Essays in Liquidity and Financial Markets

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Abstract

This thesis presents three studies related to the effects of liquidity on financial markets. The first topic explores the relationship between funding liquidity and credit default swap (CDS) spreads. Using panel estimations, this study provides evidence that a tightening of funding liquidity increases spreads, effect which is three times larger in magnitude for high-CDS entities compared to low-CDS firms. Moreover, this paper highlights the impact of the *'CDS Small Bang'* regulatory changes, especially the introduction of fixed coupons which induced upfront fees for trading CDSs. We find that after the introduction of the fees, funding liquidity changes have a much larger and more significant impact on CDS spread changes.

The second study presents an empirical investigation of the theoretical predictions of Brunnermeier and Pedersen (2009) connecting funding liquidity with market liquidity and volatility and an extension of these linkages to CDS spreads. Specifically, in a European context, this paper documents that: (i) funding conditions co-move with illiquidity, volatility and CDS spreads, (ii) during tight funding conditions, illiquid, volatile and high-CDS spread securities become particularly illiquid, (iii) a tightening of funding liquidity increases CDS spreads, this effect being stronger if funding conditions were already constrained, (iv) a deterioration of funding liquidity decreases contemporaneous returns, and (v) funding shocks are priced in the cross-section of illiquidity-sorted portfolios.

The third study examines the relationship between monetary policy and stock liquidity, in the context of the U.K. market. In line with the inventory paradigm of market microstructure and theories linking capital constraints with market illiquidity, this study documents that a contractionary (expansionary) monetary policy reduces (increases) stock liquidity. Moreover, this study finds that the effect of monetary policy on stock liquidity depends on the liquidity proxies chosen, decreases with firm size, increases with firm volatility, and is stronger during the 2007-2009 financial crisis.

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Introduction

Background of the study

The liquidity of financial markets is a central theme of financial research which has attracted increased attention in past decades. Liquidity is a complex concept, encompassing multiple aspects. One of these dimensions is market liquidity or the ease of trading a security.

Multiple sources of illiquidity exist. Firstly, illiquidity can arise from the presence of transaction costs such as order processing costs and brokerage fees, costs which are incurred every time a security is bought or sold. Secondly, illiquidity can occur due to search frictions relating to difficulties in locating a counterparty for trades. This type of illiquidity is especially encountered in over-the-counter markets, as there is no central marketplace where trading is executed. Thirdly, illiquidity can arise due to private information, whereby buyers and sellers are concerned that their counterparty has additional information to what is known publicly which may lead them to lose money on a specific trade. Lastly, illiquidity may occur due to demand pressure and inventory risk. Demand pressure occurs when traders want to trade a security quickly, but their natural counterparties are not immediately available. In this case, the trader may trade with a market maker, who is ready to act as a counterparty for the trade, providing liquidity to the market. However, as the market maker bears the risk of changes in the value of the security while he holds the asset, he requires compensation for his exposure. Market makers thus charge a higher price to security buyers, the ask price, and a lower price to security sellers, the bid price. The difference between the two, known as the bid-ask spread, represents the cost that the market maker demands for supplying liquidity to the market. Amihud et al. (2005) presents a survey of these sources of illiquidity and their impact on trading within financial markets.

The various sources of liquidity imply that market liquidity is an elusive and multi-faceted concept, several liquidity measures needing to be approximated to reach a more complete picture of liquidity. Therefore, market liquidity can refer to aspects such as immediacy, depth, breadth, tightness and resiliency (Kyle, 1985; Sarr and Lybek, 2002). These characteristics can be summarized as follows: immediacy refers to low transaction costs, depth relates to a market in which plentiful orders exist, breadth infers that numerous and large orders can be executed with low impact on prices, tightness refers to low transaction costs for executing trades, while resiliency refers to the speed at which liquidity recovers from shocks (Sarr and Lybek, 2002; Vayanos and Wang, 2013).

Moreover, the different sources of liquidity led to the development of two bodies of theoretical market microstructure literature. The first of these investigates information-based models (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1992) whereby market makers charge a fee that compensates them for any potential adverse selection costs they may face by entering a trade with a counterparty that owns private information. The second strand of theoretical market microstructure research examines inventory-based models (Demsetz, 1968; Stoll, 1978a; Amihud and Mendelson, 1980; Ho and Stoll, 1981) whereby market makers have a central role as liquidity providers and require compensation for holding inventory as they face risks relating to changes in the value of their holdings and time required to clear their positions, due to mismatches in the arrival of buyers and sellers.

Empirical studies highlight the importance of illiquidity for asset prices. In this respect, Amihud and Mendelson (1986) examine the effect of illiquidity on stock returns, documenting that returns are increasing and concave in transaction costs, as measured through the bid-ask spread. Brennan and Subrahmanyam (1996) investigate the relationship between monthly stock returns and measures of illiquidity extracted from intraday data, evidencing that returns are positively related to price impact, while Brennan et al. (1998) and Datar et al. (1998) provide further evidence of a positive relation between expected returns and illiquidity.

More recent papers examine the variation of illiquidity through time, its effects on expected returns and role within asset pricing. To this end, Amihud (2002) finds that, both across stocks and over time, expected stock returns increase in illiquidity, while market illiquidity lowers contemporaneous stock prices. Pastor and Stambaugh (2003) document that high liquidity risk stocks earn abnormally high expected returns, while Acharya and Pedersen (2005) develop a model illustrating that liquidity risk influences expected returns through three covariances: between stock return and aggregate illiquidity, between stock illiquidity and market return and between stock illiquidity and market illiquidity. Other studies, such as Korajczyk and Sadka (2008) and Hasbrouck (2009), find weaker evidence that illiquidity is a priced risk factor. The effects of liquidity and liquidity risk have also been studied in the context of the bond market by Lin et al. (2011) and Bongaerts et al. (2017). Moreover, in the context of the credit default swap (CDS) market, Das and Hanouna (2009) evidence a positive relationship between stock illiquidity and CDS spreads, Bongaerts et al. (2011) derive a pricing model incorporating liquidity risk and derivatives, and go on to find that a liquidity premium is earned by the CDS protection seller, while Coro et al. (2013) and Pires et al. (2015) document positive relationships between CDS spreads and CDS market illiquidity and individual CDS liquidity, respectively.

A separate literature strand investigates the degree of co-movement in the liquidity of securities, known as commonality in liquidity. Since the first pieces of evidence of commonality in liquidity, documented by Chordia et al. (2000), Huberman and Halka (2001) and Hasbrouck and Seppi (2001) in the context of the U.S. market, the literature on commonality in liquidity has investigated this effect on several markets and provided multiple insights as to what triggers the co-movement. These include demand-side explanations such as correlated trading behaviour of institutional investors (Koch et al. 2016) and level of institutional ownership (Kamara et al. 2008) and supply-side explanations focusing on trader leverage, provision of liquidity and funding liquidity (Coughenour and Saad, 2004; Comerton-Forde et al. 2010; Hameed et al. 2010; Kahraman and Tookes, 2017). The latter studies highlight the influence of another type of liquidity, namely funding liquidity, on the liquidity and co-movement in liquidity of individual stocks.

Funding liquidity represents another dimension of liquidity and is defined by Brunnermeier and Pedersen (2009) as the ease with which traders can obtain funding to finance their operations. Theoretical models suggest that, as trading requires capital, when funding liquidity is constrained, traders become unwilling to take on new positions, especially large positions in high-margin securities, dampening market liquidity and increasing volatility (Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2002; Vayanos and Wang, 2012; Kondor and Vayanos, 2016). Moreover, as margins increase with market illiquidity, following a funding shock, market liquidity decreases even further, leading to higher margins which, in turn, further tighten funding liquidity (Brunnermeier and Pedersen, 2009). Therefore, market liquidity and funding liquidity are closely connected and mutually reinforcing. The model of Brunnermeier and Pedersen (2009) also provides new testable predictions. In this respect, their model suggests that: funding liquidity shocks affect market liquidity and volatility more so when funding is already constrained, funding constraints can explain commonality in liquidity and flight-to-quality, funding liquidity negatively affects contemporaneous returns and generates an expected return spread between high and low illiquidity securities.

Empirical work on the links between market liquidity and funding liquidity and their implications is rather thin and recent. In the context of the U.S. market, Fontaine et al. (2016) finds strong evidence in favour of the predictions outlined in Brunnermeier and Pedersen (2009), documenting that, following a funding shock, assets display commonality, flight to quality and lower contemporaneous returns. Moreover, they provide evidence that funding shocks have a stronger impact on illiquidity and volatility when funding is tight, and securities with higher covariance to funding shocks display a larger risk premium. Jylha (2015) finds that funding liquidity affects market liquidity following a U.S. based pilot programme that induced a reduction in margin requirements, while Adrian et al. (2017) documents that funding liquidity and market liquidity are strongly correlated only during times of market stress. In the context of the European market, Drehmann and Nikolaou (2013) find that funding liquidity risk is inversely related to market liquidity using a data set consisting of all bids in the ECB main refinancing operation auctions between June 2005 and October 2008, while Moinas et al. (2017) note that a relaxation of funding constraints improves bond market liquidity.

Monetary policy, through its effects on the cost of borrowing funds, can also be related to funding liquidity. In this sense, an expansionary (restrictive) monetary policy measured through a decrease (increase) in short-term interest rates, reduces (tightens) constraints for margin borrowing, therefore improving (dampening) the funding liquidity of participants in the market (Fernandez-Amador et al. 2013). Considering the linkages between funding liquidity and market liquidity, monetary policy should also affect the liquidity of stocks traded. Few previous studies linking monetary policy to illiquidity exist and their results are mixed. In the context of the U.S. market, Fujimoto (2003) employs a vector autoregressive approach and finds that the influence of monetary policy on liquidity is significant only before the mid-1980s. Chordia et al. (2005) document that monetary policy expansions impact liquidity only during crisis periods. Goyenko and Ukhov (2009) and Jensen and Moorman (2010) provide strong evidence supporting the positive effect of monetary policy expansions on market liquidity, while Chiu (2014) finds that monetary policy shocks do not significantly impact market liquidity. In the context of the European market, Fernandez-Amador et al. (2013) provides compelling evidence of a positive (negative) effect of expansionary (contractionary) on stock liquidity, while in the context of the U.K. market, Florackis et al. (2014) finds that the impact of monetary policy on returns is significantly stronger for the most liquid stocks and that trading activity and trading costs increase on Monetary Policy Committee meeting days.

Objectives and contributions

This thesis presents three studies examining the effects of funding constraints on different financial markets. A first investigation is with regards to the effect of funding illiquidity changes on credit default swap (CDS) changes. The second study represents an empirical examination, in a European context, of the theoretical predictions of Brunnermeier and Pedersen (2009) and an extension of these predictions to the CDS market. The third study examines the effects of U.K. monetary policy on stock liquidity.

The first objective of this thesis is the examination of the effect of funding constraints on the corporate CDS market, by investigating the impact of changes in funding liquidity on CDS spread changes. The rationale for the existence of a relationship between funding liquidity changes and CDS spread changes is closely related to liquidity. A tightening of funding constraints induces CDS dealers to face higher inventory costs and higher costs of hedging their positions. As a result, the capacity of dealers to take sides in new CDS contracts and supply liquidity to the market is impaired (Tang and Yan, 2008). Moreover, a funding liquidity contraction induces CDS traders to steer away from risky assets, thus reducing the liquidity of the CDS market (Kamga and Wilde, 2017). The resulting decrease in CDS market liquidity due to tightening of funding constraints determines CDS protection sellers to require a premium for bearing the added illiquidity, as per the findings of Bongaerts et al. (2011), resulting in an increase in CDS spreads.

Moreover, following June 2009, a set of convention changes for trading CDSs in the European market, collectively known as the ‘CDS Small Bang’ were implemented. One of the innovations brought about by the new regulatory changes is the introduction of fixed coupons for trading CDSs and the exchange of a fee between CDS buyers and sellers for trading CDSs unless the CDS spread of the reference entity on the inception date of the contract is exactly equal to one of the fixed coupons, the size of the fee depending on how far away the CDS spread is from the fixed coupon (Markit, 2009). A similar set of convention changes, the ‘CDS Big Bang’, was previously implemented in the context of the U.S. market. In a contemporaneous study to the present paper, Wang et al. (2017) examine the impact of funding constraints brought about by the introduction of a fee for trading CDSs following the CDS Big Bang and document that the new convention changes increase CDS market illiquidity and volatility. We hypothesize that the added fee for trading CDSs after the introduction of the CDS Small Bang, creates an additional funding cost which would increase CDS spreads through the effect on CDS illiquidity and volatility. Moreover, following the findings of Pires et al. (2015) that most explanatory variables impact more strongly CDS spreads of entities in top quantile of the CDS distribution, we differentiate between high and low default risk entities and examine whether the impact of funding constraints is larger for high-CDS spread entities.

Results suggest that funding illiquidity changes have a positive relationship with CDS spreads and that this effect is larger in magnitude and significance following the introduction of the upfront fees. Moreover, this effect is approximately three times larger for high default risk entities, compared to low CDS firms. Therefore, the paper attributes the increased effect, in terms of magnitude and significance, of funding illiquidity changes on CDS spread changes to the introduction of upfront fees for trading CDSs, following the 'CDS Small Bang' conventions.

The contributions of the first paper are two-fold. Firstly, we contribute to the literature investigating the effects of funding constraints on financial markets (Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2002; Gromb and Vayanos, 2010) by documenting that funding illiquidity changes positively impact CDS spread changes through their influence on CDS illiquidity and volatility. Secondly, we contribute to the growing literature examining the determinants of CDS spreads (Tang and Yan, 2008; Ericsson et al. 2009; Greatrex 2009; Annaert et al. 2013) by documenting that CDS spreads are sensitive to changes in funding illiquidity and that the effect of funding illiquidity on CDS spreads is larger in magnitude for high-default risk securities.

The second study empirically investigates the theoretical predictions postulated by Brunnermeier and Pedersen (2009) and addresses a gap in the literature with respect to the impact of funding illiquidity on market illiquidity, volatility and returns in the cross-section of European stocks, while also extending these linkages to CDS spreads. European evidence on the relationship between funding liquidity and market liquidity is particularly thin, and no European study specifically explores the predictions of the Brunnermeier and Pedersen (2009) model. Moreover, considering that the levels of funding liquidity in the European and U.S. markets exhibit certain dissimilarities, especially between mid-2011 and mid-2012, the investigation of the impact of funding liquidity on European stocks' characteristics (returns, illiquidity, volatility) emerges as an interesting avenue of research. Furthermore, as CDS spreads convey information relating to the underlying entities' stock liquidity (Das and Hanouna, 2009) and volatility (Ericsson et al. 2009), this paper tests whether the impact of funding shocks on illiquidity and volatility, which have been empirically documented in the context of the U.S. market by Fontaine et al. (2016), extend to CDS spreads.

The paper brings original contributions to the literature investigating the effects of funding constraints on the cross-section of stock returns in several respects. Firstly, by newly using, in the context of studies investigating the cross-section of stock returns, a sample of firms which are part of the European iTraxx index containing entities with the most liquid CDSs and sorting these stocks into portfolios according to their illiquidity, volatility and CDS spread levels at the end of the previous year, this paper specifically tests and documents that funding conditions co-move with illiquidity, volatility and CDS spreads; a contraction of funding conditions therefore increasing illiquidity, volatility and CDS spreads. Secondly, results also show that the most volatile portfolios see their illiquidity increase the most, highlighting a flight to quality effect. However, evidence that entities with the widest CDS spreads see their illiquidity increase the most is rather weak. Thirdly, the study extends previous U.S. based findings that a funding shock increases stocks' illiquidity and volatility to a higher extent when funding is already constrained by documenting that a similar effect is found for CDS spreads, spreads widening following a funding shock especially when funding liquidity is tight. Fourthly, by distinguishing between positive changes in funding illiquidity (tightening of funding constraints) and negative changes in funding illiquidity (relaxation of funding constraints), the paper newly documents that only a worsening of funding conditions negatively impacts contemporaneous returns, while an improvement in funding liquidity has no significant effect on contemporaneous returns. Lastly, this study documents the presence of funding risk premium in the cross-section of stock returns, funding shocks generating a return spread between the most and least illiquid portfolios of 1.21% annually, a spread which is considerably lower compared to previous evidence provided by Fontaine et al. (2016) for the U.S. stock market which found a spread in returns of between 4.25% and 5.30% annually.

The objectives of the third paper of this thesis are the investigation of the presence of an effect of U.K. monetary policy, measured through short-term interest rates, on stock liquidity and whether the magnitude of this relationship changes during the 2007-2009 financial crisis or depends on firm characteristics such as size and volatility. The motivation for investigating this topic stems from the mixed results found by previous papers on the relation between monetary policy and stock liquidity, the presence of such a relationship depending on the time-frames and markets studied. In the context of the U.K. market, only Florackis et al. (2014) address this relationship in an event study documenting that there is a significant increase in trading activity and a smaller increase in trading cost on Monetary Policy Committee meeting days. We use a different methodology, akin to Fernandez-Amador et al. (2013), and employ panel estimations to investigate this relationship. Using this approach, we can also document whether the magnitude of the 'monetary policy – stock illiquidity' relationship depends on factors such as firm size and volatility.

The rationale for the influence of monetary policy on stock liquidity stems from two sources. Firstly, according to the inventory paradigm of market microstructure (Demsetz, 1968; Stoll, 1978a) stocks' liquidity would increase if market participants perceive a low risk of holding assets and financing their holdings is not expensive. Since monetary policy affects both the perceived risk of holding securities as well as the cost of financing, monetary policy should also affect stock liquidity. Secondly, the literature associating the effects of funding constraints on liquidity (e.g. Brunnermeier and Pedersen, 2009) suggests that following a contraction of funding, traders find it difficult to meet margin requirements and shift their investment strategies, dampening the liquidity of the market. Under this framework, an expansionary (restrictive) monetary policy, through a decrease (increase) in the cost of financing, reduces (increases) margin borrowing constraints, improving (decreasing) market participants' funding liquidity, thus improving (dampening) stock liquidity. Moreover, this paper hypothesizes that the effect of monetary policy is larger for small stocks and volatile stocks. The rationale for a size effect stems from study of Amihud (2002) documenting that small stocks are more sensitive to changes in illiquidity, while large (more liquid) stocks are less affected. Similarly, a volatility effect is expected to occur since following a decrease in funding liquidity, which can be interpreted through a monetary tightening, illiquidity increases the most for volatile stocks as a flight-to-quality effect occurs, investors shifting their allocations towards safer investments (Vayanos, 2004; Brunnermeier and Pedersen, 2009).

Results confirm our hypotheses. Firstly, we find evidence that an expansionary (restrictive) monetary policy improves (reduces) stock liquidity. Moreover, by examining interaction terms between monetary policy and, in turn, market capitalization and volatility, we confirm previous findings of Fernandez-Amador et al. (2013) in the context of the European market that the effect of monetary policy on stock liquidity is stronger for small firms and newly document that the 'monetary policy – stock liquidity' relationship is increasing in stock volatility. By disentangling the effects of the financial crisis from the rest of the sample, we also find new evidence that the effect of monetary policy on stock liquidity is generally more significant during the recent financial crisis, highlighting the relevancy of monetary policy in alleviating the large drops in liquidity brought about by the 2007-2009 financial crisis. This study also illustrates the importance of investigating multiple aspects of liquidity, results showing that the ‘monetary policy – stock liquidity’ relationship is significant only when liquidity is measured via price impact of transaction measures, such as the Amivest liquidity ratio and the percentage of zero return days.

Thesis structure

This thesis comprises of three studies investigating the effects of funding constraints on several markets. These studies are presented within the next three chapters. The final section of the thesis presents the conclusions of the thesis and potential avenues for future research.

The first chapter investigates the relationship between funding illiquidity changes and CDS spread changes in the context of the European market. Using a panel data approach on a sample of companies included in the European iTraxx index comprising of entities with the most liquid CDSs between January 2008 and March 2013, this chapter documents that a tightening of funding liquidity widens CDS spreads after controlling for firm-specific credit and liquidity variables as well as macroeconomic factors previously documented to influence spreads. Moreover, by differentiating between high and low default risk entities, as measured by their CDS spread levels, the study evidences that high-CDS spread firms display a sensitivity to funding illiquidity changes which is three times larger than that of low-CDS spread firms. Moreover, this paper illustrates the influence of a set of convention changes collectively named the ‘CDS Small Bang’ affecting the European CDS market after June 2009 and, more specifically, the introduction of fixed coupons which led to the introduction of upfront fees for trading CDSs. In line with the hypothesis that the introduction of upfront fees generates an additional funding cost relating to trading CDSs, this study documents that after the introduction of upfront fees, funding illiquidity changes have a larger and more significant impact on CDS spread changes.

The second chapter represents an empirical study of the theoretical predictions outlined by Brunnermeier and Pedersen (2009) linking funding liquidity with market liquidity and volatility and extends these predictions to CDS spreads. The rationale for investigating these effects on CDS spreads stems from their sensitivity to both illiquidity and volatility. Newly using in the context of studies investigating the cross-section of stock returns a sample of firms containing the most liquid CDSs and after sorting these stocks into portfolios according to their year-end illiquidity, volatility and CDS spreads, this paper provides the first European evidence confirming the predictions of the Brunnermeier and Pedersen (2009) model. The first piece of evidence provided is that funding conditions co-move with illiquidity, volatility and CDS spreads, a tightening of funding liquidity leading to increased illiquidity, volatility and wider CDS spreads. Secondly, the paper shows that during tight funding conditions, illiquidity increases more for the most illiquid and volatile portfolios. Thridly, this study evidences that a funding contraction increases CDS spreads, this effect being larger and more significant if funding conditions are already tight. Fourthly, this study finds that only a deterioration of funding liquidity negatively impacts contemporaneous returns, while an improvement of funding conditions has no significant effect on returns. Lastly, the study finds evidence that funding shocks are priced in the cross-section of illiquidity-sorted portfolios, generating an annual return spread between the most and least illiquid securities of 1.21%.

The third chapter examines the relationship between monetary policy and stock liquidity in the context of the U.K. market between January 1999 and December 2015. In line with theories linking capital constraints with market liquidity (Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2002) and the inventory paradigm of market microstructure (Stoll, 1978a), this paper documents that an expansionary (contractionary) monetary policy, as captured through lower (higher) short term interest rates, improves (decreases) stock liquidity. This effect is significant when measuring liquidity through price impact of trades measures, but insignificant when evaluating other facets of liquidity such as traded volume and trading costs. Disentangling the effects of the 2007-2009 financial crisis from the rest of the sample, this study finds that the 'monetary policy – stock liquidity' relationship is generally larger in magnitude and more significant during the crisis period, although some evidence of this relationship outside the crisis period is also presented. Moreover, by using interaction terms between monetary policy and, in turn, market capitalization and volatility, this paper documents that the effect of monetary policy on stock liquidity decreases with firm size and increases with firm volatility.

Chapter 1: Funding Liquidity Changes as a Determinant of Credit Default Swap Spread Changes

1.1 Introduction

Credit default swaps (CDS) emerged on the financial scene in 1994 being pioneered by JP Morgan. A CDS works in the same way as an insurance contract, by providing protection against the default of a reference entity. However, differently from traditional insurance contracts, CDS contracts are traded over-the-counter and, more recently, on organised exchanges. Secondly, unlike traditional insurance contracts, CDS buyers and sellers do not have to own any of the debt obligations to which the CDS contracts relates to (Blanco et al. 2005; Stulz, 2010). The CDS market developed steadily in the first years after the introduction of CDS contracts and has seen a period of unprecedented growth in the mid-2000s, with the gross notional amount of outstanding CDS contracts rising to approximately $57 trillion by June 2008 according to the Bank for International Settlements (BIS). Tang and Yan (2008) argue that this growth stemmed from the need of banks and insurance companies to hedge their bond and loan exposures and from the willingness of hedge funds to use CDSs as a tool for speculating on credit risk. However, after the onset of the global financial crisis raised concerns over the growth and relative uses of CDSs, the CDS market contracted, reaching a notional amount of $24 trillion by June 2013, according to BIS.

Early studies on credit default swaps (e.g. Longstaff et al. 2005), considered that CDS spreads, which represent the premiums paid by the CDS buyer to insure against the default of the reference name, contain only information relating to the credit risk of the reference entity. However, more recent studies highlighted the importance of liquidity components such CDS liquidity (e.g. Tang and Yan, 2008; Bongaerts et al. 2011; Coro et al. 2013; Pires et al. 2015) and individual firm equity liquidity (Das and Hanouna, 2009) in explaining CDS spreads.

In this paper, we newly study whether funding liquidity changes, defined as changes in the ease with which traders can acquire funds and finance their operations, impact CDS spreads changes. A tightening of funding constraints impairs the capacity of dealers to take sides in new CDS contracts as they face higher costs of hedging their positions and higher inventory costs (Tang and Yan, 2008). This argument is supported by Kamga and Wilde (2017) who consider that a funding liquidity contraction drives CDS traders to steer away from risky assets, thus reducing the liquidity of the CDS market, in line with the theoretical model proposed by Brunnermeier and Pedersen (2009). Furthermore, confirming these predictions, Junge and Trolle (2015) construct a measure of CDS market liquidity which correlates strongly, among other factors, with funding liquidity, and find that liquidity risk is priced in the cross-section of single-name CDS returns. The above-mentioned studies suggest that funding liquidity positively impacts CDS market liquidity. However, as shown, among others, by Bongaerts et al. (2011) and Coro et al. (2013), CDS spreads are highly sensitive to changes in CDS liquidity, a deterioration of CDS liquidity increasing CDS spreads, as CDS protection sellers require a premium for illiquidity. Therefore, we would expect funding illiquidity changes to positively impact CDS spread changes through their effect on CDS illiquidity.

Moreover, in a contemporaneous and highly related study to ours, Wang et al. (2017) investigate the effect of the introduction of upfront fees for trading CDSs in the context of the CDS Big Bang (a set of regulatory reforms introduced in the U.S. market in April 2009) on CDS market liquidity and CDS spread volatility. They go on to find that after the introduction of the regulatory reforms, a higher funding cost reduces market liquidity and increases CDS spread volatility. A similar set of protocol changes, collectively named the '*CDS Small Bang'*, was introduced in the European market on 20th June 2009 to facilitate standardization and central clearing. Before the protocol changes came to effect, trading of CDS contracts was done at a coupon rate that fixed the contract value to zero on the inception day, no upfront fee needing to be exchanged (Wang et al. 2017). Among other regulatory changes, the CDS Small Bang conventions restrict coupon rates to be fixed at 25bps, 100bps, 500bps and 1000bps (Markit, 2009). However, the introduction of fixed coupons gave rise to upfront fees that need to be exchanged between CDS buyers and sellers, the size of the fee depending on how far away the CDS spread level is from the fixed coupons at which the contract settles (Wang et al. 2017). Periods when funding is tight should thus more strongly negatively affect CDS spread liquidity after the implementation of the CDS Small Bang regulations, due to the need of paying additional upfront fees for trading CDSs. The resulting decline in CDS liquidity would then be transmitted onto CDS spreads as CDS traders require a premium for illiquidity.

Furthermore, motivated by the findings of Pires et al. (2015) that most explanatory variables display a much stronger relationship with CDS spreads of high-CDS spread firms, compared to low CDS spread firms, we newly investigate whether changes in funding illiquidity have a larger and more significant effect on high-CDS firms, compared to low-CDS spread entities. We investigate these relationships on the entire sample as well as on two sub-samples corresponding to the periods preceding and following the implementation of the CDS Small Bang regulatory changes. We expect high-CDS spread firms to be more affected by changes in funding illiquidity as they carry more default risk and a tightening of funding liquidity would lead these entities closer to the default barrier compared to low-CDS spread firms. Moreover, on average, high-CDS spread firms are more likely to have a CDS spread further away from one of the fixed coupons introduced after the CDS Small Bang. Therefore, a higher fee would need to be exchanged between CDS buyers and sellers for contracts written on high-CDS reference entities, leading to a greater reduction in individual CDS liquidity and a higher CDS spread.

Therefore, the hypotheses examined in this study can be summarized as follows: *Firstly*, we argue that a tightening (relaxation) of funding liquidity increases (decreases) CDS spreads through its effect on CDS liquidity. *Secondly*, we suggest that the effect of funding liquidity changes on CDS spread changes is stronger in the post-June 2009 period, due to the introduction of an upfront fee that is exchanged between CDS buyers and sellers, unless the CDS spread level of an entity is exactly equal to one of the fixed coupon payments. *Thirdly*, we hypothesize that high-CDS spread firms display more sensitivity to changes in funding liquidity than low-CDS spread firms.

We test our hypotheses using monthly data on a sample spanning the period between January 2008 and March 2013, using a balanced panel of CDS spread changes of entities which are part of the European iTraxx index (containing the most liquid single-name CDSs) and associated firm-specific credit and liquidity variables as well as macroeconomic factors which have been previously documented to affect CDS spreads. The funding illiquidity measures employed, namely the three-month European TED spread measure (*EuTed*) and the three-month Euribor-Eurepo spread (*EuRepo*), are related to interbank interest rates and reflect the cost of acquiring funds to finance operations. To test whether the magnitude and significance of the impact of funding illiquidity changes on CDS spread changes increases after the introduction of the CDS Small Bang, we split our sample in two subsamples (January 2008 – June 2009 and July 2009 – March 2013) and re-run our analysis on these two subsamples. Coincidentally, this sample split also isolates the crisis period from the post-crisis period. Therefore, we can simultaneously investigate whether the effect of funding liquidity changes on CDS spread changes is different during the recent global financial crisis as compared to the post-crisis period. When evaluating the effects of funding illiquidity changes on CDS spread changes we also differentiate between high-CDS spread entities and low-CDS spread entities and examine whether the relationship is stronger in magnitude and significance for high-CDS spread (higher default risk) firms compared to low-CDS spread (lower default risk) firms.

Results suggest that changes in funding illiquidity have a significant positive effect on CDS spreads, in line with the hypothesis that a tightening of funding liquidity determines CDS protection sellers to reduce the supply of contracts in the CDS market as they incur increased inventory and hedging costs, reducing CDS market liquidity (Tang and Yan, 2008). Moreover, we find that changes in funding illiquidity have a three times larger effect on high-CDS entities as compared to low-CDS entities, in line with previous findings of Pires et al. (2015) that most explanatory variables have a larger impact on high-CDS entities, compared to entities which carry less default risk. Furthermore, by splitting our sample in two sub-samples corresponding to the pre-CDS Small Bang period, which overlaps with the crisis period, and the post-CDS Small Bang period, which can also be interpreted as the post-crisis period, we find that funding illiquidity changes positively affect CDS spread changes much more significantly and to a much higher magnitude in the post-CDS Small Bang period, in line with our expectations. Finally, by examining the results for the explanatory variables used in our models, we document a strong time-varying behaviour of the impact of different explanatory variables on CDS spread changes, with CDS illiquidity changes and risk-free rate changes having a stronger effect during the crisis period, while stock returns and market volatility have a stronger effect in the post-crisis period.

Through this study, we contribute to two strands of literature. Firstly, we add to the literature investigating the effects of funding constraints on financial markets (e.g. Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2002; Gromb and Vayanos, 2010; Comerton-Forde et al., 2010). Most notably, Brunnermeier and Pedersen (2009) theorize that under certain market conditions, such as when capital availability is scarce, a deterioration of funding liquidity negatively impacts investors' willingness and ability to invest in high-risk securities as they add on more risk, thus leading to reductions in market liquidity and increased volatility. Moreover, the resulting reduction in market liquidity further increases the sensitivity of market liquidity to future funding liquidity changes. Secondly, by documenting that funding illiquidity changes affect CDS spread changes, this paper contributes to the growing literature investigating the determinants of CDS spreads (e.g. Blanco et al. 2005; Tang and Yan 2008; Ericsson et al. 2009; Greatrex 2009; Coro et al. 2013; Annaert et al. 2013; Galil et al. 2014; Pires et al. 2015). Research examining the determinants of CDS spreads (and CDS spread changes) has gone a long way in explaining CDS spreads, from early studies attributing the level of the CDS spread of an entity only to credit risk variables (e.g. Longstaff et al. 2005, Zhang et al. 2009) to ascribing part of the CDS spread variability to liquidity components and market-wide variables (e.g. Bongaerts et al. 2011; Coro et al. 2013; Galil et al. 2014; Pires et al. 2015).

The rest of the paper is organised as follows: section 1.2 describes the data and variables used in our analysis, section 1.3 describes the models employed, section 1.4 presents the empirical results, section 1.5 presents robustness checks performed, section 1.6 discusses the policy recommendations that can be extracted from our results, while section 1.7 concludes.

1.2 Data

Our dataset combines two main sources, Bloomberg and Thomson Reuters Datastream. From the former we source data on CDS spread mid, bid and ask quotes as well as market rates on the three-month Euribor rate and German Government BuBill maturing in three months.[1] From the latter, we source stock market data such as bid, ask and adjusted close stock prices for the reference entities on which the CDS contracts are written. Macroeconomic interest rate data such as the ten-year and three-year Euro-area Government Benchmark bond yields, stock market index and market wide implied volatility are also collected from Thomson Reuters Datastream. The three-month Eurepo rate is collected from the European Money Market Institute database.

The dataset covers a period of 63 months, from January 2008 to March 2013. The sample starts in January 2008 to preserve the number of firms in our sample due to data availability on CDS quotes as well as associated stock market data on reference entities. The companies selected are all the non-financial companies included in the European iTraxx index on March 2013 (index roll 19)[2]. The Markit iTraxx Europe index comprises of 125 investment-grade entities with the most liquid single-name CDSs in the European market. The constituent list includes 100 non-financial firms and 25 companies that operate in the financial sector. Previous studies using data from the iTraxx Europe index include Alexander and Kaeck (2008) and Breitenfellner and Wagner (2012) which examine the determinants of the CDS indices, Berndt and Obreja (2010) who use index data to construct

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[1] Das and Hanouna (2009) and Nashikkar et al (2011) also use CDS information obtained from Bloomberg in their analyses of determinants of CDS spreads and CDS bond-basis, respectively.

[2] The European Markit iTraxx index constituent list is reviewed with respect to liquidity and investment grade of entities every six months, with one index roll occurring in March and one in September. To preserve the number of companies in our cross-section, we also include any entities which were listed as part of the Markit iTraxx index as of March 2013, but which have been previously part of the Markit iTraxx Crossover Index encompassing the 75 most liquid sub-investment grade entities due to a rating downgrade event occurring during our sample period. It is worth noting that throughout the time frame of the study, the constituent list of the European iTraxx index changes are minor. This observation is also highlighted by Breitenfellner and Wagner (2012) who find only neglectable effects of index roll changes on spread changes.

a factor mimicking economic catastrophe risk and Junge and Trolle (2015) who construct a new measure of CDS market liquidity and analyse whether liquidity risk impacts expected CDS returns.

Following Bai and Wu (2016), we restrict our sample to non-financial entities due to the important differences in terms of regulation, funding methods, corporate governance, agency problems, capital structure, leverage levels and calculation of distance-to-default measures between financial and non-financial firms highlighted by De Haan and Vlahu (2016) and Duan and Wang (2012). Furthermore, amongst others, Alexander and Kaeck (2008) provide evidence that several variables that affect CDS spreads of non-financial entities do not impact spreads of companies from the financial sector. Following the recommendations outlined in Coro et al. (2013), we further restrict our sample to include only CDS contracts that satisfy the following conditions: the CDS contract maturity is five years, the most-liquid CDS maturity (Meng and Gwilym, 2008), contracts are denominated in Euros, and the underlying debt is senior-unsecured. Finally, we only select entities for which we can source stock market data for the entire time-series from Thomson Reuters Datastream. Unfortunately, data on identity of buyers and sellers, volume of transactions, market depth and buy and sell orders is not available. Data on these variables would be a useful complement to an analysis of the impact of funding liquidity on CDS spreads due to the interconnectedness between market liquidity and funding liquidity documented, among others, by Brunnermeier and Pedersen (2009).

Restricting our data using the above-mentioned filters yields us a balanced panel of 76 European entities observed throughout a period of 63 months. In line with Collin-Dufresne et al. (2001), Coro et al. (2013), Galil et al. (2014) and Pires et al. (2015) we conduct our empirical analysis using monthly data, as CDS contracts are known to not trade frequently. In his analysis, Zhu (2006) finds that only 20% of days in his sample period contain valid CDS quotes.

1.2.1 Credit default swaps

The size of the CDS market has seen large fluctuations throughout time. *Figure 1.1* plots the gross total notional amounts of single name CDSs and investment-grade single-name CDSs over time. Single-name CDSs have seen a period of high growth in the 2000s reaching a peak of 33.4$ trillion in June 2008, according to data from the Bank for International Settlements (BIS). However, despite their many advantages in making financial markets more efficient, following the financial crisis many observers have highlighted the potential negative impact of CDSs on financial stability, CDSs being associated with losses and uncertainty at some institutions (Stulz, 2010). Consequently, according to BIS data, the outstanding notional amounts of single-name CDS have steadily decreased after June 2008, reaching 13.1$ trillion at the end of June 2013. *Figure 1.1* also depicts that the proportion of single-name investment-grade CDSs to total single-name CDSs has largely remained constant, representing between 64% and 70% over our sample period.

Figure 1.2 plots the evolution of average CDS spread levels (panel A) and CDS spread changes (panel B) over time. The solid lines represent averages for our entire sample, while the dotted lines represent averages for the top and bottom terciles of the respective distributions. We note a great deal of variation in both average CDS spread levels and changes throughout our sample period. Investigating panel A, we note that average spread levels fluctuated from highs of 253 bps in December 2008 to lows of 76 bps recorded in January 2008 and December 2009. Moreover, the average spread in the upper tercile of CDS spreads displays even greater variation, reaching peaks of 445 bps in December 2008 and 270 bps in September 2011 and lows of 104 bps in January 2008 and 108 bps in December 2009. Examining panel B, we note that average CDS spread changes also display variation throughout our sample, from large negative changes of -57 bps in January 2009 and -35 bps in October 2011 to large positive changes of +73 bps in October 2008. The very large variation in average CDS spread changes for the top tercile of CDS spreads during the financial crisis is also remarkable, spreads widening by 138 bps in October 2008 at the peak of the crisis and shrinking by 98 bps and 96 bps in January 2009 and April 2009, respectively.

In the empirical analysis, we focus on examining CDS spread changes, rather than CDS spread levels because, after examining stationarity via the panel unit root test of Levin et al. (2002), we cannot reject the null of a unit root for CDS spread levels, whereas spread changes are stationary.[3] Moreover, as Ericsson et al. (2009) notes, CDS spread differences should be harder to explain than CDS levels. Therefore, by performing our estimations in first differences, we perform a stricter test of CDS determinants. For each month *t* and company *i*, CDS spread changes are calculated as the first difference of CDS spread levels from the last day of each month, as shown in equation (1.1):

$$\Delta CDS_{i,t} = CDS_{i,t} - CDS_{i,t-1} \qquad \textbf{(1.1)}$$

By performing panel regressions using first differences of our variables, rather than levels, we contribute to the growing literature examining the determinants of CDS spread changes (e.g. Collin-Dufresne et al. 2001; Ericsson et al. 2009; Greatrex, 2009).

[3] Previous studies investigating the determinants of CDS spread changes in the European market (Coro et al. 2013; Annaert et al. 2013) and in the U.S. market (Galil et al. 2014) also found evidence of non-stationarity in CDS spread levels.

1.2.2 Funding liquidity

Low funding liquidity leads CDS protection sellers to steer away from risky assets, thus decreasing the liquidity of the CDS market (Kamga and Wilde, 2017). This argument is supported by the findings of Tang and Yan (2008) who find that a tightening of funding liquidity determines dealers with excess inventory to face higher costs of hedging their positions and higher inventory costs, in turn affecting the supply of CDS contracts in the market. Separately, Junge and Trolle (2015) construct a measure of CDS market liquidity that correlates strongly, among others, with funding costs, and go on to find that liquidity risk is priced in the cross-section of single-name CDS returns. These arguments suggest that funding illiquidity affects CDS spreads through their effect on CDS market illiquidity. As shown by Bongaerts et al. (2011), Coro et al (2013) and Pires et al. (2015), CDS market liquidity, as well as individual CDS liquidity, are important determinants of CDS spreads, a decrease in CDS liquidity leading to a widening of CDS spreads.

Furthermore, we expect funding illiquidity changes to have a stronger impact on CDS spread changes after June 2009, due to the implementation of the CDS Small Bang which brought about a set of convention changes to the European CDS market meant to improve central clearing (Markit, 2009). Before the CDS Small Bang convention changes came into effect, CDS contracts were traded at a coupon rate that set the contract value to zero on the start date of the contract, thus no upfront fee was needed (Wang et al, 2017). According to Markit (2009), one of the changes implemented through the CDS Small Bang is the implementation of fixed coupons (25bps, 100bps, 500bps and 1000bps). If the CDS spread for an entity at the date of the contract does not amount exactly to one of the implemented fixed coupons, upfront fees are exchanged depending on the CDS spread level, with the fees being larger the further away the CDS spread is from the newly established fixed coupons. Periods of tight funding should thus affect more strongly CDS spreads after the implementation of the new regulations, due to the need of paying additional fees for trading CDSs which would decrease CDS market liquidity. These effects are closely tied to those documented by Wang et al. (2017) in relation to the CDS Big Bang, a similar protocol to the CDS Small Bang implemented in the U.S. market prior to the introduction of the CDS Small Bang in the European market. Wang et al. (2017) go on to find that the higher funding cost due to the introduction of upfront fees for trading CDSs reduces CDS market liquidity and increases CDS spread volatility.

The above arguments suggest that we expect a positive relationship between funding illiquidity changes and CDS spread changes, effect which should be larger after June 2009 due to the implementation of the CDS Small Bang regulations. We use two proxies to measure funding illiquidity. Firstly, we examine the European TED spread measure (*EuTed*) calculated as the difference between the three-month Euribor rate and three-month German Government BuBill. This measure can be considered a European equivalent of the widely used TED spread funding liquidity measure (Garleanu and Pedersen, 2011; Boudt et al, 2017) in the context of the European market. Secondly, in line with Moinas et al. (2017) and Dunne et al. (2013), we investigate a funding liquidity measure relying on repo rates, namely the Eurepo spread (*EuRepo*) calculated as the spread between the three-month Euribor and three-month Eurepo rates. The Eurepo rate is collected from the European Money Market Institute database and represents the rate at which one prime bank offers funds in Euro to another prime bank, with the Eurepo General Collateral serving as the collateral in the transaction (Moinas et al, 2017). As suggested by Moinas et al. (2017), a higher Eurepo spread indicates higher risk aversion and a higher preference for cash.

1.2.3 Control variables

We investigate the presence of a relationship between changes in funding illiquidity and CDS spread changes, while controlling for a set of additional firm-specific and macro-economic credit risk and liquidity variables previously documented to impact credit spreads. The choice of control variables is inspired by the Merton (1974) model and by more recent studies documenting the influence of liquidity and macroeconomic factors on CDS spreads (e.g. Coro et al. 2013; Bongaerts et al. 2011; Annaert et al. 2013).

1.2.3.1 Firm-specific credit risk variables

1.2.3.1.1 Stock return

The model introduced by Merton (1974) suggests that a decrease in a firm's market value of equity leads to a higher probability of default for the respective firm. In line with Galil et al. (2014), we use monthly stock returns as indicators of changes in a firm's market value of equity. We expect a negative relationship between stock returns and CDS spread changes as a decrease in stock returns would reduce the market value of equity and thus increase the probability of default of the firm, which would be captured through an increase in the CDS spread of the respective entity. Alternatively, following Collin-Dufresne et al. (2001), Blanco et al. (2005), Cremers et al. (2008) and Greatrex (2009), a firm's stock return can be considered a high-frequency measure of leverage. Under this hypothesis, a decrease in stock returns would increase the market value of leverage, increasing the probability of default and CDS spreads. Additionally, following Annaert et al. (2013) stock returns can be considered a measure of a firm's future prospects. A decrease in stock returns would increase the default risk of firms, leading to higher CDS spreads. Therefore, we expect a negative relationship between a firm's stock return and CDS spread changes.

1.2.3.1.2 Stock return volatility

In the framework of Merton (1974), higher firm value volatility increases the probability of reaching the default threshold. Therefore, higher firm value volatility would increase the CDS spread of an entity. However, firm value volatility is unobservable, but can be approximated through the historical volatility of stock returns (Alexander and Kaeck, 2008; Ericsson et al. 2009; Annaert et al. 2013). Following Annaert et al. (2013), monthly volatility is measured as the monthly historical standard deviation of daily stock returns over the past month.

1.2.3.2 Firm-specific liquidity variables

1.2.3.2.1 Scaled equity bid-ask spread

Das and Hanouna (2009) develop a hedging mechanism evidencing that illiquidity costs from the equity market are transmitted to CDS spreads. In this framework, CDS contract sellers actively hedge their positions and the cost of hedging increases with transaction costs, measured through the scaled equity bid-ask spread (Das and Hanouna, 2009). CDS sellers would therefore attempt to recover the added cost of hedging their positions through a higher CDS spread. Therefore, we would expect a positive relationship between equity illiquidity and CDS spreads. Following Amihud and Mendelson (1986) and Das and Hanouna (2009), we use the scaled equity bid-ask spread, measured as the difference between the ask and bid prices divided by the mid-point of the two, to proxy for equity illiquidity transaction costs.

1.2.3.2.2 Absolute CDS bid-ask spread

Tang and Yan (2008) and Pires et al. (2015) show that an important determinant of CDS spreads are CDS illiquidity costs. Moreover, Bongaerts et al. (2011) develop a model where

CDS returns depend on CDS transaction costs, a liquidity premium being earned by the CDS contract seller. These results are in line with the hypothesis that liquidity providers such as CDS contract sellers require a premium for illiquidity. Alternatively, considering CDS contracts to be similar to insurance contracts, Acharya and Johnson (2007) show that information asymmetries increase the insurance premium. Assuming that the CDS bid-ask spread can be considered a good proxy for information asymmetries in the market, as suggested by Pires et al. (2015), a higher CDS bid-ask spread should lead to a higher CDS spread. We follow Bongaerts et al. (2011) and Pires et al. (2015) and focus on the absolute, rather than the relative, bid-ask spread, as Pires et al. (2015) convincingly show that the absolute measure should be used in the context of the CDS market. The reason behind this choice is that, contrary to stock prices, CDS spreads are already expressed in a comparable way between entities (basis points per annum of the notional amount of the contract) and further dividing the CDS by the mid-quote could bias the comparison (Pires et al. 2015).

1.2.3.3 Market-wide variables

1.2.3.3.1 Risk-free rate

The level of the riskless interest rate has been considered an important component of default probability since the model of Merton (1974). On one hand, the risk-free rate determines the risk-adjusted drift of firm value, an increase in rates decreasing the risk-adjusted default probability leading to a decrease in spreads (Longstaff and Schwartz, 1995; Collin-Dufresne et al, 2001). Moreover, following Tang and Yan (2006), an increase in the risk-free rate positively affects economic growth prospects, leading to a decrease in default risk. These arguments suggest a negative relationship between the level of interest rates and CDS spreads. On the other hand, as Coro et al (2013) argue, higher interest rates can also suppress growth through an increase in borrowing costs, such an effect being more prominent in a period of increased sovereign risk such as seen in the European market starting from late 2009. This would lead to a positive relationship between the risk-free rate and CDS spreads. Therefore, due to these two diverging arguments, we consider the relationship between the riskless interest rate and CDS spreads as undetermined, and investigate whether the effect of the risk-free rate on CDS spreads changes throughout the sample periods. We measure the risk-free interest rate as in Coro et al. (2013) through the Euro-area government bond with a maturity of 10-years.

1.2.3.3.2 Term structure slope

Among others, Alexander and Kaeck (2008) and Collin-Dufresne et al. (2001) suggest that an increase in the slope of the yield curve predicts economic growth and improves recovery rates. This leads to an expected negative relationship between the term structure slope and CDS spreads. However, a steepening of the slope could also reduce the number of positive net present value projects available to firms, leading to an increase in default probability (Galil et al, 2014). This argument indicates a positive relationship between the slope of the term structure of interest rate and the CDS spread. Therefore, as with the risk-free rate, we leave the expected relationship between the slope of the term structure and CDS spreads as undetermined and check whether the relationship changes within the different sub-samples investigated. The term-structure slope is measured through the difference between the ten-year and three-year Euro-area Government bond yields.

1.2.3.3.3 Market-wide volatility

Market-wide volatility can be considered a measure of business climate, an increase in market-wide volatility indicating heightened uncertainty regarding economic prospects (Annaert et al. 2013; Greatrex, 2009). Therefore, as with firm-specific volatility, we expect a positive relationship between market volatility and CDS spreads. We measure market volatility through the VSTOXX implied volatility index obtained from options written on the Euro STOXX 50 index.

A description of the explanatory variables as well as a summary of the expected relationships between the changes in explanatory variables and changes in CDS spreads are presented in *Table 1.1*.

1.3 Methodology

To test the impact of funding illiquidity and other firm-specific and macroeconomic factors on CDS spread changes, we estimate the following set of multivariate regressions:

M1: $$\Delta CDS_{i,t} = \alpha_0 + \beta_1 Stock\_return_{i,t} + \beta_2 \Delta Volatility_{i,t} + \beta_3 \Delta Equity\_BAS_{i,t} + \\ + \beta_4 \Delta CDS\_BAS_{i,t} + \varepsilon_{i,t} \quad \mathbf{(1.2)}$$

M2: $$\Delta CDS_{i,t} = \alpha_0 + \beta_1 Stock\_return_{i,t} + \beta_2 \Delta Volatility_{i,t} + \beta_3 \Delta Equity\_BAS_{i,t} + \\ + \beta_4 \Delta CDS\_BAS_{i,t} + \beta_5 \Delta EuTed_t + \varepsilon_{i,t} \quad \mathbf{(1.3)}$$

M3: $$\Delta CDS_{i,t} = \alpha_0 + \beta_1 Stock\_return_{i,t} + \beta_2 \Delta Volatility_{i,t} + \beta_3 \Delta Equity\_BAS_{i,t} + \\ + \beta_4 \Delta CDS\_BAS_{i,t} + \beta_5 \Delta EuRepo_t + \varepsilon_{i,t} \quad \mathbf{(1.4)}$$

M4: $$\Delta CDS_{i,t} = \alpha_0 + \beta_1 Stock\_return_{i,t} + \beta_2 \Delta Volatility_{i,t} + \beta_3 \Delta Equity\_BAS_{i,t} + \\ + \beta_4 \Delta CDS\_BAS_{i,t} + \beta_5 \Delta EuTed_t + \beta_6 \Delta Riskfree_t + \beta_7 \Delta Slope\_yield_t + \\ + \beta_8 \Delta Mkt\_volatility_t + \varepsilon_{i,t} \quad \mathbf{(1.5)}$$

M5: $$\Delta CDS_{i,t} = \alpha_0 + \beta_1 Stock\_return_{i,t} + \beta_2 \Delta Volatility_{i,t} + \beta_3 \Delta Equity\_BAS_{i,t} + \\ + \beta_4 \Delta CDS\_BAS_{i,t} + \beta_5 \Delta EuRepo_t + \beta_6 \Delta Riskfree_t + \\ + \beta_7 \Delta Slope\_yield_t + \beta_8 \Delta Mkt\_volatility_t + \varepsilon_{i,t} \quad \mathbf{(1.6)}$$

In models M1 – M5, the dependent variable is the monthly change in the CDS spread, while the explanatory variables are as described in *Table 1.1*. Model M1 estimates the impact of firm-specific credit and liquidity factors on CDS spread changes. In models M2 and M3, we augment M1 alternatively with the two funding illiquidity factors to examine the influence of changes in funding illiquidity on CDS spread changes when controlling for firm-specific determinants. Lastly, in models M4 and M5, we investigate the role of funding illiquidity changes on CDS spread changes when controlling for both firm-specific and macro-economic variables that have been previously documented to impact CDS spread changes. Following Coro et al. (2013), models M1 – M5 are estimated using firm-level fixed effects and standard errors clustered by firm to correct for autocorrelation and heteroskedasticity.

We estimate models M1 – M5 on our entire sample of firms as well as on the top and bottom terciles (top and bottom 33%) of entities according to their CDS spread level. By performing these estimations, we can test whether CDS spread changes of high-CDS spread (high default risk) firms react differently to changes in funding illiquidity and other explanatory variables than low-CDS spread (low risk) firms. In line with previous findings documented by Pires et al. (2015), we expect the effects of explanatory variables on CDS spread changes of high-CDS firms to be larger in magnitude than on low-CDS firms, as negative shocks to either credit or liquidity variables would drive high-CDS entities, which carry more credit and liquidity risk, closer to the default barrier.

Furthermore, we conduct a sub-sample analysis to isolate the effects of the crisis period and the effects of the regulatory changes introduced through the CDS Small Bang on June 20th, 2009. To this end, we split the sample in two sub-samples: a crisis period, from January 2008 to June 2009, which also coincides with the pre-CDS Small Bang period, and a post-crisis period, from July 2009 to March 2013, which also represents the post-CDS Small Bang regime[4]. We estimate models M1 – M5 during the two sub-samples separately using the entire sample of firms as well as the top and bottom terciles of entities according to their CDS spread level. We expect changes in funding illiquidity to have a more pronounced effect on CDS spread changes in the post-CDS Small Bang sample due to the

[4] Galil et al. (2014) also consider June 2009 as the last month of the most intense phase of the Global Financial Crisis.

introduction of an upfront fee, which increases the funding cost for trading CDSs, reducing traders' willingness to trade, leading to a reduction in CDS market liquidity and an increase in CDS spreads.

1.4 Empirical results

1.4.1 Descriptive statistics

Table 1.2 presents descriptive statistics for the dependent and independent variables along with CDS spread and funding liquidity levels. Panel A presents summary statistics for the whole sample, while panels B and C present results for the crisis and post-crisis periods, respectively. All variables are calculated with monthly frequency. Investigating panel A, we note that the average CDS spread for the entire sample is 119.66 bps, while the mean monthly CDS spread change is 1.09 bps. We also observe large variations in the CDS spread levels between entities, the lowest CDS spread recorded being 20.53 bps, while the largest being 759.58 bps. Comparing the two funding liquidity measures, we note that *EuTed* has a larger mean value and displays higher volatility than *EuRepo*. Moreover, monthly changes in the *EuTed* spread are, on average, larger in magnitude than monthly changes in the *EuRepo* spread.

Comparing the summary statistics between the crisis and post-crisis periods, displayed in panel B and panel C, respectively, we note that the average CDS spread as well as the monthly average CDS spread changes are larger in the crisis period, while the average monthly stock return is -2.93 percent in the crisis period compared to 0.60 percent in the post-crisis period. CDS volatility, CDS illiquidity as well as stock return volatility are also larger in the crisis period. Together, these statistics highlight the heightened default risk during the 2007-2009 Global Financial Crisis. In addition, during the crisis period, on average, funding illiquidity is more than two times higher than in the post-crisis period, while mean monthly changes in funding illiquidity are larger.

Table 1.3 presents time-series pairwise correlations between the explanatory variables included in our models. Panel A presents correlations observed throughout the entire sample, while Panels B and C illustrate the pairwise correlations during the crisis and post-crisis periods, respectively. The signs of the correlations between the explanatory variables broadly confirm our expectations. The largest correlation is observed between the two funding liquidity proxies (0.65 for the entire sample of dates, and 0.68 during the crisis period). However, these two variables are only included alternatively in the regression models. All other pairwise correlations are smaller than +/- 0.5, except for the correlation between $\Delta EuRepo_t$ and $\Delta Mkt\_Volatility_t$ during the crisis period (0.52).

1.4.2 Results of regression estimations

1.4.2.1. Results for the full time-series sample

Table 1.4 presents the results of the multivariate regressions depicted in models M1 – M5 for the entire time-series (January 2008 - March 2013). Panel A presents the results for the entire sample of firms, while panels B and C present the results for the sub-samples containing high and low CDS spread entities. We first draw our attention to panel A. Model M1 reflects the ability of firm-specific credit and liquidity variables to explain CDS spread changes. We find that stock returns and changes in volatility, equity bid-ask spreads and CDS bid-ask spreads are highly significant determinants of CDS spread changes as previously documented by Coro et al. (2013), Pires et al. (2015) and Das and Hanouna (2009). Stock returns have an expected negative relationship with CDS spread changes, while changes in volatility, equity bid-ask spreads and CDS bid-ask spreads evidence a positive relationship with CDS spread changes. Together these variables explain 32% of CDS spread changes. In models M2 and M3, we augment model M1 with the two funding liquidity proxies separately. We find that the two funding illiquidity proxies, $\Delta EuTed_t$ and $\Delta EuRepo_t$, are significant at the 1% significance level and have a positive relationship with CDS spread changes. This is in line with our hypothesis that a tightening of funding liquidity increases CDS spreads. The firm-specific variables remain highly significant and of the expected sign. Models M4 and M5 investigate the effect of funding illiquidity changes on CDS spread changes when controlling for both firm-specific and macroeconomic variables. We find that both funding illiquidity measures remain significant. The magnitude of the coefficients for funding illiquidity drops by more than a half when adding the macroeconomic variables, compared to the specifications in models M2 and M3. Investigating the macroeconomic control variables, we find that changes in risk free rate have a significant negative relationship with changes in CDS spreads, while changes in market volatility positively affect changes in CDS spreads. These results are in line with our hypotheses and with results from previous studies such as Collin-Dufresne et al. (2001). Changes in the term structure slope do not have a significant impact on changes in CDS spreads. Models M4 and M5 explain 35% of CDS spread changes. The explanatory power of these models is 14% larger than that of a comparable model presented by Annaert et al. (2013) for a sample of CDSs between 2003 and 2010. We differ from the model presented by Annaert et al. (2013) by using monthly data compared to weekly data and by additionally testing for the influence of funding liquidity and equity illiquidity on CDS spread changes, while not examining the influence of the swap spread and corporate bond spread on CDS spread changes.

Examining panels B and C of *Table 1.4*, we find that the effect of funding illiquidity changes on CDS spread changes is significant when investigating either high-CDS firms or low-CDS firms, albeit the coefficient of $\Delta EuRepo_t$ is significant only at the 10% significance level in model M5 when investigating low default risk firms. The magnitude of the funding effect is approximately three times larger when investigating high-CDS spread entities compared to the funding effect on low-CDS spread entities. This highlights the fact that high-CDS spread (higher default risk) entities are more sensitive to changes in funding conditions compared to low-CDS (lower default risk) firms, consistent with the hypothesis that a tightening of funding liquidity would affect high risk firms more than low risk firms as investors shy away from riskier assets following a funding contraction (Brunnermeier and Pedersen, 2009). All the relationships between the explanatory variables and CDS spread changes remain significant and of the same sign compared to the estimation using the entire sample of firms, except for the equity bid-ask spread which is insignificant in the low-CDS spread subsample and the slope yield which is significant in the high-CDS subsample.

1.4.2.2. The effect of funding illiquidity changes on CDS spread changes during and after the Global Financial Crisis.

Table 1.5 and *Table 1.6* present the results of the multivariate regressions described in models M1-M5 during the Global Financial Crisis (January 2008 – June 2009) and after the Global Financial Crisis (July 2009 – March 2013), respectively. This subsample split also coincides with the periods preceding and following the implementation of the CDS Small Bang regulatory framework which took effect on June 20^{th}, 2009. Within *Table 1.5* and *Table 1.6*, panel A presents results for the entire sample of firms, while panels B and C present results for the high-CDS spread and low-CDS spread firms within the two subsamples, respectively.

Investigating *Table 1.5*, results suggest that funding illiquidity changes do not generally have a significant impact on CDS spread changes during the Global Financial Crisis period. We obtain statistically significant (at 10% significance level) and positive coefficients for the funding liquidity variables only when estimating model M3 for the high-CDS spread sample and when estimating model M2 in the low-CDS spread sample. We consider that this result arises because during the financial crisis, tightening of funding liquidity led to a reduction in CDS market liquidity and individual CDS illiquidity which dramatically increased the explanatory power of individual CDS illiquidity on CDS spread changes relative to other structural or macroeconomic factors. Indeed, the magnitude of the effect of individual CDS illiquidity changes on CDS spread changes is two to three times larger during the crisis period, compared to the post-crisis period. A similar result is documented by Annaert et al. (2013) who find that CDS bid-ask spreads are more significant during the Global Financial Crisis period, compared to the pre-crisis period and that the explanatory power of CDS bid-ask spreads in univariate regressions grows from 0.30% before the crisis to 6.96% during the crisis. Exploring the results for the other explanatory variables during the crisis period, we note that stock returns and changes in CDS bid-ask spreads, risk free rate and term-structure slope are significant in all estimations. Interestingly, during the crisis period, we obtain larger adjusted R^2 values, of up to 44%, when performing estimations on the low CDS spread entities suggesting that our explanatory variables explain better CDS spread changes of low-risk entities, contrary to previous findings.

Examining *Table 1.6*, we note that funding illiquidity changes have a positive and significant (at 1% significance level) effect on CDS spread changes in the post-CDS Small Bang (post-crisis) period. This is in line with our expectation, since the introduction of an upfront fee to be paid for all CDS transactions when the CDS spread is not equal to one of the fixed coupons introduced by the CDS Small Bang brings about an additional cost incurred by CDS traders which reduces their willingness to trade, reducing CDS market liquidity (Wang et al. 2017). In turn, this leads to a premium being demanded by CDS sellers to compensate for illiquidity, increasing CDS spreads (Bongaerts et al. 2011; Coro et al. 2013). The size of the relationship is also economically significant. The effect of funding illiquidity changes on CDS spread changes is three to five times larger in size for high CDS firms compared to low CDS firms. We also document that stock returns and changes in volatility, CDS bid-ask spreads, slope yield and market volatility have a significant impact on CDS spread changes when investigating the entire sample of firms as well as in the high and low-CDS subsamples. Interestingly, changes in risk-free rate display a positive relationship with CDS spread changes. Although surprising at first, this result is in line with the hypothesis that an increase in risk free rates increases borrowing costs, thus suppressing growth as is the case in the European market after the end of 2009 (Coro et al. 2013). During the post-crisis period, we find that our models can explain a larger part of CDS spread changes when evaluating high-CDS firms. This is in line with the findings of Pires et al. (2015). We obtain adjusted R^2 values reaching up to 41.74% for the entire sample of firms and 50.26% for high-CDS firms. However, our models perform worse in explaining changes in CDS spreads of low risk firms in the post-crisis period compared to the crisis period.

1.5 Robustness checks

To check whether we obtain a statistically significant change in the effects of funding illiquidity changes and of other explanatory variables on CDS spread changes during the crisis, when controlling for firm-specific and macroeconomic factors, we re-estimate models M4 and M5 but with the addition of a crisis dummy variable and interaction terms between all explanatory variables and the crisis dummy. The crisis dummy takes the value of '1' between January 2008 and June 2009 and '0' otherwise. We estimate this model on the whole sample of firms and on the high-CDS and low-CDS subsamples, respectively. *Table 1.7* reports the results. We confirm that the positive effect of funding illiquidity changes on CDS spread changes is significantly lower in the crisis period, while the positive relationship between CDS illiquidity changes and CDS spread changes is significantly larger in magnitude during the crisis period. Additionally, we find that changes in the riskless interest rate have a stronger negative relationship with CDS spread changes during the crisis period and that the positive relationship between changes in the term structure slope and changes in CDS spreads changes its sign and becomes negative during the crisis. This supports the mixed evidence found by literature regarding the effects of changes in risk free rate and changes in term structure slope on CDS spread changes. For example, with respect to the effect of changes in the term structure slope on spread changes, Galil et al. (2014) find a negative relationship between the two variables for a sample between February 2002 and February 2013, while Collin-Dufresne et al. (2001) document a positive relationship using a sample between 1988 and 1997. Taken together, these results suggest that the effect of funding liquidity as well as of other explanatory variables display a strong time-varying behaviour, as previously noted by Alexander and Kaeck (2008) and Annaert et al. (2013).

Adding to the explanatory variables employed in models M1 – M5, we also considered estimating the effect of funding illiquidity changes on CDS spread changes when accounting for the market return, as in Annaert et al. (2013). To proxy for market return we used the return on the Euro Stoxx 50 stock market index obtained from Thomson Datastream. However, due to the very large negative correlation between market return and $\Delta Mkt\_volatility_t$ (-0.72 for the whole sample and -0.80 in the crisis subsample), we chose to report results for models using only $\Delta Mkt\_volatility_t$ to avoid multicollinearity. In unreported results, we note that there are no significant changes in the signs or magnitudes of the coefficients for the variables included in models M1 – M5, when replacing $\Delta Mkt\_volatility_t$ with the market return.

1.6 Policy recommendations

The results of our analysis suggest that funding illiquidity changes are a significant determinant of CDS spread changes, especially during the period following the implementation of the CDS Small Bang regulatory framework in June 2009. While this result may be driven in part by the changing dynamics of the relationships between CDS spread changes and changes in firm-specific liquidity factors and macroeconomic variables during our sample, the strong positive relationship between funding illiquidity changes and CDS spread changes observed post-June 2009 may also be attributed to the introduction of an upfront fee for trading CDSs as fixed coupons have been rolled out. This creates a trade-off between the main benefit of standardization which aims to reduce systemic risk and a rise in upfront funding costs (Wang et al. 2017). As suggested by Wang et al. (2017), the introduction of the new fee may lead to a reduction in CDS market liquidity and individual CDS liquidity for entities which have a CDS spread further away from the fixed coupon at the time of the transaction, which would then lead to an increase in CDS spreads, as suggested by Tang and Yan (2008) and Bongaerts et al. (2011). These effects highlight the importance of considering funding liquidity effects when evaluating CDS spreads and standardization policies (Wang et al. 2017).

Furthermore, our results evidenced a pronounced time-varying effect of explanatory variables on CDS spread changes, finding also documented by Alexander and Kaeck (2008) and Annaert et al. (2013). Particularly during market downturns such as the 2008-2009 Global Financial Crisis, CDS spread changes display a higher sensitivity to CDS illiquidity and risk-free interest rates and a lower sensitivity to market volatility and funding liquidity. Therefore, it is important for regulators to constantly assess the relative importance of firm specific credit risk and liquidity variables as well as macroeconomic variables to extract the correct market 'signals' and implement appropriate policies (Annaert et al, 2013).

1.7 Conclusion

This study explored the effect of funding illiquidity changes on CDS spread changes while controlling for other previously documented firm-specific and macroeconomic determinants of CDS spreads. To the best of our knowledge, this is the first study exploring the effect of changes in funding illiquidity on CDS spread changes. Using panel estimations, we find that changes in funding illiquidity have a significant positive effect on CDS spread changes. This is in line with the hypothesis that a tightening of funding liquidity determines CDS protection sellers to reduce the supply of contracts in the market as they incur inventory costs and worry about the costs of hedging their positions (Tang and Yan, 2008). Moreover, we find that the effect of funding illiquidity changes on CDS spread changes is larger in magnitude and more highly significant in the post-CDS Small Bang (post-crisis) period. In line with Wang et al. (2017), we attribute this relationship to the introduction of an upfront fee that needs to be exchanged between the CDS protection buyer and CDS seller unless the CDS spread of the respective entity at the time of the transaction is exactly equal to one of the four fixed coupons (25bps, 100bps, 500bps and 1000bps) implemented through the CDS Small Bang. Moreover, we find that the magnitude of the effect of funding illiquidity changes on CDS spread changes is larger for high-CDS entities compared to low-CDS entities. We also document a strong time-varying behaviour of the impact of different firm-specific credit risk and liquidity variables, as well as macroeconomic variables, on CDS spread changes. To this end, we find that CDS illiquidity changes and changes in the risk-free rate have a stronger effect during the Global Financial Crisis, while factors such as stock return, market volatility and funding liquidity have a stronger effect in the post-crisis period.

By analysing our results, we can suggest two policy recommendations. Firstly, regulators need to consider the effect of funding illiquidity on CDS spreads when proposing new policy frameworks, our results suggesting that the introduction of the CDS Small Bang upfront fee creates a trade-off between standardization and funding costs (Wang et al, 2017). Secondly, the time-varying nature of the relationships between our explanatory variables and CDS spread changes suggests that the determinants of CDS spread changes need to be regularly investigated so that appropriate policies can be put in place according to what factors drive CDS spreads in different periods.

Figure 1.1: Notional amounts outstanding of single-name CDS

Figure 1.1 illustrates notional amounts outstanding of single-name CDS over time in trillions of U.S. dollars. The solid line plots the total gross notional amount of single-name CDS. The dashed line plots the gross notional amount of investment-grade single-name CDS. The shaded area delimitates the crisis period / pre-CDS Small Bang (December 2007 - June 2009). Semi-annual data, between December 2007 and June 2013, obtained from the Bank for International Settlements statistical warehouse.

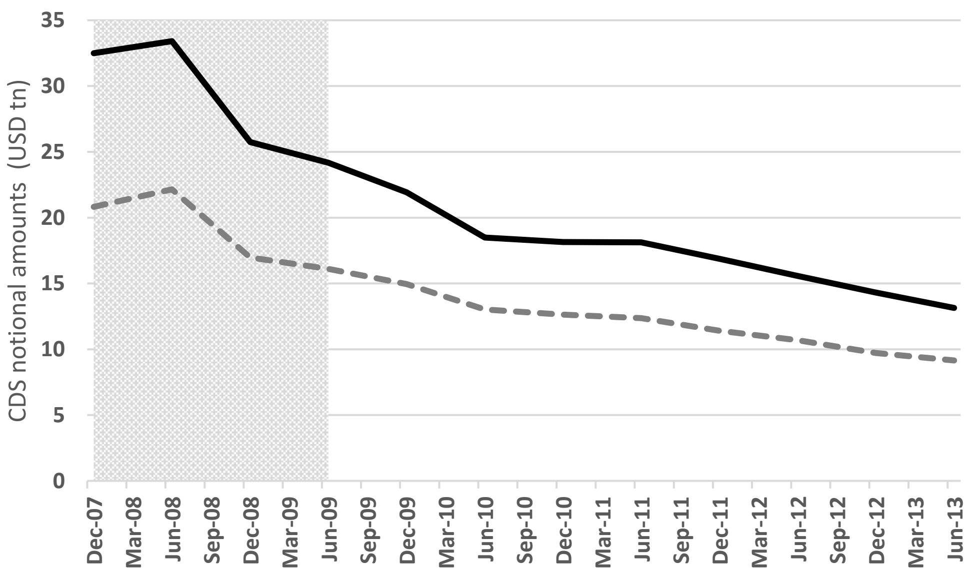
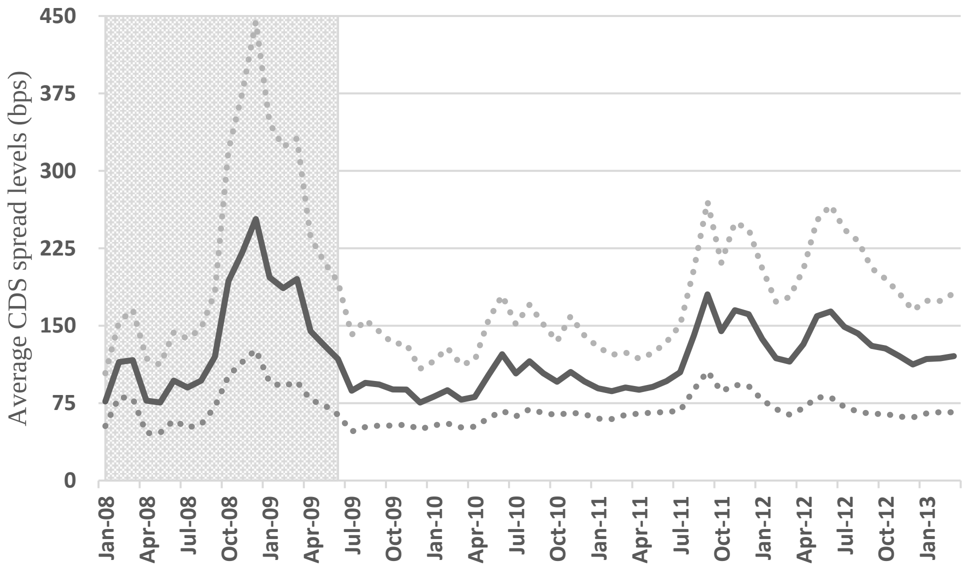


Figure 1.2: Average CDS spreads and CDS spread changes

Figure 1.2 plots average CDS spread levels (Panel A) and CDS spread changes (Panel B) over time in basis points. The solid line presents average CDS spread levels (Panel A) and average CDS spread changes (Panel B) for the entire sample of firms. The dotted lines present average CDS spread levels (Panel A) and average CDS spread changes (Panel B) for the top and bottom terciles of the respective distributions. The shaded area delimitates the crisis period / pre-CDS Small Bang period (January 2008 - June 2009). Monthly data, between January 2008 and March 2013, obtained from Bloomberg.

Panel A: Average CDS spread levels



Panel B: Average CDS spread changes

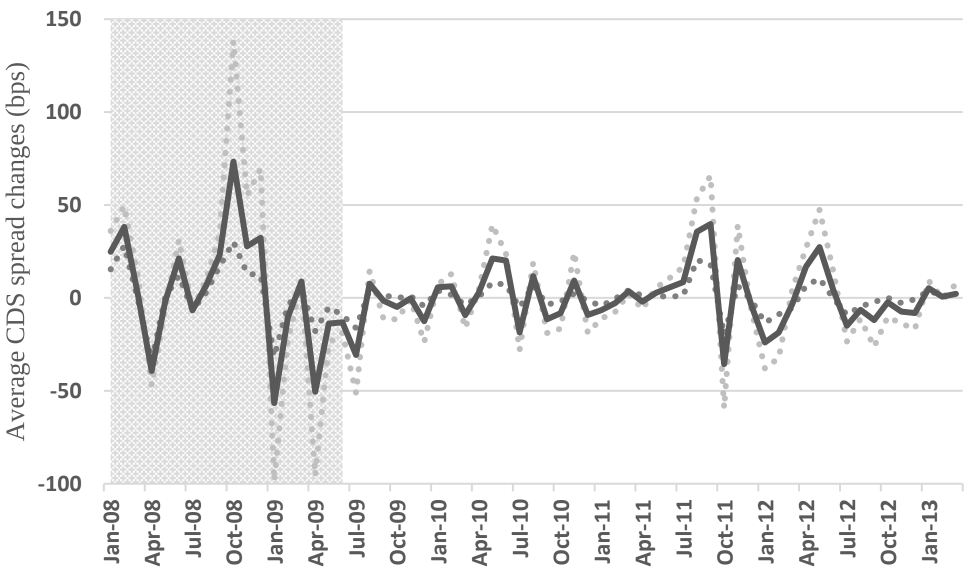


Table 1.1: Description of variables explaining CDS spread changes

Table 1.1 presents the explanatory variables used in panel regressions analysing CDS spread changes, their data source and predicted sign of the relationship with CDS spread changes. EMMI is the European Money Market Institute.

Explanatory Variable	Description	Predicted Sign	Data Source
Stock_return	Monthly stock return	-	Thomson Datastream
ΔVolatility	Change in the historical standard deviation of stock returns	+	Thomson Datastream
ΔEquity_BAS	Change in the (scaled) difference between ask and bid equity prices, divided by the average of the two	+	Thomson Datastream
ΔCDS_BAS	Change in the (absolute) difference between ask and bid CDS prices	+	Bloomberg
ΔEuTed	Change in the difference between the 3-month Euribor rate and the 3-month German Government BuBill	+	Bloomberg
ΔEuRepo	Change in the difference between the 3-month Euribor rate and the 3-month Eurepo rate	+	Bloomberg / EMMI
ΔRisk-free rate	Change in the 10-year Euro-area Government Bond Yield	+/-	Bloomberg
ΔSlope_yield	Change in the difference between the 10-year and 3-year Euro-area Government Bond Yield	+/-	Bloomberg
ΔMkt_volatility	Change in the implied volatility as measured by the Euro Stoxx 50 volatility index	+	Thomson Datastream

Table 1.2: Summary statistics of the dataset

Table 1.2 presents the mean, the median, the maximum, the minimum and the standard deviation (Std. Dev.) of the variables in our dataset. Panel A presents summary statistics for the entire sample (January 2008 - March 2013). Panel B presents summary statistics for the pre-CDS Small Bang period which also coincides with the crisis period (January 2008 - June 2009). Panel C presents summary statistics for the post-CDS Small Bang period which also coincides with post-crisis period (July 2009 - March 2013). The statistics are calculated using a sample consisting of 76 non-financial companies included in the European iTraxx index. *CDS* represents the mid CDS spread (in basis points). *ΔCDS* is the monthly change in the mid-CDS spread (in basis points). *Stock_return* is the monthly firm stock return (in percentages). *ΔVolatility* is the change in the monthly volatility of stock returns (in percentages). *ΔEquity_BAS* is the monthly change in the scaled equity bid-ask spread. *ΔCDS_BAS* is the monthly change in the CDS absolute bid-ask spread (in basis points x 10^2). *ΔEuTed* is the monthly change in the European TED spread measure (3-month Euribor rate - 3-month German Government BuBill rate). *ΔEuRepo* is the monthly change in the European repo spread (3-month Euribor rate minus 3-month Eurepo rate). *ΔRisk-free* is the monthly change in the risk free rate (10-year Euro area government bond yield). *ΔSlope_yield* is the monthly change in the slope of the yield curve (10-year Euro area government bond yield minus 3-year Euro area government bond yield). *ΔMkt_volatility* is the monthly change the implied volatility of the EuroStoxx 50 index.

Panel A: Whole Sample (January 2008 – March 2013)

	Mean	Median	Maximum	Minimum	Std. Dev.
CDS	119.664	95.165	759.580	20.533	82.691
ΔCDS	1.091	-0.185	472.219	-257.884	33.678
Stock_return	-0.407	0.173	53.375	-66.988	8.890
ΔVolatility	-0.007	-4.050	2007.110	-1863.790	96.780
ΔEquity_BAS	0.068	-0.077	890.640	-890.980	36.450
ΔCDS_BAS	0.004	-0.039	28.114	-20.276	3.411
EuTed	0.727	0.583	2.824	0.057	0.552
ΔEuTed	-0.012	-0.027	2.151	-1.029	0.362
EuRepo	0.540	0.414	1.822	0.185	0.355
ΔEuRepo	-0.007	-0.008	0.663	-0.534	0.176
ΔRisk-free	-0.048	-0.043	0.411	-0.642	0.238
ΔSlope_yield	0.016	0.007	0.621	-0.506	0.188
ΔMkt_volatility	0.045	-1.194	20.290	-11.560	6.094

Table 1.2 – Summary statistics of the dataset - continued

Panel B: Pre-CDS Small Bang period / Crisis period (January 2008 – June 2009)

	Mean	Median	Maximum	Minimum	Std. Dev.
CDS	134.504	98.447	759.580	20.533	109.702
ΔCDS	3.667	1.988	389.983	-257.884	49.718
Stock_return	-2.929	-2.303	53.375	-66.988	11.465
ΔVolatility	4.170	-5.270	2007.110	-1863.790	151.120
ΔEquity_BAS	0.302	0.087	584.870	-571.160	25.940
ΔCDS_BAS	0.266	-0.001	28.114	-20.276	3.840
EuTed	1.172	0.928	2.824	0.479	0.774
ΔEuTed	-0.027	-0.075	2.151	-1.029	0.636
EuRepo	0.813	0.736	1.822	0.394	0.398
ΔEuRepo	-0.012	-0.054	0.663	-0.534	0.279
ΔRisk-free	-0.051	-0.117	0.411	-0.642	0.272
ΔSlope_yield	0.077	0.080	0.621	-0.296	0.217
ΔMkt_volatility	0.677	-1.369	20.290	-9.233	8.166

Panel C: Post-CDS Small Bang / Post-crisis period (July 2009 – March 2013)

	Mean	Median	Maximum	Minimum	Std. Dev.
CDS	113.398	94.392	572.741	24.65	67.188
ΔCDS	0.061	-0.548	472.219	-253.347	24.414
Stock_return	0.603	0.775	34.979	-62.260	7.385
ΔVolatility	-1.680	-3.810	379.150	-278.430	63.030
ΔEquity_BAS	-0.026	-0.122	890.640	-890.980	39.890
ΔCDS_BAS	-0.101	-0.058	21.311	-19.647	3.218
EuTed	0.550	0.499	1.377	0.057	0.291
ΔEuTed	-0.007	-0.017	0.559	-0.249	0.146
EuRepo	0.431	0.345	1.216	0.185	0.271
ΔEuRepo	-0.005	-0.008	0.335	-0.248	0.110
ΔRisk-free	-0.047	-0.039	0.382	-0.553	0.223
ΔSlope_yield	-0.009	0.002	0.406	-0.506	0.170
ΔMkt_volatility	-0.208	-1.044	11.030	-11.560	5.011

Table 1.3 - Time-series pairwise correlations of variables explaining CDS spread changes

Table 1.3 presents time-series pairwise correlations of the variables used in panel regressions explaining CDS spread changes. Panel A presents correlations for the entire sample (January 2008 - March 2013). Panel B presents correlations for the crisis period (January 2008- June 2009). Panel C presents correlations for the post-crisis period. The correlations are calculate using a sample of 76 non-financial companies included in the European iTraxx index. *Stock_return* is the monthly firm stock return. *ΔVolatility* is the change in the monthly volatility of stock returns. *ΔEquity_BAS* is the monthly change in the scaled equity bid-ask spread. *ΔCDS_BAS* is the monthly change in the CDS absolute bid-ask spread. *ΔEuTed* is the monthly change in the European TED spread measure (3-month Euribor rate - 3-month German Government BuBill rate). *ΔEuRepo* is the monthly change in the European repo spread (3-month Euribor rate - 3-month Eurepo rate). *ΔRisk-free* is the monthly change in the risk free rate (10-year Euro area government bond yield). *ΔSlope_yield* is the monthly change in the slope of the yield curve (10-year Euro area government bond yield - 3-year Euro area government bond yield). *ΔMkt_volatility* is the monthly change the implied volatility of the EuroStoxx 50 index.

Panel A: Whole sample (January 2008 – March 2013)

ΔVolatility	-0.24							
ΔEquity_BAS	-0.03	0.04						
ΔCDS_BAS	-0.16	0.05	0.03					
ΔEuTed	-0.09	0.17	0.01	0.10				
ΔEuRepo	-0.20	0.37	0.02	0.16	0.65			
ΔRisk-free	0.23	-0.03	-0.01	-0.18	-0.10	-0.07		
ΔSlope_yield	-0.07	0.24	-0.01	0.11	0.07	0.30	0.23	
ΔMkt_volatility	-0.38	0.40	0.02	0.16	0.37	0.46	-0.34	0.18
	Stock_return	*ΔVolatility*	*ΔEquity_BAS*	*ΔCDS_BAS*	*ΔEuTed*	*ΔEuRepo*	*ΔRisk-free*	*ΔSlope_yield*

Table 1.3 - Time-series pairwise correlations of variables explaining CDS spread changes - continued

Panel B: Crisis period / Pre-CDS Small Bang period (January 2008 – June 2009)

	Stock_return	ΔVolatility	ΔEquity_BAS	ΔCDS_BAS	ΔEuTed	ΔEuRepo	ΔRisk-free	ΔSlope_yield
ΔVolatility	-0.21							
ΔEquity_BAS	-0.01	0.05						
ΔCDS_BAS	-0.18	0.07	0.08					
ΔEuTed	-0.13	0.23	0.04	0.13				
ΔEuRepo	-0.21	0.45	0.04	0.11	0.68			
ΔRisk-free	0.20	-0.01	-0.05	-0.38	-0.13	0.04		
ΔSlope_yield	-0.16	0.34	-0.01	0.10	0.06	0.31	-0.02	
ΔMkt_volatility	-0.39	0.51	0.03	0.16	0.45	0.52	-0.16	0.48

Panel C: Post-crisis period / Post-CDS Small Bang period (July 2009 – March 2013)

	Stock_return	ΔVolatility	ΔEquity_BAS	ΔCDS_BAS	ΔEuTed	ΔEuRepo	ΔRisk-free	ΔSlope_yield
ΔVolatility	-0.28							
ΔEquity_BAS	-0.04	0.05						
ΔCDS_BAS	-0.13	0.05	0.02					
ΔEuTed	-0.04	-0.01	0.00	0.07				
ΔEuRepo	-0.23	0.17	0.02	0.24	0.55			
ΔRisk-free	0.27	-0.05	0.00	-0.06	-0.09	-0.23		
ΔSlope_yield	0.06	0.14	-0.01	0.11	0.15	0.37	0.39	
ΔMkt_volatility	-0.37	0.26	0.02	0.16	0.27	0.39	-0.47	-0.11

Table 1.4: Determinants of CDS spread changes

Table 1.4 presents coefficient estimates of panel regressions explaining CDS spread changes. Panel A presents results for all sample of firms. Panel B presents results for high CDS spread firms (top tercile of firms CDS spreads). Panel C presents results for low CDS spread firms (bottom tercile of firms CDS spreads). The dependent variable is the change in the CDS mid-price. *Stock_return* is the monthly firm stock return. *ΔVolatility* is the change in the monthly standard deviation of stock returns. *ΔEquity_BAS* is the monthly change in the scaled equity bid-ask spread. *ΔCDS_BAS* is the monthly change in the CDS absolute bid-ask spread. *ΔEuTed* is the monthly change in the European TED spread measure (3-month Euribor rate - 3-month German Government BuBill rate). *ΔEuRepo* is the monthly change in the European repo spread (3-month Euribor rate - 3-month Eurepo rate). *ΔRisk-free* is the monthly change in the risk free rate (10-year Euro area Government bond yield). *ΔSlope_yield* is the monthly change in the slope of the yield curve (10-year minus 3-year Euro area Government bond yields). *ΔMkt_volatility* is the monthly change the implied volatility of the EuroStoxx 50 index. Regressions estimated using firm-level fixed effects and standard errors clustered by firm to correct for autocorrelation and heteroskedasticity. t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5% and 1% significance levels, respectively. Sample period: January 2008 - March 2013.

Panel A: Determinants of CDS spread changes – Whole Sample of firms

Dep. Var: ΔCDS	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	0.66***	0.74***	0.80***	-0.12	-0.08
	(16.48)	(15.92)	(15.73)	(-0.78)	(-0.49)
Stock_return	-1.03***	-1.02***	-0.99***	-0.80***	-0.79***
	(-10.66)	(-9.71)	(-10.08)	(-7.63)	(-7.50)
ΔVolatility	5.75***	5.36***	4.71***	4.07***	3.91***
	(7.93)	(7.60)	(7.02)	(5.85)	(5.66)
ΔEquity_BAS	3.33**	3.31**	3.34**	3.39**	3.38**
	(2.04)	(2.07)	(2.09)	(2.21)	(2.21)
ΔCDS_BAS	4.02***	3.97***	3.91***	3.70***	3.68***
	(11.82)	(11.49)	(11.22)	(10.30)	(10.23)
ΔEuTed		**6.50*** **		**2.75** **	
		(4.84)		**(2.18)**	
ΔEuRepo			**17.23*** **		**8.81*** **
			(4.72)		**(2.91)**
ΔRisk-free				-17.58***	-17.85***
				(-5.80)	(-5.87)
ΔSlope_yield				2.34	0.89
				(1.07)	(0.45)
ΔMkt_volatility				0.62***	0.56***
				(5.10)	(5.38)
N	4788	4788	4788	4788	4788
Adj. R^2	32.16%	32.63%	32.84%	35.41%	35.47%

Table 1.4: Determinants of CDS spread changes – continued

Panel B: Determinants of CDS spread changes – High CDS firms

Dep. Var: ΔCDS	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	1.05***	1.22***	1.35***	-0.63**	-0.53
	(12.99)	(11.35)	(12.23)	(-2.00)	(-1.62)
Stock_return	-1.37***	-1.35***	-1.27***	-0.96***	-0.94***
	(-8.79)	(-9.71)	(-7.96)	(-5.49)	(5.17)
ΔVolatility	8.50***	7.88***	6.91***	5.76***	5.46***
	(7.68)	(7.67)	(8.22)	(7.26)	(7.11)
ΔEquity_BAS	3.41*	3.30*	3.44**	3.55**	3.59**
	(1.89)	(1.94)	(1.97)	(2.19)	(2.20)
ΔCDS_BAS	4.07***	4.01***	3.94***	3.61***	3.58***
	(9.33)	(9.14)	(8.83)	(8.18)	(8.01)
ΔEuTed		**12.58*** **		**6.29** **	
		(3.95)		**(2.02)**	
ΔEuRepo			**32.78*** **		**19.46*** **
			(3.88)		**(2.78)**
ΔRisk-free				-36.17***	-36.89***
				(-5.58)	(-5.71)
ΔSlope_yield				12.26**	9.10*
				(2.36)	(1.88)
ΔMkt_volatility				0.98***	0.87***
				(3.32)	(3.41)
N	1638	1638	1638	1638	1638
Adj. R^2	33.88%	34.67%	34.97%	38.97%	39.10%

Panel C: Determinants of CDS spread changes – Low CDS firms

Dep. Var: ΔCDS	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	0.39***	0.45***	0.47***	0.09	0.1
	(45.66)	(24.72)	(19.83)	(1.31)	(1.56)
Stock_return	-0.55***	-0.55***	-0.53***	-0.40***	-0.40***
	(-11.43)	(-11.08)	(-10.87)	(-7.21)	(-7.06)
ΔVolatility	2.25***	1.89***	1.39**	0.72	0.65
	(3.32)	(2.82)	(2.14)	(1.17)	(1.05)
ΔEquity_BAS	-0.04	0.16	0.26	0.78	0.68
	(-0.02)	(0.10)	(0.02)	(0.74)	(0.64)
ΔCDS_BAS	3.44***	3.34***	3.31***	3.05***	3.05***
	(13.30)	(13.26)	(13.35)	(11.38)	(11.41)
ΔEuTed		**4.65*** **		**2.12** **	
		(4.34)		**(2.22)**	
ΔEuRepo			**11.26*** **		**4.25* **
			(3.94)		**(1.73)**
ΔRisk-free				-6.28***	-6.35***
				(-5.23)	(-5.26)
ΔSlope_yield				1.16	0.43
				(0.87)	(0.35)
ΔMkt_volatility				0.50***	0.48***
				(6.81)	(7.54)
N	1575	1575	1575	1575	1575
Adj. R^2	33.08%	34.42%	34.69%	39.32%	39.24%

Table 1.5: Determinants of CDS spread changes – Crisis period / Pre-CDS Small Bang period

Table 1.5 presents estimates of panel regressions explaining CDS spread changes during the Global Financial Crisis period (Pre-CDS Small Bang period). Panel A presents results for all sample of firms. Panel B presents results for high CDS spread firms (top tercile of firms CDS spreads). Panel C presents results for low CDS spread firms (bottom tercile of firms CDS spreads). The dependent variable is the change in the CDS mid-price. The dependent variable is the change in the CDS mid-price. *Stock_return* is the monthly firm stock return. *ΔVolatility* is the change in the monthly volatility of stock returns. *ΔEquity_BAS* is the monthly change in the scaled equity bid-ask spread. *ΔCDS_BAS* is the monthly change in the CDS absolute bid-ask spread. *ΔEuTed* is the monthly change in the European TED spread measure (3-month Euribor rate - 3-month German Government BuBill rate). *ΔEuRepo* is the monthly change in the European repo spread (3-month Euribor rate - 3-month Eurepo rate). *ΔRisk-free* is the monthly change in the risk free rate (10-year Euro area government bond yield). *ΔSlope_yield* is the monthly change in the slope of the yield curve (10-year minus 3-year Euro area Government bond yields). *ΔMkt_volatility* is the monthly change the implied volatility of the EuroStoxx 50 index. Regressions estimated using firm-level fixed effects and standard errors clustered by firm to correct for autocorrelation and heteroskedasticity. t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5% and 1% significance levels. Sample period: January 2008 - June 2009.

Panel A: All firms

Dep. Var: ΔCDS	M1	M2	M3	M4	M5
Constant	-0.68	-0.57	-0.51	-2.43***	-2.39
	(-1.28)	(-0.98)	(-0.98)	(-3.56)	(-3.73)
Stock_return	-0.83***	-0.82***	-0.81***	-0.63***	-0.64***
	(-5.48)	(-5.30)	(-5.46)	(-3.60)	(-3.52)
ΔVolatility	5.92***	5.73***	5.40***	4.18***	4.16***
	(6.78)	(6.62)	(6.78)	(4.56)	(4.65)
ΔEquity_BAS	4.32	4.23	4.26	4.17	4.12
	(1.29)	(1.28)	(1.26)	(1.29)	(1.27)
ΔCDS_BAS	6.26***	6.22***	6.23***	5.49***	5.48***
	(8.81)	(8.52)	(8.71)	(6.56)	(6.57)
ΔEuTed		**2.22**		**-0.46**	
		(1.29)		**(-0.32)**	
ΔEuRepo			**6.81**		**2.58**
			(1.54)		**(0.53)**
ΔRisk-free				-25.75***	-25.86***
				(-3.50)	(-3.37)
ΔSlope_yield				12.20**	12.82**
				(2.52)	(2.49)
ΔMkt_volatility				0.48**	0.40*
				(2.38)	(1.75)
N	1368	1368	1368	1368	1368
Adj. R^2	32.92%	32.95%	32.99%	35.25%	35.26%

Table 1.5: Determinants of CDS spread changes – Crisis period / Pre-CDS Small Bang period - continued

Panel B: High CDS firms

Dep. Var: ΔCDS	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	-0.45	-0.20	0.15	-4.12***	-3.86***
	(-0.35)	(-0.14)	(0.12)	(-2.90)	(-2.94)
Stock_return	-1.21***	-1.19***	-1.13***	-0.93***	-0.94***
	(-3.96)	(-3.80)	(-3.87)	(-2.84)	(-2.77)
ΔVolatility	8.84***	8.51***	7.68***	6.45***	6.30***
	(5.75)	(5.55)	(6.42)	(4.90)	(5.01)
ΔEquity_BAS	4.09	3.78	3.88	5.01	4.96
	(1.40)	(1.29)	(1.26)	(1.61)	(1.54)
ΔCDS_BAS	6.44***	6.38***	6.38***	5.06***	4.99***
	(6.54)	(6.29)	(6.38)	(3.92)	(3.81)
ΔEuTed		**5.20**		**0.15**	
		(1.25)		**(0.05)**	
ΔEuRepo			**19.92***		**17.37**
			(1.77)		**(1.44)**
ΔRisk-free				-55.71***	-57.81***
				(-2.97)	(-2.92)
ΔSlope_yield				26.02**	27.51**
				(2.12)	(2.10)
ΔMkt_volatility				0.78	0.39
				(1.54)	(0.70)
N	468	468	468	468	468
Adj. R^2	33.39%	33.43%	33.68%	37.30%	37.54%

Panel C: Low CDS firms

Dep. Var: ΔCDS	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	-1.00***	-0.92***	-1.00***	-1.52***	-1.56***
	(-4.05)	(-3.34)	(-3.71)	(-4.42)	(-4.47)
Stock_return	-0.53***	-0.52***	-0.53***	-0.39***	-0.36***
	(-5.27)	(-5.03)	(-5.32)	(-3.21)	(-3.12)
ΔVolatility	2.97***	2.69***	2.90***	1.34	1.41
	(3.90)	(3.51)	(3.49)	(1.28)	(1.36)
ΔEquity_BAS	3.12**	3.00**	3.12**	2.96**	3.04**
	(2.12)	(2.00)	(2.12)	(2.00)	(2.07)
ΔCDS_BAS	5.44***	5.36***	5.44***	4.73***	4.75***
	(5.57)	(5.45)	(5.55)	(4.55)	(4.59)
ΔEuTed		**1.73***		**0.54**	
		(1.73)		**(0.50)**	
ΔEuRepo			**0.08**		**-5.11**
			(0.02)		**(-1.49)**
ΔRisk-free				-9.03***	-8.90***
				(-3.17)	(-3.08)
ΔSlope_yield				4.52**	3.48
				(2.00)	(1.43)
ΔMkt_volatility				0.32*	0.47***
				(1.92)	(3.59)
N	450	450	450	450	450
Adj. R^2	41.39%	41.57%	41.25%	43.69%	43.99%

Table 1.6: Determinants of CDS spread changes – Post-Crisis / Post-CDS Small Bang period

Table 1.6 presents estimates of panel regressions explaining CDS spread changes after the Global Financial Crisis period (Post-CDS Small Bang period). Panel A presents results for all sample of firms. Panel B presents results for high CDS spread firms (top tercile of firms CDS spreads). Panel C presents results for low CDS spread firms (bottom tercile of firms CDS spreads). The dependent variable is the change in the CDS mid-price. The dependent variable is the change in the CDS mid-price. *Stock_return* is the monthly firm stock return. *ΔVolatility* is the change in the monthly volatility of stock returns. *ΔEquity_BAS* is the monthly change in the scaled equity bid-ask spread. *ΔCDS_BAS* is the monthly change in the CDS absolute bid-ask spread. *ΔEuTed* is the monthly change in the European TED spread measure (3-month Euribor rate - 3-month German Government BuBill rate). *ΔEuRepo* is the monthly change in the European repo spread (3-month Euribor rate - 3-month Eurepo rate). *ΔRisk-free* is the monthly change in the risk free rate (10-year Euro area government bond yield). *ΔSlope_yield* is the monthly change in the slope of the yield curve (10-year minus 3-year Euro area Government bond yields). *ΔMkt_volatility* is the monthly change the implied volatility of the EuroStoxx 50 index. Regressions estimated using firm-level fixed effects and standard errors clustered by firm to correct for autocorrelation and heteroskedasticity. t-statistics are reported in parentheses. *, ** and *** represent significance at the 10%, 5% and 1% significance levels. Sample period: July 2009 – March 2013.

Panel A: All firms

Dep. Var: ΔCDS	**M1**	**M2**	**M3**	**M4**	**M5**
Constant	1.15***	1.32***	1.27***	1.31***	1.51***
	(10.80)	(11.52)	(12.36)	(9.29)	(11.23)
Stock_return	-1.21***	-1.19***	-1.10***	-0.97***	-0.90***
	(-9.57)	(-9.54)	(-8.39)	(-7.19)	(-6.53)
ΔVolatility	4.98***	5.14***	4.08***	4.20***	3.61***
	(5.68)	(5.93)	(4.47)	(4.28)	(3.80)
ΔEquity_BAS	2.87**	2.84**	2.85**	2.86**	2.77**
	(2.01)	(2.12)	(2.18)	(2.17)	(2.23)
ΔCDS_BAS	2.76***	2.67***	2.43***	2.59***	2.40***
	(8.38)	(8.30)	(6.67)	(7.44)	(6.43)
ΔEuTed		**28.14*** **		**21.64*** **	
		(9.51)		**(7.57)**	
ΔEuRepo			**44.49*** **		**47.00*** **
			(7.84)		**(9.26)**
ΔRisk-free				1.55	7.43***
				(0.99)	(4.22)
ΔSlope_yield				-10.32***	-21.22***
				(-4.77)	(-9.59)
ΔMkt_volatility				0.98***	0.93***
				(6.38)	(6.99)
N	3420	3420	3420	3420	3420
Adj. R^2	33.84%	36.73%	37.46%	40.43%	41.74%

Table 1.6: Determinants of CDS spread changes – Post-Global Financial Crisis period - continued

Panel B: High CDS firms

Dep. Var: ΔCDS	M1	M2	M3	M4	M5
Constant	1.57***	1.84***	1.75***	1.93***	2.26***
	(16.37)	(15.46)	(17.04)	(7.73)	(9.02)
Stock_return	-1.66***	-1.59***	-1.42***	-1.20***	-1.05***
	(-12.98)	(-12.63)	(-11.09)	(-9.88)	(-8.50)
ΔVolatility	7.46***	7.92***	6.12***	5.81***	4.69***
	(5.29)	(6.16)	(4.79)	(4.86)	(4.12)
ΔEquity_BAS	2.93*	2.80**	3.01**	2.70**	2.74**
	(1.88)	(2.04)	(2.07)	(2.22)	(2.23)
ΔCDS_BAS	2.65***	2.53***	2.24***	2.40***	2.15***
	(9.33)	(10.23)	(8.24)	(9.41)	(7.96)
ΔEuTed		**47.99*** **		**36.09*** **	
		(8.43)		**(6.24)**	
ΔEuRepo			**75.68*** **		**77.61*** **
			(14.68)		**(14.54)**
ΔRisk-free				3.35	12.83***
				(0.84)	(3.16)
ΔSlope_yield				-11.86**	-29.28***
				(-2.41)	(-5.78)
ΔMkt_volatility				1.79***	1.78***
				(9.43)	(9.04)
N	1170	1170	1170	1170	1170
Adj. R^2	39.33%	43.62%	44.43%	48.79%	50.26%

Panel C: Low-CDS firms

Dep. Var: ΔCDS	M1	M2	M3	M4	M5
Constant	0.61***	0.67***	0.65***	0.59***	0.70***
	(8.36)	(9.09)	(9.78)	(6.29)	(7.55)
Stock_return	-0.55***	-0.55***	-0.50***	-0.39***	-0.35***
	(-8.57)	(-8.64)	(-8.64)	(-6.72)	(-6.60)
ΔVolatility	1.81***	1.84***	1.07**	1.21**	1.01**
	(3.44)	(3.32)	(2.32)	(2.03)	(2.00)
ΔEquity_BAS	-0.81	-0.11	-0.70	0.69	0.22
	(-1.03)	(-0.18)	(-1.27)	(0.89)	(0.34)
ΔCDS_BAS	1.42***	1.38***	0.98***	1.24***	1.00***
	(5.88)	(5.96)	(5.07)	(5.31)	(5.10)
ΔEuTed		**10.97*** **		**6.54*** **	
		(5.64)		**(3.78)**	
ΔEuRepo			**26.81*** **		**28.43*** **
			(10.29)		**(9.64)**
ΔRisk-free				1.20	4.62***
				(1.26)	(4.58)
ΔSlope_yield				-5.16***	-12.93***
				(-3.76)	(-7.75)
ΔMkt_volatility				0.61***	0.51***
				(12.30)	(10.26)
N	1125	1125	1125	1125	1125
Adj. R^2	21.60%	24.76%	31.39%	34.71%	41.34%

Table 1.7: Determinants of CDS spread changes with crisis period interaction effects

Table 1.7 presents the determinants of CDS spread changes using panel regressions with crisis interaction effects. Panel A presents results for the entire firm sample. Panel B presents results for the hIgh CDS firms (top tercile of CDS spread distribution). Panel C presents results for low CDS firms (bottom tercile of CDS spread distribution). The dependent variable is the change in the mid CDS spread quote. *Stock_return* is the monthly firm stock return. *ΔVolatility* is the change in the monthly volatility of stock returns. *ΔEquity_BAS* is the monthly change in the scaled equity bid-ask spread. *ΔCDS_BAS* is the monthly change in the CDS absolute bid-ask spread. *ΔEuTed* is the monthly change in the European TED spread measure (3-month Euribor rate - 3-month German Government BuBill rate). *ΔEuRepo* is the monthly change in the European repo spread (3-month Euribor rate - 3-month Eurepo rate). *ΔRisk-free* is the monthly change in the risk free rate (10-year Euro area government bond yield). *ΔSlope_yield* is the monthly change in the slope of the yield curve (10-year Euro area government bond yield - 3-year Euro area government bond yield). *ΔMkt_volatility* is the monthly change the implied volatility of the EuroStoxx 50 index. *Crisis* is a dummy variable taking the value of 1 during the global financial crisis period (January 2008 - June 2009) and 0 otherwise. Regressions estimated using firm-level fixed effects and standard errors clustered by firm to correct for autocorrelation and heteroskedasticity. t-statistics are reported in parentheses. * represents significance at 10% level, ** represents significance at the 5% level, *** represents significance at the 1% level. Sample period: January 2008 – March 2013.

Table 1.7: Determinants of CDS spread changes with crisis interaction effects - continued

Dep.Var: ΔCDS	Panel A: All sample		Panel B: High CDS		Panel C: Low CDS	
Constant	1.31***	1.51***	1.50***	1.79***	0.78***	0.91***
	(6.87)	(8.18)	(3.41)	(4.03)	(6.11)	(6.85)
Stock_return	-0.97***	-0.90***	-1.09***	-0.95***	-0.43***	-0.38***
	(-7.24)	(-6.59)	(-6.15)	(-5.41)	(-7.66)	(-7.56)
ΔVolatility	4.22***	3.63***	6.48***	5.56***	1.10*	0.69
	(4.30)	(3.82)	(6.17)	(5.64)	(1.88)	(1.34)
ΔEquity_BAS	2.85**	2.77**	2.73**	2.72**	0.95	0.19
	(2.18)	(2.23)	(2.21)	(2.23)	(1.33)	(0.41)
ΔCDS_BAS	2.59***	2.41***	2.47***	2.23***	1.72***	1.39***
	(7.49)	(6.47)	(9.71)	(8.28)	(6.11)	(5.85)
ΔEuTed	**21.65*** **		**34.64*** **		**8.78*** **	
	(7.60)		**(5.98)**		**(4.58)**	
ΔEuRepo		**46.96*** **		**74.55*** **		**32.11*** **
		(9.30)		**(13.93)**		**(9.46)**
ΔRisk-free	1.55	7.43***	-0.25	8.96**	2.86**	6.64***
	(0.99)	(4.23)	(-0.06)	(2.35)	(2.58)	(5.28)
ΔSlope_yield	-10.35***	-21.23***	-9.50**	-26.64***	-5.06***	-13.26***
	(4.79)	(-9.63)	(-1.97)	(-5.32)	(-3.88)	(-8.37)
ΔMkt_volatility	0.97***	0.93***	1.73***	1.71***	0.64***	0.55***
	(6.41)	(7.02)	(8.23)	(7.93)	(9.01)	(7.71)
Crisis	-3.73***	-3.90***	-5.45***	-5.49***	-2.11***	-2.27***
	(-6.20)	(-6.81)	(-4.40)	(-4.66)	(-5.68)	(-6.19)
*Stock_return*Crisis*	0.34*	0.26	0.26	0.13	0.08	0.03
	(1.65)	(1.23)	(0.70)	(0.33)	(0.76)	(0.29)
*ΔVolatility*Crisis*	-0.03	0.55	-0.66	0.09	-0.84	-0.39
	(-0.02)	(0.44)	(-0.37)	(0.05)	(-0.76)	(-0.34)
*ΔEquity_BAS*Crisis*	1.26	1.30	3.04	3.05	-5.49	-4.45
	(0.35)	(0.37)	(0.74)	(0.72)	(-0.52)	(-0.42)
*ΔCDS_BAS*Crisis*	2.92***	3.09***	2.64**	2.84**	3.22***	3.55***
	(3.54)	(3.74)	(2.33)	(2.50)	(3.89)	(4.20)
ΔEuTed*Crisis	**-22.11*** **		**-32.95*** **		**-8.83*** **	
	(-7.60)		**(-5.40)**		**(-3.89)**	
ΔEuRepo*Crisis		**-44.40*** **		**-59.37*** **		**-34.14*** **
		(-7.00)		**(-5.14)**		**(-6.92)**
*ΔRisk-free *Crisis*	-27.19***	-33.17***	-53.13***	-64.43***	-14.63***	-18.25***
	(-3.72)	(-4.29)	(-2.84)	(-3.28)	(-4.04)	(-4.80)
*ΔSlope_yield *Crisis*	22.54***	34.04***	36.91***	54.17***	9.06***	17.09***
	(4.01)	(5.46)	(2.65)	(3.52)	(3.51)	(6.51)
*ΔMkt_volatility*Crisis*	-0.49**	-0.53**	-0.96*	-1.20**	-0.08*	0.06
	(-2.07)	(-2.10)	(-1.87)	(-2.17)	(-0.50)	(0.46)
N	4788	4788	1638	1638	1575	1575
Adj. R^2	38.99%	39.49%	42.56%	43.21%	45.41%	47.73%

Chapter 2: Funding Liquidity and the Cross-Section of European Stock Returns

2.1 Introduction

Financial crises highlight the central role that liquidity plays for financial markets. One of the most striking features that researchers and practitioners have noted with regards to these turbulent periods is that liquidity can suddenly dry up.[1] Even prior to the global financial turmoil of 2007-2009, which marked one of the most severe and costly liquidity crises, a considerable amount of research investigated the drivers of both market and individual stocks' liquidity.[2] One such research stream investigates the degree to which individual stocks' liquidity co-moves, being driven by a common factor, phenomenon also known as commonality in liquidity.[3] The liquidity commonality literature can be divided in two broad strands offering insights into what triggers stocks' liquidity co-movement. These include demand-side explanations focusing on correlated trading behaviour of institutional investors (Koch et al. 2016) and level of institutional ownership (Kamara et al. 2008) as well as supply-side explanations centred around the provision of liquidity and funding liquidity (see

[1] Examples of stock market liquidity dry-ups during financial crisis periods include Russia's default in 1998 which led to a large drop in global financial market liquidity (Brunnermeier and Pedersen, 2009), the 1997 Asian financial crisis, the LTCM crisis of 1998 (Hameed et al. 2010) and the 2007-2009 Global Financial Crisis, when subprime losses of levered financial institutions led to significant bank losses, a deterioration of banks' balance sheets, panic asset sales, liquidity dry-ups and losses of more than 8 trillion dollars (see Brunnermeier, 2009; Brunnermeier and Pedersen, 2009; Naes et al., 2011).

[2] For an overview of the determinants of liquidity see Amihud et al. (2005).

[3] Commonality in liquidity has been studied extensively since its discovery. Notable research documenting the presence of commonality in the U.S. market includes Chordia et al. (2000), Huberman and Halka (2001), Hasbrouck and Seppi (2001) and, more recently, Koch et al. (2016). Winter (2012) finds positive evidence of commonality in liquidity in the context of the European market. Galariotis and Giouvris (2007) and Gregoriou et al. (2011) document the presence of commonality in the context of the U.K. market, while Karolyi et al. (2012) and Brockman et al. (2009) offer international evidence.

Comerton-Forde et al. 2010; Hameed et al. 2010; Brunnermeier and Pedersen, 2009; Coughenour and Saad, 2004).

In this study, we focus on the liquidity provision of market makers, and more specifically on the predictions of the theoretical model of Brunnermeier and Pedersen (2009) that links market liquidity and funding liquidity. Brunnermeier and Pedersen (2009) theorize that, under certain conditions, markedly during periods when capital availability is scarce, a deterioration of funding liquidity, defined by Drehmann and Nikolaou (2013) as the ease and costs of access to capital and ability to settle obligations with immediacy, negatively impacts investors' willingness and ability to invest in high margin securities and in stocks that co-move with funding conditions as they add on more risk – a flight to quality effect[4]. These changes in investment patterns can lead to deleveraging, market liquidity dry-ups, increased market volatility, and lower contemporaneous returns, effects which are more evident as traders operate closer to their funding constraint (see Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2002; Gromb and Vayanos, 2010; Comerton-Forde et al. 2010; Adrian et al. 2014). Moreover, the theoretical model of Brunnermeier and Pedersen (2009) indicates that available speculator capital, which is tightly linked to funding conditions, leads to the presence of a funding risk premium, where securities that co-vary more strongly with funding conditions have a higher risk premium.

These theoretical predictions have been empirically confirmed in the context of U.S. market in several studies. Fontaine, Garcia and Gungor (2016), FGG hereafter, the paper closest to ours in terms of empirical approach, empirically document the effects of worsening funding conditions on illiquidity, volatility and returns. Firstly, they find that the illiquidity and volatility of illiquidity and volatility sorted portfolios worsen in periods of

[4] The flight to quality hypothesis is also theoretically proposed by Vayanos (2004) and empirically documented by Acharya and Pedersen (2005).

high funding risk, providing evidence of commonality, and that illiquid and volatile portfolios see their illiquidity increase the most during bad funding conditions, thus evidencing flight to quality. A similar flight to quality phenomenon is reported by Comerton-Forde et al. (2010) whereby the liquidity of high volatility stocks displays more sensitivity to larger inventories and trading losses than that of low volatility stocks. FGG further document an asymmetric response of illiquidity to funding illiquidity shocks, whereby the level and dispersion of portfolio illiquidity increases following a funding shock particularly when the level of funding illiquidity was already high. In line with these results, Boudt et al. (2017) find that a regime switch occurs near a TED spread level of 48 bps whereby financiers may destabilize market liquidity by increasing rates in periods characterized by low market liquidity, leading traders to sell off positions at low prices to be able to pay off the interest payments on their loans. Moreover, FGG evidence that the decrease in the returns of illiquid and volatile stocks when funding becomes constrained is stronger in periods of low market liquidity. Lastly, FGG and Adrian et al. (2014) present evidence of a funding liquidity risk premium in the cross-section of U.S. stock returns.

Despite the empirical support found for the theoretical predictions of Brunnermeier and Pedersen (2009) in the U.S. context, European evidence is rather scarce. Notably, using a data set of 135 main refinancing operation auctions in the Euro area, Drehmann and Nikolaou (2013) find that higher funding liquidity risk corresponds to periods of lower market liquidity, effect which is only present during financial turmoil. Moreover, Moinas et al. (2017) provide evidence that a relaxation of funding constraints improves bond market liquidity while also documenting a positive feedback effect where an improvement in the liquidity of Treasury bond markets leads to an improvement in funding liquidity. Furthermore, despite the high correlation between similarly constructed measures of funding liquidity such as the U.S. TED spread (i.e. the differential between the three-month

USD LIBOR and three-month Treasury Bill) and European TED spread (i.e. the differential between the three-month EURIBOR and three-month German Government BuBill) of 0.55 during our sample period (January 2009 – December 2014), the European TED spread peaks much more during late 2011 and early 2012, reaching a spread more than three times wider during November 2011 (1.605% for the European TED spread compared to a value of just 0.46% for the U.S. TED spread), indicating much tighter funding conditions during this period in the European market as opposed to the U.S. market, as presented in *Figure 2.1*. Therefore, the differences in the levels of funding liquidity between the U.S. and European markets and the slightly thin European-focused literature make the European market an interesting setting for testing the presence of commonality, flight to quality and funding risk premium following funding liquidity shocks.

This paper tests the theoretical predictions (the presence of commonality, flight-to-quality, asymmetry and funding risk premium) outlined in Brunnermeier and Pedersen (2009) in the context of a highly liquid European market, the universe of stocks included in the European iTraxx index, consisting of the most liquid single-name credit default swaps (CDS) in the European market. Novel to this study is the sorting of portfolios of stocks according to their CDS spreads, besides sorting portfolios according to illiquidity and volatility as per FGG. Using these portfolios, we newly test whether the commonality, flight to quality and asymmetric effects of funding illiquidity shocks on illiquidity and contemporaneous returns extend to CDS spreads. The rationale for investigating the effect of funding liquidity changes on CDS spreads is that CDS spreads are used as a measure of default risk conveying information relating to the underlying entities' illiquidity, volatility and credit risk. CDS spread measures have been documented to be highly sensitive to equity illiquidity (Das and Hanouna, 2009), CDS and CDS market illiquidity (Tang and Yan, 2008; Coro et al. 2013), equity volatility (Bystrom, 2008; Ericsson et al. 2009), credit risk factors such as leverage (Ericsson et al. 2009; Coro et al. 2013) and credit ratings, more particularly downgrades (Daniels and Jensen, 2005; Hull et al. 2004). Therefore, if tightening of funding constraints has a positive effect on portfolio and market illiquidity and volatility as evidenced by FGG, due to the inherent sensitivity of CDS spreads to illiquidity and volatility variables, these effects should extend to CDS spreads. This is of interest to market participants and regulators as it would imply that CDS spreads also depend on the harshness of funding constraints, in addition to the perceived credit risk of the market and of underlying entities and individual stock, CDS or CDS market liquidity. Moreover, by focusing our funding liquidity analysis on the European market, we can make a comparison between the level of commonality, flight to quality and funding risk premium found in the European context to previous U.S. focused studies.

Therefore, following the theoretical predictions of Brunnermeier and Pedersen (2009) and extending these illiquidity, volatility and returns linkages to CDS spreads, we test the following hypotheses:

i) *Commonality*: Funding conditions co-move with illiquidity, volatility and CDS spreads.

ii) *Flight to quality*: During tight funding conditions, risky securities become especially illiquid.

iii) *Asymmetric effect of funding illiquidity on CDS spreads*: The asymmetric relationship between changes in funding illiquidity and changes in illiquidity, which increases in magnitude and significance if funding conditions are already constrained, as documented by FGG, extends to CDS spread changes.

iv) *Asymmetric effect of funding illiquidity on returns*: Returns are sensitive to positive changes in funding illiquidity (worsening of funding conditions), whereas negative changes in funding illiquidity (loosening of funding conditions) do not affect returns.

v) *Funding risk premium*: Funding shocks are priced and securities which strongly co-vary with funding conditions exhibit a higher risk premium.

Our results empirically confirm, in a European setting, the theoretical predictions proposed by Brunnermeier and Pedersen (2009) outlined above. Specifically, we find compelling evidence of commonality in the level and dispersion of liquidity, volatility and CDS spreads across tight and relaxed funding conditions for portfolios sorted by illiquidity, volatility and CDS spread levels. Secondly, we provide evidence of flight-to-quality as portfolios comprising of entities with the highest illiquidity and volatility see their illiquidity increase the most. A similar, albeit weaker, result is also found for high default risk portfolios. Thirdly, we document an asymmetric relationship between changes in funding conditions and changes in CDS spreads, whereby the positive relationship is larger in magnitude and statistically significant if speculators operate close to their funding constraint. Fourthly, we find new evidence of an asymmetric relationship between funding shocks and returns. Tighter funding conditions significantly decrease contemporaneous returns, whereas looser funding conditions have no influence on returns. Lastly, we evidence the presence of a funding risk premium in the cross-section of illiquidity-sorted portfolios and some evidence, albeit weaker, of a funding liquidity premium in the cross-section of illiquidity, volatility and CDS spread sorted portfolios taken together. The prices of risk are negative and significant. The point estimates of the funding risk factors in the case of illiquidity-sorted portfolios range between -1.81 and -1.92, when funding liquidity risk factors are considered alone, and -2.42 when the Fama-French 3 factor model is augmented with the funding risk factor. This generates a return spread between the most and least illiquid portfolios of 1.21% annually. When considering portfolios sorted by illiquidity, volatility and CDS spreads together, the point estimates of the prices of risk range between -0.75 and -0.76 when the funding risk factor is considered alone and -0.86 when added to the specification including the three Fama-French factors. These results are qualitatively similar to those found by FGG using illiquidity and volatility sorted portfolios in the context of the U.S. market, who evidence a point estimate of the price of funding risk as measured by the TED spread of -1.82, when considering the funding risk factor alone.[5]

We contribute to the existing literature in several respects. *Firstly*, to the best of our knowledge, we provide a first empirical study of the effect of funding liquidity shocks on the illiquidity, volatility and CDS spreads of European stocks. To this end, we note that we newly use in the context of studies investigating the cross-section of stock returns, data on firms included in the Markit European iTraxx index comprising of the most liquid single-name CDS entities. *Secondly*, after newly sorting stocks into portfolios according to CDS spread levels, additionally to sorting by illiquidity and volatility levels, this study documents that commonality and flight to quality are also related to default risk, besides illiquidity and volatility.[6] *Thirdly*, we document that the asymmetric positive relationship between changes in funding liquidity and illiquidity and volatility changes, respectively, empirically documented by FGG for the U.S. market, extends to CDS spreads. CDS contract sellers have to bear an added cost of hedging their portfolios in periods characterised by tight funding conditions which will be captured by an increase in CDS spread. As CDS spreads are documented to be sensitive to changes in volatility and illiquidity (see Ericsson et al. 2009; Das and Hanouna, 2009; Coro et al. 2013), and since the effect of funding shocks on

[5] FGG use as their main funding liquidity proxy a measure based on the differential between on-the-run and off-the-run securities. The estimates of the price of risk using this funding measure are approximately a third higher than those found in our study.
[6] The theoretical predictions of Brunnermeier and Pedersen (2009) have received empirical support from FGG using assets sorted with respect to illiquidity and volatility levels, illiquidity, volatility and funding illiquidity betas and double sorts.

illiquidity and volatility changes is larger when funding is scarce, as evidenced by FGG, we test and empirically show that funding illiquidity shocks impact CDS spreads positively, particularly when speculator capital is already tight. *Fourthly*, using the theoretical predictions and empirical findings outlined in Brunnermeier and Pedersen (2009), Acharya and Pedersen (2005) and Amihud (2002), we newly show that only tightening of funding conditions significantly decreases contemporaneous returns, whereas an improvement of funding conditions has no effect on returns. Therefore, we provide evidence of an asymmetric effect of funding shocks on market returns. Lastly, we find new evidence of a funding risk premium in the context of the European market, confirming previous findings from U.S. based studies such as FGG and Adrian et al. (2014).

The remainder of the paper is structured as follows: Section 2.2 describes the data, variables employed and portfolio formation procedure, section 2.3 presents the empirical methods used as well as the results obtained for the five hypotheses tested, section 2.4 investigates the robustness of results, while section 2.5 concludes.

2.2 Data and portfolio formation

2.2.1 Data description

Our sample consists of all non-financial companies included in the European iTraxx index on March 2013 (index roll 19) for which data referring to stock price, volume and CDS spread is available from Thomson Reuters Datastream for the entire time-series.[7] The use of the iTraxx Europe CDS index data is novel in the literature investigating the cross-section

[7] The Markit iTraxx Europe Index comprises of 125 investment grade rated entities with the most liquid CDSs in the European market. The constituent list includes 100 non-financial companies and 25 entities operating in the financial sector. De Haan and Vlahu (2016) and references therein highlight important differences in terms of regulation, funding methods, corporate governance, agency problems, capital structure and leverage levels between financial and non-financial companies.

of stock returns, but well-established in credit default swap research[8]. Our sample covers a period of 6 years, from January 2009 to December 2014. Data availability restrictions for the iTraxx non-financial entities yield a total sample of 80 companies.[9] Daily stock price, turnover volume and CDS spread data for each entity as well as the 3-month Euribor rates are collected from Datastream. The 3-month Eurepo rates are collected from the European Money Market Institute (EMMI) website. The European TED spread funding illiquidity measure is collected from Bloomberg, while the U.S. TED spread is obtained from the Federal Reserve Bank of St. Louis economic data depository (FRED).

2.2.2 Measuring funding illiquidity

Recent studies investigating the effects of funding liquidity on financial markets measure funding liquidity through a wide variety of measures extracted from several markets and assets.[10] Measures of funding liquidity previously employed in equity, Treasury bond, hedge fund and private equity markets include: the TED spread (Boudt et al. 2017; Boyson et al. 2010; Garleanu and Pedersen, 2011; Chudik and Fratzscher, 2011), the Euribor-OIS spread, the Euribor-Eurepo spread and the differential between the ECB main refinancing operation rate and the OIS rate (Moinas et al. 2017), the price differential between on-the-run and off-the-run securities (Fontaine and Garcia, 2012), the broker-dealer leverage factor of Adrian et al. (2014), broker-dealer asset growth (Adrian and Shin, 2010), the 3-month Libor rate,

[8] Alexander and Kaeck (2008) and Breitenfellner and Wagner (2012) investigate the determinants of CDS spreads via the European iTraxx CDS index, while Berndt and Obreja (2010) use the index to construct a new factor mimicking economic catastrophe risk

[9] The European Markit iTraxx index constituent list is reviewed with respect to liquidity and investment grade of entities every six months. To preserve the number of companies in our cross-section, we also include any entities which were listed as part of the Markit iTraxx index as of March 2013, but which have been moved to the Markit iTraxx Crossover Index encompassing the 75 most liquid sub-investment grade entities due to a rating downgrade event occurring during our sample period. It is worth noting that throughout the time frame of the study, the constituent list of the European iTraxx index changes are minor, with most of the companies that are delisted from the index being reincluded in one of the consequent index rolls.

[10] An outline of funding liquidity proxies used in literature is presented in Massa et al. (2016).

the term spread and the VIX volatility index (Ang et al. 2011), the aggregate amount of outstanding repos (Banti and Phylaktis, 2017), the cash collateral ratio of Massa et al. (2016), the betting against beta (BAB) factor of Frazzini and Pedersen (2014), and the changes in credit standards (Franzoni et al. 2012).

Given our emphasis on the European market and to add robustness to our results we use two measures of funding illiquidity that are linked to the European interbank market. The central funding illiquidity measure employed in this study is the European TED spread ($EuTed_t$) which measures the differential between secured and unsecured money market transactions and is calculated as the difference between the three-month Euribor rate and the rate on the German Government BuBill maturing in 3 months. This is the European equivalent of the U.S. TED spread measure which is widely used to measure interbank funding conditions (e.g. Boudt et al. 2017). Additionally, for robustness purposes, we also measure funding illiquidity through the 3-month spread between the Euribor rate and the European repo market reference rate or Eurepo (EE_t).[11] As Moinas et al. (2017) argue, the Euribor-Eurepo spread measures the level of funding conditions for secured European money market transactions.

The ease with which traders can access funds and settle obligations with immediacy varied widely throughout our sample. We note that, for example, the European TED spread ($EuTed_t$) fluctuated from lows of 0.17% in September 2014 to highs of 1.605% in November 2011. *Figure 2.2* plots the three-month European TED spread alongside the three-month Euribor - Eurepo spread (EE_t). We evaluate the commonality, flight to quality

[11] Moinas et al. (2017) measure funding conditions via the Euribor-Eurepo spread in a study on European Treasury bond market liquidity, while Fecht et al. (2014) employ the Euribor-Eurepo spread to measure counterparty credit risk.

and asymmetry results following shocks to the Euribor-Eurepo rate in the robustness section presented in Section 2.4.

Adapting the procedure outlined in FGG using U.S. based funding liquidity measures to our European based funding liquidity measure, changes in funding illiquidity are obtained via the first difference of the two funding illiquidity risk variables:

$$\Delta EuTed_t = EuTed_t - EuTed_{t-1} \quad \textbf{(2.1)}$$

$$\Delta EE_t = EE_t - EE_{t-1} \quad \textbf{(2.2)}$$

To isolate the unexpected component of changes in funding illiquidity and add robustness to our asset pricing results, we construct a third proxy for funding conditions, namely innovations in funding liquidity ($\Delta EuTed_t^{innov}$), by adapting the procedure outlined in Banti and Phylaktis (2015) for the computation of unexpected changes in FX market illiquidity to our main funding illiquidity risk measure. Therefore, we identify funding shocks as the residual from an AR (1) model of the changes in the European TED spread.

$$\Delta EuTed_t = \gamma_0 + \gamma_1 \Delta EuTed_{t-1} + \varepsilon_t \quad \textbf{(2.3)}$$

From equation (2.3), $\Delta EuTed_t^{innov}$ is the estimate of ε_t. The funding illiquidity innovations measure also helps eliminate any potential serial correlation from the residuals. [12]

[12] We perform autocorrelation checks on the funding illiquidity measures examined and conclude that there is no evidence of serial correlation for any of the funding proxies. The p-values of 0.24 and 0.06 for the NR^2 statistic of the Breusch-Godfrey serial correlation LM test for ΔEE_t and $\Delta EuTed_t$ respectively, do not reject the null hypothesis of no serial correlation at the 5% significance level. To complement these results, we also perform a visual inspection of the residuals and examine the Ljung-Box Q statistics. We confirm the absence of serial correlation for the two measures, all Q-statistics having associated p-values larger than 0.1 up to the 12th lag.

2.2.3. Measuring illiquidity, volatility and CDS spreads

We estimate illiquidity through the illiquidity ratio developed by Amihud (2002).[13] The Amihud illiquidity measure is well-established in the market microstructure literature and in research investigating illiquidity impacts on the cross-section of stock returns (e.g. Amihud, 2002; Chordia et al. 2009). For an individual security *i*, the monthly Amihud illiquidity ratio ($Illiq_{i,t}$) is obtained by averaging throughout month *t* the daily ratio (multiplied by 10^6) of the absolute stock return ($|Ret_{itd}|$) over the product of the number of shares traded (VO_{itd}) and stock price (P_{itd}), as outlined in (2.4):

$$Illiq_{i.t} = \frac{1}{D_{it}} \sum_{d=1}^{D_{im}} \frac{|Ret_{itd}|}{(P_{itd})\ x\ (VO_{itd})} \qquad \textbf{(2.4)}$$

We also derive a market illiquidity measure ($Illiq_t^{mkt}$) which is computed as the median monthly Amihud illiquidity measure across the entire sample of stocks. Monthly stock volatility ($Vol_{i.t}$) is calculated as the standard deviation of stock returns over the current month (realized volatility). The monthly CDS spread values ($CDS_{i.t}$) are given by the monthly average of the daily mid-spreads on the 5-year CDS contracts of each underlying entity.[14]

2.2.4 Portfolio sorting procedure

Using the monthly illiquidity, volatility and CDS spread variables described above, we follow the method outlined in FGG and construct portfolios by sorting stocks into deciles based on their previous year-end illiquidity, volatility and CDS spread values, respectively.

[13] Goyenko et al. (2009) and Fong et al. (2017) perform horseraces between illiquidity variables and find that the Amihud (2002) illiquidity measure captures well the price impact of trades, placing tied first as the best monthly cost-per-dollar volume proxy.
[14] Ramchander et al. (2011) document that CDS contracts with five-year maturity represent the most liquid CDS contracts.

We track portfolio returns, illiquidity, volatility and CDS spreads throughout the following year and rebalance portfolios at the end of each year. As in FGG, the monthly illiquidity ratio of portfolio p ($Illiq_{p,t}$) is calculated as the median monthly Amihud illiquidity ratio ($Illiq_{i,t}$) across all entities in portfolio p.[15] The monthly volatility of portfolio p ($Vol_{p,t}$) is given by the equally-weighted average monthly standard deviation ($Vol_{i.t}$) of the stocks included in portfolio p. Similarly, the monthly CDS spread of portfolio p ($CDS_{p,t}$) is calculated as the equally-weighted average monthly CDS spread ($CDS_{i.t}$) across all entities in portfolio p.

2.3 Empirical strategy and results

2.3.1 Summary statistics

Table 2.1 reports summary statistics across the Amihud illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios in Panels (a), (b) and (c), respectively. We first examine the illiquidity-sorted portfolios and find that stocks in illiquid portfolios are on average more volatile and display higher CDS spreads. Moreover, sorting by illiquidity creates an annual return spread of approximately 7.8% between the five portfolios comprising the most illiquid stocks and the five portfolios including the most liquid entities. Furthermore, we find that there is a 3% annual return differential between the two extreme portfolios. Interestingly however, we find that the widest return differential is between the 8th and 3rd decile portfolios. The result of a positive return differential between illiquid and liquid stocks is in line with findings of Amihud (2002) and FGG and can be linked to the fact that

[15] To compute the monthly portfolio illiquidity ratio (as well as the monthly market illiquidity), we use the median rather than the average of entities' monthly stock illiquidity ratios due to the wide differences in the values of the illiquidity ratio for each company. This is in line with the procedure outlined in FGG..

investors require a higher rate of return for taking on the additional risk of investing in illiquid securities.

Secondly, analyzing volatility-sorted portfolios, we find that the portfolios containing the most volatile stocks exhibit higher illiquidity and have higher average CDS spreads. We also find evidence of a return spread between the five most volatile and five least volatile portfolios of 5.5% annually. Additionally, we document a large return spread of 12.6% annually between the most volatile and least volatile portfolios. The results concerning the positive relation between volatility and returns contradict the findings of Ang et al. (2006) who note that high volatility portfolios earn low average returns, but confirm the finding of a positive return differential documented by FGG. As our methodology and portfolio sorting procedure is akin to FGG, our study differs in several respects to Ang et al. (2006). Firstly, we annually form equally-weighted portfolios, rather than monthly value-weighted portfolios. Secondly, we consider portfolios of stocks sorted by realized volatility rather than ΔVIX loadings. Lastly, we use European data compared to U.S. data and analyze a different and shorter sample period (2009-2015 compared to 1986-2000) which includes some of the most turbulent part of the recent financial crisis, marked by severe illiquidity and high volatility. Thus, we find it reasonable that investors require compensation for holding the most volatile stocks.

Thirdly, investigating the year-end CDS spread-sorted portfolios, we find that stocks in high CDS spread portfolios exhibit greater illiquidity and volatility while also earning higher returns. The magnitude of the return differential between the five portfolios with the highest and those with the lowest average CDS spread is 3.29% annually, while the return spread between the top and bottom CDS spread portfolios is 6.45% annually. As with the illiquidity-sorted results, the highest return differential does not occur between the two extreme portfolios, but between the 10th and 7th deciles. However, a general pattern of increasing return from the portfolios with the smallest CDS spreads to those with the largest CDS spreads can be distinguished. Therefore, investors require a higher return to compensate for the added risk of investing in a stock with a higher default risk as measured by the CDS spread. This is in line with the positive relationship in levels between the natural logarithm of CDS spreads and required returns documented by Da Fonseca and Gottschalk (2015) for the Asia-Pacific markets between September 2007 and December 2010. The positive CDS-return relation is not straightforward at first. However, as Ramchander et al. (2011) document, the positive CDS-return relationship can be explained under turbulent credit market conditions, consistent with the view that equity holders do not consider widening of CDS spreads as *"value deteriorating"*. Instead, equity markets anticipate such *"debt deteriorating"* events and react positively to them (Ramchander et al., 2011). Since our data sample includes the most recent financial turmoil and because recovery from the crisis was slow, our result confirms recent empirical works investigating the CDS-return relationship during and after the crisis period.

Comparing our summary statistics results to those in FGG, we observe similar illiquidity, volatility and return patterns across portfolios. Using either one of the three sorting criteria, results suggest that illiquidity, volatility and returns generally increase, albeit with some variability, from the portfolio with the smallest value of the sorting criteria to the one with the highest value. We also note that the illiquidity and return of portfolios in our study are economically smaller, compared to those presented in FGG, which is expected since the entities in our dataset are highly graded while also having the most liquidly traded CDSs. Moreover, we document a positive CDS spread differential between the more illiquid (volatile) portfolios and those with lower illiquidity (volatility), result which confirms the findings of Das and Hanouna (2008), using U.S. data, that equity illiquidity is positively related to CDS spreads and those of Ericsson et al. (2009) that stock volatility is positively linked to CDS spreads.

2.3.2 Commonality and flight to quality

We test for commonality in the level and dispersion of illiquidity, volatility and CDS spread portfolio values during good and bad funding regimes. We expect that all portfolios sorted per the three criteria will evidence higher illiquidity, increased volatility and wider CDS spreads during times of funding liquidity tightness due to the risk aversion of intermediaries particularly when funding is scarce and their tendency to shift their allocations to safer assets in periods when funding is constrained. To investigate the presence of commonality, we follow the procedure outlined in FGG and divide our sample into three subsamples according to the yearly average level of the lagged funding liquidity measure, and track the illiquidity, volatility and CDS spread of each sorted portfolio throughout the year. We then focus on the subsamples exhibiting the tightest and loosest funding illiquidity.

Table 2.2 presents the average illiquidity, volatility and CDS spread of each portfolio throughout the tight (panel (a)) and loose (panel (b)) funding illiquidity subsamples as well as differences between these two subsamples (panel (c)). Eyeballing the results presented in panels (a) and (b), we find that during the tight funding regime, portfolio illiquidity, volatility and CDS spread are larger in size compared to the loose funding liquidity period. Examining the differences between these two subsamples presented in panel (c), we note that all but four differences in the three variables are positive, indicating larger portfolio illiquidity, volatility and CDS spread in a tight funding environment. All but four of the 86 positive differences are statistically significant at the 10% level and all but six are significant at the 5% level. Only two of the four negative differences are statistically significant.

Additionally, we note an asymmetric effect of funding conditions on illiquidity and volatility, with the most illiquid portfolios seeing their illiquidity increase the most and the most volatile portfolios seeing their volatility increase the most when funding is tight. We do not find the same dispersion in commonality result for CDS spreads. Overall, these results provide compelling evidence of commonality confirming that an exogenous negative shock to speculator capital will induce an increase in market illiquidity, market volatility and market CDS spreads. Moreover, the illiquidity and volatility dispersion result empirically confirms the theoretical prediction outlined in Brunnermeier and Pedersen (2009) stating that tightening of speculator capital increases market illiquidity, through an effect which is stronger for illiquid securities.

Furthermore, by exploring the relationship between illiquidity and volatility, we observe a 'flight-to-quality' effect predicted, among others, by Brunnermeier and Pedersen (2009), high volatility and high CDS spread portfolios seeing their illiquidity increase during tight funding conditions. In the case of illiquidity and volatility-sorted portfolios, the largest illiquidity differential is captured by the 10th decile portfolio (59.79 and 5.02, respectively), whereas in the case of CDS spread portfolios, the largest illiquidity differentials are recorded by the 8th and 7th decile portfolios (3.69 and 2.33 respectively) Therefore, flight-to-quality evidence is stronger for the more illiquid and volatile stocks. Notably, the difference between the illiquidity of the most volatile portfolio (5.02) during bad and good funding conditions is almost two and a half times the average illiquidity of the highest volatility portfolio for the whole sample (2.08), reported in *Table 2.1*. Considering CDS spreads as proxy for default risk, we also find evidence of flight-to-liquidity as the illiquidity of volatile and high CDS spread portfolios increases as speculators' funding becomes constrained.

Overall, we find strong support for the commonality in the level and dispersion of illiquidity, volatility and CDS spreads, as well as some evidence backing the flight-to-quality effect theoretically proposed by Brunnermeier and Pedersen (2009) for our sample of highly liquid European stocks. This confirms the findings of commonality and flight to quality previously documented by FGG for a large sample of U.S. stocks. Interestingly, when comparing our liquidity and volatility differentials between the two subsamples to the U.S. market based results of FGG, we note that the illiquidity differentials are lower in our case, which is to be expected as our sample contains highly liquid European entities. However, the volatility differentials are slightly larger in our study, possibly due to the much smaller sample period studied in our case (January 2009 to December 2014) compared to the FGG study (January 1986 – December 2015) and because a considerable part of our sample includes the recent Global Financial Crisis period which marked a period of increased stock volatility.

2.3.3 Asymmetric relationships

2.3.3.1 The response of CDS spreads to changes in funding illiquidity, when funding is constrained

Brunnermeier and Pedersen (2009) postulate that a downward shift in speculators' capital increases market illiquidity as speculators reduce their positions. Their study also argues that this effect is nonlinear, being more pronounced if capital is already scarce and for securities with high margin. FGG empirically test this prediction and document a positive impact of funding shocks on illiquidity and volatility changes, respectively.

We extend these empirical findings by testing whether funding illiquidity changes are correlated with changes in default risk as captured by the CDS spread. Considering that

CDS spread levels and changes are positively related to equity volatility (Ericsson et al. 2009) and that equity illiquidity is a determinant factor of CDS spreads (Das and Hanouna, 2009), we expect funding shocks to be positively related to shifts in CDS spreads, as they exacerbate the illiquidity and volatility of entities and thus add to the overall default risk of the entity.[16] Moreover, corresponding to the nonlinearity predictions of Brunnermeier and Pedersen (2009), we expect this relationship to be stronger for the more illiquid, volatile and high CDS portfolios when capital availability is already tight.

To test our hypothesis, we employ a similar methodology to that outlined in FGG and estimate regressions of funding illiquidity changes on portfolio CDS spread changes using the following model:

$$\Delta CDS_{p,t} = \alpha_{0,p} + \alpha_{1,p}\Delta EuTed_t + \alpha_{2,p}\Delta EuTed_t \mathbf{1}_{EuTed_{t-1}} + e_{p,t} \qquad \textbf{(2.5)}$$

In equation (2.5), $\Delta CDS_{p,t}$ is the change in the CDS spread of portfolio *p* in month *t*, $\Delta EuTed_t$ represents the change in funding illiquidity in month *t* and $\mathbf{1}_{EuTed_{t-1}}$ is an indicator function equal to '1' when the lagged funding illiquidity is in the top one-third of its sample distribution indicating a period of capital scarcity. If funding shifts positively influence CDS spread changes, we expect both estimates of $\alpha_{1,p}$ and $\alpha_{2,p}$ to be positive. Moreover, if the relationship is stronger when speculators operate closer to their funding constraint, following FGG, we expect estimates of $\alpha_{2,p}$ to be larger in magnitude and significant since $\alpha_{2,p}$ measures sensitivity to funding liquidity changes when capital is scarce.

Table 2.3 presents the estimation results of the model outlined in equation (2.5). Firstly, except for one insignificant estimate of $\alpha_{2,p}$ for the least illiquid portfolio, all

[16] It is important to note that Coro et al. (2013) document that liquidity risk factors are more important than credit risk factors in explaining CDS price changes, irrespective of market conditions. However, the influence of credit (default) risk factors increases after the financial crisis, the period investigated in our sample.

estimates of $\alpha_{1,p}$ and $\alpha_{2,p}$ are positive. Secondly, as expected, estimates of $\alpha_{2,p}$ are larger and more statistically significant, particularly for the more illiquid, volatile and large CDS spread portfolios (with one notable exception for the highest CDS spread portfolio) as these are the most sensitive to funding shocks when capital is already tight. Estimates of $\alpha_{1,p}$ are mostly insignificant indicating the smaller effect of funding shocks on spreads during 'ordinary' funding regimes when speculators are not funding constrained. What is surprising is the large explanatory power of our model, funding shocks predicting up to 45.16% of the CDS spread changes. This is in contrast with the weak explanatory power of up to 6.09% of the similarly constructed model regressing funding shocks on illiquidity changes found by FGG using U.S. stock market data. Therefore, we provide evidence of a nonlinear, positive impact of changes in funding illiquidity on CDS spread changes.

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2.3.3.2 The return response to positive and negative changes in funding illiquidity

We investigate separately the impact on contemporaneous returns of positive and negative changes in funding illiquidity. Brunnermeier and Pedersen (2009) hypothesize that positive funding illiquidity shocks (tightening of funding liquidity) increase market illiquidity, which due to its persistence, predicts high future illiquidity causing the required return demanded by investors to increase, which in turn lowers contemporaneous prices as per the models of Acharya and Pedersen (2005) and Amihud (2002). Negative funding illiquidity shocks (relaxation of funding constraints) are expected to have a weaker effect, since they decrease market illiquidity and increase the available investor capital. Therefore, we expect a tightening of funding liquidity to decrease significantly contemporaneous returns, while an improvement in funding conditions should have a weaker effect on returns as market participants become less funding constrained.

We proceed by constructing two dummy variables: δ^{+}, taking the value of 1 when $\Delta EuTed_t$ is positive and 0 otherwise, and δ^{-}, taking the value of 1 when $\Delta EuTed_t$ is negative and 0 otherwise. We then compute the positive ($\Delta EuTed_t^{+}$) and negative ($\Delta EuTed_t^{-}$) changes in funding illiquidity by interacting the two dummy variables, in turn, with the changes in funding illiquidity, as shown in equations (2.6) and (2.7):

$$\Delta EuTed_t^{+} = \Delta EuTed_t * \delta^{+} \quad \textbf{(2.6)}$$

$$\Delta EuTed_t^{-} = \Delta EuTed_t * \delta^{-} \quad \textbf{(2.7)}$$

To test our hypothesis, we estimate separately the following two regression models, depicted in (2.8) and (2.9) on portfolios sorted by illiquidity, volatility and CDS spreads:

$$r_{p,t} = \alpha_p + \beta_p^{\Delta EuTed+} \Delta EuTed_t^{+} + \beta_p^{mkt\_liq} Illiq^{mkt} + \varepsilon_{p,t} \quad \textbf{(2.8)}$$

$$r_{p,t} = \alpha_p + \beta_p^{\Delta EuTed-} \Delta EuTed_t^{-} + \beta_p^{mkt\_liq} Illiq^{mkt} + \varepsilon_{p,t} \quad \textbf{(2.9)}$$

We expect estimates of $\beta_p^{\Delta EuTed+}$ to be negative and significant as it measures return sensitivity to funding shocks under worsening funding conditions. Similarly, we expect estimates of $\beta_p^{\Delta EuTed-}$ to be insignificant as they measure return sensitivity under improving funding conditions. We add to our models the overall market illiquidity level to isolate the effect of funding shocks and control for the overall level of liquidity.

Table 2.4 presents the results. Across the three portfolio sorts, all but one estimate of $\beta_p^{\Delta EuTed+}$ are negative. All except four coefficient estimates are also statistically significant. Moreover, estimates of $\beta_p^{\Delta EuTed-}$ are small and statistically insignificant. Therefore, we provide evidence of an asymmetric relationship between funding shocks and contemporaneous returns, a tightening of funding liquidity having a negative and statistically significant effect on contemporaneous returns, whereas the impact of an improvement in funding conditions on returns is largely insignificant.

2.3.4 Asset pricing tests

We employ a two-stage Fama-Macbeth (1973) procedure to test whether funding shocks are priced in the cross-section of illiquidity-sorted portfolios and to verify the existence of a funding risk premium. In the first step, a contemporaneous time series model is estimated, where each portfolio return is regressed against the risk factors' time series. In the second stage, we regress the cross-section of monthly portfolio returns against the monthly factor exposures from the first stage at each time point, yielding a time-series risk premium for each factor. We then average these coefficients over time to obtain the factor premia. We present two sets of asset pricing results, one for the 10 illiquidity-sorted portfolios, presented in *Table 2.5* and, following FGG, one for the 30 illiquidity, volatility and CDS spread sorts combined, presented in *Table 2.A4*. The latter results are discussed in the robustness section (Section 2.4). As in FGG, on both occasions, we perform eight estimations incorporating the following risk factors: the market risk premium *(MKT_RF*) by itself, the Fama-French (1993) three factors (the market risk premium *(MKT_RF)*, the size premium *(SMB)* and book-to-market *(HML))*, the funding illiquidity risk (*ΔEuTed*) and the innovations in funding illiquidity factor ($\Delta EuTed^{innov}$) by themselves, and the market risk premium and Fama-French three factors augmented by the two funding illiquidity proxies. We report results using Fama-Macbeth (1973) standard errors as well as standard errors that correct for the errors-in-variables problem following the Shanken (1992) approximation, since the funding illiquidity risk betas are estimated.

Investigating the results for the illiquidity-sorted portfolios, presented in *Table 2.5*, we find that the CAPM and FF3 models have very weak power in explaining the cross-sectional variation of expected returns, with R^2 values of 9.67% and 10.10%, respectively and negative adjusted R^2 values. Moreover, the prices of risk for the market risk premium

(*MKT-RF*), size premium (*SMB*) and value risk premium (*HML*) are insignificant. The two funding illiquidity factors are both significant and explain around 42% of the cross-sectional variation alone. The point estimates for the prices of risk corresponding to $\Delta EuTed^{innov}$ and $\Delta EuTed$ are -1.81 and -1.92, respectively. Moreover, the estimated $\Delta EuTed^{innov}$ betas range between -1.04 and -1.60, while the $\Delta EuTed$ betas range between -1.03 and -1.66, implying an annual return spread between the most and least illiquid portfolios of 1.02% when considering funding shocks measured by $\Delta EuTed^{innov}$ and 1.21% when measuring funding shocks via $\Delta EuTed$. Comparing our results to those found by FGG using an alternative funding risk measure based on differentials between on-the-run and off-the-run securities, in the context of the U.S. market, we note that: the explanatory power of the model incorporating the funding risk factor alone is higher in our study (42.4% compared to 24.3%) and the point estimates of the price of risk are a third smaller in our case (-1.81 and -1.92 compared to -3.38). However, when funding liquidity is measured via the U.S. TED spread in FGG, our results are almost identical to those found by FGG, who document a point estimate for the price of funding liquidity of -1.82.

The estimated intercept is insignificant both when considering the CAPM and Fama and French (1993) factors as well as when we use the funding risk factors by themselves. When using the funding risk factors, the estimated intercept is reduced to a third compared to the CAPM and Fama-French model. When we augment the CAPM and Fama French 3-factor model with the funding illiquidity risk proxies, the estimated intercepts increase considerably, but remain insignificant, when using t-statistics based on Shanken (1992) standard errors. Augmenting the CAPM and Fama-French 3-factor models with the funding liquidity risk factor results in a large explanatory power, with adjusted R^2 values ranging between 51.2% and 66.6%. The prices of risk of the funding illiquidity factors increase slightly in magnitude to point estimates ranging between -2.06 and -2.42 annually and remain statistically significant.

To examine pricing errors, we present the mean absolute pricing errors (MAPE) associated with the two asset pricing tests. When investigating the ten illiquidity sorted portfolios, we note that the MAPE values decrease by at least one third when considering the funding illiquidity factor by itself, while when augmenting the CAPM and FF3 specifications with the funding illiquidity factor, we note a small increase in MAPE, compared to the CAPM and FF3 factors specifications.

2.4 Robustness checks

We provide robustness to our commonality, flight to quality and asymmetry results by investigating an alternative European funding liquidity measure, the Euribor - Eurepo spread (*EE*). Firstly, we find qualitatively similar commonality results, presented in *Table 2.A1,* to those using the European TED spread measure as our funding liquidity proxy, when evaluating funding liquidity by the yearly average lagged Euribor - Eurepo spread to create the high and low funding illiquidity subsamples. All but five differences are positive, indicating that the illiquidity, volatility and average CDS spread of portfolios increases during tight funding conditions. However, we do not find robust evidence for a flight-to-quality phenomenon. Secondly, in *Table 2.A2*, we present results for the asymmetric effect of changes funding illiquidity, measured using the change in the Euribor-Eurepo spread (ΔEE_t), on CDS spread changes when funding conditions are already constrained, as outlined in Section 3.3.1. We note that coefficient estimates of $\alpha_{1,p}$ and $\alpha_{2,p}$ are positive, except for a small insignificant estimate for the portfolio with the lowest CDS spread. The estimate of $\alpha_{2,p}$ is significant in most of the regressions on illiquidity and CDS spread portfolios. However, counterintuitively, these are insignificant except for one portfolio when analyzing volatility-sorted portfolios. Thirdly, we investigate the effect on returns of positive and negative funding shocks following the same procedure outlined in Section 2.3.3.2. Results are presented in *Table 2.A3*. All positive funding illiquidity changes are negative and highly significant, indicating a strong relationship with contemporaneous returns. Three of the negative funding illiquidity changes are also marginally significant and negative. The coefficients measuring the sensitivity of returns to market illiquidity are insignificant.

Moreover, when evaluating the presence of a funding risk premium, besides the results for the ten illiquidity sorted portfolios, we present results for the 30 illiquidity, volatility and CDS spread sorted portfolios together in *Table 2.A4*. Inspecting these results, we note that the CAPM by itself has improved the explanatory power to over 20% compared to the illiquidity-sorted portfolios results. The estimated intercepts for all models are insignificant. The prices of risk for the funding illiquidity factors have decreased to -0.75 and -0.76 when considering the funding risk factors alone and between -0.59 and -0.86 when added to the CAPM and Fama-French models. The estimates for the prices of risk of funding risk factors are significant at the 10% level when considered alone and at the 5% significance level when added to the Fama-French 3-factor model. *MAPE* is again lowest when analysing the funding illiquidity factor alone. However, the differentials compared to the other specifications are lower.

2.5 Conclusion

This paper tests and confirms the theoretical predictions outlined by Brunnermeier and Pedersen (2009) in the context of a highly liquid European market, the non-financial stocks included in the European iTraxx index. Differently from previous studies, we newly sort stocks according to their CDS spread level, alongside the previously documented volatility and illiquidity sorts. Moreover, we extend the previous U.S. findings to the European market and to CDS spreads. Specifically, we find compelling evidence of commonality in the level and dispersion of liquidity, volatility and CDS spreads across tight and relaxed funding conditions for portfolios sorted by illiquidity, volatility and CDS spread. Secondly, we provide evidence of flight-to-quality as portfolios comprising of entities with the highest illiquidity, volatility and default risk as measured by the CDS spread see their illiquidity increase the most. Thirdly, we document a significant asymmetric relationship between changes in funding illiquidity and changes in CDS spreads, whereby the relationship is larger in magnitude and statistically significant if speculators operate close to their funding constraint. Fourthly, we evidence an asymmetric relationship between funding shocks and returns. Positive changes in funding illiquidity significantly decrease contemporaneous returns, whereas negative funding illiquidity shocks have no influence on returns. Finally, we document the presence of a funding risk premium in the cross-section of illiquidity-sorted portfolios which creates a return spread between the most and least illiquid portfolios of 1.21% annually.

***Figure 2.1*: The U.S. TED Spread and European TED Spread (*EuTed*)**

Figure 2.1 presents the time-series variability of the U.S TED spread (black line) and the European TED spread (*EuTed*) (grey line).

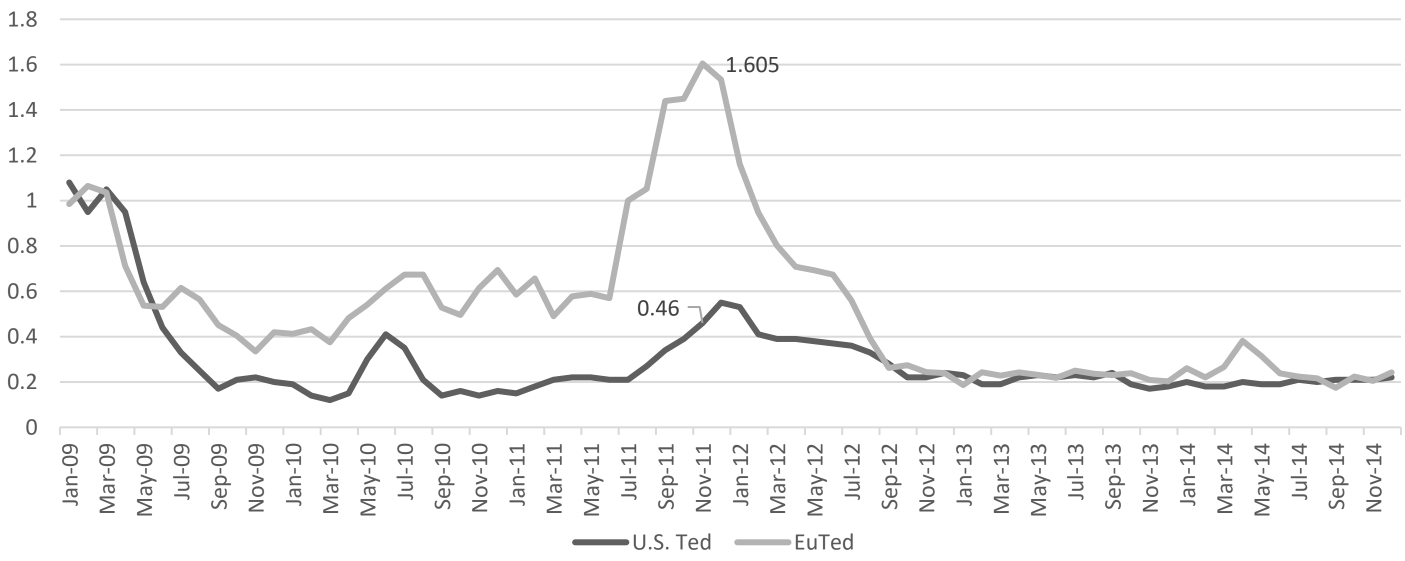

***Figure 2.2*: The European TED spread (*EuTed*) and the Euribor-Eurepo Spread (*EE*)**

Figure 2.2 presents the time-series variability of the European TED spread (*EuTed*) (grey line) and the Euribor-Eurepo Spread (*EE*) (black line).

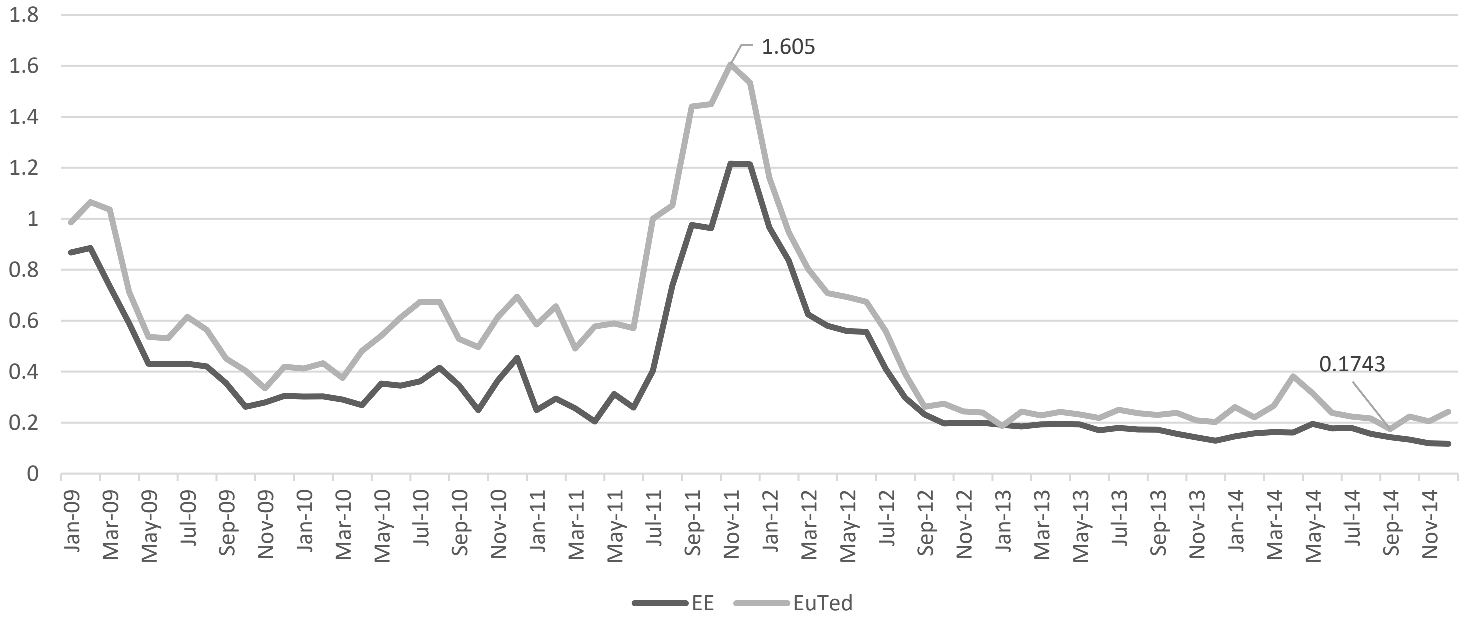

Table 2.1 **– Summary Statistics – Illiquidity, Volatility and CDS Spread Portfolios**

Time-series average sample statistics of decile portfolios of equities. Panels (a), (b) and (c) present results using illiquidity-sorted, volatility-sorted and CDS spread sorted portfolios, respectively. The illiquidity proxy used is Amihud illiquidity measure, calculated as median of all stocks in a portfolio (x100). The volatility, CDS spread and return measures are calculated as equal-weighted averages across all stocks in a portfolio (annualized % or natural logarithm). The last column in each of the panels presents the differences between the extreme portfolios, while the second to last column presents differences between the average statistics across portfolios 6 to 10 and portfolios 1 to 5, respectively. Results obtained using monthly data between January 2009 - December 2014.

Panel (a): Illiquidity-sorted portfolios

	Least	2	3	4	5	6	7	8	9	Most	P_{6-10} - P_{1-5}	$P_{10} – P_1$
Illiquidity	0.05	0.10	0.15	0.21	0.30	0.36	0.44	0.65	8.12	87.91	19.33	87.86
Volatility	21.32	23.20	24.26	26.09	27.78	27.94	28.34	27.55	26.70	28.82	3.34	7.50
CDS spread	4.30	4.35	4.50	4.60	4.66	4.62	4.67	4.62	4.48	4.50	0.10	0.20
Return	2.90	2.28	2.23	8.10	10.52	9.42	18.65	20.52	10.70	5.88	7.83	2.98

Panel (b): Volatility-sorted portfolios

	Least	2	3	4	5	6	7	8	9	Most	P_{6-10} - P_{1-5}	$P_{10} – P_1$
Illiquidity	0.20	1.34	0.32	0.31	0.32	0.89	0.35	0.35	0.79	2.08	0.39	1.88
Volatility	21.34	22.66	23.43	23.53	24.84	26.18	26.91	27.30	31.07	34.73	6.08	13.39
CDS spread	4.30	4.41	4.41	4.37	4.44	4.59	4.59	4.60	4.73	4.86	0.29	0.56
Return	0.46	6.43	7.42	13.19	3.97	10.02	10.17	11.59	14.10	13.06	5.49	12.60

Panel (c): CDS spread-sorted portfolios

	Least	2	3	4	5	6	7	8	9	Most	P_{6-10} - P_{1-5}	$P_{10} – P_1$
Illiquidity	0.23	0.28	0.30	0.26	1.62	0.30	1.31	1.58	0.34	0.34	0.24	0.11
Volatility	21.09	21.24	23.39	24.36	25.63	25.98	28.00	30.26	30.61	31.43	6.11	10.34
CDS spread	3.82	4.07	4.22	4.34	4.50	4.59	4.66	4.85	4.99	5.26	0.68	1.44
Return	9.49	6.50	3.50	9.40	8.20	11.87	-0.10	10.14	15.67	15.94	3.29	6.45

Table 2.2 **– Portfolio Illiquidity, Volatility and CDS Spread Conditional on the Level of Funding Illiquidity**

Average illiquidity (x100), volatility (annualized %) and CDS spread (natural logarithm) of illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios in subsamples conditional on the yearly average of the lagged funding illiquidity $EuTed_{t-1}$. Panel (a) reports averages when $EuTed_{t-1}$ is in the top one-third of its sample distribution, indicating high funding illiquidity. Panel (b) reports averages when $EuTed_{t-1}$ is in the bottom one-third of its sample distribution, indicating low funding illiquidity. *EuTed* is the European TED spread measure (3-month Euribor rate – 3 month German Government Bond rate). Panel (c) reports differences between the averages of the two samples, with t-statistics presented in parentheses. Results obtained using monthly data between January 2009 and December 2014.

Panel (a): Tight funding conditions (High $EuTed_{t-1}$)

	Illiquidity Portfolios			*Volatility Portfolios*			*CDS spread Portfolios*		
	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread
Least	0.05	25.15	4.43	0.24	25.87	4.58	0.44	25.33	3.96
2	0.11	26.32	4.45	3.63	29.07	4.49	0.25	26.13	4.21
3	0.18	28.98	4.58	0.39	28.61	4.54	0.27	29.22	4.39
4	0.27	32.95	4.80	0.48	27.81	4.63	0.39	29.32	4.52
5	0.38	33.70	4.73	0.45	30.33	4.64	0.34	30.62	4.59
6	0.45	36.46	5.01	0.27	33.06	4.66	0.32	32.12	4.66
7	0.55	35.75	4.67	0.37	32.49	4.73	2.55	33.87	4.74
8	0.82	31.28	4.63	0.42	33.31	4.73	4.07	38.57	4.99
9	9.69	34.61	4.76	0.69	37.85	4.82	0.38	37.46	5.17
Most	125.75	35.36	4.64	5.36	42.17	4.88	0.40	37.91	5.47

Panel (b): Loose funding conditions (Low $EuTed_{t-1}$)

	Illiquidity Portfolios			*Volatility Portfolios*			*CDS spread Portfolios*		
	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread
Least	0.04	18.40	4.00	0.16	19.80	3.98	0.08	18.08	3.55
2	0.09	20.42	4.11	0.17	20.31	4.33	0.24	18.11	3.85
3	0.13	19.93	4.28	0.37	20.61	4.14	0.27	20.28	4.04
4	0.17	21.20	4.37	0.20	20.75	4.13	0.16	20.58	4.13
5	0.23	24.69	4.59	0.31	21.14	4.27	4.17	22.10	4.27
6	0.33	23.52	4.30	1.98	21.49	4.26	0.28	21.96	4.44
7	0.35	22.38	4.44	0.37	21.80	4.35	0.23	24.60	4.47
8	0.46	23.55	4.55	0.17	21.88	4.41	0.39	25.46	4.69
9	7.84	21.27	4.15	0.28	22.13	4.62	0.28	23.92	4.67
Most	65.95	25.03	4.32	0.34	21.80	4.63	0.30	25.31	5.00

***Table 2.2* – Portfolio Illiquidity, Volatility and CDS Spread Conditional on the Level of Funding Illiquidity (cont'd)**

Panel (c): High $EuTed_{t-1}$ - Low $EuTed_{t-1}$

	Illiquidity Portfolios			*Volatility Portfolios*			*CDS spread Portfolios*		
	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread
Least	0.01	6.75	0.42	0.08	6.07	0.60	0.36	7.24	0.41
	(2.72)	(3.78)	(4.85)	(1.83)	(3.32)	(8.66)	(8.21)	(4.20)	(8.65)
2	0.02	5.90	0.34	3.46	8.76	0.16	0.00	8.02	0.36
	(2.67)	(3.28)	(6.02)	(4.36)	(4.36)	(2.06)	(0.22)	(4.82)	(8.32)
3	0.05	9.05	0.30	0.01	8.00	0.40	0.00	8.94	0.35
	(4.12)	(4.51)	(4.39)	(0.28)	(3.97)	(5.04)	(-0.03)	(4.70)	(5.31)
4	0.10	11.75	0.43	0.28	7.07	0.50	0.23	8.74	0.39
	(4.62)	(4.54)	(4.67)	(4.08)	(3.47)	(7.29)	(7.38)	(4.16)	(7.61)
5	0.15	9.00	0.13	0.13	9.19	0.37	-3.83	8.52	0.32
	(4.93)	(3.73)	(1.78)	(3.57)	(4.05)	(6.32)	(-4.37)	(3.83)	(4.86)
6	0.12	12.94	0.71	-1.71	11.57	0.39	0.04	10.17	0.22
	(3.44)	(4.56)	(9.01)	(-4.52)	(4.95)	(4.57)	(1.22)	(4.34)	(3.08)
7	0.20	13.37	0.24	0.00	10.68	0.38	2.33	9.27	0.27
	(4.23)	(4.48)	(2.66)	(-0.13)	(4.53)	(5.95)	(4.34)	(3.98)	(3.50)
8	0.36	7.73	0.08	0.25	11.43	0.32	3.69	13.11	0.30
	(7.82)	(3.97)	(1.29)	(6.43)	(5.13)	(3.76)	(4.22)	(4.11)	(3.44)
9	1.85	13.35	0.61	0.41	15.72	0.20	0.11	13.54	0.50
	(1.66)	(5.55)	(6.72)	(8.19)	(6.02)	(2.31)	(2.49)	(5.00)	(4.98)
Most	59.79	10.33	0.32	5.02	20.36	0.25	0.10	12.61	0.47
	(3.67)	(4.41)	(5.05)	(4.68)	(5.90)	(2.90)	(2.27)	(3.94)	(4.36)

Table 2.3 **– CDS Spreads and Funding Illiquidity Changes**

Regression results of CDS spread changes of each portfolio on funding illiquidity changes: $\Delta CDS_{p,t} = \alpha_{0,i} + \alpha_{1,p}\Delta EuTed_t + \alpha_{2,p}\Delta EuTed_t \mathbf{1}_{EuTed_{t-1}} + e_{p,t}$, where $\mathbf{1}_{EuTed_{t-1}}$ is an indicator function equal to 1 when the value of $EuTed_{t-1}$ is in the top one-third of its sample distribution indicating a period of high funding illiquidity. Panels (a), (b) and (c) present results for illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios, respectively. Estimations performed using Newey-West standard errors. T-statistics are reported in parentheses. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Results obtained using monthly data between January 2009 and December 2014.

	Least	2	3	4	5	6	7	8	9	Most
	Panel (a): Illiquidity Portfolios									
α_1	70.84***	20.98	20.55*	13.72	31.28*	13.61	16.49	10.93	-1.63	18.56
	(2.80)	(1.24)	(1.79)	(1.52)	(1.78)	(0.89)	(1.12)	(1.15)	(-0.13)	(1.61)
α_2	-20.28	27.57	41.44***	60.37***	27.69	71.77***	44.47**	38.08***	34.68	47.28***
	(-0.69)	(1.48)	(3.19)	(3.88)	(1.13)	(3.46)	(2.43)	(2.92)	(1.15)	(3.19)
R^2	21.64%	27.23%	40.85%	40.79%	24.98%	38.20%	29.03%	30.99%	8.41%	40.20%
	Panel (b): Volatility Portfolios									
α_1	28.85*	18.84	34.59	15.64	15.72	16.45	13.29	27.96***	19.74	28.24
	(1.91)	(1.56)	(1.52)	(1.30)	(1.27)	(0.91)	(0.83)	(2.82)	(1.424)	(1.46)
α_2	17.10	36.92***	12.54	16.91	28.21	35.04	60.73***	40.21**	0.57***	68.64***
	(0.95)	(2.73)	(0.50)	(0.61)	(1.49)	(1.52)	(3.25)	(2.62)	(3.52)	(2.99)
R^2	28.94%	40.26%	18.40%	10.54%	23.97%	20.69%	39.13%	35.89%	36.58%	43.31%
	Panel (c): CDS spread Portfolios									
α_1	17.16	6.13	8.51	4.12	32.29*	15.86	14.36	17.31	38.73	64.85**
	(1.07)	(0.75)	(1.29)	(0.51)	(1.69)	(1.40)	(1.15)	(1.14)	(1.94)	(1.96)
α_2	0.41	20.83**	30.85***	25.02**	10.67	50.40***	58.65***	77.14***	70.16**	28.92
	(0.02)	(2.34)	(3.63)	(2.50)	(0.48)	(4.02)	(4.66)	(3.73)	(2.38)	(0.52)
R^2	8.20%	34.00%	36.81%	24.67%	22.58%	45.16%	44.62%	43.70%	36.18%	15.84%

Table 2.4: Equity Returns and Positive and Negative Changes in Funding Illiquidity

Regression results of returns on positive and negative changes in funding illiquidity controlling for the level of market liquidity, as measured by the average Amihud illiquidity measure in the current month. Panels (a), (b) and (c) present results for illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios, respectively. Model 1: $r_{p,t} = \alpha_p + \beta_p^{\Delta EuTed+}\Delta EuTed_t^+ + \beta_p^{mkt\_liq} Illiq^{mkt} + \varepsilon_{p,t}$, presents results using positive changes in funding illiquidity, indicating a tightening of funding liquidity ($\Delta EuTed_t^+$), while Model 2: $r_{p,t} = \alpha_p + \beta_p^{\Delta EuTed-}\Delta EuTed_t^- + \beta_p^{mkt\_liq} Illiq^{mkt} + \varepsilon_{p,t}$ presents results using negative changes in funding illiquidity, indicating a relaxation of funding conditions ($\Delta EuTed_t^-$). $Illiq^{mkt}$ is the market illiquidity computed as the median monthly Amihud illiquidity measure across the entire sample of stocks. Estimations performed using Newey-West standard errors. T-statistics are reported in parentheses. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Results obtained using monthly data between January 2009 and December 2014.

Panel (a): Illiquidity portfolios

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Model 1	$\beta^{\Delta EuTed^+}$	-0.08**	-0.07**	-0.09***	-0.11**	-0.18***	-0.12*	-0.07*	-0.07*	-0.07*	-0.10
		(-2.45)	(-2.16)	(-2.78)	(-2.63)	(-4.61)	(-1.89)	(-1.68)	(-1.68)	(-1.67)	(-1.58)
	$\beta^{Illiq^{mkt}}$	-0.03	-0.06	-0.02	-0.04	-0.04	-0.04	0.02	-0.02	-0.06	-0.04
		(-1.03)	(-1.58)	(-0.34)	(-0.59)	(-0.79)	(-0.47)	(0.31)	(-0.40)	(-0.60)	(-0.53)
Model 2	$\beta^{\Delta EuTed^-}$	0.00	0.00	-0.01	-0.02	-0.05	0.02	-0.07	-0.07**	-0.01	-0.02
		(0.02)	(-0.02)	(-0.74)	(-0.42)	(-1.43)	(0.31)	(-1.42)	(-2.26)	(-0.17)	(-0.41)
	$\beta^{Illiq^{mkt}}$	-0.04	-0.07	-0.03	-0.06	-0.08	-0.04	-0.01	-0.06	-0.07	-0.06
		(-1.27)	(-1.63)	(-0.64)	(-0.97)	(-1.44)	(-0.53)	(-0.21)	(-0.90)	(-0.76)	(-0.68)

***Table 2.4*: Equity Returns and Positive and Negative Changes in Funding Illiquidity (cont'd)**

Panel (b): Volatility portfolios

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Model 1	$\beta^{\Delta EuTed^{+}}$	-0.05**	-0.06*	-0.15***	0.00	-0.05	-0.1***	-0.08*	-0.13***	-0.16**	-0.17***
		(-2.16)	(-1.80)	(-4.76)	(0.14)	(-1.43)	(-2.81)	(-1.67)	(-3.23)	(-2.60)	(-2.71)
	$\beta^{Illiq^{mkt}}$	-0.08*	-0.01	-0.04	-0.01	-0.08	-0.01	0.02	-0.02	-0.02	-0.04
		(-1.80)	(-0.14)	(-0.60)	(-0.30)	(-1.21)	(-0.33)	(-0.20)	(-0.46)	(-0.25)	(-0.48)
Model 2	$\beta^{\Delta EuTed^{-}}$	0.03	0.00	-0.04	0.00	-0.02	-0.03	0.04	-0.10*	-0.09	-0.04
		(1.14)	(-0.03)	(-1.13)	(0.29)	(-0.66)	(-1.01)	(0.74)	(-1.73)	(-1.08)	(-0.48)
	$\beta^{Illiq^{mkt}}$	-0.07	-0.01	-0.07	-0.01	-0.09	-0.04	-0.01	-0.08	-0.07	-0.07
		(-1.54)	(-0.24)	(-1.05)	(-0.23)	(-1.44)	(-0.70)	(-0.13)	(-1.25)	(-0.79)	(-0.79)

Panel (c): CDS spread portfolios

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Model 1	$\beta^{\Delta EuTed^{+}}$	-0.06*	-0.05*	-0.12***	-0.03	-0.08***	-0.08**	-0.11**	-0.15***	-0.17**	-0.11
		(-1.80)	(-1.72)	(-4.03)	(-1.12)	(-2.76)	(-2.39)	(-2.50)	(-2.88)	(-2.57)	(-1.66)
	$\beta^{Illiq^{mkt}}$	-0.01	-0.03	-0.06*	-0.02	-0.03	0.00	-0.08	0.01	-0.04	-0.06
		(-0.36)	(-0.56)	(-1.77)	(-0.48)	(-0.53)	(-0.01)	(-1.43)	(0.08)	(-0.52)	(-0.58)
Model 2	$\beta^{\Delta EuTed^{-}}$	-0.03*	0.00	-0.03	-0.03	0.00	-0.05	-0.06	-0.03	-0.04	0.02
		(-1.85)	(-0.31)	(-0.94)	(-0.95)	(0.19)	(-0.90)	(-1.33)	(-0.45)	(-0.73)	(0.25)
	$\beta^{Illiq^{mkt}}$	-0.03	-0.03	-0.09**	-0.03	-0.04	-0.03	-0.11*	-0.02	-0.08	-0.06
		(-0.72)	(-0.71)	(-2.03)	(-0.78)	(-0.65)	(-0.42)	(-1.76)	(-0.26)	(-0.84)	(-0.61)

Table 2.5: **Asset Pricing Tests – Illiquidity-Sorted Portfolios**

Results of two-step Fama-MacBeth regressions for ten portfolios of equities sorted by their year-end illiquidity. The intercept and prices of risk are annualized (multiplied by 12). T-statistics using Fama-MacBeth standard errors and standard errors calculated using the Shanken (1992) correction are also reported. Results obtained using monthly data between January 2009 and December 2014.

					Augmented by $\Delta EuTed^{innov}$		*Augmented by* $\Delta EuTed$	
	CAPM	*FF3*	$\Delta EuTed^{innov}$	$\Delta EuTed$	*CAPM*	*FF3*	*CAPM*	*FF3*
α	-6.54	-6.04	-2.74	-1.85	-17.11	-29.40	-13.91	-26.70
t-FM	-0.83	-0.57	-0.48	-0.34	-2.08	-2.23	-1.71	-2.04
t-Sh	-0.41	-0.38	-0.38	-0.30	-0.44	-0.44	-0.44	-0.45
$\Delta EuTed^{innov}$			-1.81		-2.06	-2.39		
t-FM			-3.35		-3.69	-3.76		
t-Sh			-3.18		-3.48	-3.52		
$\Delta EuTed$				-1.92			-2.06	-2.42
t-FM				-3.45			-3.59	-3.74
t-Sh				-3.27			-3.39	-3.50
MKT-RF	2.72	2.87			4.62	4.82	3.96	4.07
t-FM	1.11	1.29			1.84	2.04	1.59	1.76
t-Sh	1.06	1.23			1.63	1.78	1.45	1.59
SMB		0.87				0.33		0.20
t-FM		1.03				0.37		0.23
t-Sh		0.92				0.35		0.22
HML		1.68				2.45		2.08
t-FM		1.42				2.02		1.73
t-Sh		1.23				1.66		1.46
R^2	9.67%	10.10%	48.84%	49.32%	65.85%	81.44%	62.05%	80.38%
Adj. R^2	-1.62%	-34.85%	42.44%	42.99%	56.09%	66.59%	51.21%	64.69%
MAPE	0.36	0.43	0.25	0.24	0.38	0.56	0.37	0.55

***Table 2.A1* – Portfolio Illiquidity, Volatility and CDS Spread Conditional on the Level of Funding Illiquidity**

Average illiquidity (x100), volatility (annualized %) and CDS spread (natural logarithm) of illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios in subsamples conditional on the yearly average of the lagged funding illiquidity EE_{t-1}. EE represents the 3-month Euribor-Eurepo spread. Panel (a) reports averages when EE_{t-1} is in the top one-third of its sample distribution, indicating high funding illiquidity. Panel (b) reports averages when EE_{t-1} is in the bottom one-third of its sample distribution, indicating low funding illiquidity. Panel (c) reports differences between the averages of the two samples, with t-statistics presented in parentheses. Results obtained using monthly data between January 2009 and December 2014.

Panel A: Tight funding conditions (High EE_{t-1})

	Illiquidity Portfolios			*Volatility Portfolios*			*CDS spread Portfolios*		
Pno	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread
Least	0.05	22.50	4.29	0.11	22.00	4.29	0.41	22.53	3.89
2	0.11	25.66	4.58	3.70	24.87	4.47	0.39	23.25	4.15
3	0.18	27.02	4.62	0.35	24.28	4.51	0.18	24.03	4.30
4	0.26	30.43	4.84	0.51	26.77	4.62	0.36	27.13	4.48
5	0.36	29.39	4.61	0.38	28.65	4.60	0.36	29.92	4.61
6	0.42	31.92	4.93	0.27	30.54	4.96	0.41	29.58	4.70
7	0.56	35.82	4.86	0.36	32.64	4.85	1.16	31.86	4.81
8	0.77	33.41	4.74	0.54	32.51	4.67	4.03	36.91	5.07
9	10.01	31.68	4.82	1.54	35.42	4.83	0.44	35.48	5.28
Most	114.49	35.36	4.64	0.48	41.83	5.12	0.44	38.81	5.63

Panel B: Loose funding conditions (Low EE_{t-1})

	Illiquidity Portfolios			*Volatility Portfolios*			*CDS spread Portfolios*		
Pno	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread
Least	0.04	18.40	4.00	0.16	17.72	3.98	0.08	18.08	3.55
2	0.09	20.42	4.11	0.17	19.20	4.33	0.24	18.11	3.85
3	0.13	19.93	4.28	0.37	20.39	4.14	0.27	20.28	4.04
4	0.17	21.20	4.37	0.20	21.59	4.13	0.16	20.58	4.13
5	0.23	24.69	4.59	0.31	21.45	4.27	4.17	22.10	4.27
6	0.33	23.52	4.30	1.98	21.31	4.26	0.28	21.96	4.44
7	0.35	22.38	4.44	0.37	23.00	4.35	0.23	24.60	4.47
8	0.46	23.55	4.55	0.17	21.51	4.41	0.39	25.46	4.69
9	7.84	21.27	4.15	0.28	25.61	4.62	0.28	23.92	4.67
Most	65.95	25.03	4.32	0.34	28.63	4.63	0.30	25.31	5.00

Table 2.A1 – Portfolio Illiquidity, Volatility and CDS Spread Conditional on the Level of Funding Illiquidity (cont'd)

Panel C: High EE_{t-1} - Low EE_{t-1}

	Illiquidity Portfolios			*Volatility Portfolios*			*CDS spread Portfolios*		
Pno	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread	Illiquidity	Volatility	CDS spread
Least	0.01	4.10	0.29	-0.05	4.28	0.31	0.33	4.44	0.34
	(2.46)	(2.47)	(4.57)	(-1.20)	(3.20)	(5.00)	(6.84)	(2.53)	(7.52)
2	0.02	5.24	0.46	3.53	5.67	0.14	0.15	5.14	0.31
	(3.34)	(3.23)	(8.99)	(8.79)	(2.82)	(1.99)	(4.99)	(3.07)	(8.33)
3	0.05	7.09	0.34	-0.03	3.89	0.37	-0.09	3.75	0.26
	(4.73)	(4.19)	(5.80)	(-0.24)	(2.00)	(5.47)	(-4.21)	(2.42)	(5.29)
4	0.08	9.23	0.47	0.31	5.18	0.49	0.20	6.56	0.34
	(4.83)	(3.59)	(5.58)	(2.61)	(2.52)	(7.52)	(5.84)	(3.03)	(7.38)
5	0.13	4.69	0.02	0.07	7.20	0.33	-3.81	7.83	0.34
	(6.19)	(2.13)	(0.29)	(0.62)	(3.16)	(5.74)	(-4.34)	(3.96)	(5.83)
6	0.10	8.40	0.63	-1.72	9.24	0.70	0.14	7.62	0.26
	(3.26)	(2.87)	(8.30)	(-6.07)	(4.19)	(6.63)	(5.41)	(3.68)	(4.36)
7	0.20	13.44	0.42	-0.01	9.64	0.51	0.94	7.26	0.34
	(4.61)	(4.65)	(4.45)	(-0.15)	(4.24)	(8.33)	(5.00)	(3.69)	(4.85)
8	0.31	9.86	0.19	0.37	11.00	0.27	3.65	11.45	0.39
	(8.96)	(5.85)	(3.01)	(4.24)	(5.27)	(3.45)	(4.14)	(3.55)	(4.94)
9	2.17	10.42	0.68	1.27	9.81	0.21	0.16	11.56	0.61
	(2.19)	(4.48)	(8.53)	(6.06)	(4.43)	(2.77)	(4.80)	(4.80)	(6.77)
Most	48.54	10.33	0.32	0.14	13.20	0.49	0.14	13.51	0.63
	(2.81)	(4.41)	(6.41)	(1.54)	(4.13)	(7.31)	(4.26)	(4.66)	(6.51)

***Table 2.A2*. CDS spreads and Funding Illiquidity Changes**

Regression results of CDS spread changes of each portfolio on funding illiquidity changes: $\Delta CDS_{p,t} = \alpha_{0,p} + \alpha_{1,p}\Delta EE_t + \alpha_{2,p}\Delta EE_t \mathbf{1}_{EE_{t-1}} + e_{p,t}$, where $\mathbf{1}_{EE_{t-1}}$ is an indicator function equal to 1 when the value of EE_{t-1} is in the top one-third of its sample distribution indicating a period of high funding illiquidity. Panels (a), (b) and (c) present results for illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios, respectively. Estimations performed using Newey-West standard errors. T-statistics are reported in parentheses. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Results obtained using monthly data between January 2009 and December 2014.

	Least	2	3	4	5	6	7	8	9	Most
					Illiquidity Portfolios					
α_1	86.85***	38.62**	56.38	44.55**	81.39**	61.01***	40.04	17.03	38.80	30.13
	(2.85)	(2.02)	(1.52)	(2.30)	(2.49)	(3.12)	(1.33)	(0.88)	(1.35)	(1.17)
α_2	15.86	48.09*	41.65	77.14**	37.92	79.54**	49.11	67.99***	54.00	76.51**
	(0.48)	(1.91)	(1.04)	(2.36)	(1.00)	(2.48)	(1.50)	(3.40)	(1.38)	(2.48)
R^2	22.13%	28.49%	34.96%	33.15%	34.50%	35.24%	20.94%	30.66%	22.71%	34.68%
					Volatility Portfolios					
α_1	60.35**	55.82**	42.93*	48.38**	46.99**	45.25	45.40	61.86**	24.08	63.72
	(2.56)	(2.08)	(1.95)	(2.56)	(2.37)	(1.26)	(1.57)	(2.19)	(0.90)	(1.59)
α_2	22.02	31.88	41.53*	39.02	37.38	59.97	60.43	57.16	118.43***	80.08
	(0.72)	(1.07)	(1.75)	(1.55)	(1.40)	(1.59)	(1.61)	(1.90)	(3.72)	(1.64)
R^2	31.01%	34.52%	18.18%	25.17%	30.03%	28.84%	27.16%	36.53%	41.45%	32.02%
					CDS spread Portfolios					
α_1	-3.27	18.08	16.18*	17.42	57.76*	30.34	34.90	47.17	96.5**	179.71***
	(-0.24)	(1.19)	(1.80)	(0.97)	(1.88)	(1.31)	(1.36)	(1.55)	(2.17)	(2.90)
α_2	35.44**	29.52*	53.01***	39.31*	22.07	77.64**	78.18**	85.27**	95.23*	32.15
	(2.50)	(1.76)	(3.21)	(1.92)	(0.67)	(2.58)	(2.65)	(2.02)	(1.72)	(0.45)
R^2	7.41%	35.54%	37.51%	31.32%	25.04%	39.65%	35.66%	28.85%	37.71%	27.33%

***Table 2.A3.* Equity Returns and Positive and Negative Changes in Funding Illiquidity**

Regression results of returns on positive and negative changes in funding illiquidity controlling for the level of market liquidity, as measured by the average Amihud illiquidity measure in the current month. Panels (a), (b) and (c) present results for illiquidity-sorted, volatility-sorted and CDS spread-sorted portfolios, respectively. Model 1: $r_{p,t} = \alpha_p + \beta_p^{\Delta EE+} \Delta EE_t^{+} + \beta_p^{mkt\_liq} Illiq^{mkt} + \varepsilon_{p,t}$ presents results using positive changes in funding illiquidity (ΔEE_t^{+}), while Model 2: $r_{p,t} = \alpha_p + \beta_p^{\Delta EE-} \Delta EE_t^{-} + \beta_p^{mkt\_liq} Illiq^{mkt} + \varepsilon_{p,t}$ presents results using negative changes in funding illiquidity (ΔEE_t^{-}). Estimations performed using Newey-West standard errors. T-statistics are reported in parentheses. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Results obtained using monthly data between January 2009 and December 2014.

Panel A: Illiquidity Portfolios

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Model 1 (ΔEE_t^{+})	$\beta^{\Delta EE+}$	-0.21***	-0.15***	-0.17***	-0.2***	-0.28***	-0.33***	-0.19**	-0.21***	-0.36***	-0.28**
		(-5.16)	(-3.07)	(-2.69)	(-3.58)	(-4.68)	(-4.07)	(-2.51)	(-3.06)	(-2.97)	(-2.29)
	β^{Mkt_Liq}	-0.01	-0.05	0.00	-0.02	-0.02	0.00	0.04	0.00	-0.01	-0.01
		(-0.32)	(-1.11)	(-0.01)	(-0.31)	(-0.30)	(-0.04)	(0.59)	(-0.01)	(-0.12)	(-0.2)
Model 2 (ΔEE_t^{-})	$\beta^{\Delta EE-}$	-0.06	0.00	-0.05	-0.08	-0.12*	-0.08	-0.16*	-0.19*	-0.22*	-0.2**
		(-1.08)	(0.07)	(-0.78)	(-0.90)	(-1.86)	(-0.72)	(-1.77)	(-1.84)	(-1.77)	(-2.03)
	β^{Mkt_Liq}	-0.05	-0.07	-0.03	-0.07	-0.07	-0.06	-0.01	-0.06	-0.10	-0.08
		(-1.43)	(-1.59)	(-0.65)	(-0.95)	(-1.37)	(-0.77)	(-0.17)	(-0.95)	(-1.09)	(-1.05)

***Table 2.A3.* Equity Returns and Positive and Negative Changes in Funding Illiquidity (cont'd)**

Panel B: Volatility Portfolios

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Model 1 (ΔEE_t^+)	$\beta^{\Delta EE}$	-0.23***	-0.23***	-0.26***	-0.08*	-0.14***	-0.23***	-0.20***	-0.27***	-0.40***	-0.34***
		(-3.20)	(-3.46)	(-4.81)	(-1.85)	(-2.18)	(-2.93)	(-2.38)	(-4.60)	(-3.72)	(-3.61)
	β^{Mkt_Liq}	-0.05	0.02	-0.02	0.00	-0.06	0.01	0.00	0.00	0.02	-0.01
		(-1.08)	(0.41)	(-0.24)	(-0.04)	(-0.89)	(0.19)	(0.04)	(0.03)	(0.32)	(-0.14)
Model 2 (ΔEE_t^-)	$\beta^{\Delta EE}$	-0.01	-0.04	-0.14*	0.00	-0.06	-0.08	0.00	-0.30***	-0.33***	-0.2*
		(-0.20)	(-0.61)	(-1.79)	(0.05)	(-0.61)	(-1.23)	(-0.02)	(-4.41)	(-2.69)	(-1.82)
	β^{Mkt_Liq}	-0.09*	-0.02	-0.08	-0.01	-0.09	-0.04	-0.03	-0.08	-0.09	-0.09
		(-1.80)	(-0.37)	(-1.04)	(-0.27)	(-1.34)	(-0.73)	(-0.32)	(-1.58)	(-1.07)	(-1.04)

Panel C: CDS spread Portfolios

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Model 1 (ΔEE_t^+)	$\beta^{\Delta EE}$	-0.15**	-0.16***	-0.24***	-0.10**	-0.17***	-0.31***	-0.27***	-0.27***	-0.36***	-0.34***
		(-2.18)	(-3.02)	(-3.59)	(-2.32)	(-2.99)	(-3.67)	(-2.67)	(-3.53)	(-3.73)	(-4.07)
	β^{Mkt_Liq}	0.00	-0.01	-0.04	-0.01	-0.02	0.04	-0.05	0.03	-0.01	-0.02
		(0.05)	(-0.17)	(-0.98)	(-0.19)	(-0.25)	(0.58)	(-1.05)	(0.32)	(-0.11)	(-0.23)
Model 2 (ΔEE_t^-)	$\beta^{\Delta EE}$	-0.07	-0.06	-0.10	-0.03	-0.02	-0.24***	-0.14	-0.21*	-0.18*	-0.12
		(-0.88)	(-0.95)	(-1.64)	(-0.45)	(-0.27)	(-3.35)	(-1.33)	(-1.9)	(-1.71)	(-0.90)
	β^{Mkt_Liq}	-0.03	-0.04	-0.09**	-0.03	-0.05	-0.05	-0.11*	-0.04	-0.09	-0.09
		(-0.63)	(-0.77)	(-2.09)	(-0.62)	(-0.70)	(-0.75)	(-1.83)	(-0.44)	(-1.02)	(-0.92)

Table 2.A4. **Asset Pricing Tests - Illiquidity, Volatility and CDS Spread Sorted Portfolios**

Results of two-step Fama-MacBeth regressions for thirty sorted portfolios (ten portfolios sorted by year-end illiquidity, ten portfolios sorted by year end volatility and ten portfolios sorted by year-end CDS spread). The intercept and prices of risk are annualized (multiplied by 12). T-statistics calculated using Fama-MacBeth standard errors and standard errors calculated using the Shanken (1992) correction are reported. Results obtained using monthly data between January 2009 and December 2014.

					Augmented by $\Delta EuTed^{innov}$		*Augmented by $\Delta EuTed$*	
	CAPM	*FF3*	*$\Delta EuTed^{innov}$*	*$\Delta EuTed$*	*CAPM*	*FF3*	*CAPM*	*FF3*
α	-3.91	-5.03	1.04	1.58	-4.40	-9.26	-4.03	-10.22
t-FM	-0.75	-0.65	0.21	0.31	-0.84	-1.11	-0.77	-1.20
t-Sh	-0.61	-0.54	0.20	0.29	-0.67	-0.79	-0.63	-0.80
$\Delta EuTed^{innov}$			-0.76		-0.60	-0.86		
t-FM			-1.78		-1.59	-2.23		
t-Sh			-1.74		-1.56	-2.17		
$\Delta EuTed$				-0.75			-0.59	-0.84
t-FM				-1.74			-1.56	-2.17
t-Sh				-1.70			-1.53	-2.12
MKT-RF	2.02	1.72			1.90	0.95	1.86	0.81
t-FM	1.19	0.98			1.13	0.57	1.10	0.49
t-Sh	1.16	-0.88			1.10	0.57	1.08	0.49
SMB		0.13				-0.66		-0.83
t-FM		0.16				-0.79		-1.01
t-Sh		0.16				-0.72		-0.91
HML		1.02				0.77		0.65
t-FM		1.16				0.89		0.77
t-Sh		1.06				0.83		0.72
R^2	20.24%	22.11%	15.83%	15.95%	27.81%	39.78%	27.99%	41.96%
Adj. R^2	17.39%	13.12%	12.82%	12.95%	22.47%	30.15%	22.66%	32.68%
MAPE	0.24	0.32	0.22	0.23	0.24	0.34	0.24	0.35

Chapter 3: Monetary Policy and Stock Liquidity. Evidence from the U.K. market.

3.1 Introduction

Stock liquidity is a central characteristic of financial markets. Despite the multitude of research focusing on the determinants of liquidity and its relevance for market participants, liquidity remains an elusive concept as it displays different facets which cannot be captured using one liquidity measure.[1]

The importance of liquidity for financial markets is exemplified by its effect on required returns (e.g. Amihud and Mendelson, 1986; Amihud, 2002) and its implications for asset pricing (e.g. Acharya and Pedersen, 2005). Moreover, recent financial crises and especially the 2007-2009 global financial crisis, have shown that during market downturns, liquidity decreases or even completely dries up (Chordia et al. 2005; Naes et al. 2011). A separate research stream documents that liquidity displays commonality across individual assets. Chordia et al. (2000), Huberman and Halka (2001) and Hasbrouck and Seppi (2001) document commonality in liquidity in the context of the U.S. market, Galariotis and Giouvris (2007) and Foran et al. (2015) provide U.K. based evidence, while Karolyi et al (2012) and Brockman et al. (2009) offer international evidence. These studies suggest that individual asset liquidity is driven by (at least) one common macroeconomic factor. Several studies identify different common drivers of liquidity such as: the business cycle (e.g. Eisfeldt, 2004; Naes et al. 2011), negative market returns (Hameed et al. 2010), monetary

[1] See Amihud et al. (2005) for an overview of liquidity literature.

conditions (Jensen and Moorman, 2010), mutual funds' flows (Massa, 2004), yield differences between on-the-run and off-the-run bonds (Fontaine and Garcia, 2012), funding liquidity (Brunnermeier and Pedersen, 2009) and trader leverage (Kahraman and Tookes, 2017). In this paper, we investigate whether a common determinant of individual stock liquidity is monetary policy.

Several theoretical models suggest that capital constraints are connected to market liquidity (e.g. Gromb and Vayanos, 2002; Garleanu and Pedersen, 2007; Brunnermeier and Pedersen, 2009; Kondor and Vayanos, 2016). In these models, traders' ability to access funds to invest in risky assets and thus supply liquidity to the market is dependent on market frictions such as the costs associated with raising funds. In a margin trading setting, among others, Weill (2007) documents that margin traders provide ''socially optimal'' liquidity to the market during regular economic periods when access to capital is sufficient, whereas they become liquidity demanders during severe market crashes, not maintaining price continuity due to a risk of welfare loss. This argument is in line with the theoretical model of Brunnermeier and Pedersen (2009) whereby constraints in traders' ability to raise funds leads to market illiquidity, which in turn diminishes funding liquidity, leading to a liquidity loss spiral. Moreover, the inventory paradigm of market microstructure (e.g. Demsetz, 1968; Stoll, 1978a) suggests that traders' ability to provide liquidity is dependent, among other factors, on the opportunity costs and risks associated with holding securities. Taken together, these theoretical findings suggest that market liquidity is dependent on the costs and associated risks of holding assets.

In this paper, we investigate whether monetary policy (or monetary stance) is a determinant of individual stock liquidity of companies listed on the London Stock Exchange (L.S.E.), when monetary policy is measured through short-term interest rates, as in the study of Fernandez-Amador et al. (2013) focusing on the Euro-zone market.

Previous literature studying the effect of monetary policy on stock (il)liquidity is rather thin and provides mixed evidence. In the context of the U.S. market, Fujimoto (2003) employs a vector autoregressive approach and documents that the influence of monetary policy, as measured through a positive shock to non-borrowed reserves and a negative shock to the federal funds rate, on liquidity is significant only before the mid-1980s. Chordia et al. (2005) finds that monetary expansions are linked to increased liquidity only during crisis periods. Separately, Goyenko and Ukhov (2009) and Jensen and Moorman (2010) provide strong evidence to support the positive effect of expansionary monetary policy on aggregate (market-wide) stock liquidity, while Chiu (2014) documents that monetary policy shocks do not significantly impact market liquidity. In the context of the Scandinavian market, Soderberg (2008) examines the in-sample and out-of-sample predictability of fourteen macroeconomic variables providing ambiguous evidence, while, for the Euro zone (German, French and Italian) market, Fernandez-Amador et al. (2013), the study that is most closely linked to ours from a methodological standpoint, provides strong evidence of a positive (negative) effect of expansionary (contractionary) monetary policy on stock liquidity. In the context of the U.K. market, Florackis et al. (2014) document that macro-liquidity shocks' effect on returns is significantly stronger for the most liquid stocks and that trading cost increases slightly while trading activity increases significantly on Monetary Policy Committee meeting days.

Therefore, the direct relationship between monetary policy and stock (il)liquidity has not been sufficiently addressed in the context of the U.K. market. Considering the varied results obtained in previous studies investigating this relationship throughout the different markets and time-frames and the important role of London as a global financial market, the investigation of the effect of monetary policy on stock liquidity in the context of the U.K. market emerges as an interesting research question. Monetary policy through its effect on interest rates, influences both the costs of holding assets as well as the perceived risk of holding risky assets and should, therefore, affect stock liquidity (Fernandez-Amador et al. 2013).

Following this reasoning, our *first and main hypothesis* suggests that a tightening (relaxation) of monetary policy (or monetary stance) through a higher (lower) short-term interest rate leads to an increase (decrease) in borrowing costs, thus reducing (increasing) funding liquidity and stock liquidity.

To test our main hypothesis, we employ a panel data setting and examine whether expansionary (restrictive) monetary policy impacts positively stock liquidity (illiquidity). Results suggest that for two of the five (il)liquidity measures investigated (Amivest liquidity ratio and proportion of days with zero returns), we find a significant and positive, in-sample predictive relationship between monetary tightening and stock illiquidity, while for the remaining three measures (traded volume, turnover price impact and relative bid-ask spread) we could not find a statistically significant relationship. Therefore, the effect of monetary policy on stock liquidity is significant when liquidity is measured via price impact of transactions measures, but insignificant when volume-related or transaction costs liquidity measures are employed. This highlights the importance of investigating the effects of monetary policy on multiple aspects of liquidity such as trading activity, price impact of transactions and transaction costs.

A separate research strand investigates whether monetary policy has a differential effect on small companies as opposed to large firms. To this end, Gertler and Gilchrist (1994) and Kontonikas and Kostakis (2013) document that small companies should be more sensitive to increases in short-term interest rates as they have less protection against adverse changes in economic conditions. There are several reasons why we would expect a stronger effect of monetary policy on small caps: Firstly, Bernanke and Blinder (1992) document that a monetary contraction leads to a decline in aggregate bank lending, thus reducing the supply of money available for companies to finance their business. Bernanke et al. (1994) and Kontonikas and Kostakis (2013) argue that small companies cannot afford optimal risk management strategies and are less well collateralized, being more prone to the negative effects of 'flight to quality lending'. Secondly, besides reducing bank lending, Kashyap et al. (1993) documents that a monetary contraction also increases commercial paper volume. Since the ability to issue commercial paper is far more limited for small caps than large caps, small caps find it more difficult and expensive to raise new funds. Thirdly, monetary policy contractions exacerbate liquidity constraints of small firms, reducing their creditworthiness and their capacity to access funds from any external provider (Gertler and Gilchrist, 1994; Bernanke and Gertler, 1995; Kashyap and Stein, 2000).[2] Fourthly, as Jensen and Moorman (2010) document, a tightening of monetary policy leads to increased illiquidity, which according to Amihud (2002) would impact more severely small, illiquid stocks which see their illiquidity decrease the most, while larger stocks become comparatively more attractive during periods of low market liquidity. This hypothesis is also supported by the findings of Nyborg and Ostberg (2014) based on the 'liquidity pull-back' hypothesis, the authors documenting that tightening in the interbank market leads to more trading volume in liquid stocks compared to illiquid stocks.

Similarly, a monetary policy tightening should have a stronger effect on volatile stocks, compared to less volatile stocks. An increase in short-term interest rates would increase the cost of funds, thus increasing funding illiquidity. Following the theoretical predictions of Proposition 6(iv) from Brunnermeier and Pedersen (2009), after a decrease in funding liquidity, which can be interpreted through monetary tightening, illiquidity increases the most for volatile stocks as investors rush to rebalance their portfolios towards

[2] For more details, see the discussion in Kashyap and Stein (2000).

safer investments – a flight to quality effect. This prediction has been empirically proven in the context of the U.S. market by Fontaine et al. (2016), in their study of the effect of funding shocks on the cross section of asset returns. However, Fontaine et al. (2016) do not directly investigate any monetary policy variable, but rather examine funding liquidity shocks extracted from the funding liquidity measure developed by Fontaine and Garcia (2012) based on Treasury securities.

Considering the above arguments, the *second hypothesis* that we investigate is whether the effect of monetary policy on stock liquidity is stronger for small market capitalization stocks and high-volatility stocks.

To test our second hypothesis, we construct interaction terms between monetary policy and, in turn, market capitalization and volatility, measured as the monthly standard deviation of stock returns. Panel regression coefficient estimates for the interaction terms suggest that the effect of monetary policy on individual stock liquidity decreases with firm market capitalization, confirming the findings of Fernandez-Amador et al. (2013) that small caps are more sensitive to monetary policy. Similarly, this paper newly provides empirical evidence that the impact of monetary policy on liquidity is increasing with stock volatility as per the theoretical predictions of Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2016).

Moreover, recent studies (e.g. Basistha and Kurov, 2008; Kontonikas et al. 2013; Florackis et al. 2014) provide evidence that monetary policy shocks affect stock market returns differently during market recessions, especially during the 2007-2009 financial crisis. Since the recent financial crisis represented a period marked by severe market illiquidity, compared to ‘ordinary’ market periods, illiquidity should be more tightly related to monetary policy during this turmoil period.

Therefore, our *third hypothesis* is whether the effect of monetary policy on stock liquidity is more pronounced during the 2007-2009 financial crisis. To test this hypothesis, we use interaction terms between a crisis dummy and the monetary policy measures to investigate whether there is a differential effect of monetary policy on stock liquidity during the recent financial crisis, a period marked by severe market illiquidity, when compared to 'ordinary' market periods. Indeed, we document that the effect of monetary policy on stock liquidity is more significant during the recent financial crisis compared to the rest of the sample. However, depending on which measure of illiquidity is employed, we also find evidence of a positive effect of monetary relaxation on stock liquidity outside the financial crisis. We also document that the larger effect of monetary policy on the liquidity of small firms is consistent in both regimes, while the stronger impact of monetary policy on high volatility firms is only significant outside the financial crisis period.

We contribute to existing research in several ways. Firstly, we provide (to the best of our knowledge) the first study of the direct impact of Bank of England monetary policy on individual stock liquidity of entities listed on the London Stock Exchange. Secondly, we confirm, in the context of the U.K. market, the findings of Fernandez-Amador et al. (2013), based on Euro zone data, of a stronger effect of monetary policy on small market capitalization firms. Adding to the results of Fernandez-Amador et al. (2013), we also find empirical evidence that monetary policy has a larger effect on firms with higher volatility of stock returns. This result also confirms the theoretical predictions of Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2016). Thirdly, we extend the findings of existing research evidencing differential impacts of monetary policy on stock returns during crisis periods, by documenting the stronger effect of monetary policy on stock liquidity during the 2007-2009 financial crisis, compared to the rest of the sample. Moreover, we newly find that the differential response of stock liquidity to monetary tightening due to size holds both during and outside the financial crisis, while the stronger effect for high volatility firms is significant only outside the financial crisis period.

It is important to highlight that this study does not specifically look at monetary policy changes (or shocks), but rather at the overall monetary policy stance, as measured by short-term interest rate levels. To this end, this paper employs the panel framework used by Fernandez-Amador et al. (2013) to reach conclusions. Noteworthy, a vast literature investigating monetary policy (shocks) on asset prices, stock returns or liquidity, uses different methodologies to isolate monetary conditions and disentangle expected and unexpected components of monetary shocks to reach conclusions. Such methodologies include: VAR analysis procedure (e.g. Goyenko and Ukhov, 2009; Fujimoto, 2003), event study approach (Bernanke and Kuttner, 2005; Kontonikas et al. 2013), linear regression (Nyborg and Ostberg, 2014) or dynamic copulas (Chu, 2015).

The remainder of the paper is structured as follows: Section 3.2 describes the data and variables employed in our analysis. Section 3.3 illustrates the empirical setting used. Section 3.4 evidences the results of the panel estimations, section 3.5 covers the robustness checks of our results, while Section 3.6 concludes.

3.2 Data and description of variables

3.2.1 Data

We evaluate the effect of monetary policy on the illiquidity of individual stocks during the period from January 1999 to December 2015.[3] As in the study of Fernandez-Amador et al.

[3] We choose to start our sample period in 1999 in line with closely related studies investigating the effects of monetary policy on stock illiquidity (Fernandez-Amador et al, 2013) and on stock returns (Florackis et al, 2014).

(2013), we investigate this relationship at a monthly frequency (204 months) using a sample represented by all stocks listed on the London Stock Exchange at the end of our sample period. In line with previous literature, to avoid the impact of very thinly traded stocks and outliers, we exclude stocks with a share price of less than one pound sterling and fewer than 10 observations of the individual illiquidity measures in the respective month. Daily capital market data relating to close, bid and ask share prices, trading volume and number of shares outstanding is collected from Thomson Reuters Datastream and used to compute the monthly illiquidity measures as well as the monthly stock return, monthly standard deviation of daily returns and market capitalization. Macroeconomic indicators such as U.K. industrial production, consumer price index and MSCI stock market index are also constructed using data collected from Datastream. The U.K. short-term interest rates used in our analysis, i.e. the Sterling Overnight Index Average (*SONIA*), the Bank of England Base Rate (*BankRate*), the 3-month London Interbank Offer Rate (*LIBOR*) and 2-week repo rate (*Repo*).

3.2.2 Measures of stock (il)liquidity

Stock liquidity is a multi-dimensional concept related to notions of transactions costs, ease of trading, breadth, settlement time, trading activity and price impact.[4] In this respect, an asset is considered liquid if market participants can buy and sell large amounts of the respective asset quickly, at a low cost and with little impact on the market price.[5] As Amihud (2002) and Amihud et al. (2005) argue, there is no single measure or definition encapsulating all the different facets of liquidity. Moreover, since we use low-frequency

[4] Goyenko et al. (2009) and Fong et al. (2017) present overviews of different measures of liquidity.
[5] For a more detailed discussion see, for example: Amihud and Mendelson (1991), Sarr and Lybek (2002) and Amihud et al. (2005).

data to compute liquidity measures, the measurement noise increases when compared to high-frequency liquidity proxies (Amihud et al. 2005). For these reasons, we employ five different (il)liquidity measures, namely: the traded volume (*TV*), the Amivest liquidity ratio (*Amivest*), the turnover price impact ratio (*TPI*), the proportion of days with zero returns (*Zeros*) and the relative bid-ask spread (*BAS*). These measures are chosen due to their design reflecting various dimensions of liquidity such as trading activity, market price impact and transaction costs and are discussed in detail below. It is worth noting that the first two proxies measure liquidity (*TV* and *Amivest*), while the latter three measures can be considered illiquidity ratios (*TPI, Zeros* and *BAS*).

The first liquidity measure examined, the trading volume (*TV*) in Sterling is considered a measure of trading activity. Following Fernandez-Amador et al. (2013), trading volume for stock *i* in month *m* is calculated as the natural logarithm of the monthly sum over D_{im} days of the daily product between the number of traded shares (VO_{imd}) and the stock price (P_{imd}) , as described in equation (3.1):

$$TV_{im} = \ln(\sum_{d=1}^{D_{im}}(VO_{imd}\,P_{imd})) \qquad \textbf{(3.1)}$$

Amihud and Mendelson (1986) postulate that investors with short holding periods prefer liquid assets, thus these assets have a higher trading activity. Moreover, as Sarr and Lybek (2002) argue, volume-based measures of liquidity, such as the trading volume are good estimators of market depth, i.e. the existence of numerous trades and market participants. Stoll (1978b) and Glosten and Harris (1988) determine that trading volume is tightly related to the bid-ask spread and market liquidity, whereas Brennan et al. (1998)

argues that the traded volume may be a better liquidity proxy than the bid-ask spread, with a higher traded volume indicating an increase in liquidity.[6]

Given that trading volume may be high at times of low market liquidity, especially during crisis episodes, when actual price impact of transactions is high, we consider the return dimension and investigate the price impact of transactions via three liquidity measures, namely the Amivest liquidity ratio, the turnover price impact ratio and the proportion of days with zero returns.

The Amivest liquidity ratio (*Amivest*) is calculated for each stock *i* in month *m* containing D_{im} days as the monthly average of the daily ratio of the product of the number of shares traded (VO_{imd}) and stock price (P_{imd}) to the absolute stock return ($|Ret_{imd}|$), as presented in equation (3.2). The ratio is not defined on zero return days and due to its size, is commonly multiplied by 10^{-6}.

$$Amivest_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{10^{-6}\ x\ (P_{imd})\ x\ (VO_{imd})}{|Ret_{imd}|} \qquad \textbf{(3.2)}$$

Amivest has been previously used to measure liquidity in studies such as Amihud et al. (1997) and Jensen and Moorman (2010) and, by construction, is closely related to the popular Amihud (2002) illiquidity measure, the only difference stemming from the states when the two measures are undefined (zero volume days for the Amihud illiquidity ratio and zero return days for the Amivest illiquidity ratio). *Amivest* measures price impact or market depth, with a higher *Amivest* value indicating that large quantities of the respective stock can be traded without generating large price movements, implying low price impact and therefore increased liquidity (Goyenko et al. 2009, Jensen and Moorman, 2010).

[6] Despite that several papers (e.g. Brennan and Subrahmanyam, 1995; Brennan et al. 1998) have confirmed the validity of using traded volume as a measure of liquidity, it is important to also note that other research (e.g. Fleming, 2003) found the traded volume to not be related to price impact measures of liquidity or the bid-ask spread, but rather to the variance of liquidity, or liquidity risk (Johnson, 2008).

The third illiquidity measure employed is the Turnover Price Impact ratio (*TPI*) proposed by Florackis et al. (2011) and empirically used to measure liquidity of European stocks in the work of Fernandez-Amador et al. (2013). The turnover price impact of firm *i* in month *m* is calculated as the monthly average of the daily ratio between the absolute return of stock *i* and its turnover rate calculated as the number of shares traded in day *d* over the number of shares outstanding. The construction of the *TPI* measure is presented in equation (3.3). To reduce concerns regarding the presence of large *TPI* values potentially influencing results, *TPI* is winsorized by the top one percent largest values of its distribution.

$$TPI_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|Ret_{imd}|}{TR_{imd}} \qquad \textbf{(3.3)}$$

As Florackis et al. (2011) argue, *TPI* has several advantages compared to the Amivest liquidity ratio or Amihud (2002) illiquidity ratio. Firstly, it allows for comparability across different markets as it does not require information on price levels or exchange-rate adjustments. Secondly, it is free from any bias related to firms' market capitalization as turnover ratios should not be linked to a company's size, whereas trading volume which is used in place of the turnover ratio in *Amivest* and Amihud (2002) illiquidity ratio is higher for large companies. Lastly, it controls for trading costs as well as trading frequency, two important determinants of liquidity.

The fourth illiquidity measure investigated is the proportion of days with zero returns (*Zeros*) proposed by Lesmond et al. (1999) and employed by Bekaert et al. (2007) to measure illiquidity in their study on expected returns in emerging markets. *Zeros* is easily constructed as the number of days with zero returns for stock *i* in month *m* divided by the number of trading days in month *m*, as shown in equation (3.4).

$$Zeros_{im} = \frac{number\ of\ days\ with\ zero\ returns_{im}}{number\ of\ trading\ days_{m}} \qquad \textbf{(3.4)}$$

As Goyenko et al. (2009) explain, *Zeros* can be considered a measure of illiquidity as stocks with lower liquidity are more subject to having zero-volume days and thus having zero-return days. Moreover, Bekaert et al. (2007) documents, in the context of the U.S. market, that *Zeros* has a positive correlation of 0.3 with the bid-ask spread, a measure of transaction costs and a correlation of 0.91 with the Amihud (2002) illiquidity ratio, thereby indicating that *Zeros* is tightly related to the time series-variation of other well-established illiquidity measures, especially price impact proxies.

The fifth and final illiquidity measure investigated is the relative bid-ask spread (*BAS*), one of the most well established and widely used measures of trade transaction costs (Amihud and Mendelson (1986) and Amihud et al. (2005)). The relative bid-ask spread for stock *i* in month *m* is computed as the monthly average of the daily ratio of the difference between ask and bid quotes divided by the mid-point of the bid and ask quotes, as described in equation (3.5).

$$BAS_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{PA_{imd} - PB_{imd}}{\frac{(PA_{imd} + PB_{imd})}{2}} \qquad \textbf{(3.5)}$$

Besides computing monthly averages of the illiquidity measures for each individual stock in our sample which are used as dependent variables, we also compute equally-weighted cross-sectional averages of our illiquidity measures to control for the overall level of market liquidity in our panel estimations.[7]

[7] In line with previous papers (e.g. Fontaine et al. 2016), we use the cross-sectional median of *Amivest* and *TPI* to obtain the corresponding market liquidity variables, while for the other three measures we compute equally-weighted cross-sectional averages. This is due to the very high range of values obtained for *Amivest* and *TPI* due to their calculation, outliers potentially distorting the relevancy of cross-sectional averages.

3.2.3 Monetary policy variables

In line with previous studies (e.g. Sauer and Sturm, 2007; Fernandez-Amador et al. 2013; Jimenez et al. 2014), we measure monetary policy (monetary stance) through the means of the short-term interest rates. Our main monetary policy variable is Sterling Overnight Index Average (*SONIA*). For robustness, we also estimate our models using the Bank of England Base Rate (*BankRate*), the 3-month London Interbank Offer Rate (*LIBOR*) and the 2-week repo rate (*Repo*) as monetary policy variables.

Although the proposed interest rates display very high pairwise correlations between 0.98 and 0.99 throughout our sample period, it is interesting to investigate them separately, due to differences in their maturity and risks that they capture. Specifically, *SONIA* reflects banks' overnight funding rate in the Sterling unsecured market and is recommended by the Working Group on Sterling Risk-Free Reference Rates as the preferred near-risk free interest rate benchmark (Bank of England, 2017; Joyce et al. 2008). In contrast, the three-month *LIBOR* rate represents the interest rate over unsecured deposits that a bank is willing to offer to another bank over a 3-month period. Moreover, as Moinas et al (2017) describe, *LIBOR* can increase due to default or counterparty risk or due to poor interbank liquidity conditions. Finally, the two-week repo rate indicates the rate at which one bank lends funds to another bank for two weeks against an asset of suitable quality (General Collateral), thereby measuring the cost of secured lending (Moinas et al. 2017). Throughout this paper, we focus our attention on the results relating to the *SONIA* interest rate. However, for robustness, we also present results for the other three interest rates. A higher (lower) level of the proposed interest rates indicate a tightening (relaxation) of monetary policy. The interest rates are used as explanatory variables in our panel estimations. In this context, we expect interest rates to have a negative relationship with the liquidity variables (*TV, Amivest*) and a positive relationship with illiquidity variables (*TPI, Zeros, BAS*).

3.2.4 Differential effects of short-term interest rates on illiquidity

We investigate whether short-term interest rates impact illiquidity differently depending on individual stocks' market capitalization and volatility. Moreover, we also explore whether the magnitude and significance of these relationships changes before and after the financial crisis. Literature predicts that a monetary tightening, measured through a higher *SONIA* rate, would lead to higher levels of illiquidity for stocks with small market capitalization and high volatility. To empirically test these predictions, we employ two interaction terms. Firstly, to measure the differential impact of monetary policy on liquidity that is due to size we interact the natural logarithm of market value with our monetary policy variable ($MP \times \ln(MV)$). Secondly, the asymmetric relationship driven by volatility is tested by interacting the monthly standard deviation of stock returns, with the monetary policy variable ($MP \times Std.Dev$). Lastly, to investigate whether the dynamics of the relationship between monetary policy and illiquidity change during the financial crisis, we construct a dummy variable (D_{crisis}) taking the value of 1 between September 2007 and March 2009 and 0 otherwise. We then interact D_{crisis} and its correspondent for the non-crisis period (1-D_{crisis}), in turn, with the monetary policy measure and the two interaction terms. The delimitation of the financial crisis to this time-frame is in line with Kontonikas et al. (2013).

3.2.5 Control variables

The panel regression models which are employed in the empirical analysis control for both macroeconomic and individual stock variables which are known determinants of monetary policy or stock liquidity. In line with Fernandez-Amador et al. (2013), we include the monthly stock return, the monthly standard deviation of daily returns and the natural logarithm of market capitalization as individual stock variables. The inclusion of the monthly stock return (*Ret*) is motivated by the findings of Hameed et al. (2010) who document that negative returns increase stock illiquidity, especially during tight funding periods. We include the standard deviation of daily stock returns (*Std. Dev.*) because among others Stoll (2000) document that volatility of stock returns is positively related to illiquidity. Moreover, we include the natural logarithm of market value (*ln(MV)*) in line with the arguments of Amihud (2002) that stocks' market capitalization is a determinant of illiquidity. With respect to macroeconomic controls, we follow Goyenko and Ukhov (2009), Naes et al. (2011) and Fernandez-Amador et al. (2013) and include the rolling twelve-month growth rates of the U.K. industrial production (*gIP*) and consumer price index (*gCPI*) to control for inflation and the U.K. MSCI stock market index (*MSCI*) to control for stock market cyclicality. Differently from Fernandez-Amador et al. (2013) and in line with the theoretical predictions of mutual reinforcement of funding liquidity and market liquidity documented by Brunnermeier and Pedersen (2009) and to control for any other possible common factors determining liquidity for which we do not directly account, we also include the level of funding liquidity proxied by the U.K. TED spread (*TED*), measured as the difference between the three-month LIBOR rate and the three-month Sterling T-bill rate, and the level of market liquidity (*Mkt. Liq.*) measured, in turn, by the cross-sectional average of the five (il)liquidity variables.

3.3 Empirical setting

3.3.1 The effect of monetary policy on stock liquidity

To examine the influence of monetary policy on the illiquidity of individual stocks as well as the differential dispersion of illiquidity related to size and volatility, our baseline model follows the predictive panel data framework presented by Fernandez-Amador et al. (2013) and is presented in equation (3.6).

$$LIQ_{i,t} = \gamma_0 + \gamma_1 LIQ_{i,t-1} + \gamma_2 MP_{t-1} + \gamma_3 MP_{t-1} \times ln(MV)_{i,t-1} + \gamma_4 MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_5 X_{i,t-1} + \gamma_6 Y_{t-1} + c_i + u_{i,t} \quad \textbf{(3.6)}$$

Equation (3.6) models the stock liquidity of stock *i* in month *t* ($LIQ_{i,t}$) as a function of the following one-month lagged monthly variables: the (il)liquidity measure investigated ($LIQ_{i,t-1}$), the monetary policy measure examined (MP_{t-1}), interaction between monetary policy and market capitalization ($MP_{t-1} \times ln(MV)_{i,t-1}$), interaction between monetary policy and volatility ($MP_{t-1} \times Std.Dev._{i,t-1}$), microeconomic controls such as stock return ($Ret_{i,t-1}$), standard deviation of daily returns ($Std.Dev._{i,t-1}$) and natural logarithm of market capitalization ($ln(MV)_{i,t-1}$) represented by the vector $X_{i,t-1}$ and macroeconomic controls such as twelve month growth rates of industrial production (gIP_{t-1}), inflation ($gCPI_{t-1}$), the U.K. MSCI stock market index ($MSCI_{t-1}$), the level of funding liquidity (TED_{t-1}) and level of market liquidity ($Mkt.Liq_{t-1}$) represented by the vector Y_{t-1}.[8] Estimations are performed using cross-section fixed effects (c_i) and time-clustered standard errors[9,10,11,12].

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[8] We note that the model of Fernandez-Amador et al. (2013) is augmented by the interaction between monetary policy and standard deviation of daily stock returns and additionally controls for the levels of funding and market liquidity.

[9] We keep the lag length equal to one, as in Fernandez-Amador et al. (2013). Visual inspection of the residuals does not indicate the presence of autocorrelation in the residuals.

[10] We test for stationarity of the variables by applying the panel unit root test of Levin et al. (2002) and the ADF unit-root test of Dickey and Fuller (1979).

[11] We are aware that causation may run in the opposite direction, from stock liquidity to monetary policy. However, Fernandez-Amador et al (2013) finds very little evidence to support this hypothesis, causation predominantly running from monetary policy to stock liquidity.

[12] We are aware that by estimating a panel model including cross-section fixed effects and a lagged dependent variable, the estimates of the coefficients could potentially be biased, as indicated by Nickell (1981). However, the bias decreases as the number of time periods becomes large, going to zero as the time dimension becomes infinite (Nickell, 1981). Judson and Owen (1999) show that when using a panel fixed effects estimator in a panel setting with a time-dimension of 10 waves the bias can be as large as 23%. Judson and Owen (1999) further show that the bias is lowered considerably when considering longer time-dimensions; for example, with a time-dimension of 30, the bias can only be as large as 6%. These results are confirmed by Beck and Katz (2011), who find that the Nickell (1981) bias gets smaller as the time-dimension is increased; while the

3.3.2 The effect of monetary policy on stock liquidity during and outside the financial crisis period

In a second step, we augment our baseline model (3.6) to disentangle the effects of monetary policy on liquidity during and outside of the financial crisis period. To do this, we interact our lagged crisis dummy ($D_{crisis_{t-1}}$) and its correspondent for the period excluding the financial crisis (1- $D_{crisis_{t-1}}$) with our monetary policy variable and interaction terms. The resulting model, presented in (3.7), enables us to examine whether the dynamics of the monetary policy – stock liquidity relationship changed during the recent financial crisis.

$$LIQ_{i,t} = \gamma_0 + \gamma_1 LIQ_{i,t-1} + \gamma_2 D_{crisis_{t-1}} \times MP_{t-1} + \gamma_3 D_{crisis_{t-1}} \times MP_{t-1} \times \ln(MV)_{i,t-1} + \gamma_4 D_{crisis_{t-1}} \times MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_5 (1 - D_{crisis_{t-1}}) \times MP_{t-1} + \gamma_6 (1 - D_{crisis_{t-1}}) \times MP_{t-1} \times \ln(MV)_{i,t-1} + \gamma_7 (1 - D_{crisis_{t-1}}) \times MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_8 X_{i,t-1} + \gamma_9 Y_{t-1} + c_i + u_{i,t} \quad \textbf{(3.7)}$$

3.4 Empirical results

3.4.1 Summary statistics

Table 3.1 presents summary statistics for the variables included in the panel estimations. Panel (a) presents descriptive statistics for the liquidity measures employed and individual stock related controls, while Panel (b) describes the macroeconomic variables (monetary policy and controls). It is interesting to note that among the liquidity measures, *Amivest* and *TPI* vary widely throughout the sample compared to the other three liquidity measures, while the U.K. monetary policy variables display very similar statistics.

bias term is extremely large for two or three wave panels, this drops to below 3% when considering a time-dimension of 40 waves. Considering that, in this study, we use a time-dimension of 204 waves (months), we argue that this is large enough to ignore a possible Nickell (1981) bias. However, several alternative methodologies are available to estimate this relationship, such as using instrumental variables, as suggested by Anderson and Hsiao (1982) and Arellano and Bond (1991), a corrected least-squares dummy variable estimator proposed by Kiviet (1995), or estimating the relationship in first-differences, if the estimate of the lagged dependent variable is not close to unity (Abonazel, 2016)

Table 3.2 presents pairwise correlations between the individual stock related variables. Noteworthy, as expected, we find a negative relationship between the liquidity variables (*Amivest* and *TV*) and the illiquidity variables (*TPI*, *Zeros* and *BAS*). Additionally, bi-variate correlations between the five (il)liquidity variables do not exceed +/- 0.633, highlighting the different features of liquidity that they measure and reinforcing the notion that unless one's focus is to isolate one aspect of liquidity, multiple measures examining liquidity should be taken into consideration (Fernandez-Amador et al. 2013). We also find that the natural logarithm of market value has a positive (negative) correlation with liquidity (illiquidity) variables and the standard deviation of daily stock returns has a negative (positive) correlation with (il)liquidity variables, as suggested by previous research. The correlations between (il)liquidity measures and stock returns are also as expected, except for the result for *Zeros*.

3.4.2 Results of panel regressions

3.4.2.1 Effect of monetary policy on stock liquidity

We start by estimating the model presented in equation (3.6) for each of the five (il)liquidity measures and four monetary policy variables considered.[13] We focus our analysis on the results of the impact of monetary policy (stance) measured by the $SONIA_{t-1}$ interest rate on the (il)liquidity of individual stocks. However, for completeness, we also report results for the other three interest rates considered and discuss these results in the robustness section

[13] We also estimated the original model of Fernandez-Amador et al. (2013), without the inclusion of the interaction term between volatility and monetary policy and the market and funding liquidity measures. In unreported results, we find that all monetary policy variables and interaction terms between market capitalization and monetary policy are highly significant (5% significance level or higher), except for the monetary policy variable in the model where liquidity is measured by the traded volume (*TV*). The magnitudes, signs and significance of all estimated coefficients are closely comparable to the results of Fernandez-Amador et al. (2013). Therefore, we obtain qualitatively and quantitatively similar results for the U.K. market as for the German market, when using an identical model to that of Fernandez-Amador et al. (2013).

(section 3.5). Empirical results for the estimations using $SONIA_{t-1}$ as the monetary policy variable are presented in *Table 3.3*.

Investigating the results presented in *Table 3.3*, we note that a tightening of monetary policy measured by a higher $SONIA_{t-1}$ rate is associated with a significant decrease in liquidity as measured by $Amivest_t$ and a significant increase in illiquidity as measured by $Zeros_t$. Therefore, a higher $SONIA_{t-1}$ rate decreases stock liquidity, as proxied by the two price impact measures. We find insignificant results of the effect of monetary policy on (il)liquidity when the latter is measured through TV_t, TPI_t and BAS_t. Moreover, by examining the results of the interaction term ($SONIA_{t-1}$ * $MV_{i,t-1}$), we note that except for the results concerning the bid-ask spread BAS_t, we document a statistically significant stronger effect of monetary policy on small firms, the impact of monetary policy on liquidity decreasing with firm size. This result is in line with empirical evidence provided by Fernandez-Amador et al (2013) for the Euro zone market. Additionally, by investigating the second interaction factor ($SONIA_{t-1}$*$Std.Dev._{i,t-1}$), we document that the effect of monetary policy on (il)liquidity significantly increases with firm volatility, when measuring (il)liquidity with $Amivest_t, Zeros_t$ and BAS_t. Therefore, the results corresponding to the second interaction term suggest that a tightening of monetary policy leads to increased illiquidity, the effect being stronger for high volatility firms. This empirical result is novel and in line with the theoretical predictions of Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2016). The results for the selected control variables are, in large, as predicted by literature, the lagged stock return and lagged stock market capitalization having a positive effect on liquidity, while the standard deviation of daily stock returns has a negative effect on liquidity when measured by TV_t. All in all, the hypothesis that a tightening (relaxation) of monetary policy increases (decreases) the illiquidity of individual stocks is generally confirmed, this effect being particularly significant when liquidity is measured through price impact of trade proxies such as $Amivest_t$ and $Zeros_t$. Unlike results for the European market presented by Fernandez-Amador et al. (2013), we do not find a significant relationship between monetary policy and volume-related or transaction cost measures of liquidity. Results also confirm that monetary policy has a stronger effect on small stocks, as also found by Fernandez-Amador et al. (2013) and newly documents that monetary policy has a larger impact on high-volatility firms.

3.4.2.2 Effect of monetary policy on stock liquidity during and outside the 2007-2009 financial crisis

In the next step, we investigate whether the relationships found by evaluating the model presented in (3.6) change during the 2007-2009 financial crisis. This investigation is motivated by the results of Gregoriou et al. (2009), Kontonikas et al. (2013) and Florackis et al. (2014) which document that the effect of monetary policy on stock returns changes its expected sign during the recent financial crisis, highlighting the ineffectiveness of conventional monetary policy (interest rate changes) during the crisis period. To check whether there is a differential impact of monetary policy on stock illiquidity during the financial crisis, we estimated the model presented in equation (3.7).

Table 3.4 presents results when evaluating monetary policy with the $SONIA_{t-1}$ rate. The results paint a mixed picture of the effect of monetary policy on stock illiquidity during and outside the financial crisis. Overall, we find that monetary policy generally proves effective in impacting stock liquidity, more so during the financial crisis period. More specifically, we find that during the financial crisis, the $SONIA_{t-1}$ interest rate has a negative (positive) effect on the liquidity (illiquidity) measures. This suggests that a monetary tightening (relaxation) measured through a higher (lower) $SONIA_{t-1}$ decreases (increases) the liquidity of individual stocks. This result is statistically significant for all (il)liquidity variables, except for $Amivest_t$. In contrast, outside the financial crisis, monetary policy has the expected effect on liquidity only when the latter is measured through $Amivest_t$ and $Zeros_t$. We also note a significant, counter-intuitive result with respect to the effect of monetary policy on the bid-ask spread outside the financial crisis, where a higher $SONIA_{t-1}$ rate reduces transaction costs. In terms of magnitude of coefficients, the effect of monetary policy on stock liquidity is larger outside the financial crisis when measuring liquidity through $Amivest_t$ and $Zeros_t$, while the effect is larger during the financial crisis, when measuring liquidity through TV_t, TPI_t and BAS_t. We also document that the effect of monetary policy on stock liquidity is significantly larger for small stocks both during and outside the financial crisis. This result is in line with previous literature suggesting that small caps are more affected by monetary shocks (Bernanke and Gertler (1995), Kashyap and Stein (2000)). Moreover, we find that the effect of monetary policy on stock liquidity is stronger for volatile stocks only outside the financial crisis. This result is surprising as, among others, Brunnermeier and Pedersen (2009) suggest that particularly in periods of low funding liquidity, such as during the 2007-2009 financial crisis, illiquidity increases the most for volatile stocks.

3.5 Robustness checks

To provide robustness to our results, we re-estimate models (3.6) and (3.7) proxying the monetary policy variable alternatively with the other three U.K. short-term interest rates investigated (the Bank of England Base Rate (*BankRate*), the 3-month London Interbank Offer Rate (*LIBOR*) and the 2-week repo rate (*Repo*)). Summary results for the main variables of interest (MP_{t-1}, $MP_{t-1} * ln(MV)_{i,t-1}$and $MP_{t-1} * \ Std.Dev._{i,t-1}$) when estimating model (3.6) are presented in *Table 3.5*. Examining *Table 3.5*, we note that the results obtained when proxying monetary stance by $SONIA_{t-1}$ are, in large, confirmed for the other three alternative short-term interest rates. A tightening of monetary policy is associated with an increase in illiquidity as measured by $Amivest_t$ and $Zeros_t$. However, we do not find a significant impact of monetary policy on stock liquidity when evaluating liquidity via the trading volume, turnover price impact or the bid-ask spread. Monetary policy has a significant impact on illiquidity as measured by $Amivest_t$ only when we use the two-week repo rate as monetary policy measure. We also find robust evidence that the effect of monetary policy on stock liquidity is stronger for small firms, indifferent of the liquidity proxy chosen, and for high volatility firms, when evaluating (il)liquidity by $Amivest_t$, $Zeros_t$ and BAS_t.

Table 3.6 presents summary results for the main variables of interest (MP_{t-1}, MP_{t-1}* $ln(MV)_{i,t-1}$and MP_{t-1}* $Std.Dev._{i,t-1}$) during and outside the financial crisis, when evaluating MP_{t-1} with the three alternative short-term interest rates ($BankRate_{t-1}$, $LIBOR_{t-1}$ and $Repo_{t-1}$). Results suggest that, during the crisis, a monetary tightening (relaxation) decreases (increases) the liquidity of individual stocks. This relationship is significant when examining all liquidity measures except when evaluating illiquidity via $Amivest_t$. Outside the financial crisis period, monetary tightening has a positive effect on stock illiquidity only when the latter is measured by $Amivest_t$ and $Zeros_t$. The results obtained when evaluating transaction costs as measured by the bid-ask spread are counter-intuitive. The stronger monetary policy effect on small firms is present both during and outside the financial crisis, while the stronger effect of monetary policy on stock liquidity of volatile firms is more pronounced outside the financial crisis.

3.6 Conclusion

The present study uses a panel setting to explore the effect of monetary policy on the liquidity of individual stocks listed on the London Stock Exchange. We examine this relationship by employing five different measures of (il)liquidity quantifying the different aspects of liquidity such as trading activity, price impact and transaction costs. Monetary policy (monetary stance) is measured through short-term interest rates. We investigate whether monetary tightening (relaxation) as measured through a higher (lower) level of short-term interest rates induces a reduction (increase) in stock liquidity. Additionally, we analyse whether the impact of monetary policy on liquidity depends on individual stock characteristics such as market capitalization and volatility as measured by the monthly standard deviation of daily stock returns. Furthermore, we explore whether the effect of monetary policy on stock liquidity differs during the financial crisis, a period marked by severe reductions in market and funding liquidity.

We present evidence that: (1) monetary tightening (relaxation) is associated with an increase (decrease) in individual stock illiquidity, in line with previous findings for the Euro zone market presented by Fernandez-Amador et al. (2013); (2) the impact of monetary policy depends on stocks' market capitalization and volatility, a monetary tightening having a stronger effect on small market capitalization stocks and stocks with high volatility; (3) the effect of monetary policy on stock liquidity is more significant during the recent financial crisis compared to the rest of the sample. The asymmetric impact of monetary policy on stock liquidity associated with firm size is statistically significant in both regimes, while the asymmetric relationship due to volatility is only significant outside the financial crisis.

Although the models are estimated using cross-section fixed effects and include two monetary policy interaction terms, with market capitalization and volatility, respectively, as well as control for the overall level of market liquidity and funding liquidity this may not be enough to account for all possible forms of cross-sectional heterogeneity and future work could account differently for the potential problem of cross-sectional heterogeneity which may not be sufficiently addressed. Moreover, future research could investigate the effect of monetary policy on bond market liquidity and hedge fund liquidity.

Table 3.1: Descriptive Statistics

Panel (a): Panel Variables	***TV***	***AMIVEST***	***TPI***	***ZEROS***	***BAS***	***RET***	***STDEV***	***MV***
Mean of monthly means	14.135	202.782	126.672	0.174	0.026	0.004	0.025	5.750
Median of monthly means	13.975	6.769	5.697	0.100	0.014	0.006	0.020	5.676
Maximum monthly mean	22.399	25347.900	9099.128	0.565	1.737	2.520	1.464	12.272
Minimum monthly mean	2.763	0.000	0.000	0.000	0.000	-4.397	0.001	-4.605
Mean of monthly standard deviation	2.544	819.887	559.353	0.163	0.043	0.154	0.021	2.112
Mean of monthly skewness	0.180	9.698	8.973	0.859	8.655	-0.338	8.466	0.105

Panel (b): Time variables	***SONIA***	***BankRate***	***LIBOR***	***Repo***	***TED***	***gCPI***	***gIP***
Mean	2.488	2.528	2.743	2.481	0.333	0.021	-0.006
Median	0.536	0.500	1.206	0.541	0.194	0.020	-0.001
Maximum	6.126	6.038	6.581	5.872	2.268	0.052	0.057
Minimum	0.410	0.500	0.484	0.415	0.063	-0.001	-0.113
Standard Deviation	2.207	2.195	2.226	2.174	0.348	0.012	0.031
Skewness	0.279	0.267	0.280	0.278	3.035	0.306	-1.396

Notes: Panel (a) provides descriptive statistics of the five illiquidity measures (traded volume (*TV*), Amivest measure of liquidity (*AMIVEST*), turnover price impact (*TPI*), proportion of days with zero returns (*ZEROS*) and relative bid-ask spread (*BAS*)), stock return (*RET*), standard deviation of stock returns (*STDEV*) and the natural logarithm of the market capitalization (*MV*) for all stocks trading on the London Stock Exchange as of December 2015. Panel (b) provides summary statistics for the five monetary policy measures (Sterling mean overnight interbank lending rate (*SONIA*), official Bank of England Bank Rate (*BANKRATE*), three-month London Interbank Offer Rate (LIBOR) and two-week Repo rate (Repo)), the U.K. TED spread (*TED*), rolling 12-month inflation rate (*gCPI*) and rolling 12-month growth rate of U.K. industrial production (*gIP*). Time span: January 1999 - December 2015.

Table 3.2: Correlation matrix of time-series means of the monthly bivariate cross-sectional correlations

	AMIVEST	***TV***	***TPI***	***ZEROS***	***BAS***	***RET***	***STDEV***	***MV***
AMIVEST	1	0.454	-0.051	-0.181	-0.139	0.000	-0.116	0.473
TV		1	-0.191	-0.633	-0.503	0.029	-0.231	0.903
TPI			1	0.104	0.199	-0.036	0.164	-0.054
ZEROS				1	0.425	0.020	0.101	-0.634
BAS					1	-0.002	0.379	-0.541
RET						1	-0.023	0.029
STDEV							1	-0.383
MV								1

Notes: Table 3.2 presents pairwise cross-sectional correlations between the five (il)liquidity variables (traded volume (*TV*), Amivest measure of liquidity (*AMIVEST*), turnover price impact (*TPI*), proportion of days with zero returns (*ZEROS*) and relative bid-ask spread (*BAS*)), stock return (*RET*), standard deviation of stock returns (*STDEV*) and the natural logarithm of the market capitalization (*MV*) for all stocks trading on the London Stock Exchange as of December 2015. Time span: January 1999 - December 2015.

Table 3.3: The effect of monetary policy on stock liquidity - SONIA

	Liquidity measures	Illiquidity measures			
	Trading activity	Price impact			Transaction costs
Dep. Var. ($Liq.measure_{i,t}$)	***TV***	***Amivest***	***TPI***	***Zeros***	***BAS***
$Liq.measure_{i,t-1}$	0.538***	0.536***	0.467***	0.598***	0.840***
	(107.848)	(16.627)	(32.913)	(121.122)	(57.322)
$SONIA_{t-1}$	**-0.010**	**-20.122***	**3.010**	**0.010*****	**0.000**
	(-0.652)	**(-1.716)**	**(1.101)**	**(6.367)**	**(0.09)**
$SONIA_{t-1}$* $ln(MV)_{i,t-1}$	**0.012*****	**5.622*****	**-0.739****	**-0.001*****	**-0.000**
	(9.318)	**(2.893)**	**(-2.128)**	**(-3.085)**	**(-1.617)**
$SONIA_{t-1}$*$Std.Dev._{i,t-1}$	**-0.081**	**-130.357*****	**7.296**	**0.033****	**0.026*****
	(-0.707)	**(-2.958)**	**(0.534)**	**(2.046)**	**(3.575)**
$Ret_{i,t-1}$	-0.016	9.780	-8.545	-0.018***	-0.029***
	(-0.489)	(1.109)	(-0.594)	(-3.324)	(-17.227)
$Std.Dev._{i,t-1}$	-0.999***	137.162	-19.882**	-0.100**	-0.105***
	(-2.645)	(1.349)	(-0.331)	(-2.093)	(-4.855)
$ln(MV)_{i,t-1}$	0.396***	23.457***	-7.367***	-0.040***	-0.004***
	(43.472)	(5.364)	(2.915)	(-37.918)	(-8.418)
gIP_{t-1}	-1.166**	-300.859***	-115.673	0.029	0.006
	(-2.233)	(-2.629)	(-1.579)	(0.311)	(0.779)
$gCPI_{t-1}$	0.125	375.264	619.634***	-0.357	0.010
	(0.093)	(1.056)	(3.019)	(-1.265)	(0.382)
$MSCI_{t-1}$	0.145	80.245***	-2.513	-0.044**	0.000
	(1.542)	(3.562)	(-0.188)	(-2.335)	(-0.16)
TED_{t-1}	-0.144***	-42.036**	20.842***	-0.024*	0.003
	(-2.591)	(-2.497)	(2.737)	(-1.774)	(1.486)
$Mkt.Liq._{t-1}$	-0.122	-3.192**	0.001	-0.259***	0.054***
	(-1.279)	(-2.123)	(0.641)	(-4.319)	(2.984)
N	1196	1092	1188	1232	1232
Adj.R^2	0.928	0.759	0.466	0.839	0.877

Notes: Table 3.3 presents results for the estimation of the baseline model presented in (3.6): $LIQ_{i,t} = \gamma_0 + \gamma_1 LIQ_{i,t-1} + \gamma_2 MP_{t-1} + \gamma_3 MP_{t-1} \times \ln(MV)_{i,t-1} + \gamma_4 MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_5 X_{i,t-1} + \gamma_6 Y_{t-1} + c_i + u_{i,t}$. The five (il)liquidity measures tested are: traded volume (*TV*), Amivest measure of liquidity (*Amivest*), turnover price impact (*TPI*), proportion of days with zero returns (*Zeros*) and relative bid-ask spread (*BAS*). Monetary policy is measured by the Sterling Overnight Index Average (*SONIA*). *Ret* is the monthly stock return. *Std.Dev.* is the monthly standard deviation of stock returns. *ln(MV)* is the natural logarithm of market value. *gIP* is the growth in industrial production. $gCPI$ is the growth in the consumer price index. *MSCI* is the U.K. MSCI stock market index. *TED* is the U.K. TED spread. *Mkt.Liq.* represents the market liquidity. Estimation is performed using cross-section fixed effects and period-clustered standard errors. t-statistics are presented in parentheses. ***, ** and * stand for significance at the 1%, 5% and 10% levels. Time span: January 1999 – December 2015.

Table 3.4: Effect of monetary policy on stock liquidity during and outside the financial crisis - SONIA

	Liquidity Measures	Illiquidity Measures			
	Trading activity	Price impact			Transaction costs
Dep. Var. ($Liq.measure_{i,t}$)	***TV***	***Amivest***	***TPI***	***Zeros***	***BAS***
$Liq.measure_{i,t-1}$	0.537***	0.534***	0.467***	0.595***	0.839***
	(108.705)	(16.597)	(32.887)	(124.748)	(57.620)
$D_{crisis_{t-1}}*SONIA_{t-1}$	**-0.061*** **	**2.877**	**14.139*** **	**0.006** **	**0.002** **
	(-3.632)	**(0.147)**	**(3.081)**	**(2.237)**	**(2.027)**
$D_{crisis_{t-1}}*SONIA_{t-1}*ln(MV)_{i,t-1}$	**0.019*** **	**0.859**	**-1.979*** **	**-0.001*** **	**-0.000*** **
	(11.127)	**(0.243)**	**(-2.753)**	**(-2.848**	**(-2.669)**
$D_{crisis_{t-1}}*SONIA_{t-1}*Std.Dev._{i,t-1}$	**-0.129**	**11.375**	**4.964**	**0.036**	**0.024**
	(-0.986)	**(0.216)**	**(0.253)**	**(1.306)**	**(1.575)**
$(1-D_{crisis_{t-1}})*SONIA_{t-1}$	0.018	-27.798**	-0.850	0.011***	-0.001**
	(1.137)	(-2.052)	(-0.323)	(6.914)	(-2.494)
$(1-D_{crisis_{t-1}})*SONIA_{t-1}*ln(MV)_{i,t-1}$	0.009***	7.478***	-0.247	-0.001**	0.000
	(7.106)	(3.385)	(-0.826)	(-2.511	(0.913)
$(1-D_{crisis_{t-1}})*SONIA_{t-1}*Std.Dev._{i,t-1}$	-0.038	-173.569***	7.426	0.043**	0.028***
	(-0.310)	(-2.977)	(0.538)	(2.403	(4.223)
$Ret_{i,t-1}$	-0.024	16.938**	-6.625	-0.019***	-0.029***
	(-0.726)	(2.105)	(-0.456)	(-3.542)	(-18.067)
$Std.Dev._{i,t-1}$	-1.06***	142.703	-15.469	-0.13***	-0.104***
	(-2.807)	(1.344)	(-0.258)	(-2.735)	(-4.827)
$ln(MV)_{i,t-1}$	0.403***	23.062***	-8.662***	-0.039***	-0.004***
	(45.588)	(5.257)	(-3.416)	(-37.720)	(-9.029)
gIP_{t-1}	-0.972*	-287.851**	-152.282**	0.063	0.005
	(-1.838)	(-2.393)	(-2.156)	(0.689)	(0.705)
$gCPI_{t-1}$	-0.114	333.614	645.744***	-0.373	0.009
	(-0.087)	(0.944)	(3.278)	(-1.371)	(0.367)
$MSCI_{t-1}$	0.194**	84.5***	-7.793	-0.039**	0.000
	(2.063)	(3.854)	(-0.598)	(-2.078)	(-0.176)
TED_{t-1}	-0.065	-39.15**	1.128	-0.003	0.002
	(-0.994)	(-2.442)	(0.124)	(-0.224)	(1.359)
$Mkt.Liq._{t-1}$	-0.193**	-4.293**	0.002	-0.287***	0.055***
	(-1.989)	(-2.385)	(0.799)	(-4.643)	(3.131)
N	1196	1092	1188	1232	1232
Adj.R²	0.928	0.759	0.466	0.839	0.877

Notes: Table 3.4 presents results for the estimation of the model presented in (3.7): $LIQ_{i,t} = \gamma_0 + \gamma_1 LIQ_{i,t-1} + \gamma_2 D_{crisis_{t-1}} \times MP_{t-1} + \gamma_3 D_{crisis_{t-1}} \times MP_{t-1} \times \ln(MV)._{i,t-1} + \gamma_4 D_{crisis_{t-1}} \times MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_5(1-D_{crisis_{t-1}}) \times MP_{t-1} + \gamma_6(1-D_{crisis_{t-1}}) \times MP_{t-1} \times \ln(MV)_{i,t-1} + \gamma_7(1-D_{crisis_{t-1}}) \times MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_8 X_{i,t-1} + \gamma_9 Y_{t-1} + c_i + u_{i,t}$. The five (il)liquidity measures tested are: traded volume (*TV*), Amivest liquidity (*Amivest*), turnover price impact (*TPI*), proportion of days with zero returns (*Zeros*) and relative bid-ask spread (*BAS*). *Ret* is the monthly stock return. *Std.Dev.* is the monthly standard deviation of stock returns. *ln(MV)* is the natural logarithm of market value. *gIP* is the growth in industrial production. $gCPI$ is the consumer price index growth. *MSCI* is the MSCI stock market index. *TED* is the U.K. TED spread. *Mkt.Liq.* represents the market liquidity. t-statistics are presented in parentheses. ***, ** and * stand for significance at the 1%, 5% and 10% levels. Time span: January 1999 - December 2015.

Table 3.5: The effect of monetary policy on stock liquidity - Alternative monetary policy measures

	Liquidity Measures	Illiquidity Measures			
	Trading activity	Price impact			Transaction costs
Dep. Var. ($Liq.measure_{i,t}$)	***TV***	***Amivest***	***TPI***	***Zeros***	***BAS***
$BankRate_{t-1}$	**-0.011**	**-17.170**	**2.883**	**0.010*** **	**0.000**
	(-0.721)	(-1.458)	(1.036)	(6.48)	(0.213)
$BankRate_{t-1}* ln(MV)_{i,t-1}$	**0.012*** **	**5.069*** **	**-0.725** **	**-0.001*** **	**-0.000** *
	(9.245)	(2.599)	(-2.061)	(-3.087)	(-1.734)
$BankRate_{t-1}*Std.Dev._{i,t-1}$	**-0.068**	**-136.218*** **	**7.922**	**0.033** **	**0.026*** **
	(-0.594)	(-3.137)	(0.574)	(2.025)	(3.673)
$LIBOR_{t-1}$	**-0.013**	**-13.361**	**4.404**	**0.010*** **	**0.000**
	(-0.783)	(-1.144)	(1.630)	(6.196)	(0.812)
$LIBOR_{t-1}* ln(MV)_{i,t-1}$	**0.012*** **	**4.465** **	**-0.943*** **	**-0.001*** **	**-0.000** **
	(10.181)	(2.268)	(-2.650)	(-3.388)	(-2.187)
$LIBOR_{t-1}*Std.Dev._{i,t-1}$	**0.019**	**-109.671*** **	**4.705**	**0.034** **	**0.025*** **
	(0.181)	(-2.613)	(0.371)	(2.017)	(3.432)
$Repo_{t-1}$	**-0.011**	**-19.989** *	**3.100**	**0.010*** **	**0.000**
	(-0.723)	(-1.676)	(1.106)	(6.301)	(0.183)
$Repo_{t-1}* ln(MV)_{i,t-1}$	**0.012*** **	**5.618*** **	**-0.755** **	**-0.001*** **	**-0.000** *
	(9.401)	(2.836)	(-2.119)	(-3.11)	(-1.662)
$Repo_{t-1}*Std.Dev._{i,t-1}$	**-0.068**	**-131.529*** **	**7.842**	**0.033** **	**0.026*** **
	(-0.594)	(-2.96)	(0.564)	(1.994)	(3.567)
N	1196	1092	1188	1232	1232
$Adj.R^2$	0.93	0.76	0.47	0.84	0.88

Notes: Table 3.5 presents summary results for the main variables of interest (MP_{t-1}, $MP_{t-1}*MV_{i,t-1}$ and $MP_{t-1}* Std.Dev._{i,t-1}$) of the estimations of the baseline model presented in (3.6): $LIQ_{i,t} = \gamma_0 + \gamma_1 LIQ_{i,t-1} + \gamma_2 MP_{t-1} + \gamma_3 MP_{t-1} \times \ln(MV)_{i,t-1} + \gamma_4 MP_{t-1} \times Std.Dev._{i,t-1} + \gamma_5 X_{i,t-1} + \gamma_6 Y_{t-1} + c_i + u_{i,t}$. The five (il)liquidity measures tested are: traded volume (*TV*), Amivest measure of liquidity (*Amivest*), turnover price impact (*TPI*), proportion of days with zero returns (*Zeros*) and relative bid-ask spread (*BAS*). The alternative monetary policy (*MP*) measures are the Bank of England Base Rate (*BankRate*), the 3-month London Interbank Offer Rate (*LIBOR*), the two-week repo rate (*Repo*). T-statistics are reported in parentheses. ***, ** and * stand for significance at the 1%, 5% and 10% levels. Estimations are performed using cross-section fixed effects and period-clustered standard errors. Time span: January 1999 – December 2015.

Table 3.6: The effect of monetary policy on stock liquidity during and outside the financial crisis – Alternative monetary policy measures

	Liquidity Measures	Illiquidity Measures			
	Trading activity	Price impact			Transaction costs
Dep. Var. $(Liq.measure_{i,t})$	***TV***	***Amivest***	***TPI***	***Zeros***	***BAS***
$D_{crisis_{t-1}}$*$BankRate_{t-1}$	**-0.063******	**6.115**	**14.259******	**0.007****	**0.002****
	(-3.643)	**(0.315)**	**(3.065)**	**(2.296)**	**(2.132)**
$D_{crisis_{t-1}}$* $BankRate_{t-1}$* $ln(MV)_{i,t-1}$	**0.020******	**0.355**	**-1.987******	**-0.001******	**-0.000******
	(11.258)	**(0.101)**	**(-2.772)**	**(-2.884)**	**(-2.769)**
$D_{crisis_{t-1}}$* $BankRate_{t-1}$*$Std.Dev._{i,t-1}$	**-0.114**	**2.363**	**5.213**	**0.036**	**0.025***
	(-0.862)	**(0.046)**	**(0.270)**	**(1.284)**	**(1.669)**
(1-$D_{crisis_{t-1}}$)* $BankRate_{t-1}$	0.015	-25.118*	-1.064	0.011***	-0.001**
	(0.968)	(-1.845)	(-0.400)	(7.043)	(-2.391)
(1-$D_{crisis_{t-1}}$)* $BankRate_{t-1}$* $ln(MV)_{i,t-1}$	0.009***	6.894***	-0.223	-0.001**	0.000
	(7.080)	(3.111)	(-0.737)	(-2.51)	(0.742)
(1-$D_{crisis_{t-1}}$)* $BankRate_{t-1}$*$Std.Dev_{i,t-1}$	-0.037	-184.67***	8.613	0.042**	0.028***
	(-0.297)	(-3.244)	(0.616)	(2.279)	(4.352)
$D_{crisis_{t-1}}$*$LIBOR_{t-1}$	**-0.049******	**9.015**	**13.337******	**0.006****	**0.002****
	(-2.961)	**(0.533)**	**(3.226)**	**(2.388)**	**(2.431)**
$D_{crisis_{t-1}}$* $LIBOR_{t-1}$* $ln(MV)_{i,t-1}$	**0.018******	**0.073**	**-1.844******	**-0.001******	**-0.000******
	(12.183)	**(0.024)**	**(-3.038)**	**(-3.118)**	**(-3.033)**
$D_{crisis_{t-1}}$* $LIBOR_{t-1}$*$Std.Dev._{i,t-1}$	**0.020**	**0.066**	**1.504**	**0.035**	**0.021***
	(0.171)	**(0.001)**	**(0.096)**	**(1.326)**	**(1.757)**
(1-$D_{crisis_{t-1}}$)* $LIBOR_{t-1}$	0.016	-24.806*	0.063	0.011***	-0.001**
	(1.000)	(-1.762)	(0.025)	(6.913)	(-2.246)
(1-$D_{crisis_{t-1}}$)* $LIBOR_{t-1}$ * $ln(MV)_{i,t-1}$	0.01***	7.003***	-0.397	-0.001***	0.000
	(7.589)	(3.046)	(-1.318)	(-2.708)	(0.353)
(1-$D_{crisis_{t-1}}$)* $LIBOR_{t-1}$ *$Std.Dev_{i,t-1}$	0.030	-178.83***	7.405	0.042**	0.029***
	(0.241)	(-3.000)	(0.556)	(2.202)	(4.508)
$D_{crisis_{t-1}}$*$Repo_{t-1}$	**-0.062******	**2.519**	**14.205****	**0.006****	**0.002****
	(-3.593)	**(0.125)**	**(4.629)**	**(2.226)**	**(2.069)**
$D_{crisis_{t-1}}$* $Repo_{t-1}$* $ln(MV)_{i,t-1}$	**0.02******	**0.825**	**-1.986******	**-0.001******	**-0.000******
	(11.331)	**(0.234)**	**(-2.753)**	**(-2.875)**	**(-2.691)**
$D_{crisis_{t-1}}$* $Repo_{t-1}$*$Std.Dev._{i,t-1}$	**-0.111**	**14.961**	**4.705**	**0.036**	**0.024**
	(-0.862)	**(0.29)**	**(-0.241)**	**(1.294)**	**(1.578)**
(1-$D_{crisis_{t-1}}$)* $Repo_{t-1}$	0.017	-32.837**	-0.931	0.011***	-0.001**
	(1.081)	(-2.554)	(-0.346)	(6.896)	(-2.437)
(1-$D_{crisis_{t-1}}$)* $Repo_{t-1}$ * $ln(MV)_{i,t-1}$	0.009***	7.501***	-0.244	-0.001**	0.000
	(7.163)	(3.323)	(-0.801)	(-2.53)	(0.878)
(1-$D_{crisis_{t-1}}$)* $Repo_{t-1}$ *$Std.Dev_{i,t-1}$	-0.025	-160.68***	8.424	0.043**	0.028***
	(-0.208)	(-2.894)	(0.596)	(2.333)	(4.257)

Notes: Table 3.6 presents summary results for the main variables of interest (MP_{t-1}, MP_{t-1}*$MV_{i,t-1}$ and MP_{t-1}* $Std.Dev._{i,t-1}$) during the financial crisis (interactions with ($D_{crisis_{t-1}}$)) and outside of the financial crisis (interactions with ($1 - D_{crisis_{t-1}}$)) of the estimations of the model presented in equation (3.7) The five (il)liquidity measures tested are: traded volume (*TV*), Amivest measure of liquidity (*Amivest*), turnover price impact (*TPI*), proportion of days with zero returns (*Zeros*) and relative bid-ask spread (*BAS*). The alternative monetary policy (*MP*) measures are the Bank of England Base Rate (*BankRate*), the 3-month London Interbank Offer Rate (*LIBOR*), the two-week repo rate (*Repo*). t-statistics are presented in parentheses. ***, ** and * stand for significance at the 1%, 5% and 10% levels. Estimations are performed using cross-section fixed effects and period-clustered standard errors. Time span: January 1999 – December 2015.

Concluding Remarks

The liquidity of financial markets has been an important topic of investigation in the finance literature throughout the past decades. The multitude of research investigating the effects of liquidity on financial markets highlights the multiple dimensions of liquidity. One of these aspects is market liquidity, defined as the ease with which market participants can transact or the capability of markets to handle large transactions without a large impact on prices. Market liquidity is itself a multi-faceted concept, referring to aspects such as market depth, resiliency and tightness; no one measure being able to encompass all the features comprising liquidity.

Another dimension of liquidity relates to funding liquidity, defined as the ease with which traders can finance their operations. Despite receiving more attention from researchers over the past decade, the effect of funding liquidity on financial markets remains a relatively less studied research area, albeit one of key significance for traders and policy makers alike. As shown, among others, in the models of Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2002), funding liquidity and market liquidity are inherently linked. These studies suggest that, as trading requires capital, when the funding available to traders is tight, traders change their investment patterns becoming reluctant to take on large positions in high-margin securities. This leads to a deterioration of market liquidity and increased volatility. In turn, the decline in market liquidity further reduces traders' funding liquidity through higher margin requirements, potentially leading to a liquidity loss spiral. This thesis builds upon these theoretical insights and empirically investigates the effects of funding constraints in the context of the credit default swap (CDS) market and stock market, highlighting their implications for illiquidity, volatility and CDS spreads.

The first study investigates the effect of funding liquidity on the corporate CDS market, by examining the impact of changes in funding illiquidity on CDS spread changes. By employing panel estimation methods on a sample of European entities with the most liquid CDSs, the paper evidences a positive relationship between changes in funding illiquidity and credit default swap changes; a deterioration of funding conditions widening CDS spreads. Distinguishing between high and low default risk entities, as measured by the average CDS spread level, the study newly finds that the effect of changes in funding liquidity on CDS spread changes is approximately three times larger in magnitude when examining high-CDS entities compared to low-CDS entities.

Furthermore, by separating the recent financial crisis period from the post-crisis period, results suggest that the positive relation between funding illiquidity changes and CDS spread changes is mostly driven by the post-crisis period, with results for the crisis period being largely insignificant. Coincidentally, the post-crisis period also overlaps with the period following the introduction of a set of contractual and convention changes affecting the European CDS market, collectively known as the ‘CDS Small Bang’. In the pursuit of standardizing CDS contracts, among other regulatory innovations, the CDS Small Bang conventions restrict coupon rates to be fixed at one of four levels. However, the introduction of fixed coupons gave rise to upfront fees that need to be exchanged between CDS buyers and sellers, with the size of the fee depending on how far away the CDS spread level is from the fixed coupons at inception. Therefore, the paper attributes the increased effect, in terms of magnitude and significance, of funding illiquidity changes on CDS spread changes to the introduction of upfront fees for trading CDSs, following the ‘CDS Small Bang’ conventions.

The second study empirically examines the connection between funding illiquidity, market illiquidity, volatility and returns in the cross-section of European stock returns, following the theoretical framework proposed by Brunnermeier and Pedersen (2009), and extends these linkages to CDS spreads. Theory suggests that under certain conditions, markedly when funding is tight, traders shift their allocations towards low risk securities, displaying a reluctance to invest in high margin assets. This change in investment patterns leads to lower market liquidity, increased volatility, de-leveraging, lower contemporaneous returns and the presence of a funding risk premium. The rationale for extending the effects of funding shocks to CDS spreads is motivated by recent findings documenting that spreads are highly sensitive to equity illiquidity and equity volatility, an increase in these variables, due to a tightening of funding constraints, leading to increased default risk which would be captured through CDS spreads.

Newly using, in the context of studies investigating the cross-section of stock returns, a sample of firms which are part of the European iTraxx index containing entities with the most liquid CDSs, the first piece of evidence presented is that funding conditions co-move with illiquidity, volatility and CDS spreads; a decrease in funding liquidity thus increasing portfolio illiquidity, volatility and CDS spreads. Secondly, this chapter provides evidence of flight-to-quality following a funding shock; the most volatile portfolios seeing their illiquidity increase the most. Thirdly, this study documents that the positive relationship between funding illiquidity changes and CDS spread changes is asymmetric, the impact of funding illiquidity shocks on CDS spreads increasing in magnitude and significance if speculators are already funding constrained. Fourthly, the paper provides new evidence of an asymmetric relationship between funding conditions and contemporaneous returns. Differentiating between positive and negative funding illiquidity changes, this study documents that only a tightening of funding liquidity significantly decreases contemporaneous returns, whereas an improvement of funding conditions has no effect on returns. Lastly, this chapter documents the presence of a funding risk premium in the cross-section of equity returns, generating a return spread between the most and least illiquid portfolios of 1.21% annually.

The third study examines the relationship between monetary policy, measured through short-term interest rates and stock liquidity, in the context of the U.K. market. The inventory paradigm of market microstructure suggests that stock liquidity is dependent on traders' perceived risk of holding assets and the cost of financing their holdings. Since monetary policy affects both aspects, stock liquidity should display sensitivity to monetary policy. Moreover, the literature on funding constraints suggests that as funding becomes tight, traders find it difficult to meet margin requirements, dampening the liquidity of the market. Since monetary policy increases the cost of borrowing, this induces traders to operate closer to their funding constraint, leading to a reduction of liquidity provision. Therefore, the central hypothesis investigated in this study is that a restrictive (expansionary) monetary policy, by increasing (lowering) short-term interest rates, leads to an increase (decrease) in borrowing costs, thus reducing (improving) stock liquidity.

Indeed, in line with the above arguments, we find that a contractionary (expansionary) monetary policy reduces (increases) stock liquidity. However, this effect is significant only when investigating price impact of trades measures, whereas liquidity measures related to trading volume or transaction costs appear to not be impacted by monetary policy shifts, highlighting the importance of investigating the different facets of liquidity. This study also documents that the impact of monetary policy on stock liquidity is larger in magnitude for small and volatile stocks; these securities seeing their illiquidity increase the most following an increase in short-term rates. Moreover, by investigating separately the 2007-2009 financial crisis period, the paper documents that the 'monetary policy – stock liquidity' relationship is larger in magnitude, more significant and it affects all three facets of stock liquidity during the crisis period, whereas outside the crisis period, the relationship is significant only when investigating price impact of trade measures of liquidity.

This thesis provides contributions to the increasing literature documenting the effects of funding constraints on financial markets, illustrating the influence of these constraints in the context of the credit default swap market, within chapter one, and stock market, within chapters two and three. This thesis fills in gaps in the liquidity literature and extends previous studies focusing on the understanding of market liquidity, funding liquidity and their linkages throughout different markets and documents the importance of these findings for market participants and policy makers.

This thesis presents multiple avenues for future research. Within chapter one, the finding that funding illiquidity changes influence CDS spread changes mostly after the introduction of the CDS Small Bang regulations affecting the European CDS market can be investigated further by measuring the actual increase in the CDS spreads that is due to the introduction of upfront fees for trading CDSs. Moreover, future research can provide additional evidence as to whether the largely insignificant results found between funding liquidity and CDS spreads during the 2008-2009 period extend previously in time, thus clearly evidencing that the introduction of upfront fees, after June 2009, is the factor that determines the effect of funding liquidity on CDS spreads. Regarding chapter two, a possible theme of further investigation is whether the extension of the linkages between funding liquidity, market liquidity and volatility to CDS spreads hold for a sample of all stocks traded on a large stock market, rather than focusing only on a sample of stocks containing the European entities with the most liquid CDSs. Finally, within chapter three, the influence of monetary policy on stock liquidity could be further investigated by employing alternative measures of monetary policy, besides short-term interest rates, or by investigating this relationship within a different methodology, such as an event study. Moreover, future research could examine the effect of monetary policy on bond market liquidity and hedge fund liquidity as well as the impact of foreign monetary policy on liquidity.

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