BANK OF ENGLAND

Staff Working Paper No. 642

Identifying contagion in a banking network

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January 2017

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Abstract

This paper studies the impact of trading profits and losses on bank counterparty borrowing costs using data from a derivatives trade depositary. We use the network of credit default swap (CDS) transactions between banks to identify bank CDS returns attributable to counterparty losses. Any bank's exposure to corporate default increases whenever counterparties from whom it has purchased default protection themselves experience losses. In line with this statement, we document an increase in the own CDS spread of such a bank. We find no such effect from losses of non-counterparties, nor from counterparties who have bought protection from, rather than sold protection to, the bank. We also find that the effect on bank CDS returns through this counterparty loss channel is large relative to the direct effect on a bank's CDS returns from its own trading losses.

Key words: Contagion, counterparty risk, credit default swaps, networks.

JEL classification: G21, G28.

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We thank Paul Bedford, Zijun Liu, David Murphy, Pedro Gurrola-Perez, Kathy Yuan, and participants at the Bank of England, the 2016 Financial Stability Conference organised by the US Office of Financial Research and the Federal Reserve Bank of Cleveland, the International Conference on Financial Cycles, Systemic Risk, Interconnectedness, and Policy Options for Resilience, and the Fourth Annual Conference on Systemic Risk Modelling at London School of Economics for helpful comments and suggestions. Alan Morrison and Mungo Wilson are grateful for funding from the Oxford Man Institute and from ESRC grant ES/K005561/1. The views expressed in this paper are those of the authors and not necessarily those of the Bank of England or any of its committees, or the Federal Reserve Board or any other person associated with the Federal Reserve System.

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ISSN 1749-9135 (on-line)

1. Introduction

The Financial Crisis of 2008–09 inspired a wealth of academic studies into systemic risk in banks. An array of theoretical studies extends our understanding of the mechanisms that could trigger systemic events, and several authors have identified strong evidence that bank values co-vary, either as a result of common shocks, or as a consequence of trouble at one bank. But, to date, it has proved impossible to identify micro-level evidence of the transmission of shocks between banks in the developed world.[1]

In this paper, we identify bank- and shock-level evidence of contagion in a network constructed from a unique dataset of all exposures in the UK single-name Credit Default Swap (CDS) market between 2009 to 2013, inclusive. The type of contagion that we identify arises in situations where Bank A has purchased protection from Bank B against losses arising from default by corporate reference entity X.[2] In this situation, a reduction in the creditworthiness of Bank B reduces the value of the protection it has sold to Bank A. As a result, Bank A's exposure to entity X increases and, in turn, Bank A's creditworthiness declines. This effect occurs in addition both to the events that caused Bank B's creditworthiness to decline, and to any independent losses that Bank A's own portfolio sustains. It should therefore be possible to identify it in a regression that controls for these effects.

We identify the market perception of a bank's creditworthiness with the cost of purchasing protection against the bank's default: that is, with its CDS spread. In the situation described above, losses by Bank B should cause Bank A's CDS spread to widen, too. We find economically and statistically significant evidence that credit risk is transmitted through this channel. When Bank A has purchased default protection from Bank B then, after controlling for Bank A's own CDS losses, other banks' CDS losses and standard system-wide effects like equity index returns, a one standard deviation aggregate daily loss on Bank B's CDS positions increases Bank A's CDS spread by 0.28%. The *transmission hypothesis* is the

[1] An important study of contagion between banks in India, which uses data that predates the credit crisis, is Iyer and Peydro (2011)

[2] Banks' mutual economic exposures are not confined to the CDS market and the effects that we document could also obtain more generally.

claim that this effect is driven by the mechanism described in the previous paragraph.

An alternative explanation of our finding is that both banks A and B share a common risk exposure. We rule out this *common exposure hypothesis* in favour of the transmission hypothesis for two reasons. First, we show that equivalent losses by non-counterparties are not associated with a significant change in Bank A's CDS spread so that the common exposure must be peculiar to banks A and B. Second, we examine the relationship between loss transmission and the identity of the protection buyer. Under the common exposure hypothesis, a loss by Bank B is associated with an increase in Bank A's CDS spread regardless of whether Bank A is a buyer of protection from or a seller of protection to Bank B. By contrast, under the transmission hypothesis, Bank A's CDS spread should increase only when Bank A is a buyer of protection from Bank B. The effect we document is confined to losses by protection sellers and, hence, our results are consistent with the transmission hypothesis and not with the common exposure hypothesis. To the best of our knowledge, this is the first study to use this restriction in order to identify transmission as opposed to common exposure.

As a fraction of bank capitalisation, banks in our sample have very low net CDS exposures. In line with this observation, the economic magnitudes that we find are very small: a one-standard deviation exposure-weighted loss on their CDS positions by a typical bank's counterparties, other things equal, implies an increase in the bank's CDS spread of 1.5 bps in our baseline specification. The standard deviation of CDS spread changes in our panel is 11.6 bps. Nevertheless, these magnitudes are statistically significant. They are also economically real: if B owes A one euro, and becomes one euro poorer, A's cost of protection should increase, even if both A and B are millionaires. We identify small levels of contagion even in relatively benign markets. Presumably, contagion effects would be far more important in times of heightened systemic fragility. An important caveat is that the kind of relatively benign contagion which we document, i.e. the transmission of everyday small shocks, may operate in a qualitatively different manner from contagion in times of heightened systemic risk.

Our results demonstrate a contemporaneous response of CDS spreads to losses on CDS positions by protection seller counterparties. They therefore have the surprising implication that the marginal CDS trader in some sense understands the structure of interbank CDS exposures. It is plausible that this type of understanding could be achieved in relatively dense trading networks where most deals are performed over the telephone. Alternatively, it is possible that the counterparties themselves, who know both the bank's exposures to themselves and their own losses, update their quotes for protection on bank i in the light of their own losses. While it occurs via a different channel, this is nevertheless still a form of transmission. Consistent with this explanation, we find that the effect we document is orders of magnitude stronger when the bank has only one counterparty CDS dealer. The effect is also proportionally reduced for a larger number of counterparties.

Our work extends a rich literature on systemic risk and contagion effects. Theoretical explanations of systemic risk fall into three broad, and overlapping, categories. The first defines systemic risk as exposure to a common shock. Hence, for example, if all banks have an exposure to commercial real estate loans, then a shock to the real estate sector causes losses to every bank in the system. This type of exposure could arise as a natural consequence of bank diversification (Wagner, 2010); it could also reflect a strategic decision to take advantage of limited liability so as to externalise some of the costs of failure (Acharya, 2009) or to capitalise upon the regulator's unwillingness to allow many banks to fail together (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

The second approach to systemic risk is concerned with structural funding risks in the banking sector. Precisely because banks fund long-lived and hard-to-sell assets with short-dated deposits and wholesale loans, they are exposed to runs, either by depositors or short-term bank lenders. It is well-understood that an unexpectedly large withdrawal of funds can cause bank insolvency (Diamond and Dybvig, 1983). Banks therefore have a natural incentive to pool their supply of ready liquidity: this allows large withdrawals from one bank to be offset against smaller withdrawals at another, so that banks can put more of their money to work in the profitable (and socially important) corporate sector. This approach is effective so long as withdrawals are not so large as to exhaust the aggregate supply of liquidity in the banking sector: when that happens, a problem that could have been contained within a few banks is transmitted to the entire banking sector, and causes widespread bank failure (see Allen and Gale, 2000; Freixas, Parigi, and Rochet, 2000). Iyer and Peydro (2011) present an excellent study of this phenomenon, but their analysis uses data from Indian banks, where banking institutions are still developing.[3]

The type of theory outlined in the previous paragraph relies upon shocks to the liability side of the bank's balance sheet. But those shocks need not be independent of the bank's assets. When banks have common exposures then depositors may respond to bad news by withdrawing in anticipation of the systemic effects above (Allen, Babus, and Carletti, 2012); they may equally mistake liquidity effects elsewhere for bad news about common asset exposures and so withdraw unnecessarily (Chari and Jagannathan, 1988; Chen, 1999).[4] Heider, Hoerova, and Holthausen (2015) show that adverse selection over the quality of bank assets can cause the interbank market to dry up, so that liquidity sharing fails precisely when it is most important. In short, theories of systemic risk that lean on the asset side of the bank's balance sheet are closely related to those that rely upon liabilities. Indeed, fragile interbank linkages may be a rational response to problems monitoring bank assets (Rochet and Tirole, 1996; Morrison and Walther, 2015).

A final strand of the theoretical literature on contagion concentrates upon the topology of the networks through which shocks are transmitted. For example, and in line with Allen and Gale's (2000) pioneering work, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) show that densely-connected networks are better able to absorb small shocks, but that they amplify the effects of larger shocks. May, Levin, and Sugihara (2008) and Haldane and May (2011) use techniques from epidemiology to explain the propagation of shocks through banking networks, and, in related work, Gai, Haldane, and Kapadia (2011) use numerical simulations

[3]While India has a well-capitalised banking sector and an effective retail deposit insurance scheme, in a recent Country Report the IMF (2013, p. 5) referred to "weaknesses in the financial architecture," particularly concerning the "inherent conflict of interest when supervising state owned banks," and identifying "a number of opportunities to better align current supervisory policies and procedures to international best practice."

[4]See also Morrison and White (2013), who show that funding may be withdrawn when idiosyncratic losses in one bank are interpreted as evidence that all banks are poorly regulated.

to study the emergence of systemic liquidity crises in such networks; Gai *et al.* (2011) find that more complex networks can amplify systemic effects. Blume, Easley, Kleinberg, Kleinberg, and Tardos (2011) study network formation, and identify optimal network structures, and confirm that small levels of "over-linking" can have profound systemic effects.

Our work identifies a contagion channel that has received little attention in the theoretical literature. Shocks are transmitted in the literature discussed above through an interbank market that is designed to absorb funding risks that derive from a structural maturity mismatch between the two sides of the bank's balance sheet. But we exhibit a contagion channel through a network that is intended to distribute risks to bank assets. Any impact of this contagion upon funding is a second order effect.

Systemic risk and contagion are addressed in a rapidly expanding empirical literature. Several authors attempt to quantify the scale of systemic risk in real networks by taking data about real-life networks and simulating the effects of hypothetical shocks (see, e.g., Mistrulli, 2007; Degryse and Nguyen, 2007; Gai, Haldane, and Kapadia, 2011; Cont, Moussa, and Santos, 2013). Of course, such simulations are only as good as the economic reasoning that informs their design.

An alternative approach to systemic risk attempts to identify it by examining stock price effects in banking networks. Such studies often examine the way that share prices in one bank react to changes in another as, for example, in Hartmann, Straetmans, and de Vries (2005) and Gropp, Lo Duca, and Vesala (2009). Adrian and Brunnermeier (2011) suggest an empirical quantification of systemic risk that depends upon Value at Risk measures rather than upon network structure. Albuquerque, Ramadorai, and Watugala (2015) study contagion in a non-banking network of cross-border trading firms, and demonstrate that firms with high trade credit in producer countries experience returns that can be predicted using returns in associated consumer countries. But, in general, as Forbes and Rigobon (2002) emphasise, it is hard to separate contagion from interdependence.

Our data allow us to analyse correlation by studying the transmission of individual shocks through a well-defined network. We believe that this is the first time that analysis at this level has been performed. We are able to identify counterparty relationships and to control for losses on banks' own portfolios and, hence, can be confident that we identify contagion rather than interdependence. Furthermore, because we can see the linkages along which shocks are transmitted and the scale of their effects, we do not need to take a theoretical position upon systemic effects, and our conclusions are not subject to a dual hypothesis problem.

The rest of this paper is organized as follows. Section 2 describes our data and the network of CDS counterparties; Section 3 presents our main results. Section 4 concludes.

2. Data and methods

In our analysis we use transaction data from the UK single-name CDS market, which we obtain from the Depositary Trust & Clearing Corporation (DTCC). The DTCC data contain all CDS transactions written on UK reference entities, which are corporations whose shares have their primary listing on the UK stock exchange. In two recent descriptive papers, Benos, Wetherilt, and Zikes (2013) and Ali, Vause, and Zikes (2016) study the structure of this market using similar data and sample period. Instead of replicating their work, we briefly summarize their main findings here.

2.1 *The UK single-name CDS market*

The UK single-name CDS market is sizable. Ali, Vause, and Zikes (2016) report that the gross notional amount outstanding varied between EUR 540 billion and EUR 640 billion between 2009 and 2011, while the net notional amount outstanding decreased from EUR 26.5 billion to EUR 24.5 billion during the same period. Needless to say, the notional amount considerably overestimates the economic value of the outstanding positions. In terms of market value, the gross positions dropped from EUR 50 billion to around EUR 15 billion and the net positions from EUR 3 billion to EUR 1 billion between 2009 and 2011. Typical daily trading volume equaled EUR 1 billion (Benos, Wetherilt, and Zikes, 2013).

The UK CDS network has a core-periphery structure, where the G16 dealers form the core and the non-dealers, such as banks, asset managers, hedge funds and insurers populate the periphery (Ali, Vause, and Zikes, 2016). The total number of counterparties in the network increased from 300 to 350 and the overall connectivity of the network dropped roughly from 3% to 2% between 2009 and 2011. The interdealer network is almost fully connected, as dealers actively use the interdealer market for sharing inventory risk. The periphery is significantly sparser. Non-dealers are connected to dealers with probability of around 20% indicating that most buy-side firms have established relationships with only a few dealers. Non-dealers almost never trade with each other, which explains the low overall connectivity of the network mentioned above. It also implies that the G16 dealers are the main liquidity providers in the CDS market; according to Benos, Wetherilt, and Zikes (2013), they account for more than 70% of trading volume.[5]

2.2 *Variable construction*

For every pair i and j of banks and for every UK reference entity k, we define $P_{i,j,k,t}$ to be the total amount of outstanding protection that bank i has bought from bank j on entity k at date t. Bank i's date t net CDS exposure to reference entity k with bank j is therefore

$$NP_{i,j,k,t} = P_{i,j,k,t} - P_{j,i,k,t}.$$

$NP_{i,j,k,t}$ is positive when bank i is a net buyer of protection from bank j, and negative when bank i is a net seller. We use net position figures NP to compute net exposures to reference entities and banks as follows.

First, bank i's date t net position on reference entity k is

$$NP^{\text{Ent}}_{i,k,t} = \sum_{j \neq i} NP_{i,j,k,t}.$$

[5]The two-tier structure of the CDS market is similar to that of other OTC markets. For example, Benos, Payne, and Vasios (2016) report that the share of interdealer activity in the interest rate swap (IRS) market is about 55%, with the rest consisting of primarily dealer-to-client trading.

We measure $NP^{\text{Ent}}_{i,k,t}$ in millions of euros; once again, a positive value for $NP^{\text{Ent}}_{i,k,t}$ indicates that, at date t, bank i is a net buyer of protection on reference entity k.

Second, bank i's date t net exposure to bank j is

$$NP^{\text{Bank}}_{i,j,t} = \sum_k NP_{i,j,k,t}.$$

We can write this expression as

$$NP^{\text{Bank}}_{i,j,t} = NP^{\text{Bank,B}}_{i,j,t} - NP^{\text{Bank,S}}_{i,j,t}, \tag{1}$$

where

$$NP^{\text{Bank,B}}_{i,j,t} = \max\left(NP^{\text{Bank}}_{i,j,t}, 0\right) \tag{2}$$

is bank i's *net bought* CDS position with bank j and

$$NP^{\text{Bank,S}}_{i,j,t} = -\min\left(NP^{\text{Bank}}_{i,j,t}, 0\right) \tag{3}$$

is bank i's *net sold* CDS position with bank j. If bank i is a net buyer of protection from bank j, so that its creditworthiness can be affected by bank j's, then $NP^{\text{Bank,B}}_{i,j,t}$ is positive and $NP^{\text{Bank,S}}_{i,j,t}$ is zero.

We infer CDS spreads and returns from Markit CDS price data. Given the date t CDS spread $CDS_{k,t}$ of reference asset k, we can approximate the daily CDS return $R_{k,t}$ of asset k as the change in the logarithm of its gross spread:

$$R_{k,t} = \ln CDS_{k,t} - \ln CDS_{k,t-1}.$$

This approximation is extremely accurate at a daily frequency (see Acharya and Johnson, 2007; Hilscher, Pollet, and Wilson, 2015).

Bank i's profit or loss on its CDS exposure to reference entity k between date t and date

$t+1$ is therefore

$$\Pi^{\text{Ent}}_{i,k,t+1} = NP^{\text{Ent}}_{i,k,t} R_{k,t+1},$$

and its profit or loss on all of its open CDS positions over the same period is

$$\Pi_{i,t} = \sum_{k} \Pi^{\text{Ent}}_{i,k,t}.$$

Our baseline regression examines the impact of profits or losses $\Pi_{j,t}$ at bank j between time t and time $t+1$ upon bank i's CDS return (the change in log spread), $R_{i,t+1}$. In the regression, we scale bank j's profits or losses on its own CDS positions $\Pi_{j,t}$ by bank i's exposure to bank j in the CDS market. The term of interest in our baseline regression is therefore bank i's time t exposure-weighted counterparty profit $K_{i,t}$, which we define as follows:

$$K_{i,t} = \sum_{j \neq i} NP^{\text{Bank}}_{i,j,t} \Pi_{j,t}.$$

We define bank i's counterparty profits $K^B_{i,t}$ and $K^S_{i,t}$ for counterparties with whom it has a net bought and a net sold position, respectively, as follows:

$$K^B_{i,t} = \sum_{j \neq i} NP^{\text{Bank,B}}_{i,j,t} \Pi_{j,t}; \tag{4}$$

$$K^S_{i,t} = \sum_{j \neq i} NP^{\text{Bank,S}}_{i,j,t} \Pi_{j,t}. \tag{5}$$

If exposure-weighted counterparty losses (negative values of $K_{i,t}$) cause increases in bank i's CDS spread (positive returns on a bank i CDS spread) after controlling for general loss levels at other banks as well as at bank i, then we can reasonably argue that we have identified contagion, and, hence, that we have evidence that shocks are transmitted through the network of interbank exposures. We therefore run variations of the following regression:

$$R_{i,t} = \beta \Pi_{i,t} + \gamma K_{i,t} + \delta \sum_{j \neq i} \Pi_{j,t} + \zeta \sum_{j \neq i} NP^{\text{Bank}}_{i,j,t} + \mathit{controls} + \varepsilon_{i,t+1}. \tag{6}$$

The coefficient γ in Model (6) measures the propagation effect of other banks' losses through the counterparty risk channel. If γ is negative then bank i's own CDS spread increases when the counterparties to whom it has large CDS exposures experience losses on their own CDS positions.

To understand γ, consider a bank i that has purchased CDS protection from a number of other banks, including a bank j, but has not itself sold CDS protection to any other banks. Then we would expect losses at the other banks to affect bank i's value. We refer to those losses as *first-order*, because no other bank relies upon bank i for CDS protection and, hence, bank i's losses are not transmitted further. In general, however, bank i may have sold protection itself. Its first order losses therefore cause further losses at other banks that, in turn, may have sold CDS protection and, hence, may transmit the loss further through the CDS network. In particular, the losses may be experienced at bank j (and others that sold protection to bank i) and, hence, could have a further effect upon bank i. The *higher order* losses attributable to this type of feedback loop are referred to by Ota (2013) as *systemic*. If market participants rationally anticipate the total effect of counterparty losses in a CDS network, then the γ coefficient in Model (6) captures the total effect of CDS losses, including all systemic effects.

We ignore the other constituents of bank balance sheets in our analysis. Banks have debt liabilities to depositors and to other banks, and they have complex asset holdings, including bonds, cash, real assets, various derivative and swap positions, repos, and other money market instruments. The validity of our results is unaffected by the exclusion of these items, although their interpretation may not be. It is possible that γ inadvertently measures an effect related to one of the items identified above. For example, γ could conceivably capture an effect of own loan losses (rather than counterparty CDS losses) on bank CDS spreads. We view this type of effect as highly unlikely, especially as we find the effect only for protection-buying banks, and not for protection-selling banks.

3. Results

Our sample is an unbalanced panel of CDS spreads and positions for 41 banks between 2009 and 2013, inclusive. Our dataset includes transactions with about 800 counterparties, including banks, hedge funds, and other asset managers. This yields about 44,000 bank days of data for CDS returns, and 50,000 bank days of equity return data. We trim equity and CDS returns at the 1% and 99% levels (our results are qualitatively unchanged if we do not trim).

Table 1 presents summary statistics on our variables. As reported in the first row of the Table, average daily bank equity returns over the period that we study were 0.6 basis points per day. But those returns varied widely over the period, with a standard deviation of 2.46%. Average CDS returns were consequently negative (-4.56 bps), but with a larger standard deviation (3.21%). Although average daily returns were small, average spread changes were tiny: the average spread change was -0.037 bps (about 4% of a hundredth of a percent) with a standard deviation of 11.65 bps. Of course, there was widespread variation across banks, which our study exploits.

On average, banks experienced a small loss ($\Pi_{i,t}$) on their own CDS portfolios of around 30,000 euros per day. The standard deviation of this figure was 23.8 million euros, which reflects the asymmetric nature of CDS market participation: most banks in our sample were insurance buyers, with a few large banks selling insurance to the others.

Because all banks had some exposure to the large protection-selling banks, the average exposure-weighted counterparty profit (the average value of $K_{i,t}$ across banks i and dates t) was large, amounting to an average 1.69 billion euros per day across all counterparties. The average exposure-weighted profit $K_{i,t}$ was also very variable, with a standard deviation of 61 billion euros. Equations (4) and (5) define the average exposure-weighted counterparty profits $K^B_{i,t}$ and $K^S_{i,t}$ for bank i for counterparties with whom bank i is, respectively, a net buyer and a net seller of protection. Recall from Equations (3) and (5) that $K^S_{i,t}$ is negative when the counterparties to whom bank i sells protection make losses on their positions (i.e. the CDS spreads on which they have bought protection decline). The average $K^S_{i,t}$ is -840 million euros per day. We distinguish between the effects of losses to net bought and net sold counterparties in Table 4 below.

Finally, note that, by virtue of the higher-order systemic loss effects discussed at the end of Section 2.2, losses experienced at banks with whom bank i has no direct CDS exposure could still cause losses to bank i. The average scale of such losses in our sample was 2.8 million euros per day, with a standard deviation of about 50 million euros.

The remaining variables reported in Table 1 are standard: log returns on the MSCI Global, S&P 500 and FTSE 100 indices (all justifiable proxies for UK bank systematic risk); levels and log changes in VIX (the implied volatility index for the S&P 500) and the FVIX (the equivalent for the FTSE 100). We also control for the average CDS spread of all parties (about 800) in our sample, which averaged 1.82% over the T-bill rate and had a standard deviation of 0.9%. The highest observed average spread in our sample was 5.9%, and the highest log change 9.98% (approximately). CDS spread log changes can be volatile.

3.1 *Bank counterparty losses*

Table 2 presents our main result. Column (1) reports our baseline specification, with bank and year fixed effects. We cluster standard errors by bank. Bank CDS returns are negatively related to the bank's losses on its own CDS positions, but the coefficient in the baseline regression is not significant (it is in other specifications). However, there is a negative relationship between a bank's own CDS spread and the exposure-weighted average profit of its CDS counterparties (i.e., to $K_{i,t}$) that has a better than 1% significance level. The coefficient of -0.00137 relates (exposure-weighted) losses in squared millions of euros to CDS returns in basis points.

Table 1 reports a mean own CDS loss of -0.03 million euros, with standard deviation of 23.8 or just under 24 million. Thus, according to specification (1), a one-standard deviation loss raises a bank's own CDS spread by $0.381 \times 24 = 9.1$ bps. (That is, a spread of 100 bps increases to 1.00091x100 = 100.091 bps.)

The coefficient on the exposure-weighted average counterparty profits (that is, on $K_{i,t}$)

coefficient also relates squared millions of euros in profits to a bank's own CDS spreads in bps. Table 1 reports a mean $K_{i,t}$ of 1,690 squared millions of euros and a standard deviation of 60,904 squared millions of euros. Hence, according to specification (1), a one-standard deviation combined loss by bank i's counterparties $K_{i,t}$ corresponds to an increase of $60,904 \times 0.00137 = 83.4$ bps in bank i's own CDS spread (later specifications imply changes about one third of this magnitude), rather larger than the effect of bank i's own CDS losses. One simple possible explanation for this difference in magnitudes is that most banks are protection buyers for other assets on their balance sheet, so that their own CDS losses offset gains elsewhere, whereas some banks' CDS losses are not similarly offset. That is, our banks are mostly hedgers, but some banks, which tend to be their counterparties and probably the major dealers, may not have fully hedged CDS positions.[6]

Of our sample of 41 banks, 28 are on average, throughout our sample, daily net buyers of protection. The smaller the bank in terms of UK CDS gross notional exposures, the more it is a net buyer: 65% of the gross notional across names of the 20 smallest banks is net bought, increasing to 80% for the 10 smallest. The largest 15 banks are marginally net sellers, and since they are unlikely to be net short the underlying corporate loans or bonds, this suggests they hold, to a small economic extent, residual net exposures to losses on their own CDS positions which are not fully offset by gains on underlying assets.

Even this very sparse specification, with just bank and year-dummies, bank own CDS losses and exposure-weighted average bank counterparty CDS profits and losses explain about 7% of the variation in bank daily CDS returns, with an adjusted R^2 of 7.2% (5.1% for the untrimmed variables).

The remaining columns add a variety of controls to the baseline specification (1). Stock index returns are, unsurprisingly, strongly negatively related to bank CDS returns, with coefficients ranging from -0.21 to -1.14 depending on the index and specification used (we use all of MSCI global, S&P500 and FTSE100). Average CDS spread changes, which reflect general credit conditions controlling for stock index returns, are highly significantly corre-

[6]If true, this is another argument against the common exposure explanation for our findings.

lated with individual bank CDS spread changes, with a coefficient of 0.86 to 0.90. Adding index returns and average CDS spread changes increases the adjusted R^2 to about 34%. Changes in VIX are not significantly related to our dependent variable, but changes in the UK equivalent, FVIX, are: an increase in UK index volatility of 1% is associated with an increase in bank CDS spreads of about 3 bps, although the additional explanatory power of changes in volatility given stock returns is low.

In columns (4), (5) and (7) we control for total bank CDS profits (both counterparties and non-counterparties, of whom the majority are non-counterparties) (i.e. all bank profits except bank i's own profits). These are positively related to a bank's own CDS returns when we control for stock index returns and average CDS spread changes, with a coefficient of 0.24, so that CDS losses in the general population of banks result in a *reduction* in own-bank CDS spread (of around 12 bps for a one standard deviation loss by all other banks). Thus, while a bank's counterparties' losses do tend to increase its own CDS spread, losses by other banks in general have the opposite effect. Non-counterparty losses are important, with the expected sign, only if we control for FVIX and average CDS spread levels, rather than changes, as shown in column (7). If changes in spreads are correlated with other bank CDS losses, which they likely are, then the effect of changes appears to be picked up by other bank losses.

Including stock index returns and volatility changes reduces the coefficient on counterparty losses in magnitude from -0.00152 to -0.00042 (column (2), with the MSCI global index) or -0.00043 (column (3) which uses instead S&P500 and FTSE 100 index returns), and these magnitudes are hardly affected in columns (4) and (5). The implied effect on own CDS spread of a one standard-deviation exposure-weighted aggregate loss by all counterparties together shrinks to 27-28 bps, which is still over three times as large as the own CDS-loss implied effect from a one-standard deviation move. We suspect that this is because the network is two-tier, with a few large dealers acting as counterparties to almost everyone, and everyone else engaging in only small operations with perhaps one or two other banks.

Our results are robust to using levels instead of changes in average CDS spreads and implied-volatility indices, and in fact the estimated effect from counterparty losses is stronger, as shown in columns (6) and (7). Own CDS losses in these specifications are significantly related to a bank's own CDS spreads, but the effect is about 40% as strong as for counterparty losses (about a 12 bp return on CDS spreads for a one-standard deviation own CDS loss versus a 28 bp return on a one-standard deviation exposure-weighted loss by counterparties).

3.2 *Bought versus sold*

We argue that contagion arises when writers of CDS protection experience losses on their CDS positions, which in turn negatively affect their solvency levels, and which therefore reduce the value of protection provided by them to their counterparties, in turn negatively affecting those counterparties' solvency levels and increasing those counterparties' own CDS spreads. If this argument is correct, then solvency shocks should be transmitted to a given bank i only from counterparties that have *sold* i CDS protection; the creditworthiness of a claim that protection *buyers* have upon i is unaffected by shocks to their own solvency, although they may exert indirect systemic effects upon i, as noted at the end of Section 2.2.[7]

We test this hypothesis by distinguishing between the effect of a given bank i's net bought and net sold positions $K^B_{i,t}$ and $K^S_{i,t}$: Equations (2) and (3) state that these are the average exposure-weighted counterparty profits of banks with which bank i is, respectively, a net buyer and a seller of CDS protection. Recall that, if its counterparties make positive profits between date $t-1$ and t, both $K^B_{i,t}$ and $K^S_{i,t}$ are positive.

Our arguments yield the hypothesis that the coefficient on $K^B_{i,t}$ should be negative and significant, while that on $K^S_{i,t}$ should be negligible, although, because of systemic effects, it need not be precisely zero.

Table 3 tests this hypothesis. The setup is exactly as for Table 2, except that net exposure-weighted counterparty profits $K_{i,t}$ are broken into net bought and net sold exposures (it is a consequence of Equation (1) that the two sum to $K_{i,t}$). As reported in the

[7]There will be some counterparty risk on both sides, but with asymmetric risk on the part of the protection buyer.

second and third rows of the table, coefficients for exposure-weighted counterparty profits are negative and significant for counterparties from whom the bank is a net protection buyer; the coefficients for banks to whom the bank is a net protection seller are positive but not significant in any of our specifications. These observations are consistent with our hypothesis. Note that, because the coefficient is no longer damped down by the effect of net sold positions, the coefficient on net bought profits is slightly higher in the Table 3 specification than the corresponding Table 2 coefficient in all specifications.

3.3 *How does information about counterparty losses affect bank CDS spreads?*

An obvious question given our results so far is how bank i CDS spreads can change contemporaneously with bank i counterparty losses (and only when the bank has bought protection from that counterparty)? The question is how and when this information is observed and communicated to broker-dealers, who alter their spreads accordingly. Bank i's counterparties themselves are aware of how much protection they have written to (or received from) bank i, and are therefore able to estimate the impact of their own losses on bank i's creditworthiness. The fewer such counterparties bank i has, the more accurate this estimate will be: in the limit of a single counterparty (who knows they are the only counterparty), this estimate must amount to knowledge.[8] This explanation predicts that the counterparty loss coefficient γ should be larger when bank i has fewer counterparties, and largest when it has only one counterparty. We now test this prediction.

We create a dummy variable that equals 1 if bank i has only one counterparty and zero otherwise. We include this variable both on its own (as a control) and also its interaction with exposure-weighted counterparty losses. The coefficient on the interaction term is the coefficient of interest: it measures by how much γ is larger when a bank has only one counterparty.

Table 8 reports these results for all the corresponding specifications as in the other tables.

[8] Bank i might itself assist this kind of knowledge transfer by 'shopping' around its usual counterparties when one of its counterparties suffers a loss (although this begs the question of how bank i itself knows of such losses), and thus partially revealing its own need for 'top-up' protection.

First, the other coefficients of interest are not much changed and in the case of the exposure to general counterparty loss still negative and statistically significant and similar in magnitude to those in table 3. However, the interaction coefficient is large and negative in all but the first column, where we exclude most of the obvious control variables. For example, in column (2) the coefficient on the interaction is -0.312, pretty much the same in columns (3) through (5) and about -0.01 in columns (6) and (7) (which control for the levels, rather than the changes, in average spreads in the market). All of these coefficients are highly statistically significant. What is more, they are orders of magnitude larger than the average effect, although this is partly because the general level of exposure-weighted counterparty loss is a much larger number than a single counterparty's loss. This finding is consistent with the claim that it is the informed counterparty itself which is changing prices for protection on bank i.

With two counterparties, the effect is similar to only one, but weaker, just as our explanation would suggest (as neither of the two counterparties now has perfect information all the time about bank i's exposure-weighted counterparty losses). This is similarly the case with 3 counterparties. In fact, the interaction coefficient for the case of two counterparties is about one half of the coefficient on just one (in columns (2) through (5)) and about one third in the case of three. This is consistent with counterparties updating bank i's credit spread only when they themselves suffer a loss, and bank i spreading its protection across all of its counterparties roughly equally. Just to check, we also used a variable which counted the number of bank i counterparties, and the relevant interaction in our standard specifications, and the result is that γ is indeed decreasing in the number of bank i's counterparties. For brevity, we have reported the results for only one counterparty. All our other results are available upon request.

These results are consistent with the hypothesis that information about a bank's counterparty losses is transmitted to its own CDS spread by the counterparties themselves.

3.4 *Equity returns*

In a Modigliani-Miller world, equity returns ought to reflect changes in CDS spreads contemporaneously. In particular, anything that causes a bank's CDS spreads to increase (positive CDS returns) should reduce the value of the bank's debt and equity, so that the first order effect on bank i's equity return of counterparty CDS profits, which we argue implies improved creditworthiness for bank i, should be positive.

Table 4 checks for this effect, using equity returns, rather than CDS returns, as the dependent variable. As reported on the second line of the table, exposure-weighted counterparty CDS profits have a positive effect on bank equity returns when we include no controls (other than year fixed effects), implying a one-standard deviation increase in total exposure-weighted counterparty losses induces a negative bank equity return of 30 bps.

However, we find no effect on own equity returns once we include index returns, average CDS spreads and other controls in our regressions. There is a small, significant *negative* effect upon a bank's equity returns of other bank CDS profits in columns (4) and (5), as well as a strong negative relationship with changes in average CDS spreads, but the former effect flips sign in the last specification, column (7).

When we exclude the ten largest banks from our sample, we find results that are more strongly consistent with our main hypothesis. Table 5 reports these results, and now the coefficients on exposure-weighted counterparty profits are strongly positive in all columns. A one-standard deviation exposure-weighted counterparty loss is associated with a 29 bps negative equity return in column (4) for example - almost exactly the same as the implied increase in the bank's own CDS spread. For the ten largest banks, we find the opposite result.[9]

Our results are therefore consistent with standard corporate finance accounting, with the possible exception of the largest ten banks. For these banks, we speculate that their far greater concentration of all the CDS trading may give them an information advantage which does not immediately translate into equity markets, where there are many more traders (see

[9]This result is available from the authors upon request.

Benos, Wetherilt, and Zikes, 2013). Nor is this finding inconsistent with Hilscher, Pollet, and Wilson (2015), who find that equity returns generally predict CDS returns, since Hilscher et al. (2015) consider all news, rather than just news that relates to losses by CDS traders. It would be interesting, but beyond the scope of this paper, if large bank CDS returns were to predict other firms' equity returns.

3.5 *Further results and robustness tests*

Our results for CDS returns are also stronger if we exclude the ten largest banks. Table 6 reports the same results as table 2, but excludes the largest 10 banks. The magnitude of the estimate of the coefficient γ is much increased. In column (4) for example, which controls for index inclusions, FVIX changes and CDS average spread changes, γ is estimated to be -0.0017 (compared to -0.000437 for all banks), about 3.9 times larger. The corresponding coefficients for large banks are also negative, but much smaller in magnitude than those reported in table 2.[10] These results are consistent with our equity results.

Finally, we consider the impact of exposure-weighted counterparty CDS losses on next-day CDS spreads. Table 7 reports our results when all of the independent variables are lagged by one trading day. The coefficient in column (1), which excludes all controls, is marginally statistically significantly negative, but is economically negligible at about one twentieth the magnitude of the corresponding contemporaneous figure in Table 2. Columns (2)-(5) include our usual controls. The coefficients in those columns are statistically significantly positive and are about 30% the magnitude of their analogues in Table 2. These data appear consistent with partial reversion in CDS spreads the day after a shock to counterparty creditworthiness.

4. Conclusion

We present the first micro-level evidence of the transmission of shocks through financial networks. Our study uses a novel dataset on actual CDS contracts on UK names to estimate

[10] The results for large banks only are available from the authors on request.

the differential effects of three types of losses (on CDS positions) on UK bank spreads: the bank's own loss, losses by all other banks, and losses by the bank's counterparties. We find that own losses and counterparty losses are both associated with an increase in bank CDS spreads, whereas all other bank losses are not. Our results are consistent with contagion, and the magnitudes of the two channels (own loss and counterparty loss) are consistent with most banks using CDS contracts to hedge, while most large counterparties have some net exposure. Hence, in contrast to previous work in this field, we identify actual (as opposed to theoretical or hypothetical) propagation of shocks from one agent to another in a sophisticated OTC market, and we distinguish it from interdependence by showing that the counterparty loss channel is confined to losses by protection providers: there is no effect of losses by protection consumers.

Although the effects we document are statistically significant, they are economically extremely small. In fact the effect on changes in the level (as opposed to the log) of bank credit spreads are of the order of hundredths of basis points in any given day. Given that bank net CDS exposures are very small as a proportion of their total assets, these magnitudes are economically plausible.

We also show that the effects we document are much larger when the ten largest banks are excluded, and in that case also have the expected effects on bank equity returns as well. We show that the effect on CDS spreads partially unwinds the following day but that this unwinding is not statistically significant.

Finally we show results consistent with an explanation of how such information about counterparty losses is transmitted to a bank's own CDS spread: through the counterparties themselves changing their quotes on bank i CDS protection in the light of knowledge of their own losses and bank i's exposure to themselves. Our contagion effect is shown to be much stronger for banks with only one counterparty, and decreasing in the number of such counterparties.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi. 2015. Systemic Risk and Stability in Financial Networks. *American Economic Review*, 105:564–608.

Acharya, V. V.. 2009. A Theory of Systemic Risk and Design of Prudential Bank Regulation. *Journal of Financial Stability*, 5:224–255.

Acharya, V. V., and T. C. Johnson. 2007. Insider trading in credit derivatives. *Journal of Financial Economics*, 84:110–141.

Acharya, V. V., and T. Yorulmazer. 2007. Too many to fail—An analysis of time-inconsistency. *Journal of Financial Intermediation*, 16:1–31.

Adrian, T., and M. K. Brunnermeier. 2011. CoVaR. Working Paper 17454, NBER, Cambridge, MA.

Albuquerque, R. A., T. Ramadorai, and S. Watugala. 2015. Trade credit and cross-country predictable firm returns. *Journal of Financial Economics*, 115:592–613.

Ali, R., N. Vause, and F. Zikes. 2016. Systemic risk in derivatives markets: A pilot study using CDS data. Financial stability paper (forthcoming), Bank of England, London, UK.

Allen, F., A. Babus, and E. Carletti. 2012. Asset Commonality, Debt Maturity and Systemic Risk. *Journal of Financial Economics*, 104:519–534.

Allen, F., and D. Gale. 2000. Financial Contagion. *Journal of Political Economy*, 108:1 – 33.

Benos, E., R. Payne, and M. Vasios. 2016. Centralised trading, transparency and interest rate swap market liquidity: Evidence from the implementation of the Dodd-Frank Act. Staff Working Paper 580, Bank of England, London, UK.

Benos, E., A. Wetherilt, and F. Zikes. 2013. The structure and dynamics of the UK credit default swap market. Financial Stability Paper 25, Bank of England, London, UK.

Blume, L., D. Easley, J. Kleinberg, R. Kleinberg, and E. Tardos. 2011. Network formation in the presence of contagious risk. Discussion paper, Proceedings of the 12th ACM Conference on Electronic Commerce.

Chari, V. V., and R. Jagannathan. 1988. Banking Panics, Information and Rational Expectations. *Journal of Finance*, 43:749–61.

Chen, Y.. 1999. Banking Panics: The Role of the First-Come, First-Served Rule and Information Externalities. *Journal of Political Economy*, 107:946 – 968.

Cont, R., A. Moussa, and E. D. Santos. 2013. *Network structure and systemic risk in banking systems* . pp. 327–368, Cambridge University Press, Cambridge, UK.

Degryse, H., and G. Nguyen. 2007. Interbank Exposures: An Empirical Examination of Contagion Risk in the Belgian Banking System. *International Journal of Central Banking.*

Diamond, D. W., and P. H. Dybvig. 1983. Bank Runs, Deposit Insurance and Liquidity. *Journal of Political Economy*, 91:401 – 419.

Farhi, E., and J. Tirole. 2012. Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts. *American Economic Review*, 102:60–93.

Forbes, K. J., and R. Rigobon. 2002. No contagion, only interdependence: measuing stock market comovements. *Journal of Finance*, 57:2223–2261.

Freixas, X., B. Parigi, and J.-C. Rochet. 2000. Systemic Risk, Interbank Relations and Liquidity Provision by the Central Bank. *Journal of Money, Credit, and Banking*, 32:611 – 638.

Gai, P., A. Haldane, and S. Kapadia. 2011. Complexity, concentration and contagion. *Journal of Monetary Economics*, 58:453–470.

Gropp, R., M. Lo Duca, and J. Vesala. 2009. Cross-Border Bank Contagion in Europe. *International Journal of Central Banking, International Journal of Central Banking*, 5:97–139.

Haldane, A. G., and R. May. 2011. Systemic risk in banking ecosystems. *Nature*, 469:351–355.

Hartmann, P., S. Straetmans, and C. de Vries. 2005. Banking System Stability: A Cross-Atlantic Perspective. Working Paper 11698, National Bureau of Economic Research, Cambridge, Mass.

Heider, F., M. Hoerova, and C. Holthausen. 2015. Liquidity hoarding and interbank market spreads: The role of counterparty risk. *Journal of Financial Economics*, 118:336–354.

Hilscher, J., J. M. Pollet, and M. Wilson. 2015. Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets. *Journal of Financial and Quantitative Analysis*, 50:543–567.

IMF. 2013. India: Financial Sector Assessment Program—Detailed Assessments Report on Basel Core Principles for Effective Banking Supervision. Country Report 13/267, International Monetary Fund, Washington, DC.

Iyer, R., and J.-L. Peydro. 2011. Interbank contagion at work: Evidence from a natural experiment. *Review of Financial Studies*, 24:1337–1377.

May, R. M., S. A. Levin, and G. Sugihara. 2008. Ecology for bankers. *Nature*, 451:893–895.

Mistrulli, P. E.. 2007. Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. Working Paper 641, Bank of Italy, Rome, Italy.

Morrison, A. D., and A. Walther. 2015. Soft budget constraints and systemic risk. Mimeo, Saïd Business School, University of Oxford.

Morrison, A. D., and L. White. 2013. Reputational Contagion and Optimal Regulatory Forebearance. *Journal of Financial Economics*, 110:642–658.

Ota, T.. 2013. Marginal contagion: A new approachto systemic credit risk. Wroking paper, Bank of England, London, UK.

Rochet, J.-C., and J. Tirole. 1996. Interbank Lending and Systemic Risk. *Journal of Money, Credit and Banking*, 28:733–762.

Wagner, W.. 2010. Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation*, 19:373–386.

Table 1.
Summary statistics for daily bank CDS positions.

We report log equity returns and CDS returns in bps for a sample of 41 UK banks between 2009 and 2013, inclusive. For each bank and all of its counterparties (about 800 in the sample, including banks, hedge funds, and asset managers), we observe outstanding CDS contracts from the DTCC. We obtain average CDS price quotes from Markit. CDS profits and losses are calculated as price change multiplied by number of contracts written per reference entity, multiplied by the notional exposure of each contract (usually €10 mn). Net positions are gross long positions minus gross short positions, aggregated across every reference entity for which we have data (mainly UK-listed reference entities). FVIX is the FTSE 100 implied volatility index. *Net sold* is total exposure-weighted bank CDS profit from counterparties that are net protection buyers from the bank. *Net bought* (not reported) is the difference between net exposure-weighted profit and net sold.

	Mean	**Std. Dev.**
Log of bank equity returns (bps)	0.60	245.85
Change in log of bank CDS spread (bps)	−4.56	321.44
Spread CDS changes (bps)	−0.037	11.65
Bank own net CDS profits (€ millions)	−0.03	23.80
Net exposure-weighted counterparty CDS profits (€ millions)	1,690.42	60,904.22
Net sold exposure-weighted counterparty CDS profits (€ millions)	−839.75	28,973.89
Total net CDS exposure (€ millions)	19.72	1,153.97
Total net sold CDS exposure(€ millions)	839.74	1,221.91
Other bank CDS profits (€ millions)	−2.79	49.67
MSCI Developed Markets Index log return (bps)	4.16	108.24
S&P 500 log returns (bps)	5.02	119.88
FTSE 100 log returns (bps)	3.21	111.79
VIX level	21.88	8.34
Changes in log VIX (bps)	−11.49	676.50
FVIX level	20.78	7.36
Change in log FVIX (bps)	−14.97	640.82
Average CDS spread (bps)	181.67	87.51
Change in average log CDS spread (bps)	−12.91	162.17

Table 2.
Impact of exposure-weighted counterparty CDS losses on bank CDS spreads

The dependent variable is the daily change in log (gross) CDS spread for a bank in our sample. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 43,854 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	-0.381	-0.224	-0.225	-0.000733	0.000313	-0.307	-0.955
	[1.011]	[0.459]	[0.465]	[0.469]	[0.475]	[0.758]	[0.718]
Exposure-wted c/party CDS profits	**-0.00137*****	**-0.000419****	**-0.000433****	**-0.000437****	**-0.000450****	**-0.000946*****	**-0.000865*****
	[0.000416]	**[0.000191]**	**[0.000192]**	**[0.000196]**	**[0.000198]**	**[0.000313]**	**[0.000294]**
Total CDS exposure				-0.00254	-0.00256		-0.00284
				[0.00205]	[0.00204]		[0.00250]
All other bank CDS profits				0.239**	0.241**		-0.683***
				[0.0995]	[0.0998]		[0.137]
MSCI Devd. Mkts. Index log return		-0.564***		-0.559***		-1.142***	
		[0.0691]		[0.0687]		[0.107]	
SP 500 log returns			-0.210***		-0.209***		-0.141**
			[0.0585]		[0.0583]		[0.0653]
FTSE 100 log returns			-0.215***		-0.216***		-0.895***
			[0.0328]		[0.0327]		[0.0855]
VIX levels						0.859	-2.910***
						[0.559]	[0.692]
VIX changes (%)		-0.00810	-0.00628*	-0.00663	-0.00478		
		[0.00538]	[0.00331]	[0.00561]	[0.00345]		
FVIX levels							6.992***
							[0.784]
FVIX changes (%)			0.0263***		0.0256***		
			[0.00316]		[0.00303]		
Average CDS Spread						0.0652	-0.147***
						[0.0522]	[0.0510]
Average CDS Spread changes (%)		0.861***	0.877***	0.887***	0.903***		
		[0.0863]	[0.0852]	[0.0847]	[0.0836]		
Adjusted R2 (%)	0.072	0.339	0.338	0.340	0.339	0.216	0.219

Table 3.

Impact of exposure-weighted bought versus sold bank counterparty CDS losses on bank CDS spreads

The dependent variable is the daily change in log (gross) CDS spread for a bank in our sample. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 43,854 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	-0.637	-0.263	-0.265	-0.0642	-0.0640	-0.483	-0.990
	[1.191]	[0.522]	[0.529]	[0.511]	[0.518]	[0.881]	[0.823]
Exposure-wted c/party CDS profits (net bought)	**-0.00181****	**-0.000485***	**-0.000500***	**-0.000582***	**-0.000598***	**-0.00124****	**-0.000945***
	[0.000669]	**[0.000279]**	**[0.000284]**	**[0.000300]**	**[0.000305]**	**[0.000480]**	**[0.000484]**
Exposure-wted c/party CDS profits (net sold)	**0.000781**	**0.000330**	**0.000343**	**0.000248**	**0.000260**	**0.000541**	**0.000763**
	[0.00121]	**[0.000497]**	**[0.000500]**	**[0.000510]**	**[0.000513]**	**[0.000889]**	**[0.000869]**
Total CDS exposure (net bought)				-0.000167	-0.0000704		0.000334
				[0.00343]	[0.00348]		[0.00381]
Total CDS exposure (net sold)				0.00426	0.00438		0.00551*
				[0.00360]	[0.00353]		[0.00310]
All other bank CDS profits				0.260**	0.263**		-0.671***
				[0.109]	[0.110]		[0.144]
MSCI Developed Markets Index log return		-0.565***		-0.559***		-1.140***	
		[0.0691]		[0.0689]		[0.107]	
SP 500 log returns			-0.210***		-0.209***		-0.141**
			[0.0585]		[0.0583]		[0.0654]
FTSE 100 log returns			-0.215***		-0.215***		-0.895***
			[0.0328]		[0.0327]		[0.0856]
VIX levels						0.843	-2.867***
						[0.555]	[0.696]
VIX changes (%)		-0.00815	-0.00633*	-0.00658	-0.00473		
		[0.00540]	[0.00334]	[0.00561]	[0.00344]		
FVIX levels							6.960***
							[0.786]
FVIX changes (%)			0.0264***		0.0257***		
			[0.00317]		[0.00303]		
Average CDS Spread						0.0640	-0.150***
						[0.0520]	[0.0512]
Average CDS Spread changes (%)		0.860***	0.876***	0.888***	0.904***		
		[0.0863]	[0.0852]	[0.0845]	[0.0835]		
Adjusted R2 (%)	0.073	0.339	0.338	0.340	0.339	0.217	0.219

Table 4.

Impact of exposure-weighted bank counterparty CDS losses on bank equity log returns.

The dependent variable is the daily change in log equity price for a bank in our sample. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 49,569 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	0.244	0.118	0.121	-0.0142	-0.0281	0.143	0.250
	[0.514]	[0.228]	[0.234]	[0.220]	[0.226]	[0.273]	[0.277]
Exposure-wted /party CDS profits	**0.000502****	**-0.0000387**	**-0.0000217**	**-0.0000263**	**-0.00000802**	**0.0000692**	**0.0000965**
	[0.000229]	**[0.0000916]**	**[0.0000945]**	**[0.0000948]**	**[0.0000980]**	**[0.000115]**	**[0.000122]**
Total CDS exposure				0.00142	0.00141		0.00143
				[0.00148]	[0.00145]		[0.00162]
All other bank CDS profits				-0.143***	-0.161***		0.105**
				[0.0356]	[0.0353]		[0.0488]
MSCI Developed Markets Index log return		1.147***		1.142***		1.240***	
		[0.0620]		[0.0619]		[0.0710]	
SP 500 log returns			0.577***		0.575***		0.520***
			[0.0728]		[0.0727]		[0.0783]
FTSE 100 log returns			0.491***		0.491***		0.713***
			[0.0784]		[0.0782]		[0.0915]
VIX levels						0.486	4.100***
						[0.330]	[0.675]
VIX changes (%)		0.0128*	0.0175***	0.0116*	0.0161***		
		[0.00679]	[0.00271]	[0.00682]	[0.00281]		
FVIX levels							-5.765***
							[0.660]
FVIX changes (%)			-0.0164***		-0.0155***		
			[0.00316]		[0.00311]		
Average CDS Spread						0.0322	0.153***
						[0.0263]	[0.0313]
Average CDS Spread changes (%)		-0.182***	-0.240***	-0.199***	-0.260***		
		[0.0340]	[0.0282]	[0.0338]	[0.0276]		
Adjusted R2 (%)	0.018	0.305	0.304	0.305	0.304	0.295	0.288

Table 5.

Impact of exposure-weighted bank counterparty CDS losses on small bank equity log returns.

The dependent variable is the daily change in log equity price for banks other than the ten largest in our sample. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 49,569 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	0.533*	0.277**	0.292**	0.149	0.149	0.326**	0.444**
	[0.291]	[0.124]	[0.126]	[0.131]	[0.133]	[0.142]	[0.163]
Exposure-wted /party CDS profits	**0.00226*** **	**0.000433**	**0.000474**	**0.000470**	**0.000514**	**0.000862** **	**0.000900** **
	[0.000496]	**[0.000347]**	**[0.000339]**	**[0.000332]**	**[0.000322]**	**[0.000314]**	**[0.000334]**
Total CDS exposure				0.00375**	0.00379**		0.00395**
				[0.00145]	[0.00142]		[0.00150]
All other bank CDS profits				-0.143***	-0.158***		0.102
				[0.0416]	[0.0412]		[0.0606]
MSCI Developed Markets Index log return		1.075***		1.070***		1.131***	
		[0.0725]		[0.0725]		[0.0817]	
SP 500 log returns			0.476***		0.474***		0.402***
			[0.0660]		[0.0659]		[0.0684]
FTSE 100 log returns			0.501***		0.501***		0.718***
			[0.0846]		[0.0844]		[0.0962]
VIX levels						0.656	3.998***
						[0.430]	[0.854]
VIX changes (%)		0.0225***	0.0209***	0.0213***	0.0195***		
		[0.00604]	[0.00295]	[0.00610]	[0.00303]		
FVIX levels							-5.604***
							[0.807]
FVIX changes (%)			-0.0156***		-0.0148***		
			[0.00399]		[0.00392]		
Average CDS Spread						-0.00492	0.127***
						[0.0316]	[0.0361]
Average CDS Spread changes (%)		-0.186***	-0.235***	-0.204***	-0.254***		
		[0.0399]	[0.0356]	[0.0390]	[0.0345]		
Adjusted R2 (%)							

Table 6.
Impact of exposure-weighted counterparty CDS losses on small bank CDS spreads

The dependent variable is the daily change in log (gross) CDS spread for banks other than the ten largest in our sample. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 43,854 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	-1.129	-0.854*	-0.859*	-0.704	-0.712	-1.019*	-1.647***
	[0.670]	[0.422]	[0.422]	[0.439]	[0.439]	[0.544]	[0.541]
Exposure-wted /party CDS profits	**-0.00468*****	**-0.00167****	**-0.00171****	**-0.00170****	**-0.00174****	**-0.00343*****	**-0.00312*****
	[0.00116]	**[0.000756]**	**[0.000755]**	**[0.000754]**	**[0.000754]**	**[0.000938]**	**[0.000904]**
Total CDS exposure				-0.00797***	-0.00808***		-0.00889***
				[0.00275]	[0.00277]		[0.00283]
All other bank CDS profits				0.177	0.175		-0.685***
				[0.117]	[0.117]		[0.141]
MSCI Developed Markets Index log return		-0.401***		-0.397***		-0.908***	
		[0.0624]		[0.0622]		[0.119]	
SP 500 log returns			-0.0858**		-0.0847**		-0.00980
			[0.0403]		[0.0404]		[0.0366]
FTSE 100 log returns			-0.164***		-0.164***		-0.788***
			[0.0396]		[0.0394]		[0.101]
VIX levels						0.908	-3.399***
						[0.789]	[0.887]
VIX changes (%)		-0.0166***	-0.0101***	-0.0155***	-0.00892***		
		[0.00321]	[0.00307]	[0.00331]	[0.00310]		
FVIX levels							7.456***
							[0.967]
FVIX changes (%)			0.0249***		0.0243***		
			[0.00415]		[0.00392]		
Average CDS Spread						0.0671	-0.135*
						[0.0778]	[0.0762]
Average CDS Spread changes (%)		0.793***	0.798***	0.814***	0.818***		
		[0.0986]	[0.0983]	[0.0993]	[0.0986]		
Adjusted R2 (%)	0.071	0.295	0.294	0.296	0.295	0.175	0.185

Table 7.

Impact of lagged exposure-weighted counterparty CDS losses on bank CDS spreads

The dependent variable is the daily change in log (gross) CDS spread for a bank in our sample. All dependent variables are lagged by one period. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 43,854 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	-0.0315	0.0109	0.0147	0.0607	0.0817	0.0106	-0.0105
	[0.136]	[0.0579]	[0.0574]	[0.0651]	[0.0650]	[0.0574]	[0.0673]
Exposure-wted c/party CDS profits	**-0.0000871***	**0.000119****	**0.000117****	**0.000114****	**0.000111****	**0.000130****	**0.0000720***
	[0.0000488]	**[0.0000354]**	**[0.0000346]**	**[0.0000345]**	**[0.0000335]**	**[0.0000353]**	**[0.0000277]**
Total CDS exposure				-0.00142	-0.00148		-0.00144
				[0.00185]	[0.00192]		[0.00184]
All other bank CDS profits				0.0562*	0.0749**		-0.0147
				[0.0327]	[0.0325]		[0.0291]
MSCI Devd. Mkts. Index log return		-0.458***		-0.456***		-0.562***	
		[0.0414]		[0.0415]		[0.0486]	
SP 500 log returns			-0.628***		-0.626***		-0.578***
			[0.0513]		[0.0514]		[0.0504]
FTSE 100 log returns			0.0571***		0.0562***		0.011
			[0.0153]		[0.0153]		[0.0166]
VIX levels						0.583	0.638
						[0.386]	[0.731]
VIX changes (%)		0.0249***	-0.00878***	0.0254***	-0.00804***		
		[0.00358]	[0.00294]	[0.00353]	[0.00294]		
FVIX levels							-0.664
							[0.965]
FVIX changes (%)			-0.00578**		-0.00633**		
			[0.00249]		[0.00246]		
Average CDS Spread						-0.0643*	-0.0229
						[0.0361]	[0.0383]
Average CDS Spread changes (%)		-0.00107	0.0830***	0.00597	0.0923***		
		[0.0166]	[0.0164]	[0.0183]	[0.0179]		
Adjusted R2 (%)	0.004	0.041	0.051	0.041	0.051	0.039	0.049

Table 8.

Impact of exposure-weighted single counterparty CDS losses on bank CDS spreads

The dependent variable is the daily change in log (gross) CDS spread for a bank in our sample. All dependent variables are lagged by one period. Standard errors, clustered by bank, are in brackets beneath coefficient estimates. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively. All regressions include bank and year fixed effects. Financial firms are excluded from the CDS reference entities used to calculate CDS gains and losses. Other variables are defined in Table 1 and Section 2.2. Sample period is from 2009 to 2013, inclusive, giving a panel of 43,854 bank-days.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CDS profits	-0.381	-0.224	-0.225	-0.00297	-0.00182	-0.307	-0.957
	[1.011]	[0.459]	[0.464]	[0.469]	[0.474]	[0.758]	[0.718]
Exposure-wted c/party CDS profits	-0.00137***	-0.000417**	-0.000431**	-0.000435**	-0.000449**	-0.000946***	-0.000864***
	[0.000416]	[0.000190]	[0.000192]	[0.000196]	[0.000198]	[0.000313]	[0.000294]
Single counterparty	10.48	10.53	10.36	10.16	10	20.33	16.83
	[13.13]	[18.86]	[18.30]	[19.15]	[18.60]	[15.66]	[15.39]
Single counterparty * c/party CDS profits	**0.134*****	**-0.312*****	**-0.302*****	**-0.302*****	**-0.291*****	**-0.0954*****	**-0.115*****
	[0.0294]	**[0.0531]**	**[0.0512]**	**[0.0527]**	**[0.0508]**	**[0.0270]**	**[0.0319]**
Total CDS exposure				-0.00254	-0.00256		-0.00284
				[0.00205]	[0.00204]		[0.00250]
All other bank CDS profits				0.236**	0.239**		-0.684***
				[0.0995]	[0.0998]		[0.137]
MSCI Devd. Mkts. Index log return		-0.565***		-0.560***		-1.143***	
		[0.0691]		[0.0687]		[0.107]	
SP 500 log returns			-0.211***		-0.209***		-0.141**
			[0.0586]		[0.0584]		[0.0653]
FTSE 100 log returns			-0.215***		-0.216***		-0.895***
			[0.0328]		[0.0327]		[0.0855]
VIX levels						0.856	-2.905***
						[0.560]	[0.690]
VIX changes (%)		-0.00811	-0.00629*	-0.00666	-0.0048		
		[0.00538]	[0.00332]	[0.00561]	[0.00345]		
FVIX levels							6.984***
							[0.784]
FVIX changes (%)			0.0263***		0.0256***		
			[0.00316]		[0.00303]		
Average CDS Spread						0.0669	-0.145***
						[0.0525]	[0.0512]
Average CDS Spread changes (%)		0.862***	0.878***	0.888***	0.905***		
		[0.0860]	[0.0849]	[0.0845]	[0.0834]		
Adjusted R2 (%)	0.072	0.339	0.338	0.34	0.339	0.216	0.219