Limited Investment Capital and Credit Spreads

Emil N. Siriwardane[*]

ABSTRACT

Using proprietary credit default swap (CDS) data, I investigate how capital shocks at protection sellers impact pricing in the CDS market. Seller capital shocks — measured as CDS portfolio margin payments — account for 12% of the time-series variation in weekly spread changes, a significant amount given that standard credit factors account for 18% during my sample. In addition, seller shocks possess information for spreads that is independent of institution-wide measures of constraints. These findings imply a high degree of market segmentation and suggest that frictions within specialized financial institutions prevent capital from flowing into the market at shorter horizons.

A core assumption in neoclassical asset pricing theories is that capital can always flow friction-lessly to investment opportunities. Yet for many asset classes there are barriers to capital entry because investment requires specialized knowledge and technology, or capital itself may be scarce due to agency problems. For instance, financial institutions that participate in derivatives markets must have access to a steady source of funding, employ traders that have the requisite knowledge to properly evaluate risk, and possess the infrastructure to execute and process trades.

Moreover, within financial institutions, internal capital market frictions can impede the flow of investment resources in the short run. In particular, while many financial institutions are active in a number of different asset classes, trading desks within these institutions often focus on a specific market or a specific firm. In turn, specialized trading desks are allocated a pool of capital to finance trading activity, but this capital is not easily replenished on short notice due, for example, to agency problems within the firm (He and Xiong (2013)).

In the presence of such capital market frictions, asset prices may behave quite differently than what neoclassical theory would predict, at least at high frequencies. Specifically, price dynamics may depend not only on exposure to fundamental risk factors, but also on changes in the capital position of a small subset of trading desks in the market.

The spirit of this idea is at the heart of theories of limits to arbitrage (Shleifer and Vishny (1997), Kyle and Xiong (2001)), slow moving capital (Duffie (2010)), and financial intermediary-based asset pricing (He and Krishnamurthy (2013)). In these models, exogenous shocks to the capital positions of active market participants cause movements in asset prices, with the usual intuition being that less capital means higher risk premiums and lower prices. However, establishing a causal relationship between capital and asset prices is difficult to do empirically because researchers generally can not observe the identities of market participants and their portfolio positions. Moreover, without granular data, it is difficult to know the degree to which markets are

segmented. In the absence of such data, much of the existing work in the field has linked high-level measures of capital, like intermediary leverage, to asset price dynamics (Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)).[1]

In this paper, I attempt to overcome these hurdles using a proprietary data set of nearly one billion credit default swap (CDS) positions that cover the entire U.S. market from 2010 to 2016.[2] I start by showing that both net buyers and net sellers of CDS protection are highly concentrated, with sellers more concentrated than buyers. The top five sellers, which comprise only 0.1% of all CDS traders, account for nearly 65% of all net selling. This feature of the CDS market makes it an attractive venue to study capital market frictions because investment capital is more likely to face barriers to entry — and therefore affect asset prices — when asset markets are dominated by a small subset of financial institutions.

To tease out the causal impact of capital shocks on spreads, ideally one would study two firms, A and B, that are identical in terms of their underlying default risk and their exposure to systematic risk factors. Next, suppose that firm A's CDS sellers are hit with a capital shock from an unrelated part of their portfolio, but firm B's sellers are not. It follows that any subsequent movement in firm A's spreads relative to those of B must come from the negative capital shock. Furthermore, because firm A and firm B have equal exposure to systematic risk factors, the fact that firm A's spreads move at all is also an indication of segmentation. In an integrated market, spreads should not respond to shocks that are specific to firm A's sellers (Gabaix, Krishnamurthy, and Vigneron (2007)).

My analysis is designed to approximate this ideal experiment in the data. In particular, I examine how the CDS spread of a firm responds when that firm's default insurance sellers or buyers

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[1]Other examples include Froot and O'Connell (1999), Mitchell, Pedersen, and Pulvino (2007), Coval and Stafford (2007), Acharya, Schaefer, and Zhang (2015), and Chen, Joslin, and Ni (2019).

[2]In a CDS contract, the buyer of insurance pays a premium to a seller for protection against an underlying firm's (or reference entity's) corporate default. The buyer and seller in the trade are often called counterparties.

suffer capital losses. I compute seller (or buyer) capital shocks based on changes in the value of their CDS portfolio, which for institutional reasons also correspond to CDS portfolio margin payments (Duffie, Scheicher, and Vuillemey (2015)). Importantly, my capital shock variables derive from positions taken on unrelated firms. Thus, it is unlikely that losses reflect changes in fundamental default risk factors that are not already absorbed by the various fixed effects and controls in my regression tests.

I find that when a firm's sellers experience a one billion dollar capital loss (roughly 1.5 standard deviations), the level of CDS spreads increases by 2.7% per week. This elasticity is economically large, as the standard deviation of weekly spread movements is 5.2% for the average firm in my sample. Seller capital shocks also explain 12% of weekly spread variation, a large amount given that standard credit factors account for 18% of weekly spread variation during the sample period. Intuitively, capital losses raise the effective risk aversion of sellers, so they require a higher premium for providing protection. As mentioned above, these results also imply that the CDS market is at least partially segmented at the firm level. Consequently, in the short run, one can view the CDS market for a particular firm as a standalone market whose risk pricing is not integrated with that of other firms.

Next, I show that seller capital shocks possess information for spreads that is independent of institutional-level measures of capital constraints, like financial leverage. Indeed, capital shocks that are specific to the CDS desks of sellers are important for explaining weekly changes in spreads. This finding suggests that protection sellers act as if they are more risk-averse following losses, regardless of whether their institution is well capitalized. Thus, frictions within a financial institution play an important role in preventing capital from flowing into the CDS market at shorter horizons.

Given enough time, however, one would expect capital to eventually enter the CDS market and undo any pricing effects stemming from losses. This is a signature prediction of most theories of

slow moving capital (e.g., Duffie and Strulovici (2012)). Accordingly, I document that the effect of seller losses on CDS spreads dissipates rapidly, reverting completely after about nine weeks. It is not surprising that the pricing effects die out quickly because segmentation at the firm level is a rather extreme form of capital market segmentation and hence one would not expect it to persist for long periods.

To better understand the mechanism driving these results, I investigate how the quantity of protection sold responds to capital shocks. Using individual position data, I show that incumbent sellers do not adjust their portfolios by a meaningful amount in response to losses — they simply become reluctant to take on more positions after they are initially hit with a negative capital shock. Moreover, after incumbent sellers experience a negative shock and spreads rise, there is no evidence that new sellers enter the market to offer more competitive prices. Instead, as internal capital market frictions at incumbent sellers' institutions thaw in the weeks following a capital loss, sellers regain their risk appetite and decrease their reservation price for providing protection.[3]

It seems reasonable to wonder whether the link between seller capital and spreads depends on the composition of active financial institutions in the market at a given point in time. Indeed, since the 2008 financial crisis, a notable trend in the data is that asset managers (e.g., hedge funds) have steadily replaced dealers as the largest net sellers of CDS protection. Motivated by this trend, I also test whether capital losses impact spreads differently depending on whether dealers or asset managers have a large market share. I find that losses at asset managers have a stronger effect on spreads than losses at dealers, suggesting that capital market frictions are larger for asset managers than dealers.

One limitation of my analysis is that I do not observe market players' holdings of underlying bonds. This is primarily an issue for net buyers of credit protection, who typically use CDS to

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[3]I use CDS spreads from Markit, which provides a composite spread based on both transactions and quotes. Thus, a supply shift does not necessarily imply a price change from Markit. I discuss this issue in detail in Section II.E.

hedge an underlying corporate bond portfolio. Thus, losses at the CDS desk for net buyers may be offset by gains in their corporate bond portfolio. Consistent with this view, I find little evidence of a relationship between credit spreads and my measure of buyer capital shocks. Hedging is less likely to be an issue for large net sellers, as directly hedging a sold CDS position requires costly shorting of the underlying bond (Asquith et al. (2013)). Moreover, if sellers were hedged, one would not expect shocks based only on their CDS portfolio to explain spreads.

Finally, to provide further evidence of the causal link between capital and pricing, I use the 2011 Japanese tsunami to study how an exogenous shock to seller risk-bearing capacity affected CDS spreads on U.S. firms. To trace out the impact of the tsunami, I exploit the fact that U.S. counterparties had large and heterogeneous CDS exposures to Japanese firms prior to the tsunami. I then compare U.S. firms whose sellers had large Japanese CDS exposures to firms whose sellers had low exposure. In the week after the tsunami, CDS spreads rose 2.5% for firms whose protection sellers had high exposure to Japan, relative to firms whose sellers had low exposure. I also find no evidence of buyers transmitting the shock of the tsunami to U.S. firms.

The remainder of the paper is organized as follows. I begin in Section I by summarizing my primary data sources and presenting some facts about the CDS market that motivate why it is a good setting to explore how limited capital impacts asset prices. In Section II, I establish how seller capital losses affect CDS pricing, the degree of segmentation in the market, and the role that internal capital market frictions play in preventing capital from flowing into the CDS market. In Section III, I discuss the plausibility and robustness of my central findings. In Section IV, I explore whether the link between capital and pricing depends on the type of active institution in the market. I also present a case study where I investigate how the 2011 Japanese tsunami was transmitted to U.S. CDS markets by protection sellers, and I report results of suggestive analysis linking CDS and bond markets. Finally, I conclude in Section V.

I. Data and Motivating Facts

A. *Data Description*

The main data for this study were provided to the U.S. Treasury's Office of Finance Research (OFR) by the Depository Trust and Clearing Corporation (DTCC).[4] The data are part of the DTCC's Trade Information Warehouse (TIW) and cover both CDS transactions and positions. Transactions represent flows in CDS, while positions represent stocks. The DTCC uses its own algorithms to convert transactions to open positions before reporting both to the OFR.

For both transactions and positions, I observe full information on the counterparties in the trade, as well as pricing terms, swap type, notional amount, initiation date, and so forth. The DTCC provides the OFR with data on any transaction or position that meets one of two conditions: (i) the underlying firm covered by the swap is based in the U.S. or (ii) at least one of the counterparties in the swap is registered in the U.S. In addition, the DTCC CDS data include all North American index swap transactions and positions (i.e., the index family is "CDX.NA."). Taken together, this dataset effectively covers the entire CDS market for all U.S. firms, which is the portion of the market that I analyze in this study.[5] The data begin in 2010 and are updated continuously on a weekly basis. I work primarily with the positional data and truncate my analysis in October 2016. The DTCC's positional data set contains over 57 million index positions and nearly 760 million single-name positions. To save space, details regarding data construction and processing are provided in the Internet Appendix.

I also merge the DTCC data with a number of data sources. The main focus of this study is to understand weekly movements in CDS spreads, which I obtain from Markit. Markit CDS spreads

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[4]Schachar (2012), Chen et al. (2011), Boyarchenko et al. (2017), and Oehmke and Zawadowski (2017) also use versions of the DTCC data.

[5]Throughout this paper, I refer to the underlying company whose default is covered by a CDS contract as the "firm" or the "underlying firm." A common term used in the CDS market is the "underlying reference entity."

represent a composite spread that is computed using quotes and transaction information from 30 major market participants. Specifically, I use five-year CDS spreads with a modified restructuring (MR) clause, written on senior unsecured debt, and denominated in USD. To account for changes in fundamental risk, I use data from Moody's expected default frequency (EDF) database. Moody's EDF is a standard database of expected firm default probabilities that is derived from structural models of credit risk (Merton (1974)). The EDF database also contains information on firm-level equity valuations and ratings information from S&P. In some of my analyses below, I examine how the leverage of market participants interacts with CDS spreads. I define leverage as the book value of debt divided by the market value of equity, both of which I obtain from CRSP/COMPUSTAT. Table I contains some basic summary statistics for this data.

(Table I Goes About Here)

The Treatment of Index Swaps   As shown in Appendix A.1, nearly half of the credit risk transfers in the CDS market occur through index swaps. Thus, to fully understand a counterparty's true risk exposure, it is important to account for positions in both index and single-name swap positions. For example, suppose a trader sells $100 of notional on an index swap that contains 100 different firms, each with equal weight in the index. Like a single-name swap, if one of the firms defaults, the trader must pay up to $1 = $100×(1/100) in notional to the buyer of the index swap, depending on the recovery rate of the underlying firm's bonds. After this payment, 99 firms remain in the index. Writing $100 in protection via an index is therefore equivalent to writing 100 different single-name swaps, each worth $1 in notional. Thus, when considering the amount of credit risk exposure to a single firm, I disaggregate index swaps into their single-name equivalents and then net them against any true single name exposures. The full data set of true single-name exposures and index-implied single-name exposures contains nearly 4.4 billion positions. The Internet

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Appendix contains details on this procedure.

B. *Concentration in the CDS Market*

Investment capital is more likely to face barriers to entry — and therefore impact asset prices — when asset markets are concentrated and dominated by a small subset of financial institutions. I now document that CDS markets fit this description, making them a natural setting to examine asset pricing theories based on capital market frictions (e.g., Shleifer and Vishny (1997) and Gromb and Vayanos (2002)). In particular, I show that a handful of sellers provide the bulk of the credit insurance in this market. Buyers of protection are also concentrated, though less so than sellers.

To establish these facts, let f define the underlying firm on which a CDS is written and c represent a counterparty. Further, let $NS_{c,f,t}$ denote the net amount of protection sold by c on firm f as of date t.[6] Positive values of $NS_{c,f,t}$ indicate that c is a net seller of f, while negative values indicate that c is a net buyer. For instance, if trader c sells \$100 of protection on firm f in one trade, and buys \$25 protection on f in a different trade, then $NS_{c,f,t} = \$75$. Again, I account for indirect exposures through index swaps and direct exposures through single-name swaps when computing $NS_{c,f,t}$. Finally, let C_t be the set of counterparties with open positions on date t, and F_t be the set of firms covered by open CDS contracts as of date t.

With this notation in mind, I define counterparty c's share of net selling on firm f as:

$$MS_{c,f,t} := NS_{c,f,t} \times (NO_{f,t})^{-1}, \tag{1}$$

where $NO_{f,t}$ is the net notional outstanding for firm f at time t, computed by summing $NS_{c,f,t}$ across the net sellers of firm f and $MS_{c,f,t}$ is counterparty c's share of net selling in firm f. For

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[6]I define c at the institution level. This is reasonable when a majority of CDS trading at an institution happens at one desk, as is often the case. For simplicity, I also collapse the maturity of positions when defining $NS_{c,f,t}$.

example, $MS_{c,f,t} = 20\%$ means that c is responsible for 20% of the total net protection sold on f. Conversely, $MS_{c,f,t} = -20\%$ means that c accounts for 20% of the total net bought on f.

Next, to compute a measure of the *aggregate* market share for each counterparty, I take a size-weighted average of c's shares across all firms,

$$MS_{c,t} \;\; := \;\; \sum_{f \in F_t} \omega_{ft} \times MS_{c,f,t}, \tag{2}$$

where $\omega_{f,t} := NO_{f,t} / \sum NO_{f,t}$ is based on the size of f's CDS market. In computing $MS_{c,t}$, I use a size-weighted rather than an equal-weighted average to offset the influence of firms with very small CDS markets, as these firms usually have only one net buyer and one net seller.

Note that $MS_{c,t}$ is a parsimonious measure of the importance of c as a seller (or buyer) for the overall CDS market. If c is consistently a seller of protection on firms with the largest CDS markets, then $MS_{c,t}$ will be large and positive. If instead a counterparty offsets net positions across firms (i.e., sells in one name and buys in another), then its aggregate share will tend towards zero.

In turn, I define the top five aggregate sellers at each point in time as the traders with the largest $MS_{c,t}$ and the top five buyers as the five counterparties with the most negative $MS_{c,t}$. Figure 1 plots the total share of the top five sellers and buyers, respectively, over time. In the figure, I report buyer market shares as a positive number because my definition otherwise assigns them negative shares.

(Figure 1 Goes About Here)

Net sellers of CDS are highly concentrated, and in general have been more so than buyers. By my measure of market share, the top five sellers accounted for 75% of all protection sold in 2010. To put this into context, there are around 1,700 counterparties in the market, so 75% of

all selling was in the hands of less than 0.1% of potential counterparties. Sellers have become less concentrated over time, with their aggregate share falling to around 50% by 2016. Buyer concentration has stayed relatively stable over time, with the top five buyers accounting for about half of aggregate net buying.

While the CDS market is certainly concentrated, it may still be the case that the identities of the largest buyers and sellers change rapidly over time. For instance, a dealer concerned with inventory management may be a large net buyer today, but would quickly reduce its position in the future. In Appendix A.2 I find evidence contrary to story, instead showing that the market is persistently dominated by the same set of net buyers and sellers. This structure makes the CDS market a natural place to test asset pricing theories of limited investment capital.

At this juncture, it is reasonable to ask whether one can draw broad conclusions about asset price formation from a specialized market like CDS. In Appendix A.1, I document that the U.S. CDS market is large in terms of the amount of net notional credit risk transferred, with a conservative lower bound of around $1 trillion. Moreover, CDS markets played an important role in the 2008 financial crisis, perhaps most famously with the government intervention into AIG. Finally, the barriers to entry in the CDS market are similar to those in many large derivatives markets, such as interest rate swaps.[7] Thus, the forces governing price dynamics in the CDS market are likely to apply to other important markets as well.

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[7]I discuss some key barriers to entry into the CDS market in the Internet Appendix.

II. Capital and Spreads

A. Empirical Approach

A.1. A Simple Asset Pricing Framework

Before turning to the link between capital and spreads, I start by developing a simple framework that will be useful for organizing my interpretation of the paper's main results. Consider a reduced-form model of credit (Duffie and Singleton (1999)), where defaults for firm f are captured by a hazard rate process, $\Lambda_{f,t}^{\mathbb{P}}$. Under some simplifying assumptions, it well known that CDS spreads can be written as[8]

$$CDS_{f,t} = \Lambda_{f,t}^{\mathbb{Q}} \times \Psi_{f,t}^{\mathbb{P}},$$

where $\Lambda_{f,t}^{\mathbb{Q}}$ is the firm's risk-neutral hazard rate at time t and $\Psi_{f,t}^{\mathbb{P}}$ is the physical loss given default (LGD). Firm f's risk premium, defined as $\Pi_{f,t} := \Lambda_{f,t}^{\mathbb{Q}}/\Lambda_{f,t}^{\mathbb{P}}$, is the compensation required by the market for bearing each unit of default risk. These identities imply that log-changes in spreads can be written as

$$\Delta cds_{f,t} = \Delta \lambda_{f,t}^{\mathbb{P}} + \Delta \psi_{f,t}^{\mathbb{P}} + \Delta \pi_{f,t},$$

where $cds_{f,t} := \log(CDS_{f,t})$ and lower-case Greek letters denote logs, for example $\lambda = \log(\Lambda)$. To illustrate, I express the default risk premium portion of spreads as a linear function of K systematic factor exposures and an idiosyncratic component,

$$\pi_{f,t} = \sum_{k=1}^{K} \beta_{f,k}\theta_{k,t} + \nu_{f,t},$$

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[8]One must assume that the term structure of default risk is flat in each period. To simplify the exposition, I also assume that risk-neutral and physical LGDs are equal, though this is not necessary for my basic argument.

where $\beta_{f,k}$ is firm f's exposure to systematic risk factor k and $\theta_{k,t}$ is that factor's price of risk. I define $\kappa_{f,t}^s \equiv \sum_k \beta_{f,k}\theta_{k,t}$ to be the total risk premium for f that comes from exposure to systematic risk factors. I refer to $\nu_{f,t}$ as the firm-specific or idiosyncratic component of firm f's risk premium. Note that this formulation also allows factor prices of risk (θ) to differ across firms. In this case, any deviations between a firm's factor price of risk and the cross-sectional average are simply absorbed into $\nu_{f,t}$. In this generalized setup, spread changes can come from movements in fundamental default risk, systematic risk premiums, or firm-specific risk premiums,

$$\Delta cds_{f,t} = \Delta\lambda_{f,t}^{\mathbb{P}} + \Delta\psi_{f,t}^{\mathbb{P}} + \overbrace{\Delta\kappa_{f,t}^s + \Delta\nu_{f,t}}^{\Delta\pi_{f,t}}. \tag{3}$$

When markets are well integrated, the only risks that earn a premium are those that cannot be diversified away. For example, in the classic CAPM, $\pi_{f,t} = \kappa_{f,t}^s$ is determined by f's exposure to the aggregate wealth portfolio and the price of risk for each unit of exposure. Furthermore, if markets are well integrated, two firms that are exposed to the same set of aggregate risks (e.g., their $\beta_{f,k}$'s are the same) should also have the same default risk premium ($\pi_{f,t}$). The integrated markets view therefore predicts that $\nu_{f,t} = 0$.[9] In contrast, when markets are segmented, $\nu_{f,t}$ can differ from zero because the same set of aggregate risks may be priced differently across segments or segment-specific risk premiums may exist (Gabaix, Krishnamurthy, and Vigneron (2007)).

The primary contribution of this paper is to provide empirical evidence that CDS markets are indeed segmented at the firm level, at least in the short run. In the data, movements in firm-specific risk premiums play a meaningful role in determining CDS spread dynamics overall. As with any asset pricing test of this kind, one major challenge I face is disentangling shocks to default risk premiums $\pi_{f,t}$ from shocks to fundamentals ($\lambda_{f,t}^{\mathbb{P}}$ and $\psi_{f,t}^{\mathbb{P}}$). When pinning down segmentation, a

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[9]Asset pricing models based on household consumption (Campbell and Cochrane (1999)) and intermediary wealth (He and Krishnamurthy (2013)) both restrict $\nu_{f,t} = 0$, but differ in the systematic risk factors that are priced.

second hurdle is separating shocks to the systematic component of default risk premiums $\kappa_{f,t}^s$ from shocks to the firm-specific component of risk premiums $\nu_{f,t}$. My empirical approach focuses on addressing these identification challenges, and hence my regressions are designed with these issues in mind.

Conditional on overcoming the identification challenges, the pertinent economic question is what drives shocks to $\nu_{f,t}$. Standard asset pricing intuition suggests that $\nu_{f,t}$ is determined by the stochastic discount factor (SDF) of firm f's marginal pricers. Motivated by this intuition, I first identify the marginal pricers. I then construct various proxies for changes in their SDF. In the remainder of the paper, I refer to changes in a trader's SDF interchangeably with changes in a trader's effective risk aversion or risk appetite.

A.2. Measuring Changes in Risk Appetite with Margin Payments

I use capital shocks — measured as CDS portfolio margin payments — as my proxy for changes in a trader's risk appetite. This approach stems from the idea that traders have less of a risk appetite when they've suffered negative capital shocks (e.g., He and Krishnamurthy (2013)). Formally, at each date t, I define the capital shocks of buyers and sellers of firm f's CDS as

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\begin{aligned}
SC_{f,t} &:= \sum_{c \in \mathcal{S}_{f,t-1}} \Delta V_{c,t}^{CDS} \\
BC_{f,t} &:= \sum_{c \in \mathcal{B}_{f,t-1}} \Delta V_{c,t}^{CDS},
\end{aligned}
\tag{4}
$$

where $\mathcal{S}_{f,t-1}$ is the set of f's net protection sellers at time $t-1$, $\mathcal{B}_{f,t-1}$ are f's net protection buyers, and $\Delta V_{c,t}^{CDS}$ is the weekly change in counterparty c's CDS portfolio value, computed using the ISDA Standard Pricing Model. Because of post-crisis collateralization rules, $\Delta V_{c,t}^{CDS}$ measures

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the net amount of variation margin payments made by c to its counterparties over the course of the week.[10] These margin payments are fully collateralized, paid daily, and draw on the desk's liquid capital buffer (e.g., Duffie, Scheicher, and Vuillemey (2015)). Thus, $\Delta V_{c,t}^{CDS}$ is a natural measure of capital shocks at the CDS desk of each counterparty. For example, if $\Delta V_{c,t}^{CDS} = -\$100$, then counterparty c will have paid $100 in variation margin payments over the week.

My proxy for seller capital shocks, $SC_{f,t}$, sums the net variation margin payments made by f's protection sellers. Similarly, $BC_{f,t}$ sums the net variation margin payments made by f's buyers. For reasons discussed below, I exclude positions written on firms in f's industry when computing both $SC_{f,t}$ and $BC_{f,t}$. Importantly, whether these capital shock variables are good proxies for changes in risk aversion depends on the extent to which buyers and sellers hedge. For instance, if each dollar of variation margin paid by sellers on their CDS portfolio is offset by an incoming margin payment from their hedge portfolio, then there is no actual capital drain for the CDS desk. I argue that it is unlikely that sellers are hedged in Section III.A, after presenting my main results.

Table II reports basic summary statistics for $SC_{f,t}$ and $BC_{f,t}$. For net sellers, the average capital shock at the CDS desk is basically centered around zero, but has a weekly standard deviation of around $675 million dollars. There are also weeks of extreme gains and losses, with the minimum shock equal to around -$6.2 billion and the maximum of $4.3 billion. Capital shocks at the CDS desks of buyers display a similar, albeit slightly more muted pattern. The standard deviation of $BC_{f,t}$ is around $455 million, with a minimum of -$5.8 billion and a maximum of $4.1 billion. I discuss the magnitude of these shocks in more detail in Section III.B.

(Table II Goes About Here)

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[10]According to standard ISDA protocol, variation margin payments between two counterparties must be paid daily. According to ICE Clearing, cleared positions may have larger or more frequent margin payments depending on market conditions like volatility. See https://www.theice.com/publicdocs/How_Clearing_Works.pdf. Continuous variation margins were uncommon before the crisis.

B.   Capital Shocks and CDS Spreads

B.1.   Workhorse Regression and Identification

To link CDS spread movements to capital shocks, I use the following workhorse regression:

$$\Delta cds_{f,t} = a_f + a_{i,t} + \Delta cds_{f,t-1} + \boldsymbol{\beta}_1' \Delta \mathbf{Z}_{f,t} + \zeta_s SC_{f,t} + \zeta_b BC_{f,t} + \varepsilon_{f,t}, \tag{5}$$

where $cds_{f,t}$ is the logarithm of the five-year CDS spread of firm f at time t. To allow for autocorrelation in spread movements, the regression also includes the lagged log-change in f's CDS spread.[11] Firm and industry-by-time fixed effects are given by a_f and $a_{i,t}$, respectively. I use Markit's definition of industries to construct $a_{i,t}$.

In terms of equation (3), my goal is to test whether capital shocks induce movements in the firm-specific default risk premium ($\nu_{f,t}$). Again, this should occur only if CDS markets are segmented at the firm level. The ideal way to test this empirically would be to study two firms A and B that have the same fundamentals ($\lambda_{A,t}^{\mathbb{P}} = \lambda_{B,t}^{\mathbb{P}}$ and $\psi_{A,t}^{\mathbb{P}} = \psi_{B,t}^{\mathbb{P}}$). In addition, A and B should be equally exposed to systematic risk factors, so that the systematic components of their default risk premiums are equal ($\kappa_{A,t}^s = \kappa_{B,t}^s$). Now suppose that firm A's sellers experience a negative capital shock, but firm B's do not. In this case, equation (3) implies that any movement in A's spreads relative to B's must arise because the seller capital shock caused a change in A's firm-specific risk premium $\nu_{A,t}$. Presumably this shift occurs because firm A's sellers became more risk-averse.

Regression (5) allows me to approximate this ideal experiment in the data. The firm-specific variables $\mathbf{Z}_{f,t}$ control for fundamentals ($\lambda_{f,t}^{\mathbb{P}}$ and $\psi_{f,t}^{\mathbb{P}}$), as does the industry-by-time fixed effect $a_{i,t}$. The vector of firm-level controls $\mathbf{Z}_{f,t}$ contains the log of Moody's five-year expected default

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[11]In regression (5), standard estimation techniques are potentially inconsistent due to the Nickell (1981) bias. However, the usual dynamic panel data corrections (e.g., Arellano and Bond (1991)) deliver nearly identical results. The reason is that the time-series dimension of the panel is large enough to effectively nullify the Nickell (1981) bias.

frequency (EDF) and Markit's expected LGD. In addition, $\mathbf{Z}_{f,t}$ contains a measure of market depth from Markit and f's contemporaneous equity return. In some versions of regression (5), I also include information on firm f that comes from the options market (e.g., implied volatility). The firm fixed effect a_f absorbs any time-invariant firm characteristics. As mentioned above, I exclude positions on firms in f's industry when computing my capital shock measures, which is another way to allay concerns that they proxy for changes in fundamentals.

The industry-by-time fixed effect $a_{i,t}$ in the regression means that in effect I am comparing the spread changes of firms within a given industry. Firms in the same industry are more likely to have similar exposure to systematic risk factors, and hence a similar default risk premium for exposure to these factors. In some cases I extend this logic by comparing firms in the same industry and rating class at each point in time. Note that, to the extent that firms within an industry have differential exposure to systematic risk factors, these differences should be naturally captured by each firm's own equity and option prices (contained in $\mathbf{Z}_{f,t}$).

B.2. Baseline Results

Table III presents the results of regression (5). Column (1) provides the first piece of evidence relating seller capital shocks to CDS spreads. In both economic and statistical terms, my proxy for changes in seller risk appetite is an important determinant of spread movements. Specifically, a \$1 billion capital loss to net sellers results in a 2.7% increase in the level of f's CDS spread. To put this quantity into perspective, the standard deviation of spread movements in my sample is 5.2% and the standard deviation of $SC_{f,t}$ is about \$675 million. Intuitively, when sellers experience a negative capital shock, their effective risk aversion increases and thus they require a higher premium for selling protection. This is one of the main results of the paper. Much of the analysis below confirms the strength of this finding.

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(Table III Goes About Here)

Column (2) of Table III shows that the point estimate on $SC_{f,t}$ is robust to including each firm's option-implied CDS spread and at-the-money (ATM) volatility.[12] The specification in column (3) controls for observable macroeconomic variables that might also drive spreads, such as changes in the VIX. I choose these controls based on theoretical models of credit risk and previous research on the determinants of credit spread variation (e.g., Collin-Dufresne, Goldstein, and Martin (2001)), with more details in Appendix B.2. In this case, the point estimate on seller capital is reduced slightly in absolute value, which is unsurprising because seller capital shocks are themselves likely to be driven by macroeconomic factors. The coefficient on $SC_{f,t}$ is similar when I include both option-based and macroeconomic controls in column (4).

Seller capital shocks account for a large amount of spread variation. As shown in the Internet Appendix, firm-level variables explain about 10% of spread variation on their own. Column (1) of Table III shows that this R^2 increases to 22% when including buyer and seller capital shocks, and effectively all of the incremental R^2 of 12% comes from the inclusion of seller capital shocks. For additional context, in the Internet Appendix I show that firm-level and macroeconomic variables together explain only 18% of spread variation. Hence, seller capital shocks rival standard credit risk factors in terms of their explanatory power for spreads.

Columns (5) to (8) contain the strongest evidence that seller capital shocks do indeed drive movements in CDS spread. Column (5) removes macroeconomic controls from the regression and replaces them with an industry-by-time fixed effect, which absorbs any common factors that impact firms in the same industry. The point estimate of -2.04 on seller capital shrinks slightly towards zero, but remains statistically significant. Column (6) adds option-implied CDS spreads and ATM volatilities to the regression, with little change. I also obtain similar results in columns (7) and

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[12]I compute an option-implied CDS spread for firm f based on Carr and Wu (2011). See Appendix B.1 for details.

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(8), where I use a rating-industry-time fixed effect instead of an industry-by-time fixed effect. This fixed effect is particularly useful in isolating the causal impact of seller shocks on spreads because two firms in the same industry and rating class likely have similar systematic risk exposures. In all of these specifications, the impact of buyer capital shocks on CDS spread dynamics appears to be negligible.

Based on these results, what would one have to believe to reject the idea that seller capital shocks cause spread movements? Consider the example of Ford. The exclusion restriction for the regression would fail if $SC_{f,t}$ — which only reflects positions written on firms *outside* of the auto industry — captures some omitted factor that drives Ford's CDS spread, but in a way that is (i) not common to the auto industry, as ruled out by the industry-by-time fixed effect and not captured by Ford's own (ii) equity return or (iii) option prices.[13] This alternative seems unlikely in my view.

The fact that regression (5) is tightly identified is the key to my interpretation throughout the paper. As discussed in Section II.B.1, absent identification issues, any impact of $SC_{f,t}$ on spreads has to work through the firm-specific risk premium channel. Textbook asset pricing dictates that this risk premium is determined by the risk appetite of the marginal trader(s) in CDS. Thus, because $\zeta_s \neq 0$, it is natural to conclude that $SC_{f,t}$ correlates with changes in the risk appetite of CDS sellers. Relying on identification in this way imposes a useful form of economic discipline when thinking about the validity of my capital variable — any debate ultimately centers on whether $SC_{f,t}$ picks up on firm fundamentals or systematic risk exposures (after including other controls).

In many respects, the point estimates reported in Table III are also lower bounds on the effect of seller capital shocks on prices. For the purpose of identification, $SC_{f,t}$ excludes shocks coming from positions written on firms in f's industry. Moreover, $SC_{f,t}$ does not reflect any leverage embedded in sellers' positions. Leverage would only amplify the impact that seller capital shocks

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[13]I implicitly assume that Ford's CDS spread does not drive $SC_{f,t}$ or $BC_{f,t}$. This seems reasonable because (i) both reflect positions outside of the auto industry and (ii) the position in Ford is negligible relative to the whole portfolio.

have on spreads. Finally, any effect of counterparty risk on pricing would mitigate the extent to which spreads rise in response to seller losses.[14] To see why, notice that buyers of protection would view undercapitalized sellers as risky counterparties. Consequently, after a negative capital shock to sellers, one would expect any counterparty risk effects to lower spreads, not raise them.

The final thing to note from this exercise is that, relative to seller capital shocks, buyer capital appears to play much less of a role in explaining weekly CDS spread movements. In almost all specifications, the coefficient on buyer capital shocks is statistically insignificant and generally very small in economic magnitude. Thus, like in the market for catastrophe insurance (Froot and O'Connell (1999)), local demand shocks for CDS insurance are less important than local supply shocks for understanding CDS price movements over this time period at a weekly frequency.

C. *Internal Capital Market Frictions*

The evidence thus far suggests that capital shocks at the CDS desks of firm f's protection sellers induce spread movements by changing firm f's firm-specific risk premium ($\nu_{f,t}$ in equation (3)). Part of my explanation for this fact is that capital shocks at protection sellers cause a shift in their risk appetite. Of course, changes in sellers' risk appetite can arise from a number of sources. Consequently, even if the exclusion restriction holds, regression (5) can not determine whether capital shocks specific to the CDS desk cause changes in risk appetite or whether they just correlate with some other source. It certainly seems reasonable that changes in the risk-bearing capacity of a seller's overall institution — which could correlate with capital shocks at the CDS desk — might also influence the risk appetite of CDS traders. I shed light on this tension by

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[14]As argued by Arora et al. (2012), the impact of counterparty risk on CDS pricing is likely to be quite small.

augmenting my workhorse regression as follows:

$$\Delta cds_{f,t} = a_f + a_{i,t} + \Delta cds_{f,t-1} + \boldsymbol{\beta}_1' \Delta \mathbf{Z}_{f,t} + \zeta_s SC_{f,t} + \zeta_b BC_{f,t} + \theta_s ISC_{f,t} + \theta_b IBC_{f,t} + \varepsilon_{f,t}, \quad (6)$$

where $ISC_{f,t}$ is the average change across f's sellers in one of three variables: (i) leverage, measured as the ratio of market equity to debt, (ii) CDS spreads, or (iii) SRISK. SRISK is an estimate of the amount of capital that a financial institution would need to raise to function normally in the event of a financial crisis (Brownlees and Engle (2017)).[15] ISC stands for "institutional seller capital" because it is measured at the institution level, as opposed to the CDS desk level. Institutional buyer capital, $IBC_{f,t}$, is constructed analogously for buyers of firm f's protection.

The proxies ISC and ISB provide an alternative way to measure changes in the risk appetite of CDS traders.[16] For example, if shocks at the CDS desk of sellers do not cause changes in their effective risk aversion, but merely correlate with changes in institution-wide risk aversion, then ISC should drive out SC in the regression. In all of these tests, I restrict attention to firms for which dealers are responsible for a majority of the protection sold. I do so because institution-wide measures of capital are only available for dealers.

Table IV presents the estimates of equation (6). As a baseline, column (1) runs the regression excluding any institution-wide measures of capital for the full sample for firms. Column (2) runs the same regression but only for firms with a majority of sellers that are dealers. As can be seen, the coefficient on seller capital drops in magnitude, indicating that CDS-derived capital shocks impact spreads less when sellers are dealers. I discuss the interpretation of this result below.

(Table IV Goes About Here)

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[15]Table II and Table IAIII in the Internet Appendix provide summary statistics for these variables.

[16]He and Krishnamurthy (2013) provide a theoretical foundation for why changes in net worth (e.g., leverage) are a good proxy for changes to a financial firm's effective risk aversion.

Column (3) presents results for the specification where I use leverage to measure shocks to institutional capital. Consistent with the intuition in He, Kelly, and Manela (2017), sellers require a high premium for selling protection when they are more levered. While the point estimate is measured precisely, the magnitude of the effect is not overwhelming: a one-standard-deviation increase in seller leverage leads to a 0.8% increase CDS spreads. Importantly, the impact of desk-level shocks is unchanged when including institution-wide leverage. The coefficient on $SC_{f,t}$ in column (3) is comparable to that in column (2), and remains statistically significant at conventional levels. In terms of relative importance, a negative desk-specific capital shock has twice the impact that an institution-wide shock has on spreads.[17] The broader takeaway here is that institution-wide and CDS-derived capital shocks appear to impact spreads in a complimentary way. Again, my identifying assumption is that this link occurs through the firm-specific risk premium in equation (3).

In contrast, my proxy for desk-specific buyer shocks continues to have no statistically meaningful impact on spreads. Interestingly, there is a positive and statistically significant relationship between changes in buyers' leverage and CDS spreads. While certainly not definitive proof, this finding is consistent with buyers using CDS to partially hedge corporate bond positions. When buyers are more constrained at an institution level, their hedging motive increases and they bid CDS spreads up. However, the magnitude of the effect is quite small: a one-standard-deviation increase in buyer leverage coincides with only a 0.35% increase in CDS spreads.

Column (4) runs the regression using CDS spreads to compute ISC and IBC. The point estimate on $SC_{f,t}$ is not driven out by the inclusion of seller CDS spreads. As before, the point estimate on $BC_{f,t}$ continues to show no statistically relevant information for CDS spread changes. Column (5) reports results for the same regression when using changes in SRISK to compute

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[17]This follows from combining the point estimates in column (3) with the summary statistics in Table II.

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ISC and IBC. A similar pattern emerges. For all regressions in columns (3) to (5), the point estimates on $SC_{f,t}$ also compare favorably that in column (2). In sum, my CDS-derived capital shock for sellers ($SC_{f,t}$) possesses robust and independent explanatory power for firm f's spread movements. Because I control for institution-wide capital, these findings are highly suggestive that shocks specific to the CDS desk have a causal impact on the effective risk aversion of protection sellers, which ultimately leads to movements in CDS spreads.

A subtle implication of these results is that the risk appetite of the CDS desk — the relevant one for understanding spreads — does not necessarily coincide with the risk appetite of the entire institution. Similar to the story in Mitchell, Pedersen, and Pulvino (2007), losses at the CDS desk become important when internal capital market frictions at sellers prevent immediate recapital-ization of the CDS desk or division. Along this line, the fact that $SC_{f,t}$ has a smaller impact on spreads when dealers sell protection supports the view that dealers are more diversified internally than non-dealers. In turn, CDS desk shocks matter less for traders' risk appetite. While I do not have data that allows me to directly test for internal capital market frictions, the preceding results are consistent with this interpretation. The existence of similar frictions inside of financial institu-tions has also been recently documented by Murfin (2012). He finds strong causal evidence that lenders tighten covenants on borrowers after suffering defaults on their loan portfolio, even if the lender's broader institution is well capitalized.

To be clear, this is not to say that institution-wide capital does not impact the effective risk aversion of CDS sellers. If changes in institution-wide capital (e.g., leverage) are correlated across sellers, then this variation will be absorbed at least in part by the industry-by-time fixed effect (and other controls) in regression (6). Indeed, in a univariate regression of spread changes on changes in seller leverage, the point estimate on leverage equals 0.84 — almost three times the coefficient

in column (3) — and is highly significant (t-statistic = 9.08).[18] I further explore the interaction between desk-specific and firm-wide constraints in Section II.D of the Internet Appendix, showing that the response of spreads to seller losses is exacerbated when sellers have high overall leverage.

D.   Segmentation

D.1.   Placebo Tests

As outlined in Section II.A.1, in an integrated market, spreads should not respond to shocks that are specific to firm f's sellers (Gabaix, Krishnamurthy, and Vigneron (2007)). The results from Section II.B.2 therefore imply that CDS markets are segmented at the firm level, at least at a weekly frequency. To bolster this interpretation, I run the regression

$$Ret_{f,t}^{Equity} = a_f + a_{i,t} + \eta_s SC_{f,t} + \eta_b BC_{f,t} + \varepsilon_{f,t}, \tag{7}$$

where $Ret_{f,t}^{Equity}$ is the equity return of firm f. Under my assertion that $SC_{f,t}$ measures changes in the risk appetite of CDS protection sellers, η_s should equal zero in this regression, for two reasons. First, equity markets are likely to be better integrated across firms. In terms of the asset pricing equation (3), this means that there is no firm-specific risk premium ($\nu_{f,t}$) because only systematic risk exposures earn a premium in the cross section. Second, if SC is really proxying for shocks to the risk appetite of CDS traders, there is no reason to expect these shocks to impact equity pricing.

Table V presents the results of regression (7). As expected, column (1) shows that seller (and buyer) capital shocks possess no explanatory power for equity returns. Column (2) runs the regression using CDS spread changes that are implied by options markets (Carr and Wu (2011)). Once

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[18]Murfin (2012) also finds that overall bank capital leads lenders to tighten covenants, but in a way that is independent of lenders' losses on their loan book. Furthermore, the prediction that leverage should impact pricing is consistent with the theory of He and Krishnamurthy (2013) and with the empirical findings of He, Kelly, and Manela (2017).

again, $SC_{f,t}$ is not significant in the regression. These placebo tests lend credence to the argument that $SC_{f,t}$ measures changes in the risk aversion of traders who are marginal pricers in the market for firm f's CDS. A shock to these trader's risk aversion induces movements in a firm f's spread because its CDS market is not perfectly integrated with other firms.

(Table V Goes About Here)

Taken together, the empirical findings above support the theoretical model of He and Xiong (2013), who study the optimal incentive contract for delegated investment managers. In their model, segmentation can endogenously arise at a granular level because it is optimal for financial institutions (the principal) to implement a narrow investment mandate for their traders (the agent) when agency frictions make it difficult to discern luck from skill. According to their model, a narrow mandate — which can be interpreted as specializing on a small subset of firms or assets — is especially useful when traders have access to outside investments like CDS that have large negative skewness.

D.2. Is Every Firm's CDS Market Segmented?

The preceding analysis confirms that the CDS market for the average firm is segmented from other firms. However, one might not expect such segmentation to occur for firms that comprise a credit index. Arbitragers in the CDS market commonly exploit the relative pricing of an index against the basket of its constituents, meaning that firms in the most actively traded credit indices are often traded in tandem. We should therefore expect their collective CDS markets to be more integrated. Column (3) of Table V confirms this intuition by running regression (5) on the set of firms that are in the on-the-run CDX Investment Grade Index, by far the most actively traded index in the market. For this subset of firms, seller capital shocks no longer impact spreads in

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a statistically or economically meaningful way. Section II.E of the Internet Appendix contains several additional tests that further support the robustness of this analysis. Moreover, the within-group R^2 of 63% in this regression is much higher than its full-sample counterpart of 38% (column (5) in Table III). The fact that aggregate factors explain more of the price variation for this subset of firms implies that their CDS markets more closely resemble a frictionless paradigm.

D.3. Horizon Dependence

The primary economic mechanism linking seller capital to CDS pricing derives from asset pricing theories with segmentation and limited investment capital. A signature prediction of these theories is that, given time, capital is able to flow into a segmented market and thus any pricing effects stemming from capital shocks should disappear over longer horizons. To evaluate this prediction, I run the following regression for various horizons h:

$$\log\left(\frac{CDS_{f,t+h-1}}{CDS_{f,t-1}}\right) = a_f + \boldsymbol{\beta}_1' \Delta\mathbf{Z}_{f,t}(h) + \boldsymbol{\beta}_2' \Delta\mathbf{X}_t(h) - \zeta_s(h) \times SC_{f,t} + \zeta_b(h) \times BC_{f,t},$$

where $\Delta\mathbf{Z}_{f,t}(h) = \mathbf{Z}_{f,t+h-1} - \mathbf{Z}_{f,t-1}$ and $\Delta\mathbf{X}_t(h) = \mathbf{X}_{t+h-1} - \mathbf{X}_{t-1}$. Note that the sign of $\zeta_s(h)$ in the above regression means that it measures the effect of seller capital *losses* on CDS spreads from $t-1$ to $t+h-1$. The regressions from the previous subsections were run for $h = 1$. If the effect of seller losses on CDS pricing decays with time, then $\zeta_s(h)$ should tend towards zero as h increases. Furthermore, the regression is run without industry-by-time fixed effects, because here I want to trace out the time-series effect of a capital shock today on future spreads.

Akin to an impulse response function, Figure 2 plots the point estimate of $\zeta_s(h)$ along with 95% confidence bands for various horizons h. Consistent with the idea that the price impact of seller losses reverses as capital flows into the market, $\zeta_s(h)$ declines as h increases, with a half-life

of about two weeks. As illustrated by the 95% confidence bands in Figure 2, the pricing effects of seller capital losses are basically undone after about nine weeks.

(Figure 2 Goes About Here)

It is not surprising that the pricing effects die out rather quickly because segmentation at the firm level is an extreme form of capital market segmentation and thus one would not expect it to persist for long periods. Moreover, it seems reasonable that internal capital market frictions at large financial institutions are resolved over short horizons as well. This interpretation is also consistent with He, Kelly, and Manela (2017), who show that at a quarterly frequency, the leverage of primary dealers explains CDS returns. Importantly, they measure capital at the holding company level, which implies that, at a quarterly frequency, external capital market frictions are an important component to pricing. Their findings, combined with the pattern of decay that I document, paint a natural picture: in the short run, price dynamics are influenced by internal capital market frictions and segmentation at the firm level. However, external capital market frictions for financial institutions that are active in the CDS market are more relevant for long-run price dynamics.

E.   *Exploring the Mechanism*

The evidence above shows that credit spreads rise in response to negative capital shocks at the CDS desks of protection sellers. There are a number of reasons why this may occur. For instance, it could be the case that sellers reduce the quantity of protection sold after negative capital shocks. Even in the absence of a change in the quantity sold, sellers could simply become more reluctant to take on new positions, thereby increasing their reservation price for selling protection (i.e., the quoted price at which they would sell a new position).[19] In addition, I document that spreads mean-

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[19]Importantly, CDS spreads provided by Markit are aggregated from transactions and quotes from dealers in the market. In addition, because this market is OTC, a quantity shift in supply or demand does not necessarily have to

revert quickly after negative seller capital shocks. Is this because new and better-capitalized sellers enter the market? Or do internal capital market frictions at incumbent sellers loosen, leading to a decrease in their reservation price for selling protection?

I shed light on these questions by examining whether sellers and buyers adjust their net positions in response to capital shocks to their CDS portfolio. I do so via the regression

$$\Delta NS_{c,f,t} = a_{c,f} + \gamma \times Y_{c,t}, \tag{8}$$

where $Y_{c,t}$ is either the dollar change in counterparty c's CDS portfolio value or the return on c's CDS portfolio.[20] Recall that $NS_{c,f,t}$ is the net amount sold by counterparty c on firm f's CDS at time t. The term $a_{c,f}$ is a counterparty-by-firm fixed effect. Regression (8) therefore quantifies how each counterparty c adjusts its position on f in response to CDS portfolio gains or losses. Table VI presents the regression results.

(Table VI Goes About Here)

In column (1), I run the regression for the subset of the largest net sellers, which I define as the set of counterparties in the top 10% of total net sold across all firms. The positive coefficient implies that net sellers decrease the net amount sold in response to losses. However, the estimated coefficient is very small in economic magnitude: a one-standard-deviation capital loss only leads to a 0.0014×203 mm$/5.3$ mm $= 5.4\%$ standard deviation change in the net amount of protection sold. In column (2), using returns instead of dollar losses tells the same story, with a statistically significant but economically small positive relationship between seller positions and their CDS portfolio returns. Thus, while the response of positions to seller losses goes in the right direction,

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accompany a price change from Markit. Quotes are typically binding in this market, so they represent the price that counterparties are willing to transact (Arora, Gandhi, and Longstaff (2012)).

[20]I coarsely estimate CDS portfolio returns based on FINRA's margin requirements. See the Internet Appendix.

the small economic magnitude of the response suggests that quantities are not particularly sensitive to capital shocks at the CDS desk.

Columns (3) and (4) of Table VI rerun the analysis for large net buyers of protection. The point estimates in the regression show that buyers slightly increase the amount of protection bought following losses on their CDS portfolio. The effect is once again very small, albeit measured with good statistical precision. From column (3), a one-standard-deviation dollar capital loss leads to a 6% standard deviation increase in the amount of protection bought. A similar magnitude arises when using returns in column (4).

In the Internet Appendix, I complement the above analysis by looking at whether new sellers enter the market after losses occur at incumbent sellers. I do not find much evidence to support this hypothesis. The data thus points to the following economic mechanism relating capital and CDS spreads: after sellers of firm f experience negative capital shocks, their reservation price for selling protection rises as they are hesitant to take on more positions (Section II.B). This interpretation is consistent with the fact that quantities do not move in a meaningful way in response to negative shocks. As internal capital market frictions at the sellers' institutions thaw in the weeks following a capital loss, sellers decrease their reservation price for providing protection, leading to the mean-reversion in spreads documented in Section II.D.3.

III.   Other Considerations and Robustness

The preceding section documents a strong link between seller capital shocks and risk premiums in the CDS market. I argue that this link exists because capital shocks at the CDS desks of sellers directly impact their risk appetite. This assertion relies heavily on my regression tests being well identified, as otherwise we would not observe subsequent spread movements. To bolster this

interpretation, I now discuss: i) whether sellers or buyers are hedged, as this would weaken the argument that my capital measures correlate with changes in risk appetite, (ii) whether my capital shocks are large enough to plausibly induce a change in the risk appetite of sellers, and (iii) whether my main results are robust to alternative constructions of my CDS-based capital variables.

A. Hedging

To the extent that there exists hedging activity that is unobserved, the capital shock variables $SC_{f,t}$ and $BC_{f,t}$ do not accurately reflect changes in the effective risk aversion of CDS traders. Suppose, for instance, that sellers of protection are fully hedged. Then their variation margin payments are perfectly offset by flows from their hedges. In turn, changes in the risk appetite of sellers will not be captured by shocks to the CDS portfolio alone. However, in this case, one would not expect $SC_{f,t}$ to have any ability to explain spreads in regression (5), after controlling for industry-wide and firm-level factors. Section II.B shows that this story is strongly refuted by the data.

Practically speaking, it is also unlikely that the largest protection sellers are directly hedged. For the largest sellers, the total amount of protection sold often approaches $100 billion in net notional. A direct and complete hedge would therefore require an enormous short of corporate bonds, which is likely to be quite costly in practice (Nashikkar and Pedersen (2007)). For example, Asquith et al. (2013) estimate that the daily average par value of bonds shorted for the *entire* market was $85.6 billion in the mid-2000s. Moreover, Boyarchenko et al. (2017) use regulatory data to show that, for dealers, the flow of new net protection sold is largely unhedged by any shorting activity in the corporate bond market.

A similar framework applies for buyers of protection. A salient feature of regression (5) is that CDS-derived buyer capital shocks $BC_{f,t}$ do not reliably relate to spread movements. To be

clear, my interpretation of this observation is not that buyers are inconsequential for CDS pricing. Regression (5) is designed to test whether $BC_{f,t}$ influences f's *firm-specific* risk premium, which arises from market segmentation. It could be the case that buyers impact CDS pricing by changing the compensation required for holding firm f's exposure to systematic risk factors. It could also be the case that $BC_{f,t}$ is simply not a good proxy for shocks to the effective risk aversion of buyers, a reasonable conclusion if buyers are partially hedged with a long position in corporate bonds.

Of course, I cannot make conclusive statements about hedging because I do not directly observe the entire portfolio of buyers or sellers. Still, it is difficult to imagine an alternative explanation that would not only explain my empirical results, but also account for the fact that the largest sellers likely cannot scale a hedge to match the size of their CDS portfolio. Overall, it therefore seems reasonable to think that the largest net protection sellers execute their positions to gain exposure to credit risk, as opposed to those exposures being hedged by other positions in their corporate bond portfolio. It is harder to make more definitive statements about buyers, though empirically my results are consistent with some of them hedging.

B.   Are Capital Shocks at the CDS Desk Large?

Even if hedging is not an issue, is it plausible that my CDS-based capital shocks are large enough to induce a change in the risk appetite of sellers? Recall from Table II that the average capital shock for net sellers has a weekly standard deviation of around $675 million dollars. To give this number some context, I obtain a measure of dealer trading capital from 2010 SEC FOCUS filings, which I match with the top five dealers in terms of net protection sold at that time. I focus on 2010 because dealers were the primary sellers of protection in the U.S. at that time (see Figure 5). Additionally, I focus on the top five dealers because the top five sellers for the average firm account for about 80% of all selling in 2010 (see Section IV.A). For these five dealers, excess net

capital — a measure of cash-equivalent capital for trading purposes — is about $24 billion. This estimate overstates the true amount of unencumbered net excess capital because many of these reserves are re-lent through repo transactions (Singh (2011)).

As a simple thought experiment, suppose the $24 billion capital cushion for these five dealers is designed to accommodate stress over the course of a quarter. Broker-dealers are active in several asset classes; for illustration, suppose there are five such classes: commodities, currencies, equities, fixed income, and credit. Across the five broker-dealers, this means that each subdivision or desk has about $24 billion / 5 = $4.8 billion to finance trading activity over the course of the quarter. Scaling this down from a quarterly to a weekly number means that the CDS desk has a $4.8 billion / 12 = $400 million capital cushion on a week-to-week basis. Compared to this cushion, $675 million in weekly capital movements at the CDS desk of sellers seems economically meaningful.

As an empirical matter, I do not necessarily need my CDS-based capital shocks to be massive. The identification strategy in the paper requires only that they are reasonably large enough to detect changes in the risk appetite of traders. Insofar as my regression tests are well identified, the fact that seller capital shocks possess any explanatory power at all for spreads implies that they are meaningful enough to change seller risk appetite.

C. *Alternative Construction Methodologies*

My analysis thus far uses dollar-based measures of capital because I do not observe the initial margins paid by each counterparty. As a result, it is difficult to compute the return of a given counterparty's CDS portfolio without making further parametric assumptions. In the Internet Appendix, I approximate the initial margin supporting each counterparty's CDS portfolio by loosely following FINRA's margin guidelines. In the same appendix, I then estimate the regression in equation (5) using this alternative measure of capital, which I summarize here. I interpret the results using

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returns with some degree of caution, mainly because my methodology for computing returns relies on strong assumptions about initial margins.

With that said, the results from this exercise confirm the negative relationship between seller capital shocks and CDS spreads. When measuring capital in returns, the point estimate on seller capital shocks is negative and measured with statistical precision. It is also comforting that the economic impact of a seller loss on spreads also lines up well with the main results in Section II.B.2. For buyers, there does appear to be a statistically significant and positive relationship between portfolio returns and CDS spreads, although the magnitude of the effect is quite small. Furthermore, buyer capital shocks are not robust to measuring capital shocks in dollars versus returns, so it seems less likely that I am detecting a robust relationship between buyer capital and spreads.

IV.   Additional Analysis

In this section I investigate additional channels through which the structure of the CDS market may interact with pricing. More specifically, I explore whether the relationship between capital shocks and pricing has changed over time. A related feature of the CDS market that I explore is whether heterogeneity in the types of active financial institutions impacts pricing. This channel is particularly important because, as I document, asset managers have steadily replaced dealers as the primary providers of default insurance since 2010. In addition, I reinforce the causal nature of my main findings using the 2011 Japanese tsunami as a case study. Finally, I provide some suggestive evidence that seller losses in the CDS market also impact bond market pricing.

A.   *Do Capital Losses Matter More after the Crisis?*

In the aftermath of the 2008 crisis, the CDS market has undergone deep structural reforms in terms of how trading is organized, margin requirements, etc. A natural question that arises is whether the price impact of seller capital shocks has also changed. The following regression assesses this possibility:

$$\Delta \log(CDS_{f,t}) = a_f + a_{i,t} - \sum_{Y=2010}^{2016} \beta_{S,Y} \times SC_{f,t} \times 1(Year = Y) + \beta_B \times BC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t} + \varepsilon_{f,t},$$

where $1(Year = Y)$ is a dummy variable indicating when the year of date t equals Y. The coefficients $\beta_{S,Y}$ measure how a dollar loss at firm f's sellers impacts spreads in year Y. I plot these coefficients and their 95% confidence intervals in Figure 3. As can be seen in the plot, seller capital shocks have had a steadily larger effect on spreads as time has passed since the crisis. In 2010, a billion dollar seller loss raised spreads by 1.5%, whereas in 2016 the same loss raised spreads by nearly 5%.

(Figure 3 Goes About Here)

What might explain these results? One potential answer is based on the fact that asset managers have steadily replaced dealers as the primary providers of CDS protection. To visualize this compositional shift, I compute the proportion of net selling and buying done by various types of financial institutions at each point in time. The specific details of which are contained in Appendix A.3. Examples of institution types are commercial banks, insurance companies, asset managers (e.g., hedge funds), dealers, etc.

Figures 4 and 5 plot the share of net selling and buying, respectively, for both dealers and asset managers. I focus on these two counterparty types because they are by far the largest two types for

both buyers and sellers. As can be seen in Figure 4, dealers have consistently purchased around half of all protection, with almost all of the remaining buying going to asset managers.

(Figure 4 Goes About Here)

The aggregate proportion of selling by counterparty types is displayed in Figure 5. In contrast to the composition of buyers, that of sellers has changed dramatically since 2010. At the beginning of the sample, dealers accounted for 80% of all protection sold in U.S. CDS markets. Moreover, 50% of aggregate selling was in the hands of less than five dealers. The total proportion sold by dealers has declined over time, however, with dealers accounting for less than 30% of total selling by the end of the sample. Instead, asset managers have come to play a much larger role in providing default insurance for the U.S. market.

(Figure 5 Goes About Here)

To check whether this shift translates into pricing, column (4) of Table V interacts seller capital shocks with the share of selling by asset managers as follows:

$$\Delta cds_{f,t} = \Delta cds_{f,t-1} + \boldsymbol{\beta}_1' \Delta \mathbf{Z}_{f,t} + \zeta_b BC_{f,t} + \zeta_s SC_{f,t} + \zeta_{sa} SC_{f,t} \times AMS_{f,t} + \zeta_a AMS_{f,t} + \varepsilon_{f,t},$$

The regression also includes a firm fixed effect a_f and an industry-by-time fixed effect $a_{i,t}$, but I omit them to save space. The coefficient of interest is ζ_{sa}, which measures whether capital shocks have a differential impact on pricing when asset managers are responsible for more selling. The results indicate that seller capital losses have a larger impact on spreads if sellers are asset managers. The interaction term between asset manager share and seller capital is significantly negative and fairly large in magnitude. For example, from 2010 to 2014, the share of selling by asset managers moved from roughly 15% to 75%. In turn, the interaction term implies that the

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impact of a $1 billion seller capital loss on spreads has changed from 1.4% to 3.5% over this same time period. One way to rationalize this finding is that asset managers have a higher shadow cost of capital than dealers, who were the primary provider of credit insurance at the beginning of the sample. This interpretation is reasonable given that, relative to dealers, hedge funds are more specialized and generally have a smaller capital base and thus they are more likely to face external and internal capital market frictions. On balance then, it seems plausible that the increased response of CDS spreads to seller capital losses can be attributed to the fact that asset managers have replaced dealers as the primary insurance providers in the CDS market since 2010.

B. The 2011 Japanese Tsunami as a Case Study

I now turn to a natural experiment that further establishes a causal link between capital losses and CDS pricing. The event I focus on is the Japanese tsunami of March 2011, which was the result of a magnitude 9.0 earthquake off the coast of Tohoku. The tsunami occurred on a Friday, and had a significant impact on the risk of the country as a whole. For example, Japan's sovereign CDS spread increased by nearly 50% from 80 to 115 basis points on the following Monday. In this subsection, I summarize the key components of this analysis. The Internet Appendix contains additional details, as well as additional background information on the tsunami.

To illustrate the logic of my approach, suppose Hedge Fund A had sold a great deal of CDS protection on Japanese firms, but Hedge Fund B had not. After the tsunami hits, Hedge Fund A has more capital at risk than Hedge Fund B. Broadly speaking, the results from Section II suggest that Hedge Fund A should be more risk averse than Hedge Fund B. Consequently, U.S. firms for which Hedge Fund A is a large net seller should see their spreads rise relative to firms for which Hedge Fund B is a large seller.

To formalize the preceding thought experiment, I construct measures of how exposed a U.S.

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firm f was to the tsunami through its sellers:

$$\Gamma_{S,f} \; := \; \sum_{f \in \mathcal{S}_f} \left[\frac{|NS_{c,f}|}{NO_f} \right] \times NS_{c,JPN},$$

where $NS_{c,JPN}$ is the net amount sold by counterparty c on Japanese firms, $\mathcal{S}_f$ is the set of sellers for firm f prior to the tsunami, and $\Gamma_{S,f}$ is the weighted-average exposure of f's sellers to Japan. The term in brackets is the weight, which is given as the proportion of total net outstanding for f that is sold by c. The weighted-average exposure of f's buyers to Japan, $\Gamma_{B,f}$, is defined in similar fashion. I take the absolute value of $NS_{c,f}$ in the definition above to ensure that the weights are positive and sum to one, regardless of whether defining Γ_S or Γ_B.

All of my measures are computed as of March 11, 2011, so I omit time-dependencies for brevity. As a result, the above Γ measures capture the ex-ante risk that a negative shock to Japan impacts f's sellers or buyers. This distinction is important for a few reasons. First, after the tsunami hit, there was widespread concern about the possibility of a nuclear meltdown at the Fukushima plant. The consensus view at the time was that a meltdown would cause catastrophic damage to many Japanese firms and the broader economy. These losses never materialized because the Japanese government was able to stave off a nuclear meltdown. Using realized losses on Japanese positions would therefore potentially miss the large ex-ante risk faced by CDS market participants exposed to Japan, and in turn, the influence of these participants on pricing in the U.S. market. These Γ measures also provide an complimentary way to proxy for shocks to the risk appetite of sellers. Unlike the capital shock proxies used in Section II.B, the Γ measures do not derive from realized gains or losses. In a sense, the Γ measures thus provide a robustness check of the paper's primary finding that fluctuations in the risk appetite of CDS traders transmit to spreads.

To test my main hypothesis, I estimate variants of the following cross-sectional regression:

$$\Delta \log(CDS_{f,1}) = a + \phi_1 \Gamma_{S,f} + \phi_2 \Gamma_{B,f} + \boldsymbol{\beta}' \Delta \mathbf{Z}_f + \varepsilon_f, \qquad (9)$$

where $\mathbf{Z}_f$ contains the same set of firm-level controls used in Section II. As before, I use Moody's five-year EDF, the change in Markit's LGD, and the firm's equity return. Because certain industries may have been more exposed to Japanese firms, in some specifications I also include an industry fixed effect that is based on each firm's NAICS code. I further include the level of CDS spreads for each firm on March 11, 2011 to control for the possibility that Γ captures sellers/buyers who specialize in riskier credits. Finally, I include the 90-day running volatility of each firm's CDS spread (in log-changes), which accounts for the possibility that reference entities that experienced large spread movements post-tsunami are those that have larger volatility.

The dependent variable, $\Delta \log(CDS_{f,1})$, is the log-change in f's CDS spread in the week following the tsunami. To reiterate, I consider only U.S. firms. There are certain to be identification issues with attributing changes in CDS spreads after the tsunami with high levels of Γ, as regression (9) would suggest. One obvious example is that sellers with large Japanese exposures also specialize in U.S. firms that are fundamentally linked to the Japanese economy. In Section III of Internet Appendix, I fully frame the identification issues and rule out this "specialization" hypothesis for both buyers and sellers of U.S. firms. Table VII summarizes the results of running variations of regression (9).

(Table VII Goes About Here)

Consistent with the results in Section II.B, there is no evidence of a transmission channel via buyers of CDS. Indeed, the coefficient on $\Gamma_{B,f}$ is small and insignificant in all specifications. In contrast, the coefficient on $\Gamma_{S,f}$ indicates a strong, positive effect of seller exposure to Japan and subsequent U.S. CDS spread movements. Column (1) includes only the Γ variables, and

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columns (3) to (5) sequentially add other control variables. The coefficient on $\Gamma_{S,f}$ remains stable throughout. Interestingly, including an industry fixed effect in the regression has a negligible effect on the point estimate of $\Gamma_{S,f}$. This is because the regression also includes each firm's own equity return, and thus any information contained in the industry fixed effect is subsumed by the more granular information contained in individual equity returns. Lastly, column (6) adds controls for the average change in buyer and seller leverage. As in Section II.C, controlling for leverage does not drive out $\Gamma_{S,f}$ in the regression, a result that is consistent with some form of internal capital market frictions.

To get a sense of the magnitude of these effects, consider a U.S. firm whose sellers were in the 90th percentile in terms of their exposure to Japanese firms. Similarly, consider a U.S. firm whose sellers were in the 10th percentile. Firms in the 90th percentile saw their spread levels increase 2.5%, relative to firms in the 10th percentile, in the week following the tsunami. While this is not overwhelmingly large, it is important to note that Japanese exposures comprise only a fraction of the largest sellers' CDS exposures. Accordingly, one would not necessarily expect a massive response of U.S. sellers to the threat of a Japanese shock. More importantly, this natural experiment provides strong causal evidence of the channel through which sellers in the CDS market impact spreads.

As a placebo test, columns (8) and (9) of Table VII use each firm's equity return in the week after the tsunami, as opposed to CDS spread changes, as the dependent variable. The logic behind this placebo test mirrors the test in Section II.D.1. First, the equity holders of firm f are probably different than f's CDS sellers. In addition, equity markets are less likely to suffer from the frictions that afflict the CDS market — presumably, capital can flow much faster to investment opportunities in equities — and thus one would not expect increased risk aversion of CDS sellers to impact equity returns. As expected, columns (8) and (9) indicate that whether or not a firm's CDS sellers were

exposed to Japan has no explanatory power for equity returns after the tsunami — the transmission mechanism appears to be specific to the CDS market.

C.   *The Bond Market*

CDS markets are tightly linked to bond markets through no-arbitrage conditions (Duffie (1999)). Given that I find a tight link between the capital of protection sellers and CDS spreads, a natural question that arises is whether this same link exists for corporate bond markets. To study this in more detail, I test whether capital shocks for CDS market participants impacts the CDS-Bond basis. Loosely speaking, the CDS-Bond basis is the difference between CDS spreads for firm f and maturity-matched bond yields for the same firm. By no-arbitrage, the CDS-Bond basis should be zero, but there are well-documented times when the basis diverges from zero (e.g., Bai and Collin-Dufresne (Forthcoming)). If shocks at protection sellers only impact CDS markets, then the basis should also move in response to these shocks. Alternatively, if changes in seller capital also lead to changes in corporate bond pricing, then the basis should be unaffected by seller shocks.

The following regression tests these two potential hypotheses:

$$\Delta Basis_{f,t} = a_f + \boldsymbol{\beta}'_1 \Delta \mathbf{Z}_{f,t} + \boldsymbol{\beta}'_2 \Delta \mathbf{X}_t + \theta_s SC_{f,t} + \theta_b BC_{f,t} + \varepsilon_{f,t}, \tag{10}$$

where $Basis_{f,t}$ is the CDS-Bond basis for firm f at time t, with the basis measured using "Z-Spreads" from Bloomberg (see the Internet Appendix for details). $\mathbf{Z}_{f,t}$ is the same vector of firm-level controls used in regression (5), as is the vector of macroeconomic controls $\mathbf{X}_t$. My workhorse capital shock measure for f's CDS sellers is $SC_{f,t}$ and $BC_{f,t}$ is the same variable for f's buyers.

Columns (5) and (6) of Table V present the results from estimating regression (10). It is important to note two important caveats to this analysis. First, Z-Spreads are a noisy proxy for bond

yields, so the regression must be interpreted with some caution.[21] Second, due to the lack of reliable basis data, the sample size for this regression is small relative to that used in the main analysis in Section II. With these caveats in mind, column (5) indicates that there is not much evidence that seller or buyer shocks in the CDS market change the CDS-Bond basis. The point estimates on $SC_{f,t}$ and $BC_{f,t}$ are both statistically indistinguishable from zero. Column (6) replaces the macroeconomic controls with an industry-by-time fixed effect. Seller capital shocks again have no statistically discernible influence on the CDS-Bond basis. In contrast, the coefficient on buyer capital shocks is statistically significant in this regression. Still, the magnitude of the effect is small: a one-standard-deviation buyer capital shock leads to a 2 basis point increase in the basis. Moreover, given the results in column (5), the positive relationship between the basis and $BC_{f,t}$ does not seem to be robust.

While by no means conclusive, this evidence suggests that the response of the bond market to seller and buyer capital shocks echoes that of the CDS market. A negative capital shock to sellers leads to an increase in CDS spreads, and because the CDS-bond basis does not change, bond yields also rise. This finding is consistent with previous research showing that pricing in the CDS market leads the corporate bond market (e.g., Blanco, Brennan, and Marsh (2005), Zhu (2006), Norden and Weber (2009)). A natural reason to expect CDS markets to lead bond markets is that active money managers like hedge funds prefer to trade in the CDS market for liquidity reasons (Longstaff, Mithal, and Neis (2005), Oehmke and Zawadowski (2017)), whereas bond holders tend to be buy-and-hold investors like pension funds.

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[21]See the Internet Appendix for a complete discussion.

V. Conclusion

This paper uses data on CDS positions to show that the capital of CDS protection sellers plays a significant role in determining CDS spread dynamics. My evidence suggests that a firm's short-run CDS spread fluctuations are driven in part by the capital of the CDS desks at financial institutions that provide default insurance on the firm. In contrast to neoclassical asset pricing models, these findings imply that the CDS market for a given name is segmented in the short run.

In addition, my results suggest that internal capital market frictions at financial institutions — whether due to agency issues, optimal risk management, or a simple lack of capital — can act as an additional layer of segmentation in markets where outside capital is slow to enter. In this sense, one can view the trading desks at large financial institutions as individual silos whose capital base is not instantaneously integrated with the larger firm. These types of segmentation issues are most likely to impact asset classes where investment requires a fair amount of specialization and expertise.

Heterogeneity in the type of financial institution that acts as a net seller of protection is an important determinant of spread dynamics as well. A striking trend in the data is that dealers have been replaced as the primary sellers of protection by asset managers. A likely explanation for this pattern is that new regulation has made it less profitable (or even possible) for dealers to ultimately bear credit risk via CDS. Still, the evidence in this paper indicates that capital losses at asset managers have a stronger impact on pricing than losses at dealers. Put differently, a potential unintended consequence of post-crisis regulation is that CDS prices are now influenced by the capital positions of a few players in the market to an even greater extent.

Appendix A.   Additional Facts about the CDS Market

In this appendix, I document two additional facts about the CDS market: (i) the U.S. CDS market is large in terms of net notional credit risk transferred, with a conservative lower bound of around $1 trillion and (ii) the identities of the largest buyers and sellers are persistent through time. The first fact suggests that the pricing effects that I document in this paper are relevant for a relatively large asset class. The second fact establishes that the largest buyers and sellers in the CDS market maintain directional positions for long periods of time, as opposed to simply managing their inventories.

A.1.   The Size of the CDS Market

To quantify the size of the CDS market, I consider two alternative measures. The first is the gross notional size of the market, which is just the sum of the notional amount of all outstanding positions. Gross notional is thus a measure of volume. Importantly, however, it does not speak to the net amount of credit risk transfer for a given firm or for the entire market.

The second measure of market size that I use is the net notional outstanding of all positions. I define the net notional amount of credit risk outstanding for a *given firm* as

$$NO_{f,t} := \sum_{c \in C_t} \max\left(NS_{c,f,t}, 0\right). \tag{A1}$$

In (A1), $NO_{f,t}$ is analogous to the face value of debt outstanding in bond markets — it captures the net amount of protection sold (or, equivalently, bought) on a particular firm.

I next measure the total net outstanding for the whole market by summing $NO_{f,t}$ over all firms:

$$NO_t := \sum_{f \in F_t} NO_{f,t}. \tag{A2}$$

Figures A1 and A2 plot the net notional outstanding and the gross notional outstanding of the entire U.S. CDS market over time. Both measures provide a conservative lower bound on the size of the U.S. market because I only include firms that I can definitively classify as being based in theU.S.. The Internet Appendix contains details on this classification procedure.

(Figures A1 and A2 Go About Here)

According to both measures, the size of the CDS market has declined steadily since the beginning of 2010. In January 2010, the gross notional size of the U.S. market was roughly \$9 trillion, but by October 2016 had halved to around \$4 trillion.[22] The net notional outstanding of the CDS market has declined by a similar amount over this same time period, falling from a little over \$1 trillion in 2010 to about \$500 billion in 2016.

Despite the downward trend in the size of the CDS market, the overall amount of notional credit risk transferred is still fairly large. As a rough comparison of magnitudes, the face value of debt outstanding in U.S. corporate bond markets is approximately \$9 trillion. Thus, conservatively speaking, the size of the CDS market is about one-twelfth of the size of the corporate bond market.

I further decompose $NO_{f,t}$ into the portion coming from indirect exposures through index swaps and direct exposures through single-name swaps. To do so, I first expand the net sold by a

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[22]These statistics roughly accord with aggregate data provided by the Bank for International Settlements (BIS): http://www.bis.org/publ/qtrpdf/r_qt1512_charts.pdf. The BIS double-counts notional, meaning that a \$1 notional position between two traders gets reported as \$2 of gross notional. I instead count it as \$1 of notional. After multiplying my calculations by two, the gross notional that I report is still slightly less than the BIS's estimate. This is not surprising because I focus only on the U.S. CDS market. The net notional outstanding is new to this paper, given that one must net single-name exposures against index exposures to compute this statistic.

given counterparty into two parts, $NS_{c,f,t} = NS_{c,f,t}^{I} + NS_{c,f,t}^{S}$, where NS^{I} is the net sold through index exposures and NS^{S} is the net sold through single-name exposures. When computing $NO_{f,t}$, the portion coming from index exposures, $NO_{f,t}^{I}$, is then

$$NO_{f,t}^{I} = \sum_{c \in \mathcal{S}_{f,t}} NS_{c,f,t}^{I},$$

where $\mathcal{S}_{f,t}$ is the set of f's net sellers at time t. I further calculate the overall size of the market coming from index swaps by summing NO^{I} across all firms. The analogous statistics for net outstanding via direct single-name exposures are computed in similar fashion.

Decomposing the portion of the CDS market coming from index and single-name swaps reveals an interesting trend in the market. As shown by the hashed and shaded markers in Figures A1 and A2, most of the decline in CDS market size is driven by the fact that the single-name market is shrinking. In contrast, the size of the index CDS market has remained relatively constant over time. I suspect that this trend is related to two forces: (i) the introduction of central clearing for major CDS indices and (ii) the cost of selling protection for dealers has increased due to post-crisis regulation. Further exploration of this pattern is outside the scope of this study.

A.2.   *Are the Identities of Large Sellers and Buyers Persistent?*

While the CDS market is certainly concentrated, it may still be the case that the identities of the largest buyers and sellers are changing rapidly over time. For instance, a dealer that absorbs a large net buy position in a given week may appear as a large net seller. However, if this dealer manages its inventory back to a more neutral stance, this concentration will be short lived. To better understand the persistence of individual positions, and thus the persistence of the identities

of the largest buyers and sellers, I run the regression

$$NS_{c,f,t} = a_{c,f} + \phi \times NS_{c,f,t-1}. \tag{A3}$$

In equation (A3), $a_{c,r}$ is a counterparty-by-firm fixed effect, which means that this regression identifies ϕ using time-series variation in net amount sold by a counterparty on firm f. Column (1) of Table AI presents the point estimate for ϕ when pooling all counterparties together. According to this regression, $\phi \approx 0.98$, which indicates that the half-life of the average position is about nine months. Columns (2) and (3) rerun the regression using only the largest net sellers and buyers, respectively. I find very similar values for ϕ.[23] The results thus show that the largest buyers and sellers in the CDS market maintain directional positions for long periods of time, as opposed to simply managing their inventories.

(Table AI Goes About Here)

A.3. Market Share by Counterparty Type

This subsection describes how I compute the aggregate market share of buying or selling by a particular type of counterparty. I start by manually assigning each counterparty in the data set to one of the following types: CCP (Central Counterparty), commercial bank, investment bank, dealer, government agency, asset manager (e.g., hedge fund), insurance firm, nonfinancial firm, or other. Next, for a particular firm f, I compute the proportion of total net outstanding bought by type y at time t, which I denote by $P_B(y, f, t)$. Similarly, the proportion sold by type y at time t on reference entity r is given by $P_S(y, f, t)$. The aggregate amount bought by a particular type is then

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[23]Similar to regression (5), the Nickell (1981) bias is not an issue for this regression because the time-series dimension of the panel is large enough to effectively nullify the bias.

the weighted average of $P_B(y, f, t)$ across firms, where the weight is proportional to the size of the firm's CDS market. The same goes for the aggregate amount sold by a particular type. Formally, this means

$$
\begin{aligned}
\overline{P}_B(y,t) &= \sum_{f \in F_t} \omega_{ft} P_B(y, f, t) \\
\overline{P}_S(y,t) &= \sum_{f \in F_t} \omega_{ft} P_S(y, f, t),
\end{aligned}
\tag{A4}
$$

where $\omega_{ft} = NO_{f,t} / \sum_f NO(f, t)$. The aggregate statistics $\bar{P}_B$ and $\bar{P}_S$ are the basis of Figures 4 and 5.

Appendix B.   Additional Information

B.1.   *Option Implied CDS Spreads*

This section describes how I use American option prices to compute an implied CDS spread. For a complete theoretical treatment of this procedure, see Carr and Wu (2013), henceforth CW. In the interest of space, I present only the relevant formulas and data descriptors used in the main text.

To start, Carr and Wu (2013) define what they call a "unit recovery claim" that pays a dollar if there is a default event prior to an option's expiration, and zero otherwise. CW assume that there exists a default corridor $[A, B]$ that the underlying equity price can never enter. If the equity price hits the level B, there is a default and the stock price immediately jumps to a level that is bounded above by A. In their empirical work, they set $A = 0$, which means that the equity value drops to zero upon default. I maintain this assumption in the remainder of my treatment.

Under this assumption, CW show that regardless of the underlying asset process, there is a

robust link between the unit recovery claim and CDS spreads. The unit recovery claim is defined
as

$$U^O(t,T) = \frac{P_t(K_2,T) - P(K_1,T)}{K_2 - K_1},$$
(B1)

where $A \leq K_1 < K_2 \leq B$. It is easy to see that, under the assumption of the default corridor, this
pays one dollar if there is default and zero otherwise.

Next, CW show that under the assumption of a constant arrival rate and constant interest rate,
the CDS spread of a firm is related to the price of the unit recovery claim as follows:

$$U^O(t,T) = \xi k \times \frac{1 - \exp\left(-(r + \xi k)(T - t)\right)}{r(t,T) + \xi k},$$
(B2)

where $\xi = 1/(1 - R)$, R is the recovery of the bond upon default, k is the CDS spread, and $r(t,T)$
is the continuously compounded interest rate between t and T. Here, T is meant to capture the
expiration of both the CDS contract and the option contract. For my purposes, I will always set
$T - t = 5$.

Equation (B2) provides a simple way to recover the CDS spread implied by option prices.
Using observed option prices, one first computes the value of the unit recovery claim. A numerical
inversion then delivers the implied CDS spread.

To implement this procedure in practice, I merge my panel of CDS spreads with American
option prices from OptionsMetrics using six-digit CUSIPs. Furthermore, because I follow CW in
assuming $A = 0$, the unit recovery claim is simply the price of a deep out-of-the-money put option
divided by its own strike price. I use a set of filters on the options data that is similar to CW: (i)
I take the option price to be the midpoint of the bid and offer; (ii) I consider options whose bid
is strictly positive; (iii) I consider options whose open interest is strictly positive; (iv) I consider
options for which the maturity is greater than 365 days; (iv) I use the put option that satisfies all of

the preceding qualities and that has the delta closest to zero and less than -0.15. ATM volatilities are taken from the put option that is out of the money but is closest to being at the money.

Naturally, there is a maturity mismatch in using options that might have an expiration of two years to compute an implied CDS spread of five years. There is no real way to avoid this bias. See CW for a richer discussion. As in other parts of the paper, the risk-free rate is obtained from interpolating the USD swap rate curve. Finally, I use the Markit reported recovery rate.

B.2. *Macroeconomic Control Variables*

In Section II, I estimate variants of the regression

$$\Delta cds_{f,t} = a_f + a_{i,t} + \Delta cds_{f,t-1} + \boldsymbol{\beta}'_1 \Delta \mathbf{Z}_{f,t} + \zeta_s SC_{f,t} + \zeta_b BC_{f,t}.$$

One of the important features of this regression is the industry-by-time fixed effect $a_{i,t}$. In some cases, I replace the industry-by-time fixed effect with observable macroeconomic controls. I choose the controls based on theoretical models of credit risk and previous research on the determinants of credit spread variation (e.g., Collin-Dufresne, Goldstein, and Martin (2001)). These variables are the VIX, TED, CFNAI, 10-year Treasury yield, and 10-year-minus-two-year Treasury yield. After first differencing these controls, I also include the three Fama-French factors.

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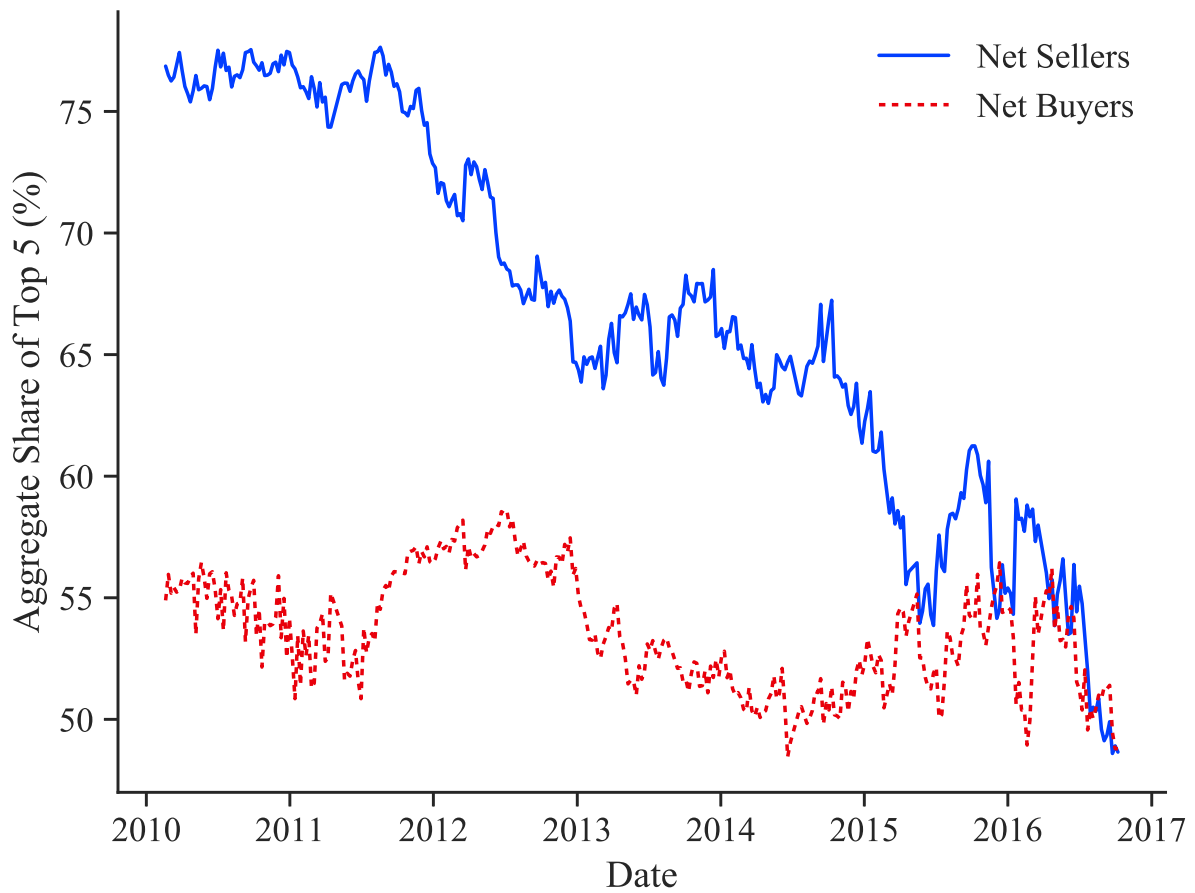
Figure 1. Concentration of net sellers and buyers. This figure plots an aggregate measure of the share of selling (or buying) by the top five sellers (or buyers) in the CDS market. For each firm f, I first compute the share of the top five net sellers and net buyers. The share of selling by a counterparty on a firm is the net amount sold on that firm divided by the net notional outstanding on the firm (ignoring maturity). Net buy shares are defined analogously. At each point in time, I then take a weighted average of these share measures across all firms, where the weights are determined by the net notional outstanding of each firm f. See Section I for complete variable definitions. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.
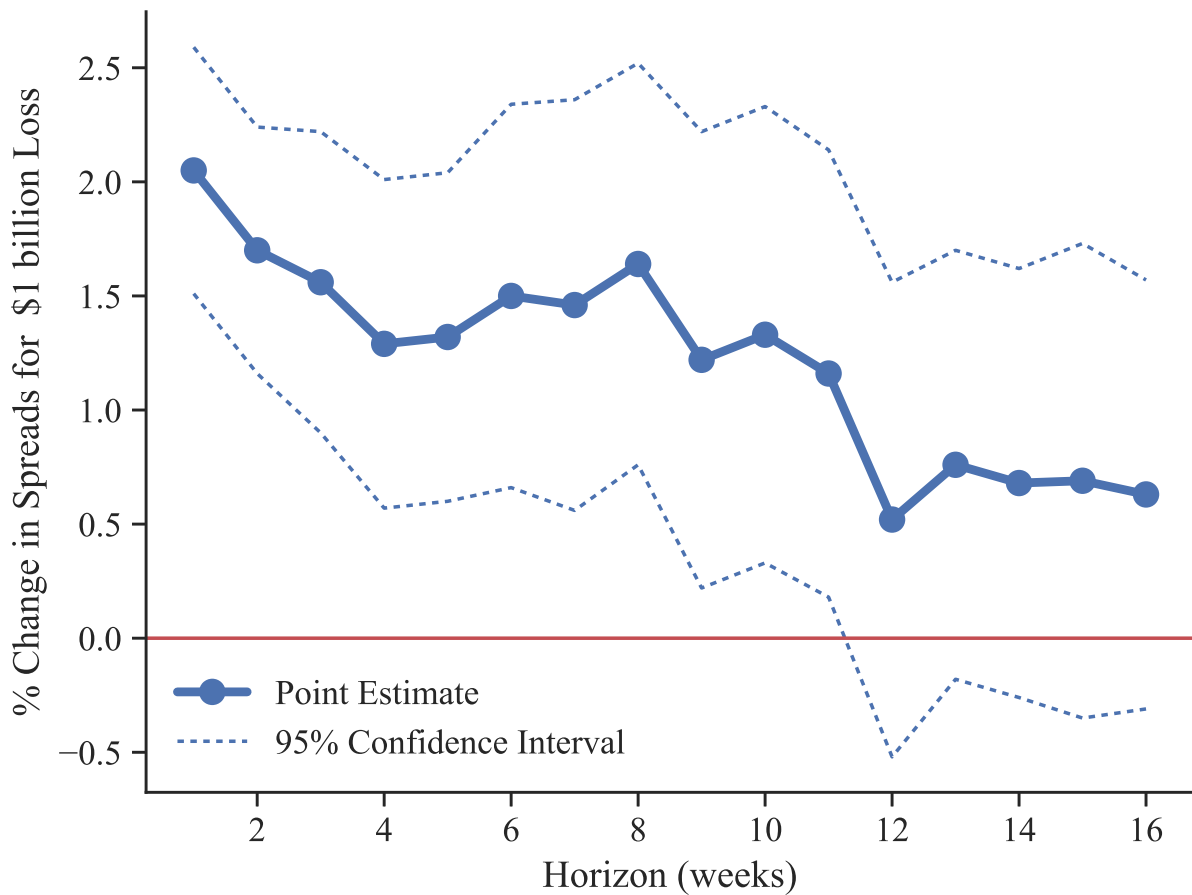
Figure 2. The response of CDS spreads to seller losses by horizon. This figure plots the coefficients ζ_s from the following regression: $\Delta_h \log(CDS_{f,t+h-1}) = a_f - \zeta_s(h) \times SC_{f,t} + \zeta_b(h) \times BC_{f,t} + \mathbf{\Gamma}' \Delta_h \mathbf{Z}_{f,t+h-1} + \boldsymbol{\theta}' \Delta_k X_{t+h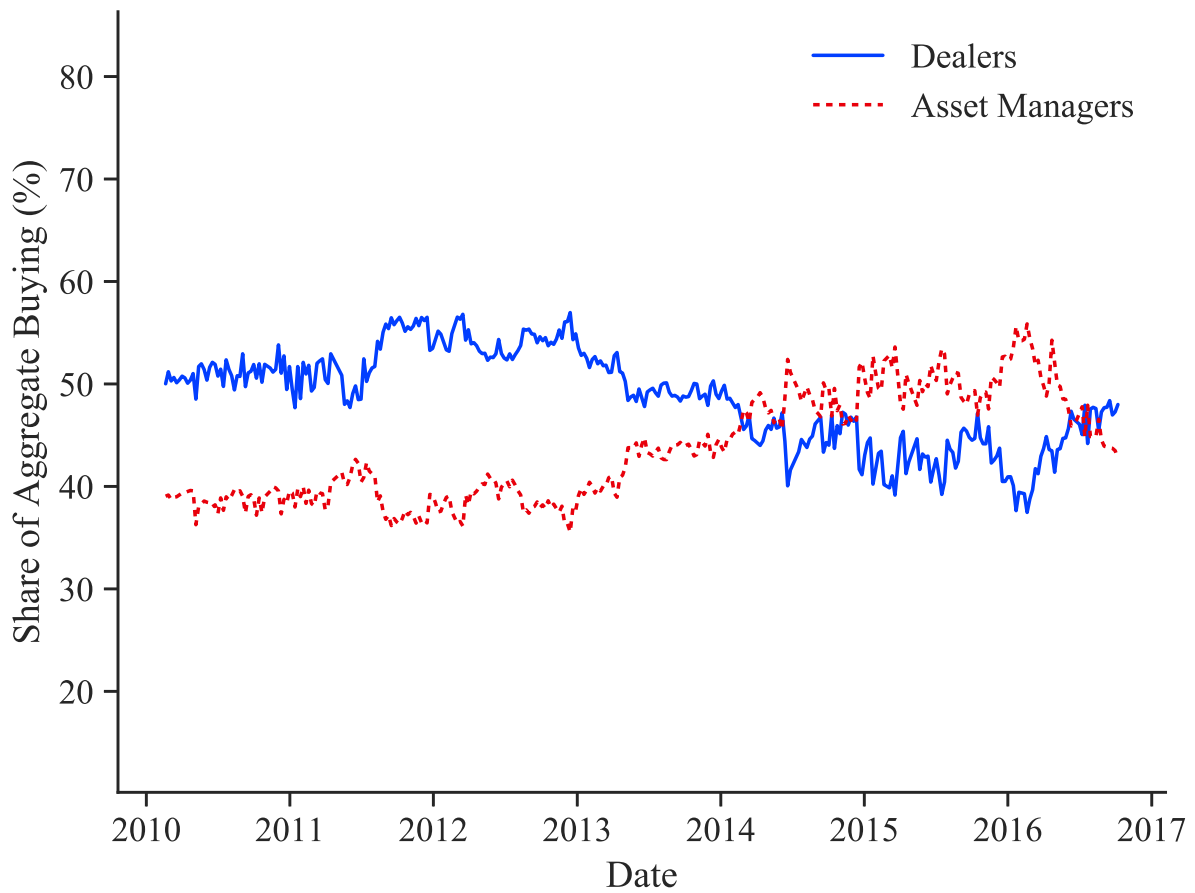-1}$. The Δ_h operator takes the difference between a variable at time $t-1+h$ and time $t-1$. $SC_{f,t}$ measures the dollar change from time $t-1$ to t (in \$ billion, denoted \$ bn) in the mark-to-market value of firm f's net sellers, excluding all positions written on firms in the same industry as f. $BC_{f,t}$ is the same variable, except for f's net buyers. $Z_{f,t}$ 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. a_f is a firm fixed effect. The 95% confidence interval is based on standard errors from the regression. To compute standard errors, I first use a within-firm Newey-West correction. I then compute standard errors that are double clustered by firm and time. To be conservative, I use the larger of the two to compute confidence bands. CDS spreads come from Markit, have a five-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 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 U.S.; (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 nonzero net notional outstanding; and (iv) the CDS spread must be less than 5,000 bps. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.
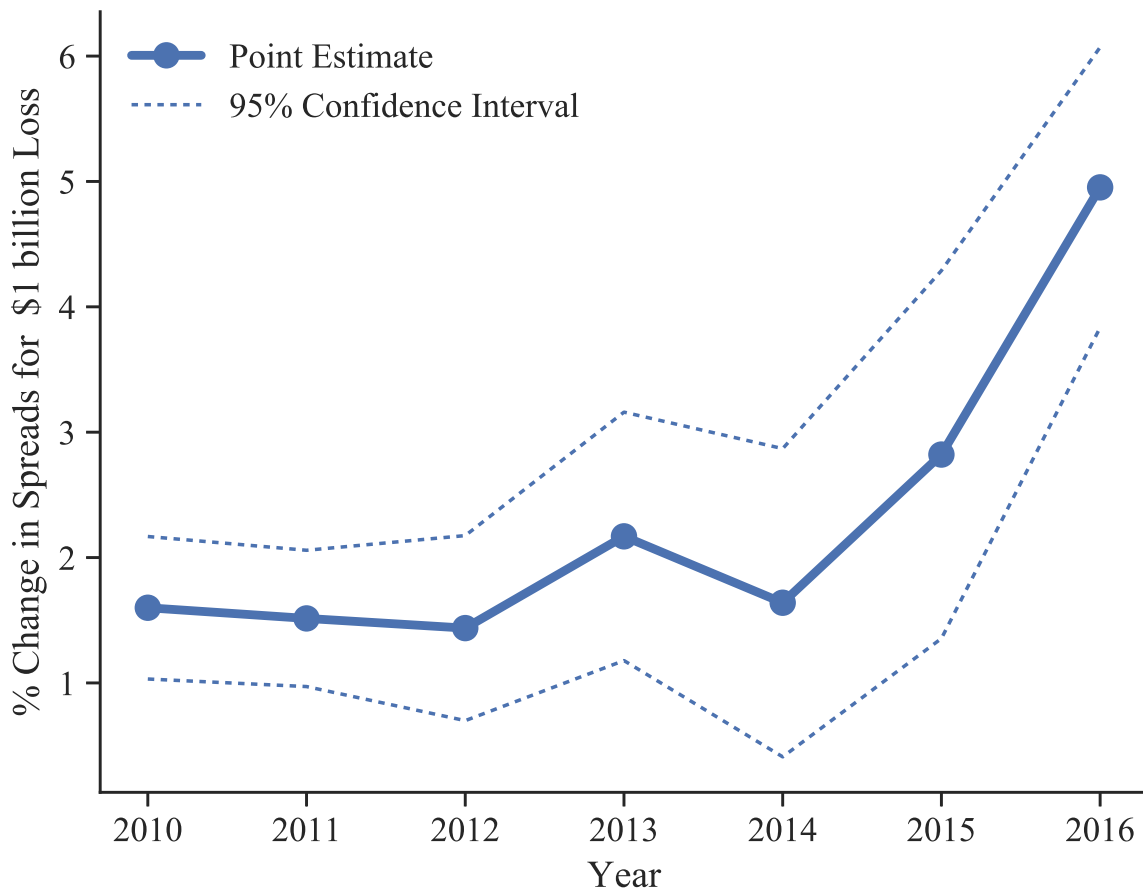
Figure 3. The response of CDS spreads to seller losses by year. This figure plots the coefficients $-\beta_{S,Y}$ from the following regression: $\Delta \log(CDS_{f,t}) = a_f + a_{i,t} + \sum_{Y=2010}^{2016} \beta_{S,Y} \times SC_{f,t} \times 1(Year = Y) + \beta_B \times BC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t}$. $1(Year = Y)$ is a dummy variable for when the year of t equals Y. $SC_{f,t}$ measures the dollar change (in \$ billion, denoted \$ 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. $Z_{f,t}$ 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. $a_{i,t}$ is an industry-by-time fixed effect, where the industry is defined by Markit. a_f is a firm fixed effect. The 95% confidence interval is based on standard errors from the regression, which are double clustered by firm and time. CDS spreads come from Markit, have a five-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 U.S.; (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 nonzero net notional outstanding; and (iv) the CDS spread must be less than 5,000 bps. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Figure 4. Share of net buying by dealers and asset managers. This figure plots an aggregate measure of the share of protection buying by dealers and asset managers in the CDS market. For each firm f, I first compute the share of buying by a given counterparty type. The share of buying by a counterparty type on a firm is the net amount bought on that firm divided by the net notional outstanding on the firm (ignoring maturity). At each point in time, I then take a weighted average of these share measures across all firms, where the weights are determined by the net notional outstanding of each firm f. See Appendix A.3 for complete variable definitions. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.
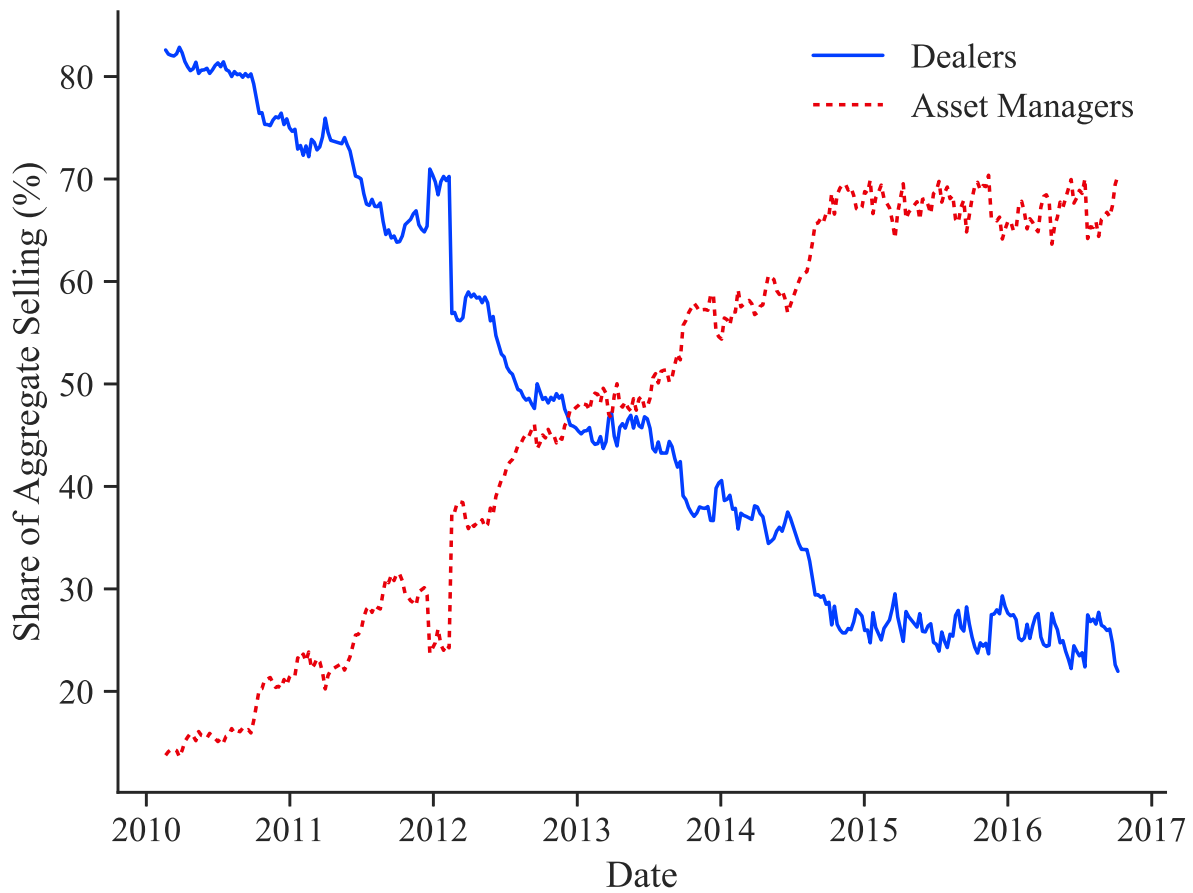
Figure 5. Share of net selling by dealers and asset managers. This figure plots an aggregate measure of the share of protection selling by dealers and asset managers in the CDS market. For each firm f, I first compute the share of selling by a given counterparty type. The share of selling by a counterparty type on a firm is the net amount sold on that firm divided by the net notional outstanding on the firm (ignoring maturity). At each point in time, I then take a weighted average of these share measures across all firms, where the weights are determined by the net notional outstanding of each firm f. See Appendix A.3 for complete variable definitions. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.
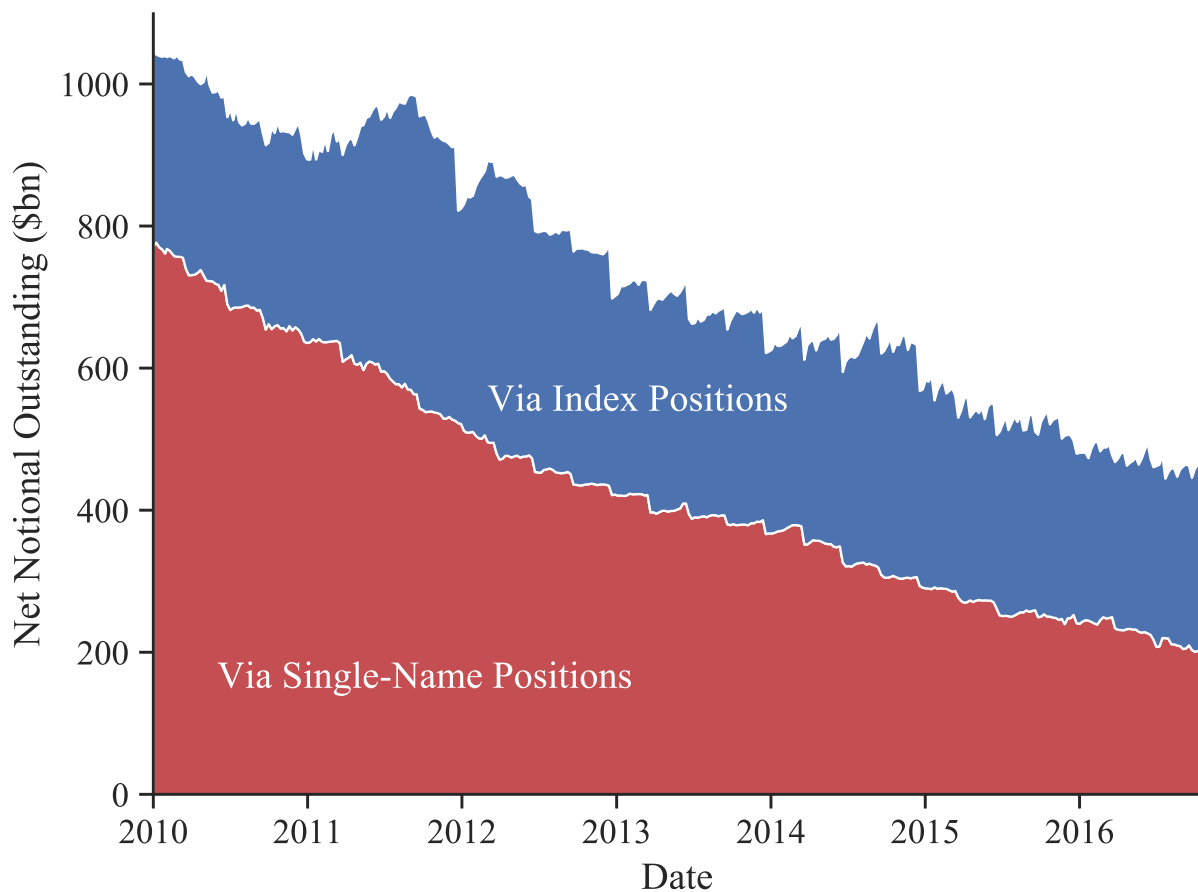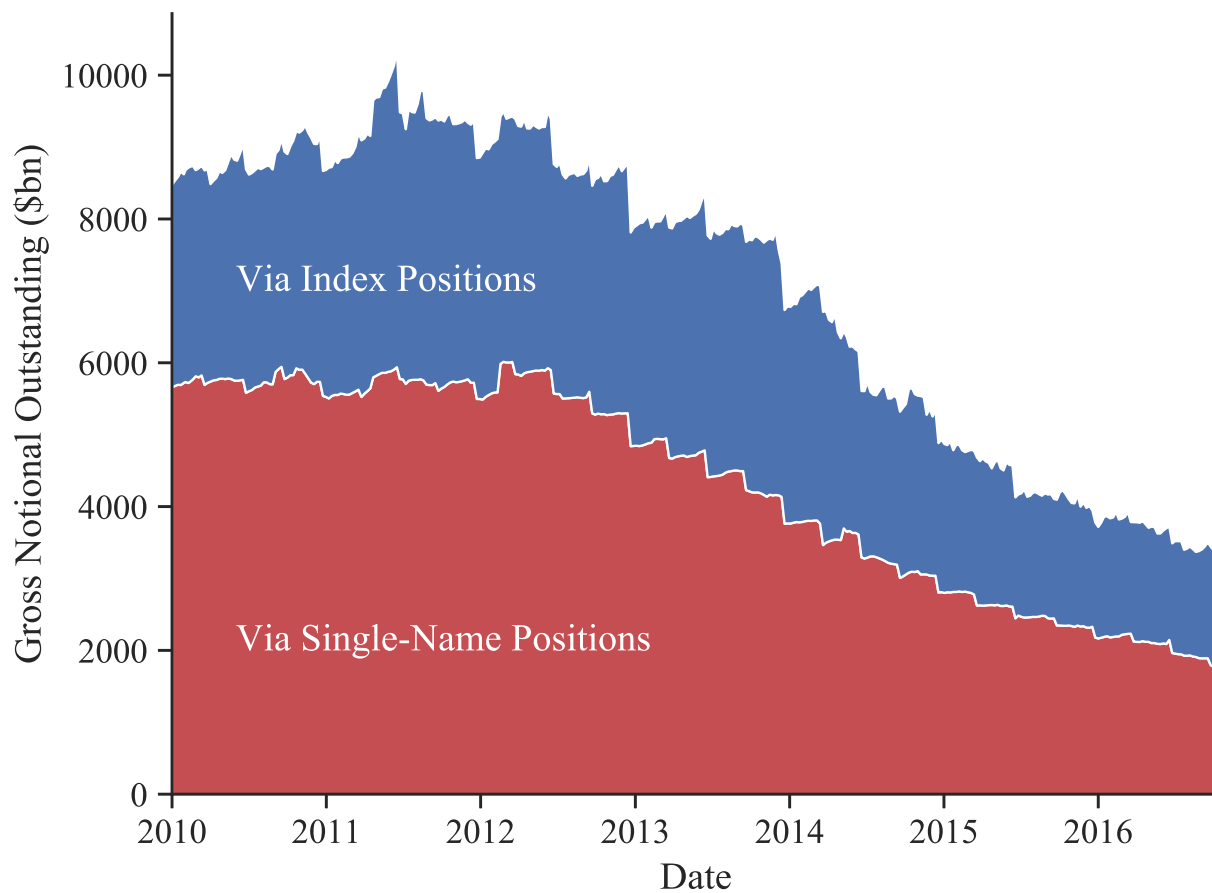
Figure A1. The size of the U.S. CDS market (net notional). This figure plots the net notional outstanding in the U.S. CDS market. For a given firm f, the total net notional sold is the sum of the net amount sold by all counterparties that are net sellers of protection on f. To compute the net amount sold by a counterparty c on f, I disaggregate index positions and net them against any single-name positions. See the Internet Appendix for complete details. The total size of the market is then the sum of the net notional outstanding across all firms. For this analysis, a firm is defined as a combination of the underlying firm name (e.g., Ford) and a maturity bucket (e.g., 0-2 years). The maturity buckets I consider are (in years): 0-2, 2-4, 4-6, 6-8, 8-10, and 10+. The hashed area in the plot shows the total net notional outstanding that comes from actual single-name positions, and the shaded area shows the amount that comes indirectly through index positions. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Figure A2. The size of the U.S. CDS market (gross notional). This figure plots the gross notional outstanding in the U.S. CDS market. For a given firm f, the total gross notional sold is the sum of the gross notional exposure by all counterparties that trade in f. The total size of the market is then the sum of the gross notional outstanding across all firms. For this analysis, a firm is defined as a combination of the underlying firm name (e.g., Ford) and a maturity bucket (e.g., 0-2 years). The maturity buckets I consider are (in years): 0-2, 2-4, 4-6, 6-8, 8-10, and 10+. The hashed area in the plot shows the total gross notional outstanding that comes from actual single-name positions, and the shaded area shows the amount that comes indirectly through index positions. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Table I
Summary Statistics of Credit Metrics

This table reports summary statistics for CDS spreads, expected default frequencies (EDF), and loss given default (LGD). CDS spreads come from Markit, have a five-year maturity, are denominated in USD, and cover senior unsecured debt with documentation clause MR. EDFs come from Moody's and are five-year expected default probabilities. LGDs also come from Markit. For data in levels, CDS and EDFs are expressed in basis points (bps) and LGD is expressed in percentage points. For log-differences, all quantities are expressed in percentage points. I apply the following filters to the data: (i) the underlying firm must be registered in the U.S.; (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 nonzero net notional outstanding; and (iv) the CDS spread must be less than 5,000 bps. I winsorize log-differenced data at the 1% tails. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

	CDS Spread		EDF		LGD	
	Level (bps)	Log-Diff (%)	Level (bps)	Log-Diff (%)	Level (%)	Log-Diff (%)
Mean	177.23	-0.09	79.44	-0.07	60.56	0.00
Std. Dev.	232.44	5.23	145.45	4.10	3.02	1.17
p25	60.57	-2.36	14.88	-1.68	60.00	0.00
p50	104.61	-0.02	36.71	-0.05	60.00	0.00
p75	199.45	1.75	90.06	1.51	60.00	0.00
Min	10.19	-15.95	3.46	-13.84	31.50	-28.77
Max	4991.84	19.58	3217.55	14.29	92.60	31.13
N	128,243	128,243	128,243	128,243	128,243	128,243

Table II
Summary Statistics of Capital Measures

This table reports summary statistics for various capital measures used to explain changes in credit spreads. Capital measures are computed each week for net sellers and net buyers of protection for each firm f (see Table I for a description of firm selection). For firm f's net sellers (buyers), $SC_{f,t}$ ($BC_{f,t}$) measures the dollar change in the mark-to-market value of their CDS portfolio, excluding positions written on firms in the same industry as f. For example, consider firm f in industry i at time t. $SC_{f,t}$ is computed by summing the weekly change in market value of CDS positions over all of f's net sellers, excluding all of their positions on firms in industry i. Leverage is the average debt-to-equity ratio for net sellers (or buyers) of a firm, computed for sellers (or buyers) with available leverage data. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

	Sellers			Buyers		
	SC ($mm)	Leverage	$\Delta Leverage$	BC ($mm)	Leverage	ΔLeverage
Mean	-4.49	29.53	0.01	-6.81	30.11	0.00
Std. Dev.	676.70	11.73	1.83	455.70	11.28	1.76
p10	-676.42	17.08	-1.72	-462.86	18.37	-1.73
p25	-240.73	21.30	-0.77	-194.81	22.72	-0.77
p50	-0.93	27.22	-0.05	-9.64	27.62	-0.06
p75	259.66	35.81	0.78	173.04	36.07	0.80
p90	666.27	45.23	1.73	452.57	45.92	1.72
Min	-6222.00	6.88	-19.71	-5750.97	6.88	-61.07
Max	4312.58	110.63	20.06	4095.81	113.14	42.52
N	128,243	127,760	127,752	128,243	127,772	127,766

Table III
CDS Spread Dynamics and Capital

This table reports regressions of the form: $\Delta \log(CDS_{f,t}) = c + \zeta_s \times SC_{f,t} + \zeta_b \times BC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t} + \boldsymbol{\theta}' \mathbf{X}_t$. The table reports the estimates for ζ_s and ζ_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. When included, macro controls are: returns to the three Fama-French factors, the change in the slope of the Treasury yield curve, the change in the 10-year Treasury yield, the change in the VIX, and the change in the TED spread. $SC_{f,t}$ measures the dollar change (in $ billion) 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 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. Columns (7) and (8) use a fixed effect based on the intersection of industry, rating, and time, where ratings are obtained from S&P. CDS spreads come from Markit, have a five-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 filters from Table I to the data. All standard errors are double-clustered by firm and time, and listed below point estimates in parentheses. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Dep. Variable	$\Delta \log(CDS_{f,t})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SC_{f,t}$	-2.72**	-2.75**	-2.06**	-2.11**	-2.04**	-1.76**	-2.27**	-1.82**
	(0.27)	(0.30)	(0.27)	(0.31)	(0.23)	(0.30)	(0.24)	(0.33)
$BC_{f,t}$	0.17	0.05	0.47	0.35	-0.04	-0.01	-0.26	-0.06
	(0.32)	(0.38)	(0.29)	(0.34)	(0.19)	(0.26)	(0.20)	(-0.21)
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Option-Mkt Controls		Y		Y		Y		Y
Macro Controls		Y	Y	Y				
FE					(i,t)	(i,t)	(i,r,t)	(i,r,t)
Within-f R^2	0.22	0.26	0.24	0.28	0.38	0.46	0.53	0.47
# of f	399	240	399	240	399	240	375	221
N	128,243	59,578	118,956	58,460	128,243	59,545	111,966	47,232

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

This table reports regressions of the form: $\Delta \log(CDS_{f,t}) = c + + \zeta_s SC_{f,t} + \zeta_b BC_{f,t} + \theta_s ISC_{f,t} + \theta_b IBC_{f,t} + \mathbf{\Gamma}' \mathbf{Z}_{f,t} + \varepsilon_{f,t}$. $\mathbf{Z}_{f,t}$ 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 \$ billion) 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. $ISC_{f,t}$ is the average change across f's sellers in one of three variables: 1) leverage, measured as the ratio of market equity to debt; 2) CDS spreads; or 3) SRISK. ISC stands for "institutional seller capital" because it is measured at the institution level, not the trading desk level. $IBC_{f,t}$ is the same variable, except for buyers of firm f's protection. SRISK is an estimate of the amount of capital that a financial institution would need to raise to function normally in the event of a financial crisis (Brownlees and Engle (2017)). Column (1) runs the regression without the institutional-based controls for the full sample, and corresponds to column (5) of Table 3. Column (2) re-runs the baseline regression for only the sample of firms where dealers are responsible for the majority of net selling. CDS spreads come from Markit, have a five-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 filters from Table I to the data. 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 parentheses. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Dep. Variable	$\Delta \log(CDS_{f,t})$				
	(1)	(2)	(3)	(4)	(5)
$SC_{f,t}$	-2.04**	-1.64**	-1.51**	-1.63**	-1.61**
	(0.23)	(0.21)	(0.21)	(0.21)	(0.22)
$BC_{f,t}$	-0.04	0.15	0.21	0.16	0.19
	(0.19)	(0.17)	(0.17)	(0.17)	(0.18)
ΔSeller Leverage$_{f,t}$			0.26**		
			(0.07)		
ΔBuyer Leverage$_{f,t}$			0.11**		
			(0.05)		
ΔSeller CDS$_{f,t}$				-1.08	
				(1.31)	
ΔBuyer CDS$_{f,t}$				-0.22	
				(1.04)	
ΔSeller SRISK$_{f,t}$					-0.02
					(0.02)
ΔBuyer SRISK$_{f,t}$					-0.01
					(0.02)
Dealers Majority Sellers	N	Y	Y	Y	Y
Within f-group R^2	0.38	0.36	0.34	0.36	0.37
# of f	399	396	396	396	396
N	128,243	91,027	90,398	89,850	84,727

Table V
Additional Analysis of CDS Spread Dynamics and the CDS-Bond Basis

This table reports regressions of several different dependent variables on buyer and seller capital shocks, BC and SC, respectively. $SC_{f,t}$ measures the dollar change (in $ billion) 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, firm level controls include: the lagged log-change in CDS spread, the 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. In column (1), the dependent variable is the equity return on firm f. In column (2) it is the log-change in firm f's option-implied CDS spread (Carr and Wu (2011)), denoted by $\Delta \log(\text{OIC}_{f,t})$. In columns (3) and (4), the dependent variable is the log-change in CDS spreads. In column (3), the analysis is run using only the set of firms that are in the on-the-run CDX investment grade index. In column (4), $SC_{f,t}$ is interacted with the share of net selling done by asset managers ($AMS_{f,t}$, which is also included as a standalone regressor). In columns (5) and (6), the dependent variable in the regression is the CDS-bond basis, measured as the Z-spread from Bloomberg. In both columns (5) and (6), firm controls are the same as in columns (3)-(4). When included, macro controls are: returns to the three Fama-French factors, the change in the slope of the Treasury yield curve, the change in the 10-year Treasury yield, the change in the VIX, and the change in the TED spread. 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 five-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 filters from Table I to the data. Standard errors are double-clustered by firm and time, and are listed below point estimates in parentheses. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Dep. Variable	$Ret_{f,t}^{Equity}$	$\Delta \log(\text{OIC}_{f,t})$	$\Delta \log(CDS_{f,t})$		$\Delta Basis_{f,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$SC_{f,t}$	-0.08	-0.40	1.45	-1.15**	-1.34	3.30
	(0.09)	(0.57)	(0.95)	(0.22)	(1.21)	(2.18)
$BC_{f,t}$	-0.07	0.26	1.50	-0.31*	0.40	5.03**
	(0.09)	(0.53)	(0.95)	(0.19)	(1.19)	(2.05)
$SC_{f,t} \times AMS_{f,t}$				-3.40**		
				(0.42)		
Firm Controls			Y	Y	Y	Y
Macro Controls					Y	
Firms in IG Index			Y			
FE	(i,t)	(i,t)	(i,t)	(i,t)		(i,t)
Within f-group R^2	0.33	0.31	0.65	0.39	0.01	0.44
# of f	399	240	109	399	113	113
N	128,243	59,544	31,676	128,243	11,005	10,857

Table VI
Individual Position Dynamics

This table reports regressions of the form: $\Delta NS_{c,f,t} = a_{c,f} + \gamma Y_{c,t}$, where $Y_{f,t}$ is either the dollar change in the market value of c's CDS portfolio (Cap) or the percentage return of c's CDS portfolio (Ret^{CDS}). To compute returns, I assume initial margin requirements for each CDS position that mimic FINRA's margin requirements. See the Internet Appendix for a complete description of how initial margins are set. $\sigma(Y)$ w.r.t. $\sigma(X)$ indicates the number of standard deviations the Y-variable moves in response to a one-standard-deviation move in the X-variable. Column headers labeled "Sellers" or "Buyers" refers to the top 10% of net sellers or net buyers, where the top 10% is determined by their total net sold (or bought) across all firms f. Standard errors are listed below each point estimate and are double-clustered by c and t. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Dep. Variable	$\Delta NS_{c,f,t}$			
	Sellers	Sellers	Buyers	Buyers
	(1)	(2)	(3)	(4)
$\Delta Cap_{c,t}$	0.0014**		0.0029**	
	(4.6e-4)		(4.8e-4)	
$Ret^{CDS}_{c,t}$		375,346**		328,848**
		(119,513)		(68,835)
$\sigma(Y)$ w.r.t $\sigma(X)$	5.4%	8.1%	6.2%	6.1%
R^2	0.00	0.01	0.00	0.00
# of c	121	121	81	81
# of f	489	489	493	493
N	1,521,050	1,521,050	1,523,307	1,523,307

Table VII
Transmission of Japanese Tsunami to U.S. CDS Markets

The table presents results from the regression: $\Delta \log(CDS_{f,1}) = a + \phi_1\Gamma_{S,f} + \phi_2\Gamma_{B,f} + \boldsymbol{\beta}'X_f + \varepsilon_f$. The dependent variable is the 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. Exposure is defined as the net amount of protection sold on Japanese firms (\$1 billion), which means that the units of $\Gamma_{S,f}$ and $\Gamma_{B,f}$ are in billions of dollar notional. The control variables are (for each firm f): the change in the five-year Moody's expected default frequency (EDF), the change in Markit's loss given default (LGD), the change in Markit's estimate of depth, 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. Column (6) also adds the average change in seller and buyer leverage to the regression. In column (7), I exclude the change in five-year Moody's EDF as a control because it effectively reflects equity returns. CDS spreads come from Markit, have a five-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 the point estimates. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. When industry fixed effects are included with the controls, the reported R^2 is within each industry group. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation

Dependent Variable	$\Delta \log(CDS_{f,1})$						$Ret_{f,1}^{equity} \times 100$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Gamma_{S,f}$	3.23**		3.35**	3.41**	2.95**	3.47**	-0.57	0.69
	(1.00)		(1.00)	(0.89)	(1.35)	(1.19)	(0.83)	(0.84)
$\Gamma_{B,f}$		0.47	0.94	0.97	0.33	0.77	0.23	0.54
		(1.04)	(1.06)	(0.94)	(1.02)	(1.01)	(0.67)	(0.61)
Control Variables				Y	Y	Y		Y
Industry FE					Y	Y		Y
Institution-Wide Leverage						Y		Y
Total N	288	288	288	280	280	280	288	288
Adj. R^2 (%)	2.3	0.0	2.4	26.0	24.0	26.1	0.0	15.4

Table AI
Individual Position Dynamics

This table report results from the following regression: $NS_{c,f,t} = a_{c,f} + \phi \times NS_{c,f,t-1}$, where $NS_{c,f,t}$ is the net sold by counterparty c on firm f at time t. $a_{c,f}$ is a counterparty-by-firm fixed effect. Standard errors are listed below each point estimate and are double-clustered by c and t. * indicates a p-value of less than 0.1 and ** indicates a p-value of less than 0.05. Data are weekly and span 2/19/2010 to 10/7/2016. Source: Author's analysis, which uses Data provided to the OFR by the Depository Trust & Clearing Corporation.

Dep. Variable	$NS_{c,f,t}$		
	All	Sellers	Buyers
	(1)	(2)	(3)
$NS_{c,f,t-1}$	0.979**	0.982**	0.975**
	(0.01)	(0.01)	(0.00)
R^2	0.96	0.96	0.95
# of c	1,087	121	81
# of f	496	489	493
N	15,234,431	1,521,050	1,523,307