)
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Option-Based Controls			Y			Y			Y
FE		(i, t)	(i, t)		(i, t)	(i, t)		(i, t)	(i, t)
Within r -group R^2	0.20	0.37	0.46	0.23	0.38	0.46	0.20	0.37	0.46
N	128,243	128,243	59,545	128,243	128,243	59,545	128,243	128,243	59,545

Notes: This table reports regressions of the form: $\Delta \log(CDS_{f,t}) = c + \beta_S \times SC_{f,t} + \beta_B \times BC_{f,t} + \Gamma' Z_{f,t}$. The table reports the estimates for β_S and β_B . $Z_{f,t}$ is a vector of firm-level controls. These include: the lagged log-change in CDS spread, each firm's own equity return, the log-change in Moody's expected default frequency (EDF), the log-change in loss-given-default (LGD) from Markit, and the change in Markit depth. When included, the option-based controls are: the log-change in option-implied CDS spreads (computed according to Carr and Wu (2011)) and the change in ATM volatility from option prices. All regression specifications include a firm fixed effect, and reported R^2 are computed within each firm-group. Some regressions also include an industry-by-time fixed effect, where the industry is defined by Markit. CDS spreads come from Markit, have a 5-year maturity, are denominated in USD, and cover senior unsecured debt with documentation clause MR. Log-changes in CDS spreads are winsorized at the 1% level and are reported in percentage terms (scaled by 100). Additionally, I apply the following filters to the data: (i) the underlying firm must be registered in the United States; (ii) each firm must have at least 162 observations, which is the 5th percentile in terms of observations per firm; (iii) the firm must have a non-zero net notional outstanding; and (iv) the CDS spread must be less than 5000 bps. In columns (1)-(3), $SC_{f,t}$ measures the percent return to the CDS portfolio of f 's net sellers, excluding all positions written on firms in the same industry as f . In columns (4)-(6), $SC_{f,t}$ measures the dollar change (in \$ bn) in the mark-to-market value of f 's net sellers, excluding all positions written on f . In columns (7)-(9), $SC_{f,t}$ measures the percent return to the CDS portfolio of f 's net sellers, excluding all positions written on f . In all cases, $BC_{f,t}$ mimics the same construction, but for f 's net buyers of protection. In addition, return-based capital measures are winsorized at the 1% level. To compute returns, I assume initial margin requirements for each CDS position that mimic FINRA's margin requirements. See the Section 5.3 of the Online Appendix for a complete description of how initial margins are set. All standard errors are double clustered by firm and time, and listed below point estimates in parenthesis. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A6: CDS Spread Dynamics, Portfolio-Level Capital, and Institution-Wide Capital

Dep. Variable	$\Delta \log(CDS_{f,t})$	
	(1)	(2)
$BC_{f,t}$	-0.06 (0.19)	0.10 (0.16)
$SC_{f,t} \times 1_{LSL} \times 1_{LSCL}$	-1.93** (0.25)	-1.33** (0.22)
$SC_{f,t} \times 1_{LSL} \times 1_{HSCL}$	-2.12** (0.28)	-2.01** (0.28)
$SC_{f,t} \times 1_{HSL} \times 1_{LSCL}$	-2.27** (0.27)	-2.04** (0.26)
$SC_{f,t} \times 1_{HSL} \times 1_{HSCL}$	-2.51** (0.27)	-2.35** (0.26)
Dealers Majority Sellers	N	Y
Within f -group R^2	0.36	0.38
# of f	399	399
N	128,243	91,027

Notes: This table reports regressions of the form: $\Delta \log(CDS_{f,t}) = c + \zeta_s SC_{f,t} + \zeta_b BC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t} + \varepsilon_{f,t}$. $\mathbf{Z}_{f,t}$ is the following vector of firm-level controls: the lagged log-change in CDS spread, firm's equity return, the log-change in Moody's expected default frequency (EDF), the log-change in loss-given-default (LGD) from Markit, and the change in Markit depth. All regression specifications include a firm fixed effect and an industry-by-time fixed effect, where the industry is defined by Markit. $SC_{f,t}$ measures the dollar change (in \$ bn) in the mark-to-market value of f 's net sellers, excluding all positions written on firms in the same industry as f . $BC_{f,t}$ is the same variable, except for f 's net buyers. In the regressions $SC_{f,t}$ is interacted with a two sets of dummy variables: (i) indicating whether the lagged level of seller leverage high (HSL) or low (LSL); and (ii) indicating whether trailing 4-week cumulative dollar losses on the CDS portfolio of sellers are low (LSCL) or high (HSCL). Leverage is defined as high when it is in its 10% tail, and trailing 4-week CDS portfolio losses are defined analogously. CDS spreads come from Markit, have a 5-year maturity, are denominated in USD, and cover senior unsecured debt with documentation clause MR. Log-changes in CDS spreads are winsorized at the 1% level and are reported in percentage terms (scaled by 100). Additionally, I apply the following filters to the data: (i) the underlying firm must be registered in the United States; (ii) each firm must have at least 162 spread observations, which is the 5th percentile in terms of observations per firm; (iii) the firm must have a non-zero net notional outstanding; and (iv) the CDS spread must be less than 5000 bps. The reported R^2 is computed within each firm fixed effect group. Standard errors are double clustered by firm and time, and listed below point estimates in parenthesis. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A7: Additional Robustness Tests

Dep. Variable	$\Delta \log(CDS_{f,t})$						
	(1) Baseline	(2) CDX IG	(3) IG + No CDX	(4) HY	(5) Small	(6) Big	(7) Excl. Dealers
$SC_{f,t}$	-2.04** (0.23)	1.45 (0.95)	-1.79** (0.24)	-1.10** (0.42)	-1.75** (0.25)	-2.20** (0.30)	-4.87** (0.37)
$BC_{f,t}$	-0.04 (0.19)	1.50 (0.95)	-0.90** (0.20)	0.80** (0.39)	0.24 (0.23)	-0.40* (0.23)	0.90** (0.14)
Firm Controls	Y	Y	Y	Y	Y	Y	Y
FE	(i, t)	(i, t)	(i, t)	(i, t)	(i, t)	(i, t)	(i, t)
Within- f R^2	0.38	0.65	0.29	0.49	0.38	0.45	0.40
# of f	399	109	228	124	261	260	399
N	128,243	31,676	65,988	30,579	62,130	66,109	128,243

Notes: This table reports regressions of the form: $\Delta \log(CDS_{f,t}) = c + \beta_S \times SC_{f,t} + \beta_B \times BC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t} + \varepsilon_{f,t}$. The table reports the estimates for β_S and β_B . $\mathbf{Z}_{f,t}$ is a vector of firm-level controls. These include: the lagged log-change in CDS spread, each firm's own equity return, the log-change in Moody's expected default frequency (EDF), the log-change in loss-given-default (LGD) from Markit, and the change in Markit depth. $SC_{f,t}$ measures the dollar change (in \$ bn) in the mark-to-market value of f 's net sellers, excluding all positions written on firms in the same industry as f . $BC_{f,t}$ is the same variable, except for f 's net buyers. All regression specifications include a firm fixed effect and an industry-by-time fixed effect, where the industry is defined by Markit. The reported R^2 is computed within each firm group. CDS spreads come from Markit, have a 5-year maturity, are denominated in USD, and cover senior unsecured debt with documentation clause MR. Log-changes in CDS spreads are winsorized at the 1% level and are reported in percentage terms (scaled by 100). Additionally, I apply the following filters to the data: (i) the underlying firm must be registered in the United States; (ii) each firm must have at least 162 spread observations, which is the 5th percentile in terms of observations per firm; (iii) the firm must have a non-zero net notional outstanding; and (iv) the CDS spread must be less than 5000 bps. Column (1) contains the full sample of firms. Column (2) runs the regression for firms who are in the on-the-run CDX Investment Grade (IG) Index. Column (3) uses firms that are of IG quality, but are not in the on-the-run index. Column (4) focuses on high-yield firms (HY) based on S&P credit ratings. Columns (5) and (6) splits the full sample into small and large firms based on median equity market capitalization. In Column (7), $SC_{f,t}$ is constructed excluding any sellers who are dealers. All standard errors are double clustered by firm and time, and listed below point estimates in parenthesis. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A8: Capital Losses, Entry, and Exit

Panel A: Dollars

Dep. Variable	$NNS_{f,t-1 \rightarrow t-1+k}$					$NNB_{f,t-1 \rightarrow t-1+k}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta SCAP_{f,t-1 \rightarrow t}$	-0.21**	-0.29**	-0.20	-0.22*	-0.24*					
	(-0.08)	(-0.11)	(-0.12)	(-0.13)	(-0.14)					
$\Delta BCAP_{f,t-1 \rightarrow t}$						0.20**	0.22**	0.22*	0.19	0.06
						(0.08)	(0.11)	(0.13)	(0.12)	(0.13)
k	1	2	3	4	5	1	2	3	4	5
R^2	0.69	0.72	0.74	0.75	0.76	0.71	0.25	0.77	0.77	0.78
N	119,572	119,572	119,572	119,572	119,572	119,572	119,572	119,572	119,572	119,572

Panel B: Returns

Dep. Variable	$NNS_{f,t-1 \rightarrow t-1+k}$					$NNB_{f,t-1 \rightarrow t-1+k}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta SCAP_{f,t-1 \rightarrow t}$	-0.16**	-0.20**	-0.11	-0.09	-0.13					
	(0.06)	(0.09)	(0.10)	(0.11)	(0.11)					
$\Delta BCAP_{f,t-1 \rightarrow t}$						0.13**	0.17**	0.16*	0.14	0.06
						(0.06)	(0.08)	(0.09)	(0.09)	(0.10)
k	1	2	3	4	5	1	2	3	4	5
R^2	0.69	0.72	0.74	0.75	0.76	0.71	0.75	0.77	0.77	0.78
N	119,572	119,572	119,572	119,572	119,572	119,572	119,572	119,572	119,572	119,572

Notes: Columns (1)-(5) of both panels in this table reports results of regressions of the following form: $NNS_{f,t-1 \rightarrow t-1+k} = a_{i,t} + \Delta SCAP_{f,t-1 \rightarrow t}$, where $NNS_{f,t-1 \rightarrow t-1+k}$ is the number of new sellers of CDS on firm f , between date $t-1$ and $t-1+k$. $\Delta SCAP_{f,t-1 \rightarrow t}$ is the change in capital of f 's net sellers (as of time $t-1$). Columns (6)-(10) reports the same set of regressions, except for new buyers of protection on firm f . $a_{i,t}$ is an industry-by-time fixed effect, where a firm f 's industry is defined by Market. In Panel A, capital is measured using the dollar (\$bn) change in market-value of the entire CDS portfolio of sellers (or buyers). In Panel B, capital is measured as the percentage return on the pooled of CDS portfolio of sellers (or buyers). To compute returns, I assume initial margin requirements for each CDS position that mimic FINRA's margin requirements. See the Section 5.3 of the Online Appendix for a complete description of how initial margins are set. In all specifications, capital is winsorized, then standardized to have a mean zero and variance one. Standard errors are listed below each point estimate and are double clustered by f and t . * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data is weekly and spans 2/19/2010 to 10/7/2016.

Table A9: Transmission of Japanese Tsunami to U.S. CDS Markets

Dependent Variable	$\Delta \log(CDS_{f,1})$		
	(1)	(2)	(3)
$\Gamma_{S,f}$		3.07**	
		(1.27)	
$\Gamma_{B,f}$		1.11	
		(0.89)	
$\Gamma_{S,f}^{avg}$	0.81	-0.77	
	(3.43)	(3.46)	
$\Gamma_{B,f}^{avg}$	-1.33	-1.47	
	(1.38)	(1.27)	
$\omega_{J,f}$			8.55**
			(3.00)
Control Variables	Y	Y	Y
Industry FE	Y	Y	Y
Total N	288	288	175
Adj. R^2 (%)	17.5	21.0	24.4%

Notes: Columns (1) and (2) of the table presents results from the regression: $\Delta \log(CDS_{f,1}) = a + \phi_1 \Gamma_{S,f} + \phi_2 \Gamma_{B,f} + \theta_1 \Gamma_{S,f}^{avg} + \theta_2 \Gamma_{B,f}^{avg} + \beta' X_f$. The dependent variable is the log-change in CDS spread for U.S. firms from March 11, 2011 to March 17, 2011. $\Gamma_{S,f}$ and $\Gamma_{B,f}$ are the share-weighted average CDS exposure of f 's net sellers and buyers, respectively, to Japanese firms. Γ^{avg} are the equal-weighted versions of the same variables. Exposure is defined as the net amount of protection sold on Japanese firms (\$1 bn), meaning the units of $\Gamma_{S,f}$ and $\Gamma_{B,f}$ are in billions of dollar notional. Column (3) presents results from the regression: $\Delta \log(CDS_{f,1}) = a + \eta_J \omega_{J,f} + \beta' X_f$. $\omega_{J,f}$ is the share of counterparty J in the net selling of firm f . J is the counterparty who had the largest exposure to Japanese firms prior to the tsunami. The regression in Column (3) includes only firms for which $\omega_{J,f} \neq 0$. The control variables are (for each firm f): the change in the 5-year Moody's expected default frequency (EDF), the change in Markit's loss-given-default, the weekly equity return, the 90-day trailing correlation of (changes in) f 's CDS spread with the country of Japan's CDS spread, the 90-day trailing volatility of f 's CDS spread, a fixed effect based on the NAICS code of each firm, and the level of the CDS spread for f on the day of the tsunami. CDS spreads come from Markit, have a 5-year maturity, are denominated in USD, and cover senior unsecured debt with documentation clause MR. Log-changes in CDS spreads are winsorized at the 1% level and are reported in percentage terms (scaled by 100). Standard errors are clustered within each industry group and reported below point estimates. ** indicate statistical significance at the 5 percent level. When industry fixed effects are included with the controls, the reported R^2 is within each industry group.

Table A10: Initial Margin Conventions

		<i>Credit Rating</i>		
		AAA-A	BBB-BB	B and below
<i>Maturity</i>	0-3 years	1.50%	5.50%	13.33%
	3-6 years	4.17%	10.83%	20.83%
	6+ years	8.50%	18.75%	31.94%

Notes: This table shows the conventions that I assume when computing each counterparty's initial margin. The table reports the margin that net sellers post to buyers for a net position on a given firm and for a given maturity bucket. I assume buyers post half of the margin reported above. See Section 5.3 for complete details.

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