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Abstract

We investigate the information flow from credit default swap (CDS) spreads to macroeconomic activity using combined financial data from a new set of twelve European countries in addition to the United States. We show that single-name CDS contracts across maturities and sectors provide significant information that anticipates future contractions. The more heavily traded 5-year maturity contracts and the Markit iTraxx Europe/Markit CDX North American CDS indexes show stronger results, indicating that these forward-looking and highly liquid instruments confer an economically *and* statistically significant financial signal for future economic activity. Focusing only on the most liquid CDS contracts, we find that better liquidity strengthens the information flow from the CDS market mainly through selling of protection, and this flow intensifies as we approach credit events, which provide a useful signal in themselves of future economic downturns. Finally, we decompose the CDS premium into a liquidity and a residual component (proxying credit and other market risks), and find that liquidity plays a major role in explaining the rise in the CDS spreads with detrimental impact on future macroeconomic activity over the sample period.

JEL: E32, E44, G12
Keywords: credit default swaps, liquidity, credit risk, economic activity

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1. **Introduction**

A large number of studies have explored how important innovations in the equity, fixed income and credit markets provide information that can potentially improve the efficiency of other financial markets. Kwan (1996), Alexander *et al.* (2000), Hotchkiss and Ronen (2002), Maxwell and Stephens (2003), Gebhardt *et al.* (2005), Downing *et al.* (2009) and Ronen and Zhou (2013) consider feedback between stock returns and bond yields. More recently Hull *et al.* (2004), Blanco *et al.* (2005) and Das *et al.* (2014) have focused on information flows between CDS and bond markets, while Forte and Pena (2009) consider markets for stocks, bonds and CDS. The focus of these important studies shows information flows from one market to another with stocks and CDS price movements generally preceding bond price movements. While this analysis has been confined entirely to the financial markets, it is now widely accepted that movements in credit spreads also contain important signals on the state and future outlook of the macroeconomy. Gilchrist, Yankov, and Zakrajšek (2009), Gilchrist and Zakrajšek (2012) and Faust *et al*. (2013) use US corporate bond data to show a bond spread index (as a measure of credit risk) is a good predictor of future real activity up to two years ahead. Further work by Bleaney *et al.* (2016) confirms these results for a panel of eight European countries.

A common feature of many studies that utilize bond level data is that they obtain the credit spreads indirectly by estimating the yield to maturity of corporate bonds. The most recent approach by Gilchrist and Zakrajšek (2012) takes the difference between the estimated corporate yield and the riskless yield to produce the credit spread. The methods of Gilchrist and Zakrajšek (2012) are pioneering and informative, but they rely on estimates of the yield to maturity of the corporate bond and a constructed hypothetical risk-free rate, and the construction method is labour intensive. If studies of information flow mentioned above reveal that CDS markets are typically more efficient than bond markets, a simpler and less-model dependent signal of credit risk would involve use of CDS prices.

Recent research by Das *et al.* (2014) argues that more actively traded CDS contracts in markets dominated by institutional investors are a more convenient location for the trading of credit risk compared to the bond market. Their research documents the effects of a demographic shift in trading away from bonds and into CDS over time, reducing the relative efficiency and liquidity of bond markets versus CDS markets. CDS lead bonds in the price discovery process according to Blanco *et al.* (2005), who provided one of the earliest studies of the efficiency of the CDS market. Acharya and Johnson (2007) and Qiu and Yu (2012) explore US data after the CDS market was fully established and they find that the information flow from dealers with superior information is considerable, and increases with the number of relationships brokers have with the reference entities. Chen *et al.* (2011) and Benos *et al.* (2013) indicate that dealers in CDS provide the market with liquidity, which is not constrained even in crisis periods. Even where trading volumes in CDS are relatively low compared to securities markets, CDS remain relatively liquid.[2]

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[2] CDS have other advantages over bond spreads. As Longstaff *et al.* (2005) has indicated, CDS spreads offer a pure measure of default risk. Bonds include many other risks, such as liquidity and prepayment risks, which can be taken into account, but this is a labour intensive process, and may be somewhat imperfect. Blanco *et al.* (2005)

Our contribution is to explore the information flow from the widely traded CDS contracts for financial and non-financial firms to the real economy, as an indicator of incipient recession. Our focus is on firms issuing CDS contracts in the United States and twelve European countries including Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and the UK. The data are available from January 2001 on Bloomberg. US CDS are traded in dollars, while the dominant currency of traded volumes traded in CDS in Europe is the euro, covering over 90% of the CDS volumes issued according to Chen *et al.* (2011) and Benos *et al.* (2013). We employ a little used panel data methodology based on mean group estimation (MGE) due to Pesaran and Smith (1995) to evaluate the relationship between information from credit derivatives and real activity.

In this paper we focus on several hypotheses. The first hypothesis is that all CDS markets provide significant information flow useful for anticipating future macroeconomic activity. This hypothesis builds on the literature on information flow in financial markets (c.f. Hull *et al.,* 2004; Blanco *et al.*, 2005; Das *et al.*, 2014; and Forte and Pena, 2009) and the finding that bond spreads help predict recessions (c.f. Gilchrist, Yankov, and Zakrajšek, 2009; Gilchrist and Zakrajšek, 2012; Faust *et al*., 2013; and Bleaney *et al*. 2016). We test our hypothesis using country-level average spreads from all single name CDS at all maturities to explain real GDP growth, employment growth and investment growth four quarters ahead, and find a significant negative relationship that supports our hypothesis. We then explore the quality of the signal from this source, by testing two sub-hypotheses: that more highly traded CDS at the 5 year maturity offer a stronger signal than less highly traded CDS at other maturities, and that the even more highly traded readily available indexes contain a stronger signal. Using country-level average spreads from 5-year maturity single name CDS as an alternative to the signal from CDS at all other maturities to predict real activity, we find the relationship (based on coefficient magnitude and significance) is stronger for highly traded 5-year maturity CDS than less traded maturities. We then explore the role of highly traded indexes, as they dominate the multiple name contracts, as potentially they may also signal global shocks. The correlation between the Markit iTraxx Europe and the Markit CDX North American investment grade CDS indexes is very high (correlation coefficient=0.87), therefore while they pick up signals from their respective CDS markets, there also appears to be a global factor present. We find supporting evidence that these CDS indexes predict real activity. Lastly, to confirm that our results are not influenced by the inclusion of the nascent CDS market, we omit data from before 2004 when CDS markets were in a development phase, and explore the predictions from CDS spreads taken from the mature market. The results are not materially different to the full sample.

The second hypothesis is derived from the insights of Acharya and Johnson (2007) and Qiu and Yu (2012) that account for endogenous behavior associated with informed trading and

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document that in comparison to bond markets, CDS contracts offer better liquidity because secondary markets for bonds are influenced by buy-and-hold investors, while the CDS market is a forum for trading credit risk, particularly for participants with loan exposures or counterparty risk to hedge. Besides the synthetic nature of the CDS market, it does not suffer from short-sales constraints as the secondary bond market does. The ready availability of CDS spreads on financial data platforms makes them a convenient alternative to bond spreads.

information asymmetry in the CDS market. Endogenous liquidity, arising from the provision of CDS market liquidity by major banks, which also supply credit to private sector firms, could influence the behavior of CDS prices around the time of credit events as defined by Acharya and Johnson (2007) and Qiu and Yu (2012). These credit events could in turn provide a signal of deterioration in real activity, based on the exceptional variation in prices (and liquidity) that occurs at these times. Therefore, we test whether liquidity provision is related to informed trading to validate the results of Qiu and Yu (2012) for a wider range of countries and a longer sample period. We find that better liquidity provision tends to strengthen the information flow from the CDS market to the stock market. We then examine the effect of liquidity on CDS returns, since more liquidity may lower the CDS premium (a competitiveness effect) or raise it if there is more trading by informed dealers (an asymmetric information effect). In contrast to Qiu and Yu (2012), we find that the competitiveness effect dominates and becomes even more significant as the market liquidity declines. Furthermore, using an indicator based on the number of credit events as a signal of deteriorating credit conditions, we find consistent prediction of lower macroeconomic growth indicators.

Our final hypothesis is that liquidity risk plays an important part in explaining the general rise in CDS spreads and this has significant signalling value for future economic downturns. This separation into a liquidity and residual component is rooted in the *credit spread puzzle* literature (c.f. Elton, Gruber, Agrawal and Mann, 2001; Collin-Dufresne, Goldstein, and Martin, 2001; Huang and Huang, 2012). Acharya and Pedersen (2005) and more recently, Bongaerts, de Jong and Driessen (2011) show that by incorporating liquidity effects a considerable part of the expected return on bonds can be explained. Thus, the predicted component of the CDS premium is obtained by a nonlinear regression of the CDS premium on the bid-ask spread at contract level and daily frequency controlling for the Global Financial and Sovereign Debt crises. This allows us to separate the liquidity component and a residual element in the original CDS premium. We find that the liquidity component provides the strongest signal for future real activity compared to the residual, which implies the liquidity element around credit events is the key determinant of movements in the CDS and has a negative impact on economic activity four quarters ahead.

In summary, our paper has three novel implications. Firstly, CDS spreads provide clear signals of a deterioration in future real activity with a lead time of a year. Given that information typically flows from CDS prices to bond prices, we propose the CDS spread as a superior measure with many technical advantages, which also seems to capture a global risk factor anticipating recessions. Second, we find that better liquidity provision in CDS markets is linked to informed trading which becomes stronger around credit events that often precede recessions. We also show that endogenous liquidity mainly affects CDS prices through a competition effect, and that an indicator based on the occurrence of credit events provides a statistically significant signal of deteriorating future economic activity. Finally, by decomposing the CDS premium into a liquidity risk component based on the bid-ask spread, and a residual component which captures credit risk and other unpredicted factors such as global systemic risk or market volatility, we find evidence that the liquidity component has significant explanatory power for future macroeconomic outcomes.

The paper is organized as follows. Section 2 reviews the recent literature. We then explain our data in section 3 and Sections 4-6 provides our main results. We draw our findings together in a conclusion in Section 7.

2. **Related Literature**

The CDS market has been investigated for more than a decade as an over-the-counter market for trading credit risk (Blanco *et al.* 2005; Duffie, 2008; Stulz, 2010). Although CDS represents only 2.8% of the OTCD market, the sheer notional amount of all contracts outstanding is comparable to the annual GDP of the US and Euro area combined. CDS contracts are fairly evenly divided between bought and sold protection of $12,227bn (bought) and $11,889bn (sold). Approximately $9,041bn is bought and sold in single name contracts, and $7,350bn bought and sold in multiple name contracts, of which $6,741bn were index contracts according to 2014 year-end data reported by Bank for International Settlements (2015). Half of the total number of contracts (47.1%) were written with reporting dealers, and most of the remainder were written with other financial institutions, of which the larger constituents were central counterparties (29.2% of the total) or banks and securities firms (8.2% of the total).

2.1 Information flow and CDS markets

The study of the transmission of information from bond prices and stock prices has a long history dating back before the inception of the CDS market. Studying the US financial markets, Kwan (1996) provided an assessment of the relative efficiency of bond and stock markets, with a study that showed firm-level information was transmitted to stock prices ahead of bond prices. However, when responding to news, Hotchkiss and Ronen (2002) indicate that bond prices respond as quickly as stock prices, which may reflect improvements in transparency in bond markets that occurred after the introduction of the fixed-income pricing system (FIPS) by the National Association of Securities Dealers in 1994. Longstaff *et al.* (2005) consider the lag-lead relationships between CDS spreads, bond spreads and stock returns in a VAR. They find the CDS and stock market lead the bond market, but it is not possible to identify the direction of the information flow between the stock and CDS markets. Norden and Weber (2009) consider the US and European markets using weekly data from 2000-2002 and find stock returns lead bond and CDS markets, while CDS dominate the bond market. Forte and Pena (2009) also conduct a study of the relative efficiency of bond, equity and CDS markets, finding that stock markets lead the other two more often than the other way around, and CDS lead bond markets. It seems to be the case that the rank ordering of efficiency matches the ordering of the number of trades that occur in each market. Ronen and Zhou (2013) found that the introduction of TRACE may have made the bond market a more attractive location for trading in credit risk, by further improving transparency and efficiency in the market. Downing *et al.* (2009) argue that stock markets are generally more efficient in transmitting information to prices than bond markets, and partly this reflects the complexity of many bonds and their illiquidity. However, Das *et al.* (2014) argue that more actively traded CDS contracts in markets dominated by institutional investors are a more convenient location for trading of credit risk than the bond market. They run relative efficiency tests and difference-in-difference tests for firms prior to and after the introduction of CDS trading to determine whether bond markets had efficient price responses to new information on the firm. Their research documents declining efficiency in bond markets and liquidity of bond markets after the introduction of CDS trading. This has led to a demographic shift in trading away from bonds and into CDS over time and a migration from bonds to CDS for the evaluation of the price of credit risk.

2.2 Real activity and credit default swaps

The literature linking measures of credit risk and real activity has a long pedigree beginning with Harvey (1988), Estrella and Hardouvelis (1991), Estrella and Mishkin (1998) and Hamilton and Kim (2002), who made use of the Commercial Paper-Treasury Bill spread (CP-Bill spread) and the difference in yields between corporate bonds with high quality ratings and low quality ratings (i.e. the Baa-Aaa spread). Gertler and Lown (1999), Mody and Taylor (2004) and King *et al.* (2007) used high yield spreads to predict real activity in the 1990s and 2000s suggesting that high-yield bonds have a relatively large component that is due to bond risks, and a smaller component that reflects prepayment or liquidity risk, and are therefore better indicators of credit risk than the Baa–Treasury spreads which are more exposed to prepayment risk. In their study, Gertler and Lown (1999) show that the US high-yield spread has explanatory power for GDP growth one quarter and four quarters ahead for a sample period between 1980Q1 and 1999Q1. Two further studies by Mody and Taylor (2004) and King *et al.* (2007) confirm this view.

The most recent research on the relationship between bond yields and real activity by Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajšek (2012) and Faust *et al*. (2013) uses US bond market data. The distinguishing feature of these papers is that they select individual bonds to create a credit spread index that is corrected for distortions from bonds with embedded options and low liquidity, by removing prepayment and liquidity risks, see Duca (1999).[3, 4] These selection criteria and careful choice of the maturity structure at business cycle frequencies improve on the approach of Gertler and Lown (1999), Mody and Taylor (2004) and King *et al.* (2007). Their findings are that bond spreads anticipate movements in real activity particularly during downturns over a sample from 1973 – 2010.

A similar approach is undertaken by Bleaney *et al*. (2016) using a panel of European data on 500 corporate bonds between January 1999-May 2011 for Austria, Belgium, France, Germany, Italy, Netherlands, and Spain – and from July 1994-May 2011 for the United Kingdom. Their findings correspond closely with those in the US, showing a negative relationship between bond spreads and changes in future real activity. A comparison of the relationship between bond

[3] Recognising that embedded options in callable bonds could substantially alter the information content of movements in corporate bond yields, these authors identify callable bonds and model the predictable part of the spreads separately for callable and non-callable bonds. This reduces the distortion due to prepayment risk.

[4] Dropping small corporate issues or issues with a remaining term-to-maturity of less than one year or more than 30 years that are likely to influence the spread through the high liquidity premia they lower the influence of liquidity risk. The illiquidity of the market for corporate bonds as institutional investors acquire a larger proportion of the outstanding bonds can require additional yields to compensate other investors, as evidenced by Longstaff *et al.* (2005).

spreads and economic activity in individual countries within the euro area and outside the euroarea reveals heterogeneous responses of macro outcomes to financial tightening.

Daula (2011) is the only paper that considers the relationship between CDS and real activity. The data are drawn from a sample for the United States from 1990 – 2008, although these contracts were only liquid from 2003. The study examines the impact of adding CDS spreads as an explanatory variable to an autoregressive forecasting equation for growth of industrial production and employment over a 3-month horizon. Results of the significance of the coefficients and their forecast performance are reported for each equation, estimated using OLS. The findings demonstrate CDS have predictive ability for real activity, but more so for employment than for industrial production. Daula (2011) also uses a quarterly index of CDS to compare the performance of a factor model based on 45 financial time series using the model of Hatzius *et al.* (2010) versus a model that also includes CDS spreads. The results indicate that CDS does not add significantly to the forecast performance of the Hatzius *et al.* (2010) model. Daula concludes that in a sufficiently rich data environment it is possible to extract the information contained in CDS spreads. Valuable as this information may be, there are important and interesting hypotheses that are untested, for example, whether CDS spreads – which are readily available and more easily utilized than data in a fully dynamic factor model – anticipate contractions in real activity for a wider range of countries. This is one of several questions that we will address in this paper.

2.3 Market liquidity and other signals

Acharya and Johnson (2007) and Qiu and Yu (2012) [hereafter AJ and QY, respectively] consider the information flow between CDS and stock markets during periods of intense trading activity. AJ analyse the incremental information provided from the CDS market by comparing the stock market impact of quoted CDS prices and bid-ask spreads, which they take to be a proxy for publicly available information. While their main interest is insider trading, their study reveals a great deal about the direction of information flow in financial markets, showing that CDS prices lead stock prices. They also show that the information flow from the CDS market to the stock market increases in periods when credit events occur, when CDS prices are elevated and when better informed traders are more active. This is consistent with the incentives for insiders to trade on information derived from the lending side of their business. Following a series of tests, they establish that information flow increases during these intense episodes.

A further analysis by QY considers endogenous liquidity provision by informed traders. They find that better liquidity provision strengthens the information flow from CDS to stock markets prior to significant credit events. These authors stress the "crucial role" played by banks in providing the CDS market with liquidity. A quote-driven CDS market has similarities with the limit order market. Their main contribution is to recognize that liquidity provision by banks is endogenous, and the decision to provide liquidity in the CDS market is a strategic step by traders that have access to superior information. This reflects the nature of trading in the CDS market where those seeking credit protection first obtain indicative quotes from dealers from a platform such as Bloomberg, and then seek a request-for-quote (RFQ) with one or more dealers that may either provide a legally binding quote intended to win the contract, or offer a non-competitive quote with a large bid-ask spread, or neglect to respond. The nature of the response is revealing, resulting in greater liquidity when there are more informed traders in the market. Empirically, the authors use data on CDS market in the United States over the sample 2001–2008 for 732 CDS obligors, and find that while firm characteristics such as size and investment grade matter, the number of quote providers rises with the number of banking relationships that obligors have (using methods introduced by Bharath, Dahiya, Saunders and Srinivasan, 2007), which implies that liquidity is positively associated with informed trading. They confirm this by showing that the information flow from the CDS market to the stock market is increasing in the number of CDS quote providers. They also find a generally positive correlation between CDS liquidity and transaction demand, but this relationship can turn negative close to credit events, suggesting some dealers neglect to respond to RFQs when they think other dealers may have better information on which to trade. Further investigating the effect of liquidity on CDS pricing, they find a generally negative relationship, but this can turn positive when there is greater information asymmetry in the market (i.e. the existing number of dealers is large).

Recent empirical evidence suggests that the effects of liquidity during the recent financial crisis actually dominated credit effects for a variety of risk spreads, such as inter-bank and sovereign rate spreads (Panyanukul, 2009; Schwartz, 2015); and corporate bond spreads (Xing, Zhang, and Zhou, 2007, Bao, Pan and Wang, 2011, Friewald et al. 2012, Lin, Wang, and Wu, 2012, Acharya, Amihud and Bharath, 2013) independent of credit quality, maturity and other characteristics. Although CDS spreads are considered to be a pure measure of credit risk, the existence of a potentially significant liquidity component has been suggested by Blanco, Brennan and Marsh (2005) who find higher average CDS spreads compared to the underlying corporate bond spreads. Tang and Yan (2008) look at different liquidity proxies and conclude that CDS spreads are significantly and positively related to their liquidity measures. Buhler and Trapp (2009) consider heterogeneous liquidity factors for the bond and CDS markets. Bongaerts, de Jong and Driessen (2011) develop an equilibrium asset pricing model for derivatives which is different given the zero net supply feature of the market and depends on investors' net non-traded risk exposure. They find strong evidence for an expected liquidity premium earned by the seller of credit protection. Arakelyan, et al. (2013) more recently propose that an illiquidity market-wide premium is also priced into CDS spreads and consider credit-quality sorted portfolios, suggesting that credit protection traders require not only an expected default compensation but also significant compensation against the negative aggregate illiquidity shocks generated in the CDS market. These papers lead us to consider a liquidity component priced in the CDS spread of individual entities in order to explore its economic impact and significance which can be gleaned prior to a sustained real economic downturn.

3. Data and Methodology

3.1 Data

We construct a dataset covering all constant-maturity CDS spreads for financial and non-financial firms in the United States and twelve EU countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and the UK between 2001Q2 and 2014Q3.

The data is extracted from Bloomberg at quarterly frequency to match the frequency of our real activity used to determine the signaling value of CDS data, and also at daily frequency to explore CDS liquidity provision on informed trading. This dataset contains 6,827 unique CDS contracts that have at least one quarterly spread available during the period of analysis, which map onto 1,014 unique underlying entities; we refer to this as the full sample dataset. The CDS contracts in our sample refer to senior debt with a maturity in the range 1Y to 10Y. We create seven CDS measures based on the following criteria: (a) single name CDS contracts for all industries and maturities; (b) financial and (c) non-financial firms of all maturities; (d) financial and (e) non-financial of 5-year maturity; (f) CDS contracts of 5-year maturity only and all industries; and (g) CDS contracts for all industries excluding 5-year maturity. To ensure that our results are not driven by a small number of extreme observations we eliminate all CDS/month observations with a CDS below 1 basis point and greater than 3,500 basis points. These data are used to compare the information signal from single-name CDS contracts for all types of issuing firms, contracts of varying maturity and for financial and non-financial firms. These data reflect the changes in credit views from the CDS market across a wide range of sectors including financial and non-financial firms in combination and separately.

Furthermore we make use of data from two heavily traded CDS indexes, the Markit iTraxx Europe and the Markit CDX North American investment grade indexes (see Figure 2). The Markit iTraxx Europe index comprises 125 equally weighted credit default swaps on investment grade European corporate firms across 4 sector categories: Financials (Senior & Subordinated), Non-Financials and HiVol. In order to examine the information embedded in CDS for the US market, we use the Markit CDX North American Index, which also comprises 125 equally weighted credit default swaps on investment grade corporations across 5 sector categories: High Volatility, Consumer, Financial, Industrial, and Technology, Media & Tele-communications.

The early period of our sample covers an episode when the CDS market was in a nascent phase, therefore following the approach used by Das *et al.* (2014), we remove the initial observations for years 2001-2004. This truncated sample removes the period when CDS contracts were thinly traded, and when updates to credit views of the issuers were slowly reflected in the price due to poor price discovery. We would expect this period to be different from the later period when price discovery and liquidity improved and spilled over to the bond market (see Blanco *et al.* 2005; Forte and Pena, 2009; Norden and Weber, 2009; and Das *et al.* 2014).

In our study of CDS spreads as predictors of future change in real activity, our explanatory variables are real GDP, employment and investment which are obtained from Eurostat at quarterly frequency. Further variables are constructed to act as controls including country-specific term spreads and real interest rates to capture monetary policy stance and the term premium used by Harvey (1988), Estrella and Hardouvelis (1991), Estrella and Mishkin (1998) and Hamilton and Kim (2002). The term spread is defined as the difference between the 10-year and the 3-month generic government bond yields, which are the country-specific benchmark bond yields of constant maturity available from Bloomberg. The real interest rate is defined as the difference between the official nominal interest rate available on Bloomberg and the inflation rate obtained from IMF's IFS database. We also use the OECD's country-specific composite leading indicators (CLI) utilized by Bleaney *et al.* (2016) to provide early signals of turning points (peaks and troughs) between expansions and slowdowns of economic activity.[5]

When we consider the effects of endogenous liquidity on the CDS premium we extract further data at daily frequency from Bloomberg on the bid-ask spread (constructed as $\frac{Ask\ price - Bid\ price}{Ask\ price}$ measuring liquidity in the CDS market), the stock trading volume, the S&P credit rating, the share price (used to calculate the daily stock return, the average stock return and the stock return volatility over the past 252 trading days), and the CDS spread (also used to calculate the CDS return).[6] We include these variables which are standard in the literature (AJ, 2007) to capture firm characteristics (such as size and credit risk of the reference entities) which may be correlated with both liquidity and informed trading. The bid and ask prices are the regional Bloomberg Generic end of the day prices taken at 5pm local time in each of the two regions (London and New York). These prices are collected and computed by a proprietary composite algorithm which identifies the level where quotes are most heavily concentrated excluding the highest and the lowest generating a final price only when there are five or more quote contributors.

3.2 Descriptive Statistics

Table 1 Panel A contains descriptive statistics for the seven separate CDS measures defined in the previous section, and the Markit iTraxx Europe and the Markit CDX North American indexes. These indexes have lower mean spreads and lower standard deviations compared to the single name CDS contracts which have spreads that are roughly double those of the indexes but at the cost of higher volatility, which is four or five times higher. The average financial CDS has a lower mean spread than the average non-financial CDS, but the comparatively larger standard deviations make these differences statistically insignificant.

Table 1 Panel B compares the correlations between CDS for all firms at all maturities, CDS for financial firms at all maturities, CDS for nonfinancial firms at all maturities and similar CDS 5 year maturities, and CDS of all other maturities. What is apparent is the high degree of correlation among these CDS measures with CDS All maturities having a correlation 0.8 or above with other CDS spreads. The correlation between 5-year financial and non-financial CDS is about 0.7. Considering the correlation between CDS All and the European index it is lower at around 0.6 and with and US index it is lower still at around 0.5. The two indexes themselves move closely together with a correlation coefficient of 0.87.

Table 1 Panel C reports the descriptive statistics on quarterly data for our dependent variables (real GDP, employment, investment) and control variables (term spread, real interest rate and the OECD CLI indicator). The real interest rate exhibits the highest variation with a mean of 0.03% and a standard deviation of 1.52%. The observed low and occasionally negative

[5] The series used in our analysis is the amplitude-adjusted monthly series transformed into a four-quarter difference, where the actual original series in levels is centred on 100.

[6] The 5-year CDS spread, stock price and the bid-ask spread data have been winsorised at the 1st and 99th percentiles.

real interest rates and term premia for the sampled countries are due to the recent period of monetary policy easing, low inflation and slow growth. The OECD CLI is an index value centred at 100 and is included in our regressions as the first difference between period t and $t-4$.

Table 1 Panel D contains descriptive statistics for the variables used in sections 5 and 6 at daily frequency (in these sections we focus only on CDS contracts of 5-year maturity as these are the most frequently traded in order to investigate issues arising from (endogenous) liquidity). We can note the average CDS contract in our sample has a mean premium of 1.61% and a bid-ask spread of 9.3%, while the average underlying entity's average stock price is 2.87% with an average stock trading volume of 8.9 million.

Table 1 Panel E compares the correlations among these variables at daily frequency. The most notable are the positive correlation of CDS premium with the S&P credit rating and the stock return volatility; and the negative correlation of the CDS premium with the average stock return, which suggests that increased credit risk and a deteriorating credit outlook for the reference entity (a higher CDS premium and more unfavourable credit rating) has a negative impact on the stock return and volatility.

3.2 Methodology

We wish to allow for cross-country heterogeneity in dynamic models of employment, investment, and real GDP growth containing lagged values of the dependent variable to allow for cyclical behaviour of these real activity variables. We do this using a dynamic panel method that has not been used in this context before.

Random effects (RE) or fixed effect (FE) models control for unobserved effects in dynamic panel data models through the removal of unobserved effects through differencing or demeaning. But the presence of the lagged dependent variable is problematic because it will be correlated with the error term. RE and FE models are asymptotically equivalent in terms of efficiency, but inconsistent even with large T when variables are endogenous. The problem can be mitigated using instrumental variables (IV) or generalised method of moments (GMM), but, while GMM is more efficient than IV, both methods tend to suffer from overfitting when T is large. However, consistent estimates can be obtained using the mean group estimator (MGE) due to Pesaran and Smith (1995), even with large T and that is how we estimate our models.

Taking our real activity measure and the set of explanatory variables including CDS spreads or liquidity measures described above, various controls for other macroeconomic developments or financial conditions affecting the obligor, we can write a dynamic panel model as a stacked set of 13 individual autoregressive distributed lag equations relating real activity to our explanatory variables. The reported coefficients are average coefficient values across the group (the mean-group estimates) therefore for each of the parameters of the equations specified in the sections below we report one coefficient (the mean group estimate (MGE)) from the stack of 13 country-level estimates obtained from the full information in our panel. Therefore while equations contain a subscript i on coefficients to be estimated (indicating the country, i=1,2,…,13) the reported results give averaged values of these coefficients in the tables.

4. Real activity and CDS spreads

To assess our first main question whether CDS have predictive ability over future real activity we consider whether the contemporaneous value of the CDS spread is a significant explanatory variable for the change in three real economic activity measures four quarters ahead. The dependent variable in this model is 4-quarter ahead (annualized) growth rate in one of three economic activity indicators: employment, investment or real GDP. [7] These variables have been chosen as indicators of *real* activity, to gauge the extent to which credit derivatives signal the future growth path for labour, capital and output.

Our initial specification is motivated by Faust *et al.* (2013):

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * CDS_{it} + \sum_{l=1}^{L} d_{il}\, X_{ilt} + e_{it+4}$$

[Equation 1.]

To control for information contained in past GDP, we allow for the 1-quarter lags of the growth in economic activity in line with Faust *et al.* (2013), up to a maximum lag, *K*, determined by the Akaike Information Criterion (AIC).[8] CDS_{it} denotes several individually defined measures of the CDS spread as a signal of the credit view in the CDS market. Finally, we add controls, X_{ilt} for the term spread, the real interest rate, and the OECD CLI. Equation (1) is estimated on a panel of thirteen countries over a sample from 2001Q2 to 2014Q3. a_i, b_{ik}, c_i and d_{il} are the coefficients to be estimated and e_{it+4} is the idiosyncratic error. These parameters are each estimated for every country and the reported results in the Appendix provide a mean group estimator as an average of the estimated parameters across countries.

4.1 Use of CDS single name contracts

Single name contracts are written for financial and non-financial entities, and also for multiple entities. In Table 2 Panel A, we report the relationship between the growth in real GDP, investment and employment at a 4-quarter horizon, using various measures of the CDS spread and other controls as per Equation 1 above. [9] The CDS variable is measured in three ways: as simple averages of single name CDS spreads for all firms at all maturities by country (CDS All); as the CDS spreads for the financial sector firms in each country (CDS Financial); and as the CDS spreads for the non-financial sector firms in each country (CDS Non-Financial). Since our aim is to use the information from thirteen countries to determine the extent to which real activity is

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[7] The annualised 4-quarter ahead growth rate in country *i* is defined as: $Growth_{it+4} = \frac{400}{5} \ln\left(\frac{Y_{it+h}}{Y_{it-1}}\right)$, where *Y* is the economic activity indicator (i.e. real GDP, investment and employment). The 1-quarter lags of GDP growth are defined as: $Quarterly\ Growth_{it-k} = 400 * \ln\left(\frac{Y_{it-k}}{Y_{it-k-1}}\right)$, where k=1,…K and h=0.

[8] Given that the dependent variable is constructed as a 4-quarter ahead growth rate, including previous lags of this same variable would lead to serial correlation due to overlapping observations.

[9] Our reported results concentrate on activity four quarters ahead, but our results are consistent with horizons of one quarter and eight quarters ahead. Results are available from the authors on request.

predicted by the CDS spread after controlling for other influences from monetary policy and leading indicators of activity, significance of the coefficient associated with the CDS spread gives an indication of the importance of the signal from transactions in the CDS market.[10] We expect the coefficient associated with this variable to be negative and significant, implying that an increase in credit risk perceived in the CDS markets reduces growth in real output, employment and investment activity of firms in Europe. A 100 bp increase in the CDS All spread lowers real GDP growth by 116 bp, employment growth by 40 bp and investment growth by 222 bp (columns 1-3). The result for CDS of financial firms in columns 4-6 shows the effect of a 100bp increase in the spread is greater for investment growth than for real GDP or employment growth. It is possible that all CDS spreads provide a signal for future real activity, but by observing the CDS spread of financial sector firms in isolation we allow for the possibility that these may have a stronger signalling role due to their role as financial intermediaries. Columns 7-9 report the results for the non-financial CDS. The magnitude of the non-financial spread coefficients is smaller compared to the financial CDS for all growth measures, while the financial CDS is greater than the CDS All spread for real GDP and investment measures. We conclude that the sign and significance of the coefficients associated with *CDS All*, *CDS Financial* and *CDS Non-financial* do not differ very much, making them all effective signals of rising perceived credit risk and deteriorating growth prospects.

These results underline that a deteriorating credit outlook (measured by the widening CDS spread) on growth (measured by employment, investment and real GDP growth) is consistently important, but not uniform. Investment growth is more strongly influenced by signals from credit derivatives than real output or employment growth, since at the margin investment projects may be postponed or cancelled if financial stresses emerge, not least because the cost of finance required to implement them may increase.

4.2 Use of highly traded 5-year CDS contracts

The 5-year maturity contracts are considered to be the most liquid and frequently traded, and notional sizes are largely standardized on \$5mn (€5mn) or \$10mn (€10mn) amounts. The CDS contracts of maturity up to one year comprise 18.4% of the total amounts outstanding of \$16,339bn in December 2014 according to Bank for International Settlements (2015), while contracts of maturity above one year and up to five years comprise 75.4%, and over five year maturity 6.2% of the total. The five year maturity clearly dominates the market. Since many single name CDS have few transactions, we test the hypothesis that highly traded CDS offer a clearer signal than less highly traded CDS over real activity. Thus, by comparing our results for the 5 year contracts versus all other contracts excluding 5-year maturities, we can test the hypothesis that predictive ability is related to the trading volume.

[10] If CDS are a pure measure of default risk, as the literature suggests, then following the logic of Bernanke *et al.* (1999), CDS spreads should be a good proxy for the excess finance premium on bonds or equities issued in the markets. CDS All is a direct measure of this premium for all types of firms that have CDS contracts written, while the financial CDS are direct measures of this premium for banks that may have an indirect effect on activity of the firms that use their services.

In Table 2 Panel B, we report results for financial and non-financial CDS contracts of 5-year maturity. We observe the coefficient values for estimates of equation 1 using 5-year financial CDS and non-financial CDS in Panel B, columns 4-6 and 7-9 respectively, and these are larger and more significant than the corresponding coefficients in Panel A, columns 4-6 and 7-9. Thus, highly traded CDS provide a stronger signal of lower future growth in real activity, as these spreads are determined in markets that are more liquid.

Table 2 Panel C columns 1-3 present the results for the CDS of 5-year maturity only (for all industries), while columns 4-6 present the results for the CDS of all other maturities, excluding the 5-year contracts (for all industries). We note that both measures provide a statistically significant signal of deteriorating future macroeconomic conditions, with the CDS excluding the 5-year maturities having a marginally smaller magnitude.

4.3 Use of CDS Indexes

Single name CDS contracts are not as heavily traded as investment grade European or North American indexes of CDS contracts, despite attempts by the industry to increase volumes (*Financial Times*, 5 June 2015). Trading frequencies of CDS contracts vary considerably. The top 50 traded corporate reference entities are traded on average 10 times a day, variations in trading frequencies tend to reflect changes in credit outlook for certain sectors or entities. CDS for the financial sector tend to be more actively traded than other sectors such as telecoms, commodities, consumer goods, consumer services and industrial goods, with financials representing almost 50% of trades. Trading in credit indexes for firms with similar characteristics is greater than for single-name CDS, but here too there is concentration in the top names, with on-the-run indices being more actively traded than off-the-run indices. This poses an interesting question: is the higher trading frequency connected to indexes useful to predict future movements in real activity? We calculate the CDS spread for the Markit iTraxx Europe and CDX North American investment grade indexes as a replacement for the single-name CDS spreads used in Panel A. The high correlation between the two indexes suggests that they both contain a global risk factor common to both geographical regions.

Our results in Table 2 Panel D show that the Markit iTraxx Europe index predicts real activity across the 13 countries in our sample. The significance is as strong as for the 5-year single-name CDS, but the magnitude of the coefficients in equations for real activity measures is much greater than for single name contracts. A 100bp increase in the Markit iTraxx Europe CDS spread results in a 368 bp fall in real GDP growth, a 679 bp reduction in investment growth, and a 142 bp reduction in employment growth. This is mostly due to a scaling issue with the indexes, since the same ordering of the degree of response to CDS spreads is observed with investment growth being most sensitive, followed by output and employment growth. The same result is observed when we substitute the Markit CDX North American investment grade index for the European index. The fact that both indexes predict a reduction in real activity growth four quarters ahead for the panel that includes both European and US CDS contracts illustrates that these indexes pick up global rather than regional shocks to credit risk.[11] This is one of the channels through which financial signals are transmitted across borders from financial markets to real activity.

The simplicity of the index as signal of future growth – which is the easiest CDS measure to collect and does not require aggregation – is a great advantage. The fact that the Markit CDX North American index predicts growth for all sampled countries including European countries only indicates that CDS spreads pick up a global risk shock that ripples out from the US to other regions.

4.4 Comparison of results excluding data from a nascent CDS market

We recognise that the early period of our sample covers an episode when the CDS market was in a nascent phase, therefore following the approach used by Das *et al.* (2014) we remove the initial observations for years 2001-2004. In this way we use a truncated sample that removes the period when CDS contracts were thinly traded, and when updates to credit views of the issuers were slowly reflected in the price due to poor price discovery. We expect the later period to show improved price discovery and liquidity (see Blanco *et al.* 2005; Forte and Pena, 2009; Norden and Weber, 2009; and Das *et al.* 2014). Table 3 reports the results using the same CDS spread indexes used in Table 2 but for a shorter sample from 2005Q1 – 2014Q3. When we observe the coefficient on the CDS spread we find the response to the *CDS All* spread is negative and significant, and the magnitudes of the responses are very similar and match the ordering in Table 2 Panel A. The same pattern of results is found for the 5 year CDS and the financial and non-financial CDS indexes (these are not reported to save space). We conclude that the qualitative results are unaffected by the choice of the sample period.

The results in this section support the first hypothesis that all CDS markets provide significant information flow useful for anticipating future macroeconomic activity. Moreover the more actively traded markets give a stronger signal than the less active ones. Since CDS spreads, and particularly the indexes, are easy to collect, and suffer from fewer drawbacks than bond spreads, the use of CDS indicators is an improvement on the financial market indicators used to date.

5. Credit events, market liquidity and predictive signals

The results in section 4 offer some encouraging signs that CDS markets anticipate recessions, but it is still essential to disentangle the liquidity and credit components of the CDS spread, to understand why spreads widened, and that is the focus of this section. During the global financial crisis many financial instruments experienced lack of liquidity in response to the unusual trading conditions. These shortages of liquidity around credit events have been the focus of independent studies, but they can also be informative about the relative importance of increases in credit risk and liquidity premia in driving CDS spreads upwards, which then have signalling value for future

[11] When we exclude the US from the panel, we continue to find evidence that the Markit CDX North American index is a significant predictor of economic activity for the 12 European countries, however the Markit iTraxx Europe index is not a significant predictor of US economic activity.

macroeconomic measures of real activity. In this section we disentangle the liquidity and credit components of the CDS spread to explore their individual impact.

QY and AJ have argued that trading in the CDS market is dominated by the major banks who offer direct or electronic trading (with the assistance of inter-dealer brokers) to their customers. These banks play a critical role in providing liquidity to the market, and therefore liquidity in the CDS market is akin to endogenous liquidity provision in a limit order market (see Kyle, 1985; Glosten and Milgrom, 1985; and Boulatov and George, 2013). Like AJ, QY show that information in the CDS market signals a fall in the stock price just *ahead* of a credit event. This is quite distinct from the liquidity shortage that tends to occur during a credit event. QY use a modified event indicator based on occasions when a change in the CDS price exceeds the average change by four standard deviations of the daily change in the CDS. Following a similar methodology, we investigate in Table 4 whether the information flow increases with better liquidity provision and intensifies prior to negative credit events. We then examine how liquidity affects the CDS premium in Table 5 and finally, use a credit events indicator to predict future real activity in Table 6.

5.1 Informed trading and CDS liquidity

The recent literature has suggested that informed trading plays an important role in liquidity provision in the CDS market which is dominated by large dealers who trade on their private information. We use the method proposed by AJ to measure informed trading in the European and US CDS markets by the lead-lag relationship between CDS markets and the stock market. More specifically, assuming that stock markets are efficient and all publicly available information is already incorporated in stock prices, any trading that occurs before major credit events materialize may be evidence that informed dealers are trading on their superior private information by purchasing credit protection or updating their quotes to reflect their information advantage. This assumption leads AJ to measure the amount of informed trading by the information flow from the CDS market to the stock market before credit events (AJ define a credit event as a daily increase in the CDS premium larger than 50 bps).

In this section we present new evidence on such information flow for a new set of European countries in addition to the US for an extended sample period and using both AJ's and QY's definitions of credit events.[12] First, we obtain a *CDS innovation* as information unique to the CDS market by removing the influence of contemporaneous and past shock in the stock market and past shocks in the CDS markets from the CDS return. [13] We then explore the lead-lag relationship between CDS and stock markets by lagging the CDS innovation by one day, and also in the period up to 30 days before each credit event. We focus only on CDS contracts of 5-year

[12] We consider three different event windows of 5, 30 and 90 days. For brevity, we present only results based on the 30-day window.

[13] The regression specification is: $(CDS\ return_{it}) = a_i + \sum_{k=0}^{5}\left(b_{it} + \frac{c_{it}}{CDS\ premium_{it}}\right)(Stock\ return_{i,t-k}) + \sum_{k=1}^{5} d_{ik} CDS\ return_{i,t-k} + u_{it}$.

maturity as these are deemed to be the most liquid, and use the bid-ask spread as a proxy for market liquidity.[14] The baseline specification is as follows:

$$\begin{aligned} Stock\ return_{it} \\ &= a_i + b_i * CDS\ innovation^{+}_{i,t-1} + \ c_i * CDS\ innovation^{-}_{i,t-1} \\ &+ \sum_{k=1}^{5} d_{ik} Stock\ return_{i,t-k} + e_{it} \end{aligned}$$

[Equation 2.]

The results are reported in Table 4 which investigates the effect of the CDS innovation in period *t-1* on today's stock return. We distinguish between the impact of both positive and negative CDS innovations as, in contrast to QY, we do not find significant evidence for the overall level of information flow.

Column (1) suggests that both positive and negative CDS innovations have a statistically significant impact on stock returns the following day. This implies that a positive CDS innovation reflecting deteriorating news in the CDS market leads to a negative response in the stock market in the following period (confirming for a new set of countries the results reported by QY on North American reference entities). Moreover, positive news in the CDS market (equivalent to negative CDS innovations) lead to a positive response in the stock market the following day (in contrast to results from QY who report no impact from negative innovations for North American reference entities). This suggests that informed trading takes place through buying *(and selling)* credit protection prior to deteriorating (*and improving)* news on CDS obligors.

In column (2), we condition the information flow from both positive and negative CDS innovations to the stock market on liquidity provision, as measured by the bid-ask spread. Without the credit events, the results are consistent with column (1), and, in addition, suggest that, better liquidity provision (associated with lower bid-ask spreads) tends to strengthen the information flow from the CDS market to the stock market only for negative CDS innovations only.

In column (3), we examine the effect of liquidity provision conditional on there being a credit event within the next 30 days by taking interactions with a credit conditions dummy. For both positive and negative CDS innovations we find that the information flow from the CDS market to the stock market is dominated by the response prior to a credit event (as indicated by the greater magnitude of the coefficients on the interaction between the CDS innovations and the credit condition dummy). Furthermore, we find evidence that the dependence of the

[14] Fleming (2003) finds that the realized bid-ask spread is a better measure of liquidity than the quote size, trade size, on-the-run/off-the-run spread, and other competing metrics. Arakelyan et al. (2013) also use cross-sectional average of the absolute bid-ask spreads as a proportional measure of liquidity that does not require rescaling. However, for robustness we checked our results using the number of CDS quote providers as a measure of liquidity in line with QY in equation (2) and found our results to be unchanged (available from the authors on request).

information flow on liquidity provision is stronger during the credit event window and statistically significant for negative CDS innovations.[15]

Finally, in column (4), we investigate whether our results are robust when we allow for the possibility that CDS liquidity may be driven by firm characteristics such as size and credit risk (there may be more quote providers for reference entities that are larger and/or considered more safe) using interactions between the CDS innovations and characteristics of the reference entities. Similar to QY, we find that only stock volatility has any effect, increasing the impact of negative innovations (good news events) when volatility is lower, while the remaining interactions have no effect.

Overall, we find strong evidence of information flowing from the CDS market to the stock market occurring through both positive and negative innovations in the CDS market. We also find that better liquidity provision tends to strengthen the information flow from the CDS market to the stock market mainly through negative CDS innovations, which is robust to the inclusion of firm-level characteristics.

5.2 CDS pricing and endogenous liquidity

We further investigate the effect of liquidity on the pricing of CDS contracts. Liquidity can influence the CDS premium either positively or negatively depending on two channels. Firstly, greater liquidity in the market means a greater number of dealers competing to provide CDS quotes which would result in a *lower* CDS premium through the "competitiveness" effect (more quote providers offering credit protection increases competition and lowers the price). Secondly, as we have shown that more informed trading implies greater liquidity around negative credit events, it follows that ahead of these events there will be more dealers in possession of private information who will buy credit protection, driving up the CDS premium. Thus, through this "asymmetric information" effect, higher liquidity in the market (or equivalently, a smaller bid-ask spread or a larger number of quote providers), would result in a *higher* CDS premium.

In line with QY, we estimate the effect of lagged changes in the bid-ask spread on the CDS return at daily frequency. We also control for lags of the CDS returns, stock returns and bid-ask spread changes, and also consider the interaction of each of these with the credit condition dummy to distinguish between the effects inside and outside the 30-day credit event period.

The regression specification is as follows[16]:

[15] Comparing b_1^-=-0.0075*** and b_2^-=-0.0006 versus $b_1^- + b_1^{d-}$=0.017*** and $b_2^- + b_2^{d-}$=-0.091*** for negative innovations; and comparing b_1^+=0.005 and b_2^+=-0.011 versus $b_1^+ + b_1^{d+}$=-0.015*** and =$b_2^+ + b_2^{d+} = 0.066$ for positive innovations.

[16] The low bid-ask spread dummy is also included but not reported in the regressions, since results do not change either quantitatively or qualitatively.

$$CDS\ return_{it} = a_{0i} + \sum_{k=1}^{5} a_{1ik} CDS\ return_{i,t-k} + \sum_{k=1}^{5} a_{2ik} Stock\ return_{i,t-k}$$
$$+ \left(a_{3i} + a_{4i} Bidask\ spread_{i,t-1}\right) \Delta Bidask\ spread_{i,t-1} + Credit\ condition\ dummy_{it} *$$
$$\left[b_{0i} + \sum_{k=1}^{5} b_{1k} CDS\ return_{i,t-k} + \sum_{k=1}^{5} b_{2ik} Stock\ return_{i,t-k} \right.$$
$$\left. + \left(b_{3i} + b_{4i} Bidask\ spread_{i,t-1}\right) \Delta Bidask\ spread_{i,t-1} \right] + e_{it}$$

[Equation 3.]

Our key variable of interest is $\Delta Bidask\ spread_{i,t-1}$ and we expect a positive coefficient if the competitiveness effect dominates, suggesting that a lower bid-ask spread (or higher liquidity provision) implies a smaller CDS premium; by the same token, we expect a negative coefficient if the asymmetric information effect dominates, suggesting that a lower bid-ask spread leads to a higher CDS premium. To mitigate endogeneity concerns we take the lag of the bid-ask spread change. [17]

Table 5 column 1 shows a positive relationship between the bid-ask spread and the CDS premium in line with the competitiveness effect (as indicated by the signs on the coefficients, a_3=0.00015** and $(a_3 + b_3)$=0.005**), which is statistically significant both outside and inside the credit event window.

In columns 2 and 3 of Table 5, we investigate whether this relationship becomes weaker (or indeed turns negative) when the existing liquidity provision is high (number of dealers is large, or bid-ask spread is low). In order to do this, we firstly interact $\Delta Bidask\ spread_{i,t-1}$ with the lagged bid-ask spread which captures the prevailing liquidity provision in the market (column 2); secondly, we interact the $\Delta Bidask\ spread_{i,t-1}$ with the low bid-ask spread dummy, which takes the value of 1 if the bid-ask spread is below the median value of the distribution and 0 otherwise (column 3). We examine this for both inside and outside the credit event windows.

If the market is already competitive we expect the marginal benefit from a higher degree of competitiveness to decrease with a lower bid-ask spread. Thus, with the competitiveness effect, the marginal reduction in the CDS premium decreases with further reductions in the bid-ask spread. Conversely, with the asymmetric information effect, when the prevailing market liquidity is high the probability that the marginal dealer is informed is also high and we observe marginal increases in the CDS premium increasing with further reductions in the bid-ask spread. The intuition is that high liquidity means that the dealers trading and entering the market are

[17] On the one hand, bonds with greater default risk will experience significant deterioration in liquidity (see Edwards, *et al.*, 2007, and Bao *et al.*, 2011). On the other hand, a deterioration in market liquidity, by affecting firms' refinancing operations negatively, can incentivise equity holders to default (see He and Xiong, 2012, and He and Milbradt, 2014).

doing so based on private information, which discourages other uninformed agents to enter driving up the cost of credit protection despite the market being highly liquid.

We can note in Table 5, column (2) that, *outside the 30-day pre event window*, the coefficients on a_3=-0.00013 and $(a_3 + a_4)$ =0.002** suggest that the competitiveness effect dominates and is significant only when conditioning on the pre-existing level of liquidity. *Within the pre-event window*, we find that the asymmetric information effect dominates as indicated by $(a_3 + b_3)$ =-0.0044* but when conditioning on the pre-existing level of liquidity the competitiveness effect is stronger as indicated by a greater magnitude and a positive sign on $(a_3 + b_3 + a_4 + b_4)$=0.0779***. Overall, we find that the competitiveness effect dominates both inside and outside the event window when conditioning on the existing level of liquidity.

Column (3) of Table 5 also suggests that *outside the pre event window* the coefficient on a_3=0.00025*** is positive and significant suggesting that the competitiveness effect dominates in line with column (1). When conditioning on high market liquidity, the coefficient on $(a_3 + a_5)$=-0.0001 is insignificant (it also becomes negative suggesting that the asymmetric information effect dominates). *Inside the pre event window*, the coefficient on $(a_3 + b_3)$=0.011*** is greater in magnitude compared to a_3 implying that inside the credit event window the competitiveness effect becomes stronger; while the coefficient on $(a_3 + b_3 + a_5 + b_5)$=-0.002 is not statistically significant.

Overall, our results document a robust negative relationship between liquidity and CDS pricing, suggesting that better liquidity leads to a lower CDS premium. In contrast to QY's results, we also find consistent evidence that the competitiveness effect dominates over the asymmetric information effect (both inside and outside the event window) and it becomes stronger when there is an increasing bid-ask spread (or low market liquidity).

5.3 Credit events as predictors of growth

Based on our daily CDS data from earlier sub-sections, we construct a measure of credit events defined in two ways: Firstly, as a dummy variable equal to 1 if there is a daily increase in the CDS premium greater than 50 bp as per AJ; and second, if the average plus four times the standard deviation of the CDS daily change, as per Berndt and Ostrovnaya (2014) and QY. The dummy equals 0 otherwise. We refer to the two measures as the AJ measure and the QY measure, respectively.

As shown in Figure 3, the QY measure yields a higher number of credit events, and according to both measures, the US has the highest number of credit events, followed by the UK. The peak number of credit events is registered in 2008Q4, after the Lehman collapse, followed by the next largest spikes in 2010Q2 and 2011Q3, after the sovereign debt crisis in Europe. These coincide with the spikes in both the single-name CDS index and the highly traded Markit CDX North American index.

The specification is the same as in section 5.5, where the CDS spread is now replaced by a credit event indicator taking the value of 1 if there is at least one credit event in a given country-quarter, and 0 otherwise:

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * Credit\ event\ indicator_{it} + \sum_{l=1}^{L} d_{il} X_{ilt} + e_{it+4}$$

[Equation 4.]

The results in Table 6 are estimated using MGE as before, and suggest that the occurrence of credit events in a given quarter has a statistically significant and negative impact on macroeconomic growth measured four quarters ahead. The magnitude of the coefficients follows the same order as previous estimates in Tables 2-4, with investment growth being the most responsive to an increase in the number of credit events, followed by output growth and then employment growth. Thus, the coefficients using either of the two measures of credit events are very similar and both predict a downturn in growth for all three activity indicators when credit events occur.

6. Liquidity or Credit Risk?

6.1 Decomposing the CDS premium

The 2007-2009 financial crisis was marked by an unusual increase in the price of risk and growing concerns over both credit and liquidity risk of underlying assets (see Dick-Nielsen, Feldhutter and Lando, 2012, and Bao, Pan and Wang, 2011, which show evidence of spikes during the financial crisis). On the one hand, a rise in CDS spreads represents the cost of insuring against a higher likelihood of default. On the other hand, it may represent a premium to induce investors to transact in, or unwind, positions in comparatively illiquid assets.[18] Recent literature supports the presence of a liquidity component in a variety of risk spreads: inter-bank and sovereign interest rate spreads (Panyanukul, 2009, and Schwartz, 2015); bond spreads (Bongaerts, de Jong and Driessen, 2011; Bao, Pan and Wang, 2011; Friewald et al. 2012, Lin, Wang, and Wu, 2012; and Acharya, Amihud and Bharath, 2013) independent of credit quality, maturity and type. There is also emerging evidence of a market-wide liquidity premium in the pricing of CDS spreads (Arakelyan, Rubio and Serrano, 2013).

In this section we investigate whether liquidity risk plays an important part in explaining the general rise in CDS spreads and whether this has significant signalling power for changes in future real activity. Using identical data to section 5 at daily frequency, we decompose the CDS premium into a predicted component based on our liquidity measures (i.e. the bid-ask spread and the number of quote providers[19]) and a residual component which captures credit risk and any other *unpredicted* risk factors such as global systemic risk or market volatility.

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[18] According to Brunnermeier and Pedersen (2009), during a crisis market makers may face more severe funding constraints and reduce their risk-taking capacity thus tightening liquidity. Liquidity may also be impaired due to higher inventory holding costs and search costs (Duffie, Gârleanu and Pedersen, 2007).

[19] Results based on the number of quote providers obtained from Markit for a subsample of countries are qualitatively similar to those based on the bid-ask spread, and are available from the authors upon request.

The bid-ask spread is used to predict the CDS premium for CDS contracts of 5-year maturity at daily frequency. Higher order terms of the bid-ask spread are included to capture any nonlinearities in the relationship between liquidity and the CDS premium. As mentioned in section 5, the relationship between the bid-ask spread and the CDS premium can be either positive or negative depending on whether the competitiveness effect or the asymmetric information effect dominates.

The regression specification is as follows:[20]

$$CDS\ Premium_{it} = a_i + \sum_{k=1}^{3} b_{ik} * [\ln(1 + Bidask\ spread_{it-1})]^k + e_{it}$$

[Equation 5.]

Our results reported in Table 7A confirm a statistically significant and non-linear relationship between liquidity and the CDS premium. When we checked our results after adjusting the bid-ask spread for counterparty risk by first subtracting the LIBOR-OIS spread, our results were unchanged.[21] Consistent with our findings in Section 5, the results here also indicate that the competition effect dominates, whereby a 100 bp increase in the spread implies a 42 basis point *increase* in the CDS premium (based on the total estimated coefficient)[22].

The predicted CDS spread is obtained as the fitted values from equation (5) above, based on model (3) in Table 7A, and we refer to it as the "liquidity component". The residual CDS spread is obtained as the difference between the original CDS premium and the liquidity component at CDS contract level and daily frequency, as follows: $residual\ CDS_{it} = CDS\ premium_{it} - predicted\ CDS_{it}$. As Figure 4 suggests, the components, aggregated at country level by averaging across time within a given country, exhibit a similar pattern around the two crises in our sample period.

6.2 The CDS components and real activity

In this section we investigate whether the liquidity or residual component of the CDS spread accounts for its explanatory power for the growth in economic activity.

We aggregate the daily liquidity and residual components over 90-days (a quarter) to provide a country-specific measure at quarterly frequency to match the frequency of the

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[20] As per Equation (3), we include the lag of the bid-ask spread to mitigate endogeneity concerns.

[21] We use the LIBOR-OIS spread to measure counterparty risk as the LIBOR rate requires compensation for counterparty risk since the lending bank loans cash to the borrowing bank, while the OIS rate involves both counterparties swapping the floating rate of interest for the fixed rate of interest and not the principal. Mancini et al. (2014) use the LIBOR-OIS spread and the spread from the Repo versus the interbank market as alternative measures of counterparty risk.

[22] The nonlinearity indicates that with further increases in the bid-ask spread (equivalent to times when market liquidity is poor) the competitiveness effect dominates which is consistent with our earlier findings in section 5.

economic growth variables. We check our results using both the quarter average, and the last daily observation of a given quarter.

The specification is as in section 5.1, where the CDS spread is now replaced by the liquidity and residual components in a given country-quarter as follows:

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * Liquidity\ Component_{it} + d_i * Residual\ Component_{it} + \sum_{l=1}^{L} f_{il} * X_{ilt} + e_{it+4}$$

[Equation 6.]

The results, estimated using MGE as before and reported in Table 7B, indicate that both components are statistically significant predictors of future economic downturn, with the liquidity component having a more negative impact on future growth than the residual component. Results in columns 1-3 show a 100 bp increase in the liquidity component based on the quarter average (last day of quarter observation) leads to a 329 bp (275bp) decrease in in the four quarters ahead growth rate of real GDP, while an equal size increase in the residual component leads to a 72 bp (51 bp) decline in real GDP growth. As before investment is the most sensitive to deteriorating information flow from the CDS market. Then in columns 4-6 using last quarter observations, a 100 bp increase in the liquidity premium leads to a 275bp, 497bp and 97bp decrease in the year-ahead growth rate of real GDP, investment and employment, respectively. The effects of the residual component are smaller for both the average and the end of quarter measures and hardly statistically significant. [23]

Overall, these results suggest that the liquidity component plays a greater and more significant role for a future deterioration in economic activity than the unpredictable part of the CDS spread.

7. Conclusions

In this paper we examine the information flow from credit default swap (CDS) spreads to macroeconomic activity in the United States and twelve European countries. We make three important contributions. Firstly, we show that CDS contracts across maturities and sectors provide significant information that anticipates future contractions in real activity. The more heavily traded 5-year maturity contracts and Markit iTraxx Europe/Markit CDX North American CDS indexes show stronger results, indicating that these forward-looking and highly liquid instruments confer an economically and statistically significant financial signal for future economic activity. These results are confirmed when we strip out the early CDS market by restricting our sample to 2004 onwards.

[23] To ensure that the results are not driven by the Global Financial Crisis (GFC) and the Sovereign Debt Crisis (SDC), the level and higher order terms of the bid-ask spread are each interacted with the two dummies: a Global Financial Crisis dummy that equals 1 between 2007Q1 and 2009Q2, and 0 otherwise for all countries; and a Sovereign Debt Crisis dummy that equals 1 between 2010Q1 and 2014Q2, and 0 otherwise for all countries except the US. Our results are unchanged and we do not report them for space considerations.

Secondly, we find that informed trading (measured based on the insights of AJ) takes place through both buying *and selling* credit protection prior to deteriorating *and improving* news on CDS obligors. In contrast to QY however, we find that better liquidity provision tends to strengthen the information flow from the CDS market to the stock market mainly through negative CDS innovations, which is robust to the inclusion of firm-level characteristics. This flow intensifies prior to credit events and the occurrence of credit events itself provides a signal of future anticipated downturns in real activity. We also shed light on the relationship between liquidity and the price of CDS protection, and in contrast to QY, we find that the CDS market pricing is governed by the competitiveness effect rather than an asymmetric information effect. This corroborates earlier evidence that high spreads and low competition in CDS market are detrimental to future growth.

Finally, we extract a liquidity-related component from the CDS spread by accounting for the non-linear relationship between CDS premia and liquidity provision proxied by the bid-ask spread. We find that liquidity risk explained the major part of the general rise in CDS spread and this has important signalling power for changes in future real activity over the sample period.

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Figure 1. The simple average CDS of All, Financial and Nonfinancial single-name contracts of 5-year maturity

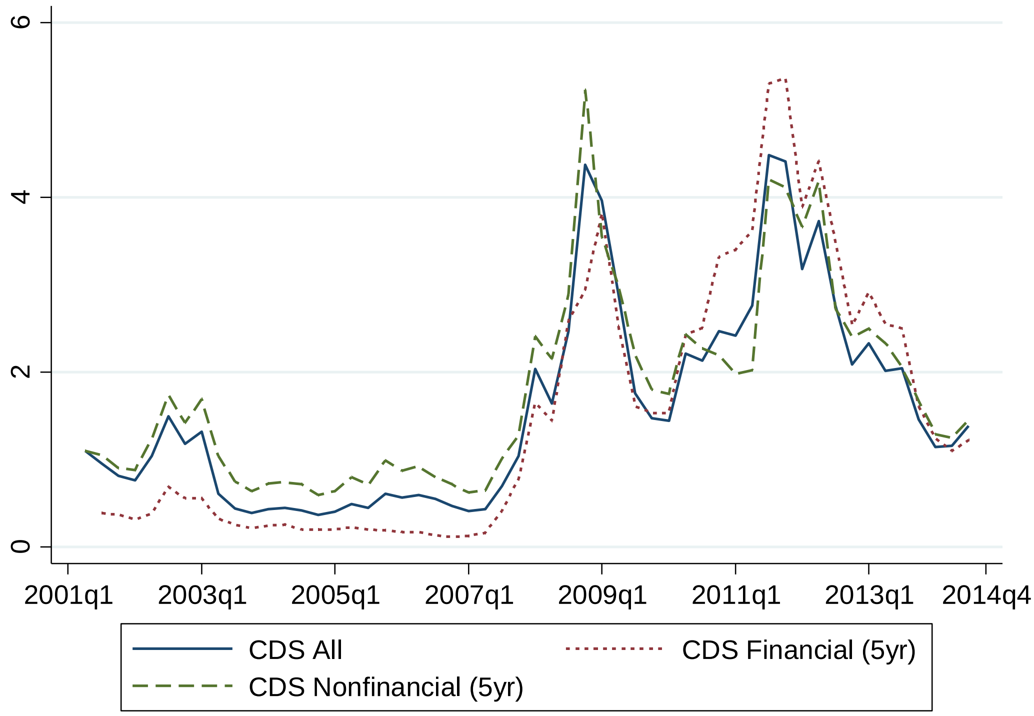


Figure 2. The simple average CDS of All single-name contracts and the Markit iTraxx Europe and Markit CDX North American Indices

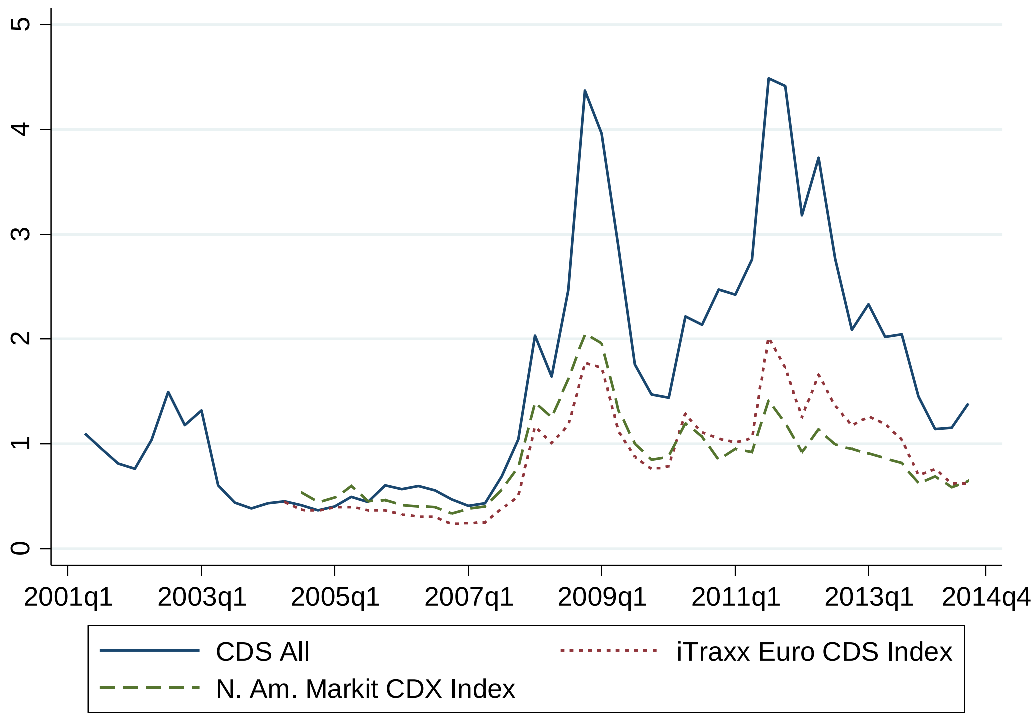
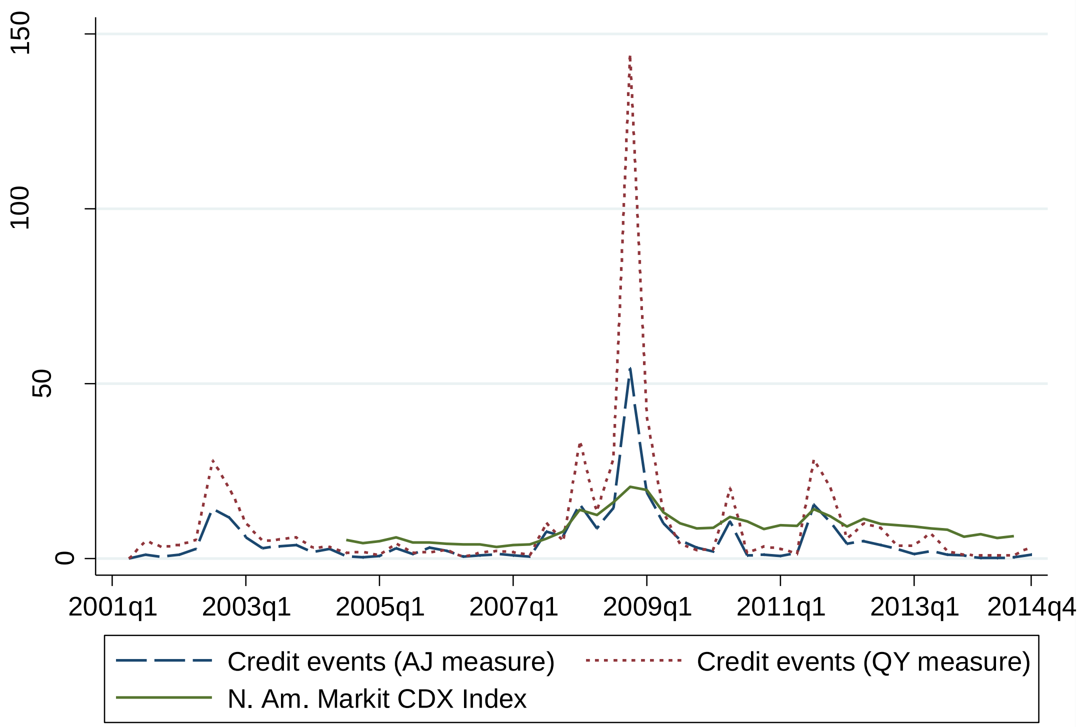


Figure 3. Total number of credit events[1] and the Markit CDX North American Index



[1] Total number of credit events as per AJ (QY, respectively) measures for: AT 3(32), BE 4(22), DE 121(491), FI 76(99), FR 274(691), GB 378(703), IE 10(6), IT 178(246), LU 8(20), NL 27(126), PT 12(17), SP 76(169), and US 2243(4080).

Figure 4. The Single-name CDS All and the CDS components

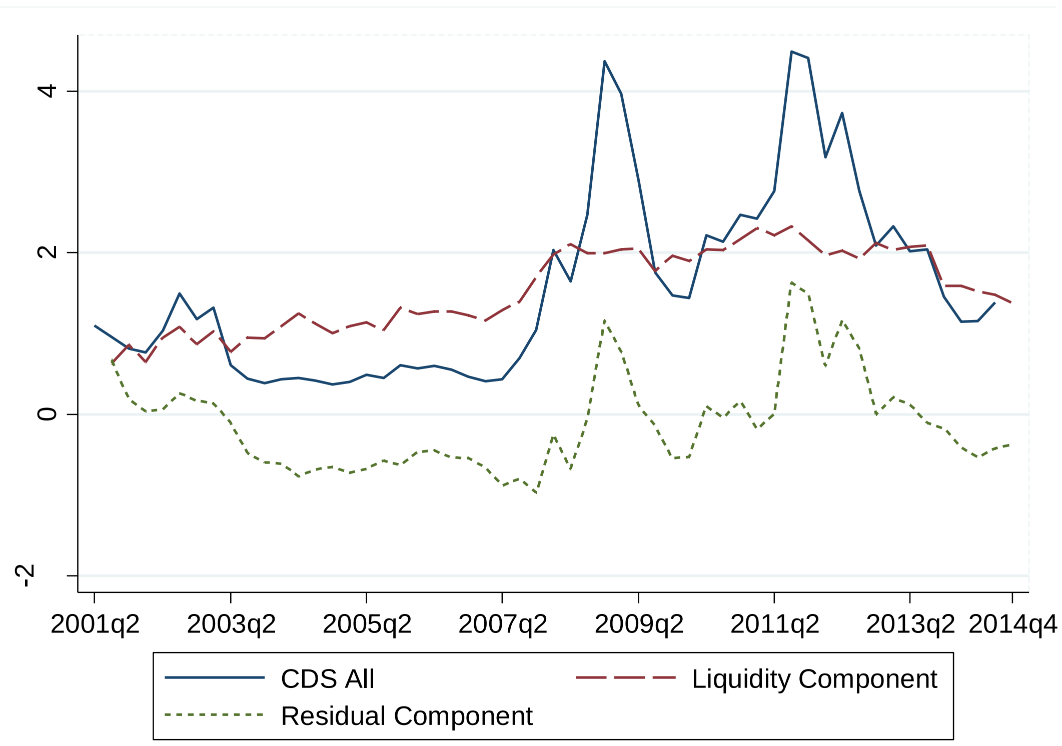

4
2
0
-2
2001q2
2003q2
2005q2
2007q2
2009q2
2011q2
2013q2
2014q4
CDS All
Liquidity Component
Residual Component

TABLE 1a. Descriptive Statistics CDS spreads and indexes

This table presents the descriptive statistics for the CDS spreads and indexes. The CDS premium is the daily single-name country-level average of all maturities and all sectors (All), financial (Fin), non-financial (Non-fin), financial of 5-year maturity (Fin 5 yr), non-financial of 5-year maturity (Non-fin 5 yr), of 5-year maturity for all sectors (5 yr), and of all other maturities for all sectors (All excl. 5 yr) entities. The Markit iTraxx Europe and the Markit CDX North American CDS indexes each comprise 125 equally weighted credit default swaps on investment grade European and American corporate entities, respectively. All data have been obtained from Bloomberg at quarterly frequency and are measured in percentage points.

Variable	Obs	Mean	Std. Dev.	Min	Max
CDS All	665	1.60	1.70	0.11	12.52
CDS Fin	551	1.52	2.17	0.07	16.82
CDS Fin 5yr	551	1.58	2.11	0.07	16.56
CDS Non-fin	647	1.61	1.49	0.13	14.16
CDS Non-fin 5yr	647	1.82	1.64	0.13	14.08
CDS 5yr	678	1.74	1.73	0.11	12.24
CDS All excl. 5yr	599	1.60	1.77	0.11	13.03
iTraxx Europe Index	546	0.87	0.49	0.23	2.01
CDX N. Am. Index	533	0.87	0.41	0.34	2.05

Sample period: 2001Q2-2014Q3; No. of firms = 1014 [EU/US (357/657)]; No. of CDS contracts = 6827 [EU/US (2585/4242)]; Financial EU/US (876/841); Nonfinancial EU/US (1709/3401); No. of industry sectors = 11; No. of countries = 13; No. of CDS contracts/quarters for Austria (43/46), Belgium (42/47), Finland (49/54), France (412/55), Germany (405/54), Ireland (47/47), Italy (175/54), Luxembourg (34/51), Netherlands (175/54), Portugal (49/54), Spain (152/54), UK (1002/54), and US (4242/54).

TABLE 1b. Cross-correlations of CDS spreads and indexes

This table presents the correlations among the variables used in the first part of our study at quarterly frequency. Sample period 2001-2014; No. of countries = 13.

	CDS All	CDS Fin	CDS Fin 5yr	CDS Non-fin	CDS Non-fin 5yr	CDS 5yr	CDS All excl. 5yr	iTraxx Europe Index	CDX N. Am. Index
CDS All	1								
CDS Fin	0.949	1							
CDS Fin 5yr	0.942	0.996	1						
CDS Non-fin	0.824	0.638	0.640	1					
CDS Non-fin 5yr	0.848	0.705	0.711	0.934	1				
CDS 5yr	0.985	0.943	0.945	0.817	0.890	1			
CDS All excl. 5yr	0.999	0.946	0.938	0.823	0.837	0.978	1		
iTraxx Europe Index	0.624	0.606	0.633	0.588	0.599	0.646	0.620	1	
CDX N. Am. Index	0.531	0.466	0.480	0.586	0.542	0.528	0.531	0.869	1

TABLE 1c. Descriptive statistics (macro study: quarterly frequency)

This table presents the descriptive statistics for the dependent and control variables used for the macro study. The data on real GDP, employment and investment are obtained from Eurostat and are transformed to obtain the annualised four quarter ahead growth rate for each country as $Growth_{it+4} = \frac{400}{5} \ln\left(\frac{\mathrm{Y_{it+h}}}{\mathrm{Y_{it-1}}}\right)$, where Y represents the respective economic activity indicator. The term spread is calculated as the difference between the 10-year and the 3-month generic government bond yields obtained from Bloomberg. The real interest rate is calculated as the difference between the official nominal interest rate and inflation obtained from Bloomberg and IMF IFS, respectively. The CLI represents the Composite Leading Indicator obtained from OECD and is included in our regressions as the first difference between period t and t-4.

Variable	Obs	Mean	Std. Dev.	Min	Max
Real GDP	710	202,420	209,324	7,550	681,233
Employment	690	23,379	34,804	274	139,481
Investment	707	41,099	41,511	1,341	138,662
Term spread	655	1.95	1.57	-0.91	11.95
Real interest rate	715	0.03	1.52	-4.24	7.11
OECD CLI	711	99.95	1.54	94.20	105.46

TABLE 1d. Descriptive statistics (CDS liquidity study: daily frequency)

This table presents the descriptive statistics for the variables used in the second part of our paper which investigates CDS liquidity and informed trading at daily frequency, and the role liquidity plays in the CDS spread's predictive content for future economic activity. The CDS premium is the 5-year maturity single-name CDS average at daily frequency. The Stock Price is the daily share price of the reference entity. The bid-ask spread is calculated as the difference between the ask price and the bid price divided by the ask price. Daily Trading Volume is the daily stock trading volume for sample firms. Credit Rating is the S&P's long term issuer credit rating converted into a numerical scale from AAA (1) to D (22). Average Stock Return is a firm's annualized 252-day average stock return. Stock Return Volatility is a firm's annualized 252-day stock return standard deviation. All data have been obtained from Bloomberg. Sample period 31 July 2001-28

November 2014; No. of firms=994; No. of CDS contracts=994; No. of sectors=11; No. of countries = 13.

Variable	Obs	Mean	Std. Dev.	Min	Max
CDS Premium (%)	1,735,197	1.61	2.03	0.094	15.7
Stock Price (%)	1,238,663	2.866	49.91	0.0002	2,293
Bid-Ask Spread (%)	1,735,197	9.31	5.45	1.57	31.2
LIBOR-OIS Spread (%)	1,733,845	0.305	0.376	0.004	3.644
Stock Trading Volume (mln)	191,165	8.9	25.2	2	1950
S&P Rating	1,207,378	8.769	2.896	1	18
Average Stock Return	1,212,303	0.000085	0.0063	-1.185	0.99
Stock Return Volatility	1,211,423	0.023	0.017	0.00	0.95

TABLE 1e. Cross-correlations (CDS liquidity study: daily frequency)

This table presents the correlations among the variables (defined in Table 1d above) used in the second part of our study investigating CDS liquidity and informed trading at daily frequency. Sample period 2001Q2-2014Q3; No. of countries = 13.

	CDS Premium	Stock Price	Bid-Ask Spread	LIBOR-OIS	Stock Trading Volume (mln)	S&P Rating	Average Stock Return	Stock Return Volatility
CDS Premium	1							
Stock Price	-0.1072	1						
Bid-Ask Spread	-0.3939	0.0776	1					
LIBOR-OIS	0.3275	0.0112	-0.2942	1				
Stock Trading Volume (mln)	0.0491	0.0236	0.013	0.0231	1			
S&P Rating	0.3863	-0.1908	-0.1978	-0.0205	0.0312	1		
Average Stock Return	-0.268	0.0174	0.0562	-0.2265	-0.0236	-0.0706	1	
Stock Return Volatility	0.4927	-0.0703	-0.047	0.3228	0.0529	0.0768	-0.4552	1

TABLE 2. All-maturity CDS, 5-year financial and non-financial CDS and CDS indices and real economic activity in a dynamic setting

This table investigates the information content of various CDS indexes for future real activity. The regression specification is as follows:

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * CDS_{it} + \sum_{l=1}^{L} d_{il}\, X_{ilt} + e_{it+4}$$

Where *CDS* includes single-name CDS of all maturities and sectors, single-name CDS of financial, non-financial (Panel A), financial of 5-year maturity and non-financial of 5-year maturity (Panel B), and the Markit iTraxx Europe and the Markit CDX North American CDS indexes (Panel C). X is a vector of controls including monetary policy indicators (Real Interest Rate and Term Spread), the Country Composite Leading Indicator (OECD CLI). The dependent variable in each column is annualised quarterly Real GDP growth (RGDP), Employment growth (EMP) and Fixed Capital Investment growth (INV). We also include lagged first-differenced terms in the dependent variable Y_{it-k}, where the maximum lag, k, is determined by the Akaike Information Criterion (AIC). Sample period 2001Q2-2014Q3; No. of countries =13. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2. Mean Group Estimation - Forecast Horizon: 4 quarters

PANEL A: Sample period: 2001Q2 - 2014Q3

Financial Indicator	RGDP (1)	INV (2)	EMP (3)	RGDP (4)	INV (5)	EMP (6)	RGDP (7)	INV (8)	EMP (9)
Term Spread	0.649***	1.394	0.368	0.767***	1.804*	0.433	0.470***	1.255	0.34
	(0.223)	(0.940)	(0.307)	(0.283)	(1.052)	(0.364)	(0.136)	(0.811)	(0.256)
Real Interest Rate	0.202***	-0.273	0.065	-0.0295	-0.754	-0.12	0.400***	0.372	0.226**
	(0.073)	(0.575)	(0.075)	(0.083)	(0.539)	(0.095)	(0.087)	(0.461)	(0.113)
OECD CLI	0.390***	0.932***	0.230***	0.389***	0.910***	0.263***	0.512***	1.205***	0.296***
	(0.069)	(0.171)	(0.057)	(0.080)	(0.189)	(0.049)	(0.101)	(0.201)	(0.083)
CDS All	-1.159***	-2.218***	-0.401***						
	(0.143)	(0.616)	(0.072)						
CDS Financial				-1.243***	-2.410***	-0.467***			
				(0.198)	(0.624)	(0.155)			
CDS Non-Financial							-0.819***	-1.602***	-0.251**
							(0.185)	(0.564)	(0.103)
RMSE	1.557	4.356	0.927	1.384	4.292	0.886	1.619	4.322	0.975
Observations	608	605	588	511	508	491	590	587	570
# countries	13	13	13	11	11	11	13	13	13

PANEL B: Sample period: 2001Q2 - 2014Q3						
Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.758***	1.804*	0.436	0.481***	1.19	0.302
	(0.287)	(1.064)	(0.363)	(0.148)	(0.793)	(0.248)
Real Interest Rate	-0.146	-0.964*	-0.127	0.263***	0.0317	0.133
	(0.092)	(0.568)	(0.089)	(0.099)	(0.390)	(0.088)
OECD CLI	0.397***	0.925***	0.260***	0.470***	1.145***	0.257***
	(0.076)	(0.182)	(0.046)	(0.089)	(0.198)	(0.053)
CDS Fin 5 yrs	-1.304***	-2.536***	-0.476***			
	(0.213)	(0.641)	(0.149)			
CDS Non-fin 5 yrs				-0.866***	-1.827***	-0.350***
				(0.141)	(0.630)	(0.089)
RMSE	1.351	4.229	0.898	1.589	4.248	0.955
Observations	511	508	491	590	587	570
# countries	11	11	11	13	13	13

PANEL C: Sample period: 2001Q2 - 2014Q3						
Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.640***	1.349	0.341	0.515***	1.341	0.258
	(0.245)	(0.945)	(0.303)	(0.192)	(0.823)	(0.302)
Real Interest Rate	0.0386	-0.632	-0.0107	0.122	-0.216	-0.018
	(0.085)	(0.550)	(0.052)	(0.096)	(0.442)	(0.073)
OECD CLI	0.377***	0.911***	0.213***	0.521***	1.204***	0.351**
	(0.069)	(0.174)	(0.042)	(0.123)	(0.301)	(0.139)
CDS 5 yrs	-1.219***	-2.411***	-0.450***			
	(0.149)	(0.708)	(0.103)			
CDS All excl. 5 yrs				-1.288***	-2.463***	-0.409***

				(0.225)	(0.662)	(0.091)
RMSE	1.515	4.275	0.918	1.547	4.139	0.884
Observations	608	605	588	538	535	518
# countries	13	13	13	13	13	13

PANEL D: Sample period: 2001Q2 - 2014Q3

Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.484***	1.385	0.262	0.340**	1.037	0.132
	(0.139)	(0.863)	(0.238)	(0.148)	(0.754)	(0.131)
Real Interest Rate	-0.330*	-0.951	-0.0603	0.142	-0.134	0.0694
	(0.180)	(0.796)	(0.115)	(0.205)	(0.768)	(0.110)
OECD CLI	0.548***	1.240***	0.310***	0.309***	0.725***	0.101*
	(0.121)	(0.301)	(0.110)	(0.093)	(0.241)	(0.056)
iTraxx Europe Index	-3.680***	-6.792***	-1.424***			
	(0.608)	(1.798)	(0.401)			
CDX N. Am. Index				-4.741***	-8.994***	-2.268***
				(0.610)	(2.094)	(0.533)
RMSE	1.425	3.968	0.883	1.262	3.797	0.822
Observations	489	486	469	476	473	456
# countries	13	13	13	13	13	13

TABLE 3. All-maturity CDS, 5-year financial and non-financial CDS and CDS indices and real economic activity (excluding the nascent pre-2004 period) in a dynamic setting

This table investigates the information content of various CDS indexes for future real activity. The regression specification is as follows:

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * CDS_{it} + \sum_{l=1}^{L} d_{il} X_{ilt} + e_{it+4}$$

Where *CDS* includes single-name CDS of all maturities and sectors, single-name CDS of financial, non-financial (Panel A), financial of 5-year maturity and non-financial of 5-year maturity (Panel B), and the Markit iTraxx Europe and the Markit CDX North American CDS indexes (Panel C). *X* is a vector of controls including monetary policy indicators (Real Interest Rate and Term Spread), the Country Composite Leading Indicator (OECD CLI). The dependent variable in each column is annualised quarterly Real GDP growth (RGDP), Employment growth (EMP) and Fixed Capital Investment growth (INV). Sample period 2005Q1-2014Q3; No. of countries =13. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 3. Mean Group Estimation - Forecast Horizon: 4 quarters									
PANEL A: Sample period: 2005Q1 - 2014Q3									
Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**	**RGDP (7)**	**INV (8)**	**EMP (9)**
Term Spread	0.470*	1.568	0.201	0.626**	1.870*	0.263	0.245	1.366	0.129
	(0.243)	(0.955)	(0.311)	(0.316)	(1.125)	(0.362)	(0.206)	(0.934)	(0.241)
Real Interest Rate	0.122	-0.022	-0.039	-0.061	-0.507	-0.21	0.259	0.329	0.106
	(0.170)	(0.591)	(0.082)	(0.166)	(0.731)	(0.134)	(0.178)	(0.457)	(0.103)
OECD CLI	0.588***	1.537***	0.353**	0.587***	1.589***	0.424**	0.708***	1.700***	0.409**
	(0.186)	(0.461)	(0.172)	(0.193)	(0.481)	(0.170)	(0.204)	(0.522)	(0.189)
CDS All	-1.342***	-2.460***	-0.537***						
	(0.283)	(0.883)	(0.115)						
CDS Financial				-1.366***	-2.473***	-0.484***			
				(0.356)	(0.931)	(0.115)			
CDS Non-Financial							-1.142***	-2.358**	-0.399**
							(0.398)	(1.074)	(0.166)
RMSE	1.587	3.978	0.879	1.414	3.992	0.875	1.604	4.078	0.935
Observations	450	447	430	382	379	362	446	443	426
# countries	13	13	13	11	11	11	13	13	13

PANEL B: Sample period: 2005Q1 - 2014Q3						
Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.446***	1.459*	0.199	0.292*	0.989	0.0858
	(0.149)	(0.872)	(0.234)	(0.161)	(0.792)	(0.131)
Real Interest Rate	-0.335*	-0.991	-0.07	0.116	-0.165	0.0649
	(0.181)	(0.807)	(0.121)	(0.215)	(0.773)	(0.117)
OECD CLI	0.569***	1.354***	0.318***	0.319***	0.821***	0.0876
	(0.132)	(0.329)	(0.122)	(0.099)	(0.247)	(0.068)
CDS Fin 5 yrs	-3.687***	-7.252***	-1.407***			
	(0.626)	(1.801)	(0.408)			
CDS Non-fin 5 yrs				-4.732***	-9.023***	-2.327***
				(0.607)	(2.090)	(0.535)
RMSE	1.4362	3.8746	0.8821	1.2699	3.7559	0.806
Observations	450	447	430	450	447	430
# countries	13	13	13	13	13	13

PANEL C: Sample period: 2001Q2 - 2014Q3						
Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.601*	1.563	0.176	0.443*	1.543	0.204
	(0.325)	(0.955)	(0.311)	(0.231)	(0.947)	(0.310)
Real Interest Rate	-0.019	-0.392	-0.133	0.148	0.0238	-0.017
	(0.171)	(0.584)	(0.100)	(0.171)	(0.582)	(0.085)
OECD CLI	0.547***	1.446***	0.337**	0.606***	1.562***	0.363**
	(0.174)	(0.400)	(0.148)	(0.189)	(0.482)	(0.178)
CDS 5 yrs	-1.445***	-2.764***	-0.583***			
	(0.291)	(0.922)	(0.110)			
CDS All excl. 5 yrs				-1.292***	-2.423***	-0.510***

				(0.283)	(0.850)	(0.120)
RMSE	1.532	3.878	0.872	1.601	4.002	0.879
Observations	450	447	430	450	447	430
# countries	13	13	13	13	13	13

PANEL D: Sample period: 2005Q1 - 2014Q3

Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.681**	1.875*	0.291	0.299	1.381	0.102
	(0.318)	(1.108)	(0.365)	(0.209)	(0.933)	(0.245)
Real Interest Rate	-0.154	-0.729	-0.195*	0.153	0.0111	0.0005
	(0.145)	(0.718)	(0.116)	(0.182)	(0.454)	(0.108)
OECD CLI	0.564***	1.581***	0.416**	0.659***	1.542***	0.370**
	(0.174)	(0.476)	(0.168)	(0.184)	(0.405)	(0.150)
iTraxx Europe Index	-1.474***	-2.694***	-0.480***			
	(0.368)	(0.955)	(0.092)			
CDX N. Am. Index				-1.152***	-2.553**	-0.489***
				(0.344)	(1.068)	(0.126)
RMSE	1.3746	3.914	0.8918	1.5789	3.982	0.9132
Observations	382	379	362	446	443	426
# countries	11	11	11	13	13	13

TABLE 4. Information flow from the CDS market to the stock market – Interactions with liquidity provision

This table presents the impact of liquidity provision on the relation between stock returns and CDS innovations at daily frequency. The regression specification in column (1) is:

$$Stock\ return_{it} = a_i + b_i^+ * CDS\ innovation_{i,t-1}^+ + b_i^- * CDS\ innovation_{i,t-1}^- + \sum_{k=1}^{5} c_{ik} Stock\ return_{i,t-k} + e_{it}$$

In column (2) we allow for interactions between the CDS innovations and the bid-ask spread as follows:

$$Stock\ return_{it} = a_i + (b_{i1}^+ + b_{i2}^+ Bidask\ spread_{it}) CDS\ innovation_{i,t-1}^+ + (b_{i1}^- + b_{i2}^- Bidask\ spread_{it}) CDS\ innovation_{i,t-1}^- + \sum_{k=1}^{5} d_{ik} Stock\ return_{i,t-k} + e_{it}$$

, where the CDS and stock returns are defined as the first difference in the logarithm of CDS premium and stock price, respectively. The bid-ask spread is defined as $\frac{Ask\ rate - Bid\ rate}{Ask\ rate}$, and the CDS innovation represents news unique to the CDS market and is obtained as the residual from the regression $(CDS\ return_{it}) = a_i + \sum_{k=0}^{5} \left(b_{it} + \frac{c_{it}}{CDS\ premium_{it}}\right)(Stock\ return_{i,t-k}) + \sum_{k=1}^{5} d_{ik} CDS\ return_{i,t-k} + u_{it}$.

Column (3) extends the specification in column (2) by allowing for an interaction between the CDS innovations and a credit condition dummy, which equals 1 if the firm experiences a one-day increase in the CDS premium greater than 50 bps within the next 30 days.
Column (4) includes interactions between the CDS innovation and a set of $\sum_{m=1}^{4} d_m^{+,-}$ firm characteristics which are defined in Table 2a. The coefficients on the intercept and lagged stock returns are not reported. Heteroskedasticity-robust standard errors adjusted for clustering within firms are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Coefficient	Variables	(1)	(2)	(3)	(4)
b_1^+	CDS innovation$^+_{t-1}$	-0.004*	-0.0059*	0.0052	-0.009
		(0.002)	(0.003)	(0.004)	(0.023)
b_1^-	CDS innovation$^-_{t-1}$	0.0018*	0.0047***	-0.0075***	-0.001
		(0.001)	(0.002)	(0.002)	(0.014)
b_2^+	Bid-ask spread$_t$ x CDS innovation$^+_{t-1}$		0.024	-0.011	-0.021
			(0.027)	(0.031)	(0.041)
b_2^-	Bid-ask spread$_t$ x CDS innovation$^-_{t-1}$		-0.036**	-0.0006	-0.0084
			(0.016)	(0.024)	(0.034)
b_1^{d+}	Credit condition dummy$_t$ x CDS innovation$^+_{t-1}$			-0.0201***	-0.0243***

				(0.006)	(0.006)
b_1^{d-}	Credit condition dummy$_t$ x CDS innovation$^-_{t-1}$			0.025***	0.028***
				(0.004)	(0.005)
b_2^{d+}	Credit condition dummy$_t$ x Bid-ask spread$_t$ x CDS innovation$^+_{t-1}$			0.077	0.075
				(0.049)	(0.054)
b_2^{d-}	Credit condition dummy$_t$ x Bid-ask spread$_t$ x CDS innovation$^-_{t-1}$			-0.0901***	-0.0944**
				(0.035)	(0.046)
d_1^+	Volatility$_t$ x CDS innovation$^+_{t-1}$				0.00237*
					(0.001)
d_1^-	Volatility$_t$ x CDS innovation$^-_{t-1}$				-0.000945***
					(0.000)
d_2^+	Average stock return$_t$ x CDS innovation$^+_{t-1}$				-0.003
					(0.003)
d_2^-	Average stock return$_t$ x CDS innovation$^-_{t-1}$				-0.001
					(0.001)
d_3^+	Credit rating$_t$ x CDS innovation$^+_{t-1}$				0.002
					(0.004)
d_3^-	Credit rating$_t$ x CDS innovation$^-_{t-1}$				-0.00004
					(0.002)
d_4^+	Credit rating^2_t x CDS innovation$^+_{t-1}$				-0.0001
					(0.000)
d_4^-	Credit rating^2_t x CDS innovation$^-_{t-1}$				-7.05E-06
					(0.000)
	Observations	1,208,768	1,208,768	1,208,768	919,291

TABLE 5. Effect of CDS liquidity on the CDS premium

This table documents the effect of CDS liquidity on the CDS premium. The regression specification in column (1) is:

$$CDS\ return_{it} = a_{0i} + \sum_{k=1}^{5} a_{1ik} CDS\ return_{i,t-k} + \sum_{k=1}^{5} a_{2ik} Stock\ return_{i,t-k} + a_{3i}\Delta Bidask\ spread_{i,t-1}$$
$$+ Credit\ condition\ dummy_{it}\left[b_{0i} + \sum_{k=1}^{5} b_{1ik} CDS\ return_{i,t-k} + \sum_{k=1}^{5} b_{2ik} Stock\ return_{i,t-k} + b_{3i}\Delta Bidask\ spread_{i,t-1}\right] + e_{it}$$

Where the CDS and stock returns are defined as the first difference in the logarithm of CDS premium and stock price, respectively. The bid-ask spread is defined as $\frac{Ask\ rate - Bid\ rate}{Ask\ rate}$, and the CDS innovation represents news unique to the CDS market and is obtained as the residual from the regression $(CDS\ return_{it}) = a_i + \sum_{k=0}^{5}\left(b_{it} + \frac{c_{it}}{CDS\ premium_{it}}\right)(Stock\ return_{i,t-k}) + \sum_{k=1}^{5} d_{ik} CDS\ return_{i,t-k} + u_{it}$.

Column (2) allows for the interaction between the differenced bid-ask spread, $\Delta Bidask\ spread_{i,t-1}$ and the prevailing bid-ask rate in the market, $Bidask\ spread_{i,t-1}$ at time *t-1*. The regression specification is as follows:

$$CDS\ return_{it} = a_{0i} + \sum_{k=1}^{5} a_{1ik} CDS\ return_{i,t-k} + \sum_{k=1}^{5} a_{2ik} Stock\ return_{i,t-k} + (a_{3i} + a_{4i} Bidask\ spread_{i,t-1})\Delta Bidask\ spread_{i,t-1}$$
$$+ Credit\ condition\ dumy_{it}$$
$$* \left[b_{0i} + \sum_{k=1}^{5} b_{1ik} CDS\ return_{i,t-k} + \sum_{k=1}^{5} b_{2ik} Stock\ return_{i,t-k} + (b_{3i} + b_{4i} Bidask\ spread_{i,t-1})\Delta Bidask\ spread_{i,t-1}\right] + e_{it}$$

Column (3) replaces the interaction $Bidask\ spread_{i,t-1}\Delta Bidask\ spread_{i,t-1}$ with $Low\ Bidask\ spread_{i,t-1}\Delta Bidask\ spread_{i,t-1}$, where $Low\ Bidask\ spread_{i,t-1}$ is a dummy variable equal to 1 if the bid-ask spread is below the median of the distribution, and 0 otherwise.

$\sum_{k=1}^{5} a_{1ik}$, $\sum_{k=1}^{5} a_{2ik}$, $\sum_{k=1}^{5} b_{1ik}$, and $\sum_{k=1}^{5} b_{2ik}$ report the summation of coefficients for the lagged CDS and stock returns, respectively. Heteroskedasticity-robust standard errors adjusted for clustering within firms are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Coefficient	Variables	(1)	(2)	(3)
a_0	Intercept	-0.00001***	-0.00001***	-0.00001***
		(0.000)	(0.000)	(0.000)
$\sum_{k=1}^{5} a_{1ik}$	CDS return$_{t-k}$, k=1,..5	0.099***	0.099***	0.099***
		(0.014)	(0.014)	(0.014)

$\sum_{k=1}^{5} a_{2ik}$	Stock return$_{t-k}$, k=1,..5	-0.006***	-0.006***	-0.006***
		(0.000)	(0.000)	(0.000)
a_3	ΔBid-ask spread$_{t-1}$	0.0002**	-0.001	0.0003***
		(0.000)	(0.000)	(0.000)
a_4	Bid-ask spread$_{t-1}$ x ΔBid-ask spread$_{t-1}$		0.002**	
			(0.001)	
a_5	Low Bid-ask spread$_{t-1}$ x ΔBid-ask spread$_{t-1}$			-0.0004***
				(0.000)
b_0	Credit condition dummy$_t$	0.0003***	0.0003***	0.0003***
		(0.000)	(0.000)	(0.000)
$\sum_{k=1}^{5} b_{1ik}$	Credit condition dummy$_t$ x CDS return$_{t-k}$, k=1,..5	-0.171**	-0.171**	-0.171**
		(0.088)	(0.088)	(0.088)
$\sum_{k=1}^{5} b_{2ik}$	Credit condition dummy$_t$ x Stock return$_{t-k}$, k=1,..5	-0.02***	-0.02***	-0.02***
		(0.003)	(0.003)	(0.003)
b_3	Credit condition dummy$_t$ x ΔBid-ask spread$_{t-1}$	0.0046*	-0.004*	0.011***
		(0.002)	(0.002)	(0.004)
b_4	Credit condition dummy$_t$ x Bid-ask spread$_{t-1}$ x ΔBid-ask spread$_{t-1}$		0.08***	
			(0.024)	
b_5	Credit condition dummy$_t$ x Low Bid-ask spread$_{t-1}$ x ΔBid-ask spread$_{t-1}$			-0.013***
				(0.004)
	Observations	1,209,547	1,209,547	1,209,547

TABLE 6. Credit events and real economic activity in a dynamic setting

This table investigates the information content of various CDS indexes for future real activity. The regression specification is as follows:

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * Credit\ event\ indicator_{it} + \sum_{l=1}^{L} d_{il}\, X_{ilt} + e_{it+4}$$

Where *Credit events* represents the number of credit events in a given quarter, where a credit event is defined as a daily increase in the CDS premium that is greater than 50 bps (AJ measure) or greater than the average plus four times the standard deviation of the CDS daily change (QY measure). X is a vector of controls including monetary policy indicators (Real Interest Rate and Term Spread), the Country Composite Leading Indicator (OECD CLI). The dependent variable in each column is annualised quarterly Real GDP growth (RGDP), Employment growth (EMP) and Fixed Capital Investment growth (INV). We also include lagged first-differenced terms in the dependent variable Y_{it-k}, where the maximum lag, k, is determined by the Akaike Information Criterion (AIC). Sample period 2001Q2-2014Q3; No. of countries =13. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6. Mean Group Estimation - Forecast Horizon: 4 quarters

Sample period: 2001Q1 - 2014Q3

Financial Indicator	RGDP (1)	INV (2)	EMP (3)	RGDP (4)	INV (5)	EMP (6)
Term Spread	0.468**	1.448	0.35	0.557**	1.578	0.382
	(0.225)	(1.040)	(0.333)	(0.276)	(1.134)	(0.379)
Real Interest Rate	0.282	0.0157	0.159	0.412***	0.277	0.193*
	(0.172)	(0.995)	(0.105)	(0.102)	(0.668)	(0.114)
OECD CLI	0.685q***	1.410***	0.346***	0.639***	1.373***	0.318***
	(0.078)	(0.214)	(0.082)	(0.072)	(0.194)	(0.070)
Credit event indicator (AJ measure)	-0.897**	-1.989	-0.34			
	(0.422)	(1.773)	(0.341)			
Credit event indicator (QY measure)				-1.249***	-2.305***	-0.538**
				(0.244)	(0.890)	(0.222)
RMSE	1.681	4.146	0.939	1.658	4.232	0.961
Observations	586	583	566	586	583	566
# countries	13	13	13	13	13	13

TABLE 7A. Decomposing the CDS premium

This tables reports the prediction results of the CDS premium using the bid-ask spread at CDS contract level and daily frequency. Higher order terms of the bid-ask spread are included to capture any non-linearities in the relationship between liquidity and the CDS premium. The regression specification is as follows:

$$CDS\ Premium_{it} = a_i + \sum_{k=1}^{3} b_{ik} * [\ln(1 + Bidask\ spread_{it-1})]^k + e_{it}$$

The Predicted CDS spread is obtained as the fitted values of this regression and we refer to it as the Liquidity component, and the Residual CDS spread is calculated as the difference: $Residual\ CDS_{it} = CDS\ Premium_{it} - Predicted\ CDS_{it}$. Sample period 2001Q2-2014Q3; No. of countries =13. Clustered standard errors at both country and time dimensions are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7A. Decomposing the CDS spread

	(1)	**(2)**
$\ln(1 + bidask\ spread_{it-1})$	-0.105***	-0.273***
	(0.008)	(0.022)
$[\ln(1 + bidask\ spread_{it-1})]^2$		0.696***
		(0.063)
Industry fixed effects	0.000	0.000
Credit rating fixed effects	0.000	0.000
Observations	1,207,378	1,207,378
R-squared	0.429	0.442

TABLE 7B. The Predicted and Residual Components of the CDS premium and real economic activity in a dynamic setting

This table investigates the information content of CDS components for future real activity. The regression specification is as follows:

$$Growth_{it+4} = a_i + \sum_{k=1}^{K} b_{ik} * Quarterly\ Growth_{it-k} + c_i * Liquidity\ Component_{it} + d_i * Residual\ Component_{it} + \sum_{l=1}^{L} f_{il} * X_{ilt} + e_{it+4}$$

Where *CDS Components* include the quarter average[1] (models 1-3) and the last quarterly observation[2] (models 4-6) of daily Predicted CDS and Residual CDS spreads obtained as per Table 7A above. A country-specific index at quarterly frequency is then obtained as the cross-sectional average across CDS contracts in a given period. As before, X is a vector of controls including monetary policy indicators (Real Interest Rate and Term Spread), the Country Composite Leading Indicator (OECD CLI). The dependent variable in each column is annualised quarterly Real GDP growth (RGDP), Employment growth (EMP) and Fixed Capital Investment growth (INV). We also include lagged first-differenced terms in the dependent variable Y_{it-k}, where the maximum lag, k, is determined by the Akaike Information Criterion (AIC). Sample period 2001Q2-2014Q3; No. of countries =13. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7B. Mean Group Estimation - Forecast Horizon: 4 quarters						
Sample period: 2001Q1 - 2014Q3						
Financial Indicator	**RGDP (1)**	**INV (2)**	**EMP (3)**	**RGDP (4)**	**INV (5)**	**EMP (6)**
Term Spread	0.538***	1.394*	0.205	0.502***	1.206*	0.217
	(0.155)	(0.712)	(0.175)	(0.124)	(0.615)	(0.184)
Real Interest Rate	0.0446	0.0367	0.121	0.0758	-0.141	0.0948
	(0.150)	(0.345)	(0.114)	(0.139)	(0.275)	(0.094)
OECD CLI	0.509***	1.404***	0.264***	0.585***	1.550***	0.297***
	(0.122)	(0.221)	(0.091)	(0.074)	(0.271)	(0.077)
Liquidity component[1]	-3.293***	-5.866***	-1.177**			
	(0.806)	(2.123)	(0.576)			
Residual component[1]	-0.721*	-1.046	-0.216			
	(0.379)	(0.858)	(0.187)			
Liquidity component[2]				-2.746***	-4.967***	-0.974**
				(0.415)	(1.636)	(0.414)
Residual component[2]				-0.503*	-0.852	-0.193
				(0.261)	(0.760)	(0.124)

RMSE	1.353	3.830	0.748	1.365	3.863	0.805
Observations	578	575	558	577	574	557
# countries	13	13	13	13	13	13