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Derivatives Markets: From Bank Risk Management to Financial Stability

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Abstract

Derivative Markets: From Bank Risk Management to Financial Stability

by Guillaume VUILLEMEY

Derivatives markets have been growing extremely fast over the past two decades, and represent the largest contract class worldwide, in notional terms. Both the growth and the size of the market, illustrated in chapter 1 in figure 1.1 raise a number of questions, both for economic theory and for central banks, regulatory authorities and market participants. This thesis aims to contribute to a better understanding, both theoretical and empirical, of a number of important economic and policy issues related to derivatives markets.

Until very recently, most of the research related to derivatives markets has focused on the *pricing* of these contracts. Theoretically, a vast literature seeks to price a variety of derivatives contracts, from plain-vanilla interest rate swaps (Duffie and Singleton, 1997) or credit default swaps (Duffie, 1999) to non-standard contracts. Empirically, publicly observable derivatives prices have been widely used to extract unobservable pieces of information which, according to theoretical works, are relevant for pricing. For example, interest rate swap prices have been used to compute inflation expectations, while CDS spreads have been used to compute default probabilities.

In contrast, the research work related to *exposures* in derivatives markets has been relatively limited. While prices (or, at least, quotes) can usually be publicly observed, exposures—i.e. quantities—are typically not observed. Several features of derivatives markets raise topical questions when working on derivatives exposures. First, most derivatives markets are over-the-counter (OTC), implying that the market is relatively opaque and the network structure possibly difficult to represent. A second set of difficulties arises from the off-balance sheet nature of derivative exposures. The measurement of exposures raises a number of theoretical and practical questions. Notional values, which may at times be observed, are not capturing true underlying exposures. In the interest rate derivatives market, for example, notional values are never paid—they are used only for the calculation of interest rate cash flows. Aggregate numbers may also mask large bilateral or multilateral netting opportunities, which should be accounted for when computing end-user exposures. Finally, derivatives are long-term contracts that have a zero net present value at inception. They turn in- or out-of-the-money as time passes. The long-term nature of the contracts implies that the most important risk to be managed in not credit risk (as for on-balance sheet assets, such as bonds) but counterparty risk.

This thesis proceeds in two natural steps. The first part, "Derivative markets and optimal bank capital structure" studies the optimal use of derivatives for risk management by financial intermediaries, restricting attention to interest rate derivatives. By modelling the optimal capital structure policy of a bank, it discusses how hedging using derivatives affects a number of standard outcomes in corporate finance: bank lending, maturity mismatching, payout policies ou default probabilities. The second part "Derivative markets and financial stability", in contrast, takes a system-wide perspective. This shift in perspective from the micro to the macro level is usual in economic theory and builds upon the idea that decisions which are privately optimal, at an institution level, may have undesirable consequences at a system level. This is the case if externalities (arising, for example, from counterparty risk) are not internalized. This thesis, however, does not take a strong stance on whether such externalities are likely a first-order concern in derivatives market. The system-wide investigation of derivatives markets is limited to a detailed description of one derivative network—the CDS network—and to an empirical study of ongoing regulatory reforms.

The first chapter "Derivatives and Risk Management by Commercial Banks" studies how hedging using interest rate derivatives affects banks' capital structure. It introduces interest rate derivatives into the capital structure model of a financial intermediary. In contrast with other types of derivatives, in particular credit derivatives, the interest rate derivatives market has been the object of suprisingly little scrutiny. I study how hedging using derivatives affects banks' risk management, in particular their level of maturity mismatching and the types of positions they are taking. I show that both increases and decreases in interest rates can be optimally hedged, as also observed in the cross-section of U.S. commercial banks. With respect to bank lending, I show that using derivatives induces a "procyclical but asymmetric" lending policy, i.e. that user banks are better able to exploit profitable lending opportunities in good times, but cut lending to a lower extent in recessions or monetary contractions. I also study the occurrence of banks defaults. The main result is that, even though derivatives are used only for hedging, they do not necessarily reduce the occurrence of bank defaults. They may, at times, increase it. The prevailing effect is endogenous. Finally, despite attractive insurance properties of derivative contracts, not all banks optimally take derivative positions, as also seen in the data. Overall, the model provides a comprehensive framework to study banks' interest rate risk management using several instruments. This question of interest rate risk management is, I believe, topical in the current interest rate environment, characterized by low or negative interest rates, and by a flat yield curve.

The second chapter "The Network Structure of the CDS Market and its Determinants" uses a new and unique dataset on bilateral exposures to CDS contracts, in order to provide a detailed description of the CDS network structure. It shows that the CDS

market is highly concentrated and centered around 14 dealers. Another important finding is that a large share of investors are net CDS buyers, implying that total credit risk exposure is fairly concentrated. In contrast with many papers in the literature on financial networks, which focus on one network only (e.g. the interbank network), this chapter then turns to analyzing the heterogeneity across CDS networks (642 different CDS networks for sovereign and financial names). It uses an econometric approach to relate properties of the network structure (e.g. number of active market participants, concentration, etc.) with characteristics of the CDS or of the underlying bond. Consistent with the theoretical literature on the use of CDS, the chapter shows that the debt volume outstanding and its structure (maturity and collateralization), the CDS spread volatility and market beta, as well as the type (sovereign/financial) of the underlying bond are statistically significantly related—with expected signs—to structural characteristics of the CDS market.

The third chapter "Central Clearing and Collateral Demand" turns to regulatory issues related to derivatives markets. The central clearing of standardized derivatives—meant to become mandatory both in Europe and in the United States—has been the most important reform of derivative markets in at least two decades. Any trade between two market participants will have to be novated to a central clearing party (CCP), which will become buyer to every seller, and seller to every buyer. CCPs are thus set to manage counterparty risk for a very large share of derivatives markets and market participants, and thus to become "systemic" institutions. This chapter studies the amount of collateral to be demanded for all portfolios to be safely cleared, given the market structure observed in CDS exposure data. Importantly, the amount being demanded depends on the market structure that prevails (e.g. number of CCPs, possibility of rehypothecation, client clearing). The trade-offs involved in central clearing are being studied under these market structures.

There are, of course, a number of related an important questions which are being left over, and which leave room for future research. The most important ongoing follow-up work is an empirical project related to Chapter 1, which aims to study banks' risk management when they are faced with net worth shocks or when they are close to distress. Other theoretical work is also in progress.

Contents

Part I

Derivative markets and optimal bank capital structure

Chapter 1

Derivatives and Risk Management by Commercial Banks

1.1 Abstract

How do derivatives markets affect corporate decisions of financial intermediaries? I introduce interest rate swaps in a capital structure model of a bank. Two opposite motives for risk management coexist, implying that both pay-fixed and pay-float positions can be used for hedging. The model's predictions match a number of yet unexplained stylized facts. The use of derivatives induces a "procyclical but asymmetric" lending policy, whereby derivatives users are better able to exploit transitory lending opportunities, but cut lending to a lower extent in a contractionary environment. Furthermore, derivatives hedging may either mitigate or exacerbate the agency conflict between debt and equity holders and the occurrence of defaults. Which effect dominates is endogenous. Finally, despite attractive insurance properties of derivative contracts, not all banks optimally take derivative positions, as in the data. The shadow value of collateral pledged on swaps may outweigh the benefits of hedging. The results have implications for financial stability and for monetary policy. Several new testable predictions are obtained.

1.2 Introduction

The interest rate derivatives market is the largest market globally, with an aggegate notional size of 563 trillion USD as of June 2014 (BIS, 2014). Most of these contracts

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are held by commercial banks. Yet, despite the size and rapid growth of this asset class over the past 15 years, as depicted in figure 1.1, very little is known as to how hedging through interest rate derivatives affects other corporate decisions of financial intermediaries. For example, what is the impact of derivatives on bank lending? Or, pertaining to financial stability, how does the use of derivatives affect the occurrence of bank defaults and other aspects of banks' risk management?

I introduce derivatives in the capital structure model of a financial intermediary. Banks finance long-term loans with equity and short-term debt. Their debt capacity is limited because of a lack of commitment to repay, and issuing equity is costly. These frictions provide an incentive to engage in risk management: Banks optimally manage internal funds and debt capacity across periods and states so as to hold enough funds and be able to exploit lending opportunities as they arise. A shortage of funds when lending opportunities are large would result in under-investment. Derivatives, modeled as interest rate swaps, make it possible to exchange, in future periods, a fixed rate against a floating rate ("pay-fixed" position), or the contrary ("pay-float" position). They transfer funds across future states associated with particular realizations of the short-term interest rate, and are thus valuable for hedging.

This paper provides four contributions. First, I investigate theoretically the impact of derivatives hedging on risk management and lending by financial intermediaries. The model jointly rationalizes a number of yet unexplained stylized facts. In particular, the use of derivatives gives rise to a "procyclical but asymmetric" lending policy: Derivatives users are better able to exploit transitory lending opportunities arising from real shocks, but cut lending to a lower extent than non-users in a contractionary environment. This pattern is supported by the data.

Second, I show the existence of two opposite motives for interest rate risk management. Banks are incentivized to transfer funds both to states in which the short rate is high and to states in which it is low. Which motive dominates is endogenous. This implies that both pay-fixed and pay-float derivatives may be used optimally. The fact that banks take pay-float exposures (i.e. take exposure to interest rate spikes) has been considered earlier either as a puzzle or as evidence of speculation. I show that it can also be consistent with hedging.

Third, I provide the first theoretical model which investigates the effect of derivatives on bank default. In equilibrium, the use of derivatives may both decrease and increase the occurrence of bank defaults. Which effect dominates is endogenous and depends on the relative weight of the structural frictions. An increase in bank defaults may occur even in the absence of a speculative motive, if bankruptcy costs are low relative to financing costs.
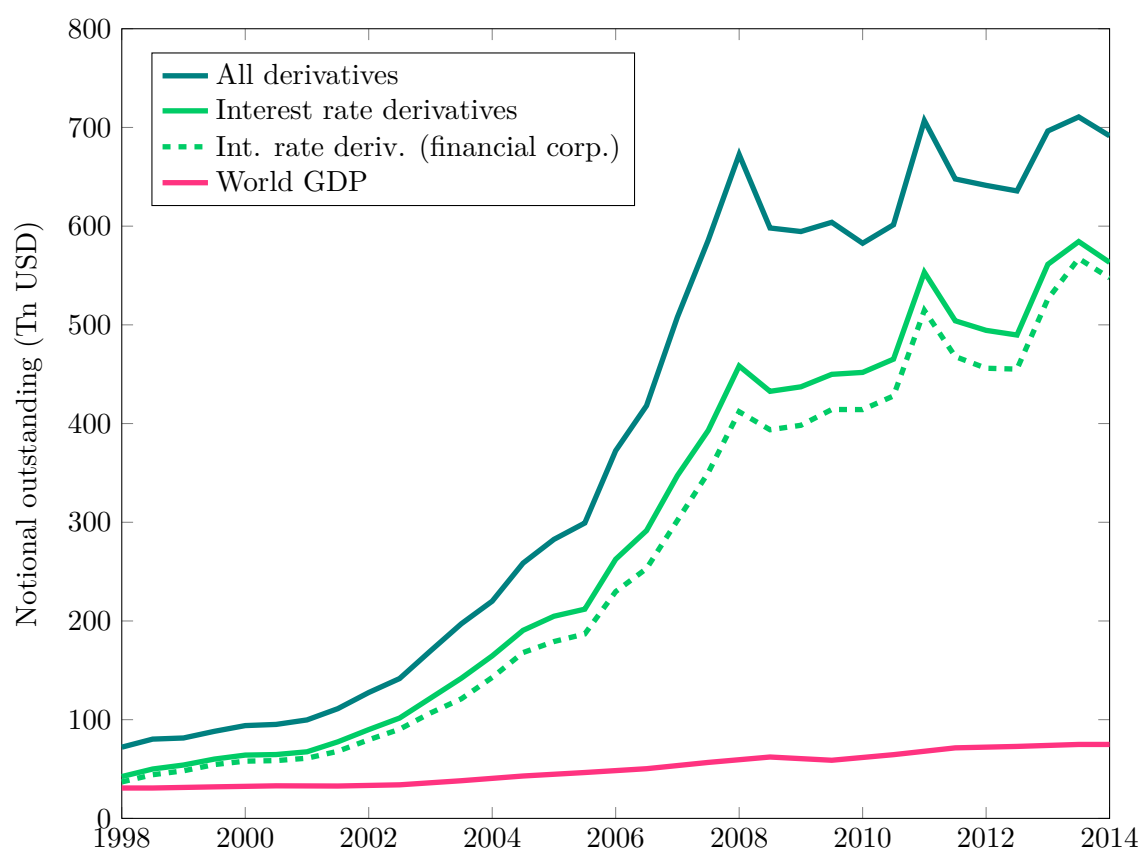
FIGURE 1.1: The growth of derivatives markets. This figure represents the gross notional amount outstanding of all over-the-counter (OTC) derivative contracts worldwide (blue line). Its most sizeable component is the interest rate swaps market (green line). It is compared with the global nominal GDP (red line) over the period from 1998 to 2014. Data sources: BIS (for derivatives data) and World Bank (for GDP data).

Fourth, I endogenize the sorting between users and non-users of derivatives. In the United States, only about 14% of commercial banks use interest rate derivatives, which has been considered puzzling. In the model, derivatives are not optimally used by all banks, in spite of attractive insurance properties. The cross-sectional and time series distribution of bank types is endogenous. When debt is collateralized, sorting arises because increasing derivatives hedging reduces the pool of collateral assets available for debt financing. Consistent with Rampini and Viswanathan (2010), the opportunity cost of hedging, i.e. foregone financing, is particularly high for banks with a high marginal profitability of lending, among which are small banks. These banks may abstain from hedging. I extend and qualify this result in a setup where debt is not collateralized and defaultable.

Key to the model structure is the existence of financial frictions. As in Froot et al. (1993), risk-neutral banks are effectively risk-averse in the face of financial frictions and optimally engage in risk management. There are two frictions in the baseline model: *(i)* external equity financing is costly, implying that internal and external funds are not perfect substitutes, and *(ii)* banks have limited commitment to repay debt. I study two setups with limited commitment. First, most results are obtained in a model where debt is limited by a collateral constraint. Second, the model is extended to allow default. Faced with these constraints, the risk management problem for the bank amounts to managing internal funds and debt capacity so as to optimally balance the expected future costs associated with financial frictions against the present cost of foregoing lending. Derivative contracts make it possible to transfer resources between future states that are more or less associated with costly frictions. Even though they have a zero expected payoff, they are thus valuable.

The model features two motives for interest rate risk management, which I call "financing motive" and "investment motive" and which had not been modeled earlier. First, there is a risk that the future cost of debt financing will be high in states where profitable lending opportunities are numerous. This risk gives rise to a "financing motive" for risk management, whereby the bank optimally wants to transfer resources from future states where the short rate is low to states where it is high. Second, provided the bank's cash flows are negatively related to the short rate, optimal lending is higher when the short rate is lower. The "investment motive" for risk management arises as the bank optimally preserves resources to meet these lending opportunities. In contrast with the financing motive, the investment motive is such that the bank wants to transfer resources from future states associated with a high short rate to states associated with a low short rate. Which motive dominates is endogenous and depends on the structural parameters and on the past and current shock realizations. It also implies that both pay-fixed and

pay-float positions may be used for hedging, which has been considered a puzzle in most earlier discussions.

Apart from derivatives, banks have two other margins for risk management. First, the bank optimally does not take on short-term debt up to its borrowing limit, i.e. preserves debt capacity for next-period investment. It foregoes present lending opportunities and keeps maturity mismatching at a moderate level. The second margin for risk management, implicitely defined, is "payout flexibility", whereby the bank optimally trades off present and future dividend distributions to equity holders. By choosing a more flexible payout policy, it can increase present investment. Risk management decisions on these two margins and on derivatives need to be jointly optimal. As such, the paper provides an integrated framework to study risk management in banking. Maturity mismatching, which is part of the model structure, has been relatively neglected in the post-crisis literature on banks' capital structure (while leverage has been the object of intense theoretical and empirical scrutiny, see e.g. Adrian and Shin, 2010, 2014). I am not aware of comparable models in the banking literature.

Empirically, the model jointly rationalizes a number of stylized facts, some of them being yet unexplained. First, large banks tend to use more derivatives. Second, derivatives users rely more on wholesale funding. Third, they lend more and keep less cash. Fourth, derivatives users cut less lending when faced with a higher short rate (consistent with Purnanandam, 2007). Fifth, interest rate derivatives enable user banks to actively exploit transitory profit oppotunities arising from real shocks, even when these shocks are uncorrelated with interest rate realizations. Together, the last two facts support the "procyclical by asymmetric" lending policy implied by the model. Sixth, as documented by Bonaimé et al. (2013), derivatives users smooth dividend distributions to equity holders. A substitution between the use of derivatives and payout flexibility arises endogenously. The model also yields novel testable predictions on the asymmetric effects of positive and negative shocks and on bank characteristics associated with pay-fixed and pay-float swap positions.

To study the effect of derivatives on the occurrence of defaults, I relax the assumption that debt is collateralized. Banks may optimally default. Because default decisions are taken in the interest of shareholders and are costly, a debt-equity agency conflict exists. I study the effect of derivatives on this conflict. For banks using derivatives, the effects of the two costs (to external financing and to bankruptcy) are asymmetric. Costs of external financing are paid in periods where lending outlays are optimally large relative to internal funds, i.e. when "good" shocks hit. Risk management motivated by equity issuance costs thus requires transferring funds from future "bad" to future "good" states. In contrast, bankruptcy costs are paid in "bad" future states, when the proceeds from

the assets in place are low compared to debt repayments. To be hedged, costly distress requires transfers from future "good" to future "bad" states.

The effect of derivatives on the agency conflict between debt and equity and on the occurrence of bank defaults depends on the relative magnitude of the structural frictions. When deadweight default costs are large relative to equity issuance costs, banks are relatively more incentivized to avoid default states, thus to use swaps in order to transfer resources from future "good" states to future "bad" states. Using swaps reduces the occurrence of default, while enabling the bank to use more debt in the present period.[1] On the contrary, when the cost of equity financing is relatively large, the bank optimally aims to transfer resources from future "bad" states to future "good" states. Using swaps to do so increases the set of short rate realizations for which the bank optimally defaults. It can thus be the case that, while derivatives are used for hedging purposes only (there is no speculative motive), their use may increase the occurrence of bank defaults.

The paper's results have real implications. First, for the efficiency of the transmission of monetary policy through the bank lending channel. Faced with a rising short rate, derivatives non-users cut lending to a larger extent than users. Monetary policy has thus distributional effects across banks. In addition, the model highlights asymmetric effects of positive and negative shocks on bank lending.

By studying optimal risk management and the effects of derivatives on banks' default policy, the paper also has implications for the stability of the financial system. It provides a comprehensive framework to analyse maturity mismatching and trading on interest rate derivatives by financial institutions. Well-managed interest rate risk is arguably a first-order concern when the term structure of interest rates is such that banks are incentivized to load on short-term liabilities (e.g. interbank debt, repurchase agreements or commercial paper), as was the case before 2008 (Brunnermeier, 2009; Fahri and Tirole, 2012), or as may be the case in the present low-interest rates environment.

The remainder of the paper is structured as follows. Section 1.3 briefly reviews the relevant literature. Section 3.3 presents stylized facts to be matched or explained. Section 3.4 and 3.5 present the baseline model with riskless debt, without and with interest rate swaps respectively. Section 3.6 extends the model to a setup with endogenous default and a debt-equity agency conflict. Section 3.7 discusses the model's implications and outlines directions for future research.

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[1]Because hedging drives the bank away from some future default states, its debt capacity increases. As it borrows more, however, its probability of default increases. The optimal debt and hedging policy is an equilibrium condition which balances both effects.

1.3 Relevant literature

The model structure is inspired by dynamic models of corporate leverage. It is most closely related to Hennessy and Whited (2005), Riddick and Whited (2009) and DeAngelo et al. (2011).[2] I do not focus primarily on non-financial firms' *leverage*, but instead on financial institutions engaged in *maturity mismatching*. I introduce interest rate derivatives and focus on their interaction with on-balance sheet instruments for risk management, i.e. debt capacity and payout flexibility. There are very few comparable papers focusing on the effect of derivatives other corporate decisions of financial intermediaries. In addition to standard real "productivity" shocks, I consider an environment with stochastic short-term interest rates. The model features two motives for interest rate risk management, a "financing" and an "investment" motive, which had not been modeled earlier. Risk is optimally managed dynamically.

A second literature strand to which the paper relates is that on hedging. In the model, shareholders are risk-neutral and hedging is motivated by a friction that makes equity issuance costly. As in Froot et al. (1993), a cost of external finance induces effective risk aversion with respect to next-period cash flows. Other motives for hedging have been investigated. They include reducing the expected cost of financial distress, lowering expected tax payments under a convex tax schedule (both motives are discussed in Smith and Stulz, 1985) and reducing the volatility of executive compensation (DeMarzo and Duffie, 1995). Holmström and Tirole (2000) emphasize firms' concern for refinancing as a rationale for risk management.

More closely related to my paper in the literature on hedging is Rampini and Viswanathan (2010). They relate firm hedging decisions with debt capacity and show—in contrast with previously received theory—that more constrained firms engage less in risk management, as the opportunity cost of collateral pledged on derivatives (i.e. lower debt capacity and foregone investment) is too high for them. Rampini et al. (2014) illustrate this effect for commodity price risk management by U.S. airlines. Li et al. (2014) structurally estimate their model. My model features a similar effect in the banking sector and for another type of risk. I also devote more attention to other margins for risk management, such as payout flexibility. I document the real impact of risk management, through lending decisions. A model extension also generalizes several results to a setup with defaultable debt.

While all of the above papers are concerned with non-financial corporations, my focus is explicitly on financial institutions. This paper can be seen as bridging a gap between

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[2]A related contribution in continuous time is by Bolton et al. (2011). A review of the literature is by Strebulaev and Whited (2012).

the banking literature and these works in corporate finance. I do not model explicitly the optimality of maturity mismatching within the space of feasible contracts. Contractual banking arrangements provide insurance against privately observed, idiosyncratic, liquidity shocks (Diamond and Dybvig, 1983). Diamond (1984) shows that, in order to provide monitoring incentives when a long-term project is to be funded, the optimal contract is a deposit contract. The optimality of short-term debt to prevent opportunistic behaviour from bank managers has also been modeled by Calomiris and Kahn (1991), Rajan (1992), Flannery (1994) and Diamond and Rajan (2001). Dang et al. (2012) derive the optimality of debt from its information-insensitiveness.[3]

Given that maturity transformation exposes banks to interest rate risk, the effects of interest rate shocks on banks' stock returns has been studied by Flannery and James (1984). Landier et al. (2013) investigate the consequences of interest rate risk for the transmission of monetary policy. Relatedly, the use of interest rate derivatives by commercial banks has been documented empirically by Purnanandam (2007), who shows that derivatives enable banks to shield against monetary policy shocks. Hirtle (1997) discusses the use of derivatives to increase or reduce exposure to interest rate risk. Begenau et al. (2013) quantity the interest rate risk exposure that U.S. banks both through on- and off-balance sheet instruments.

Finally, in a broader perspective, this paper relates to recent strands of the macroeconomic literature on the cyclicality of short-term funding and risk exposures. This fact has been documented empirically by Brunnermeier (2009) and Gorton et al. (2014). In a related work, Adrian and Shin (2010) provide evidence for the procyclical leverage of U.S. investment banks. Damar et al. (2013) relate the dynamics of leverage with that of short-term funding. Theoretically, Fahri and Tirole (2012) model banks' incentives to engage in maturity mismatching following monetary policy shocks.

1.4 Cross-sectional and time series stylized facts

This section lists a number of stylized facts related to the use of derivatives by commercial banks. These facts are jointly matched by the model developed from section 3.4 on and should be seen as an empirical benchmark against which the predictive ability of the model can be assessed. The model, however, has a broader scope and richer predictions, including novel testable predictions. This section should not be seen as a full-fledged empirical investigation of cross-sectional and time series differences between users and

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[3]These papers are related to a broader literature where short-term debt is shown to address agency problems arising from informational asymmetries and associated either with under-investment (Myers, 1977) or risk-shifting (Barnea et al., 1980).

non-users. It relies, to the extent possible, on the existing literature. For brevity, the empirical investigation of these facts is relegated to appendix 1.10.

1.4.1 Data

Throughout the paper, either to discuss stylized facts or to relate theoretical predictions to the data, I use call reports data for U.S. commercial banks, obtained from the FDIC Central Data Repository. For brevity, the description of the dataset and of the variables is relegated in appendix 1.11. The data is obtained at a quarterly frequency from 2001 Q1 to 2013 Q2. The full dataset contains 339,415 bank-quarter observations, i.e. about 6,788 observations per quarter.

Stylized facts rely on a partition of the universe of banks between interest rate derivatives users and non-users. A dummy variable, equal to one for users, is constructed, as detailed in appendix. I thus follow the existing literature (e.g. Purnanandam, 2007) by treating separately the decision to use derivatives and the extent of derivatives use. Throughout this section, only the former is considered. The extent of derivatives use is related to the model's predictions in later sections. The share of derivatives users, together with the total number of sampled banks, is pictured in figure 1.2.

1.4.2 Summary of the stylized facts

This subsection summarizes six stylized facts being matched by the model.

> **Stylized fact 1**: Larger banks (as measured by total assets) tend to use more derivatives than smaller banks.

> **Stylized fact 2**: Derivatives user banks rely less on stable funding sources such as deposits, and more on wholesale funding.

> **Stylized fact 3**: Derivatives user banks hold a larger share of their assets as loans, and consequently hold lower cash and liquid asset buffers.

> **Stylized fact 4**: When faced with an increase in the short rate, users of derivatives cut less lending than non-users of derivatives.

> **Stylized fact 5**: When faced with a positive real shock, proxied by a GDP shock, users of derivatives increase lending more than non-users of derivatives.
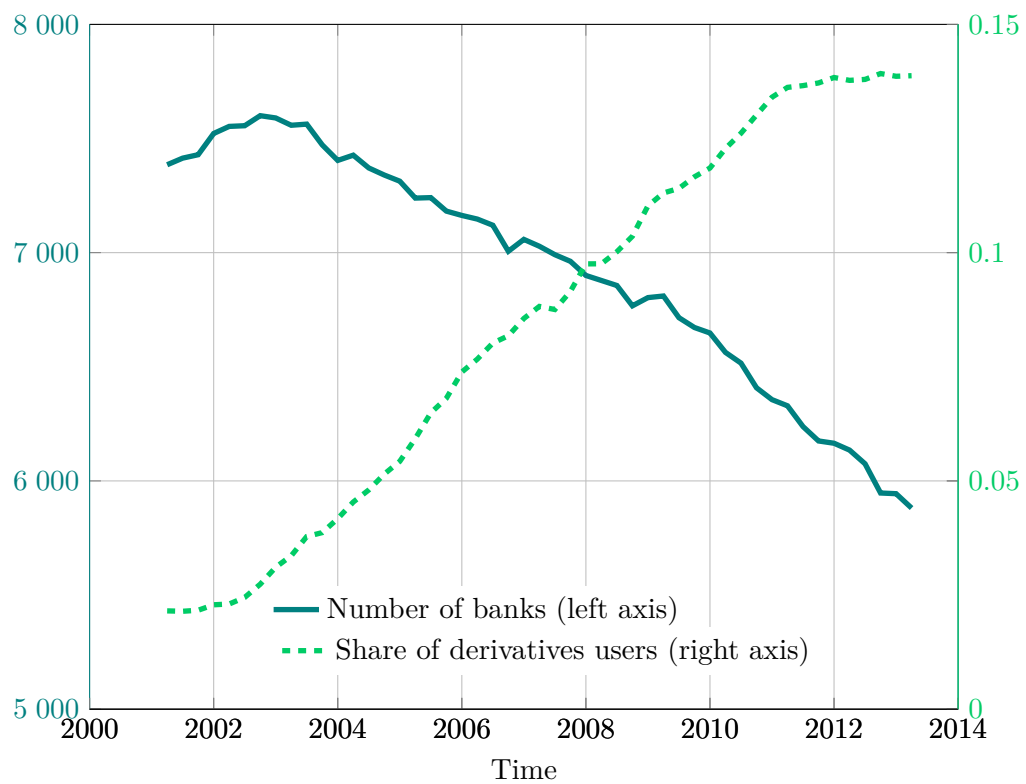
FIGURE 1.2: Number of banks and share of derivatives users. This figure shows the number of banks and the share of derivatives users in each quarter. The number of sample banks is represented by the solid blue line, while the share of user banks is represented by the dashed green line. The criteria for qualifying as a user bank are detailed in section . Data is for U.S. commercial banks, as detailed in this appendix.

> **Stylized fact 6**: Derivatives user banks smooth their dividend payout policy over time.

These six facts are established, using bank-level data, in appendix 1.10. Stylized facts 1 to 3 are descriptive cross-sectional statements about characteristics associated with the use and non-use of derivatives. Stylized facts 4 to 6 relates to the differential response, in the time dimension, of derivatives users and non-users to exogenous shocks. The model developed from section 3.4 on features both endogenous sorting between users and non-users and differential responses to shocks by banks of each type, i.e. cross-sectional and time series predictions respectively, to be compared with the data.

Stylized facts 1 to 3 are briefly discussed in Purnanandam (2007). In the latter paper, stylized fact 4 is established. Stylized fact 6 is established in Bonaimé et al. (2013). Stylized fact 5 has not been discussed so far, and is established in appendix 1.10, using a simple extension of the analysis by Purnanandam (2007).

1.5 Riskless debt without interest rate derivatives

This section introduces the baseline capital structure model in the absence of interest rate derivatives. Derivative contracts are introduced in section 3.5.

1.5.1 Model setup

I proceed with the introduction of *(i)* long-term loans and cash flows, of *(ii)* debt financing, of *(iii)* equity financing and of *(iv)* the value function.

1.5.1.1 Long-term loans and cash flows

Time is discrete and the horizon infinite. Any variable x at date t is denoted $x \equiv x_t$ and, at date $t+1$, $x' \equiv x_{t+1}$. The bank's managers take decisions upon long-term assets and equity or debt financing to maximize discounted dividend payments to equity holders. Operating cash flows before financing and lending decisions take place are denoted $\pi(a, z, r)$, in which a is the stock of long-term assets (loans), z an aggregate real shock to the bank's portfolio and r the one-period short rate. $\pi(a, z, r)$ is continuous and concave, with $\pi(0, z, r) = 0$, $\pi_z(a, z, r) > 0$, $\pi_r(a, z, r) < 0$, $\pi_a(a, z, r) > 0$, $\pi_{aa}(a, z, r) < 0$ and $\lim_{a \to \infty} \pi_a(a, z, r) = 0$. The bank pays a proportional tax at rate $\tau \in [0, 1]$ upon receipt of $\pi(.)$.

The cash flow function is assumed to take the functional form

$$\pi\left(a, z, r\right) = z\left(R - r\right)^{\gamma} a^{\theta}, \tag{1.1}$$

where a^{θ} is standard in the investment literature. $\theta \in [0; 1]$ ensures the concavity of the cash flow function. For a bank, it is microfounded in the decreasing creditworthiness of the marginal borrower when lending increases, as documented empirically by Dell'Ariccia et al. (2012). Two shocks affect operational cash flows. The realization of z, or "productivity shock", captures the stochastic component of *real* drivers of a bank's cash flows, such as nonaccrual loans above ($z < 1$) or below ($z > 1$) their mean-stationary level.

The term $(R - r)^{\gamma}$, where $\gamma \in [0; 1]$, captures the sensitivity of the bank's cash flows to the short rate. $(R - r)$ is the yield curve slope, where R is the constant per-unit per-period net long-term yield. This term is interpreted as capturing either the negative relation between the level of interest rates and real economic activity (e.g. Friedman and Schwartz, 1982; Fuerst, 1992), or the dependence between the term structure of interest rates and real economic activity (Estrella and Hardouvelis, 1991).

The parameter γ determines the bank's exposure to the short rate on its assets. In case $\gamma = 0$, the cash flow function does not depend on r. Whenever $\gamma > 0$, an increase in the short rate decreases the bank's operating cash flows, through its effects on the real activity. This effect of r on cash flows combines with an effect of r on the cost of debt financing, as discussed below.

The productivity shock z takes values in the compact set $Z \equiv [\underline{z}; \overline{z}]$. It follows a first-order Markov process $g_z\left(z'|z\right)$ satisfying the Feller property. Following Gomes (2001), I parameterize the process for z as a AR(1) in logs, i.e.

$$\ln\left(z'\right) = \rho_z \ln\left(z\right) + \epsilon'_z, \tag{1.2}$$

in which $\epsilon'_z \sim N\left(0, \sigma_z^2\right)$.

Long-term lending a is modelled under the simplifying assumption that a constant share $0 < \delta < 1$ of loans matures each period. This assumption resembles that of constant refinancing policy made by Leland (1998) and Diamond and He (2014) in continuous time models. There is thus a single state variable for long-term assets. Investment (i.e. newly-issued loans[4]) i is defined as

$$i \equiv a' - (1 - \delta)a, \tag{1.3}$$

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[4]Both terms are used interchangeably.

The average loan maturity is $1/\delta$, and $\delta < 1$ ensures that the average maturity of the assets exceeds that of the one-period debt, i.e. that the bank engages in maturity mismatching. Long-term assets are bought and sold at a price of one.

1.5.1.2 Debt financing

The bank has four potential sources of funds: internally generated cash flows $\pi(.)$, internal savings in the form of cash, short-term one-period debt and external equity. I focus on one-period net debt, denoted b. It is debt if $b > 0$ and cash otherwise. Cash is defined as $c = -\min\{0, b\}$. It earns the risk-free rate r.

In the baseline model, attention is restricted to risk-free debt contracts. Risky debt contracts are introduced in the model extension of section 3.6. A potential justification for riskless debt contracts follows from Stiglitz and Weiss (1981), who show that lenders may prefer credit rationing over higher required interest rates when faced with adverse selection or asset substitution problems. The use of short-term collateralized debt by banks is widespread in the form of repurchase agreements or other forms of short-term secured borrowing (Acharya and Öncü, 2010). Full enforcement is assumed, i.e. the bank owners cannot abscond with part of the existing cash flows or asset stock. For the debt to be risk-free, lenders requires the bank to repay the debt in all states of the world, i.e. the collateral constraint writes

$$b' \leq (1 - \tau) \underline{z} (R - \bar{r})^{\gamma} a'^{\theta} + \kappa a'. \tag{1.4}$$

The first term on the right-hand side is the lowest after-tax cash flow next period. The second term is the bank's liquidation value, where $\kappa \in [0, 1]$ is the liquidation value of one unit of the long-term asset. The justification for $\kappa < 1$ follows from Asquith et al. (1994), who show that asset liquidation is a common response to financial distress. The collateral constraint puts an upper bound on the amount of debt.

There is a tax advantage of debt. It equals $\tau r b' / (1 + r)^2$, i.e. the present value of the tax deduction on interest paid. Even though a departure from the reality—as tax benefits of debt in reality are recognized once interest has been paid—, this assumption simplifies the model solution, as it prevents the inclusion of the interest rate realization at $t - 1$ as an additional state variable.

The net short rate r is stochastic. It follows a first-order Markov process $g_r(r'|r)$ parameterized as a discrete-time Vacisek process (Vacisek, 1977; Backus et al., 2000)

$$r' = \rho_r r + (1 - \rho_r) r^* + \sigma_r \epsilon_r', \tag{1.5}$$

in which $\epsilon_r' \sim N(0,1)$. The unconditional mean of r is r^*. Its conditional and unconditional variance are respectively σ_r^2 and $\sigma_r^2 / (1 - \rho_r^2)$. ρ_r drives mean reversion. I further assume that r takes values in the compact set $[\underline{r}; \overline{r}]$. While these boundary values can be chosen so that the probability of the unbounded process to hit them is low, this assumption guarantees the full collateralization of debt contracts in all future states.[5]

1.5.1.3 Equity financing

The last source of finance is external equity. It is denoted $e(a, a', b, b', z, r)$ and determined jointly with investment and net debt through the accounting identity

$$e(a, a', b, b', z, r) = (1 - \tau)\pi(a, z, r) - (a' - (1 - \delta)a) + \frac{\tau r b'}{(1 + r)^2} + \frac{b'}{1 + r} - b \quad (1.6)$$

Whenever $e(.) > 0$, the bank is distributing a dividend to shareholders. It issues equity if $e(.) < 0$.

The only friction in the model is a cost to external equity financing. This cost can arise from flotation and tax costs, as well as from informational asymmetries (Myers and Majluf, 1984) or agency problems (Myers, 1977). It is captured through a linear-quadratic and weakly convex reduced-form function $\eta(e(.))$. A detailed discussion of the functional form is in Hennessy and Whited (2007).

$$\eta(e(a, a', b, b', z, r)) = \mathbb{1}_{\{e(.)<0\}}\left(-\eta_1 e(.) + \frac{1}{2}\eta_2 e(.)^2 \right), \quad (1.7)$$

with $\eta_i \geq 0$, $i = 1, 2$. Net equity issuance/distribution equals $e(.) - \eta(e(.))$.

1.5.1.4 Value function

The bank chooses a' and b' each period to maximize the expected value of future distributions to shareholders, discounted by a factor $1/(1+r)$ capturing the opportunity cost of funds. The Bellman equation is

$$V(a, b, z, r) = \sup_{a', b'} \left\{ e(.) - \eta(e(.)) + \frac{1}{1+r} \int \int V(a', b', z', r') \, dg_z(z'|z) \, dg_r(r'|r) \right\}, \quad (1.8)$$

subject to the collateral constraint (1.4). The first two terms are the equity distribution/infusion, net of issuance costs. The last term is the discounted continuation value. The model yields a unique policy function $\{a', b'\} = \Gamma(a, b, z, r)$. The policy function

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[5]This assumption does not change the policy and value functions solved for below, as numerical solutions are obtained using grid search algorithms that feature boundary values for shock realizations.

gives the optimal response to the trade-off between the cost of increased lending and expectations about future productivity and short rate, while optimally balancing current and future financing needs in a set-up where equity issuance is costly and the short-term rate stochastic.

1.5.2 Optimal policy

I examine the optimality conditions of the model, under the asssumption that V is once differentiable. This assumption is not needed for the existence of a solution to equation (1.8) or for that of an optimal policy function (Stokey and Lucas, 1989).

1.5.2.1 Investment Euler equation

Differentiating equation (1.8) with respect to a' and using the envelope condition yields the investment Euler equation.

$$1 - \mathbb{1}_{\{e(.)<0\}}\left(-\eta_1 + \eta_2 e\left(.\right)\right) = \tag{1.9}$$
$$\frac{1}{1+r}\int\int\left(1 - \mathbb{1}_{\{e'(.)<0\}}\left(-\eta_1 + \eta_2 e'\left(.\right)\right)\right)\left[\left(1-\tau\right)\pi_a\left(a',z',r'\right)\right.$$
$$\left. + \left(1-\delta\right)\right]\mathrm{d}g_z\left(z'|z\right)\mathrm{d}g_r\left(r'|r\right)$$

When making an optimal choice, the bank is indifferent at the margin between increasing long-term lending by one unit at date t and waiting to lend it at date $t+1$. The shadow value of a unit of the long-term asset equals its marginal cost. Assuming $\eta_1 = \eta_2 = 0$ (no cost of external finance), to simplify the expression, the marginal cost of the long-term asset is its price, equal to 1. The shadow value of a marginal unit of asset at date t (right-hand side of equation (1.9)) equals the same marginal cost—discounted by both $1/\left(1+r\right)$ and $\left(1-\delta\right)$—plus the foregone marginal product of capital captured by $\left(1-\tau\right)\pi_a\left(.\right)$. With costly external finance, the marginal cost terms at t and $t+1$ are scaled up whenever the optimal investment policy requires equity to be issued.

1.5.2.2 Debt policy

Let λ be the Kuhn-Tucker multiplier on the collateral constraint (equation 1.4). The first-order condition for the optimal debt policy is given by

$$\left(1 + \frac{\tau r}{1+r}\right)\left(1 - \mathbb{1}_{\{e(.)<0\}}\left(-\eta_1 + \eta_2 e\left(.\right)\right)\right) = \tag{1.10}$$
$$-\int\int\left[V_b\left(a',b',z',r'\right) + \lambda'\right]\mathrm{d}g_z\left(z'|z\right)\mathrm{d}g_r\left(r'|r\right)$$

Rewriting using the envelope theorem, I obtain

$$\left(1 + \frac{\tau r}{1+r}\right)\left(1 - \mathbb{1}_{\{e(.)<0\}}\left(-\eta_1 + \eta_2 e\left(.\right)\right)\right) + \lambda = \tag{1.11}$$

$$\int\int\left[-\mathbb{1}_{\{e'(.)<0\}}\left(-\eta_1 + \eta_2 e\left(.\right)\right) + \lambda'\right] \mathrm{d}g_z\left(z'|z\right)\mathrm{d}g_r\left(r'|r\right)$$

The optimal debt policy is such that the marginal benefit of a unit of debt (left-hand side of equation (1.11)) equals it marginal cost (right-hand side). Debt is valuable for two reasons. First, because of the tax benefit it gives. Second, debt derives value because equity issuance is costly. Debt is more valuable whenever $e\left(.\right) < 0$, because an additional unit of debt, in these states, enables saving the marginal cost of equity finance, for a given level of investment.

The cost of an extra unit of debt is the interest rate to be paid next period. This cost also depends on present expectations over both $e'\left(.\right)$ and λ'. The first term in the expectation term implies that one additional unit of debt today is more costly if the bank is more likely to issue costly equity next period. It highlights the only rationale for risk management in the baseline model. The existence of a friction by which external equity finance is costly makes the bank effectively risk-averse with respect to next-period cash flows. Increasing debt at t implies that interest payments will absorb a larger share of the bank's cash flows at $t + 1$. If investment opportunities are large next period, the bank will resort to larger equity financing and pay the associated cost, or forego investment. Debt capacity is more valuable in such states. The second term in the expectation implies that an additional unit of debt is more costly at t if the collateral constraint is more likely to be binding at $t + 1$.

The fact that *(i)* external equity financing is costly and that *(ii)* debt is capped by the collateral constraint implies that there are benefits from preserving free debt capacity, or "financial flexibility" for next-period investment. The mechanism is similar to that featured in Gamba and Triantis (2008) and DeAngelo et al. (2011). The optimal debt policy, however, is driven by expectations over both productivity and the short rate. The dependence on the short rate has a number of implications for risk management, discussed below.

1.5.2.3 Policy function

I solve numerically for the policy function Γ. The calibration of the parameters is discussed in appendix 1.13. Figures 1.3 and 1.4 plot the optimal lending, debt and equity distribution as a function of the productivity shock z and of the short rate r

respectively. The policy function is evaluated at the steady state asset stock, given by

$$a^* = \left[\frac{r^* + \delta}{(1 - \tau)\,\theta\,(R - r^*)^\gamma} \right]^{\frac{1}{\theta - 1}} \tag{1.12}$$

This section yields two main results. First, the bank preserves free debt capacity. Its collateral constraint is not binding in all states. The bank optimally foregoes current lending opportunities so as to be able to exploit future lending opportunities. The amount of debt capacity preserved depends on the present state (z, r). If current investment is highly profitable, because z is high, foregone investment is more costly. The bank preserves less or no debt capacity in such states (right-hand side of figure 1.3). It instead preserves more debt capacity when z is low. Free debt capacity is counter-cyclical. The preservation of debt capacity related to shocks to r involves two effects, and is discussed in section 1.5.3. It is also more costly to preserve debt capacity for a small banks, due to the concavity of $\pi\,(.)$ in a.

The second main result relates to the cyclical patterns of lending and financing. Optimal lending rises with the productivity shock, as lending opportunities become more profitable. Increased lending is funded from two sources. First, dividend distributions to equity holders are cut, as a larger share of internal funds is used for investment. Payout flexibility contributes to intertemporal investment decisions: The bank foregoes present dividend distributions, which are traded off against future dividends out of current investment's proceeds. Second, the bank optimally takes on more short-term debt. The debt-to-assets ratio—a proxy for maturity mismatching in this model—increases with z. Equity is issued in a few states where large lending is optimal (high z) and both internal funds and free debt capacity are insufficient to meet funding needs.

Shocks to the short rate produce a related dynamics (figure 1.4). Optimal lending is increasing when r decreases. This effect is driven by three forces. First, cash flows $\pi\,(.)$ are negatively related to r if $\gamma > 0$, i.e. cash flows increase as the short rate decreases. The marginal profitability of lending is greater. Second, for a given profitability of the asset, more investment can be sustained if debt financing is cheaper (r lower) as less debt capacity needs to be preserved. A lower short rate implies that more present debt can be obtained for a given asset stock. These two mechanisms by which changes in the short rate drive the firm's capital structure ("investment motive" and "financing motive" respectively) are discussed in lengthier details in section 1.5.3. A third effect is through the discount factor, $1/\,(1 + r)$. As r decreases, equity holders value future dividend distributions to a larger extent. The bank optimally invest more at date t, out of current internal resources. It trades off present versus future dividend distributions.
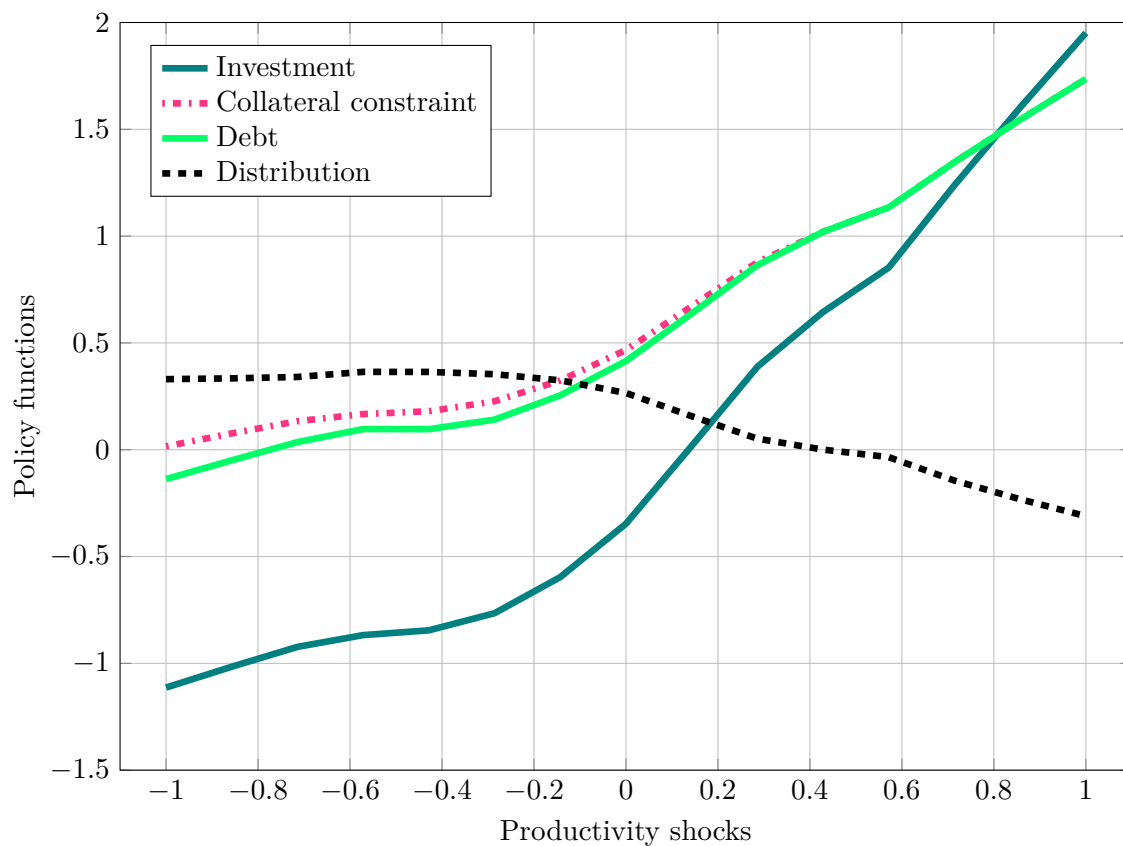
FIGURE 1.3: Policy functions. This figure depicts the policy function of the model with riskless debt and no interest rate swaps. Each function maps the current log productivity shock and the optimal future investment (lending), optimal future debt and optimal future distributions to shareholders. The policy functions are computed at the steady state capital stock. Each variable is scaled by the steady state capital stock. The collateral constraint is also depicted.
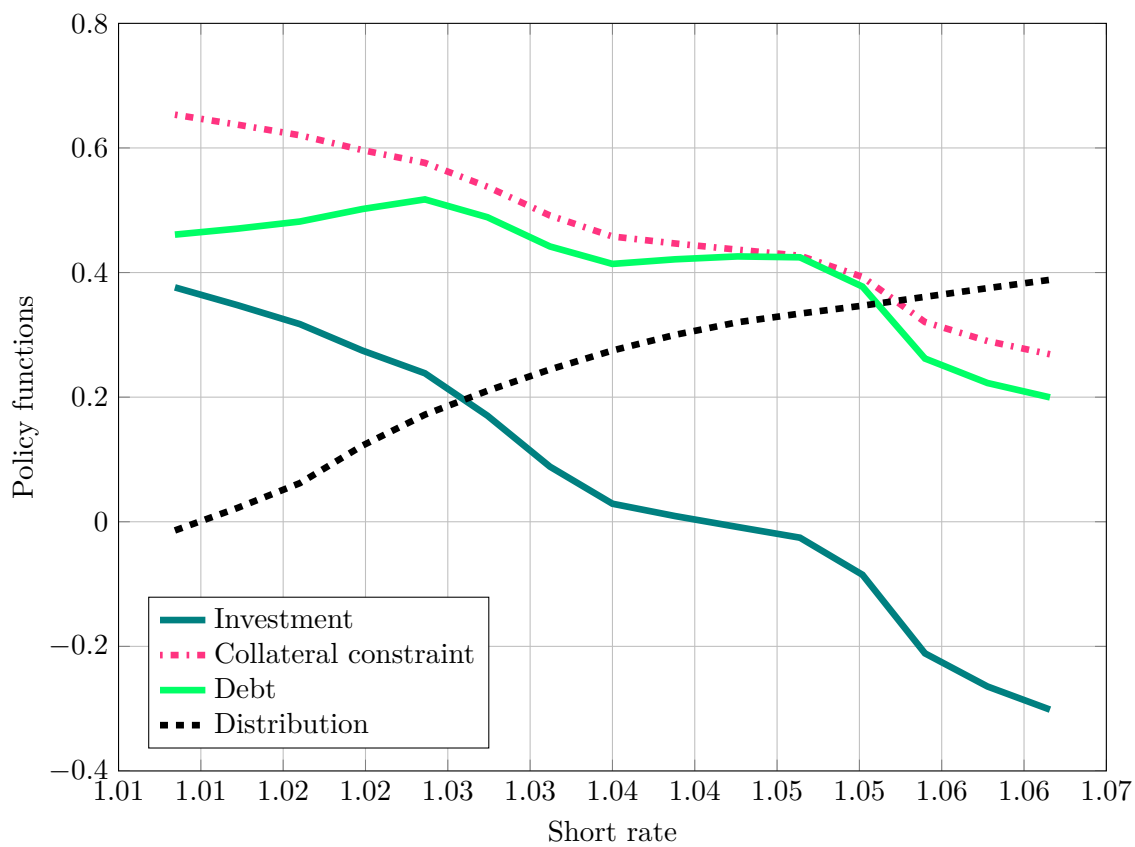
FIGURE 1.4: Policy functions. This figure depicts the policy function of the model with riskless debt and no interest rate swaps. Each function maps the current interest rate realization and the optimal future investment (lending), optimal future debt and optimal future distributions to shareholders. The policy functions are computed at the steady state capital stock. Each variable is scaled by the steady state capital stock. The collateral constraint is also depicted.

Dividend distributions are thus lower when r is low. First, equity holders value future dividends more. Second, for a given discount factor, the bank optimally uses a larger share of cash flows to finance new loans in such states.

There are two main effects of shocks to the short rate on the bank's capital structure. First, a decrease in the short rate increases long-term lending, thus the bank's size. Second, the bank loads on short-term debt and increases maturity mismatching when the short rate is lower. Equity is issued only when debt capacity is exhausted and internal funds are not sufficient to meet optimal investment expenses. For high realizations of the short rate, the bank may find it optimal to hold cash ($b' < 0$). It thus keeps resources for future investment.

1.5.3 Financing and investment motives for interest rate risk management

The model features two motives for interest rate risk management, which I call "financing motive" and "investment motive". They are defined in this section. Each of these motives implies that the bank optimally aims to hold sufficient resources in certain future states. Both, however, are targeted towards different states. Their respective role is important for the dynamics of risk management in the model.

Absent a stochastic short rate, the incentive for risk management arises only from *(i)* productivity being stochastic and from *(ii)* external equity being costly. Debt capacity is preserved in order to meet future investment opportunities arising from high realizations of z. The bank optimally transfers resources from "low z" to "high z" states.

The introduction of a stochastic short rate in the model affects both the bank's assets and liabilities. Optimal risk management balances the risk exposure arising from both. On the liability side, a stochastic short rate affects the cost of debt financing. Ceteris paribus, there is a risk that the future cost of debt financing will be high precisely in states where profitable lending opportunities will be large. This may cause future lending opportunities to be foregone. This risk is optimally managed ex ante by keeping additional debt capacity if next-period debt financing is likely expensive, and profit opportunities likely large. This is the "financing motive" for interest rate risk management. The financing motive implies that the bank optimally wants to transfer resources from future states where r is low to future states where r is high.

To see this, it is useful to compute moments from the simulated model. I fix γ to 0, so that the bank is exposed to r only through its debt. For 3 values of σ_r ranging from 0 to 0.015, I solve for the value function and simulate the model for 5,200 periods. In

		$\gamma = 0$			$\sigma_r = 0.007$		
		$\sigma_r = 0$		$\sigma_r = 0.015$	$\gamma = 0$		$\gamma = 0.15$
1	Average investment (i/a)	0.245	0.253	0.263	0.259	0.260	0.245
2	Standard deviation of investment (i/a)	0.484	0.506	0.529	0.531	0.557	0.610
3	Average debt-to-assets ratio (b/a)	0.508	0.494	0.477	0.435	0.366	0.257
4	Standard deviation of (b/a)	0.164	0.150	0.180	0.214	0.300	0.474
5	Frequency of positive debt outstanding	0.992	0.993	0.963	0.919	0.903	0.852
6	Average of positive (b/a) values	0.520	0.503	0.503	0.483	0.447	0.449
7	Average cash balances	0.007	0.005	0.007	0.009	0.037	0.126
8	Frequency of collateral constraint binding	0.247	0.280	0.250	0.310	0.116	0.052
9	Percent of debt capacity used	0.870	0.842	0.815	0.753	0.686	0.656
10	Average equity distribution (e/a)	0.080	0.081	0.082	0.085	0.077	0.065
11	Standard deviation of (e/a)	0.108	0.121	0.152	0.113	0.122	0.112
12	Equity issuance frequency	0.066	0.063	0.092	0.039	0.039	0.035
13	Average of non-zero equity issuance	0.100	0.126	0.122	0.122	0.127	0.123

TABLE 1.1: Financing and investment motives for interest rate risk management. This table presents investment, debt and payout statistics computed using data simulated from the baseline model. The model is simulated for 5,200 periods in which the bank receives stochastic productivity and interest rate shocks (z, r) each period. The first 200 periods of simulated data are dropped. In each simulation, one parameter is varied. The first three columns illustrate the financing motive for risk management. The sensitivity of cash flows to the short rate is set to $\gamma = 0$, i.e. there is no investment motive for risk management. The standard deviation of the short rate is varied from 0 to 0.015. In the last three columns, σ_r is set to its baseline value and γ is varied from 0 (no investment motive) to 0.15. The investment motive for risk management becomes more important as γ increases. Other parameters are kept at their baseline value. The value function is solved for each new parameter value. Cash balances correspond to b/a if $b < 0$. Equity is issued when $e < 0$.

each period, the bank receives stochastic productivity and interest rate shocks (z, r). The first 200 periods of simulated data are dropped. Descriptive statistics are in the first three columns of table 1.1. When $\sigma_r = 0$, the short rate is deterministic. There is no financing motive for risk management, and debt capacity is preserved only to accomodate stochastic real shocks to z. As σ_r increases, the financing motive becomes more important and the bank keeps a lower debt-to-assets ratio (row 3) and uses a lower percentage of its debt capacity (row 9).

Turning to the asset side, a decrease in the short rate positively affects the bank's cash flows, provided $\gamma > 0$. The dependence of $\pi(.)$ on γ implies that there are investment opportunities arising from decreases in the short rate. The bank optimally keeps debt capacity so that these investment opportunities are not foregone when they arise. This is the "investment motive" for interest rate risk management. The effect is similar to the preservation of debt capacity for investment in future states in which z is high. In contrast to the financing motive, the investment motive implies that the bank optimally wants to transfer resources from future states where r is high to future states where it is low. There are two opposing forces involved in optimal interest rate risk management. For a given value of γ, the investment motive is reinforced by the fact that, as r is lower, future dividend distributions are less discounted: Not only is current investment more profitable but, for a given investment profitability, the bank is also more willing to invest in the long-term asset rather than distributing internal resources as dividends.

To see the investment motive in the simulations, I fix σ_r to its baseline value and vary γ. As γ increases, the investment for risk management motive becomes more important. As seen in the last three columns of table 1.1, the bank holds less debt on average (row 3), keeps more cash (row 7) and uses a smaller share of its debt capacity (row 9).

Whether the financing motive or the investment motive dominates depends on the sensitivity of cash flows to the short rate, γ. For some parameter values, the dynamics of risk management is non-monotonic in γ. A change in γ involves two opposite effects driven by both risk management motives. For $\gamma = 0$, only the financing motive exists. The pure investment motive is absent, even though the incentive to increase investment as r falls is still present, through the impact of r on the discount factor. Profit opportunities arise from shocks to z only and are uncorrelated with the cost of debt financing, given by r. Debt capacity is kept in order to manage the risk that debt financing may be expensive (r high) in states where investment opportunities arising from shocks to z are profitable. Ceteris paribus, more debt capacity is kept when the short rate is low, as also seen in the policy function of figure 1.4.

As γ increases, cash flows $\pi(.)$ become negatively correlated with the cost of debt financing. Cash flows are ceteris paribus higher when debt financing is cheap. The negative

correlation implies that it is less likely that debt financing is expensive precisely in states where large lending outlays are optimal, as a high short rate also has a negative effect on cash flows. This effect is further reinforced by the effect of r on the discount factor. The financing motive for risk management is less important than when $\gamma = 0$. Therefore, less debt capacity is optimally kept to meet this motive. The investment motive, however, kicks in. Low realizations of the short rate are associated with profitable lending opportunities. The bank optimally keeps debt capacity so that these investment opportunities are not foregone when they arise. The investment motive requires more debt capacity as γ increases. As γ increases, the investment motive overrides the financing motive, and is further reinforced by changes in the discount factor.

1.5.4 Comparative statics for investment and risk management

This section compares simulated moments of the bank's capital structure and of its risk management policy when the baseline parameters are varied. First, it focuses on changes in the volatility and persistence of the shocks to z and r. Second, it explores the model's comparative statics for changes in parameters θ and δ. There are two margins for risk management: the preservation of debt capacity and payout flexibility. The simulation of the model is similar to that of section 1.5.3.

1.5.4.1 Shock volatility and persistence

Tables 1.2 and 1.3 compare a number of moments obtained from simulated data when the standard deviation and the persistence of the productivity and short rate shocks are varied. σ_z takes values in $[0.05, 0.5]$, σ_r in $[0.001, 0.015]$ and ρ_z and ρ_r in $\{0.2, 0.9\}$.

When either shock is more volatile or more persistent, the bank optimally preserves more free debt capacity and adopts a more flexible payout policy. Intuitively, the debt, lending and payout policies optimally balance the costs and benefits of current versus future investment opportunities. A higher volatility of z implies that large lending opportunities are more likely to arise next period. Similarly, a higher volatility of r implies either that debt finance is more likely to be costly when needed for future investment, or that lending opportunities arising from a low level of the short rate are more likely to arise (depending on whether the financing or the investment motive dominates). If no debt capacity were kept in either case, costly external equity would have to be issued in order to invest. The shadow value of current debt (i.e. foregone debt capacity next period) is higher when the volatility of investment opportunities or the cost of debt finance are higher. More debt capacity is thus kept, despite tax incentives to borrow.

		St. Dev. of productivity σ_z				Persistence ρ_z	
		Low			High	0.2	0.9
1	Average investment (i/a)	0.183	0.265	0.338	0.385	0.185	0.265
2	Standard deviation of investment (i/a)	0.278	0.554	0.827	1.183	0.277	0.617
3	Average debt-to-assets ratio (b/a)	0.521	0.405	0.187	0.103	0.473	0.316
4	Standard deviation of (b/a)	0.075	0.225	0.433	0.514	0.080	0.389
5	Frequency of positive debt outstanding	1	0.968	0.628	0.619	1	0.880
6	Average of positive (b/a) values	0.521	0.434	0.468	0.450	0.473	0.437
7	Average cash balances	0	0.015	0.108	0.176	0	0.069
8	Frequency of collateral constraint binding	0.072	0.178	0.155	0.076	0.072	0.263
9	Percent of debt capacity used	0.727	0.714	0.548	0.539	0.729	0.690
10	Average equity distribution (e/a)	0.106	0.075	0.082	0.108	0.111	0.081
11	Standard deviation of (e/a)	0.067	0.116	0.239	0.469	0.073	0.163
12	Equity issuance frequency	0	0.037	0.070	0.090	0	0.062
13	Average of non-zero equity issuance (e/a)	0	0.150	0.383	0.622	0	0.240

TABLE 1.2: Capital structure moments and properties of the process for z. This table presents investment, debt and payout statistics computed using data simulated from the baseline model. The model is simulated for 5,200 periods in which the bank receives stochastic productivity and interest rate shocks (z, r) each period. The first 200 periods of simulated data are dropped. In each simulation, one parameter is varied, while the others are kept at their baseline value. The value function is solved for each new parameter value. In the first four columns, the standard deviation of the productivity shock (σ_z) takes four equally-spaced values between 0.05 and 0.5. In the last two columns, the persistence of the productivity shock (ρ_z) takes value in $\{0.2, 0.9\}$. Cash balances correspond to b/a if $b < 0$. Equity is issued when $e < 0$.

		St. Dev. of short rate σ_r				Persistence ρ_r	
		Low			High	0.2	0.9
1	Average investment (i/a)	0.237	0.263	0.270	0.271	0.260	0.266
2	Standard deviation of investment (i/a)	0.473	0.546	0.571	0.578	0.539	0.556
3	Average debt-to-assets ratio (b/a)	0.438	0.405	0.387	0.396	0.414	0.388
4	Standard deviation of (b/a)	0.176	0.223	0.276	0.289	0.203	0.266
5	Frequency of positive debt outstanding	0.987	0.969	0.931	0.929	0.950	0.925
6	Average of positive (b/a) values	0.453	0.433	0.447	0.461	0.447	0.448
7	Average cash balances	0.009	0.015	0.029	0.033	0.011	0.026
8	Frequency of collateral constraint binding	0.190	0.198	0.170	0.072	0.204	0.192
9	Percent of debt capacity used	0.760	0.713	0.707	0.724	0.722	0.704
10	Average equity distribution (e/a)	0.073	0.076	0.076	0.074	0.075	0.076
11	Standard deviation of (e/a)	0.103	0.111	0.124	0.147	0.108	0.115
12	Equity issuance frequency	0.033	0.035	0.037	0.080	0.032	0.039
13	Average of non-zero equity issuance	0.159	0.143	0.173	0.123	0.148	0.131

TABLE 1.3: Capital structure moments and properties of the process for r. This table presents investment, debt and payout statistics computed using data simulated from the baseline model. The model is simulated for 5,200 periods in which the bank receives stochastic productivity and interest rate shocks (z, r) each period. The first 200 periods of simulated data are dropped. In each simulation, one parameter is varied, while the others are kept at their baseline value. The value function is solved for each new parameter value. In the first four columns, the standard deviation of the short-term interest rate shock (σ_r) takes four equally-spaced values between 0.001 and 0.015. In the last two columns, the persistence of the interest rate shock (ρ_r) takes value in $\{0.2, 0.9\}$. Cash balances correspond to b/a if $b < 0$. Equity is issued when $e < 0$.

		δ					θ		φ_1		
		Low				High	0.6	0.9	0	0.06	0.12
1	Average investment (i/a)	0.202	0.366	0.543	0.676	0.795	0.238	0.459	0.265	0.200	0.182
2	Standard deviation of investment (i/a)	0.505	0.619	0.777	0.768	0.802	0.456	1.513	0.554	0.330	0.264
3	Average debt-to-assets ratio (b/a)	0.394	0.421	0.478	0.627	0.678	0.494	0.006	0.405	0.463	0.471
4	Standard deviation of (b/a)	0.217	0.273	0.307	0.282	0.209	0.112	0.635	0.225	0.131	0.114
5	Frequency of positive debt outstanding	0.916	0.944	0.927	0.934	0.980	0.998	0.609	0.968	0.988	0.987
6	Average of positive (b/a) values	0.441	0.479	0.559	0.697	0.695	0.497	0.477	0.434	0.472	0.480
7	Average cash balances	0.010	0.031	0.040	0.024	0.002	0.002	0.284	0.015	0.004	0.003
8	Frequency of collateral constraint binding	0.140	0.230	0.244	0.543	0.618	0.230	0.122	0.178	0.220	0.228
9	Percent of debt capacity used	-0.554	0.487	0.622	0.815	0.836	0.816	0.512	0.714	0.785	0.792
10	Average equity distribution (e/a)	0.063	0.102	0.145	0.196	0.246	0.115	-0.019	0.075	0.087	0.101
11	Standard deviation of (e/a)	0.116	0.123	0.126	0.154	0.179	0.096	0.562	0.116	0.078	0.068
12	Equity issuance frequency	0.048	0.026	0.017	0.016	0.051	0.012	0.146	0.037	0.011	0
13	Average of non-zero equity issuance	0.0127	0.210	0.247	0.183	0.022	0.088	0.643	0.150	0.039	—

TABLE 1.4: Capital structure moments and model parameters. This table presents investment, debt and payout statistics computed using data simulated from the baseline model. The model is simulated for 5,200 periods in which the bank receives stochastic productivity and interest rate shocks (z, r) each period. The first 200 periods of simulated data are dropped. In each simulation, one parameter is varied, while the others are kept at their baseline value. The value function is solved for each new parameter value. In the first four columns, sensitivity of cash flow to the share of loans maturing each period (δ) takes four equally-spaced values between 0.1 and 0.6. In the next two columns, the marginal profitability of loans (θ) takes value in $\{0.6, 0.9\}$. In the last three column, the convex adjustment cost parameter φ_1 (in the first model extension) takes three values between 0 and 0.12. The fixed cost parameter φ_0 is set to zero. Cash balances correspond to b/a if $b < 0$. Equity is issued when $e < 0$.

Similarly, a higher persistence ρ_z implies that a profitable investment opportunity brings more future cash flows on expectation. Foregoing these investment opportunities when they arise is more costly. More debt capacity is also optimally preserved ex ante. A higher value of ρ_r also implies that a high cost of debt financing persists for a longer period on expectation, potentially hindering the bank's ability to invest for a longer period. More debt capacity is kept in order to meet these investment opportunities. The average debt-to-assets ratio (b/a) is lower when σ_z, σ_r, ρ_z and ρ_r are higher (row 3). The percentage of debt capacity used is also lower, while the bank keeps cash in more periods (rows 9 and 7).

The second margin for risk management is payout flexibility, whereby the bank cuts current dividends to increase investment. In the results, debt capacity and payout flexibility co-move, i.e. payout flexibility is high in model parameterizations where free debt capacity is also high. Cutting dividends is more valuable if current investment is more profitable or if profitability is more persistent. When σ_z, σ_r, ρ_z and ρ_r increase, the standard deviation of equity distributions (e/a) increases (row 11). The frequency of equity issuances and the average amount issued also increases (rows 12 and 13). In spite of the associated cost, the issuance of equity is increasingly optimal when shocks can be larger or when they are more persistent. Investment is also more volatile for a bank faced with these shock properties (row 2).

1.5.4.2 Other parameters

The marginal profitability of lending, θ, and the per-period share of maturing loans, δ, are varied. Descriptive statistics are in table 1.4. As θ increases to 1, the concavity of the cash flow function $\pi(.)$ is reduced. Thus, for a given shock realization, a higher value of θ implies that the optimal lending outlay is larger. Consequently, the bank preserves a larger debt capacity and adopts a more flexible payout policy.

More debt capacity is also kept when δ is low, i.e. when the average maturity of the asset, $1/\delta$, is high. A higher average debt maturity implies that a loan unit installed today is kept on balance sheet for a longer period. Foregoing an investment opportunity when it arises is thus costlier in this case. The average debt-to-assets ratio decreases with δ (row 3). The collateral constraint also binds less often when δ is low (row 8), and the percentage of debt capacity used is lower (row 9).

1.6 Riskless debt with interest rate derivatives

This section introduces one-period interest rate swaps in the baseline model as a third margin for risk management. Short-term debt is riskless. Default decisions are introduced in the next section.

1.6.1 Interest rate swap contracts

A one-unit swap contract traded at date t mandates the payment at date $t+1$ of a fixed swap rate (known at t) in exchange for the variable rate r' (realized at $t+1$). Even though restrictive (because other contracts with finer state-contingent specifications could provide interest rate hedging), this contract specificiation has several advantages. First, it is very close to real-world interest rate swap contracts (e.g. Titman, 1992).[6] Second, given r and $g_r\left(r'|r\right)$, the swap contract is fully described by one control variable. Finer state-contingent contracts would be defined by more than one control variable and add to the numerical complexity of the model solution. A numerical solution is needed as I am interested in position signs (pay-fixed vs. pay-float). Third, it can be shown that this swap contract structure approximates reasonably well the outcome of finer contract specifications bringing the problem closer to complete markets.[7]

Interest rate swap contracts are provided by risk-neutral dealers.[8] They are fairly priced, i.e. the present expected value of the fixed leg and of the floating leg of the contract are equal. The swap rate equals the short rate at t plus a (potentially negative) premium p, which solves

$$r + p = \int g_r\left(r'|r\right) r' \mathrm{d}r' \tag{1.13}$$

The notional amount of swap contracts bought at t is denoted d'. Whenever $d' > 0$, the bank has a pay-fixed position. It has a pay-float position if $d' < 0$.

---

[6]Note that, when restricting attention to one-period contracts, an interest rate swap is equivalently described as a forward or a future.

[7]I solve the problem for a contract specifying both a notional amount (as below) and an interest rate threshold r^{swap}, both optimally chosen by the bank. If the bank has a pay-fixed (resp. pay-float) position, then it commits to pay the swap rate (resp. the short rate r') in all future states at $t+1$, while receiving the floating rate r' (resp. the swap rate) only if $r' > r^{\mathrm{swap}}$ (resp. $r' < r^{\mathrm{swap}}$). As compared to the contract modeled below, this contract has the advantage that swap payments can be funneled more precisely to future states where equity would otherwise be optimally issued. If swap payments are received in a smaller set of states, then the price of hedging is also lower. With this contract specification, the bank's value and optimaly policy are qualitatively and quantitatively similar to those obtained with the chosen swap specification.

[8]The presence of risk-neutral dealers is exogenously assumed. The intermediation of long and short swap contracts is not endogenized (see the discussion in section 1.8.3). The model is thus fit for representing non-dealer commercial banks. The distinction between dealers and end-users in derivatives markets is sharp, implying that the assumption is granted empirically. In the CDS market, where the network structure is best documented (Peltonen et al., 2014), there are 14 dealers concentrating most intermediary activities between hundreds of end-users. Similar suggestive evidence is put forth by Fleming et al. (2012) for the interest rate derivatives market.

There is a cost $c(d')$ of taking non-zero swap positions. It is paid at t in the period when d' is chosen and writes as

$$c(d') = c_f \cdot \mathbb{1}_{\{d' \neq 0\}} + \chi \frac{d'^2}{2}, \tag{1.14}$$

where $c_f \geq 0$ and $\chi \geq 0$. c_f is a fixed cost, interpreted as the fixed cost of running a derivatives trading desk. The second component is a convex cost, interpreted as the cost of managing large exposures. The existence of a cost $c(d')$ has the additional advantage that it pins down a unique solution $d' = 0$ at times the bank is effectively risk neutral, i.e. when the optimal policy next period does not require equity issuance in any state (z', r'). Absent this cost, multiple choices of d' could be equally optimal ex ante, as swap contracts yield an expected return of zero.

The equity distribution/issuance function rewrites

$$
\begin{aligned}
e\left(a, a', b, b', d, d', z, r, r_{-1}\right) &= (1-\tau)\,\pi\left(a, z, r\right) - \left(a' - (1-\delta)a\right) + \frac{\tau r b'}{(1+r)^2} \\
&\quad + \frac{b'}{1+r} - b + d\left(r - (r_{-1} + p_{-1})\right) - c\left(d'\right),
\end{aligned}
\tag{1.15}
$$

where r_{-1} is a state variable equal to the short rate at $t-1$ and p_{-1} the agreed-upon premium at that date (solved for using equation (1.13)). The value function rewrites

$$V(a, b, d, z, r, r_{-1}) = \sup_{a', b', d'} \left\{ e(.) - \eta\left(e(.)\right) + \frac{1}{1+r} \int \int V\left(a', b', d', z', r', r\right) \mathrm{d}g_z\left(z'|z\right) \mathrm{d}g_r\left(r'|r\right) \right\}, \tag{1.16}$$

Swap contracts enter contemporaneous payoffs only through their cost $c(d')$. In contrast with debt contracts, cash or payout flexibility, swaps cannot be used to transfer resources across periods, only across future states. They cannot be used contemporaneously for financing and instead are used only for risk management. They have an indirect effect on present financing and debt capacity, however, through the collateral constraint.

1.6.2 Collateral constraint with swaps

Swap contracts are fully collateralized, thus riskless. Future cash flows and the asset stock to be used as collateral are the same for both short-term debt and swaps. The collateral constraint is such that both debt and swaps are fully repaid in all possible states (z', r') at $t+1$. Collateral constraints for pay-fixed and pay-float positions are derived separately.

In case the bank has a pay-float position ($d' < 0$), future states in which cash flows are low and states where it is a net swap payer coincide. The worst realization of r' for the bank is $\overline{r}$. The collateral constraint writes as

$$b' - d' \left(\overline{r} - \left(r + p\left(r \right) \right) \right) \leq \left(1 - \tau \right) \underline{z} \left(R - \overline{r} \right)^{\gamma} a'^{\theta} + \kappa a' \tag{1.17}$$

The bank receives the swap rate $r + p\left(r \right)$ at $t + 1$ and must hold enough resources to pay the worst-case floating rate $r' = \overline{r}$, if realized.

In case the bank has a pay-fixed position ($d' > 0$), in contrast, $\overline{r}$ need not be the worst ralization of the short rate at $t+1$, even if it is associated with the lowest cash flows from assets-in-place. The bank receives net swap payments $\overline{r} - \left(r + p\left(r \right) \right) \geq 0$ per notional unit of swap in this state. Which realization of r' is the worst for the bank depends on the relative magnitude of the effect of r' on both swap payments and operating cash flows next period. The worst-case interest rate realization for which the bank must hold sufficient funds next period is denoted $\breve{r}$ and solves

$$\breve{r} = \arg \min_{r' \in [\underline{r}, \overline{r}]} \pi \left(a', \underline{z}, r' \right) - d' \left(\left(r + p\left(r \right) \right) - r' \right). \tag{1.18}$$

By monotonicity of the two terms in r', $\breve{r}$ is uniquely defined. The collateral constraint writes as

$$b' + d' \left(\left(r + p\left(r \right) \right) - \breve{r} \right) \leq \left(1 - \tau \right) \underline{z} \left(R - \breve{r} \right)^{\gamma} a'^{\theta} + \kappa a'. \tag{1.19}$$

A particular case to be noted is that where $\gamma = 0$, i.e. operating cash flows do not depend on the short rate. In this case, $\breve{r} = \underline{r}$, as the lowest possible floating rate is received. Together, equations (1.17) and (1.19) impose a lower and an upper bound on d', which thus lies in a compact set.

1.6.3 Optimal hedging policy

This section derives the optimal swap hedging policy.

1.6.3.1 First-order condition for swaps

Swap contracts are valuable because they make possible redistributions across future states, conditional on a present choice of a' and b': from future states (z', r') where no external equity will be optimally issued to finance investment to states where external equity financing would, absent swap payments, be optimally needed (or needed to a larger extend).

Assuming no fixed cost ($c_f = 0$), the optimal swap policy satisfies

$$
\chi d' \left(1 - \mathbb{1}_{\{e(.)<0\}} \left(-\eta_1 + \eta_2 e\left(.\right) \right) \right)
$$
$$
+ \int \int \lambda' \left[\mu \left((r + p\left(r\right)) - \breve{r} \right) - (1-\mu) \left(\overline{r} - (r + p\left(r\right)) \right) \right] \mathrm{d}g_z \left(z'|z \right) \mathrm{d}g_r \left(r'|r \right)
$$
$$
= \int \int \left[r' - (r+p) \right] \left(1 - \mathbb{1}_{\{e'(.)<0\}} \left(-\eta_1 + \eta_2 e'\left(.\right) \right) \right) \mathrm{d}g_z \left(z'|z \right) \mathrm{d}g_r \left(r'|r \right), \quad (1.20)
$$

where μ is an indicator variable that equal 1 if $d' > 0$ and 0 otherwise. Equation (1.20) equalizes the expected marginal cost and marginal benefit of an additional swap unit. As can be seen on the right-hand side, swap contracts derive value because equity issuance is costly. In case $\eta_1 = \eta_2 = 0$, there would be no expected benefit from swap trading, as the expression would simplify to zero, using the pricing condition (1.13).

Swaps are costly for two reasons. First, because of trading costs. Second, taking swap positions makes the collateral constraint (to which the Lagrange multiplier λ is associated) more likely to bind next period in some states, as seen on the left-hand side of equation (1.20). If the collateral constraint is binding, the bank's debt capacity is reduced. Its investment can be reduced as a consequence.

The fact that both debt and swaps are collateralized using the same cash flows and asset stock produces an effect similar to that modeled by Rampini and Viswanathan (2010). In their set-up, firms with a low net worth hedge less or forego hedging, as collateral for them is more usefully deployed to increase debt and finance investment. The same effect arises for banks in this model.

To see this, note that the opportunity cost of collateral pledged on swaps is foregone present debt capacity. As it increases its notional exposure to swaps, the bank must put aside pledgeable resources for future states in which a realization of r' will imply net swap payments. The bank's debt capacity is reduced accordingly. Technically, the Kuhn-Tucker multiplier on the collateral constraint next period, λ', appears in the first-order conditions with respect to both b' and d'.

The optimal hedging policy trades off the benefits from hedging (lower issuance of costly equity if large lending is optimal next period) and the cost of foregone present investment or equity distributions. The opportunity cost of hedging is particularly large if the bank's marginal profitability today is high. This cost is thus large for small banks, due to the concavity of $\pi\left(.\right)$ in a, and when z is high. Foregoing investment is more costly for these banks. They engage less in swap trading and may optimally choose not to hedge. Sorting between users and non-users arises even in the absence of a cost to swap trading, if $c\left(d'\right) = 0$ when $d' \neq 0$. Sorting is discussed in greater details in the model extension with heterogeneous banks of section 1.6.6.

Finally, whether pay-fixed or pay-float swap positions are taken is seen indirectly in the first-order condition (1.20). In the right-hand side, the benefits from swap hedging depend on the expectation over $e'\left(.\right)$ being negative for some future realizations of r'. The position sign that is optimally chosen depends on whether future states with large lending outlays are associated with high or low realizations of r'. Both can arise, as discussed below, implying that both pay-fixed and pay-float positions can be optimally chosen.

1.6.3.2 Hedging and debt capacity

The optimality conditions for hedging make it clear that debt and hedging policies are dynamically related. This section uses simulations to further document the interaction between on- and off-balance sheet risk management. Each model, with and without swaps, is simulated for 5,200 periods. The first 200 periods are dropped. Descriptive statistics for both models are given in table 1.5, while table 1.6 summarizes the dynamics of both models by reporting correlations between moments of the simulated capital structure with the shock realizations.

There are two important results. First, there is a substitution between swaps and debt capacity for risk management. In the model with swaps, the bank optimally preserves less free debt capacity on average. As compared to debt capacity, swap contracts have the advantage that they primarily achieve transfers across future periods, so that their cost in terms of foregone investment in the present may be lower. The bank uses about 43.7% of its total debt capacity (given by the collateral constraint) on average in the model with swaps, as compared to 25.1% in the model without swaps (row 9). The bank has a higher debt-to-assets ratio on average (row 3) and keeps less cash (row 7). The substitution between swaps and debt capacity is further seen through the fact that, in periods where it is trading non-zero swaps ($d' \neq 0$), the bank is closer to its upper debt limit than in the average period (rows 10 and 11).

Second, swaps are not optimally used in all periods. In states where the bank is small (has low collateral value) or highly profitable, foregone lending opportunities when hedging increases are costly. The cost in terms of lost debt capacity is larger than the benefit from hedging, and the bank optimally does not hedge (see section 1.6.3.1). In these states, risk is eventually managed on-balance sheet only through debt capacity, or foregone completely. In the baseline calibration, swaps are optimally used in about 16.4% of the periods only (row 22).

Finally, the opportunity to hedge using swaps does not imply that the bank no longer keeps debt capacity. Some debt capacity is still preserved in almost all periods (row

		Without swaps	With swaps
1	Average investment (i/a)	0.171	0.196
2	Standard deviation of investment (i/a)	0.397	0.436
3	Average debt to assets ratio (b/a)	-0.032	0.155
4	Standard deviation of (b/a)	0.492	0.384
5	Frequency of positive debt outstanding	0.492	0.715
6	Average of positive (b/a) values	0.317	0.381
7	Average cash balances to assets	0.188	0.117
8	Frequency of collateral constraint binding	0.004	0.003
9	Percent of debt capacity used	0.251	0.437
10	Percent of debt capacity used when $d' > 0$	—	0.457
11	Percent of debt capacity used when $d' < 0$	—	0.533
12	Average equity distribution (e/a)	0.091	0.089
13	Standard deviation of equity distribution (e/a)	0.116	0.102
14	Equity issuance frequency	0.265	0.215
15	Average of non-zero equity issuance/assets	0.032	0.007
16	Avg. fraction of expenses (incl. lending) funded from:		
17	Current cash flow	0.4601	0.4392
18	Cash balances	0.3018	0.1683
19	Debt issuance	0.2341	0.3887
20	Equity issuance	0.0040	0.0036
21	Swap payoffs	—	0.002
22	Frequency of swaps use	—	0.164

TABLE 1.5: Moments of the capital structure, with and without swaps. This table shows the moments of the bank capital structure, as obtained from simulated data. Two models are simulated: The model without swaps of section 3.4 and the model with swaps described in the present section. The parameter calibrations are given in appendix 1.13. Each model is simulated for 5,200 periods in which the bank receives stochastic productivity and interest rate shocks (z, r) each period. The first 200 periods are dropped before moments are calculated.

8). The relationship between the use of swaps and the optimal debt capacity is an equilibrium condition. A state in which the increased use of swap contracts can relax the need to preserve debt capacity (thus enabling larger investment or equity distributions) cannot be an equilibrium. Provided the equilibrium is not a corner solution—in which case no swaps are used—, the optimal policy equalizes the value of present versus future investment (or present debt versus future debt capacity), while equalizing the marginal value of collateral pledged for both debt and swap contracts.

When the bank optimally preserves less free debt capacity as a consequence of the use of derivatives, additional short-term debt can be used either to increase lending or be distributed to equity holders. The next two subsections focus respectively on the interaction between hedging and *(i)* payout policy and *(ii)* lending policy.

1.6.3.3   Hedging, equity issuance and payout policy

The second margin for risk management that is altered with the introduction of swaps is payout flexibility. Hedging using swaps has a notable effect on the bank's optimal payout to equity holders and on equity issuance (table 1.5).

First, the frequency of equity issuance is lower for the simulated bank in the model with swaps. Conditional on equity issuance, the amount being issued is also significantly lower. For the simulated bank, equity is issued in about 26.5% of the periods in the model without swaps and in 21.5% in the model with swaps (table 1.5, row 14). Furthermore, the average equity issuance represents 3.2% of a bank's capital, as compared to 0.7% in the model with swaps (row 15).

The effect is driven by the nature of each margin for risk management. Each of the margins available to a non-user bank implies interetemporal transfers that are non-state contingent. Risk management through debt capacity trades off present versus future investment opportunities. Payout flexibility trades off present versus future equity distributions. These transfers occur regardless of whether equity issuance will indeed be needed next period, so that their cost is paid in all present states while their benefit is obtained in some future states only. Swap payoffs, in contrast, can be targeted more precisely to future states in which equity will be optimally issued. The optimal choice of each margin for risk management is an equilibrium condition; however, for a bank that engages in risk management, swaps can be relatively less costly, due to their state-contingent payoffs. It is the case that banks in the model without swaps engage less in risk management and optimally choose to issue equity more often.

Second, the volatility of equity distributions is lower. The standard deviation of $e\left(.\right)$ is 0.102 in the model with swaps and 0.116 in the model without swaps. This finding

	Shock	Model without swaps	Model with swaps
Bank value (V)	z	0.488	0.513
	r	-0.500	-0.560
Debt-to-assets (b/a)	z	0.463	0.546
	r	0.095	0.109
Investment (i)	z	0.337	0.364
	r	-0.102	-0.106
Equity distribution (e)	z	0.179	0.209
	r	0.134	0.125

TABLE 1.6: Correlation of capital structure moments with shock realizations. This table shows the pairwise correlations between *(i)* bank value, debt-to-assets ratio, investment and equity distributions, and *(ii)* the realizations of the shocks to productivity (z) and to the short rate (r). The correlations are given both for the model without swaps and for the model with swaps. Each model is simulated for 5,200 periods and the first 200 periods are dropped. In each period, stochastic values for both z and r are realized. The same paths of shocks are used for the simulation of both models. These simulations are run using the baseline parameter calibrations. The fact that the correlation of the model's moments with the shocks are consistently higher with shocks to z than with shocks to r primarily reflects the fact that z is more volatile than r in the model calibration. It thus drives the results to a relatively larger extent.

	(1)	(2)	(3)	(4)	(5)
	Pooled	$\Delta z > 0$	$\Delta z < 0$	$\Delta r > 0$	$\Delta r < 0$
Δz	-6.254***	-9.717***	-1.830***	-2.049***	-3.061***
	(-23.99)	(-20.31)	(-3.63)	(-7.17)	(-11.30)
Δr	120.7***	107.7***	89.76***	73.64***	158.0***
	(20.34)	(18.56)	(14.80)	(6.14)	(13.96)
L.z	-3.679***	-4.918***	-2.365***	-3.818***	-4.107***
	(-15.23)	(-15.33)	(-6.74)	(-10.66)	(-12.17)
L.r	82.95***	84.91***	81.72***	82.70***	89.70***
	(26.46)	(19.79)	(18.52)	(17.64)	(20.31)
L.d_e	-0.468***	-0.429***	-0.492***	-0.481***	-0.453***
	(-67.45)	(-42.18)	(-53.22)	(-47.79)	(-45.39)
Size (a)	8.581***	7.744***	9.503***	9.841***	7.818***
	(49.74)	(33.18)	(38.60)	(38.36)	(32.64)
Debt-to-assets (b/a)	-22.04***	-19.34***	-28.02***	-25.17***	-19.75***
	(-53.89)	(-35.18)	(-43.75)	(-40.57)	(-33.36)
Δz * User	7.455***	10.77***	2.361***		
	(21.34)	(21.50)	(4.63)		
Δr * User	-44.57***			47.77***	-119.6***
	(-5.42)			(3.82)	(-10.00)
Obs.	9996	5002	4994	4930	4924
R2	0.531	0.483	0.584	0.534	0.472

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.7: Equity distributions and shocks to z and r (simulated data). The first difference of the bank's equity distribution, $\Delta e = e_t - e_{t-1}$, is regressed on innovations to the productivity and to the short rate, respectively $\Delta z = z_t - z_{t-1}$ and $\Delta r = r_t - r_{t-1}$. There are additional control variables for previous shock realizations, for bank size (a) and debt-to-assets ratio (b/a). There are two interaction terms. Innovations to z and r are interacted with a dummy variable ("User") equal to 1 if the observation has been simulated using the model with swaps and to 0 if it has been simulated using the model without swaps. 5,000 observations are simulated with each model, using the baseline calibration of the parameters. The resulting 10,000 observations are pooled in one dataset. The main coefficients of interest are those on "$\Delta z * \text{User}$" and "$\Delta r * \text{User}$". In the first column, all bank-period observations. Other columns correspond respectively to observations where $\Delta z > 0$, $\Delta z < 0$, $\Delta r > 0$ and $\Delta r < 0$. For size and investment variables, I take the natural logatithm of the actual value.

is consistent with the use of payout flexibility as a substitute to derivatives hedging for risk management. For example, Bonaimé et al. (2013) show that U.S. bank holding companies (BHCs) that use derivatives for hedging purposes also smooth equity payout, and that the causality does not go from hedging to payout smoothing. Their result implies that hedging and payout decisions are jointly determined, as in my model. They find that both are substitutes for risk management in the cross-section of BHCs and in the time dimension (within-BHC variation). Their empirical results are fully consistent with the predictions of the model, which can be seen as providing a theoretical microfoundation for this substitution effect.

Third, the correlation between dividend distributions to equity holders and real shocks is larger in the model with swaps than in the model without swaps, as shown in table 1.6. When faced with a positive shock to z, the bank in both models increases lending: Investment has a strong positive correlation with z, as seen in table 1.6. The resources used to do so differ in both models. Both banks increase short-term debt. The bank in the model without swaps, however, uses a greater share of current cash flows to increase lending. It cuts dividend distributions. In contrast, a derivatives user bank had optimally transferred resources to states in which large investment is optimal. When such a state is realized, it uses a lower share of present cash flows to finance investment, and can instead maintain or increase distributions to equity holders to a larger extent. This mechanism implies a larger positive correlation between $e\left(.\right)$ and z for users than for non-users. The fact that, in the model without swaps, the bank uses a larger share of current cash flows to increase lending and finance current expenses is also seen in table 1.5.

The effect of swaps on the response of payout to shocks is further seen using a regression analysis on simulated data. An equal number of 5,200 bank-period observations simulated from each model are pooled. I focus on the dynamics of equity distribution, conditional on shock realizations. A first-difference regression analysis is conducted. The first difference of the bank's equity distribution, $\Delta e \equiv e_t - e_{t-1}$, is regressed on the contemporaneous change in productivity and short rate (denoted $\Delta z_t \equiv z_t - z_{t-1}$ and $\Delta r_t \equiv r_t - r_{t-1}$). I control for shock realizations in the previous period, i.e. z_{t-1} and r_{t-1}, for change in dividend distribution in the previous period, Δe_{t-1}, and for bank size and debt-to-assets ratio at the beginning of period t, before e is decided upon. The results are in table 1.7.

In the sample with all bank-period observations, an increase in z is associated with a lower dividend distribution. An increasing short rate is also associated with a decreasing dividend. These patterns are consistent with the idea that, when high lending is optimal, the bank uses a greater share of current cash flows to finance investment, and therefore

cuts dividend distributions. The coefficients on the interaction terms, however, are significant at a 1% level and indicate that users increase distributions when faced with a higher z. Banks with a higher debt-to-assets ratio distribute lower dividends. A larger share of their cash flows is used to meet interest payments and investment outlays are paid for by distributing lower dividends ceteris paribus. Furthermore, in columns (2) to (5), the asymmetric effects of positive and negative shocks to z and r are analyzed. The regression is run on subsamples restricted to positive and negative values of Δz and Δr. The magnitude of most coefficients is different for positive and negative shocks, highlighting the asymmetric effects of positive and negative shocks on payout policy. Noticeably, while users on average increase or maintain dividend distributions when $\Delta z > 0$, banks in the model without swaps cut payout.

1.6.3.4 Hedging and lending dynamics

How is lending affected by the possibility to trade swaps? This section yields two main results. First, there are significant differences between users and non-users in the response of bank lending to both interest rate *and* real shocks. Derivatives users are better able to exploit positive shocks than non-users. The standard deviation of lending is also lower for banks using derivatives, implying that lending by user banks is less sensitive to aggregate shocks. Second, differences in lending between users and non-users are larger is periods when bad shock realizations hit, i.e. either when the short rate rises or when productivity decreases.

A regression approach is used to provide a granular view of the impact of derivatives on bank lending. An equal number of 5,000 bank-period observations simulated from each model are pooled. Investment i is regressed on Δz_t and Δr_t. I control for shock realizations in the previous period, for investment in the previous period, i_{t-1}, and for bank size at the beginning of period t, before i is decided upon. Given concave returns on loans, a larger bank must increase lending less when faced with a marginal loan opportunity. A larger debt-to-assets ratio may also be detrimental to the bank's ability to lend, because contemporaneous interest payments are higher. I do not include it, however, because it is highly correlated with previous shock realizations (and, as expected, it correlates negatively with current investment). I finally include interaction terms between either Δz_t or Δr_t and a dummy variable, denoted "User", that equals 1 if the observation has been generated using the model with swaps and 0 otherwise. The coefficient of interest is that on this interaction term, as derivatives users and non-users are expected to react differently to the same innovations Δz_t or Δr_t. Regression results obtained with the OLS estimator are in tables 1.8 and 1.9.

	(1)	(2)	(3)	(4)
	i	i	i	i
Δr	-59.00***	-58.97***	-82.88***	-29.30***
	(-15.60)	(-20.86)	(-14.83)	(-5.57)
z_t-1	-0.0686	2.229***	2.191***	2.252***
	(-0.93)	(26.60)	(18.09)	(19.36)
r_t-1	-10.51***	-14.12***	-13.23***	-14.50***
	(-6.83)	(-11.74)	(-7.47)	(-8.61)
i_t-1	-0.0938***	-0.0643***	-0.0799***	-0.0717***
	(-8.79)	(-7.62)	(-6.51)	(-6.10)
Δr * User	18.13***	17.85***	55.58***	-19.36***
	(3.46)	(4.56)	(9.73)	(-3.61)
Δz		6.903***	7.173***	6.624***
		(88.70)	(63.75)	(61.70)
Size (a)		-0.294***	-0.300***	-0.254***
		(-10.61)	(-7.30)	(-6.73)
Obs.	9998	9998	4932	4924
R2	0.043	0.465	0.472	0.450

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.8: Bank lending and interest rate shocks (simulated data). New loans or "investment", denoted i, is regressed on innovations to the productivity and to the short rate, respectively $\Delta z = z_t - z_{t-1}$ and $\Delta r = r_t - r_{t-1}$. There are additional control variables for previous shock realizations, for bank size (a) and debt-to-assets ratio (b/a). The innovation to r is interacted with a dummy variable ("User") equal to 1 if the observation has been simulated using the model with swaps and to 0 if it has been simulated using the model without swaps. 5,000 observations are simulated with each model, using the baseline calibration of the parameters. The resulting 10,000 observations are pooled in one dataset. The coefficient of interest is that on "Δr * User". The first and second specifications use all bank-period observations. In the third column, the model is estimated only for observations in which $\Delta r > 0$. In the fourth column, the model is estimated only for observations in which $\Delta r < 0$.
For size and investment variables, I take the natural logatithm of the actual value.

	(1)	(2)	(3)	(4)
	i	i	i	i
Δz	8.614***	8.590***	5.871***	10.65***
	(89.94)	(92.60)	(44.90)	(53.20)
z_t-1	1.539***	1.910***	2.454***	1.811***
	(26.75)	(23.61)	(28.73)	(13.65)
r_t-1	-2.452**	-12.28***	-15.65***	-11.24***
	(-2.24)	(-10.65)	(-12.79)	(-6.13)
i_t-1	-0.0854***	-0.0712***	-0.0632***	-0.0876***
	(-10.81)	(-8.81)	(-7.17)	(-6.95)
Δz * User	-4.571***	-4.436***	-2.675***	-6.148***
	(-30.90)	(-30.53)	(-17.33)	(-25.76)
Δr		-50.03***	-41.51***	-59.84***
		(-25.62)	(-19.98)	(-19.43)
Size (a)		-0.156***	-0.0681***	-0.445***
		(-5.79)	(-2.63)	(-8.86)
Obs.	9998	9998	4995	5002
R2	0.476	0.510	0.408	0.416

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.9: Bank lending and real shocks to z (simulated data). New loans or "investment", denoted i, is regressed on innovations to the productivity and to the short rate, respectively $\Delta z = z_t - z_{t-1}$ and $\Delta r = r_t - r_{t-1}$. There are additional control variables for previous shock realizations, for bank size (a) and debt-to-assets ratio (b/a). The innovation to z is interacted with a dummy variable ("User") equal to 1 if the observation has been simulated using the model with swaps and to 0 if it has been simulated using the model without swaps. 5,000 observations are simulated with each model, using the baseline calibration of the parameters. The resulting 10,000 observations are pooled in one dataset. The coefficient of interest is that on "$\Delta z * $User". The first and second specifications use all bank-period observations. In the third column, the model is estimated only for observations in which $\Delta z > 0$. In the fourth column, the model is estimated only for observations in which $\Delta z < 0$. For size and investment variables, I take the natural logatithm of the actual value.

All coefficients on the shocks and on the control variables have the expected signs. To investigate the effect of the use of derivatives on lending, I proceed in two steps. First, all bank-period observations are pooled. Second, the sample is split either between periods when $\Delta z > 0$ and $\Delta z < 0$ or between periods when $\Delta r > 0$ and $\Delta r < 0$. These regressions conditional on shock signs are in the third and fourth columns of tables 1.8 and 1.9.

As regards the interest rate shock (table 1.8), a positive coefficient is obtained in the whole sample on "$\Delta r * \text{User}$", while that on Δr is negative. Both are significant at a 1% level. As such, these results indicate that lending by derivatives users reacts less to interest rate shocks than for non-users, in line with empirical evidence by Purnanandam (2007). Results on the split sample, however, indicate that the positive coefficient sign on the interaction term is driven by periods in which $\Delta r > 0$. Instead, when restricted to periods in which $\Delta r < 0$, the coefficient sign flips to negative. These results indicate that derivatives users increase lending more than non-users when faced with a lower short rate and cut lending less when positive interest rate shocks hit. The magnitude of the coefficients on the interaction term is also different for upward and downward interest rate shocks. While the difference in lending between users and non-users when $\Delta r < 0$ is significant, it is sizeably larger in periods in which $\Delta r > 0$. Differences in lending between users and non-users are larger at times the short rate rises. Users are better able to maintain their credit policy at times the interest rate environment is contractionary.

Lending by users and non-users also responds differently to real shocks (table 1.9), even if innovations to z are uncorrelated with innovations to the short rate. A similar pattern is observed. A negative coefficient on "$\Delta z * \text{User}$" is obtained in the whole sample, while that on Δz is positive. Results in the split sample make it clear that the negative coefficient sign on the interaction term is driven by periods in which $\Delta z < 0$, i.e. downturns. When $\Delta z > 0$, the coefficient sign flips to positive. These results indicate that derivative users increase lending more than non-users when faced with positive real shocks and cut lending less in face of a negative real shock. The magnitude of the estimated coefficients also implies that differences in lending between users and non-users are likely larger in downturns. If derivatives non-users are forced to downsize to a larger extent in states where cash flows are low, they may be unable to seize profitable investment opportunities in such states. As in Rampini and Viswanathan (2010), capital may be less productively allocated during downturns.

How are these results brought about in the model? Swaps are not used for the purpose of smoothing lending, but for that of actively exploiting transitory profit opportunities. This optimally yields an asymmetric response to "good" and "bad" shock realizations.

To see this, consider first a "bad" realization of a shock, either a low z or a high r. The bank, whether user or not of derivatives, optimally cuts lending. It does so for two reasons. First, because the marginal profitability of lending no longer outweighs the cost of funds. It downsizes to regain profitability. Second, because it wants to restore debt capacity for future investment. It is indeed the case that the bank optimally preserves debt capacity when "bad" shocks hit and exhausts debt capacity when "good" shocks hit (see section 1.5.2.3). Given that a user bank needs to preserve less debt capacity on average, it optimally cuts lending to a lower extent when faced with a "bad" shock realization, either to productivity or to the short rate.

On the upside, the fact that derivatives users are better able to exploit profit opportunities arising from "good" shock realizations can be explained from the fact that they issue less equity on average. Given the convex component of $\eta\left(e\left(.\right)\right)$, banks relying on external equity for financing loans are likely to under-invest to a severe extent, compared to a frictionless benchmark. This comparison between users and non-users holds after controlling for size: Unconditionally, non-user banks, which are smaller on average, may increase lending more when faced with a good shock realization, due to the concavity of $\pi\left(.\right)$ in a. These intuitions from the model are consistent both with the stylized facts of section 1.10.2.1 and with the simulations.

1.6.3.5   Pay-fixed versus pay-float positions

As an outcome of the model, both pay-fixed and pay-float positions can be optimally chosen by the bank. This section discusses the incentives behind the choice of each position type and the bank characteristics associated with each position sign.

First, regarding any type of swap position, the average bank size a and value V is larger in periods where $d' \neq 0$, as compared to the average size over all periods. This is true even if the fixed cost of using swaps, c_f, is zero. It is reflective of the fact, discussed above, that larger banks have a larger stock of collateral and a lower opportunity cost of collateral pledged for derivative positions.

Second, whether a bank chooses a pay-fixed or a pay-float position depends on whether equity is likely to be issued in the next period for high or for low realizations of the short rate r'. When the financing motive for interest rate risk management dominates, the bank manages the risk that the cost of debt financing may be high at times lending opportunities driven by shocks to z are large. It thus aims at transferring resources from future states where r' is low to states where it is high. Such transfers to states in which r' is high can be achieved using pay-fixed swaps ($d' > 0$), which yield a positive payoff when the future short rate is above the present swap rate.

Instead, if the bank's motivation for risk management arises from investment concerns, or because its investment policy is very sensitive to changes in its discount factor $1/(1+r)$, it aims to transfer resources to future states in which r' is low. The bank aims to invest in states where r' is low because cash flows are higher in such states, and because future dividend distributions are valued to a relatively larger extend, as compared to present distributions. Transfers to these states where investment opportunities arise from low realizations of r' are made possible by pay-float swaps ($d' < 0$). Pay-float swaps yield a net positive payoff whenever the future short rate is below the present swap rate.

Consequently, pay-fixed and pay-float swap positions are associated with different balance sheet characteristics and shock realizations. The financing motive is relatively more important when z' is expected to be high next period, or when the volatility σ_z is larger. Pay-fixed positions tend to be associated with such characteristics. In contrast, the investment motive for risk management becomes more prevalent as γ increases. A higher value of γ is thus associated with an increasing reliance on pay-float positions.

1.6.4 Relation to stylized facts

This section relates some of the model's predictions with the data. The predictions about cross-sectional and time series differences between derivatives users and non-users are discussed in relation with the stylized facts of section 3.3.

1.6.4.1 Cross-sectional predictions

In the cross-section, the model predicts that banks using derivatives are larger on average. This is consistent with the first stylized fact of section 3.3.

Turning to predictions about the composition of assets and liabilities, the main results also match the stylized facts of section 3.3. On the liability side, banks in the model with swaps have a higher ratio of short-term debt to assets. In the data, derivatives users rely more on wholesale funding and less on deposits, i.e. they are more exposed to liabilities being sensitive to fluctuations of the short rate. The model's predictions are thus consistent with the second stylized fact.

The equity ratio, observed in the data, is not explicitly part of the model. However, the fact that equity is issued more often in the model without swaps, and as a larger proportion of total assets, can be seen as suggestive evidence that equity financing is relatively more important for non-user banks than for derivatives users. Furthermore, the greater use of "payout flexibility" by non-users for risk management is fully consistent

with stylized fact 6 and with the empirical evidence by Bonaimé et al. (2013), as discussed in section 1.6.3.3.

On the asset side, the bank in the model with swaps holds more loans than the bank without swaps, consistent with stylized fact 3. In the data, it is also observed that user banks have a higher ratio of loans to total assets. Moreover, non-user banks hold a larger fraction of their assets as liquid assets such as cash and securities. The model also predicts that banks in the model without swaps keep more cash on average. The number of periods in which they hold positive cash, and the amount held on average, are both larger. This is also consistent with the descriptive statistics in table 1.11.

1.6.4.2 Time series predictions

In the time dimension, the most important predictions of the model are related to the dynamics of bank lending. They are broadly consistent with the main results by Purnanandam (2007) and with those of section 1.10.2. Another set of time series predictions relates to the dynamics of payout policy, and has been discussed on empirical grounds in section 1.6.3.3.

Derivatives users are able to shield their lending policy from interest rate shocks. Both in the data and in the model, banks that do not use derivatives reduce lending to a significant extent when the short rate rises. Such states can be interpreted as periods of contractionary monetary policy. In contrast, banks that use derivatives are able to maintain their lending policy to a larger extent. This is fully consistent with stylized fact 4. The response to GDP shocks is also consistent with stylized fact 5.

At a more granular level, the model predicts that differences in lending between derivatives users and non-users are larger and more significant at times "bad" shocks hit, i.e. either at times the short rate rises or when the GDP decreases. Existing papers do not provide empirical evidence on the asymmetric effects of "good" and "bad" shock realization on derivatives-driven differences in lending patterns. The preliminary analysis of section 1.10.2, however, based on a replication of Purnanandam (2007) for a later time period, provides suggestive evidence consistent with the model.

In the data, the negative relation between the Fed funds rate and bank lending for non-users is driven by periods in which ΔFED is above its sample median, i.e. mainly by quarters in which the Fed funds rate rises. Similarly, the positive relation between GDP and bank lending is driven to a larger extent, for both users and non-users, by the subset of periods in which ΔGDP is below its median value, inclusing periods of GDP contraction. The full documentation of these asymmatric patterns is left for future

research. They suggest, however, that the strongly asymmetric effects, driven by periods in which "bad" shocks hit, predicted by the model and discussed in section 1.6.3.4, are also observed in the data.

1.6.5 Extension 1: Cost to asset adjustment

This section extends the baseline model by adding a second friction, in the form of an adjustment cost to the long-term asset stock. Adjustment costs are a realistic feature for banking firms. They have a direct effect on the optimal risk management policy.

1.6.5.1 Functional form

In the baseline model, the only friction relates to the bank's financing. Equity is costly and debt is limited by the collateral constraint. Costs related to the adjustment of the asset stock are also a realistic feature. Banks do not choose their whole asset portfolio each period. They instead enter each period with a portfolio of long-term loans or other commitments that may not be liquidated costlessly. Adjustment costs are particularly relevant for banks engaged in maturity mismatching, as assets are in place for a longer time period than liabilities.

Adjustment costs can be of several types. First, for a bank willing to increase a, there are increasing search, screening and monitoring costs as the quality of the marginal borrower deteriorates. Second, if a is to be decreased, part of the long-term assets may be illiquid and have a liquidation value below their net present value (Diamond and Dybvig, 1983; Shleifer and Vishny, 1992). Alternatively, loan sales and securitization entail costs such as issuance expenses of debt, credit enhancements, rating and structuring fees or management time (Ashcraft and Schuermann, 2008).

The cost to asset adjustment is incurred when investment i is non-zero. It is given by

$$C\left(a,i\right) = \varphi_0 a \mathbb{1}_{\{i \neq 0\}} + \varphi_1 \frac{i^2}{2a} \tag{1.21}$$

The functional form for $C\left(a,i\right)$ is a standard choice in the empirical investment literature, inspired by Cooper and Haltiwanger (2006). The first term is a fixed adjustment cost with $\varphi_0 \geq 0$, proportional to the loan stock, so that the bank does not grow out of the fixed cost. The second component is convex with $\varphi_1 \geq 0$. The convex component is lower for larger banks, based on the idea that investment is less disruptive for them.

After inclusion of the adjustment cost, the equity distribution rewrites as

$$
\begin{aligned}
e\left(a, a', b, b', d, z, r, r_{-1}\right) =\ & (1-\tau)\,\pi\left(a, z, r\right) - C\left(a, i\right) - \left(a' - (1-\delta)a\right) + \frac{\tau r b'}{\left(1+r\right)^2} \\
& + \frac{b'}{1+r} - b + d\left(r - \left(r_{-1} + p_{-1}\right)\right) - c\left(d'\right),
\end{aligned}
$$

(1.22)

and the value function in equation (1.16) is re-expressed accordingly.

1.6.5.2 Costly asset adjustment and risk management

Costs to asset adjustment introduce a new form of path-dependency in the bank's capital structure. Date-t's decisions about the asset stock may hinder the bank's optimal investment policy at $t+1$ if adjustment costs are large. This is particularly true is the adjustment cost has a convex component, in which case the bank has an incentive to smooth investment over time. For example, if reducing the bank's asset stock is costly, the bank may optimally invest less ex ante, when faced with lending opportunities.

The optimal risk management policy is altered by the introduction of a cost to asset adjustment. First, the bank trades off present versus future investment, by taking adjustment costs into account. In contrast with the investment Euler equation of section 1.5.2.1, in which the cost of foregone investment is the marginal profitability of a, the bank here also optimally balances the cost of present adjustment and the expected cost of future adjustment. To see this, rewrite the investment Euler equation, assuming $\eta_1 = \eta_2 = 0$, for simplicity. One obtains

$$
\begin{aligned}
1 + C_i\left(a, i\right) = \frac{1}{1+r} \int \int \Big[& (1-\tau)\,\pi_a\left(a', z', r'\right) - C_a\left(a', i'\right) \\
& + (1-\delta)\left(1 + C_i\left(a', i'\right)\right) \Big] \mathrm{d}g_z\left(z'|z\right) \mathrm{d}g_r\left(r'|r\right)
\end{aligned}
$$

(1.23)

This condition equalizes the marginal cost of investment at dates t and $t+1$. Increasing lending by an additional unit at date t costs its price of 1, plus the additional adjustment cost to be paid, $C_i\left(a, i\right)$. The shadow cost of lending at $t+1$ is the foregone marginal product of investment today, $(1-\tau)\,\pi_a\left(.\right) - C_a\left(.\right)$, plus the marginal cost of investment next period, $1 + C_i\left(a', i'\right)$. The term $C_i\left(a', i'\right)$ is the expectation over the future investment cost conditional on choosing a' today and on i' being optimal next period. Equation (1.23) makes it clear that the bank trades-off present and future adjustment costs. It may optimally forego present lending opportunities if the expectation over future adjustment costs is too high.

The introduction of a cost to asset adjustment affects the risk management policy through its impact on optimal investment. If the adjustment cost is highly convex, a given profit opportunity will be exploited will be exploited with a smaller lending outlay. Investment is less volatile and future investment expenditures are more predictable. Consequently, the bank finds it optimal to preserve less debt capacity and to maintain a less flexible payout policy. This can be seen by simulating the model without swaps for several values of φ_1. Results in table 1.4 show that the bank maintains a higher debt-to-assets ratio (row 3), keeps positive debt in more periods (row 5) and user a larger percentage of its debt capacity (row 9).

The optimal swap hedging policy also changes. Overall, the bank uses swaps in fewer periods, and the average holdings of swaps is of smaller size. This is consistent with the fact that the bank engages in less risk management overall. Whether pay-fixed or pay-float positions are used to a larger extent depends importantly on other structural parameters such as ρ_z and ρ_r. Intuitively, the bank is more willing to increase lending marginally, thus to pay the adjustment cost, if it can enjoy a higher marginal profitability for a longer time period. Whether risk management arises primarily from financing or investment motives depends on the shock properties.

1.6.6 Extension 2: Heterogeneous banks

This section presents a simple extension of the model with swaps. It considers a continuum of heterogeneous banks, rather than one bank facing an aggregate shock. There is both transitory and permanent heterogeneity. Instead of comparing the models with and without swaps, this model extension uses only the model with swaps, and yields an endogenous sorting of swap users and non-users. Both types co-exist simultaneously.

Transitory and permanent heterogeneity play a different role. Transitory heterogeneity arising from idiosyncratic shocks enables the coexistence within each period of both pay-fixed and pay-float positions in the set of banks. Permanent heterogeneity enables matching the persistence in the use of derivatives in the time dimension, i.e. the fact that banks actively using swaps in one quarter tend to actively use swaps next quarter.

1.6.6.1 Heterogeneity between banks

There is a continuum of incumbent banks. For concision, both permanent and idiosyncratic heterogeneity are introduced simultaneously. They are, however, discussed seperately in the results.

Permanent and transitory heterogeneity are interpreted differently. Permanent heterogeneity across bank can reflect time-invariant differences in business models, in organization or in location, among others. Transitory heterogeneity comes in the forms of an idiosyncratic shock s in addition to the aggregate shock z. In the context of banking firms, the combination of z and s can be thought of as reflecting respectively aggregate loan performance conditions and bank-specific exposures to sectoral loans, geographical areas or asset classes with heterogeneous returns. It has a natural interpretation in terms of systematic and idiosyncratic components of a bank's exposure.

Each bank has an idiosyncratic and time-invariant profit-making ability h drawn from a probability distribution $\mathcal{H}$ with bounded support $\left[\underline{h}, \overline{h}\right]$. The realization of the idiosyncratic factor entering a bank's payoff function is denoted s. It follows a Markov process $g_s\left(s'|s\right)$ given by

$$\ln\left(s'\right) = \rho_s\ln\left(s\right) + \epsilon_s', \tag{1.24}$$

in which $\epsilon_s' \sim N\left(0, \sigma_s^2\right)$. Both z ans s shocks are independently distributed.

The profit function (equation 1.1) is rewritten as

$$\pi\left(a, z, s, r\right) = hzs\left(R - r\right)^\gamma a^\theta. \tag{1.25}$$

The equity distribution $e\left(.\right)$ and the value function are rewritten by plugging $\pi\left(a, z, s, r\right)$ in equations (1.15) and (1.16) respectively.

1.6.6.2 Sorting between users and non-users

The model is solved using the calibrations given in appendix 1.13.2. The number of simulated banks is $N = 1,000$.

The model with heterogeneous banks yields endogenous sorting between derivatives users and non-users in the cross-section of banks each period. Sorting is based on two mechanisms. First, the direct cost of using swaps (equation 1.14) outweights the benefits of hedging for some banks. Second, the mechanism detailed in section 1.6.3.1 is a play. Because both debt and swaps are collateralized, hedging implies that the bank's debt capacity, thus its ability to exploit present lending opportunities, are reduced. This shadow cost increases as the present marginal productivity of investment is higher. It is thus higher for small banks. This effect prevails even if there is no direct cost of using swaps, $c\left(d'\right) = 0$.

Each type of heterogeneity plays a distinct role in the sorting mechanism. Permanent heterogeneity introduces permament differences in the steady state size of banks. Because larger banks use more derivatives in the model (because the marginal profitability of foregone investment is lower for them), permanent heterogeneity makes it possible to match the fact that the use of derivatives is persistent over time. In the data, banks that do not use derivatives in one quarter have a high probability of not using them in the next quarter, and vice versa.

Transitory heterogeneity through idiosyncratic shocks, in contrast, makes it possible to explain the co-existence of both pay-fixed and pay-float positions within one period. Absent idiosyncratic heterogeneity, both positions signs arise in different periods only. The aggregate shock z ensures that there can be market-wide shifts (excluding positions held by market makers or outside the banking system) in the type of positions held.

1.6.7   Extension 3: Correlation between shocks

This section considers a third extension. In the baseline model, the realizations of ϵ_z and ϵ_r were assumed to be uncorrelated. This correlation, denoted $\mathrm{Corr}\,(\epsilon_z, \epsilon_r)$, is assumed to be non-zero in this section. In my sample period, from 2001 to 2013, the correlation between ΔFED and ΔGDP, at a quarterly frequency, is 0.51. Driven by monetary policy, the short rate tends to be high at times the GDP is also high.

A non-zero correlation between the realizations of ϵ_z and ϵ_r changes the relative magnitude of the financing and of the investment motive for risk management. First, recall that even when $\mathrm{Corr}\,(\epsilon_z, \epsilon_r) = 0$, the optimal hedging policy is linked to the current realizations of z and to expectations about real productivity z' next period, as the bank trades off present versus future investment when engaging in risk management.

A positive correlation between ϵ_z and ϵ_r implies that the cost of debt financing is higher on expectation at times investment opportunities arising from real factors are high. The financing motive for risk management becomes more important. In contrast, it is less likely that the bank is highly profitable at times the short rate is low, implying that the investment motive for risk management vanishes as $\mathrm{Corr}\,(\epsilon_z, \epsilon_r)$ increases.

The effect of correlated shocks on debt capacity is seen on figure 1.5, where the optimal debt policy and the collateral constraint is plotted in both models with correlated and uncorrelated shocks. In the correlated case, $\mathrm{Corr}\,(\epsilon_z, \epsilon_r) = 0.5$. There are two results. First, for high values of r, the bank optimally has a higher debt, as high realizations of the short rate are also statistically associated with high productivity shocks. The opposite effect is true for low values of r, where the bank holds less debt when shocks
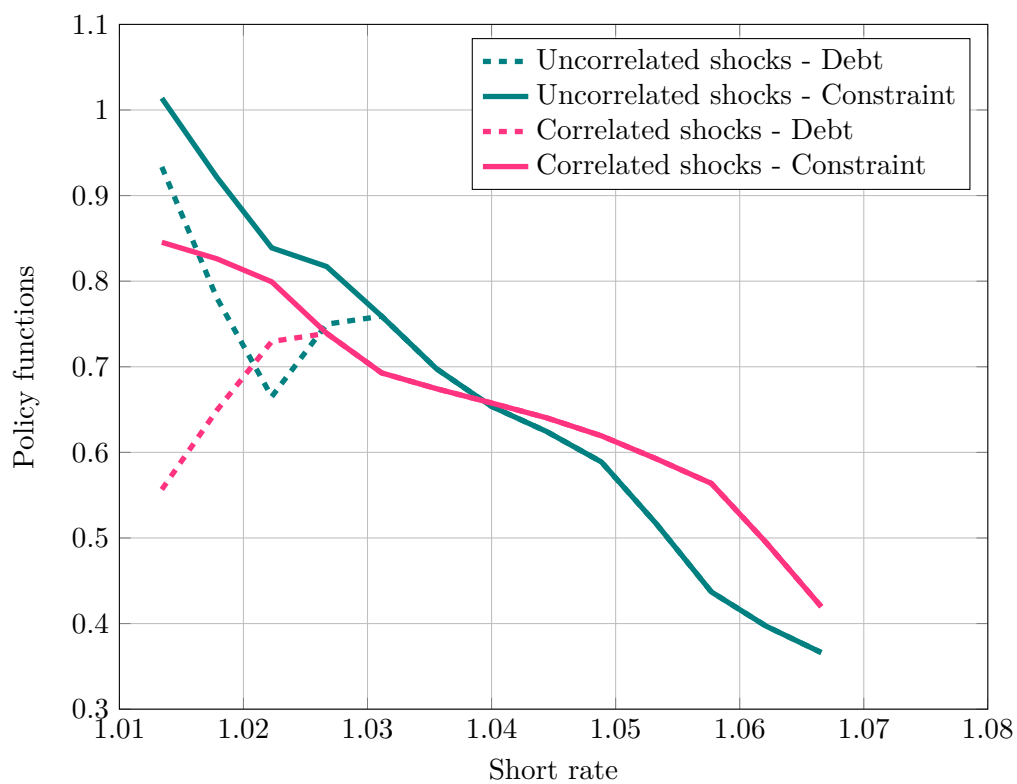
FIGURE 1.5: Debt policy with correlated and uncorrelated shocks This chart plots the optimal debt policy and the collateral constraint for the model with uncorrelated (in blue) and correlated (in red) shocks to z and r. In each case the debt policy is in dashed lines. Each policy function is normalized by the steady state capital shock. The correlation between the two shocks is $\text{Corr}\,(\epsilon_z, \epsilon_r) = 0.5$. Other calibrations are those of the baseline model.

are correlated. Second, when r is low, the bank keeps more free debt capacity (seen as the difference between the constraint and actual debt) when shocks are positively correlated, as the financing motive is higher for this bank. Given that the financing motive is more important as $\text{Corr}(\epsilon_z, \epsilon_r) > 0$, the bank also optimally uses more pay-fixed positions, i.e. transfers more resources toward future states where r is high.

1.7 Risk management with defaultable debt

This section extends the model by relaxing the assumption that debt contracts are collateralized. Banks may optimally choose to default on their debt. The results of the preceding section are generalized. A new set of questions also arises, as introducing default decisions—when decisions are taken in the interest of shareholders—creates an agency problem between debt and equity holders. I document whether derivatives hedging mitigates or exacerbates this conflict, thus decreases or increases the frequency of bank defaults. The focus of this section is theoretical and its purpose is exploratory. Empirical predictions and tests of the model with defaultable debt are left for future work.

There are a number of differences between this extension and the baseline model. First, the interest rate paid by the bank is no longer the risk-free rate r, but incorporates a default premium. Swap contracts are collateralized and senior in case of default. Because debt is not collateralized, debt and swaps no longer interact through the collateral constraint, as earlier.

Second, bank default is costly. Upon default, the creditors recover only a fraction of the bank's cash flows and of the liquidation value of the assets. The cost to bankruptcy provides an additional motive for risk management and introduces an agency conflict betwen debt and equity holders. This is because default is costly, but decisions are taken in the interest of shareholders, who may find it optimal to default for some shock realizations.

While risk management arising from the cost to equity financing makes it necessary to transfer resources from future states where productivity is low to states where it is high, risk management aimed at avoiding costly bankruptcy requires the inverse transfer. The overall effect also depends on the relative magnitude of the financing and of the investment motive for risk management and on the relative magnitude of both frictions (cost of equity financing and bankruptcy cost). The model yields endogenous sorting between banks engaged in each type of risk management.

There is a dual effect of swap hedging on the bank's debt capacity. First, trading swaps may drive the bank's probability of default up or down. Second, it also changes the expected recovery value for creditors upon default. Together, these effects imply that using swaps may increase or decrease the bank's debt capacity, depending on the type of risk management it engages in. Agency conflicts can be more or less severe and defaults more or less frequent. In case they are more frequent, a trade-off between shareholder value and default exists.

Even though most short-term bank debt is collateralized (in the form of repurchase agreements, among others), risky debt has additional interesting features. It can be more realistic than riskless debt under some circumstances. It allows for interest rate spikes driven by counterparty risk (see Afonso et al., 2011, for an empirical analysis of borrower-specific counterparty risk in the Fed funds market). Moreover, when extending the model with heterogeneous banks of section 1.6.6 to a set-up with entry and exit (a la Hopenhayn (1992) and Cooley and Quadrini (2001)), the exit process can be microfounded, with default being endogenized as an optimal choice. A full-fledged heterogeneous model of this kind is left for future research.

1.7.1 Defaultable debt contracts

Each period the bank has the option to default. Default is defined by $V(.) = \bar{D}$, where the default threshold $\bar{D}$ is normalized to 0. Each period, the bank value is

$$V(.) = \max \left\{ V^{ND}(.), V^{D}(.) = 0 \right\}, \tag{1.26}$$

where V^{ND} is the bank value when repaying outstanding debt (defined below) and V^{D} the bank value when defaulting.

1.7.1.1 Risky debt

The modelling of risky debt follows that by Moyen (2004) and Hennessy and Whited (2007). Upon default, shareholders receive the threshold value $\bar{D} = 0$. Both the bank's cash flows and the asset stock incur a deadweight cost of default $\xi > 0$. The total recovery value in default, denoted $\mathcal{R}$, is thus:

$$\mathcal{R}(a, z, r) = (1 - \xi)\left[(1 - \delta)a + (1 - \tau)\pi(a, z, r)\right]. \tag{1.27}$$

$\mathcal{R}(.)$ is shared between debtholders and counterparties in the swap market. I assume that swap contracts are senior in the default process. This assumption mimicks the

exclusion of swap contracts from automatic stays in banktuptcy, as described by Duffie
and Skeel (2012) and Bolton and Oehmke (2014). Furthermore, I assume that swaps are
fully collateralized and always paid in full, i.e. that the recovery value of equation (1.27)
must be greater than the largest swap payment that the bank may have to honor at
$t + 1$. This implicitly defines boundary values on the maximum pay-fixed and pay-float
positions that the bank may take. It also implies that default probabilities do not enter
the swap pricing formula (equation 1.13).

In contrast, the pricing of debt depends on the recovery value in default for creditors,
conditional on swap contracts being senior and paid in full. Given the shock realizations,
the recovery value in default for debtholders, denoted $\mathcal{R}^B$, is:

$$\mathcal{R}^B\left(a, d, z, r, r_{-1}\right) = \mathcal{R}\left(a, z, r\right) + d\left(r - \left(r_{-1} + p_{-1}\right)\right) \tag{1.28}$$

The bank pays a risky interest rate, denoted $\tilde{r} \equiv \tilde{r}\left(z, r, a', b', d'\right)$, that incorporates
a default premium. It is a function of both current shocks and next-period control
variables. Given the default threshold $\bar{D} = 0$ and the value function, the bank knows
the set of future default states, i.e. values of the control variables and future shock
realizations such that $V^{ND}\left(z', r', a', b', d'\right) \leq 0$. For a given set of control variables
(a', b', d') and current shocks (z, r), the bank knows from g_z and g_r the probability
distribution over future default states corresponding to its choice of controls. Denote
$\Delta\left(a, b, d\right)$ the set of states and realization of the shocks such that the bank finds it
optimal to default, i.e.:

$$\Delta\left(a, b, d\right) = \left\{\left(z, r\right) \text{ s.t. } V\left(a, b, d, z, r\right) \leq 0\right\} \tag{1.29}$$

Lenders are risk-neutral. The risky interest rate is set such that they break even in
expectation. $\tilde{r}\left(.\right)$ solves:

$$\begin{aligned}
\left(1 + r\right) b' &= \left(1 - \text{Pr}_{z,r}\left(\Delta\left(a', b', d'\right)\right)\right)\left(1 + \tilde{r}\right) b' \\
&\quad + \text{Pr}_{z,r}\left(\Delta\left(a', b', d'\right)\right) \int \int \mathcal{R}^B\left(a', d', z', r', r\right) \mathrm{d}g_z\left(z'|z\right) \mathrm{d}g_r\left(r'|r\right),
\end{aligned} \tag{1.30}$$

where $\text{Pr}_{z,r}\left(.\right)$ is the probability of being in the default state next period conditional on
observing current shock realizations (z, r). The first term on the right-hand side is the
return on risky debt if the bank does not default. The second term is the expectation
over the recovery value in the event of default. The expected return on the risky bond
equals the risk-free rate.

When solving for the optimal level of debt b', attention can be restricted to a subset of
combinations of b' and $\tilde{r}$. First, note that the bank can always issue some amount of

riskless debt at rate r. Unless its swap position d' is such that, for some realizations of the short rate r', all future collateral value is absorbed by swap payments, the bank can pledge part of its future cash flows and asset stock to its creditors. For a low enough value of b', the bank never optimally defaults. Its cash flow $\pi(.)$ can always be greater than the debt to be repaid, in which case the equity holders obtain either a positive present payoff or a positive continuation value, or both. Turning to the region where debt is modestly risky, $\tilde{r}$ is increasing in b' and the bank can raise more debt by promising a higher yield. However, as $\tilde{r}$ increases, the bank reaches a region where further increases in $\tilde{r}$ reduces b'. Such pairs $\{b', \tilde{r}\}$ are dominated on efficiency grounds. Attention can be restricted to pairs $\{b', \tilde{r}\}$ where b' is increasing in $\tilde{r}$.

1.7.1.2 Agency conflict between debt and equity

The model embeds an agency conflict between debt and equity holders, which yields to under-investment. This conflict arises from the existence of deadweight bankruptcy costs. Because of deadweight default costs, the ex post efficient policy would entail never defaulting. However, default losses are paid by debt holders, while the bank's managers take decisions in the interest of equity holders. Thus, when the maturing debt level is sufficiently high, the bank optimally defaults for some shock realizations associated with low cash inflows and continuation value. The value of installed capital is reduced by the possibility of default. This effect depresses lending compared to the first best.

1.7.1.3 Value function

Given the definition of the risky rate in equation (1.30), the equity distribution/issuance function (1.15) rewrites as

$$
\begin{aligned}
e(.) &= (1-\tau)\pi(a,z,r) - (a' - (1-\delta)a) + \frac{b'}{1+\tilde{r}} \\
&\quad + \frac{\tau\tilde{r}b'}{(1+\tilde{r})(1+r)} - b + d(r - (r_{-1} + p_{-1})) - c(d'),
\end{aligned}
$$
(1.31)

where $\tilde{r}$ is the risky interest rate paid by the bank.

While the bank pays a rate $\tilde{r} \geq r$ on its short-term debt, it trades the risk-free rate r through its swap contracts. The difference between both rates highlights a feature of swaps contracts, also discussed by Titman (1992). Swaps isolate the default-free component of interest rates from the default premium. Only the default-free component is traded, as the default premium in $\tilde{r}$ does not enter the swap payoff function.

The Bellman equation with defaultable debt rewrites:

$$V^{ND}(a, b, d, z, r, r_{-1}) = \sup_{a', b', d'} \Big\{ e(.) - \eta(e(.)) \tag{1.32}$$

$$+ \frac{1}{1+r} \int \int V(a', b', d', z', r', r) \, dg_z(z'|z) \, dg_r(r'|r) \Big\}, \tag{1.33}$$

where the continuation value is discounted by the riskless rate, which is the opportunity cost of funds.

When solving for (1.32), attention is restricted to swap usage for hedging truly-held underlying exposures, i.e.

$$\frac{\partial}{\partial r'} \left[(1-\tau) \pi(k', z', r') + d(r' - (r+p)) \right] \le 0 \tag{1.34}$$

This ensures that the current payoff that the bank gets is decreasing in r. While swaps may be used to transfer resources from "low r" to "high r" states, if $d' > 0$, swap exposures cannot be taken to the extent that the firm is overall better off when facing a higher short rate. Under mild assumptions, this is a natural outcome of the model solution and does not add any additional constraint.

Furthermore, it is useful to establish the monotonicity of the value function in z 1 does.

Proposition 1. Given state variables $\{a, b, d, r_{-1}\}$ and a realization of r, the value function V^{ND} is nondecreasing in z.

Proof 1. See appendix 1.14.2.

1.7.1.4 Default threshold

To examine optimal risk management in this model, it is useful to refine the notations. Let $r^d(a', b', d', r, z')$ be the critical short rate realization inducing default at date $t+1$, given the current short rate r, a choice of controls a', b' and d' and a future realization of the productivity shock z'. $r^d(.)$ is such that the firm defaults if $r' > r^d$ and continues operating otherwise.

The existence of $r^d(.)$ follows from the fact that V^{ND} is nonincreasing in r. It is implicitly defined by

$$V^{ND}(.) = 0 \tag{1.35}$$

The default threshold is increasing in its first and fifth argument, and decreasing in its second and fourth argument. These properties follow from the monotonicity of V^{ND} in these arguments. Whether r^d increases or decreases in its third argument, d', depends

on whether pay-fixed ($d' > 0$) or pay-float ($d' < 0$) positions are held. If $d' > 0$, the swap position is pay-fixed and transfers resources from future states in which r is low to states where it is high, i.e. to states associated with bank default to a larger extent. r^d is increasing in its third argument in this case. Conversely, r^d is decreasing in d' when $d' < 0$.

Given the definition of r^d and that of the value function in equation (1.26), the continuation value in equation (1.32) can be rewritten as

$$\int \int V\left(.\right) \mathrm{d}g_z\left(z'|z\right) \mathrm{d}g_r\left(r'|r\right) = \int_{\underline{z}}^{\overline{z}} \int_{\underline{r}}^{r^d(.)} V\left(.\right) \mathrm{d}g_r\left(r'|r\right) \mathrm{d}g_z\left(z'|z\right), \qquad (1.36)$$

where I use the fact that the probability that the bank continues operating next period conditional on a vector of controls is

$$1 - \mathrm{Pr}_{z,r}\left(\Delta\left(a',b',d'\right)\right) = \int_{\underline{z}}^{\overline{z}} \int_{\underline{r}}^{r^d(.)} \mathrm{d}g_r\left(r'|r\right) \mathrm{d}g_z\left(z'|z\right) \qquad (1.37)$$

1.7.2   Risk management

This section discusses the optimal risk management policy with endogenous default. It pays particular attention to the impact of swap trading on the bank's debt capacity, on the debt-equity agency conflict and on the default policy.

1.7.2.1   Risk management using debt capacity

The introduction of a cost to bankruptcy, ξ, creates a second incentive for risk management. The bank optimally takes decisions over short-term debt, dividend payout and swap hedging to avoid paying both deadweight default costs and costs to equity issuance. Risk management targeted to avoid paying bankruptcy costs is greater if ξ is high.

The bank's debt capacity is not limited by any collateral constraint. Instead, increasing short-term debt b' increases the required risky rate $\tilde{r}$. The bank optimally keeps short-term debt at a moderate level so that the cost of its debt service does not push it into the default region next period, or does not absorb a too large share of its future cash flows, which would reduce its ability to exploit investment opportunities. Risk management through debt capacity balances the benefits from exploiting current lending opportunities with both the probability that default costs are paid next period and that the equity issuance costs are paid, in case cash flows at $t+1$ are used for debt service while lending opportunities are large. These effects are further seen when deriving the

model's first-order condition with respect to b'. It writes as

$$\left(1 - \mathbb{1}_{\{e(.)<0\}}\left(-\eta_1 + \eta_2 e(.)\right)\right) \quad \cdot \quad \left(1 + \frac{\tau \tilde{r}(b')}{1+r} + b'\frac{\partial \tilde{r}(b')}{\partial b'}\left(-\frac{1}{1+\tilde{r}(b')} + \frac{\tau}{(1+r)(1+\tilde{r}(b'))}\right)\right)$$
$$= -\frac{1+\tilde{r}(b')}{1+r}\int\int V_b\left(a',b',d',z',r',r\right)\mathrm{d}g_z\left(z'|z\right)\mathrm{d}g_r\left(r'|r\right),$$
$$(1.38)$$

where $\tilde{r}(.)$ has been rewritten as $\tilde{r}(b')$ to make notations more explicit. There are a number of differences between equation (1.38) and the first-order condition in the problem with riskless debt (equation 1.10). As earlier, one additional unit of debt at date t provides one unit of financing that can be used for investment or distributed as dividend. It also provides an increased tax benefit (second term). Moreover, it is more valuable if costly equity is issued at t (fourth term). The third term accounts for the fact that a change in b' translates into a change in the interest rate $\tilde{r}(.)$ to be paid on each outstanding unit of debt, i.e. $b' \cdot \partial\tilde{r}(b')/\partial b'$. As b' increases, the change in $\tilde{r}$ affects negatively the debt amount that the bank gets, and positively its tax advantage.

On the right-hand side, the cost of debt is the interest rate to be paid. Furthermore, V at $t+1$ is lower for the bank if equity is issued. As earlier, additional debt at t is costly as equity is more likely to be issued next period. An additional effect follows from the definition of the value function once default is endogenous (equation 1.26). An increase in b' at t increases the likelihood that the bank is in the default region at $t+1$ through its effect on r^d. To see this, note that the right-hand side in equation (1.38) can be rewritten, using Leibniz's rule and equation (1.36), as

$$-\frac{1+\tilde{r}(b')}{1+r}\int_{\underline{z}}^{\overline{z}}\int_{\underline{r}}^{r^d(a',b',d',r,z')}V_b^{ND}\left(a',b',d',z',r',r\right)g_r\left(r'|r\right)$$
$$-\frac{\partial r^d(b')}{\partial b'}V\left(a',b',d',z',r^d(b'),r\right)\mathrm{d}g_z\left(z'|z\right),\qquad(1.39)$$

where the second term captures the increased likelihood that the bank finds it optimal to default next period, if $\partial r^d(b')/\partial b' \neq 0$. Increased debt b' is costly as such.

1.7.2.2 Swap hedging and risky debt capacity

What is the effect of swap trading on the bank's debt capacity? Debt is not collateralized, implying that debt and swaps do not directly interact through the collateral constraint, as in the baseline model. Sorting between users and non-users based on the opportunity cost of collateral no longer arises as a direct outcome of the model. Instead, the impact of swap trading on the bank's debt capacity is through its effect on the risky interest rate $\tilde{r}(.)$ charged by risk-neutral creditors for a given choice of swaps d'. There are two

effects of the bank's swap policy that are priced into $\tilde{r}(.)$. First, a particular choice d' may increase or decrease the bank's probability of default next period. Second, it changes the expected recovery value for creditors upon default. Both effects go in the same direction.

For illustrative purposes, let me first consider the hypothetical case in which default decisions would be independent from current and future realizations of r'. Under this assumption, the pricing equation (1.13) implies

$$\mathbb{E}\left[\mathcal{R}^B\left(a', d', z', r', r\right)\right] = \mathbb{E}\left[\mathcal{R}\left(a', z', r'\right)\right], \qquad (1.40)$$

, i.e. the expected recovery values before and after swap payments are equal. Swap payoffs may change the variance of the recovery value for debt holders ex post, but not its expected value, $\mathbb{E}_{z,r}\left[\mathcal{R}^B\left(.\right)\right]$. The difference between the total recovery value $\mathcal{R}$ and the recovery value for bond holders $\mathcal{R}^B$, i.e. $d\left(r - \left(r_{-1} + p_{-1}\right)\right)$ has an expectation that is independent from default states by hypothesis and equal to 0. In this case, swap contracts do not matter for the pricing of debt by risk-neutral creditors. Trading swaps has no effect on debt capacity if default events are uncorrelated with swap payoffs.

Default states, however, are not independent from realizations of the short rate, thus from swap payoffs. Swaps achieve transfers across future states. Thus, whether avoiding default is the primary motive for risk management or not, swaps transfer resources across states that are more or less associated with default events. Before turning to the detailed analysis of the impact of swap trading on the bank's debt capacity, it is useful to summarize the types of transfers motivated by each form of risk management in the model.

There are two frictions that give an incentive to engage in risk management. First, risk management motivated by the cost to equity financing can be implemented using two types of transfers, as discussed in section 1.5.3. When motivated by investment concerns, it is implemented using swap positions that transfer resources from future states where the short rate is high to states where it is low, i.e. to states where large investment outlays are optimal. When motivated by financing concerns, it aims at transfers from future states where the short rate is low to states where it is high. Second, when risk management arises from the existence of bankruptcy costs, the bank optimally uses swaps to transfer resources from future states where it does not default to future states where it would otherwise optimally default. For a given productivity level, these states are those where the short rate is high. The objectives of risk management motivated by the existence of a cost to bankruptcy are thus at odds with those of risk management for investment motives.

There are two mechanisms through which a bank's swap position affects its debt capacity. First, a change in d' given other controls changes the bank's probability of default $\Pr_{z,r}(\Delta(a',b',d'))$ or, equivalently, its default threshold $r^d(.)$. Second, conditional on being in a default state, the bank's swap position also affects the expected recovery value for creditors after swap payoffs have been received or paid, i.e. $\mathbb{E}_{z,r}\left[\mathcal{R}^B(a',d',z',r',r)\right]$.

Before turning to the impact of swap positions on the bank's debt capacity, two intermediate results are needed. From the monotonicity of the value function in r' and from the types of transfers achieved with swap contracts, it follows that

$$\frac{\partial r^d(.)}{\partial d'} > 0 \quad \text{if} \quad d' > 0 \tag{1.41}$$

$$\frac{\partial r^d(.)}{\partial d'} < 0 \quad \text{if} \quad d' < 0 \tag{1.42}$$

The default threshold $r^d(.)$ is such that the bank defaults if $r' > r^d$. Given controls a' and b', pay-fixed swaps $d' > 0$ achieve transfers from future states where r' is low to states where it is high. By continuity of the value function, it prevents default for some future realizations r' given controls and a realization of z'. $r^d(.)$ is thus increasing in d' when $d' > 0$. Equivalently, by equation (1.37), the probability that the bank is in a default state is lower.

To show the impact of a swap position on the bank's debt capacity, I focus next on the sign of $\partial\tilde{r}(.)/\partial d'$. If the interest rate required by creditors increases when the bank chooses a larger swap position, then swap hedging reduces the bank's debt capacity, as in the model with riskless debt.

I derive the risky interest rate with respect to d' for a given choice of debt d'. Note first that $\tilde{r}(.)$ can be rewritten as

$$\tilde{r}(.) = \frac{1 + r - \int_{\underline{z}}^{\overline{z}}\int_{r^d(a',b',d',r,z')}^{\overline{r}}\mathcal{R}^B(a',d',z',r',r)/b'\,\mathrm{d}g_r(r'|r)\,\mathrm{d}g_z(z'|z)}{\int_{\underline{z}}^{\overline{z}}\int_{\underline{r}}^{r^d(a',b',d',r,z')}\mathrm{d}g_r(r'|r)\,\mathrm{d}g_z(z'|z)} - 1 \tag{1.43}$$

Then, taking the derivative with respect to d', using Leibniz's rule, and re-arranging,

$$\begin{aligned}
\frac{\partial\tilde{r}(d')}{\partial d'}\int_{\underline{z}}^{\overline{z}}\int_{\underline{r}}^{r^d(d')}\mathrm{d}g_r\mathrm{d}g_z &= -(1+\tilde{r}(d'))\frac{\partial}{\partial d'}\left[\int_{\underline{z}}^{\overline{z}}\int_{\underline{r}}^{r^d(d')}\mathrm{d}g_r\mathrm{d}g_z\right] \\
&\quad -\frac{\partial}{\partial d'}\int_{\underline{z}}^{\overline{z}}\int_{r^d(d')}^{\overline{r}}\frac{\mathcal{R}^B(d')}{b'}\mathrm{d}g_r\mathrm{d}g_z,
\end{aligned} \tag{1.44}$$

where notations have been simplified, $\tilde{r}(d') \equiv \tilde{r}(.)$, $r^d(d') \equiv r^d(a',b',d',r,z')$, $\mathcal{R}^B(d') \equiv \mathcal{R}^B(a',d',z',r',r)$, $g_z \equiv g_z(z'|z)$ and $g_r \equiv g_r(r'|r)$. Equation (1.44) makes it clear that the change in interest rate paid, $\partial\tilde{r}(d')/\partial d'$ must be such that it compensates for the

change, as d' increases, in both the bank's probability of default and for the change in expected recovery value upon default. The first term on the right-hand side is the change in the probability that the gross return $(1 + \tilde{r}(d'))$ is paid. The second term is the change in the expected recovery value per unit of debt outstanding, also accounting for the change in the probability that the bank indeed defaults.

From equation (1.44), two results follow:

$$\frac{\partial \tilde{r}(d')}{\partial d'} < 0 \quad \text{if} \quad d' > 0 \tag{1.45}$$

$$\frac{\partial \tilde{r}(d')}{\partial d'} > 0 \quad \text{if} \quad d' < 0 \tag{1.46}$$

To show this, note first that it is sufficient to restrict attention to the sign of the first term on the right-hand side of equation (1.44), denoted

$$A(d') \equiv -\left(1 + \tilde{r}(d')\right) \frac{\partial}{\partial d'} \left[\int_{\underline{z}}^{\overline{z}} \int_{\underline{r}}^{r^d(d')} \mathrm{d}g_r \mathrm{d}g_z\right] \tag{1.47}$$

for simplicity. Because of deadweight default costs, it cannot be that, for a given rate $\tilde{r}(.)$, creditors are better off with the bank defaulting in more states, even if the expected recovery value is larger in these states. When $d' > 0$, $\partial r^d(.)/\partial d' > 0$ by equation (1.41). The partial derivative in $A(d')$, which captures the change in the probability that the bank does not default, has a positive sign. Thus, $A(d') < 0$ when $d' > 0$. The risky interest rate $\tilde{r}$ decreases when $d' > 0$, implying that the bank's debt capacity increases. By a similar argument, and using equation (1.42), $\tilde{r}$ increases when $d' < 0$ and the bank's debt capacity decreases.

Even though most bank debt is collateralized, this section highlights the fact that, when default is allowed, it need not be the case increased hedging reduces the bank's debt capacity. Intuitively, if the bank optimally defaults in states where r' is high and holds a pay-float position $d' < 0$, it defaults in more states and tends to be a swap payer in states where it defaults. The expected return, including the recovery value in default states, decreases as the bank takes on larger pay-float positions. The required interest rate to be paid is higher and the bank's debt capacity is lower. Pay-fixed swaps have the opposite effect, as the bank defaults in fewer states and tends to be a net swap receiver at times it defaults. Its debt capacity increases with hedging.

From this model extension, a number of theoretical and empirical consequences follow, whose exploration is left for future work. First, given the coexistence of several motives for risk management, there is endogenous sorting between banks engaged in each type of hedging. Cross-sectional predictions on the position signs associated with each type of risk management can follow. Second, because the effect of hedging on a bank's debt

capacity can be both positive or negative in a setup with defaultable debt, predictions on debt patterns associated with particular derivative positions can be obtained and tested.

1.7.2.3 Agency conflicts and default policy

From the above results, the effects of swap hedging on debt-equity agency conflicts and on the bank's default policy can be obtained. First recall that the agency conflit between debt and equity holders arises because *(i)* default is costly and *(ii)* decisions are taken in the interest of shareholders. These conditions imply that, for some shock realizations, the shareholders may find it optimal to default, even though defaulting destroys value for the firm as a whole (including creditors). The occurrence of defaults is thus related to the magnitude of agency conflicts.

Equations (1.41) and (1.42) specify the relation between swap hedging d' and the optimal default decision. When the bank uses swaps to transfer resources from "low r" to "high r" states, its default region is smaller at $t+1$, because it holds more resources in "high r" states that would otherwise be associated with default decisions. Hedging using swaps to achieve such transfers reduces the debt-equity agency conflict and the occurrence of bank defaults. On the contrary, if swaps are used to transfer resources from "high r" to "low r" states, the banks holds less resources in states that are associated with default. It optimally defaults for more realizations of r', given a choice of controls.

Whether one effect dominates depends essentially on two factors. First, it depends on the relative weight of the financial frictions. As the bankruptcy costs become relatively high compared to equity issuance costs, avoiding default becomes a more pressing concern, and the bank tends to use more pay-fixed swaps. The agency conflict is mitigated and defaults occurs at a lower frequency. If, in contrast, equity issuance costs are high relative to bankruptcy costs, hedging using derivatives may exacerbate the agency conflicts by giving incentives for the bank to use more pay-float swaps. In this case, the bank finds it optimal to default more often. A trade-off between shareholder value creation and bank defaults arises. If it is the case that financial frictions are heterogeneous in the cross-section of banks, then both effects may co-exist.

Second, the overall effect also depends on the relative magnitude of the financing and of the investment motives for risk management. At times the financing motive for risk management is relatively more important, the bank optimally transfers resources to future periods where the short rate is high. The agency conflict is reduced and the default region is smaller. If, in contrast, the investment motive overrides the financing motive, the agency conflict is again exacerbated.

Empirically, the predictions of the model are more refined than those tested in the existing literature on risk management. The co-existence of banks associated with either hedging type, and associated cross-sectional characteristics, is also a new prediction. Its test is left for future work. Suffice is to say that, because it predicts that derivatives hedging can be associated both with increased and reduced debt capacity, this theory of hedging with defaultable debt can reconcile contradicting theories (Froot et al., 1993; Rampini and Viswanathan, 2010) and empirical evidence (Purnanandam, 2007; Rampini et al., 2014) about the cross-section of hedging banks or firms.

1.8 Discussion and further research

This section discusses a few implications of the paper's results. It also outlines several directions for future research.

1.8.1 The transmission of monetary policy

The paper's results are relevant to the literature on the transmission of monetary policy through the bank lending channel. Two results call for refined empirical research. First, existing papers on the impact of the use of derivatives on bank lending (e.g. Purnanandam, 2007) pool observations associated with both positive and negative interest rate shocks. In contrast, the regression results obtained on simulated data (tables 1.8 and 1.9) are suggestive of a strongly asymmetric response of bank lending to either increases or decreases in the short rate. As discussed in section 1.6.3.4, while the response of lending by derivatives user and non-user banks is not statistically different for good shocks (high z or low r), this difference is consistently significant at a 1% level for bad shock realizations. Regression coefficients obtained without conditioning on shock signs are likely biased and unreflective of the asymmetric nature of the underlying economic mechanism.

Second, empirical tests of the bank lending channel, even if unrelated to the role of derivatives, shall benefit from incorporating the asymmetric effects of positive and negative shock realizations. Existing papers on the asymmetric effects of "good" and "bad" shocks on the transmission of monetary policy have focused on channels unrelated to the bank lending channel, such as credit or demand channels (Cover, 1992; Karras and Stokes, 1999). In contrast, this paper suggests the existence of asymmetric effects arising of monetary policy transmission arising from the balance sheet channel. The balance sheet channel arises from a failure of the Modigliani-Miller theorem, by which all sources

of financing are not perfect substitutes. In the regression results using simulated data, both the significance and the sign of coefficients not directly related to derivatives may change when the asymmetric response to positive and negative shocks is acknowledged.

1.8.2 Financial stability

The model yields procyclical maturity mismatching by financial institutions. The bank's reliance on short-term debt increases when lending opportunities arise. Such patterns have been broadly documented in the years preceding the 2008 crisis. At a micro level, Shin (2009) shows that the increased reliance on short-term wholesale funding, rather than securitization, was the main driver of Northern Rock's failure in 2007. At a macro level, Hahm et al. (2013) show that banks tend to increase their reliance on non-core liabilities (i.e. other than retail deposits) during booms.

In future research, the model can be enriched to address a number of questions related to financial stability. An extension of the heterogeneous model of section 1.6.6 that would include defaults, as in section 3.6, could be used to document more extensively the cross-sectional characteristics associated with bank default. As suggested by the main result in section 1.7.2.2, derivatives can both enlarge and reduce the set if default states, depending on the hedging incentive that dominates (either costly external equity or costly bankruptcy). In the model, both are associated with different bank characteristics and realizations of the aggregate shocks. Consequently, the effect of derivatives on bank failures likely depends on the business cycle. Additional testable predictions could be obtained.

1.8.3 Endogenous provision of swap contracts

The model with risk-neutral swap dealers is such that the expected profit from trading swaps is zero. Therefore, the analysis can be restricted to swap trading motivated by hedging concerns only, and to its interaction with the optimal capital structure policy.

One extension to be considered in future research is the endogeneization of the supply of swap contracts. Risk-neutral swap providers (dealers) in the model can take arbitrarily large positions, eventually one-sided. In the data, however, market makers tend to take offsetting positions across counterparties, even though they provide each end-user with non-zero net positions (see Peltonen et al., 2014, for an example in the CDS market). One shortcoming of the model is that, for credible parameterizations, one type of swap position (pay-fixed or pay-float) is chosen more often than the other. Furthermore, user banks in the heterogenous model tend to take positions in the same direction at each

date. It cannot be credibly argued that offsetting positions are held to a large extent outside the banking sector.

For swap contracts to be endogenously provided, a direction for further research is to drop the pricing equation (1.13) and instead solve for the premium p which, in each period, clears the market for swaps within the system of heterogeneous banks of section 1.6.6. This premium would equalize the demand for pay-fixed and pay-float contracts given each bank's balance sheet and the probability distributions g_z and g_r. All swap providers may then be effectively risk-averse. Swaps may also yield an positive profit on expectation for some traders.

This model extension would yield additional predictions on the use of swaps, as a distinction between two groups of traders would endogenously arise. First, a subset of banks would continue using the derivatives market for hedging purposes. Their demand for swaps would be a function of the market premium. Second, a subset of traders would benefit from accomodating hedger's demand, thus yielding an endogenous "trading" motive on derivatives. This could be interpreted as market making, as in the model by Viswanathan and Wang (2004). In addition to an endogenous sorting between "hedgers" or "traders" in the swap market, this model would yield testable predictions about other balance sheet and capital structure characteristics associated with either position type.

1.8.4 Derivative contracts in international finance

Apart from banking firms, derivatives are used by a large variety of non-financial firms. One of the most important example is the use of foreign exchange (FX) derivatives by multinational and exporting firms. Empirical evidence on these exposures is limited (e.g. Allayannis and Ofek, 2001), despite large notional amounts being traded. Theoretically, the impact of FX derivatives on firms' capital structure and ability to exploit investment opportunities domestically and abroad is not modeled. Building on existing models of firm investment (Hennessy and Whited, 2005; DeAngelo et al., 2011), and introducing derivatives as in this paper, could help adressing a number of pending questions in international finance, such as the relation between currency mismatches and derivative positions or the optimal issuance of debt denominated in local or foreign currency when hedging is possible.

1.9   Conclusion

This paper models the real effects of derivatives on the capital structure of financial intermediaries. It presents a dynamic capital structure model of a financial intermediary, for which risk management is motivated by a cost to external equity financing. Both productivity and the short rate are stochastic. Risk can be managed on-balance sheet—with debt capacity and payout flexibility—and off-balance sheet, with derivative contracts. The optimal capital structure is derived.

Interest rate derivatives enable commercial banks to shield their lending policy against interest rate shocks, to better exploit lending opportunities arising from real shocks and to smooth dividend distributions. These predictions match stylized facts.

When extended to a setup with endogenous default, the paper shows that the use of derivatives can both increase or reduce the occurrence of bank defaults, while exacerbating or mitigating the agency conflict between debt and equity claimants. This is because swaps can be optimally used to achieve transfers between states that are less associated with default to states that are more associated with default, or the contrary. Which effect dominates depends importantly on the relative weight of the financial frictions (costs to equity issuance and bankruptcy costs). In the case where the use of swaps increases the occurrence of bank defaults, a trade-off exists between shareholder value creation and default costs.

Finally, despite desirable properties, derivative are traded only by a subset of banks, as in the data. The model yields endogenous sorting between derivatives users and non-users. Not all banks optimally take a positive exposure on derivatives. Banks with a high opportunity cost of collateral may abstain from hedging, and instead manage risk using on-balance sheet instruments only.

This work can be expanded along several dimensions. Empirically, novel predictions can be tested. Theoretically, the endogenization of the provision of swaps may yield a richer dynamics and more realistic predictions on bank characteristics associated with long and short positions, as well as with "hedging" and "trading" motives. The model extension with endogenous default can also be refined to yield predictions about the characteristics of defaulting banks, either users or non-users.

1.10 Appendix 1: Stylized facts

This appendix uses bank-level data to establish the six stylized facts listed in section 3.3.

1.10.1 Cross-sectional stylized facts

Stylized facts 1 to 3 pertain to the cross-section of banks. The statistics being provided, and their significance levels, are economically very close to those obtained by Purnanandam (2007), based on a different time period. Thus, the motivating facts are not driven by the choice of the sample period, and likely reflect structural underlying economic mechanisms.

The first stylized fact relates the use of derivatives to bank size.

> **Stylized fact 1**: Larger banks (as measured by total assets) tend to use more derivatives than smaller banks.

Stylized fact 1 asserts that there is a sorting between users and non-users based on bank size. A breakdown by quintiles of the number of derivatives users for selected quarters is provided in table 1.10. The number of derivatives users is significantly higher in upper quantiles, as compared to lower quantiles. This sorting persists over time, even as the number of derivatives users increases. On average over all periods, 66% of all users are in the top 20% of the size distribution, while 1% of users only are in the bottom 20%.

Table 1.10 also exploits a breakdown in the call reports data between derivative contracts "held for trading" and "held for purposes other than trading". The latter category includes contracts for hedging purposes (see appendix 1.11 for details). At an aggregate level, notional amounts for derivatives used for trading represent the vast majority of interest rate derivatives (Begenau et al., 2013). Derivatives used for hedging represent only between 1% and 5% of the total notional amount in my sample. The model's predictions, however, pertain to derivative exposures held for hedging purposes.

The breakdown between contracts used for trading and for hedging shows that, even if they represent a small percentage of the aggregated market, derivatives for hedging are more widely used than derivatives for trading. On average over all quarters, 465 banks use derivatives for hedging, while only 105 use derivatives for trading. Most banks that use derivatives for hedging do not use them jointly for trading purposes. In contrast, very few banks use derivatives for trading purposes only. Derivatives for trading are

Quarter				Size quintiles			Total
		1	2	3	4	5	
2001Q1	All users	0	0	2	3	153	158
	For hedging	0	0	1	3	140	144
	For trading	0	0	1	0	56	57
2005Q1	All users	1	7	19	62	287	376
	For hedging	0	6	18	59	258	341
	For trading	1	1	1	3	77	83
2009Q1	All users	7	49	66	151	457	730
	For hedging	6	45	58	142	414	665
	For trading	1	4	8	11	115	139
2013Q2	All users	16	51	95	168	438	768
	For hedging	13	49	89	158	402	711
	For trading	3	2	9	13	114	141
Average	All users	6	26.75	45.5	96	333.75	508
	For hedging	4.75	25	41.5	90.5	303.5	465.25
	For trading	1.25	1.75	4.75	6.75	90.5	105
Percent	All users	0.01	0.05	0.09	0.19	0.66	1
	For hedging	0.01	0.05	0.09	0.19	0.65	1
	For trading	0.01	0.02	0.05	0.06	0.86	1

TABLE 1.10: Distribution of derivatives users across size quintiles. This table shows the distribution of interest rate derivatives users across five quintiles constructed based on total assets, for four selected quarters. Quintile 1 corresponds to the smallest banks and quintile 5 to the largest banks. The number of banks using derivatives for trading purposes and for purposes other than trading ("hedging") is also reported. The fifth section of the table averages the number of users over all four quarters, while the sixth section reports the share of users in each quintile.

more concentrated in the upper quintile than derivatives for hedging (86% versus 66%). Within the upper quintile, derivatives for trading are highly concentrated within a subset of 5 to 6 dealer institutions. These institutions account on average for 98% of the gross notional amount of derivatives for trading market-wide. For most banks, the relevant exposure to be considered is than on derivatives used for hedging, as I do. For these types of exposures, sorting between users and non-users based on size is observed as well.

Two additional stylized facts in the cross-section of banks are established.

> **Stylized fact 2**: Derivatives user banks rely less on stable funding sources such as deposits, and more on wholesale funding.

> **Stylized fact 3**: Derivatives user banks hold a larger share of their assets as loans, and consequently hold lower cash and liquid asset buffers.

Stylized facts 2 and 3 are seen in table 1.11, where a number of bank characteristics are given for both users and non-users of derivatives. The table focuses on median values, so that a lower weight is given to extreme values. The results remain qualitatively unchanged with mean values, as also seen in Purnanandam (2007, table 3).

All statistics are computed based on the whole sample of banks, and after controlling for bank size. To control for bank size, I restrict the sample to banks with total assets above 1 billion USD. Restricting attention to large banks serves two purposes. First, it is empirically documented that size is associated with a number of other bank characteristics (Kashyap and Stein, 2000). If this is the case, cross-sectional differences could be attributed to the use of derivatives, while they arise from their relation to bank size. Second, the number of bank-quarter observations is roughly equal for user and non-user banks in this restricted sample. I test for the equality of the sample medians using the Wilcoxon statistics.

The composition of both assets and liabilities differs between user and non-user banks. Most coefficients are significant at a 1% level and all but one hold after restricting the sample to large commercial banks. Consistent with stylized fact 2, non-users rely significantly more on deposits than derivatives users, and also much less on wholesale funding, i.e. primarily Fed funds bought (see appendix 1.11 for details on the variables). The share of financing being sensitive to fluctuations in the short rate is thus higher for derivatives users.

Turning to differences in assets, derivatives users hold a larger share of their assets as loans, as asserted by stylized fact 3. In the sample restricted to large banks, the difference is of about 2.5 percentage points. In contrast, derivatives non-users hold a larger share of their assets as liquid assets, including cash and securities.

1.10.2 Stylized facts in the time dimension

Stylized facts 4 to 6 are related to the time dimension of bank activity. Throughout this section, I treat the fact of being a derivatives user or non-user as exogenous. One outcome of the model below, however, is that being a user bank shall be considered an endogenous outcome of the interaction between a bank's capital structure and idiosyncratic or aggregate shocks. One variable predicted by the model to be strongly associated with the use of derivatives, consistent with the data (see above section), is size, measured by total assets. As a partial fix for endogeneity, I consistently control for bank size in the specification of the regression models.

1.10.2.1 Lending activity

There are two stylized facts relating derivatives hedging with bank lending in the time dimension.

> **Stylized fact 4**: When faced with an increase in the short rate, users of derivatives cut less lending than non-users of derivatives.

> **Stylized fact 5**: When faced with a positive real shock, proxied by a GDP shock, users of derivatives increase lending more than non-users of derivatives.

The most important paper documenting differences in the lending patterns of derivatives users and non-users is by Purnanandam (2007). To a large extent, this section reproduces his main regression specification. It shows that his results, to a large extent, hold for the longer time period for which my dataset is available. While Purnanandam (2007) pays close attention to the response of lending to shocks to the Fed funds rate, I also discuss the response to GDP shocks. At a more granular level, I also distinguish between the effects of "good" versus "bad" shock realizations on the estimated coefficients.

In the main specification, the lending growth of banks in group $j \in \{\text{Users}; \text{Non users}\}$ in quarter t is regressed on four lags on this variable, as well as on four lags of the first

	Derivatives users		Derivatives non-users		Users minus Non users	
	All	> 1 bn	All	> 1 bn	All	> 1 bn
Size (log Total assets)	13.350	15.130	11.600	14.365	1.750***	0.765***
Growth (%)	0.010	0.011	0.012	0.014	−0.002***	−0.003***
Maturity gap (% of total assets)	0.010	0.068	−0.040	0.034	0.050***	0.034***
Equity (% of total assets)	0.094	0.095	0.099	0.095	−0.005***	0.000
Deposits (% of total assets)	0.809	0.753	0.851	0.793	−0.042***	−0.040***
Wholesale (% of total assets)	0	0.056	0.036	0.035	−0.036***	−0.021***
Loans (% of total assets)	0.693	0.678	0.653	0.677	0.040***	0.001**
Liquid assets (% of total assets)	0.244	0.241	0.297	0.258	−0.053***	−0.017***
Cash (% of total assets)	0.021	0.020	0.028	0.020	−0.007***	−0.000*
Net income (% of total assets)	0.009	0.010	0.009	0.010	0.000	0.000***
Non-perf. assets (% of total assets)	0.014	0.012	0.014	0.013	0.000***	−0.001***
Dividends (% of total assets)	0.004	0.004	0.003	0.003	0.001***	0.001***

TABLE 1.11: Descriptive statistics for derivatives users and non-users. This table presents descriptive statistics for both interest rate derivatives users and non-users. The sample consists of 339,415 bank-quarter observations, including 27.603 observations for interest rate derivatives users. I provide the median for a number of balance sheet characteristics, as well as differences in median between groups. The statistics are given for all banks and for banks with total assets over 1 billion USD (22,235 bank-quarter observations). The test for differences in medians is based on the Wilcoxon statistics. All data are from quarterly call reports.

difference of the Fed funds rate and of real GDP. The time series model is

$$
\begin{aligned}
\Delta \log (L)_{jt} \quad = \quad & \alpha_0 + \sum_{k=1}^{k=4} \alpha_k \Delta \log (L)_{jt-k} + \sum_{k=1}^{k=4} \beta_k \Delta FED_{t-k} \\
& + \sum_{k=1}^{k=4} \gamma_k \Delta \log (GDP)_{t-k} + \epsilon_{jt},
\end{aligned}
\tag{1.48}
$$

where L denotes total loans. The coefficients of interest are the sums $\sum_k \beta_k$ and $\sum_k \gamma_k$ of coefficients over past Fed funds and GDP innovations. I test the null hypotheses that these sums are equal to zero. Positive (resp. negative) and significant coefficients indicate that lending increases (resp. decreases) in response to a higher short rate or GDP realization.

To estimate the model given by equation (1.48), I construct loan growth variables $\Delta \log (L)_{jt}$ consistent with changes in sample size (failures, newly established banks) and with group switching (non-users becoming users). Bank-quarter observations with merger activities are deleted. Loan growth variables are constructed by aggregating bank-level loans for users and non-users for any two consecutive quarters, using equally-sized groups of users and non-users (as in Kashyap and Stein, 1995). Precisely, to compute $\Delta \log (L)_{jt} \equiv \log (L)_{jt} - \log (L)_{jt-1}$ between any two quarters $t-1$ and t, I keep only banks that are present in the sample at both $t-1$ and t, and which do not shift from the non-user to the user group between these dates. In order to control for size effects in the response of lending to Fed funds shocks (Kashyap and Stein, 2000), which are correlated with the use of derivatives, I aggregate bank lending by commercial banks in the higher percentiles only. Several cut-off percentiles are used, from the upper 20% to the upper 5%, to demonstrate the robustness of the results to factors related to size.

In table 1.12, I find that an increase in the short rate is associated with a decrease in bank lending by derivatives non-users. This relation is significant at a 5% or 10% level when restricting to banks in the upper 10% or 20% of the size distribution. The significance of the negative coefficient vanishes when restricting to the upper 5% or higher percentiles. For derivatives users, a negative coefficient on $\sum_k \beta_k$ is obtained, but it is never significant. This result, broadly consistent with Purnanandam (2007), suggests that the lending policy by derivatives users is less sensitive to interest rate shocks than that of non-users. Users are able to shield their lending policy from interest rate shocks. Purnanandam (2007) further investigates this result using a difference-in-differences regression design. I am not able to reproduce his results with a high level of significance.

	Non users					Users				
Quantile	$\sum_k \Delta FED_k$	p	$\sum_k \Delta GDP_k$	p	Obs.	$\sum_k \Delta FED_k$	p	$\sum_k \Delta GDP_k$	p	Obs.
Top 20%	-0.009	0.019	1.768	0.000	410	-0.004	0.501	1.863	0.005	136
Top 15%	-0.009	0.029	1.772	0.000	280	-0.004	0.509	1.863	0.005	123
Top 10%	-0.008	0.051	1.788	0.000	159	-0.004	0.527	1.884	0.005	89
Top 5%	-0.006	0.183	1.693	0.002	59	-0.004	0.533	1.954	0.004	51
Top 3%	-0.002	0.712	1.670	0.001	28	-0.004	0.552	2.006	0.005	35

TABLE 1.12: Lending growth for derivatives users and non-users. This tables provides the estimated coefficient sums for the model given by equation (1.48). The lending growth $\Delta \log (L)$ for either derivatives non-users (left panel) or users (right panel) is regressed on 4 lags of this variable, and four lags of innovations to the Fed funds rate ΔFED and to the log GDP, $\Delta \log (GDP)$. The reported coefficients are $\sum_k \beta_k$ and $\sum_k \gamma_k$ respectively for each group. The p-values are for the test that these sums are equal to 0. The sample is for U.S. commercial banks over the period 2001Q1 to 2013Q2. The model is estimated on 5 samples restricted to larger percentiles of the size distribution.

Moreover, I find a steadily positive and significant (at a 1% level) relation between GDP shocks and lending growth. This relation is robust to size controls and is true for both groups of derivatives users and non-users. The estimated sum of coefficients is higher for users than for non-users, suggesting that their lending policy is more responsive to GDP shocks, while being rather insensitive to interest rate shocks.

Finally, I further investigate the dynamics of lending growth by estimating equation (1.48) on subsets of periods in which the first lag of ΔFED or ΔGDP is either above or below its median value, as computed in the whole sample period. Regression results are reported in table 1.13. One main result is obtained. For both Fed funds and GDP shocks, the estimated coefficients of table 1.12 are mainly driven by periods in which "bad" shocks hit. For non-users, the negative sign on $\sum_k \beta_k$ is driven by periods in which ΔFED is above its median value, i.e. mainly periods in which it rises. The significance of the negative coefficient is higher in this part of the sample. Similarly, the positive coefficient sign on ΔGDP is driven by periods in which ΔGDP is below its median value, i.e. mainly GDP contractions. There are thus asymmetric effects of "good" and "bad" shock realizations on bank lending. The model is also able to reproduce this asymmetry.

Panel A: Coefficient on the Fed funds								
	Non users				Users			
Quantile	Above med.	p	Below med.	p	Above med.	p	Below med.	p
Top 20%	-0.014	0.059	-0.007	0.619	-0.011	0.599	0.020	0.323
Top 15%	-0.014	0.078	-0.006	0.715	-0.011	0.601	0.020	0.325
Top 10%	-0.011	0.165	-0.008	0.690	-0.010	0.618	0.021	0.309
Top 5%	-0.006	0.575	-0.005	0.792	-0.009	0.653	0.022	0.311
Top 3%	-0.003	0.838	-0.003	0.899	-0.009	0.670	0.023	0.307

Panel B: Coefficient on the GDP								
	Non users				Users			
Quantile	Above med.	p	Below med.	p	Above med.	p	Below med.	p
Top 20%	2.470	0.017	2.225	0.000	1.539	0.358	2.956	0.016
Top 15%	2.359	0.023	2.315	0.002	1.538	0.360	2.953	0.016
Top 10%	2.568	0.030	2.182	0.007	1.513	0.371	2.970	0.016
Top 5%	1.646	0.182	1.979	0.036	1.492	0.390	3.005	0.017
Top 3%	0.913	0.466	1.744	0.058	1.437	0.417	2.935	0.027

TABLE 1.13: Lending growth and shock realizations. This tables provides the estimated coefficient sums for the model given by equation (1.48). The lending growth $\Delta \log (L)$ for either derivatives non-users (left panel) or users (right panel) is regressed on 4 lags of this variable, and four lags of innovations to the Fed funds rate ΔFED and to the log GDP, $\Delta \log (GDP)$. The model is estimated on subsets of periods in which the first lag of ΔFED or $\Delta \log (GDP)$ is either above or below its median value, as computed on the whole sample period. In panel A, regression results for users and non-users are reported respectively when conditioning on ΔFED being above and below its median value respectively. In panel B, conditioning in on $\Delta \log (GDP)$ being above or below its median value respectively. The reported coefficients are $\sum_k \beta_k$ and $\sum_k \gamma_k$ for each group. The p-values are for the test that these sums are equal to 0. The sample is for U.S. commercial banks over the period 2001Q1 to 2013Q2. The model is estimated on 5 samples restricted to larger percentiles of the size distribution.

1.10.2.2   Payout policy

The sixth stylized fact relates derivatives hedging and payout policy by financial institutions.

> **Stylized fact 6**: Derivatives user banks smooth their dividend payout policy over time.

Bonaimé et al. (2013) argue that firms trade off financial hedging with a more or less flexible payout structure. Using data on U.S. bank holding companies over the period 1995-2008, they show that banking firms substitute hedging with payout flexibility over time, i.e. that derivative users smooth their payout policy over time. The capital structure model in this paper also generates this substitution.

1.11 Appendix 2: Construction of the variables

This appendix describes the dataset and the construction of the variables.

1.11.1 Call reports data

All bank-level data for U.S. financial institutions is obtained from the call reports in the FDIC Central Data Repository. For the consistency of the sample, savings banks are dropped and only commercial banks are kept. Bank-quarter observations corresponding to mergers and acquisitions are dropped. Data is from 2001 Q1 to 2013 Q2, yielding 339,415 bank-quarter observations (on average 6,788 observations per quarter).

1.11.2 Derivatives data

Derivatives data obtained from the call reports are used to construct two additional variables. First, a dummy variable for derivatives users. Second, the net exposure of a bank to interest rate derivatives in one quarter.

All empirical evidence relies on a breakdown in the data between derivative contracts "held for trading" and contracts "held for purposes other than trading". Attention is consistently restricted to contracts held for purposes other than hedging. Derivative contracts held for trading include *(i)* dealer and market making activities, *(ii)* taking positions with the intention to resell in the short-term or to benefit from short-term price changes *(iii)* taking positions as an accomodation for customers and *(iv)* taking positions to hedge other trading activities. Derivatives for purposes other than trading thus include contracts held for hedging. As argued by Purnanandam (2007), all sampled institutions are monitored by the FDIC, the OCC or the Fed on a regular basis, so that the reporting is likely truthful.

1.11.2.1 Users versus non-users

I construct a dummy variable that equals 1 for interest rate derivatives users and 0 for non-users. All types of interest rate derivatives are used to assign banks within the "user" and "non user" groups. They include swaps (id: 3450), futures (id: 8693), forwards (id: 8697) and options (id: 8701, 8705, 8709 and 8713).[9] The assignment of

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[9] All variable identifiers reported in this appendix refer to call reports data and must be preceded by the relevant prefix *RCON*, *RCFD* or *RIAD* (for income statement variables).

banks to either group is done on a quarterly basis. The gross notional positions on all interest rate derivatives are summed for each bank-quarter observation.

A bank qualifies as a user if it meets two criteria. First, its total notional exposure to interest rate derivatives must be strictly positive in a given quarter. Thus, a bank entering the swap market at date t is considered non-user until $t-1$. Second, across quarters, a bank qualifies as a derivatives user only if it *actively* manages a derivatives portfolio from t on. Consider a bank that enters a single 5-year interest rate swap in quarter t and never trades henceforth. Its notional exposure will be strictly positive until quarter $t+19$. Nevertheless, it is hard to argue that its on-balance sheet maturity mismatching, its payout policy and its off-balance sheet derivatives portfolio are *jointly* determined each quarter until that date. Consequently, banks for which quarter-to-quarter changes in interest rate swap notional exposure are zero in more than 80% of the quarters (after entry in the market) are considered non-users.

The number of derivatives users varies between 154 (in 2001 Q2) to 826 (in 2011 Q3). The share of user banks has been increasing over time. It ranges between 2.1% and 13.1%, and its time series is depicted in figure 1.2. The sample of derivatives users is composed of 26,499 bank-quarter observations, i.e. about 7.81% of all observations.

1.11.2.2 Net exposure to interest rate derivatives

The predictions of the model relate to banks' *net* exposure to interest rate derivatives. The call reports data, however, contains gross notional exposures and market values only. The estimation of net exposures from these two data types is econometrically challenging, as discussed in Begenau et al. (2013). For example, it requires assumptions about the maturity distribution of the contracts. A precise estimation of net exposures is not the object of this paper. Instead, suggestive evidence is put forward using subsets of the data where a proxy for the net exposure on interest rate derivatives can be constructed with a reasonable level of confidence. These suggestive pieces of evidence should not be viewed as tests of the model. The detailed exploration of the model's empirical predictions is left for future work.

A restricted sample is constructed, in which the net exposure on interest rate swaps can be proxied. Attention is restricted to swaps for two reasons. First, they represent about 71.7% of all interest rate derivatives for U.S. commercial banks. Second, a data item reports the notional amount of swaps held for purposes other than trading "on which the bank has agreed to pay a fixed rate". This variable can be used to construct a measure of whether each bank has a pay-fixed or pay-float position in net terms. No such indication is available for other types of interest rate derivatives.

The main limitation, which is the reason why the sample has to be restricted, is that the notional amount of all swaps held for hedging purposes is not reported. Instead, the notional amount of all interest rate derivatives used for hedging is available. For banks with a non-zero notional exposure to other derivative contracts (including futures, forwards and options), the notional amount of swaps used for hedging is not known, as the reported data aggregates several contract types. To build the restricted sample, I keep only bank-quarter observations for which the non-swap derivative exposure is zero. For these observations, the reported amount of swaps used for hedging is the same as the amount of all interest rate derivatives used for hedging. The notional exposure to pay-float swaps is computed, and the ratio

$$\frac{|\text{Pay-fixed swaps} - \text{Pay-float swaps}|}{\text{Total assets}} \tag{1.49}$$

is used as a proxy for the net exposure to interest rate swaps. These restrictions on the sample yield 4,464 bank-quarter observations, i.e. about 89 observations per quarter. This sample comprises about one half of the total sample of swap users (9,351 bank-quarter observations).

1.11.3 Bank-level variables

Bank-specific variables are constructed from the call reports data. Each identifier is preceded by the relevant $RCON$, $RCFD$ or $RIAD$ (for income statement variables) prefixe.

- *Size:* Natural logarithm of total assets (id: 2170).

- *Asset growth:* Growth rate of total assets over the past four quarters.

- *Maturity gap:* Sum of assets minus sum of liabilities maturing or being repriced within 1 year, scaled by total assets. Assets in the numerator include cash and balances due from depository institutions (id: 0081 and 0071), loans and leases (id: A570 and A571), closed-end loans (id: A564 and A565), Federal funds sold and repurchase agreements (id: B987 and B989), securities issued by the U.S. Treasury (id: A549 and A550), mortgage pass-through securities (id: A555 and A556) and other mortgage-backed securities (id: A248). Liabilities in the numerator include demand deposits (id: 2210), term deposits (id: A579, A580, A584 and A585), Fed funds bought (id: B993 and B995), Federal Home Loan Bank (FHLB) advances (id: F055), other borrowings (id: F060) and subordinated notes and debentures (id: G469).

- *Equity:* Ratio of total bank equity capital (id: 3210) over total assets.

- *Deposits funding:* Ratio of total deposits (id: 2200) over total assets. It includes both interest and noninterest-bearing deposits.

- *Wholesale funding:* Includes all short term liabilities included in the calculation of the maturity gap, with the exception of demand and term deposits.

- *Loans and leases:* Ratio of total loans and leases (id: 2122) over total assets.

- *Liquid assets:* Sum of cash (id: 0081 and 0071), securities held to maturity (id: 1754) and available for sale (id: 1773), and Fed funds sold (id: B987), scaled by total assets.

- *Cash:* Noninterest-bearing balances and currency and coin (id: 0081) normalized by total assets.

- *Profitability:* Ratio of net income (id: 4340) over total assets. Net income is annualized.

- *Non-performing assets:* Sum of all past due and nonaccrual loans and leases (large number of items in Schedule RC-N of the call reports), normalized by total assets.

- *Dividends:* Ratio of cash dividend to common and preferred stock (id: 4460 and 4470) over total assets.

1.11.4   Macroeconomic data

Macroeconomic data is retrieved from the Federal Reserve Bank of Saint-Louis' FRED database, at a quarterly frequency.

- *Fed funds rate:* Effective Federal funds rate (id: FEDFUNDS).

- *Real GDP:* Real GDP (id: GDPC1).

1.12 Appendix 3: Model solution

This appendix details the numerical methods used to solved the baseline model and the extension with defaultable debt.

1.12.1 Baseline model

I specify a finite state space for the state variables $\{a, b, d, r_{-1}\}$ and for the shocks (z, r). The shock processes for z and r, described by equations (1.2) and (1.5), are transformed into discrete-state Markov chains using Tauchen (1986)'s method. They each take 10 equally spaced values in $[-3\sigma_z; 3\sigma_z]$ and $[-3\sigma_r; 3\sigma_r]$ respectively.

Given bounded supports for the productivity and interest rate shocks, $[\underline{z}; \overline{z}]$ and $[\underline{r}; \overline{r}]$ respectively, a value $\bar{a}$ is defined as

$$(1 - \tau) \pi_a (\bar{a}, \overline{z}, \underline{r}) - \delta = 0, \tag{1.50}$$

such that $a > \bar{a}$ is not profitable for the bank. $\bar{a}$ is well-defined by concavity of $\pi(.)$ in a and because $\lim_{a \to \infty} \pi_a(a, z, r) = 0$. Grid values for a are restricted below $\bar{a}$ and taken as:

$$\left[\bar{a} (1 - \delta)^{20}, ..., \bar{a} (1 - \delta)^{1/2}, \bar{a} \right]. \tag{1.51}$$

Given $\bar{a}$, bounded supports for z and r, and the collateral constraint in equation (1.4), an upper bound on the debt level $\bar{b}$ is defined as $\bar{b} = (1 - \tau) \underline{z} (R - \bar{r})^\gamma \bar{a}^\theta + \kappa \bar{a}$. I let the grid values for b take 20 equally spaced values in the interval $\left[-\bar{b}/2, \bar{b} \right]$. The lower limit is never hit by the optimal choice of b.

For the problem with swaps, the collateral constraint described in section 1.6.2 also ensures a bounded support for the optimal swap choice d'. These upper and lower boundary values, $\bar{d}$ and $\underline{d}$ are such that the collateral constraint binds if $b' = 0$ and $a' = \bar{a}$. I let the grid values consist of 20 equally spaced points in the interval $\left[\underline{d}, \bar{d} \right]$. The boundary values are never hit.

The model is solved by value function iteration. It yields a policy function $\{a', b', d'\} = \Gamma(a, b, d, z, r, r_{-1})$.

1.12.2 Model with defaultable debt

The solution of the model with defaultable debt is more complicated to obtain. To solve the model, the value function $V(.)$ is needed in order to compute the default states $\Delta(.)$

and the risky interest rate $\tilde{r}(.)$. However, the interest rate is needed for the bank value to be computed.

The problem is solved for using a "loop within a loop" algorithm. In the first step, assume the interest is risk-free, i.e. $\tilde{r} = r$, and solve for the value function. With this estimate of the value function, I compute estimated default states and the corresponding risky interest rate. Using this interest rate, I recompute the value function, and repeat this procedure until the value function converges.

1.13 Appendix 4: Calibration

This appendix presents the calibration of the model parameters, summarized in table 1.14.

1.13.1 Parameter calibration for the baseline model

The calibration of the parameters for the baseline model follows that in existing papers. The linear cost of equity financing is set to 16% and the convex part to 0.4%, following the estimates by DeAngelo et al. (2011).

The calibration of the productivity shock z is similar to those is Strebulaev and Whited (2012), with a standard deviation of 0.15 and a persistence of 0.6. The unconditional mean of the risk-free rate is $r^* = 4\%$. Its standard deviation is set to 0.007 and its persistence to 0.85. The long-term yield is calibrated as $R = 8\%$. The sensitivity of the simulated moments of the model to the shock standard deviation and persistence is discussed in section 1.5.4.1

The concavity of the profit function is set to $\theta = 0.7$, close to the value estimated by DeAngelo et al. (2011) for non-financial firms. The share of maturing loans is $\delta = 0.15$, yielding an average maturity of long-term debt of 6.7 years. The tax rate equals 0.2. The sensitivity of the profit function to the short rate is set to $\gamma = 0.05$ in the baseline calibration. The robustness to alternative values is checked. The robustness to alternative values of θ and δ is discussed in section 1.5.4.1.

1.13.2 Calibrated parameter values for the model extensions

In the first model extension (section 1.6.5) two additonal parameters are the fixed and convex cost to asset adjustment, respectively φ_0 and φ_1. DeAngelo et al. (2011) structurally estimate these parameters at $\varphi_0 = 0.003$ and $\varphi_1 = 0.15$. For simplicity, I fix the fixed cost parameter to 0 and keep the convex cost at its estimated value. Even though it is likely that adjustment costs for banking firms are different from adjustment costs for non-financial firms, our main focus is not on quantitative but on qualitative model predictions.

In the second model extension (section 1.6.6), heterogeneity is introduced across banks. I set the number of banks to $N = 1,000$. There are two parameters driving the AR(1) process for the idiosyncratic shock s, which are set to $\sigma_s = 0.2$ and $\rho_s = 0.6$. The permanent heterogeneity h is assumed to be uniformly distributed on $\left[\underline{h}, \overline{h}\right]$, where $\underline{h} = 0.5$ and $\overline{h} = 1.5$.

	Parameter	Value
r^*	Unconditional mean of r	0.04
ρ_z	Persistence of z	0.6
σ_z	Standard deviation of z	0.15
ρ_r	Persistence of r	0.85
σ_r	Standard deviation of r	0.007
δ	Share of maturing loans	0.15
θ	Profit function concavity	0.7
η_1	Cost of equity financing — Linear part	0.16
η_2	Cost of equity financing — Convex part	0.004
τ	Corporate tax rate	0.2
κ	Liquidation value of an asset unit	0.5
R	Gross long-term yield	1.08
γ	Profit sensitivity to the short rate	0.05
c_f	Cost of derivatives use — Fixed part	0
χ	Cost of derivatives use — Convex part	10^{-6}

TABLE 1.14: Parameter calibration for the baseline model. This table contains the calibrated values for the parameters in the baseline model with riskless debt.

In the model extension with defaultable debt (section 3.6), the only additional parameter is the deadweight cost of bankruptcy. In line with James (1991), losses upon default are set at $\xi = 0.3$. All calibrated values for the model extensions are summarized in table 1.15.

	Parameter	Value
φ_0	Cost to asset adjustment — Fixed part	0
φ_1	Cost to asset adjustment — Convex part	0.15
σ_s	Standard deviation of idiosyncratic shock	0.2
ρ_s	Persistence of idiosyncratic shock	0.6
$\underline{h}$	Permanent heterogeneity — Lower bound	0.5
$\overline{h}$	Permanent heterogeneity — Higher bound	1.5
M	Number of heterogeneous banks	1,000
ξ	Cost of default	0.3

TABLE 1.15: Parameter calibration for the model extensions. This table contains the calibrated values for the parameters for all model extensions.

1.14 Appendix 5: Proof of proposition 1

This section proves propositions 1. For brevity, I keep notations consistent with those by Stokey and Lucas (1989) and Hennessy and Whited (2007).

1.14.1 Notations

Define

$$F\left(a, a', b, b', d, z, r, r_{-1}\right) = e\left(.\right) - \eta\left(e\left(.\right)\right). \tag{1.52}$$

Further let Ω denote the set of all nondefault states

$$\Omega \equiv \left\{\left(a', b', d', z', r', r\right) : V\left(a', b', d', z', r', r\right) > 0\right\} \tag{1.53}$$

and $C\left(\Theta\right)$ be the space of all bounded and continuous functions on an arbitrary set Θ.

Finally, let T denote the Bellman operator associated to the Bellman equation (1.32). Denoting f an arbitrary continuous function with domain Ω, T is

$$
\begin{aligned}
\left(Tf\right)\left(a, b, d, z, r, r_{-1}\right) &= \max_{\left(a', b', d'\right) \in \Gamma\left(z, r, r_{-1}\right)} F\left(a, a', b, b', d, z, r, r_{-1}\right) \\
&\quad + \frac{1}{1+r} \int \int f\left(a', b', d', z', r', r\right) \mathrm{d}g_z\left(z'|z\right) \mathrm{d}g_r\left(r'|r\right)
\end{aligned} \tag{1.54}
$$

where $\Gamma\left(z, r, r_{-1}\right)$ is the set of feasible policies. The operator $T : C\left(\Omega\right) \to C\left(\Omega\right)$ is a contraction mapping with modulus $1/\left(1+r\right)$.

1.14.2 Proof of proposition 1

The proof is close to that of proposition 4 by Hennessy and Whited (2007). Denote $C'\left(\Omega\right)$ the space of all functions in $C\left(\Omega\right)$ that are nondecreasing in their fourth argument. A corollary of the contraction mapping theorem (Stokey and Lucas, 1989) is that

$$T\left[C'\left(\Omega\right)\right] \subseteq C'\left(\Omega\right) \Rightarrow V \in C'\left(\Omega\right) \tag{1.55}$$

Fix $f \in C'\left(\Omega\right)$, current values of the state variables, r and r_{-1}. Assume that $\left(a'_1, b'_1, d'_1\right)$ and $\left(a'_2, b'_2, d'_2\right)$ attain the supremum for the bank receiving shocks z_1 and z_2 respectively,

where $z_1 > z_2$.

$$
\begin{aligned}
(Tf)(a, b, d, z_1, r, r_{-1}) &= F\left(a, a_1', b, b_1', d, d_1', z_1, r, r_{-1}\right) \\
&\quad + \frac{1}{1+r} \int \int f\left(a_1', b_1', d_1', z', r', r\right) \mathrm{d}g_z\left(z'|z_1\right) \mathrm{d}g_r\left(r'|r\right) \\
&\geq F\left(a, a_2', b, b_2', d, d_2', z_1, r, r_{-1}\right) \\
&\quad + \frac{1}{1+r} \int \int f\left(a_2', b_2', d_2', z', r', r\right) \mathrm{d}g_z\left(z'|z_1\right) \mathrm{d}g_r\left(r'|r\right) \\
&\geq F\left(a, a_2', b, b_2', d, d_2', z_2, r, r_{-1}\right) \\
&\quad + \frac{1}{1+r} \int \int f\left(a_2', b_2', d_2', z', r', r\right) \mathrm{d}g_z\left(z'|z_2\right) \mathrm{d}g_r\left(r'|r\right) \\
&= (Tf)(a, b, d, z_2, r, r_{-1}) \tag{1.56}
\end{aligned}
$$

The first inequality follows from the fact that (a_1', b_1', d_1') weakly dominates (a_2', b_2', d_2') for the bank receiving z_1, because $\Gamma(z_2) \subseteq \Gamma(z_1)$. The second inequality follows from the fact that F is increasing in z and $g_z(.)$ is monotone.

Part II

Derivative markets and financial stability

Chapter 2

The Network Structure of the CDS Market and its Determinants

2.1 Abstract

This paper analyses the network structure of the credit default swap (CDS) market and its determinants, using a unique dataset of bilateral notional exposures on 642 financial and sovereign reference entities. We find that the CDS network is centred around 14 major dealers, exhibits a "small world" structure and a scale-free degree distribution. A large share of investors are net CDS buyers, implying that total credit risk exposure is fairly concentrated. Consistent with the theoretical literature on use of

CDS, the debt volume outstanding and its structure (maturity and collateralization), the CDS spread volatility and market beta, as well as the type (sovereign/financial) of the underlying bond are statistically significantly related—with expected signs—to structural characteristics of the CDS market.

2.2 Introduction

This paper analyses the structure of bilateral exposures in the credit default swap (CDS) market. Despite its fast growth and large size, there is very little research on the structure of the CDS market. In June 2013, the gross notional amount of CDS contracts worldwide was about USD 13,135 billion for single-name instruments, substantially higher than USD 5,116 billion in 2004 (Basel Commission on Banking Supervision, 2013b). Even though important efforts have been made to standardise the contracts (especially with the ISDA "big-bang" protocol in 2009 and the increasing use of central counterparties), CDS have so far been traded over-the-counter (OTC). The prevalence of bilateral trading makes it difficult to analyse the market structure for market participants, researchers or even regulators. The opacity also implies that the potential for contagion and other forms of systemic risk in the CDS market is hard to assess, as illustrated by policymakers' concerns before the Greek credit event on 9 March 2012.

Although many papers have studied the pricing of CDS, to our knowledge, there is no research on the network arising from actual bilateral CDS exposure data, its characteristics and stability properties. Analysing the network structure is crucial for understanding the functioning and potential sources of financial stability risks of the CDS market. In particular, the OTC nature of the trades implies that counterparty risk externalities are potentially large (see Acharya and Bisin, 2014) and that their assessment has to be based on the structure of bilateral exposures. Both the concentration of the activity and the density of a network have been shown in the literature on interbank markets to be determinants of its resilience to shocks (see Acemoglu et al., 2013; Georg, 2013; Gai and Kapadia, 2010; Lee, 2013), but have not yet received attention in the analysis of derivative markets. Regarding the stability of the CDS market, existing studies do not rely on actual bilateral exposures but on maximum entropy estimations from aggregate exposures at a product level (Markose et al., 2012) or at a reference entity level (Vuillemey and Peltonen, 2013).

Our paper analyses the structure of the CDS market from three different perspectives: *(i)* the aggregated CDS network; *(ii)* various sub-networks, such as the sovereign CDS network; and *(iii)* networks for individual reference entities. A graphical motivation is

figure 2.1, where the global CDS market is pictured and its high levels of complexity and heterogeneity appear.

We provide two contributions to the literature on CDS markets. First, we characterise the topological properties of the aggregated CDS network worldwide and of several sub-networks with a lower level of aggregation. Directly related is the strand of the literature on financial networks, as surveyed by Allen and Babus (2009) or Upper (2011). A number of articles have already analysed the topological properties of payment systems (Bech and Atalay, 2010), of interbank networks (Iori et al., 2008; Martinez-Jaramillo et al., 2014) or of global banking (Minoiu and Reyes, 2013). These papers describe financial interconnections at one date or over time. Following Allen and Gale (2000), network topology has been related to stability properties and to contagion conditional on a shock. Recent examples include Battiston et al. (2012) and Georg (2013). Even though network metrics have been widely used to describe payment systems and the interbank market, so far there is no description of the CDS market in the literature.

To fill this gap, we use a novel dataset of bilateral CDS exposures as of end-2011, representing 32.7% of the global single-name CDS market. For 642 sovereign and financial reference entities, we have data on virtually all gross and net bilateral notional exposures between any two counterparties worldwide.

We find that the CDS market is highly concentrated around 14 dealers, who are also the only members of central counterparties (CCPs). The exposure network has a low density and exhibits the "small world" properties, also documented in the literature on interbank networks. The high interconnectedness among traders and the low network diameter do not arise out of a large number of direct exposures, but from the fact that almost all CDS end-users are directly connected to one or more dealers. This is further confirmed by the scale-free degree distribution in the aggregate CDS market. Such two-tiered network has been shown in the theoretical literature to be "robust yet fragile", i.e. resilient to most shocks, but vulnerable to contagion in case one of the core dealers fails. The contagion potential is reinforced by the fact that the proportion of net CDS sellers is much higher among large CDS traders than among less active end-users.

Our second contribution is to exploit the heterogeneity across reference entity networks so as to provide an econometric analysis of the determinants of the CDS network properties for individual reference entitites. Whereas previous papers on financial networks have focused on descriptive topological analysis, we exploit the richness of the data to investigate the reference entity-level determinants of CDS network properties. We are not aware of any existing comparable econometric study in the literature on networks.
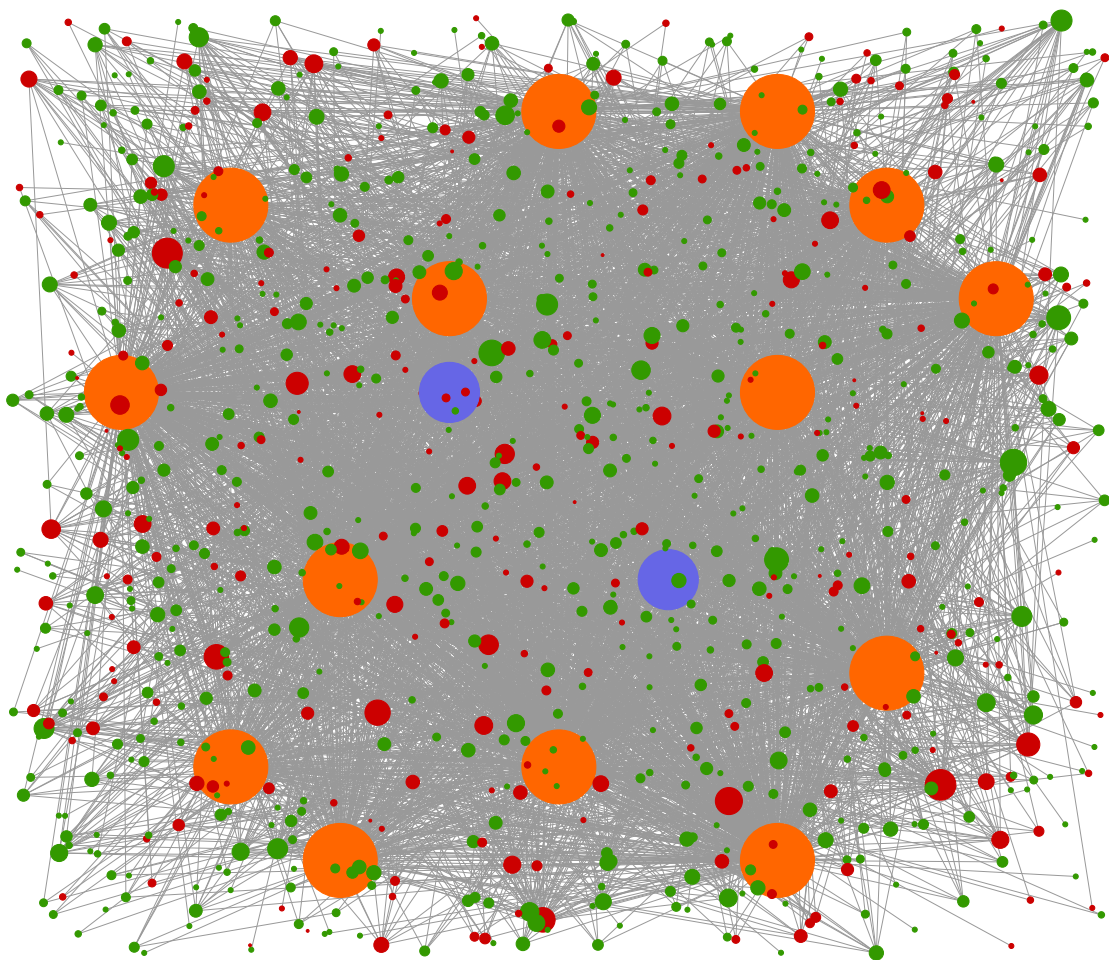
FIGURE 2.1: The global CDS network. This chart pictures the global network of net CDS exposures. Central clearing parties are in blue. Dealers are in orange. Customers are in green (resp. red) if they are net CDS buyers (resp. sellers) on average over all reference entities. The node size for customers is proportional to the square root of their net notional exposure. The node size for other agents is normalized. Given the focus on net exposures, some traders have no link to other traders: these traders are active on the CDS market in gross terms but have offsetting exposures.

We rely on previous theoretical and empirical works on CDS trading (for hedging, see Duffee and Zhou (2001); for managing counterparty risk, see Zawadowski (2013); for trading, see Acharya and Johnson (2007) and Fontana and Scheicher (2010); for regulatory arbitrage, see Yorulmazer (2012)) to formulate testable hypotheses. Using a generalized linear model, we focus on analysing the relationship between the size and activity of the CDS network and variables related to the underlying debt characteristics (e.g. volume of bonds outstanding, maturity and collateralization), risk characteristics (CDS spread, volatility and beta), as well as to the type (sovereign vs. financial) and location (European vs. non-European) of the debt issuer. Our results are consistent with uses of CDS for both hedging and trading purposes. Both uses, however, cannot be disentangled.

Our main results on the determinants of the CDS network structure are as follows. A larger volume of underlying bonds, especially if unsecured, increases the CDS network size and activity, suggesting a sizeable use of CDS for hedging. In contrast, size and activity decrease with longer underlying debt maturity, indicating the use of CDS as a hedge for roll-over risk. In terms of risk characteristics, CDS volatility and beta are more important determinants of CDS market outcomes than the absolute level of risk, as captured by the CDS spread level. This result is suggestive of the use of CDS for trading, but is also consistent with hedging uses. Furthermore, we document differences in intercept and marginal effects for sovereign names (as compared to financial names), with sign patterns consistent with the use of sovereign CDS for "proxy hedging". In contrast the European/non-European distinction is less significant for CDS market outcomes.

The hypotheses being tested have never been confronted to actual exposure data in the existing literature. Indeed, despite the large literature on CDS spreads (see Arora et al., 2012; Longstaff et al., 2011; Ejsing and Lemke, 2011; Berndt and Obreja, 2010; Fontana and Scheicher, 2010; Jorion and Zhang, 2007), research on actual CDS exposures is very limited. Oehmke and Zawadowski (2012) use public data from DTCC, aggregated at a name level, to document the determinants both of the emergence of a CDS market for particular corporate bonds and of net credit protection bought or sold. Chen et al. (2011a) use global CDS transaction data to describe the market composition, the trading dynamics and the level of standardisation in contract specifications.

The remainder of the paper is organized as follows. Section 2.3 describes the data and introduces potential determinants of the CDS network structure. Section 2.4 describes the aggregated CDS network as well as several CDS sub-networks. Section 2.5 presents the econometric methodology used to investigate the determinants of the CDS network structure, whereas section 2.6 contains the estimates and results.

2.3 The CDS dataset

This section describes our data.

2.3.1 The bilateral CDS exposure data

Our dataset on CDS exposures is provided by the Depository Trust and Clearing Corporation (DTCC) and is extracted from the Trade Information Warehouse (TIW). It is a snapshot of the world CDS market as of 30 December 2011. The TIW is a global trade repository covering the vast majority of CDS trades worldwide, and virtually all recent CDS trades. It has several unique features. First, whereas most regulators do have access to CDS transactions involving domestic counterparties or reference entities only, our dataset has a global coverage. Second, not only banks or dealers report their trades to DTCC, but all types of counterparties, so that our dataset encompasses all main non-bank institutions such as hedge funds, insurance companies, asset managers, central counterparties and potentially some industrial corporations. Finally, this data set is a legal record of party-to-party transactions, as the Warehouse Trust Company (a subsidiary of DTCC which operates the TIW) is supervised by US regulatory authorities.

Our sample covers 642 single-name reference entities, including 18 G20 sovereigns, 22 European sovereigns and 602 global financial entities[1]. It thus excludes all non-financial corporate names, as well as multi-name or index CDS. Our dataset contains the names of reference entities, but the identity of the counterparties is anonymised. The total gross notional in our sample equals EUR 4.28 trillion. At the same date (30 December 2011) the total gross notional at a world level was EUR 19.6 trillion (International Swaps and Derivatives Association, 2013). Therefore, our sample represents about 32.7% of the global single-name CDS market and 19.6% of the total CDS market (including multi-name instruments).

For each reference entity, the dataset contains gross and net bilateral exposures between any two counterparties. The overall network consists of 57 642 bilateral exposures on individual CDS and 592 083 transactions (as a bilateral exposure may result from several separate transactions). We do not have access to additional information at a transaction level. In particular, neither the market value of the CDS exposures nor their collateralization are available. A full-fledged analysis of counterparty credit risk is thus not possible using this dataset.

---

[1]Due to the DTCC definition of financials, the sample contains not only banks, but also insurance firms as well as industrial finance companies.

We perform a number of standard data quality checks. We observe 437 cases of bilateral exposure of a counterparty *vis-à-vis* itself, reflecting aggregation inconsistencies at a bank level, i.e. an internal trade between two accounts or subsidiaries/legal entities of the same firm. These observations are dropped.

2.3.2   CCPs in the sample

The CDS exposures dataset includes central counterparties (CCPs), which we identify from their business model. A counterparty is treated as a CCP if it has large gross notional exposures but consistently zero multilateral net exposure on *all* CDS names traded. Two CCPs are identified among the 50 largest traders. They clear 39 CDS names representing 7.02% of the gross notional CDS volume sample-wide. At the same date, the ISDA estimated the percentage of single-name CDS cleared at about 8%, based on a broader sample including corporate names.

Given this paper does not focus on clearing, CCPs are treated as traders like dealers or customers, unless specified otherwise. The two CCPs are linked respectively to 13 and 14 dealers only (the largest non-CCP traders) and have no link to other traders, as discussed below. A detailed analysis and descriptive statistics for the CCPs in the sample can be found in Duffie et al. (2014), who use the same dataset but focus on central clearing schemes.

2.3.3   Restricted sample

We construct a dataset of reference entity characteristics. For each reference entity, CDS exposure data are matched, when available, with CDS price data and underlying debt characteristics retrieved from Bloomberg. These variables are used both to define sub-networks (section 2.4) and as explanatory variables in the econometric analysis of the network structure determinants (section 2.5 and 2.6).

Because of a gap with the data coverage of Bloomberg, matching the DTCC exposure data with these additional variables leads to a smaller sample, which we call as the restricted sample. This approach has the additional advantage that it removes reference entities where there is very little trading, i.e. where the information content of the CDS network properties is likely to be low. The set of additional variables, described in the next subsections, is available for 191 reference entities representing a gross notional amount of EUR 3.88 trillion, i.e. 91% of the total gross notional in our full dataset. These variables are introduced below and their distributional statistics are given in table 2.1.

	Bonds	Average maturity	Unsecured debt (%)	CDS price	CDS vol.	CDS beta
Min.	0	0,46	0	42,6	0.04	0.28
25 pctile.	2,748	4.35	79.8	161.1	0.09	0.79
Median	14,317	6.19	99.4	254.4	0.11	1.03
75 pctile.	83,692	8.75	100	367.1	0.12	1.21
Max.	890,330	57.4	100	5,924.5	0.219	1.54

TABLE 2.1: Descriptive statistics for the explanatory variables. This table describes the distribution of the explanatory variables for the 191 CDS included in the restricted sample. "pctile" stands for "percentile". "Bonds" is the volume of bonds outstanding expressed in million euros. Average debt maturities are expressed in years. CDS prices are expressed in basis points. Formulas for CDS volatility ("CDS vol.") and beta are provided in section 2.3.3.2.

2.3.3.1 Debt characteristics

Given the design of CDS contracts as a hedging tool for credit risk exposures (Duffee and Zhou, 2001), we add variables related to the underlying debt characteristics[2]:

- **Volume of bonds outstanding** as of December 2011. The data includes covered bonds but excludes repurchase agreements.

- **Weighted average maturity** of the total bond volume outstanding.

- **Percentage of unsecured debt** of the total bond volume outstanding.

2.3.3.2 Risk characteristics

Moreover, given the use of CDS as a risk management tool, individual CDS network structures are likely related to the risk characteristics of the underlying reference entities (Duffee and Zhou, 2001). For two reasons, we use risk variables related to CDS spreads rather than to the underlying reference entities. First, bond data are heterogeneous both in terms of quality and of maturity, and for corporates there is usually no benchmark bond. In contrast, CDS spreads are comparable between entities for a given maturity. Second, there are uses of CDS that are likely to be directly affected by the CDS riskiness but not by the bond riskiness. This includes uses of CDS for trading rather than hedging, e.g. relative value trading strategies on CDS (Fontana and Scheicher, 2010).

We use time series of weekly data of CDS spreads spanning over 2010-11 retrieved from Bloomberg to define three risk-related variables:

- **5-year CDS spread** as of end-December 2011.

- **Volatility of the CDS spread**, computed using the time series of weekly data from 2010-11 as:
$$\text{Volatility}_i = \sigma \left(d\log \left(p_i^{CDS} \right) \right),$$
where p_i^{CDS} denotes the spread of CDS i, d the first difference and σ the standard deviation.

---

[2]Given that our sample comprise both sovereign and financial reference entities, and given the heterogeneity among financial reference entities (banks, insurance companies, finance companies), we cannot include additional balance sheet variables at an entity level as potential determinants of the CDS network properties.

- **CDS beta**, estimated using a one-factor model where the market return is defined as the simple (equally weighted) average of all individual CDS returns. The regression is computed with the weekly changes of the CDS spreads over the last two pre-sample years. We then use the estimated factor loading as an estimate of the beta for each CDS name.

2.3.3.3   Type and location of the reference entity

In addition to the debt and price characteristics, we add two dummy variables related to the underlying debt issuer:

- **Reference entity type**: The set of names is partitioned into a subset of sovereign and a subset of financial names.

- **Reference entity location**: Reference entities are distinguished according to their geographical location, being either European or non-European.

2.4   The network structure of the global CDS market

This section describes the topological properties of the aggregated CDS market. It then defines a number of CDS sub-networks, i.e. alternative aggregation schemes where CDS networks are aggregated according to reference entity characteristics.

2.4.1   Definitions and notations

We first define the *aggregated* CDS network. There is a set Ω of n counterparties indexed by i and j. The gross CDS notional sold by an institution i to an institution j on a reference entity k is denoted A_{ij}^k. The aggregate gross notional sold by i to j is denoted $A_{ij} = \sum_k A_{ij}^k$. The aggregated gross CDS network is composed of the exposures A_{ij}, for all i and j in Ω. The aggregated net CDS network is then defined by a $n \times n$ unweighted adjacency matrix N whose elements N_{ij} are given by:

$$
N_{ij} = \begin{cases} 1 & \text{if } A_{ij} > A_{ji} \\ 0 & \text{otherwise} \end{cases}
$$

	Aggr.	Sov.	Fin.	Eur.	Non Eur.	Spread <300	Spread >300	High debt	Low debt
N. CDS	642	40	602	200	442	118	75	97	96
N. traders	946	687	722	705	795	818	672	850	504
Gross not. (Bn EUR)	4 280	1 810	2474	1953	2332	2188	1699	2958	929
Net not. (Bn EUR)	349	162	187	168	181	195	111	248	58
Net / gross (%)	8.2	9.0	7.6	8.6	7.8	8.9	6.5	8.4	6.3
N. obs.	115,283	25,647	89,636	49,162	66,121	54,062	37,973	59,099	32,936
N. transac.	592,083	156,278	435,805	234,555	357,528	297,908	223,111	338,478	182,541
Avg. transac. not. (Mn EUR)	7.2	11.6	5.7	8.3	6.5	7.3	7.6	8.7	5.1
Avg. N. of counterparties	9.6	7.9	9.5	8.5	8.7	8.7	8.8	9.1	8.2
Avg. N. of CDS traded	18.7	5.6	19.2	10.6	12.9	9.4	7.8	10.1	8.7
Avg. N. transac. per CDS per link	10.3	12.2	9.7	9.5	10.8	11	11.8	11.5	11.1
Share top-10	0.73	0.72	0.74	0.72	0.73	0.71	0.76	0.72	0.76
Share net sellers	0.18	0.16	0.18	0.15	0.20	0.13	0.18	0.17	0.19

TABLE 2.2: Descriptive statistics. This table presents descriptive statistics for the aggregate CDS network and eight sub-networks. "N." abbreviates "number". "Avg. transac. not." is the average notional amount of a transaction. "Avg. N. transac. per CDS per link" is the average number of transactions that made up a bilateral exposure between any to traders on a given CDS name. "Share top 10" is the share of gross CDS sold by the 10 most active traders. "Share net sellers" is the percentage of active institutions that are net CDS sellers.

We restrict our attention to the unweighted adjacency matrix, as some metrics (diameter, mean and maximum degree in particular) are more difficult to interpret for a weighted network[3].

2.4.2 Network metrics

Following Iori et al. (2008), we compute the number of links, the density, the clustering coefficient, the diameter, the mean degree, the maximum degree, the degree distribution and its fitting to a power law. Each of these metrics has been defined in the literature (e.g. Jackson, 2008). Furthermore, each can be related to network stability or contagion properties. We briefly discuss their interpretation within the literature on financial networks, and discuss them below in the context of the CDS market.

The number of links, the mean and the maximum degree, as well as the density, measure the level of interconnectedness within the network. It is well-established, both theoretically and through simulations (see Acemoglu et al., 2013; Georg, 2013; Nier et al., 2007; Gai and Kapadia, 2010, for recent contributions), that the relation between the level of interconnectedness and contagion within a network is non-monotonic. For low levels of interconnectedness, there exists unexploited risk-sharing opportunities within the network, so that each trader is more vulnerable to idiosyncratic shocks. Increasing the network density increases risk-sharing, up to a point where the propagation of shocks is amplified ("tipping point" property).

The clustering coefficient, introduced by Watts and Strogatz (1998), measures the extent to which the network is centred around a subset of highly interconnected traders. Its impact on financial stability depends on the robustness of the subset of clustered traders (interpreted below as dealers within the context of the CDS market). While the failure of one of these nodes may drive the systemic failure of a sizeable share of the network, they may also act as shock absorbers in case they are robust enough.

The diameter (defined as the longest of all shortest paths between any two nodes) is inversely related to the potential speed of contagion within a network. A low diameter implies that no bank is remote from any potentially distressed institution within the network.

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[3]Even though they are not presented below, all results have been computed for the weighted network as well, and do not differ to a significant extent Such results are available upon request.

	High maturity	Low maturity	High unsec.	Low unsec.	High beta	Low beta	High vol.	Low vol.
N. CDS	96	95	96	95	97	96	97	96
N. traders	784	749	814	670	834	599	851	582
Gross not. (Bn EUR)	2274	1601	2082	1793	2973	915	2969	918
Net not. (Bn EUR)	185	121	185	1199	228	78	234	71
Net / gross (%)	8.1	7.6	8.9	6.7	7.7	8.5	7.9	7.8
N. obs.	50,059	41,414	43,643	47,830	60,503	31,532	60,164	31,871
N. transac.	296,737	221,793	245,079	273,451	363,595	157,424	365,280	155,739
Avg. transac. not. (Mn EUR)	7.7	7.2	8.5	6.6	8.2	5.8	8.1	5.9
Avg. N. of counterparties	8.9	8.5	8.3	9.2	9.1	8.1	9.2	8.6
Avg. N. of CDS traded	9	7.7	7.7	9.8	10.3	7.3	10	7.6
Avg. N. transac. per CDS per link	11.9	10.7	11.2	11.4	12	10	12.1	9.8
Share top-10	0.73	0.73	0.74	0.72	0.72	0.77	0.72	0.75
Share net sellers	0.18	0.17	0.19	0.20	0.18	0.17	0.19	0.19

TABLE 2.3: Descriptive statistics. This table presents descriptive statistics for eight sub-networks. "N." abbreviates "number". "Avg. transac. not." is the average notional amount of a transaction. "Avg. N. transac. per CDS per link" is the average number of transactions that made up a bilateral exposure between any to traders on a given CDS name. "Share top 10" is the share of gross CDS sold by the 10 most active traders. "Share net sellers" is the percentage of active institutions that are net CDS sellers.

2.4.3   Descriptive statistics for the aggregate CDS network

The global CDS market is illustrated in figure 2.1 and its descriptive statistics are presented in table 2.2. 946 counterparties trade on 642 reference entities, representing a total gross notional amount of EUR 4,280 billion. Compared to the gross exposure, a stylized fact is the low net exposure, which equals EUR 349 billion, implying a net-over-gross notional ratio of 8.2%.

Two features of the CDS market drive this pattern. First, intermediary and market-making activities by dealers represent a sizeable share of the market activity. CDS end-users typically have few direct exposures among themselves; on the contrary, they trade through dealers, who intermediate trades between end-users. Thus, a sizeable share of dealers' gross activity does not generate net exposures. Second, portfolio management techniques by end-users also drive the low net-over-gross ratio. When a trader is set to reduce her open CDS exposure, she usually does not cancel existing contracts, but instead enters new offsetting contracts, thus increasing gross exposures while reducing net exposures.

The average market participant is trading 18.7 reference entities and is linked to 9.6 counterparties. Both distributions, however, are highly skewed as 55% of traders have 3 counterparties or less, and 71% trade 10 CDS or less. The most-connected institution is linked to 470 counterparties. We observe 592,083 transactions that have an average notional value of EUR 7.2 million. Each exposure on a particular reference entity network on average results from 10.3 (potentially offsetting) transactions. The high number of transactions and the low net-over-gross notional ratio indicate that net CDS exposures between any two traders on a reference entity are frequently adjusted and that an exposure opened at some date is typically not kept unchanged until the maturity of the CDS contract.

Finally, an additional stylized fact relates to CDS portfolio patterns and is reported in tables 2.2 and 2.4. Market-wide, only 18% of the traders are net CDS sellers, 82% being net buyers. This implies a high concentration of ultimate credit risk-bearing among a subset of traders. Furthermore, the distribution of net CDS sellers is skewed towards largest traders. While 50% of the top-10 traders are net CDS sellers, only 17% of the traders in the lower end of the distribution are net sellers. This fact has implications for the network stability, as discussed below.

2.4.4   A tiered network structure centered around dealers

This subsection describes the aggregate CDS network by means of network metrics.

	Aggr.	Sov.	Fin.	Eur.	Non Eur.	Spread <300	Spread >300	High debt	Low debt
Top-10 traders	0.5	0.1	0.5	0.4	0.4	0.3	0.3	0.3	0.4
10-50 traders	0.4	0.42	0.37	0.4	0.42	0.4	0.32	0.4	0.4
50-end traders	0.17	0.14	0.16	0.12	0.18	0.15	0.11	0.16	0.16
	High maturity	Low maturity	High unsec.	Low unsec.	High beta	Low beta	High vol.	Low vol.	
Top-10 traders	0.3	0.6	0.5	0.6	0.5	0.5	0.4	0.5	
10-50 traders	0.42	0.45	0.47	0.37	0.42	0.3	0.45	0.35	
50-end traders	0.16	0.15	0.16	0.17	0.16	0.15	0.17	0.17	

TABLE 2.4: Percentage of CDS net sellers by percentiles. This table give the share of net CDS sellers within three groups of traders for the aggregate CDS network and for all sub-networks. The definition of the three groups (or "percentiles") is based on the total gross notional bought and sold by each counterparty within the sub-network. The figures per network do not sum up to one, as only the share of net sellers *within* groups of traders is provided.

2.4.4.1 The network interconnectedness through dealers

The aggregate CDS network has a tiered network structure and is centered around 14 dealers. We identify dealers from their membership to the two CCPs. No end-user is member of the sample CCPs. The concentration of activity among dealers is high (as previously noted by Mengle, 2010), as they concentrate 84.5% of the gross sales of CDS[4]. Moreover, the inter-dealer activity represents 75.1% of all trades, reflecting the intermediary role of dealers as a whole: When dealers buy or sell CDS to end-users, their exposures are then partially offset and hedged through a complex web of inter-dealer trades.

This network structure is more clearly seen from the network metrics presented in table 2.5. The aggregated network comprises 4,428 links between the 946 counterparties, implying a low density (equal to 0.005). Furthermore, it exhibits the "small world properties" exposed in Watts and Strogatz (1998) or Jackson (2008). "Small world" networks are first characterized by a low diameter (here equal to 5), i.e. the average number of links separating any two nodes is short[5]. They are also characterized by a clustering coefficient larger than that of an Erdős-Rényi random network of comparable density (see e.g. Iori et al., 2008). It is equal to 0.07 in the aggregate CDS market, several times higher than the density[6].

These "small world" properties further confirm the above description of the CDS market. The high clustering coefficient reflects the existence of a subset of highly interconnected intermediaries, mainly dealers. Moreover, the low diameter, together with the low density, show that the interconnectedness on the CDS market does not arise from the large number of bilateral links between any two counterparties, but because all traders are close to one another due to the existence of a few key intermediary traders.

Watts and Strogatz (1998) show that contagion in "small-world" networks is fast, given the low diameter. Intuitively, no institution is remote from other potentially distressed institutions. In the context of the interbank market, however, Georg (2013) finds that "small-world" networks are less prone to contagion on average than random networks. The reason is that, unless one of the few "money center" banks fails, contagion is unlikely. In the CDS market, one consequence is that contagion is unlikely to arise from the default of one or of a few end-users; however, the default of a dealer could propagate quickly to a large part of the network.

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[4]This figure also includes dealer-to-dealer trades cleared through the two sample CCPs.

[5]The diameter is the longest shortest path between any two nodes.

[6]The clustering coefficient in an Erdős-Rényi random graph, i.e. a graph in which each link is formed with a probability p, is equal on expectation to the network density.

	Aggr.	Sov.	Fin.	Eur.	Non Eur.	Spread <300	Spread >300	High debt	Low debt
N. edges	4,428	2,951	3,395	2,663	3,343	2,105	1,359	3,816	2,014
Mean degree	9.4	6.2	7.2	5.6	7.1	4.5	2.9	8.1	4.3
Max. degree	470	336	367	312	371	265	165	415	236
Density	0.005	0.003	0.004	0.003	0.004	0.002	0.002	0.004	0.002
Clustering	0.07	0.09	0.08	0.09	0.09	0.1	0.16	0.08	0.12
Diameter	5	5	4	5	5	5	5	4	4

		High maturity	Low maturity	High unsec.	Low unsec.	High beta	Low beta	High vol.	Low vol.
N. edges		3,421	3,118	3,318	3,016	3,723	2,362	3,848	2,323
Mean degree		7.2	6.6	7	6.4	7.9	5	8.1	4.9
Max. degree		393	343	390	340	410	277	420	264
Density		0.004	0.003	0.004	0.003	0.004	0.003	0.004	0.003
Clustering		0.08	0.09	0.08	0.1	0.08	0.1	0.07	0.11
Diameter		4	4	5	4	4	5	5	4

TABLE 2.5: Network statistics for the unweighted aggregated network and the sub-networks. This table presents the network metrics for the aggregate CDS network and all sub-networks. "N. edges" is the number of links, or edges, within the network.

2.4.4.2 A scale-free degree distribution

The network concentration and the high heterogeneity across traders is further seen through the degree distribution (i.e. the probability distribution of the number of links of each trader, see Iori et al. (2008)), found to be scale-free[7]. It is displayed in a log-log scale in figure 2.2. Most papers in the empirical literature on the interbank market or on payment systems fail to reject the hypothesis that their degree distribution follows a power law distribution, i.e. that the fraction of nodes $P(x)$ having a degree x is distributed, for values of x above some threshold $x_{\min}$, as:

$$P\left(\text{degree} = x\right) = \frac{\alpha - 1}{x_{\min}} \left(\frac{x}{x_{\min}}\right)^{-\alpha}$$

The degree distribution of the aggregate CDS market is fitted to a power law distribution using a maximum likelihood estimator (Goldstein et al., 2004). The Kolmogorov-Smirnov statistics is computed to test whether the hypothesis according to which the degree distribution follows a power law distribution can be rejected. Results are presented on table 2.6. We fail to reject the hypothesis, implying that the aggregate CDS network can be considered scale-free.

In terms of stability and contagion, scale-free networks have been shown to be more robust than random networks to the disappearance of one node, but to be highly vulnerable in case one of the few highly-connected nodes disappears (Duan et al., 2005; Georg, 2013). Such a "robust-yet-fragile" property signals the importance of the robustness of the dealers. Parallel findings for the interbank market point to the key role of money-center banks (Gai and Kapadia, 2010; **?**). For the interbank market, **?** show that bank capitalization is a driver of contagion in scale-free networks. A policy implication of our results is that the risk-bearing capacity of the dealers (capital and collateral assets) shall be properly assessed and high enough.

A number of papers, starting with Barabasi and Albert (1999), have provided theoretical underpinnings for explaining the emergence of scale-free networks. Dorogovtsev and Mendes (2003) provide a comprehensive overview of this class of models which, in order to generate scale-free degree distributions, feature characteristics such as "preferential attachment" mechanisms between nodes or "cumulative advantages". On OTC derivatives markets, "preferential attachment" can be linked to the role of a few major market participants who act as dealers, thereby trading large gross amounts but having a substantially smaller net exposure due to their intermediary role. One example here is the prime brokerage services offered by dealers to hedge funds.

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[7] Scale-free networks are a particular class of "small world" networks. **?** show they can be considered "ultrasmall worlds".

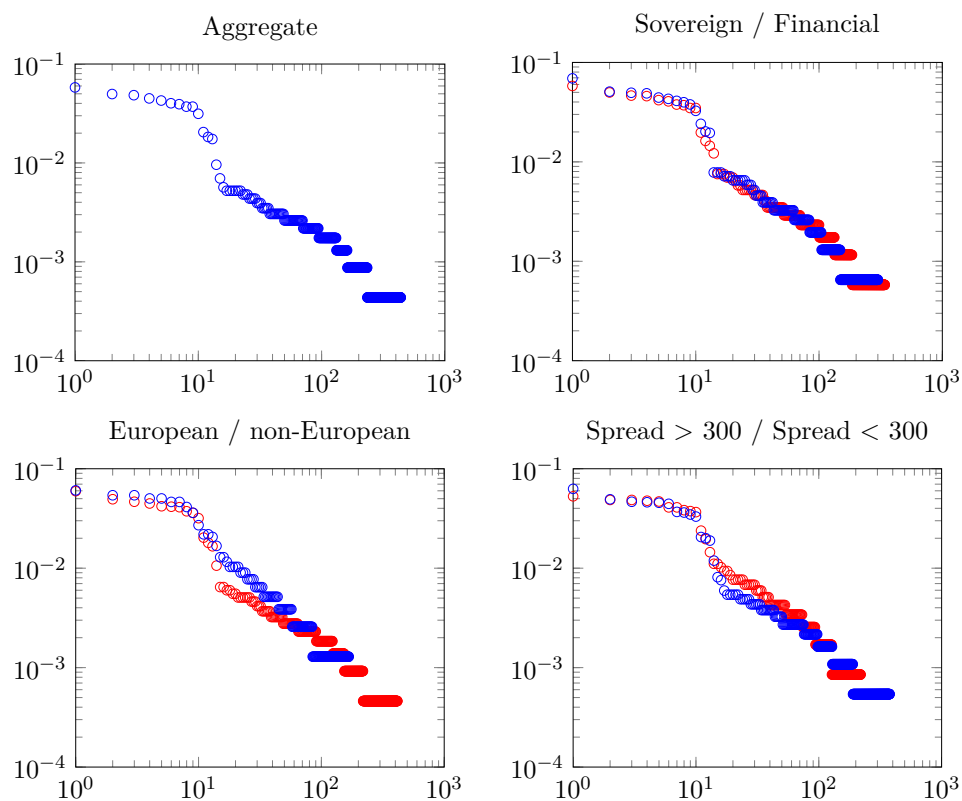FIGURE 2.2: Degree distributions. On the top right side, the blue distribution refers to the sovereign and the red distribution to the financial CDS network. On the bottom left, the blue distribution refers to the European and the red distribution to the non-European CDS network. On the bottom right, the blue distribution refers to the "high spread" and the red distribution to the "low spread" CDS network.

2.4.4.3 A graphical illustration of dealers' activity

To further illustrate dealers' activity, we adopt a graphical approch inspired by Duffie (2013), who suggests to reduce the complexity of an exposure network by focusing on 10 risk factors for the 10 largest institutions, where the 10 largest losses by counterparty would be reported. A simplified approach is taken, as we picture the 5 largest net (long or short) exposures for the 14 dealers to non-dealer counterparties on the aggregate CDS market. Figure 2.3 illustrates the structure described in the above sections.

First, the inter-dealer activity is dense, in spite of CCPs clearing exposures for eligible names. Second, end-users have no centrally cleared exposures, so that counterparty credit risk is borne in full by the dealers to which they are linked. Third, some dealers have large net open exposures to a few end-users. Within a scale-free network, where contagion is known to spread from the failure of the most-connected nodes (the network being otherwise robust), these exposures are a risk factor to be looked at in a policy perspective on financial stability. One caveat, however, is that collateralization levels are not observed here.

2.4.5 Descriptive statistics for the sub-networks

From the aggregated network, we turn to lower levels of aggregation based on the reference entity characteristics introduced earlier. For each of the eight characteristics introduced from section 2.3.3.1 to 2.3.3.3, the sample is split into two subsets. Bilateral exposures within subsets are then aggregated. The resulting CDS networks are dubbed "sub-networks". Their construction is detailed in appendix 1. Descriptive statistics for these networks are presented in tables 2.2 and 2.3, while their topological properties are in table 2.5.

The main result in this section is that the network structure documented for the aggegate CDS market still prevails for lower levels of aggregation based on reference entity characteristics, even though some heterogeneity is observed. We shall not comment tables 2.2 to 2.5 in full details[8], and instead highlight only either stylized facts or noticeable differences across networks.

Among the stylized facts for CDS sub-networks are a low density (ranging between 0.002 and 0.004) and the "small world" structure. The tiered structure exists across sub-networks, as the Kolmogorov-Smirnov statistic rejects the hypothesis that networks are scale-free in only one instance, for the "low unsecured" CDS network. Qualitatively,

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[8]A lengthier analysis can be found in the working paper version (**?**).

	Aggr.	Sov.	Fin.	Eur.	Non Eur.	CDS >300	CDS <300	High debt	Low debt
$x_{\min}$	4	3	2	4	2	2	3	2	3
α	1.66	1.63	1.5	1.77	1.51	1.68	1.75	1.51	1.75
p value	0***	0.001***	0***	0***	0.005***	0.01**	0.007***	0.004***	0.012**
		High maturity	Low maturity	High unsec.	Low unsec.	High beta	Low beta	High vol.	Low vol.
$x_{\min}$		2	4	3	4	3	4	4	2
α		1.56	1.61	1.7	1.71	1.76	1.75	1.65	1.51
p value		0.02**	0***	0.009***	0,107	0.001***	0.002***	0.005***	0***

TABLE 2.6: Power law distribution of the degree distributions. $x_{\min}$ is the value of the degree above which the degree distribution is fitted to a power law. "alpha" is the shape parameter of this power law. "p value" is the probability that the degree distribution is not drawn from the fitted power law distribution (i.e. rejection of the null hypothesis by the Kolmogorov-Smirnov test). *, ** and *** indicate a failure to reject the null hypothesis at a 10%, 5% and 1% significance level respectively.
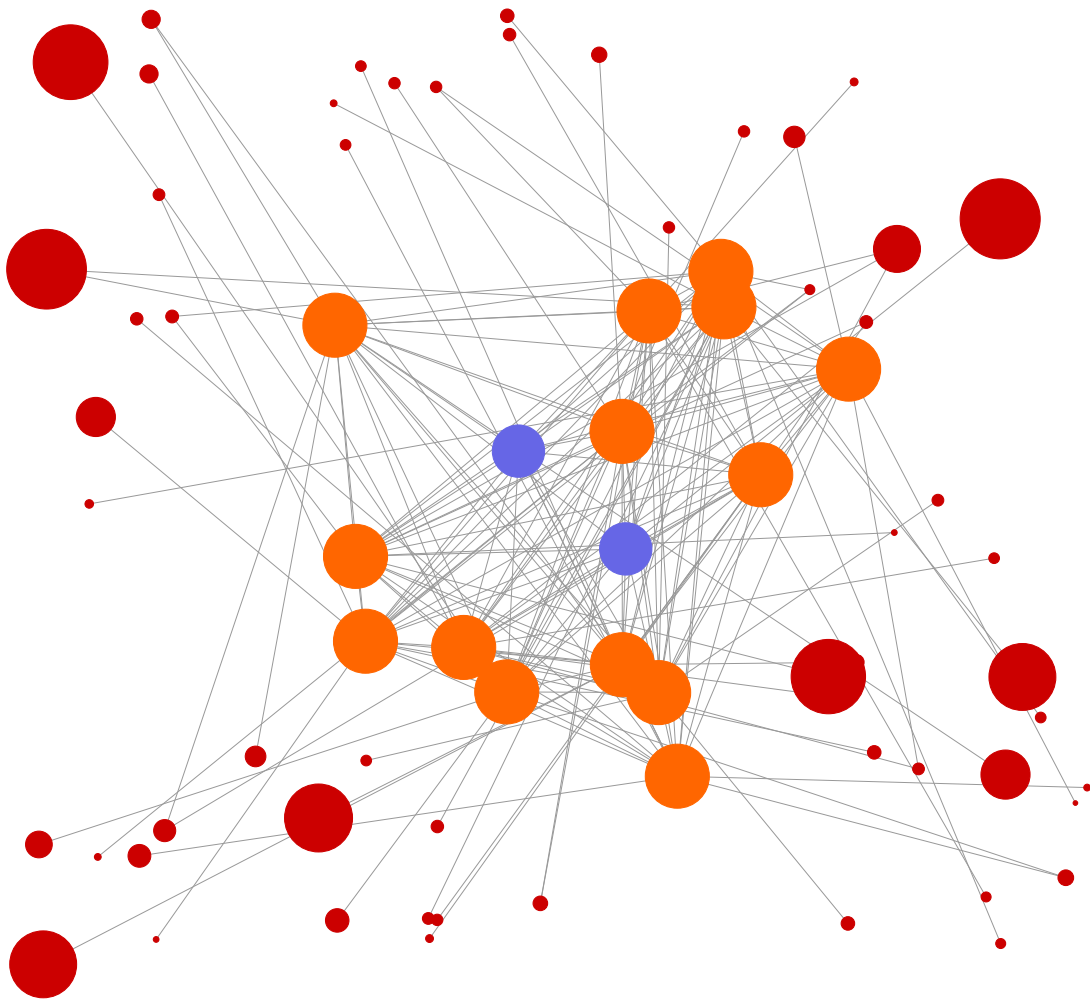
FIGURE 2.3: The global CDS network: A 14×5 approach. This chart pictures the global CDS network when restricting attention to the 14 CDS dealers and their 5 largest net exposures. Central clearing parties are in blue, dealers in orange and customers in red. Only dealers are linked to CCPs. The node size for dealers and CCPs is normalized, whereas that of customers is proportional to the square root of their total net exposures. When identifying the 5 largest net exposures of each dealer, both long and short exposures are considered.

all segments of the CDS market can thus be expected to have the stability properties discussed above ("robust-yet-fragile property"). Contagion on a subsegment only of the CDS market, however, is impossible unless a subset of traders specialize on a large scale on this particular market segment. The default of a trader indeed implies the close-out of all CDS contracts traded under the same master agreement, regardless of their type (Bliss and Kaufman, 2006).

Consistent with the power law degree distribution, the concentration (measured by the market share of the 10 largest traders) is high in all sub-networks and ranges between 71% and 77%. We observe that networks with a low density have a larger clustering coefficient. Hence, the cluster of dealers at the core of the CDS network plays a larger role in CDS markets where the density is lower. This feature reflects the fact that, when the notional volume on a CDS reference entity grows, new market participants who are not in the core group of traders account for a larger share of the links. Finally, the net-over-gross notional ratio is low in all sub-networks—ranging between 6.3% and 9%—but nevertheless larger in networks with more active counterparties: When more end-users enter the CDS market, they tend to take on net exposures.

Turning to the heterogeneity across sub-networks, we do observe significant differences in the number of active counterparties. For instance, whereas there are 850 active counterparties in the market for "high debt" CDS (i.e. CDS whose underlying bond volume is above the sample median), there are only 504 active counterparties in the market for "low debt" CDS, suggesting that the underlying debt volume is an important driver of the CDS market size and activity—an hypothesis which we test below. Similarly, sub-networks for "high unsecured debt", "high beta" and "high volatility" CDS are characterized by a larger number of active counterparties, as well as larger gross and net CDS exposures. Cross-network heterogeneity is further examined econometrically below and related to theoretical hypotheses about CDS use.

There is significant heterogeneity in the average transaction notional amount, which ranges from EUR 5.1 million (on the "low debt" CDS network) to EUR 11.6 million (on the sovereign CDS network). It is larger for sovereign than for financial reference entities (11.6 vs. 5.7 million euros), suggesting that the standardized notional amounts traded depend on the reference entity type. Overall, the average transaction notional amount is larger in networks with larger notional amounts traded. For example, it is larger for the "high debt" than for the "low debt" CDS network (8.7 vs. 5.1 million euros).

Finally, the share of active counterparties being net CDS sellers ranges between 0.13 and 0.20 across sub-networks. In aggregate, a large majority of market participants are therefore net CDS buyers, corroborating the fact that credit risk is ultimately born by a small fraction of the active institutions. The share of net sellers among market

participants is higher for the "high spread" than for the "low spread" CDS network (0.18 versus 0.13), implying that the ultimate credit risk is potentially better spread among market participants when it is higher.

Regarding the share of institutions being net sellers depending on their level of activity (table 2.4), the pattern documented for the aggregated network is observed in all subnetworks, with one exception. Overall, the proportion of net sellers increases with the level of activity. In most instances, between 30% and 60% of the institutions among the 10 most active traders are net sellers, whereas this proportion falls between 11% and 18% among the less active traders. One notable exception to this general pattern relates to the sovereign CDS network. On this market, only one out of 10 of the most active traders is a net CDS seller, implying that the vast majority of the most active dealers are net buyers of CDS on sovereign reference entities. The ultimate credit risk in this market is mostly born by institutions that have a medium level of activity (42% of them being net sellers).

2.5 Determinants of network structure: Methodology

This section turns to the investigation of the determinants of CDS network properties at a reference entity level. It describes the econometric strategy and the theoretical hypotheses being tested.

2.5.1 Econometric specification for the CDS network outcomes

In this section our aim is to understand the drivers behind differences in the cross section of reference entity networks' size and activity. Dependent variables are chosen to capture structural properties of each reference entity-level CDS network. Variables such as the network density have a support $[0; 1]$. To keep a consistent approach throughout the econometric analysis, all dependent variables are constructed as proportions. A methodology to estimate regressions with fractional response variables has been proposed by Papke and Woolridge (1996). It uses the generalized linear model (GLM) developed by Nelder and Wedderburn (1972) and Mccullagh and Nelder (1989).

In a typical GLM specification for proportions, the dependent variable is modeled by a binomial distribution, in combination with a logit link function. Given a vector of explanatory variables X, the conditional expectation of the fractional dependent variable Y is:

$$\mathbb{E}[Y|X] = \frac{1}{1 + e^{-X\beta}}$$

The vector of parameters β is estimated by maximum likelihood.

2.5.2 Dependent variables

Network metrics *per se* are not used as dependent variables. First, pairwise correlations between most of them are high (table 2.7). Second, we prefer dependent variables with a straightforward economic interpretation in terms of contagion or credit risk sharing.

We restrict attention to two types of network properties, related to the notional size and the trading activity on particular CDS[9].

2.5.2.1 Size characteristics

An important characteristic of the trading on a given reference entity is its overall size. Its size can be first measured in relative terms, i.e. by comparing a size metrics with the size of the aggregated CDS market. Second, it can be captured by reference entity-specific metrics.

Share of the net notional to the total market net notional

For each reference entity, the aggregate net notional amount of CDS sold is computed. The relative importance of a reference entity on the market is computed as the share of the net notional exposure over the total net market notional exposure.

Share of active traders

We analyse how many traders are active in a given reference entity as well as the share of links. The share of nodes (i.e. of traders) for a given reference entity is equal to the number of market participants actually active (both on the buy and on the sell side) over the total number of participants in the CDS market as a whole.

Density of the network

The density of the reference entity network is the ratio of the number of actual links over the total number of possible links in the network.

---

[9]A third set of dependent variables could relate to the concentration of name-level CDS networks. However, given the lack of theoretical literature on the determinants of CDS market concentration, this investigation is relegated to the working paper version of this paper (**?**).

	Density	Mean degree	Max. degree	Clustering	Diameter	Power law shape
Density	1					
Mean degree	1	1				
Max. degree	0.96	0.96	1			
Clustering	-0.75	-0.75	-0.82	1		
Diameter	0.06	0.06	0.1	-0,27	1	
Power law shape	-0.96	-0.96	0.92	0.77	0.14	1

TABLE 2.7: Correlation coefficients for the network metrics. This table presents the Pearson correlation for the network metrics. Correlations are computed for the restricted sample of 191 CDS reference entities.

	Dens.	% Nodes	% Net	% Trades	% Notional
Sov.	0.0005	0.108	0.013	0.013	0.017
	(0.000)	(0.01)	(0.002)	(0.003)	(0.000)
Fin.	0.0003	0.063	0.003	0.004	0.003
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
All	0.0004	0.071	0.005	0.005	0.0005
	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)
Diff. (Fin. - Sov.)	-0.0002	-0.045	-0.01	-0.009	-0.014
Pr(Diff=0)	0	0	0	0	0
Pr(Diff≠0)	1***	1***	1***	1***	1***

TABLE 2.8: Differences in mean, sovereign vs. financial CDS. This table presents a two-sample t test to document differences in mean between sovereign and financial CDS for the 5 dependent variables used in the econometric analysis. "Dens." is the network density. "% Nodes" is the share of active traders, or nodes. "% Net" is the share of net notional represented by the CDS reference entity. "% Trades" is the share of daily trades represented by the CDS reference entity. "% Notional" is the share of daily notional traded represented by the CDS reference entity. *** denotes statistical significance at a 1% level.

2.5.2.2 Activity characteristics

Given a particular size, CDS markets for individual reference entities may differ with respect to their activity. Namely, given a certain density and a certain number of market participants, CDS may be more or less actively traded, and the notional amounts traded on a daily basis may differ across entities. These activity factors are captured through two variables.

Average share of trades per day

Public data on the average number of trades per day for each reference entity is retrieved from the DTCC's website. The average is computed over the period starting in September 2011 and ending in December 2011. For each reference entity, we then compute the average share of trades per day, relative to the total number of trades per day.

Average share of gross daily notional

From the same public dataset, we retrieve information about the average daily gross notional amount traded for each reference entity. For each reference entity, we compute the average share of gross daily notional over the total daily notional, where the total is computed over all reference entities in the sample.

2.5.3 Differences in dependent variable means by debt issuer groups

This subsection documents differences in dependent variables' means for type (sovereign vs. financial) and location groups, using a two-sample t test. Results are presented in table 2.8 for the sovereign/financial distinction and in table 2.9 for the European/non-European distinction.

Differences in means between sovereign and financial reference entities are highly significant at a 1% level for all variables. Sovereign CDS networks have on average a larger size and are characterized by a more intense activity. By contrast, the distinction between European and non-European reference entities is not significant, except at a 10% level for one variable related to the network activity. These differences are further investigated and related to theoretical hypotheses below.

	Dens.	% Nodes	% Net	% Trades	% Notional
Non EU	0.0004	0.066	0.004	0.005	0.004
	(0.000)	(0.004)	(0.001)	(0.001)	(0.001)
EU	0.0004	0.076	0.005	0.006	0.007
	(0.000)	(0.005)	(0.001)	(0.001)	(0.002)
All	0.0004	0.071	0.005	0.005	0.005
	(0.000)	0.003	(0.001)	(0.001)	(0.001)
Diff. (Non Eur. - Eur.)	0	-0.01	-0.001	-0.001	-0.003
Pr(Diff=0)	0.45	0.1	0.18	0.29	0.07
Pr(Diff≠0)	0.55	0.9	0.82	0.71	0.93*

TABLE 2.9: Differences in mean, European vs. non European CDS. This table presents a two-sample t test to document differences in mean between European and non European CDS for the 5 dependent variables used in the econometric analysis. "Dens." is the network density. "% Nodes" is the share of active traders, or nodes. "% Net" is the share of net notional represented by the CDS reference entity. "% Trades" is the share of daily trades represented by the CDS reference entity. "% Notional" is the share of daily notional traded represented by the CDS reference entity. * denotes statistical significance at a 10% level.

2.5.4 Testable hypotheses and expected signs

Reference entity characteristics likely related to the CDS network structure for particular names are used as independent variables in the next section. In this sub-section, we rely on the theoretical literature on CDS use to formulate testable hypotheses. We discuss the expected sign of each explanatory variable on the CDS market size and activity. Expected signs are summarized in table 2.10.

Four uses of CDS contracts have so far been modeled in the literature. First, CDS may be used to meet the hedging demand of banks or investors, as shown by Duffee and Zhou (2001). The underlying credit exposure to be hedged may be the CDS reference entity or another entity correlated with it ("proxy hedging", discussed in greater details below). Second, Zawadowski (2013) provides theoretical underpinnings for the use of CDS as a tool to hedge counterparty credit risk. That risk may arise not from an exposure to the CDS underlying credit exposure, but from other bilateral exposures such as derivative exposures. Third, CDS may be used for outright trading rather than hedging purposes. Two examples of this practice are insider trading of CDS (Acharya and Johnson, 2007) or trading CDS vs. the underlying bonds (Fontana and Scheicher, 2010). Fourth, Yorulmazer (2012) models the use of CDS to free up regulatory capital and expand banks' balance sheets.

We shall refer to the use of CDS for *hedging* (by contrast with *trading*) when a particular CDS use requires the underlying credit exposure to be held. Given the absence of trader-level data on bond portfolios, however, our econometric analysis can only provide suggestive evidence on CDS use, relying on existing economic theory to interpret correlations between CDS network characteristics and both bond market and CDS spread properties.

2.5.4.1 Hypotheses about debt characteristics

The use of CDS for hedging (absent proxy hedging) requires traders to hold the underlying credit exposure. Two hypotheses can be formulated as regards debt characteristics.

Hypothesis 1. A larger pool of underlying debt outstanding is associated with a larger size and activity of the CDS market.

Hypothesis 1 follows from the fact that a larger insurable interest (i.e. underlying credit exposures) shall imply a larger and more active CDS market *ceteris paribus*, provided CDS are used for hedging truly held underlying exposures. Whereas all uses of CDS

	Size	Activity
Bonds outstanding	+	+
Maturity	∼	-
Unsecured debt	+	+
CDS price	+	+
Volatility	+	+
Beta	∼	∼
Sovereign	+	+
European	+	+

TABLE 2.10: Expected signs. This table presents the expected signs for the explanatory variables. "Size" and "Activity" are the two types of dependent variables which are being invetsigated econometrically. "+" and "-" denote respectively an expected positive and negative sign. A "∼" denotes the absence of theoretical prior regarding the expected sign of the regression coefficient. The theoretical rationales for these signs are detailed in section 4.3.

cannot be identified using our data, a failure to reject hypothesis 1 would be suggestive of a significant use of CDS as a hedging tool[10].

Hypothesis 2. A larger share of unsecured debt is associated with a larger size and activity of the CDS market.

Hypothesis 2 is closely related to 1. Whenever a large share of the underlying debt is secured, the need for CDS as a hedging tool is reduced, as the creditor is already (partially or totally) hedged through the assets received as collateral. A failure to reject hypothesis 2 would also be suggestive of the use of CDS for hedging purposes.

No hypothesis can be formulated as regards the underlying debt maturity. The observed sign patterns, however, may contribute to distinguish between uses of CDS by traders. All else kept equal, the probability that a reference entity experiences a credit event increases with the maturity of its debt. However, heavy reliance on short-term debt increases the roll-over risk which, in times of funding strains, may significantly increase the probability of default of an entity. The empirical motivation for this hypothesis is the inverted term structure of credit spreads for the high-yield category (Lando and Mortensen, 2005). Depending on which effect dominates, either a positive or a negative sign can be expected for the relationship between the average debt maturity and the CDS network size. Furthermore, if CDS are used for hedging purposes, we further expect activity on the CDS market to be negatively related to the average debt maturity, as CDS positions need to be adjusted more frequently if the nature of the underlying debt exposure changes at a higher frequency.

2.5.4.2 Hypotheses about risk characteristics

Given the use of CDS for portfolio management (including hedging and investing), CDS risk characteristics are likely related to CDS market size and activity. Two hypotheses are formulated about CDS spread level and volatility.

Hypothesis 3. A higher level of the CDS spread is associated with a larger size of the CDS market.

Hypothesis 3 follows from the use of CDS as a hedging tool. Treating the CDS spread level as a proxy for the underlying debt probability of default (both are linked, but not equivalent, see Jarrow (2012)), the need to hedge is *ceteris paribus* higher whenever the debt probability of default is itself higher. A failure to reject hypothesis 3 is thus

---

[10]Note, however, that the use of CDS as a hedging tool would not be perfectly identified, as the volume of underlying bonds outstanding may be correlated with unobserved variables that make CDS desirable for trading purposes (e.g. liquidity of the bond market in relative value trading strategies).

suggestive of the use of CDS for hedging purposes. To the extent that CDS spreads incorporate additional risk factors at a name level (such as risk arising from derivative exposures), it would also be consistent with the use of CDS to manage counterparty credit risk.

Hypothesis 4. A higher CDS spread volatility is associated with a larger size and activity of the CDS market.

Hypothesis 4 is consistent with all four possible uses of CDS. In a hedging perspective, the hedging need is higher whenever credit risk is more volatile. In a trading perspective, trading gains or profitable price differentials between bonds and CDS are more likely to arise whenever CDS prices are more volatile. When considering the use of CDS for regulatory arbitrage, a bank is more likely to reduce its value-at-risk, thus its capital charge, whenever the fluctuations of volatile credit risk exposures are mitigated through a CDS portfolio.

Finally, financial theory does not suggest any clear hypothesis about the relationship between a CDS' beta and CDS market characteristics.

2.6 Determinants of network structure: Results

This section presents the estimation results.

2.6.1 Baseline results using debt and risk characteristics

The baseline specification of the GLM model is estimated on the restricted sample of reference entities and does not include either dummy variables (by type or location) or interaction terms.

Denote Y_i a particular network characteristic to be explained for reference entity i. We estimate:

$$
\begin{aligned}
Y_i \;=\; & g^{-1}\big(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i \\
& + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i\big) + \epsilon_i
\end{aligned}
\tag{2.1}
$$

Results are presented in table 2.11 for five CDS network characteristics. Both coefficients on the volume of bonds outstanding and on the share of unsecured debt are positive and

significant at a 1% level. We thus fail to reject hypotheses 1 and 2, suggesting a sizeable use of CDS for hedging purposes. Coefficients on the debt maturity are consistently negative but not always significant, suggesting the existence of investors' concerns about default arising from rollover risk.

Turning to risk characteristics, we reject hypothesis 3, as the level of the CDS spread is not significant for CDS market outcomes in all instances but one. In contrast, we cannot reject hypothesis 4, suggesting that CDS spread volatility is a much more important driver of CDS market outcomes than the absolute level of credit risk, as proxied by the CDS spread level. This pattern is especially consistent with the use of CDS for trading purposes, as active traders cannot extract profits from the spread level, but from changes in the spread level.

Finally, the strong significance (consistently at a 1% level) of the CDS beta for size and activity characteristics signals that market participants are typically hedging entities bearing a high systematic risk. Such a pattern can be rationalized using portfolio choice theory. While idiosyncratic risk can be diversified away in an arbitrage portfolio choice model, the systematic component of risk (or market factor) cannot be hedged through the mere diversification of credit exposures. However, hedging of the systematic component of credit risk can be achieved through CDS if CDS sellers have lower risk aversion or are fairly compensated for bearing the risk. The pattern of coefficients supports this hypothesis.

2.6.2 Group differences in intercept and marginal effects

This section tests two additional hypotheses. The impact of group membership (sovereign vs. financial) and underlying debt issuer location (European vs. non-European) on the above-identified relationships are documented. Both differences in intercept and marginal effects are considered.

2.6.2.1 Reference entity type: sovereign vs. financial

We test hypothesis 5.

Hypothesis 5. Sovereign CDS networks are, all else kept equal, larger in size.

The asset pricing literature (see Vogel et al., 2013) suggests the use of sovereign CDS for "macro" or "proxy" hedging purposes, while financial CDS cannot. Proxy hedging occurs when a sovereign CDS on a reference entity k is bought to hedge a credit exposure

| | (1) | (2) | (3) | (4) | (5) |
	Dens.	% Nodes	% Net	% Trades	% Notional
main					
CDS price	0.433	0.376	-0.279	2.626**	2.069
	(0.75)	(0.55)	(-0.25)	(2.17)	(1.45)
CDS vol.	2.886*	3.613*	9.333***	7.401**	11.02***
	(1.75)	(1.82)	(2.72)	(1.99)	(2.61)
CDS beta	1.026***	1.266***	2.006***	2.404***	2.784***
	(7.57)	(7.58)	(5.56)	(6.95)	(6.40)
Bonds	71.33***	142.5***	268.6***	248.1***	295.3***
	(3.36)	(4.07)	(4.66)	(4.93)	(4.28)
Maturity	-5.369	-10.02**	-18.35*	-16.15	-23.66*
	(-1.37)	(-2.05)	(-1.68)	(-1.41)	(-1.80)
Unsecured	0.376***	0.426***	1.899***	1.448***	2.509***
	(3.03)	(2.94)	(4.36)	(2.66)	(3.32)
Constant	-9.540***	-4.635***	-10.29***	-10.09***	-11.90***
	(-63.67)	(-24.94)	(-17.15)	(-14.69)	(-11.99)
Obs.	191	191	191	190	190
AIC	15.18	85.41	22.86	23.86	23.60
BIC	37.94	108.17	45.63	46.58	46.33

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.11: Results for the baseline specification.This table presents the results of the estimation of the GLM model of equation 2.1. Specifications 1 to 3 and 4 to 5 feature respectively size and activity dependent variables. The outcome variables are respectively the network density, the share of active traders, the share of the market net notional exposure, and the average share of daily trades and daily notional amount traded. The model is estimated using the restricted sample. AIC and BIC are the Akaike and Bayesian information criteria respectively.

for which there is no CDS[11]. The larger set of possible hedging purposes for sovereign CDS gives ground to hypothesis 5.

We consider both differences in intercept and slope for the dependent variables, using respectively a sovereign dummy variable and interaction terms. Equations 2.2 and 2.3 are estimated.

$$
\begin{aligned}
Y_i &= g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i \\
&\quad + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Sov.) + \epsilon_i
\end{aligned}
\tag{2.2}
$$

$$
\begin{aligned}
Y_i &= g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i \\
&\quad + \beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Sov. + \beta_8 \cdot Price_i \cdot Sov. \\
&\quad + \beta_9 \cdot Volatility_i \cdot Sov. + \beta_{10} \cdot Beta_i \cdot Sov. + \beta_{11} \cdot Bonds_i \cdot Sov. \\
&\quad + \beta_{12} \cdot Maturity_i \cdot Sov.) + \epsilon_i
\end{aligned}
\tag{2.3}
$$

Results are presented in table 2.12. Their most important feature is the negative sign (significant in all specifications at a 1% level) for the interaction term between the sovereign dummy variable and the volume of bonds outstanding. This is consistent with a sizeable use of sovereign CDS for proxy hedging. Whenever proxy hedging exists, it is indeed the case that some of the CDS market activity is not related to underlying debt exposures. Furthermore, absent interaction terms, the positive and significant coefficient on the sovereign dummy variable in most instances is also suggestive of the fact that sovereign CDS networks are larger in size and more active, consistent with hypothesis 5.

2.6.2.2 Reference entity location: European vs. non-European

We test the hypothesis that the above-identified statistical relationships differ for European and non-European names[12]. The asset pricing literature does not provide rationales—other than asset characteristics themselves correlated with the debt issuer location and not captured in our dataset and econometric model—for locational differences in intercept or marginal effects. However, given our data dates back to the height of the

---

[11]A textbook example is that of a credit exposure to a public company for which no CDS exists, which is hedged through the domestic sovereign CDS.

[12]The group of European CDS consists of reference entities from the EU27, Switzerland, Norway and Russia. The total number of reference entities from Switzerland, Norway and Russia is less than 10.

	(1) Dens.	(2) Dens.	(3) % Nodes	(4) % Nodes	(5) % Net	(6) % Net	(7) % Trades	(8) % Trades
main								
CDS price	0.453	0.693	0.422	1.022*	-0.278	0.922	2.789**	3.547***
	(0.79)	(1.35)	(0.62)	(1.71)	(-0.26)	(1.01)	(2.13)	(2.76)
CDS vol.	2.643	3.398**	3.037	3.177*	6.306*	5.990**	4.347	4.778
	(1.58)	(2.28)	(1.54)	(1.93)	(1.88)	(2.19)	(1.04)	(1.17)
CDS beta	1.005***	0.599***	1.217***	0.676***	1.760***	0.879***	2.274***	1.373***
	(7.38)	(4.15)	(7.54)	(4.43)	(5.14)	(2.78)	(6.61)	(4.30)
Bonds	57.42***	3415.8***	112.8***	4705.2***	183.2***	6836.3***	172.8***	5908.0***
	(2.74)	(7.12)	(3.59)	(9.07)	(3.60)	(6.64)	(4.02)	(7.06)
Maturity	-4.088	2.222	-6.933	1.527	-1.094	10.40	-1.419	12.14
	(-1.03)	(0.51)	(-1.45)	(0.32)	(-0.12)	(1.40)	(-0.14)	(1.12)
Unsecured	0.310**	0.426***	0.267**	0.442***	0.757**	1.024***	0.548	0.656
	(2.48)	(3.48)	(1.96)	(3.68)	(2.39)	(3.69)	(1.19)	(1.52)
Sov. Dummy	0.114	0.345	0.261**	-0.184	0.993***	0.0302	0.849***	-0.438
	(1.31)	(0.70)	(2.30)	(-0.30)	(4.67)	(0.02)	(4.15)	(-0.31)
Sov. * Spread		5.159***		2.195		-2.308		3.605
		(3.33)		(0.95)		(-0.43)		(0.67)
Sov. * Vol.		-19.27**		-9.779		-2.037		-7.913
		(-2.26)		(-1.02)		(-0.11)		(-0.46)
Sov. * Beta		1.702***		1.330*		1.040		1.901
		(2.67)		(1.83)		(0.72)		(1.33)
Sov. * Bonds		-3344.9***		-4584.1***		-6653.4***		-5707.0***
		(-6.96)		(-8.81)		(-6.45)		(-6.80)
Sov. * Maturity		0.0234		0.0456*		0.0795*		0.0425
		(1.60)		(1.84)		(1.70)		(1.04)
Obs.	191	191	191	191	191	191	190	190
AIC	17.18	27.18	87.29	96.65	24.73	34.64	25.74	35.67
BIC	43.20	69.46	113.31	138.93	50.74	76.92	51.72	77.88

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.12: Sovereign vs. financial differences in intercept and marginal effects. This table presents the results of the estimation of the GLM model of equations 2.2 and 2.3. The outcome variables are respectively the network density, the share of active traders, the share of the market net notional exposure and the average share of daily trades. The constant is not reported. The interaction term between "Sov." and "Unsecured" is not included, as the overwhelming majority of sovereign debt is 100% unsecured. AIC and BIC are the Akaike and Bayesian information criteria respectively.

European sovereign debt crisis, a conjunctural effect on the relationship between debt characteristics and CDS network properties is likely to be observed. If so, European CDS networks shall be *ceteris paribus* larger in size and more active.

The same econometric approach is kept, with both a European dummy variable and interaction terms being introduced. Equations 2.4 and 2.5 are estimated.

$$
\begin{aligned}
Y_i \;=\; & g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i \\
& +\beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Eur.) + \epsilon_i
\end{aligned}
\tag{2.4}
$$

$$
\begin{aligned}
Y_i \;=\; & g^{-1}(\beta_0 + \beta_1 \cdot Price_i + \beta_2 \cdot Volatility_i + \beta_3 \cdot Beta_i + \beta_4 \cdot Bonds_i \\
& +\beta_5 \cdot Maturity_i + \beta_6 \cdot Unsecured_i + \beta_7 \cdot Eur. + \beta_8 \cdot Price_i \cdot Eur. \\
& +\beta_9 \cdot Volatility_i \cdot Eur. + \beta_{10} \cdot Beta_i \cdot Eur. + \beta_{11} \cdot Bonds_i \cdot Eur. \\
& +\beta_{12} \cdot Maturity_i \cdot Eur. + \beta_{13} \cdot Unsecured_i \cdot Eur.) + \epsilon_i
\end{aligned}
\tag{2.5}
$$

The estimation results are presented in table 2.13. The European dummy variable is never significant at a 10% level. There are, however, differences in marginal effects are regards the volume of bonds outstanding. An increase in the volume of bonds oustanding is associated with a larger CDS market size and activity for European names, compared to non-European names. One interpretation may be related to the European debt crisis at the time our sample was collected, giving rise to higher hedging needs. The European/non-European distinction is not significant for other reference entity characteristics and appears overall less relevant than the sovereign/financial distinction for CDS market outcomes.

2.7 Conclusion

Our analysis finds that the aggregated CDS network of financials and sovereign reference entities is centered around 14 dealers and has a tiered structure. Its density is low and it exhibits "small world" properties. The high degree of interconnectedness in the CDS market does not exist because of the large number of bilateral links between any two counterparties, but because virtually any trader is linked to or close to one of the core dealers. In addition, we document a scale-free degree distribution for the CDS network, implying both a high concentration of the links among a few traders and a high vulnerability in case one of these traders fails. Thus, the network can be deemed

	(1) Dens.	(2) Dens.	(3) % Nodes	(4) % Nodes	(5) % Net	(6) % Net	(7) % Trades	(8) % Trades
main
CDS price	0.438	0.566	0.421	1.088	-0.219	0.476	2.725**	3.843***
	(0.76)	(1.03)	(0.61)	(1.63)	(-0.19)	(0.43)	(2.23)	(3.24)
CDS vol.	2.949*	3.078	4.193**	2.123	10.83***	4.352	8.508**	2.590
	(1.76)	(1.59)	(1.99)	(0.81)	(2.68)	(1.05)	(1.97)	(0.51)
CDS beta	1.017***	0.867***	1.186***	1.240***	1.766***	1.995***	2.242***	2.301***
	(7.00)	(4.91)	(6.66)	(5.53)	(4.24)	(3.97)	(5.84)	(4.97)
Bonds	71.42***	44.00***	144.1***	102.9***	279.0***	220.1***	253.6***	180.8***
	(3.39)	(4.74)	(4.30)	(10.12)	(4.92)	(7.64)	(5.05)	(9.92)
Maturity	-5.294	-9.404*	-9.322*	-13.93**	-16.34	-25.60*	-14.67	-14.20
	(-1.36)	(-1.91)	(-1.94)	(-2.29)	(-1.50)	(-1.76)	(-1.32)	(-0.94)
Unsecured	0.383***	0.642***	0.488***	0.823***	2.078***	1.621***	1.555***	1.833**
	(2.96)	(2.86)	(3.11)	(3.14)	(4.49)	(2.68)	(2.67)	(2.19)
Eur. Dummy	0.0120	0.0461	0.110	0.512	0.341	0.564	0.210	0.567
	(0.20)	(0.14)	(1.35)	(1.34)	(1.53)	(0.73)	(1.00)	(0.48)
Eur. * Spread		1.219		-1.065		-3.547		-1.802
		(1.08)		(-0.69)		(-0.87)		(-0.54)
Eur. * Vol.		-0.407		3.067		6.304		9.640
		(-0.12)		(0.78)		(0.86)		(1.20)
Eur. * Beta		0.251		-0.250		-0.779		-0.342
		(0.88)		(-0.73)		(-1.02)		(-0.43)
Eur. * Bonds		385.8***		764.9***		1381.6***		1311.8***
		(5.00)		(5.15)		(9.76)		(6.37)
Eur. * Maturity		0.0148**		0.0148*		0.0236		0.00620
		(2.19)		(1.78)		(1.38)		(0.33)
Eur. * Unsecured		-0.564**		-0.814***		-0.787		-1.768*
		(-2.09)		(-2.69)		(-1.13)		(-1.83)
Obs.	191	191	191	191	191	191	190	190
AIC	17.18	29.18	87.37	98.85	24.84	36.60	25.85	37.62
BIC	43.20	74.71	113.39	144.38	50.86	82.14	51.82	83.08

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.13: European vs. non-European differences in intercept and marginal effects. This table presents the results of the estimation of the GLM model of equations 2.4 and 2.5. The outcome variables are respectively the network density, the share of active traders, the share of the market net notional exposure and the average share of daily trades. The constant is not reported. AIC and BIC are the Akaike and Bayesian information criteria respectively.

"robust-yet-fragile". One potential source of financial stability risk stems from the fact that the proportion of net CDS sellers is higher for larger traders.

We analyse the determinants of the CDS network by exploiting the heterogeneity in size and activity across networks at a reference entity level, and find a significant impact of the variables related to the underlying debt characteristics and to the risk characteristics of each CDS reference entity. Our findings are consistent with theoretical results in the literature on the use of CDS. First, a higher pool of underlying bonds outstanding, together with a higher proportion of unsecured funding, increases both the size and the activity on the particular CDS reference entity. Second, higher debt maturity decreases both the CDS network size and activity, indicating that roll-over risk of the underlying bond is an important factor determining CDS trading. Third, regarding the risk characteristics, we find that CDS volatility and beta have a larger influence on the size and activity than the absolute level of the CDS spread. Traders are more numerous and more active on reference entities whose perceived changes in creditwithiness can be larger and whose systematic risk component is higher. Fourth, concerning differences due to group membership, we document significant differences in intercepts and in effects due to differences in reference types (sovereign vs. financial reference entities). On the contrary, locational differences only influence the effects of the debt-related variables, not of the risk-related explanatory variables. European reference entities resemble non-European reference entities in that respect.

2.8 Appendix 1. Construction of the sub-networks

From the reference entity characteristics defined in sections 2.3.3.1 to 2.3.3.3, eight sub-networks are constructed. each of them aggregates bilateral CDS exposures in one out of two subsets of banks. The abbreviations used in the subsequent tables are also explained here.

- **Sovereign vs. financial sub-networks**: All reference entities are categorised according to their type sovereign (abbreviated as Sov.) and financial (abbreviated as Fin.).

- **European vs. non-European sub-networks**: All reference entities are categorised according to their geographical location: European (abbreviated as Eur.) and non-European (abbreviated as non Eur.).

- **High-vs. low-spread sub-networks**: Reference entities are categorised according to the level of their CDS spread: "High-spread CDS" have a spread above 300 basis points (abbreviated as Spread>300) whereas "low-spread CDS" have a spread below 300 basis points (abbreviated as Spread < 300)[13].

- **High vs. low debt sub-networks**: Reference entities are categorised according to whether their outstanding debt is above (abbreviated as High debt) or below (abbreviated as Low debt) the sample median.

- **High vs. low maturity sub-networks**: Reference entities are categorised according to whether the maturity of their underlying debt is above (abbreviated as High maturity) or below (abbreviated as Low maturity) the sample median.

- **High vs. low unsecured debt sub-networks**: Reference entities are categorised according to whether their share of underlying unsecured debt is above (abbreviated as High unsec.) or below (abbreviated as Low unsec.) the sample median.

- **High vs. low beta sub-network**: Reference entities are categorised according to whether the beta of their is above (abbreviated as High beta) or below (abbreviated as Low beta) the sample median.

- **High vs. low volatility sub-networks**: Reference entities are categorised according to whether the volatility of their CDS is above (abbreviated as High vol.) or below (abbreviated as Low vol.) the sample median.

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[13]A cut-off CDS spread of 300 basis points is above the median (251 basis points). Choosing the median as a cut-off, however, would not alter the significance of the results presented below.

Chapter 3

Central clearing and collateral demand

3.1 Abstract

We use an extensive data set of bilateral credit default swap (CDS) positions to estimate the impact on collateral demand of new clearing and margin regulations. The estimated collateral demands includes initial margin and the frictional demands associated with the movement of variation margin through the network of market participants. We estimate the impact on total collateral demand of more widespread initial margin requirements, increased novation of CDS to central clearing parties (CCPs), an increase in the number of clearing members, the proliferation of CCPs of both specialized and non-specialized types, collateral rehypothecation practices, and client clearing. System-wide collateral demand is increased significantly by the application of initial margin requirements for dealers, whether or not the CDS are cleared. Given these dealer-to-dealer initial margin requirements, mandatory central clearing is shown to *lower*, not raise, system-wide collateral demand, provided there is no significant proliferation of CCPs. Central clearing does, however, have significant distributional consequences for collateral requirements across market participants.

3.2   Introduction

We use an extensive data set of bilateral credit default swap (CDS) positions to esti-
mate the impact of new central clearing and margin regulations on the aggregate market
demand for collateral. In contrast to previous work based on hypothetical or roughly
calibrated exposures, we use an actual network of long and short CDS exposures. We
consider the implications for collateral demand of a variety of alternative market struc-
tures.

Central clearing for all standardized OTC derivatives is a key element of the ongoing
reform of the financial system (Financial Stability Board, 2013). A central clearing party
(CCP) steps into bilateral trades by means of novation, becoming the buyer to every
seller, and seller to every buyer. By taking on and subsequently mitigating counterparty
credit risk, CCPs insulate their members from default losses. To this end, they collect
collateral in the form of initial and variation margins, among other risk-management
procedures.

Central clearing introduces a tradeoff in collateral demand between the benefits of mul-
tilateral netting within a class of contracts against lost bilateral netting benefits across
contract types.[1] Duffie and Zhu (2011) and Cont and Kokholm (2014) demonstrate the
key role in this tradeoff of the market network structure and of the covariance of price
changes across asset classes, but do not provide a clear-cut answer as to which effect
dominates. Furthermore, these prior studies did not rely on actual bilateral exposure
and price data, and were limited to simplified market structures.

The impact of regulatory reform of the derivatives markets on collateral demand is a key
concern for policy makers. On the one hand, because CCPs are set to become direct and
large counterparties to the most important market participants, the increasing use of
central clearing raises concerns about the concentration of risk within a few institutions.[2]
High collateralization standards, central clearing, and capital requirements, among other
new regulatory standards, have become the new norm. On the other hand, there have
been concerns, for example those of Singh (2010b), over the extent to which CCPs tie
up large amounts of cash or high-grade assets. In the empirical literature, a number of
authors have assessed changes in collateral demand due to mandatory central clearing,
arriving at a broad range of estimates, recently compiled by Sidanius and Zikes (2012).

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[1]Absent a CCP, bilateral netting opportunities exist across asset classes, or with contracts that are
not eligible for central clearing. In contrast, multilateral netting through a CCP is typically possible
for one asset class only and, within an asset class, for a subset of contracts being liquid or standardized
enough. See Duffie and Zhu (2011) for a detailed theoretical investigation of this trade-off.

[2]For example, the US Financial Stability Oversight Council has designated three CCPs as systemically
important under Title VIII of the Dodd-Frank Act.

We use a comprehensive dataset of CDS bilateral exposures covering about 31.5% of the global single-name CDS market to assess the impact of a variety of margining and clearing schemes on collateral demand and its decomposition. The case of CDS is of particular interest because credit risk is correlated with systemic risk (Duffie et al., 2009). Furthermore, CDS feature jump-to-default risk, thereby increasing the volatility of market values. Our sample, obtained from the Depository Trust & Clearing Corporation (DTCC), covers virtually all CDS bilateral exposures on 184 reference entities representing 31.5% of the global single-name CDS market as of the end of 2011. Uniquely among available data sets, this data set includes all counterparties at a *global* level for each referenced name, and is thus well suited to analyze the implications of margining and netting in the aftermath of the global derivatives market reform. Prior empirical work used aggregate data releases for dealers (Heller and Vause, 2012), or market-wide data (Sidanius and Zikes, 2012) at a product-level (CDS and interest rate swaps), thus missing some key effects of network structure and of the heterogeneity of counterparty portfolios. As a result, the multilateral netting benefits of clearing may have been mis-estimated in earlier work.

We study a variety of clearing schemes and market structures. Previous work had studied only simple market structures. Starting from a base case, either with or without new dealer-to-dealer margin requirements, we analyze four effects: an increase in novation to existing CCPs, an increase in the number of clearing members, an increase in the number of CCPs, and client clearing. (In a "client clearing" regime, dealers clear the derivatives portfolio of their client end-users.) The second and the fourth of these effects had not been examined in prior work on this subject. Although the effect on collateral demand of increasing the number of CCPs had been investigated by Duffie and Zhu (2011), that study was severely limited by lack of access to bilateral exposure data. We distinguish between the impact of adding "specialized" CCPs, as opposed to "non-specialized" CCPs, which are shown to be substantially less efficient in collateral use because of lost netting and diversification opportunities. This type of CCP specialization is indeed observed in the data. As opposed to prior research, our data enable us to model both dealer and customer positions.

We estimate a fully specified margin model that allows a decomposition of margin demand both by trader type (customer or dealer) as well as by type of margin demand. Our model captures portfolio-specific initial margins, a contract-specific short charge for net CDS sellers, a precautionary buffer stock of unencumbered liquid assets designed to meet uncertain near-term variation margin calls, and the "velocity drag" of collateral movement within the financial system. The last two of these components had not been examined in previous research. We show that these frictional demands for variation margin may have a significant impact on total collateral demand. Our model

captures how these various components of margin demand incorporate the effects of cross-counterparty netting and diversification, which change with the clearing scheme and network structure.

Overall, we show that system-wide collateral demand is increased significantly by the application of initial margin requirements for dealers, whether or not CDS are cleared. Given the new requirement for dealer-to-dealer initial margins, mandatory central clearing is shown to substantially *lower* system-wide collateral demand, provided there is no significant proliferation of CCPs.

We show that client clearing reduces system-wide collateral demand provided that dealers are able to re-use a large enough share of the collateral that they receive from their clients. The drop in collateral demand is driven by cross-counterparty netting and by diversification benefits, both for customers and dealers, and depends on the size of each investor's portfolio. Netting and diversification benefits outweigh increased initial margin requirements for investors whose portfolios are large enough. Clearing thus has distributional consequences across investors, favoring traders with large and well-diversified portfolios. Collateral demand for investors with a low multilateral net-over-gross notional exposure can be significantly reduced when central clearing is implemented.

In sum, most of the increase in collateral demand associated with the new regulatory environment for CDS is caused by an increase in the set of market participants required to provide margin at standardized levels. Central clearing does not itself cause a major incremental increase in collateral usage, unless there is a further proliferation of central clearing parties. For a given level of protection against counterparty failure risk, the key determinant of collateral demand is netting. Combining offsetting and diversifying swaps in the same netting sets causes a significant lowering of collateral demand. Central clearing can either improve or reduce netting opportunities, depending on how much is cleared, how many CCPs are used, and the degree to which the same swaps are cleared in different CCPs. Although every unit of variation margin paid by some market participant is received by its counterparty, the need to retain buffer stocks of unencumbered funds suitable for variation margin payments and the frictional drag associated with the operational lags in the usability of margin funds are important components of the total demand for collateral.

The remainder of the paper is structured as follows. The relevant literature is briefly discussed in Section 3.3. The exposure data are then described in Section 3.4. The baseline model for collateral demand is presented in Section 3.5, and the basic results are then described in Section 3.6. Finally, the impact of four alternative clearing models is analyzed in Section 3.7.

3.3 Related literature

There is a growing literature on counterparty credit risk in OTC markets. **?** investigate theoretically the existence of a counterparty risk externality on opaque OTC markets, which is shown to be absent when a centralized clearing mechanism is implemented. **?** models an OTC market in which unhedged counterparty risk may lead to a systemic run of lenders in case of idiosyncratic bank failure. Thompson (2010) studies the signaling incentives induced by counterparty risk. Empirical evidence on the pricing of counterparty risk on the CDS market has been provided by **?**.

Central clearing parties as institutions mitigating counterparty risk have recently been studied theoretically and empirically. Biais et al. (2012) and Koeppl et al. (2011) analyse theoretically the optimal design of incentive-compatible clearing arrangements. The working of clearing institutions during the October 1987 crash has been discussed by Bernanke (1990). More recently, clearing in derivative markets has been described by Pirrong (2009) and Singh (2010a). Hull (2010) discusses the issue whether all OTC derivative transactions can be centrally cleared. Loon and Zhong (2014) use data on voluntarily cleared CDS contracts to document a reduction of both counterparty risk and systemic risk. The exposure of a CCP to the default of its members has been quantified by Jones and Perignon (2013).

Our results are relevant to ongoing debates on the relative magnitude of the trade-offs involved in central clearing. On the one hand, Duffie and Zhu (2011) showed that central clearing need not reduce counterparty exposure if CCPs proliferate or if an insufficient fraction of positions are centrally cleared, leading to a loss in cross-asset bilateral netting. On the other hand, Cont and Kokholm (2014) qualify these results within the same framework by considering heterogenous risk characteristics for the cleared assets. As more highly volatile assets are centrally cleared, the gains from multilateral netting are larger. In related work, Anderson et al. (2013) analyse CCP interoperability and the efficiency of multilateral netting with linked and unlinked CCP configurations. Currently, there are no interoperating CCPs for credit default swaps.

Empirically, our paper is most closely related to Heller and Vause (2012) and Sidanius and Zikes (2012), who estimate the system-wide increase in collateral demand due to mandatory central clearing. We extend their work in several respects. Rather that using simulated exposure data, we use actual bilateral pre-reform exposure data. This enables us to distinguish between customers and dealers and to account for actual netting and diversification benefits at the level of bilateral portfolios. Because of the granularity of our data, we are able to considerably refine the impact of clearing schemes and market structures. For instance, emerging client clearing practices had not been modeled earlier,

nor had the impact of the number of clearing members on collateral demand. Finally, from contract-level exposure data, our margining model enables us to document the netting and diversification benefits of increased clearing, as well as the size of each component of collateral demand. Among these, the demand for collateral in the system associated with variation margin precautionary buffers and velocity drag had not been formulated nor estimated.

3.4 The CDS exposure data

This section describes our data and some descriptive statistics concerning the CDS network structure.

3.4.1 The bilateral exposure dataset

Our CDS bilateral exposure data are provided by DTCC, as extracted from the Trade Information Warehouse (TIW)[3]. The snapshot of the world CDS market is taken as of 30 December 2011, for a large number of major reference entities. The TIW is a global trade repository covering the vast majority of CDS trades worldwide, and virtually all recent CDS trades. This data set is a legal record of party-to-party transactions, as the Warehouse Trust Company (a subsidiary of DTCC which operates the TIW) is supervised by US regulatory authorities. In addition to capturing the positions of dealers and banks, our dataset encompasses non-bank market participants such as hedge funds, insurance companies, central counterparties and potentially some industrial corporations. The dataset is unique because of the global nature of its coverage. Most national regulators use DTCC exposure data that are related only to their *domestic* reference entities or institutions.

Our sample does not include all CDS names in the TIW. It covers 184 reference entities, including 9 G20 sovereign, 22 European sovereign and 153 global financial entities. The data do not include single-name non-financial corporate names nor multi-name and index CDS. The sovereign and financial names included in our data, however, represent a sizable and growing share of the global single-name CDS market.[4] Our dataset

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[3]The data used in this paper are confidential and proprietary collected by DTCC under a regulatory mandate. Hence for legal reasons, they can not be shared.

[4]While the share of financial CDS within the global single name CDS market has been roughly constant over the past years—from 21.52% in end-December 2008 to 21.53% in December 2011 (sample date) and to 20.81% in February 2014—the share of sovereign CDS has been growing steadily—from 10.89% in end-December 2008 to 19.62% in December 2011 and to 23.80% in February 2014. This aggregated sector-wide data is retrieved from the public DTCC TIW data, "Open positions data," Table 2.

	All names	Sovereigns	Financials
Number of CDS	184	31	153
Number of traders	885	626	677
Gross notional (billion USD)	4,906	2,070	2,836
Net notional (billion USD)	375.3	178.2	197.1
Net over gross (%)	7.6	8.6	6.9
Number of Observations	44,155	10,653	33,502
Number of Positions	503,119	125,622	377,497
Avg. notional position (million USD)	9.75	15.58	7.51
Share of net sellers (%)	18.1	16.2	18.4

TABLE 3.1: Descriptive statistics of the CDS sample. Underlying data source: DTCC.

contains the names of the reference entities, but the identities of the counterparties are anonymized. A total gross notional of USD 4.91 trillion of CDS is covered by our sample. At the same date (30 December 2011) the total gross notional of the global CDS market was USD 25.9 trillion (**?**). Our sample thus represents about 31.5% of the global single-name CDS market and 18.9% of the total CDS market (including multi-name instruments). We excluded Asian names in order to partition the set of reference entities into two subsets (European and American names), which is useful when analyzing the effect of specialized versus non-specialized central clearing. As our empirical analysis relies on the use of CDS price data, all CDS for which there is no available price time series on Bloomberg have been excluded.

For each reference entity, our dataset contains gross and net bilateral exposures between any two counterparties. The overall network consists of 44,155 bilateral exposures on individual reference entities. Any bilateral exposure may result from several separate transactions, so that the number of transactions covered is 503,119. We do not have access to additional information at a transaction level. For example, we know neither the date on which a particular deal was executed nor the maturity (initial or remaining) of each position. The market values of open positions are not available. We approximate changes in market values from CDS rate data, as explained in Appendix B, using daily mid-quotes for 5-year senior CDS from Bloomberg, from January 2008 to end-December 2011.

We have performed checks on data quality. We drop 328 bilateral exposures of a counterparty vis-à-vis itself. Such exposures involve 12 individual counterparties, are negligible for our purposes, and in any case reflect aggregation inconsistencies at a bank level (an internal trade between two accounts or two subsidiaries or other legal entities of the same firm).

3.4.2 Description of the CDS network

This subsection provides general descriptive statistics for the sampled CDS network[5] (Table 3.1) and for investor portfolios (Table 3.2).

In total, 855 counterparties have been active with a position referencing at least one of the 184 reference entities. While the market-wide gross notional amount is 4.91 trillion USD, the total net exposure is significantly lower, at about 375 billion USD. In settings such as this, with a low ratio of net-to-gross notional (here only 7.6%), central clearing

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[5]A more detailed description of the CDS network, using the same dataset but a slightly larger sample (including both Asian names and names for which no CDS price data is available) can be found in Peltonen et al. (2014). They also provide a topological description of the CDS market using metrics developed in the literature on financial networks.

	Dealers	Customers
Number of traders	14	869
Avg. number of counterparties	288.4	5.0
Avg. number of names traded	182.8	11.3
Gross notional (billions USD)	8,285	1,528
Net notional (billions USD)	287.3	436.3
Net over gross (%)	3.5	28.6
Market share (%)	84.4	15.6

TABLE 3.2: Descriptive statistics for CDS market participants. This table summarizes CDS portfolio characteristics for dealers and customers. Only sovereign and financial, non-Asian, referenced names are included. The calculation of gross and net notional exposures involves double counting, as any CDS position is counted for each of its two counterparties. Market shares are based on gross exposures. Underlying data source: DTCC.

has the potential of achieving substantially improved netting benefits. Our data show low net-to-gross ratios for both sovereign and financial reference names, at 8.6% and 6.9%, respectively.

A second stylized fact is the low share of net sellers of protection, only 18.1% in our sample, indicating that the vast majority of CDS end-users are net buyers. An implication is that ultimate credit risk exposure is potentially concentrated within a relatively small subset of CDS investors. This also highlights the benefits of capturing, as we do, cross-CDS diversification effects when computing margins.

3.4.3   Empirical Identification of CCPs and Dealers

We next turn to the empirical identification of CCPs and dealers within the set of anonymous market participants.

Some of the positions in our data had already been centrally cleared.[6]   Given the anonymization of counterparties in the data and our focus on clearing schemes, we first separate the bilaterally and centrally cleared exposures. CCPs are identified by their large gross exposures but consistently zero multilateral net exposures on *all* reference entities.[7]   Among the 50 largest counterparties[8] as ranked by gross notional amounts bought and sold, we identify two CCPs with virtual certainty.

The identified CCP-cleared exposures represent 7.02% of the market gross notional amount. Consistent with this, at year-end 2011 ISDA estimated the percentage of CCP-cleared single-name CDS to be around 8%, based on a broader sample. The presence of 2 active CCPs for CDS in December 2011 is also consistent with market facts. Although 3 CCPs were active in the CDS market (ICE Clear Credit, ICE Clear Europe and LCH CDSClear), only the first two were active in single-name CDS according to the 2011 annual reports of these three firms. LCH CDSClear was active only in index CDS.

Descriptive statistics regarding the two CCPs are provided in Table 3.3. Of the 184 names referenced in our sample, we find that 39 of these have centrally cleared CDS.

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[6] Loon and Zhong (2014) discuss why centrally cleared trades may coexist with uncleared trades, following the launch of ICE Clear Credit (ICECC), a leading clearinghouse. They document reductions in both counterparty and systemic risk that are induced by central clearing.

[7]Formally, in terms of the notations introduced below (section 3.5.1), an institution i is identified as a CCP if $\sum_j \left[G^k(i,j) + G^k(j,i) \right] \geq 5.8$ billion USD and $\sum_j \left[X^k(i,j) - X^k(j,i) \right] = 0$ for all k. The threshold of 5.8 billion USD corresponds to the gross buy and sell notional amount traded by the 50th largest institution.

[8]The criteria for identifying CCPs are valid for institutions with an large activity only. Indeed, we do observe a handful of much less active institutions trading one or two CDS and having a zero multilateral net exposure. These institutions, however, are not likely to be central clearing parties. Institutions below the top-50 trade gross long and short notional amounts below 3 billion USD. An active CCP is unlikely to trade such low notional amounts.

Descriptive statistics	Sample
Number of clearable CDS	39 of 184
Volume cleared through CCPs	7.02%
Notional cleared to notional clearable	
Minimum	0.4%
Average	32%
Maximum	47.9%
Market shares (notional)	
CCP 1	64.7%
CCP 2	35.3%
Market shares (names)	
CCP 1	American
CCP 2	European

TABLE 3.3: Descriptive statistics on CCP-cleared exposures. This table describes the two CCPs identified in the dataset. No overlap in the names cleared by both of them is observed. Instead, an American/European breakdown is documented, with a larger market share for the CCP clearing American names. American names include Central and Latin America, Canada and the United States. European Names include Norway, Russia, Switzerland and the European Union. Underlying data source: DTCC.

For reference names that have some CDS cleared by at least one CCP, on average 32% of the gross notional amounts are centrally cleared. No CDS is cleared by both CCPs. One CCP clears only European names, of which there are 14. The other CCP clears only North American and Latin American names, of which there are 25, and which we shall henceforth call "American." The median gross notional amount of a cleared name is 13.5 billion USD, which is about 90% larger than the sample median, implying that clearable names are generally those with large gross notional outstanding amounts.

We next identify as dealers those market participants, other than CCPs, with very high concentrations of bilateral positions. We can easily identify 14 dealers, in line with anecdotal evidence according to which the CDS market is centered around 14 dealers (Brunnermeier et al., 2013; Peltonen et al., 2014). Dealers in the sample are the only CCP members. Comparative descriptive statistics for dealers and customers are presented in Table 3.4. The market structure is highly concentrated around these 14 dealers, who have positions in almost all CDS referenced names (182.8 on average dealers, out of 184 in total). Customers of dealers are exposed to only 11.3 names, on average. While customers have on average only 5.0 counterparties, each dealer has on average 288 counterparties. The hypothesis that exposures in the CDS market are distributed according to a power law cannot be rejected (Peltonen et al., 2014). This implies that interconnectedness in the CDS market does not arise from the large number of bilateral links between any two counterparties, but because all investors are close to one another due to the existence of a few highly-connected intermediary dealers.

Dealers are clearly the dominant intermediaries in the market. Only 3% of trades are customer-to-customer. Most customers trade with one of their prime brokers. In contrast, dealer-to-dealer trades represent 75.1% of the total number of trades. The ratio of net to gross notional exposures is 28.6% for customers; for dealers, this ratio is only 3.5%. Thus, while dealers provide net (long or short) exposures to customers, a large part of these exposures is hedged either through dealer-to-dealer trades or through offsetting exposures to other customers. Hence, the highly skewed distribution of CDS market activity (as measured by gross notional exposures) does not match that of ultimate credit risk, as proxied by net notional exposures. While dealers account for 84.4% of gross market exposures, their positions represent only 39.7% of net exposures.

3.5   Baseline model

In the baseline model studied in this section, we focus on collateral demand for the actual network of exposures. In later sections we focus on the impact of increased novation to

	Dealers	Customers
Number of institutions	14	871
Number of CDS traded		
Minimum	179	1
Median	184	5
Maximum	184	177
Gross notional (billion USD)		
Minimum	104.1	0.0002
Median	286.3	0.07
Maximum	503.7	120.5
Number of counterparties		
Minimum	102	1
Median	310	3
Maximum	460	50

TABLE 3.4: Descriptive statistics for dealers and customers. This table presents comparative descriptive statistics for dealers and customers. The *D* dealers are identified by the fact that they belong to the existing central clearing parties. Dealers consistently trade a larger number of CDS than customers and with a larger number of counterparties. With one exception, this is also true for the gross notional amount traded. Group differences in median values are highly significant. Source: DTCC.

CCPs under a variety of alternative market structures.

3.5.1 Preliminaries

A set $\Omega = \{1, \ldots, n\}$ of market participants, called "investors" for simplicity, is partitioned into two subsets based on their membership in one or more CCPs. Of the n investors, D institutions, called *dealers* or *clearing members*, are members of at least one CCP. The remaining $n - D$ investors, called *customers* or *end users*, do not have direct membership to central clearing parties. In addition, there is a set of n^{CCP} central counterparties that do not belong to Ω. Finally, there are K referenced entities. The $n \times n$ bilateral exposure matrix G^k for reference entity k has as its (i, j) element the gross CDS notional referencing k that is sold by investor i to investor j. This does not include exposures to or from CCPs. The associated $n \times n$ net bilateral exposure matrix X^k is defined by

$$X^k(i, j) = \max\left\{0; G^k(i, j) - G^k(j, i)\right\}.$$

Thus $X^k(i, j) = 0$ whenever $X^k(j, i) > 0$.

Collateral requirements are defined for four types of bilateral exposures: customer-to-dealer, dealer-to-dealer, dealer-to-CCP and customer-to-customer. Our model accounts for initial margin, a precautionary buffer stock to serve variation margin payments, and for variation margin "velocity drag" associated with limits on the speed with which payments sent by a market participant can be deployed by its receiver. In addition, we allow for differences in collateral posting and re-hypothecation between bilateral and centrally cleared positions.

Margin requirements for all types of institutions are summarized in Table 3.5. In the baseline model, these are designed to capture widespread market practices in place before mandatory central clearing was implemented. First, initial margins are posted by customers to all of their counterparties. By contrast, in the baseline model dealers do not post initial margins to customers. Dealer-to-dealer initial margins are treated parametrically so as to consider a range of cases. Ongoing regulatory reforms are set to require dealer-to-dealer initial margins (**?**). Dealers post initial margins to CCPs, whereas CCPs do not post initial margins to clearing members.

3.5.2 Initial margins

Initial margins between any two parties are computed at a bilateral portfolio level. These are calculated as the sum of a risk-based component and a short charge for net CDS

Party	Counterparty	Initial Margins	Variation Margins
Customer	Dealer	Yes	Yes
Dealer	Customer	No	Yes
Dealer	Dealer	Yes/No	Yes
Customer	Customer	Yes	Yes
Dealer	CCP	Yes	Yes
CCP	Dealer	No	Yes

TABLE 3.5: Initial and variation margin requirements. This table describes the margin requirements for all possible pairs of trader types. In the baseline case and for alternative specifications, results are presented both with and without dealer initial margins, thus enabling a reproduction of both the pre-reform and the post-reform cases.

sellers, in order to replicate current market practice, as explained in sources cited below. We define the bilateral portfolio $\mathcal{P}_{ij}$ between any i and j as the $K \times 1$ vector

$$\mathcal{P}_{ij} = \left(X^1 (i,j) - X^1 (j,i), \ldots, X^K (i,j) - X^K (j,i) \right).$$

Element k of $\mathcal{P}_{ij}$ is positive whenever i is a net seller to j on reference entity k, and negative otherwise. The absolute value of the change in the market value of $\mathcal{P}_{ij}$ over the period of T business days from $t - T + 1$ and t is

$$\phi_T^t \left(\mathcal{P}_{ij} \right) = \left| \sum_k \left(X^k (i,j) - X^k (j,i) \right) \left(p_t^k - p_{t-T+1}^k \right) \right|, \tag{3.1}$$

where p_t^k is the price of CDS k at date t. The initial margin to be posted by i to j, denoted C_{ij}^{IM}, is the worst historical change in the value of $\mathcal{P}_{ij}$ over any T-day period, computed over the last $P \geq T$ days. Throughout our analysis, we take the look-back period P to be 1000 days. This general approach to setting initial margins is used by the largest market participants, including ICE Clear Credit and ICE Clear Europe (ICE, 2012).[9] Thus,

$$C_{ij}^{IM} = \phi_T^{t*} \left(\mathcal{P}_{ij} \right), \text{ where } t^* \equiv \mathrm{argmax}_{t \in \{T+1, P\}} \ \phi_T^t \left(\mathcal{P}_{ij} \right). \tag{3.2}$$

In addition to the portfolio-based initial margin (which is equal for both i and j), we follow market practice, described for example by LCH-Clearnet (2012), by adding a *short charge* for net CDS sellers in order to account for the asymmetric nature of CDS payoffs and mitigate jump-to-default risk.

As with market practice, beyond the elements already described, our initial margin calculations do not incorporate estimates of loss at reference entity defaults, of which there are none in our sample period.[10]

Appendix B explains how we approximate changes in market values of CDS from our CDS rate data. Because we do not have data on the maturity distribution of CDS positions, the total magnitudes of collateral demand that we estimate have a significant potential estimation error. Our main focus, however, is on the *relative* effects of various alternative market structures and practices. These relative effects are largely robust to

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[9]Both ICE Clear Credit and ICE Clear Europe consider a 99% confidence level over a 5-day horizon. CME and Eurex Clearing use the same methodology. LCH-Clearnet (2012) use a closely related methodology. Minor differences exist in the look-back period P.

[10] Another source of potential minor under-estimation of collateral demand stems from the fact that, due to data limitations, each exposure $X^k (j,i)$ may aggregate CDS traded at different dates and with different maturities. Thus CDS exposures which we consider as fully offsetting may nevertheless give rise to collateral posting on actual markets, once heterogeneity with respect to these contract specifications is considered.

the effects of variation in maturity, given that changes in market value are in practice roughly proportional to maturity, as discussed in Appendix B. This proportionality approximation does not apply to jump-to-default effects, but we apply a separate and maturity-independent short charge for initial margin to cover jump-to-default risk, as is common in practice.

Customers post initial collateral to any counterparty. By contrast, dealers post initial margin only to central clearing parties and, to an extent parameterized below, to other dealers.

The total initial margin to be posted by any customer i, denoted C_i^{IM}, is

$$C_i^{IM} = \sum_j \left[\upsilon^C \phi_T^{t^*}(\mathcal{P}_{ij}) + \alpha^C \sum_k X^k(i,j) \right]. \tag{3.3}$$

The first term in the sum across counterparties is the initial margin computed from the left tail of the portfolio historical value $\phi_T^{t^*}(\mathcal{P}_{ij})$. The second component is a short charge computed on the basis of all net bilateral short exposures at a reference entity level, parameterized by α^C. Here, $\upsilon^C \in [0,1]$ is a parameter capturing the fraction of collateralization of bilaterally cleared trades relative to centrally cleared trades.[11] For a fully collateralized position, $\upsilon^C = 1$.

In our base case, we assume no rehypothecation of collateral, and later examine the impact of rehypothecation by dealers. The total base-case initial margin of dealer i is thus

$$
\begin{aligned}
C_i^{IM} &= \sum_{d=1}^{D} \left[\upsilon^D \phi_T^{t^*}(\mathcal{P}_{i,d}) + \alpha^D \sum_d X^k(i,d) \right] \\
&+ \sum_{h=1}^{n^{CCP}} \left[\phi_T^{t^*}(\mathcal{P}_{i,CCP_h}) + \alpha^{CCP} \sum_h X^k(i,CCP_h) \right],
\end{aligned} \tag{3.4}
$$

where $\mathcal{P}_{i,CCP_h}$ denotes the bilateral portfolio of a clearing member i vis-a-vis CCP h. The first term in equation (3.4) corresponds to dealer-to-dealer initial margins. The second term corresponds to margins posted to CCPs. As reflected in (3.1) and (3.2), portfolio diversification reduces initial margin requirements.

In later sections, we allow the short charge for centrally cleared positions to vary from that for bilaterally held positions. That is, $\alpha^D < \alpha^{CCP}$. We also allow for different margin parameters for customers and dealers (υ^C and υ^D for partial-collateralization,

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[11]Levels of collateralization below 1 are documented for bilaterally cleared trades by International Swaps and Derivatives Association (2011, p.14).

α^C and α^D for the short charge). We also later consider a base case in which $v^D = 0$ and $\alpha^D = 0$, that is, an absence of dealer-to-dealer initial margins.

Throughout, we ignore the paid-in components of dealer contributions to CCP default guarantee funds, which are relatively fixed. To the extent that default guarantee fund contributions vary with market structure, they could be roughly approximated as a multiple of average initial dealer margins posted at CCPs.

3.5.3 Precautionary Buffer for Variation Margin

As explained in Appendix A, in order to be prepared to pay variation margins any market participant must have a precautionary stock of unencumbered assets ready to be transferred. In industry practice, this buffer is sometimes called "pre-funded" variation margin. For investor i, this collateral buffer is computed on the basis of its whole portfolio, regardless of the distribution of positions across counterparties, and is estimated by

$$C_i^{VM} = \kappa^{VM} \sigma \left(\sum_k \sum_j \left| X^k(i,j) - X^k(j,i) \right| \right), \qquad (3.5)$$

where, for any portfolio p of positions, $\sigma(p)$ denotes the standard deviation of the one-day change in market value of the portfolio, and where $\kappa^{VM} > 0$ is a multiplier that we vary parametrically. We explain in Appendix A that κ^{VM} depends in part on the shadow price for holding idle collateral and on the cost of a need to obtain immediate liquidity in the event that the buffer stock is exhausted. The derivatives divisions of trading firms are often assigned by their group treasuries an explicit per-unit price for access to a pre-funded buffer of unencumbered assets for purposes of margin payments.

Equation (3.5) captures the benefits of portfolio diversification, including the impact on $\sigma(p)$ of covariances of changes in the market values of the CDS positions. These covariances are estimated from the trailing-1000-day sample of CDS pricing data.

3.5.4 Variation Margin Velocity Drag

As noted by Singh (2011), when considering system-wide demands for collateral related to clearing, the velocity of circulation of collateral matters. We use a simple reduced-form model of margin velocity "drag" that is further motivated in Appendix A. From the time that variation margin is committed to be transferred and until the time at which it becomes ready to deploy by the counterparty to whom it is transferred, variation margin

payments are assumed to be unavailable, and thus augment the collateral demand by a "drag" amount

$$C_i^D = \sum_j \kappa^D \sigma \left(\sum_k \left| X^k(i,j) - X^k(j,i) \right| \right), \tag{3.6}$$

where κ^D is a fixed parameter. For example, in expectation, some fraction of the margin sent from investor i to investor j on a Tuesday may not be ready to deploy by investor j until Wednesday. Whereas variation margin precautionary buffers are computed on the basis of an investor's entire portfolio (regardless of the particular counterparties), the velocity drag component of variation margin depends on the structure of bilateral exposures. The magnitude of the variation margin drag therefore changes when a CCP is interposed between dealers, or with any other change in network structure.

In order to give a sense of the amount of variation margin "in flight" on a given day, we note the 2014 ISDA Collateral Survey indicates that each of the largest dealers receives, on average, over 7 billion USD in margin payments on a given day, the vast majority of which is variation margin.[12]

3.5.5   Total Collateral Demand

The total collateral demand C at a system level is the sum of the three components,

$$C = \sum_{i=1}^{n} \hat{C}_i^{IM} + C_i^{VM} + C_i^D. \tag{3.7}$$

3.6   Baseline Collateral Demand

This section focuses on collateral demand for the baseline case, taking the allocation of positions to CCPs as observed in the data. Here, we consider the impact on collateral demand of *(i)* adding dealer-to-dealer initial-margin requirements, *(ii)* varying the number T of days used to determine the "worst-case" historical loss for the purpose of initial margin requirement, from 3 days to 10 days, and *(iii)* the rehypothecation of collateral for uncleared positions. In the following section, we consider the impact on margin demand of increasing the set of positions allocated to CCPs, and various other alternative market designs.

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[12]See Table 18 on page 22 of International Swaps and Derivatives Association (2014). Of those reporting initial margin (IM) and variation margin (VM) separately, only 0.13 billion USD received is IM, whereas 2.4 billion USD is VM.

3.6.1 Calibration

We describe here how our parameters are calibrated in order to approximate actual market practices.

Initial margins are designed to cover the potential future exposure of a party (including the CCP) over the period of days that may be needed to liquidate and replace exposures with a defaulted counterparty. At base case, initial margins are based on the "worst-case" loss at a bilateral portfolio level over a period of $T = 5$ days, as estimated from historical simulation for the $P = 1000$ trading days prior to December 2011.

Relatively little public guidance exists to calibrate the precautionary buffer stocks of collateral used to "pre-fund" variation margin payments. Conversations with industry experts coupled with the modeling in Appendix B lead us to assume a buffer that is a multiple of $\kappa^{VM} = 2$ of the daily net-payment standard deviation. For illustration, in the absence of serially correlated returns, this means that an average investor sets aside a buffer that is roughly equal to the estimated standard deviation of net variation margin payments over a 4-day period. In practice, there is variation across types of investors. We understand that some participants in CDS markets, such as asset managers acting as agents for their clients or limited partners, typically hold an excess stock of unencumbered cash-like assets, so set aside no extra amount of collateral as a variation-margin buffer. Other investors such as broker-dealers treat access to unencumbered cash-like instruments as a binding constraint and arrange at a cost for the pre-funding of over a week's worth of adverse variation-margin payments. Under new Basel guidelines for liquidity coverage regulations, bank-affiliated dealers will be forced to set aside unencumbered cash-like assets sufficient to cover 30 days of net cash outflows, including those associated with variation-margin payment on derivatives.[13]

As for the "velocity drag" on margin funds associated with the lag between the time at which margin funds are sent and the time by which they are ready to be deployed by the receiver, we assume a drag coefficient of $\kappa^D = 0.5$, corresponding roughly to the assumption that half of the funds sent on a given business day can be re-deployed by the receiver on the same day.

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[13]The final "Liqudity Coverage Ratio" rule, Basel Commission on Banking Supervision (2013a), states at Paragraph 123 that "As market practice requires collateralisation of mark-to-market exposures on derivative and other transactions, banks face potentially substantial liquidity risk exposures to these valuation changes. Inflows and outflows of transactions executed under the same master netting agreement can be treated on a net basis. Any outflow generated by increased needs related to market valuation changes should be included in the LCR calculated by identifying the largest absolute net 30-day collateral flow realised during the preceding 24 months. The absolute net collateral flow is based on both realised outflows and inflows. Supervisors may adjust the treatment flexibly according to circumstances."

Parameter	Definition	Baseline
	Baseline case	
v^C	Level of under-collateralization for customers	0.75
v^D	Level of under-collateralization for dealers	0.5
T	Initial margin period (days)	5
P	Initial margin sample period (days)	1000
α^C	Bilateral short charge for customers	0.01
α^D	Bilateral short charge for dealers	0.01
α^{CCP}	Short charge to CCP	0.02
ρ	Rehypothecation ratio	0
κ^{VM}	Variation margin buffer	2
κ^D	Variation margin drag	0.5
d	Remaining duration of CDS contracts (in years)	3
	Alternative specifications	
$\bar{t}$	Exposure-level CCP eligibility threshold	0
λ	Re-usable collateral for client clearing dealers	0.5

TABLE 3.6: Calibration for the baseline model and alternative specifications. This table presents the calibration used both for the baseline model and for alternative specifications.

The calculation of short charges in the CDS market relies on the estimation of wrong-way risk (credit event and counterparty default occurring simultaneously, see LCH-Clearnet (2012)). Given data anonymization, no such estimation is possible here. We adopt instead a simplified approach. Short charges α^C and α^D for both customers and dealers are assumed to equal 1% of their net bilateral notional exposure. CCPs are assumed to take a more conservative stance and require $\alpha^{CCP} = 0.02$.

The fractional collateralization parameter for customers, v^C, is set to 0.75, in line with the figure provided by International Swaps and Derivatives Association (2011) for the entire OTC derivatives market. We assume a lower fractional collateralization $v^D = 0.5$ for dealers, based on the view that a sizable share of dealer activity, including market making and prime brokerage, does not generate significant medium-term bilateral exposure. Finally, we assume no rehypothecation ($\rho = 0$) in the base case. These baseline parameters, and alternative specifications, are summarized in table 3.6.

3.6.2 Collateral demand decomposition, with and without dealer-to-dealer initial margins

We consider the magnitude and decomposition of collateral for two calibrations of the baseline case. In the first case, dealers do not post initial margin to each other. That is, $v^D = 0$ and $\alpha^D = 0$. In the second case, we allow variation in v^D and α^D and focus on the impact on total collateral demand of dealer-to-dealer initial margins. The first scenario is akin to the pre-reform case, while the second captures post-reform initial margin requirements.

The decomposition of collateral demand for these cases is illustrated in the first two columns of Figure 3.1. In the absence of dealer-to-dealer initial margins, 75.5% of total margin is posted by customers in the form of initial margins. Margin posted by dealers to CCPs accounts for only 7.3% of the system-wide collateral demand. Variation margins, through both precautionary buffers and velocity drag, account for 17.1% of the system-wide demand for collateral.

The introduction of dealer-to-dealer initial margins increases total collateral demand by 69.7%. The increase is purely due to dealers' collateral demand, which increases by a factor of 10.5, then representing 45.4% of system-wide collateral demand. In this decomposition, the short charge component of initial margins is relatively more important for dealers (23.9%) than for customers (11.6%). This is due to the fact that dealers manage larger CDS portfolios than customers, therefore enjoying larger diversification benefits on the part of their initial margin requirement computed at a bilateral portfolio level (as
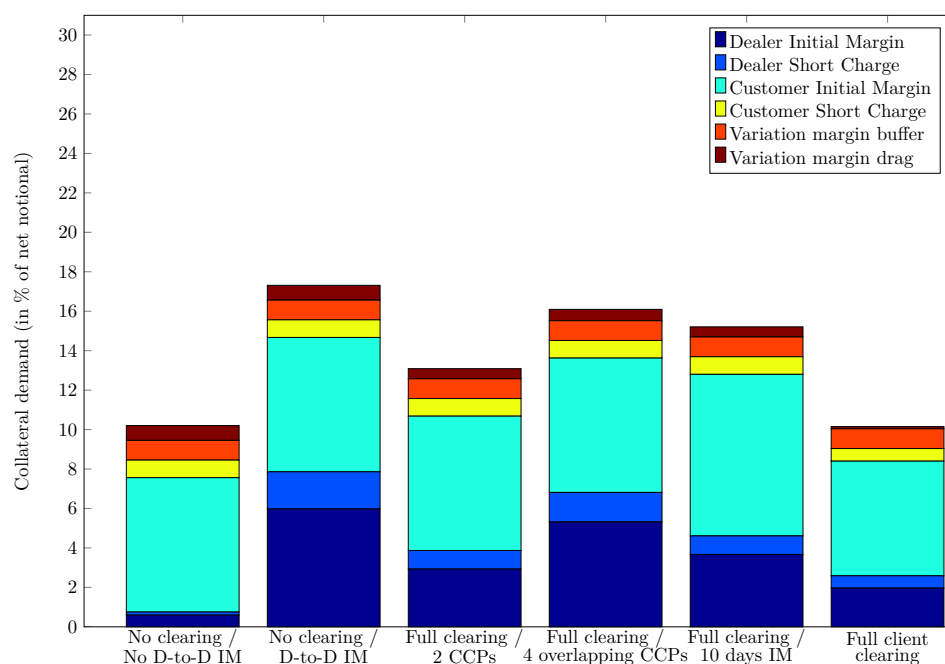
FIGURE 3.1: Summary of the results. This chart summarizes the decomposition of system-wide collateral demand under six scenarios. The results are presented as a percent of the system-wide net notional exposure. "D-to-D IM" denotes dealer-to-dealer initial margins. All calibrations are those used in the models' respective sections and summarized in table 3.6.

suggested by equation (3.2)). The definition of the short charge excludes diversification effects, and thus represents a larger share of margin demands of dealers.

In terms of magnitude, without dealer-to-dealer initial margins, system-wide collateral demand is estimated to be about 10.2% of the market-wide net notional positions and 0.78% of the market-wide gross notional positions. When including dealer-to-dealer initial margins, total collateral demand rises to 17.3% of net notional and 1.37% of gross notional. Even though our focus is less on the absolute level of collateral demand than on its decomposition and dynamics, our estimates are broadly consistent with market data. As of the end of 2011, the total reported worldwide collateral in use in OTC derivatives markets was 3.6 trillion USD (**?**), while the gross notional amount of OTC derivatives worldwide was about 598 trillion USD, according to the BIS.[14] This yields a collateral-to-gross-notional ratio of 0.6%, slightly below our estimate of 0.78%. One potential reason for this difference is that we restrict attention to CDS which, due to their jump-to-default risk and higher mark-to-market volatility than interest-rate swaps, are relatively collateral intensive. Another explanation is that, due to our focus on a subset of the CDS market, we neglect some diversification benefits with reference entities which are not included in our sample. As mentioned in Appendix B, our estimates of absolute magnitudes of collateral demand are dependent on our assumptions and parameter values, in the absence of data bearing on the cross-sectional distribution of seasoned CDS maturities, regarding the average sensitivity of market values to changes in CDS rates. However, most of the collateral demand scales linearly in the calibrated CDS duration, so that relative effects—our main concern—are preserved. For reasons of tractability, our initial-margin model also neglects components that are sometimes assessed by CCPs for recovery risk margin, liquidity, and concentration risk. LCH-Clearnet (2012) offers a technical description of each of these components.

3.6.3   Sensitivity of initial margin to coverage period

In this subsection, we analyze the sensitivity of collateral demand to the initial margin model. The number of days T on which the worst historical change in portfolio value $\phi_T\left(\mathcal{P}_{ij}\right)$ is computed (equation 3.2) is varied between 3 and 10 days. The appropriate choice of T for this purpose has been a matter of some disagreement between regulators and market participants in the United States.

Our results depend on the "clearing threshold," defined as the level of gross notional amount of CDS outstanding for a given reference name at or above which CDS for that reference name are assumed to be centrally cleared. Figure 3.2 plots total collateral

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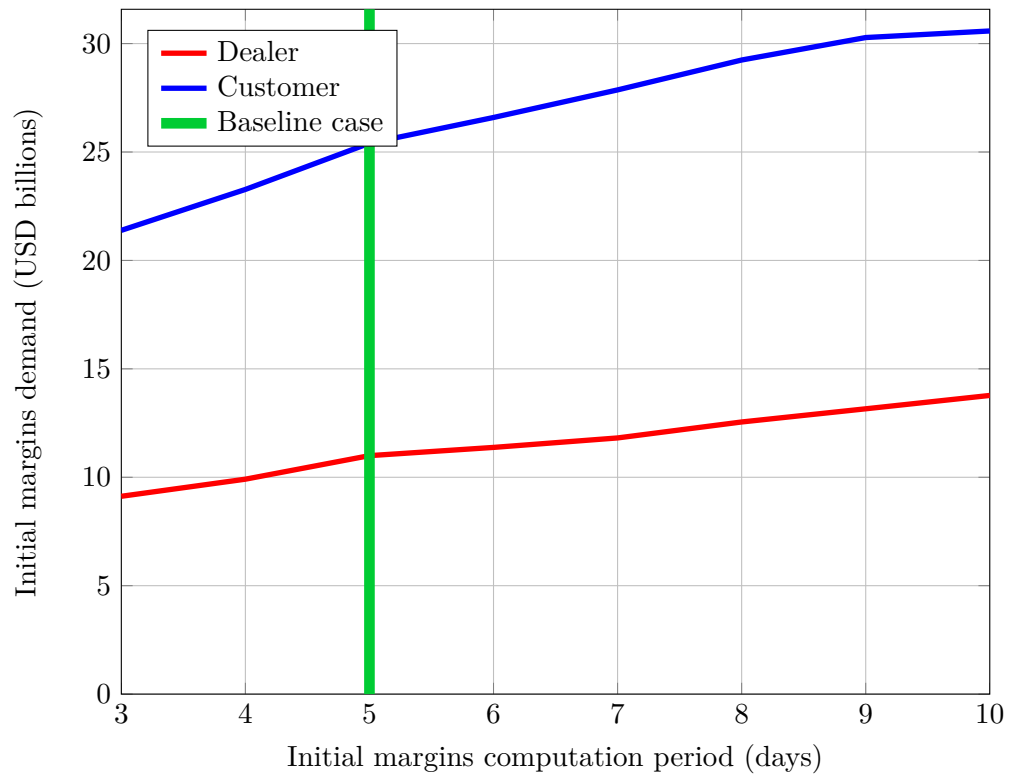[14]Semiannual OTC derivatives statistics at end-December 2011.

FIGURE 3.2: Initial margins demand as a function of T. This chart plots the initial margins demand for dealers and customers when T is varied. The short charge is not included in the initial margin, as it does not change with T. This chart is for a given clearing threshold $\bar{T} = 1.4 \cdot 10^9$ (i.e. all CDS are centrally cleared).

demand, broken down between dealers and customers, for a given clearing threshold. From the baseline case ($T = 5$), an increase in the initial margin computation period to 10 days yields an increase in collateral demand by 25.5% for dealers and by 20.4% for customers. Moreover, the slope of the initial margin demand curve as T is varied is steeper for customers than for dealers. This higher sensitivity is explained by the fact that customers typically manage smaller CDS portfolios (as shown in Table 3.4), and therefore enjoy lower diversification benefits.

3.6.4 Impact of rehypothecation

In the market for bilaterally cleared derivatives, received collateral is commonly re-pledged, as indicated by International Swaps and Derivatives Association (2014), economizing on the total amount of collateral held in the system. Because the objective of International Swaps and Derivatives Association (2014) is to measure the degree to which counterparty exposures are covered by collateral, rather than the total amount of collateralizing assets "tied down" in the system, its results do not proportionately reduce collateral usage according to the extent of rehypothecation.

In this section we analyze the first-order effect of rehypothecation or other repledging practices in reducing total collateral demand. We denote by $\rho \in [0, 1]$ the "rehypothecation ratio," that is, the proportion of received collateral that a dealer may re-use. We assume that only dealers can re-use initial margin received from others. For dealer i, the total initial margin requirement, net of rehypothecated collateral, $\hat{C}_i^{IM}$, is

$$\hat{C}_i^{IM} = \max \left\{ 0; C_i^{IM} - \rho \sum_{d=1}^{D} C_{di}^{IM} \right\}. \tag{3.8}$$

Here, the collateral drag arising from rehypothecation is ignored.

The impact of rehypothecation on collateral demand in the baseline case is illustrated in Figure 3.3. In the presence of dealer-to-dealer initial margins for uncleared trades, the impact of rehypothecation on dealers' collateral demand is sizable. Initial margins decrease linearly with ρ, to the point at which, for a bank i, $\rho \sum_{d=1}^{D} C_{di}^{IM} > C_i^{IM}$. In the base case, with $\rho = 0$, dealers' collateral demand is 5.1 times higher than when $\rho = 1$. Because CCPs do not rehypothecate collateral, the increased use of central clearing lowers the collateral efficiency associated with rehypothecation, a point emphasized by Singh (2010b) and analyzed in the next section.
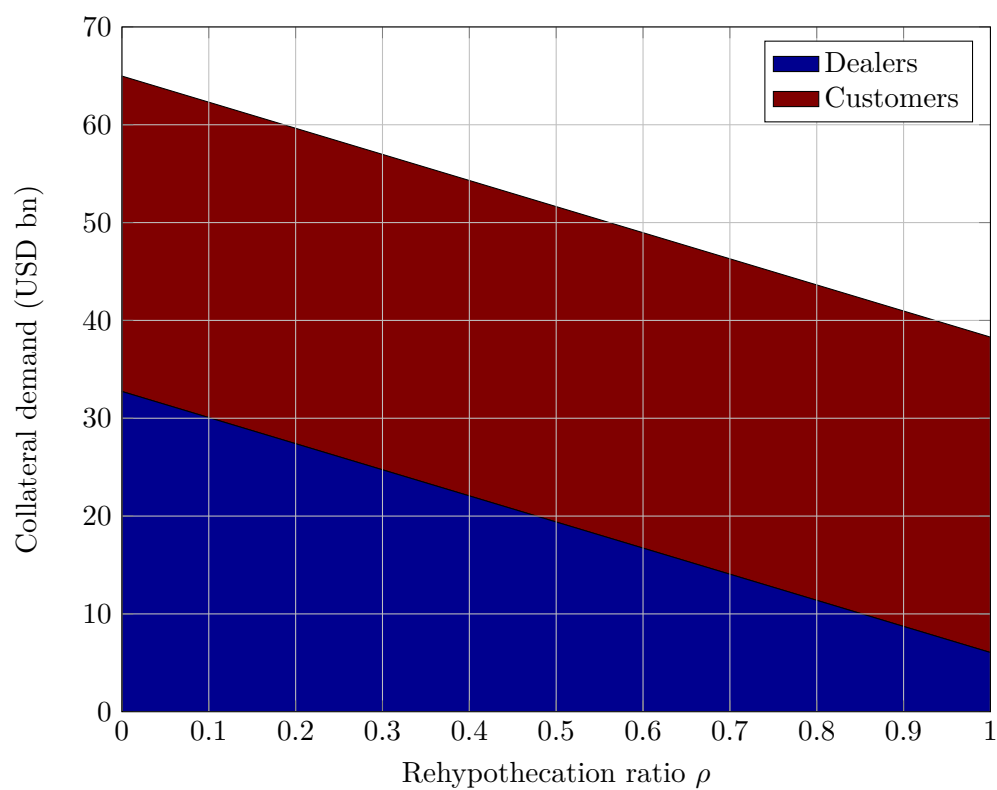
FIGURE 3.3: Baseline collateral demand as a function of ρ. This chart shows a decomposition—between dealers and customers—of the system-wide collateral demand in the baseline case, as the rehypothecation ratio ρ is varied. The baseline case is with dealer-to-dealer initial margins, and with the network of exposures (including centrally cleared exposures) observed in the data. Only dealer-to-dealer collateral received is assumed be rehypothecated. Other calibrations are those of the baseline case.

3.7 Impact of alternative clearing schemes

In this section we investigate alternative structural assumptions for the use of central clearing. We focus on the impact on collateral demand of *(i)* increasing novation to CCPs, *(ii)* increasing the subset of market participants that are clearing members of CCPs, *(iii)* increasing the number of CCPs, and *(iv)* introducing client clearing services.

3.7.1 Increased novation to CCPs

We first study the impact on collateral demand of increased novation to CCPs. We consider two base cases, with and without dealer-to-dealer initial margins.

The market-wide composition of customers, dealers, and CCPs, is kept at the baseline case. Regulatory reforms require central clearing for derivative contracts that are sufficiently standardized. We assume two requirements for a CDS exposure to be novated to a CCP. First, a CDS contract must be sufficiently actively traded. We assume that a reference entity is eligible for central clearing when its global gross notional amount is above a given threshold $\bar{T}$, a proxy for standardization. By dialing $\bar{T}$ down, we can analyze the gradual shift from the pre-reform to post-reform setting. Our dataset indeed suggests (as indicated in section 3.4.3) that CDS with the largest gross notional amounts (by referenced name) were the first to have been centrally cleared. This $\bar{T}$ is a reasonable proxy for "clearability." Second, whenever a reference entity is eligible for central clearing, only trades above a threshold $\bar{t}$ are assumed to be cleared. A justification for $\bar{t} > 0$ is that there may exist small-trader and other clearing exemptions, based on exposure-specific fixed costs associated with central clearing (data processing, information requirements). Formally, whenever

$$\sum_i \sum_j G^k(i,j) \geq \bar{T},$$

and $G^k(i,j) \geq \bar{t}$, an exposure $G^k(i,j)$ is assumed to be cleared at a CCP.

CCP Threshold (USD bn)		1	34	68	101	135	168	202	235	269	305
Customer-to-customer	Number of trades (share)	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
	Net notional (share)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Customer-to-dealer	Number of trades (share)	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
	Net notional (share)	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Dealer-to-dealer	Number of trades (share)	0	0.27	0.32	0.33	0.34	0.35	0.35	0.35	0.35	0.35
	Net notional (share)	0	0.22	0.34	0.39	0.42	0.46	0.47	0.47	0.47	0.49
Dealer-to-CCP	Number of trades (share)	0.36	0.10	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.01
	Net notional (share)	0.49	0.27	0.15	0.10	0.07	0.04	0.03	0.03	0.03	0.00

TABLE 3.7: Trade types and net notional as a function of $\bar{T}$. This table presents the share of trade types, and the share of net notional exposure they represent, for all pairs of party-to-counterparty exposures. Changes in the CCP clearing threshold $\bar{T}$ does not affect customer-to-customer or customer-to-dealer exposures. A decrease in $\bar{T}$ lowers the share of dealer-to-dealer trades and increases the share of dealer-to-CCP trades. Each column, by indicator type (share of number of trades and share of net notional), sums up to 1.

Only dealer-to-dealer exposures are eligible for central clearing in this subsection. Increased CCP membership and client clearing are explored in later subsections. The number of CDS cleared, at several alternative levels of $\bar{T}$, is presented in Table 3.8. The breakdown of trade types as a function of $\bar{T}$ is shown in Table 3.7.

We make additional assumptions on the assignment of particular exposures to CCPs. Consistent with the pattern observed in our dataset (see section 3.4.3), we assign each CDS positions to one of the two existing CCPs, based on European versus American reference names. All centrally cleared European (including European Union, Norway, Russia and Switzerland) CDS reference entities are assumed to be novated to the European CCP. All American (including Canada, Central and Latin America, and the United States) reference entities are assumed to be cleared by the existing American CCP. In the next section we investigate the case in which multiple CCPs may clear CDS transactions with the same referenced name.

Increased novation to CCPs has opposing effects on collateral demand. On the one hand, bilateral dealer-to-dealer exposures, which were not subject to initial margin requirements or which were under-collateralized to the extent captured by υ^D, are now subject to full margin requirements. On the other hand, increased novation implies increased cross-counterparty netting and diversification benefits.

Figure 3.4 plots the decomposition of system-wide collateral demand when the central clearing threshold $\bar{T}$ is reduced from that of the base case (USD 305 billion) to 0 (that is, full clearing), both with and without dealer-do-dealer initial margins. In the absence of dealer-to-dealer initial margins, total collateral demand increases by about 28.2% when shifting from the baseline scenario to full CCP clearing. This increase is driven by dealer initial margins and short charges, as well as by the velocity drag of collateral. Customers' collateral demand is unchanged at this stage as they are not clearing members. (Client clearing is investigated below.)

CCP Threshold $\bar{T}$ (USD billion)	Number of cleared CDS	Share gross notional cleared
1	184	1
34	41	0.64
68	15	0.37
101	8	0.26
135	5	0.19
168	2	0.10
202	1	0.06
235	1	0.06
269	1	0.06
305	0	0

TABLE 3.8: Distribution of cleared CDS, by CCP clearing threshold ($\bar{T}$). This table displays the number of CDS cleared and the percentage of the market gross notional they represent as a function of $\bar{T}$. CDS exposures which are already cleared in the dataset are not accounted for here. The set of values of $\bar{T}$ is the one used in all other tables and figures where $\bar{T}$ appears. A threshold $\bar{T} = 305$ bn USD corresponds to the baseline case. A share of 1 represents full central clearing. Source: DTCC.

Whereas dealer initial margins and short charges increase, the velocity drag decreases, due to the fact that increased central clearing amounts to pooling multiple bilateral exposures with one counterparty, therefore reducing the number of bilateral links and increasing netting opportunities. Accounting for changes in the velocity drag of collateral is potentially important, and had not been considered in previous research on collateral demand. A failure to account for velocity drag would result in an over-estimate of the increase in collateral demand implied by the shift to mandatory central clearing.

At a system level, the rise in collateral demand is of the same order of magnitude as that estimated by previous empirical studies. Our estimate of additional collateral demand amounts to 0.22% of the gross market notional, within the interval provided by Singh (2010b), who estimates this increase at between 0.16% and 0.33% of the gross market notional. Heller and Vause (2012), who study the whole CDS market for G-14 dealers only, provide estimates that depend on the prevailing level of market volatility. With the most conservative hypothesis, they estimate additional initial margin requirements to be above 100 billion USD. A linear extrapolation of our results (as we consider a subset of the CDS market only) yields an estimate comparable to the lowest estimates of Heller and Vause (2012). A potential explanation why we fall in the lower part of their estimated interval is that the iterative proportional fitting algorithm used by Heller and Vause (2012) tends to underestimate the extent of bilateral or multilateral netting opportunities.[15]

Our estimate of total collateral demand is above that of Sidanius and Zikes (2012), who assess the total initial margin requirement on both cleared and uncleared CDS to be between 78 and 156 billion USD (for the entire CDS market, including index and multi-name CDS). The total initial margin requirement (including the short charge) is about 43 billion USD in our sample, for a coverage of 18.9% of the global CDS market. Furthermore, we rely on actual, as opposed to simulated, bilateral exposure data, and are thus able to provide a decomposition of aggregate collateral demand.

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[15]The limitations of this iterative proportional fitting algorithm are well known in the estimation of interbank lending patterns. See Mistrulli (2011).
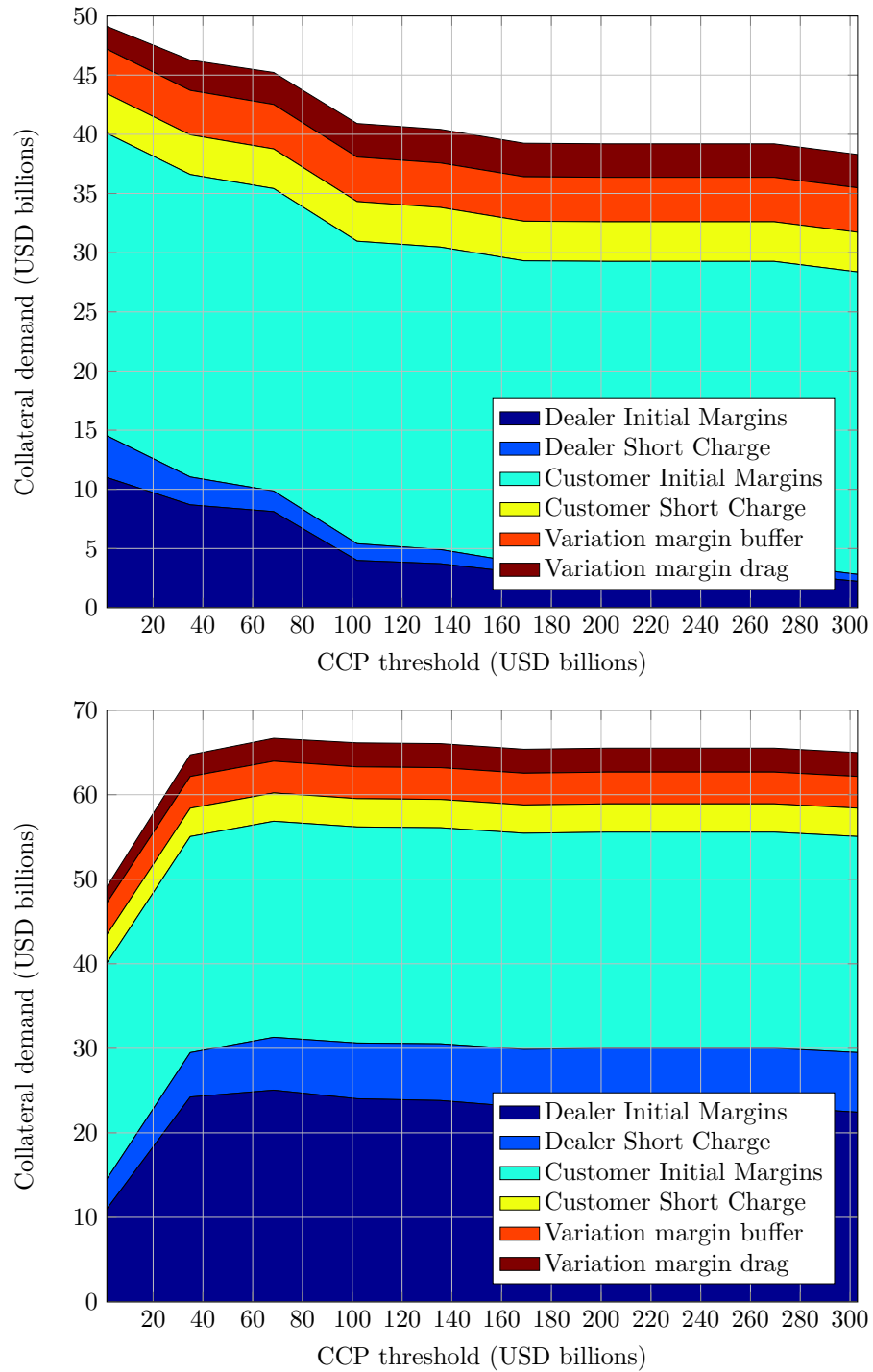
FIGURE 3.4: Decomposition of the collateral demand as a function of $\bar{T}$. Total collateral demand is decomposed into six components, for each of two base cases. For the top chart, there are no dealer-to-dealer initial margins. For the bottom chart, dealer-to-dealer initial margins apply, with $v^D = 0.5$ and $\alpha^D = 0.01$. Other calibrations are those of the baseline case. Results for $\bar{T} = 305$ billion USD correspond to the baseline case.
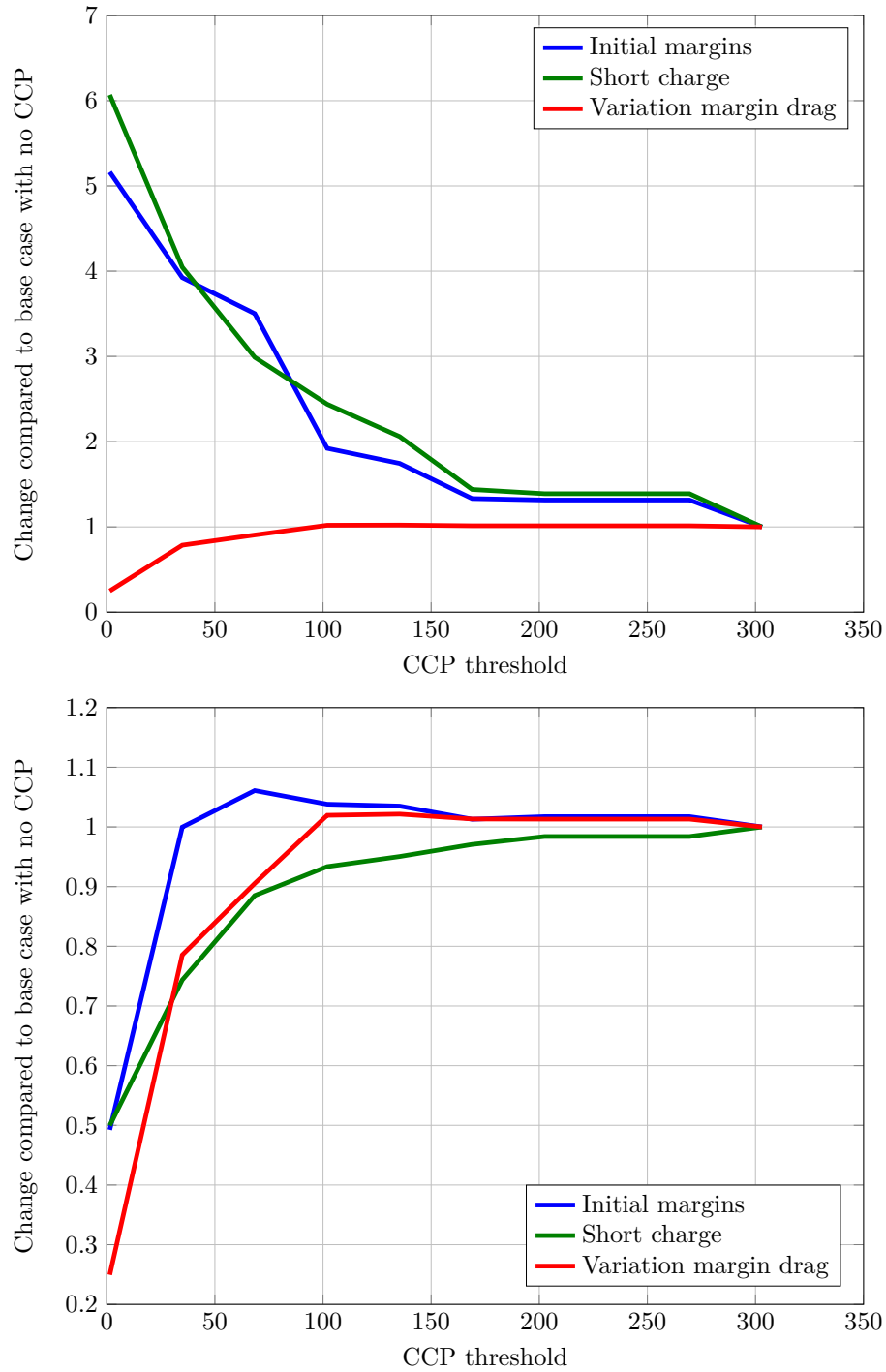
FIGURE 3.5: Change in dealers' collateral demand as a function of $\bar{T}$. This figure depicts the change in collateral demand from a base case with $\bar{T} = 305$ billion USD, with increasing novation to CCPs. Each point represents the ratio of the collateral demand for each margin type to the corresponding demand in the base case with no central clearing. The top chart features a base case with no dealer-to-dealer initial margins. The bottom chart features a base case with dealer-to-dealer initial margins calibrated with $\upsilon^D = 0.5$ and $\alpha^D = 0.01$. Results for $\bar{T} = 305$ billion USD correspond to the baseline case with no CCP in both instances, so that the ratio is always equal to 1 at $\bar{T} = 305$.

	D-to-D IM	No	Yes	No	Yes
	Client clearing	No	No	Yes	Yes
Δ demand by	Customers	0	0	-0.15	-0.15
type of trader	Dealers	1.79	-0.48	0.88	-0.65
	C-to-C	0	0	-1	-1
Δ demand by	C-to-D	0	0	-0.15	-0.15
type of exposure	D-to-D	-1	-1	-1	-1
	D-to-CCP	4.16	4.16	6.51	6.51
Δ total demand		0.28	-0.24	0.01	-0.41

TABLE 3.9: Change in collateral demand from baseline cases. This table contains estimates of changes in total collateral demand when shifting from two base cases (with and without dealer-to-dealer initial margins) and no central clearing to full central clearing with and without client clearing. Only exposures which are already cleared in the dataset are centrally cleared in the base cases. "IM" stands for "initial margins", "C" for customer, "D" for dealer. The computation of the change in collateral demand by type of exposure excludes the variation margin buffer, as it is not allocated counterparty by counterparty, but at a portfolio level.

Although collateral demand by customers does not change with the implementation of full clearing, dealers experience an increase in collateral demand of 179%, as shown in Table 3.9, from its low pre-reform level. Second, among dealers, the increase in collateral demand ranges between 49.5% and 634.1%, depending on the size and composition of the dealers' CDS portfolios. Figure 3.5 decomposes the change in collateral demand for the 14 dealers. The velocity drag component decreases when central clearing increases, but this effect is more than offset by the increase in initial margin and short charge. When $\bar{T}$ decreases, the short charge increases faster than the primary initial-margin component, because the short-charge computation formula does not allow for the increasing potential effect of diversification as portfolio size increases.

3.7.2   Increased dealer-to-dealer initial margins

Turning to the case in which dealers post initial margins between themselves, increased central clearing *reduces* total collateral demand whenever the level of dealer-to-dealer initial margin (parameterized by v^D) is high enough. At the level of individual positions, increased central clearing implies higher initial margin requirements. At a portfolio level, however, these higher collateral costs are more than offset by the cross-counterparty netting and diversification benefits of a CCP. With $v^D = 0.9$, the system-wide collateral demand, when shifting from the baseline case to full clearing, decreases by about 24.4%. In such a case, collateral demand by dealers falls by about 48.4%, with effects on individual dealer-level ranging from -25.9% and -66.1%. The above-mentioned trade-off at play in clearing is further seen through the fact that dealers' initial margin is not linear in $\bar{T}$, implying that novating few exposures to a CCP increases collateral demand, while novating the whole CDS portfolio lowers collateral demand.

Finally, we focus on the case in which dealer-to-dealer initial margins can be repledged (equation (3.8)). This amounts to analyzing the effect of repledging in the post-reform setting. Figure 3.6 plots dealers' collateral demand as a function of $\bar{T}$ for five values of ρ ranging between 0 and 1. The slope of total collateral demand is found to depend importantly on the rehypothecation ratio. When repledging is not allowed ($\rho = 0$) or allowed only to some limited extent, the collateral demand by dealers decreases as central clearing increases. In policy terms, dealers are given an incentive to novate a larger share of trades to CCPs under these conditions. When ρ is high enough, however, this effect is reversed and novation to CCPs does not provide high enough netting and diversification benefits to outweigh the loss of rehypothecation benefits. Interestingly, for a fairly broad range of values for ρ (including 0.5 and 0.75), collateral demand is not a monotonic function of $\bar{T}$, as the benefits of central clearing outweigh the loss of rehypothecation benefits only when the share of centrally cleared trades is high enough.
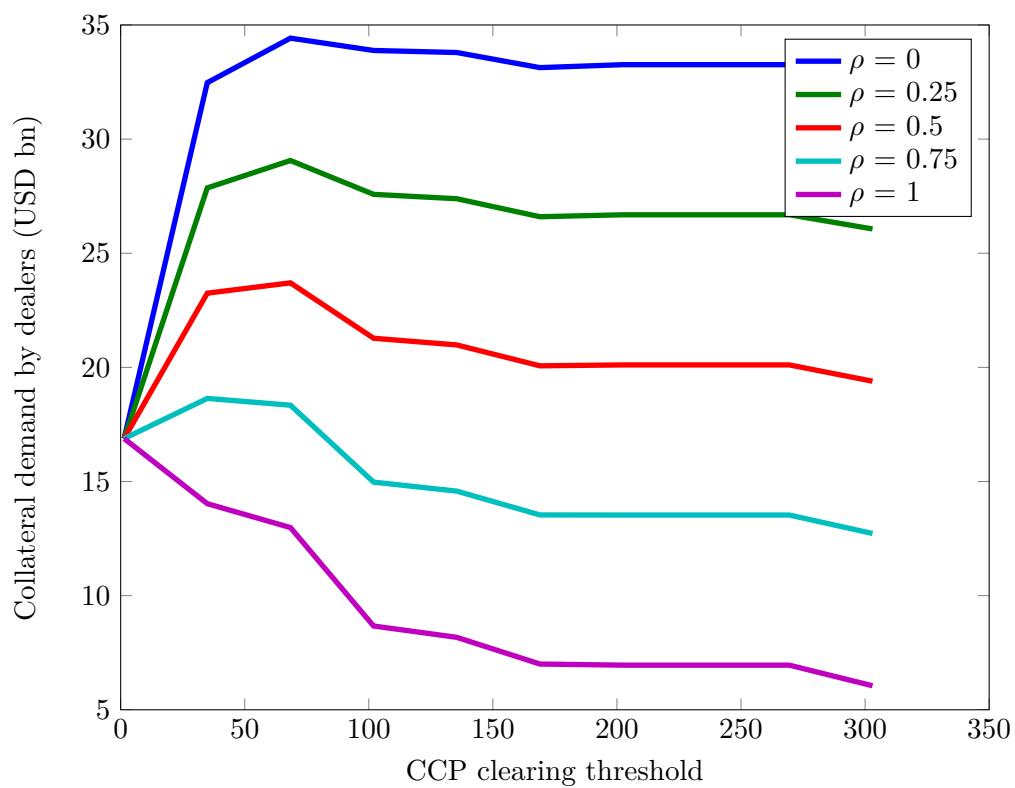
FIGURE 3.6: Collateral demand as a function of ρ and $\bar{T}$. This chart shows collateral demand by dealers when the clearing threshold $\bar{T}$ is varied, for five values of the rehypothecation ratio ρ. The base case is with dealer-to-dealer initial margins. The sign of the change of total collateral demand depends on the extent to which rehypothecation is practiced. Collateral demand by dealers drives the system-wide effect on demand in this setting.

3.7.3 Increasing the number of CCPs

We now focus on the loss of netting efficiency caused by increasing the number of CCPs. As opposed to Duffie and Zhu (2011), who do not investigate the role of CCP specialization by reference name, we study the effect of CCP specialization in referenced names along geographical lines, which we show in Section 3.4.3 to be a common market practice.

First, the set of reference entities, partitioned in the baseline case between European and American names, is further split. We create one new CCP for each geographic area. Each CDS reference entity is randomly made eligible by one of two area-wide CCPs, with equal probability of assignment. One characteristic of such a clearing scheme, similar to the baseline case, is that a CDS can be cleared at one CCP only. We call such CCPs "specialized," as there is no overlap in the set of reference entities cleared by each of them.

Second, we consider the case in which multiple CCPs clear the same CDS, within a given geographical area. Two new CCPs are added, with the same coverage and eligibility critera as those described for the baseline model. Whenever an exposure between any two dealers meets the eligibility criteria, it is randomly novated to one of the two CCPs, with equal probability. Such CCPs are called "non-specialized," given the overlap, at an area level, in the set of reference entities cleared by each of them.

Figure 3.7 shows total collateral demand with four CCPs, specialized and non-specialized, compared with collateral demand when there are only two CCPs. Whether one assumes dealer-to-dealer initial margins or not, an increase in the number of CCPs reduces the netting and diversification benefits, increasing collateral demand regardless of the clearing threshold $\bar{T}$. Whereas specialized CCPs imply only a loss of diversification benefits, non-specialized CCPs imply both netting and diversification losses. Thus, collateral demand increases to a much greater extent with non-specialized CCPs. With full clearing, an increase in the number of CCPs from 2 to 4 results in a 6.3% increase in collateral demand if CCPs are specialized, and otherwise an increase of 23.4%. This result is pertinent to the theoretical findings of Duffie and Zhu (2011), who focus on CCPs clearing different asset classes.

For the case of non-specialized CCPs, we consider the baseline case with dealer-to-dealer initial margins, shown in the bottom chart of Figure 3.7. Here, total collateral demand is not monotonic in the clearing threshold $\bar{T}$. An increasing degree of novation to CCPs first raises collateral demand, as additional margin requirements and the change in netting sets outweigh the potential cross-counterparty netting and diversification benefits a CCP
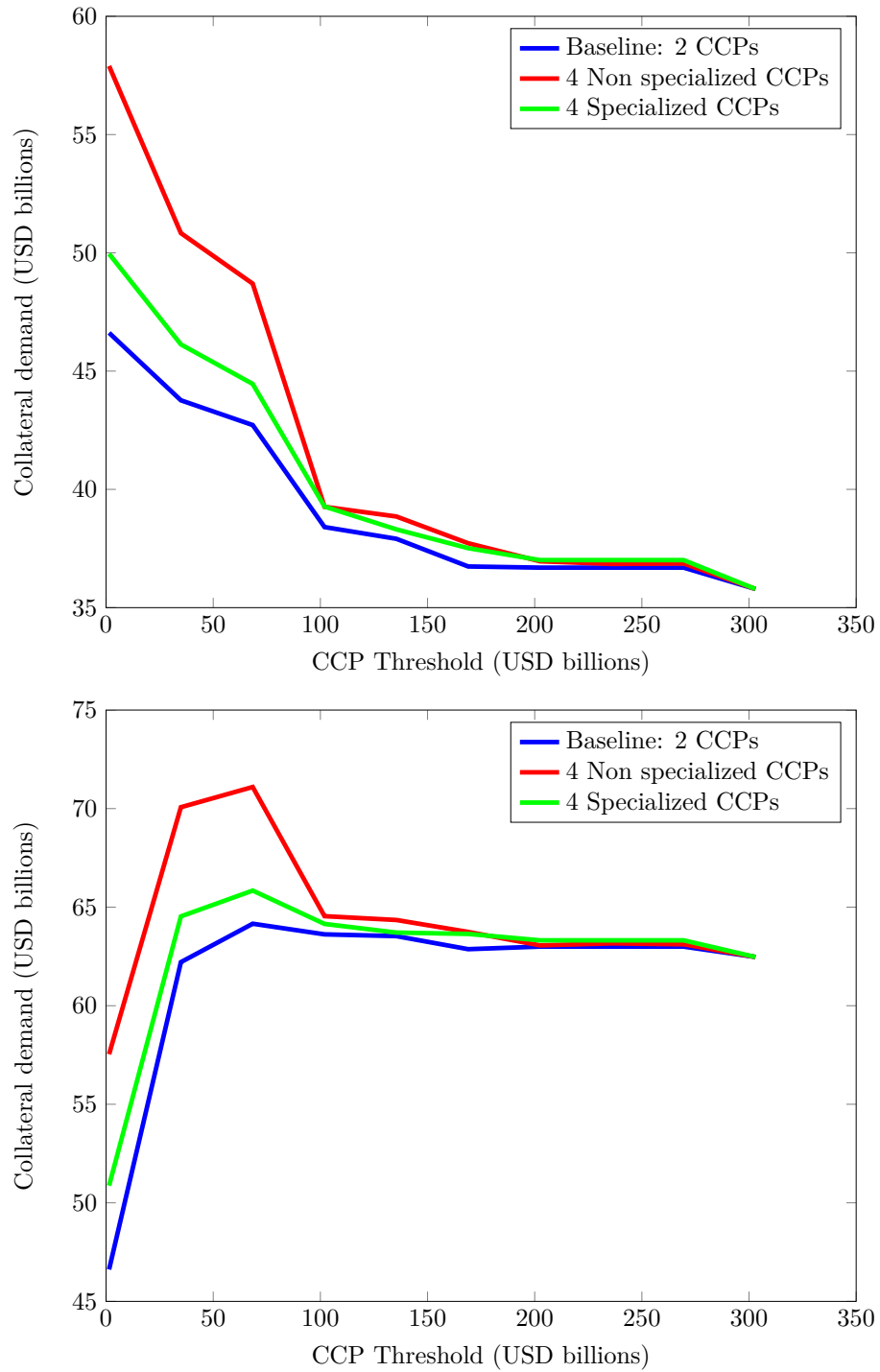
FIGURE 3.7: Collateral demand as a function of the number of CCPs and of $\bar{T}$. $D = 14$. In the top chart, there are no dealer-to-dealer initial margins. In the bottom chart, dealer-to-dealer initial margins exist with $v^D = 0.5$ and $\alpha^D = 0.01$. For "specialized" and "non-specialized" CCPs, the collateral demand is the average over 10 simulations. Other calibrations are those of the baseline model. The results for $\bar{T} = 305$ billion USD correspond to the baseline case.

may provide. Once a sufficiently large share of trades is cleared, however, these benefits prevail and collateral demand decreases relative to the base case.

3.7.4   The impact of client clearing

In the preceding analysis, only dealer-to-dealer trades were centrally cleared. In the post-reform environment, however, customer-to-dealer trades are required to be centrally cleared, putting aside special exemptions, such as those for commercial hedging and for the use of derivatives by sovereigns. When faced with this constraint, a large number of market participants with relatively lower levels of CDS market participation are likely to avoid becoming direct clearing members, given the implied costs (compliance to prudential standards, contribution to the default fund, and so). These firms are more likely to use client clearing services offered by dealers. A dealer collects CCP margins from these clients and posts the margins at the CCP on their behalf.

We refer to dealers offering client clearing services as "client clearing dealers." Each customer is assumed to have its entire CDS portfolio cleared by a unique client clearing dealer. In order for a customer-to-dealer trade to be centrally cleared, client clearing services may not be offered by a dealer that is also the counterparty to the CDS position. For each customer, we assume that a client clearing dealer is randomly assigned, with equal probabilities across the set of clearing members to which it has no direct exposure. In case a customer is linked to all D dealers, the one to which its exposure is the lowest (as measured by the number of CDS trades) is assigned as its client clearing dealer. Direct exposures to this client clearing dealers are assumed to remain uncleared. In the dataset, we find 32 such customers, whose uncleared exposures represent, in our dataset, 0.03% of the gross notional amount outstanding.

When posting collateral to their client clearing dealer, customers are assumed to post (on that part of their portfolio which is eligible for clearing) the amount of collateral they would have delivered to a CCP as a direct member. This amounts to setting $v^C = 1$ and $\alpha^C = \alpha^{CCP}$ in equation (3.3), thus requiring higher collateralization, *ceteris paribus*, for a given portfolio. However, customers also enjoy potential netting and diversification benefits, as trades with several counterparties are pooled with a single dealer. Whether one effect or the other dominates depends on the size of the portfolio of each customer, as we will emphasize later.

In this model, dealers clear the portfolios of their clients together with their own CDS positions. Thus, they enjoy potentially large netting and diversification benefits on their own initial margin requirements. However, as the size of their portfolio under
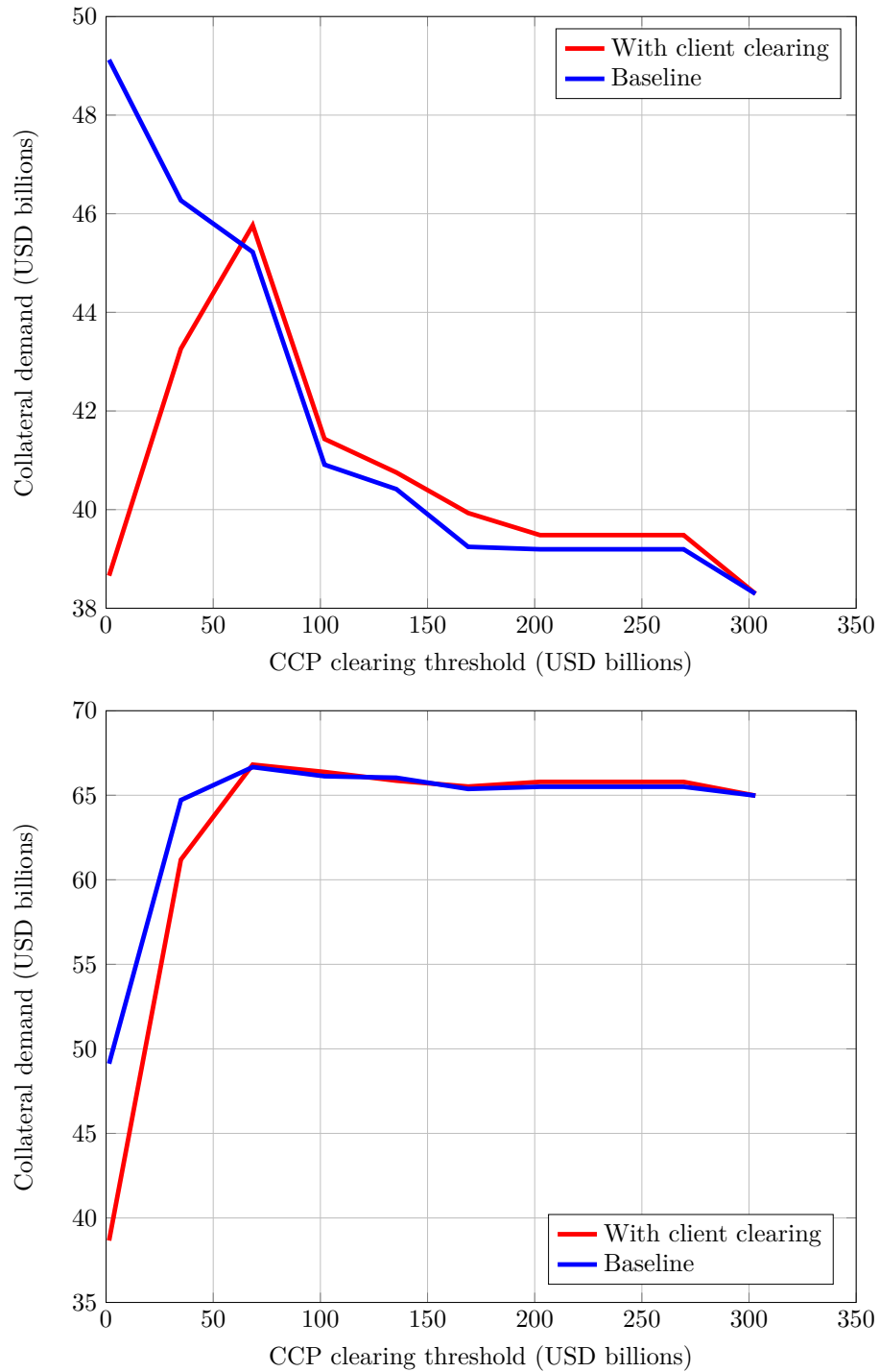
FIGURE 3.8: Collateral demand with client clearing. Both charts compare the system-wide collateral demand with and without client clearing, for two base cases, with a varying CCP-clearing threshold $\bar{T}$. In the first chart, there are no dealer-to-dealer initial margins. In the second chart, dealer-to-dealer initial margins exist with $v^D = 0.5$ and $\alpha^D = 0.01$. Both are calibrated with $\lambda = 0.5$. Results for $\bar{T} = 305$ bn USD correspond to the baseline case.

management is larger, margin requirements in absolute terms are likely to be larger. We assume that dealers can immediately re-use a fraction λ of the collateral supplied to them by customers. In the absence of regulatory constraints, λ could be below one if client-clearing dealers offer collateral transformation services or if CCPs accept a narrower range of assets as collateral than that accepted by dealers (or if CCPs impose tougher concentration limits on the share of particular assets to be delivered as margins). We note the distinct roles of λ and ρ. The former parameter pertains only to collateral received through client clearing services, whereas ρ is related to collateral received from dealers on uncleared trades.

Total collateral demand in the presence of client clearing is compared with the baseline case in Figure 3.8, both with and without dealer-to-dealer initial margins. In both cases (with minor exceptions for high values of $\bar{T}$), implementing client clearing reduces collateral demand at a system level, provided that λ is high enough. The system-wide effect is driven by several mechanisms. First, customers face higher initial margin requirements at a position level, as exposures toward client-clearing dealers are assumed to be fully collateralized ($\upsilon^C = 1$). However, because all of their bilateral exposures are pooled towards their client-clearing dealers, they also enjoy cross-counterparty netting and diversification benefits. Which of these effects dominates depends on the size and composition of the CDS portfolio under management, as discussed below.

Turning to dealers, two potentially offsetting effects are at play. Larger portfolios must be centrally cleared by dealers at CCPs, implying higher collateral requirements in absolute terms. However, these larger portfolios offer increased netting and diversification benefits. This is likely to be even more the case when a sizable share of dealers' exposures arises from their market making or intermediary activity, thus allowing for large cross-client netting benefits. Whenever dealers re-use a high enough share of the collateral that they receive from their clients, the latter effect dominates. In the absence of dealer-to-dealer initial margins (and $\lambda = 0.5$), total collateral demand is kept roughly constant (within about 1%) when shifting from the baseline case to full clearing. This can be compared to the 28% increase in collateral in the absence of client clearing. Both with and without dealer-to-dealer initial margins, system-wide collateral with client clearing for $\bar{T} = 0$ is 21.5% lower than that with full clearing but no client clearing. However, in this setting of client clearing, and in the absence of dealer-to-dealer initial margins, total collateral demand is not monotonic in $\bar{T}$, as seen in Figure 3.8. From the base case, increasing central clearing increases collateral demand, with the effect being driven by dealers (as uncollateralized trades become subject to initial margin requirements). When the share of cleared trades is high enough, the netting and diversification benefits of client clearing (together with those of central clearing) outweigh these costs,
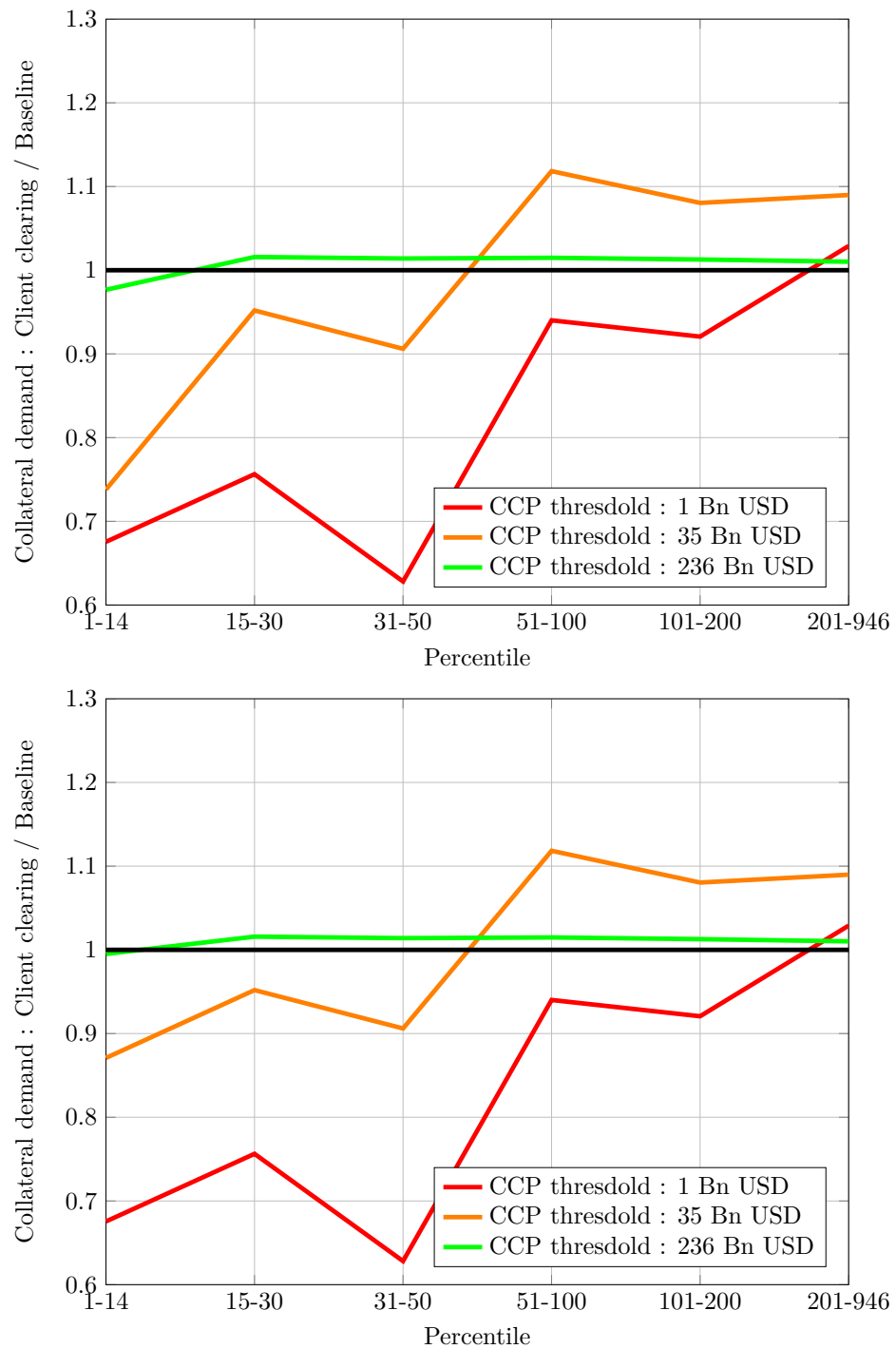
FIGURE 3.9: Distributional effects of client clearing. The top chart illustrates the distributional effect of client clearing, as captures by the ratio of collateral demand with client clearing to collateral demand in the baseline case. In the top chart, the baseline case does not feature dealer-to-dealer initial margins for uncleared trades. In the bottom chart, dealer-to-dealer initial margins apply with $v^D = 0.5$ and $\alpha^D = 0.01$. Both charts are based on a collateral re-use coefficient of $\lambda = 0.5$. Percentiles are constructed based on each counterparty's total gross notional bought and sold on the CDS market.

so that collateral demand decreases. Thus market participants may favor large-scale novation to CCPs.

At the level of a given market participant, the sign of the change in collateral demand is ultimately driven by the size and composition of the portfolio under management, as well as by the parameter λ. Whereas our previous analysis has focused on aggregate collateral demand only, we go now to a more granular level here by investigating the distributional effects of client clearing across market participants. Given the anonymization of market participants in the dataset, we distinguish counterparties according to their total level of activity (or, eventually, other portfolio-related characteristics). Counterparties are ranked according to the sum of the gross CDS notional amounts (bought or sold) on all underlying reference entities. Quantiles are constructed on this basis.

The distributional effects of client clearing are depicted in Figure 3.9, where the ratio of collateral demand in the presence of client clearing over the demand in the base case is plotted for three values of the clearing threshold $\bar{T}$. We see first that the distributional effects of client clearing, and whether particular sets of market participants must post more or less collateral compared to the baseline case, depend importantly on the share of cleared trades, as captured by $\bar{T}$. Customers in the lowest quantile must always post more collateral with the implementation of client clearing, because their increased margin requirements outweigh cross-counterparty netting and diversification benefits. This arises from the fact that they trade relatively few CDS with a very small number of counterparties. At the other end of the size spectrum of market participants, dealers always benefit from client clearing (for $\lambda = 0.5$) even when $\bar{T}$ is high. In the range between these values, for large customers (those market participants ranked 15 to 200 by size), whether netting and diversification benefits are sufficient to offset increased initial margins or not depends importantly on $\bar{T}$.

3.8 Concluding Remarks

As explained by Anderson and Joeveer (2014), there are significant economic implications for the impact of new regulations on global collateral demand. We have analyzed the implications of specific types of regulations and changes in market design for collateral demands of different types in the OTC derivatives market, focusing on CDS.

Our quantitative analysis of extensive bilateral CDS exposure data allows a decomposition of collateral demand for both customers and dealers into four components, including

the frictional demands for collateral associated with variation margin payments. We investigated the relative and absolute impacts on collateral demand of various market designs. The decomposition of collateral demands associated with some of the most salient specifications is summarized in Figure 3.1.

Among our main results is the fact that, based on year-end-2011 data, system-wide collateral demand is heavily increased by the introduction of dealer-to-dealer initial margins. Adding to that the requirement of central clearing leads to a substantial reduction in collateral demand. Our analysis provides a distinction, when considering the impact of CCP proliferation on collateral demand, between specialized and non-specialized CCPs. Our results indicate that client clearing will have significant distributional consequences for collateral demand across different types of market participants.

3.9   Appendix 1: Collateral Used for Variation Margin

This appendix provides a brief discussion of our assumption that the requirement to pay variation margin creates a net positive demand for collateral. This is so, we argue, despite the fact that any margin paid by one firm is received by another firm, which might superficially suggest zero total demand for collateral associated with variation margin.

We propose that there actually are two forms of net positive demand for collateral associated with variation margin payments: *(i)* a precautionary demand for collateral, of the same sort underlying traditional theories of the precautionary liquidity demand for money (e.g. Alvarez and Lippi, 2009), and *(ii)* a "drag" component associated with frictional delays between the time at which collateral is sent and the time by which it can be deployed by its receiver for other purposes.

In practice, as illustrated in Figure 3.10, firm i must set up some stock s_i of collateralizing assets before these assets can actually be transferred to meet margin requirements. On a given day, firm i will therefore hold in advance a precautionary amount of collateral that is likely to cover some targeted fraction of the positive part of its total net variation margin payments to all counterparties. We assume that this precautionary demand is a fraction κ^{VM} of the standard deviation of the total variation margin payment, as captured by (5). That is, the precautionary demand for collateral is proportional to the degree of uncertainty of the total payment that must eventually be made, net of payments received. This includes the benefit of netting of positives against negatives (payments to be made, net of payments to be received) across counterparties.

As illustrated in Figure 3.10, in addition to the precautionary stock s_i of collateral held by firm i, there is some additional demand for collateral associated with the fact that the collateral y_{ij} that has been sent from i to j is not immediately available for deployment by firm j elsewhere in the economy. There could be lags in availability due to operational delays for execution, settlement, and planning. For example, if \$1 million is sent as a margin payment from i to j at 15:06 on a given Tuesday, firm j cannot use the same \$1 million to settle at the same time, 15:06, a tax payment to the government or a purchase of equities from an unrelated firm. Perhaps the cash value of this margin payment from i could be effectively deployed by j for other purposes by some time later that afternoon or on the next morning.

For example, consider the following structural cash-management model, based on Chapter 7 of Harrison (2013). This continuous-time model is too stylized to be reliable for direct estimation of magnitudes, especially because it ignores other sources of flows into the cash-management buffer of the investor. We use the model only to provide some
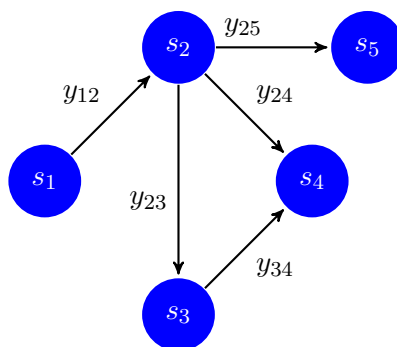
FIGURE 3.10: The variation margin obligations of each firm i imply that collateral will be held away from other uses in the economy in two forms: a precautionary stock s_i held at firm i and an amount y_{ij} that has been sent from firm i to firm j but is not yet operationally available for use by firm j.

support for the functional form of our reduced-form assumption that the precautionary buffer demand for collateral is linear with respect to the standard deviation of the net variation margin payments.

For this purpose, suppose that there is some opportunity cost $h > 0$ per unit of time for each unit of collateral held in an investor's cash-management buffer. Even if the collateral is held in interest-bearing instruments, h can be interpreted as the "convenience yield," meaning the opportunity cost associated with holding the collateral in place rather than using it for other purposes whenever convenient. We assume some incremental cost $\beta > 0$ for each unit of variation margin cash payment that must be made when the precautionary buffer is empty. This incremental cash could be obtained, for example, from a back-up liquidity source, whether internal or external. It matters only that there is some incremental cost to obtaining liquidity on short notice. We suppose that net variation margin payments are of mean zero, and that the cumulative flow of these net payments can be modeled as a Brownian motion with standard deviation parameter σ. As explained by Harrison (2013), the investor's optimal policy in this setting is to retain collateral in the buffer whenever the current buffer amount is below an optimal threshold b. Any incremental collateral above the threshold b is released for other use, given the assumed opportunity cost for holding the collateral in the buffer. By following Harrison's analysis, we have

$$b = \sigma \left(\frac{\beta}{h} \right)^{1/2}.$$

Further, the steady-state distribution of collateral held in the buffer is uniform on $[0, b]$, a property of driftless Brownian motion reflected on two barriers, 0 and b in this case. Because the mean of this uniform distribution is $b/2$, the steady-state average collateral demand in this simple model is $\alpha\sigma$, where

$$\alpha = \frac{1}{2} \left(\frac{\beta}{h} \right)^{1/2},$$

consistent with the form of our reduced-form assumption. The constant α is increasing in the ratio of the opportunity cost h of idle unencumbered liquid collateral to the cost β of obtaining cash on short notice.

We are also interested in estimating the mean collateral "velocity" drag, on average across scenarios. For this, we must first estimate the expected absolute value $E(|y_{ij}|)$ of the payment amount y_{ij} between investors i and j. For simplicity, we assume that this mean absolute payment amount is proportional to the standard deviation of y_{ij}. (For normally distributed y_{ij}, this involves no approximation error.) The frictional effect of the time lag on unavailable collateral at a point in time is approximated through a further proportional effect. For example, if the expected time lag between the send time

and the time of availability for re-use is 0.5 days, then the mean proportional amount of sent collateral that is not available for immediate re-use is 0.5 times the mean daily amount sent (assuming independence of the delay time and the amount sent). The total drag coefficient κ^D in (6) is intended to reflect both of these proportional effects. This simple reduced-form model of collateral drag could be extended to a full-blown stochastic network inventory model of the sort described by Harrison (2013), although that is beyond the goals of this paper.

As an example of the practical perception of time drags on collateral, the U.S. Commodity Futures Trading Commission has recently proposed strong limits on the ability of derivatives central clearing parties to include in their regulatory measure of cash liquidity their stock of unencumbered U.S. treasury securities, under the premise that it takes time to convert even U.S. treasury securities to cash.[16] Even a payment of central bank deposits, once sent by i, cannot be immediately be resent by j, in light of typical "back-office" operational and planning frictions.

Velocity drag on collateral is distinct from the precautionary demand for collateral, in that the "drag" amount of collateral that is sent but unavailable for immediate use is not reduced by diversification across counterparties. Rather, the delayed accessibility of cash to the economy associated with the variation payment amount y_{ij} sent by i to j is not partially offset by the delayed accessibility associated with the amount y_{ki} sent by some other firm k to firm i. There is time "drag" along every active payment link. Thus, our model (6) of variation-margin drag reflects an amount that is proportional to standard deviation of *each* variation margin payment, and is additive across payment links.

3.10 Appendix 2: Approximating Variation Margin Payments

This appendix describes our approach to estimating the changes in market values of CDS positions for purposes of our margin calculations. These changes in market values are used to estimate various forms of collateral demand, including initial margin, precautionary buffer demand for variation margin payments, and velocity drag for variation margin payments.

From our Bloomberg CDS rate data, we approximate the change in market value of a unit-notional CDS position referencing a given name from the usual duration-based

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[16]See 17 CFR Parts 39, 140, and 190, "Derivatives Clearing Organizations and International Standards" Federal Register, Volume 78, No. 159, Friday, August 16, 2013, Proposed Rules.

"dv01" formula, by which a 100 basis point change in the CDS rate causes a change in market value of approximately $0.01d$, where d is the effective duration of the position. This follows from the fact (**?**) that a protection-sold CDS position is essentially arbitrage-equivalent to a note issued by the referenced name that pays the default-risk-free floating rate plus a fixed spread equal to the CDS rate. As such, like any bond, the change in market value over a short time period such as one day is approximately equal to the change in spread (here, the change in CDS rate) multiplied by the effective duration. This effective bond duration is slightly less than the maturity of the CDS contract, except for referenced with extremely high CDS rates, of which there are very few in our sample. For example, as shown on Bloomberg's CDSW page, a typical investment-grade 5-year CDS has a dv01-implied effective duration of roughly 4.9 years. As an illustration, for such a CDS position, a one-day increase in the CDS rate of 10 basis points implies a loss in market value to the protection seller of approximately 0.49% of the notional size of the position.

In our case, unfortunately, the duration-based approximation is not nearly as important a source of approximation error as the fact that there is very limited information on the remaining maturities of the seasoned CDS positions represented in our data set. For the broad market population of U.S. CDS, the mode of the distribution of CDS maturities at origination is 5 years, with a mean of about 4 years, as indicated by Chen et al. (2011b). Public DTCC Trade Information Warehouse data[17] also show that the majority of newly issued CDS have a 5-year maturity. The maturities of previously contracted CDS are reduced, however, as the positions become seasoned. Our bilateral CDS data set does not include the remaining maturities of the CDS positions. Charts A and B of Benos et al. (2013) show a half life of CDS contracts of under six months, due to various types actions that eliminate a CDS position between two counterparties. Some of these actions, however, are assignments that need not stop the reduction in maturity. Other actions, such as compression trades and other forms of termination, eliminate the contracts entirely. Without the benefit of more detailed data, we simply adopt a crude assumption that the effective average duration of existing CDS contracts is 3 years.

We also ignore the imperfect correlation of returns on CDS positions on the same reference name across different maturities. In practice, these returns are highly correlated. For example, Palhares (2012) estimates that the first principal component of returns on CDS positions on the same reference name, at maturities of 3, 5, 7, and 10 years, captures 99% of the variance of the monthly returns of these various CDS positions.

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[17]See "Market Risk Activity Analysis", Special report available from the TIW Reports webpage.

Our resulting approximation of the magnitudes of changes in market values of CDS positions is extremely rough, but our qualitative conclusions are largely unaffected by this, given that the main source of approximation error is a re-scaling of the correct average duration, which re-scales all of the components of collateral demand that depend on changes in CDS market values (absent default) by the same factor. (In our dataset, there were no defaults, and only the short-position charge for initial margin associated with jump-to-default risk is not related to duration.) Our main conclusions are concerned with the *relative* impacts on collateral demand of various alternative market designs and regulations.

3.11   Appendix 3: Increasing the Set of Clearing Members

This appendix examines the implications for collateral demand of increasing the subset of market participants that participate in central clearing. Customers satisfying an exposure-size criterion are assumed to become clearing members. For this purpose, customers are ranked according to their total gross notional amount bought and sold on the CDS market[18], that is, $\sum_k \sum_j \left[G^k(i,j) + G^k(j,i) \right]$ for all i. Market participants for which this exposure is above some threshold are assumed to become members of both of the two central clearing parties, and are then effectively treated as dealers.

Increasing the subset of market participants that centrally clear has a material impact on the global demand for collateral. On the one hand, there are benefits from acquiring a dealer status, as dealers do not post initial margins to customers, and post no margins to other dealers in the base case (if $v^D = 0$) or reduced margins (whenever $v^D < v^C$). On the other hand, central clearing may be associated with higher collateral requirements than bilateral clearing for a given set of exposures (whenever $v^D < 1$). Finally, central clearing offers cross-counterparty netting opportunities and diversification benefits, especially for institutions with a large number of bilateral counterparties. Which of these effects dominate depends on the CCP-clearing threshold $\bar{T}$, that is, on the share of cleared trades.

Figure 3.11 plots total collateral demand as the number D of clearing members and the clearing threshold $\bar{T}$ are varied. For a high CCP-clearing threshold (that is, a low share of centrally-cleared trades), an increase in the number of clearing members lowers total collateral demand. Once a major fraction of CDS are centrally cleared, total collateral demand is no longer monotonically dependent on the number of clearing members. This

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[18]Given the anonymization of the data at a counterparty level, the set of counterparty-specific variables to be used to construct quantiles is limited. Other possible characteristics include the number of traded CDS or the number of counterparties. Spearman rank correlation with the total gross notional traded are respectively 0.77 and 0.84.
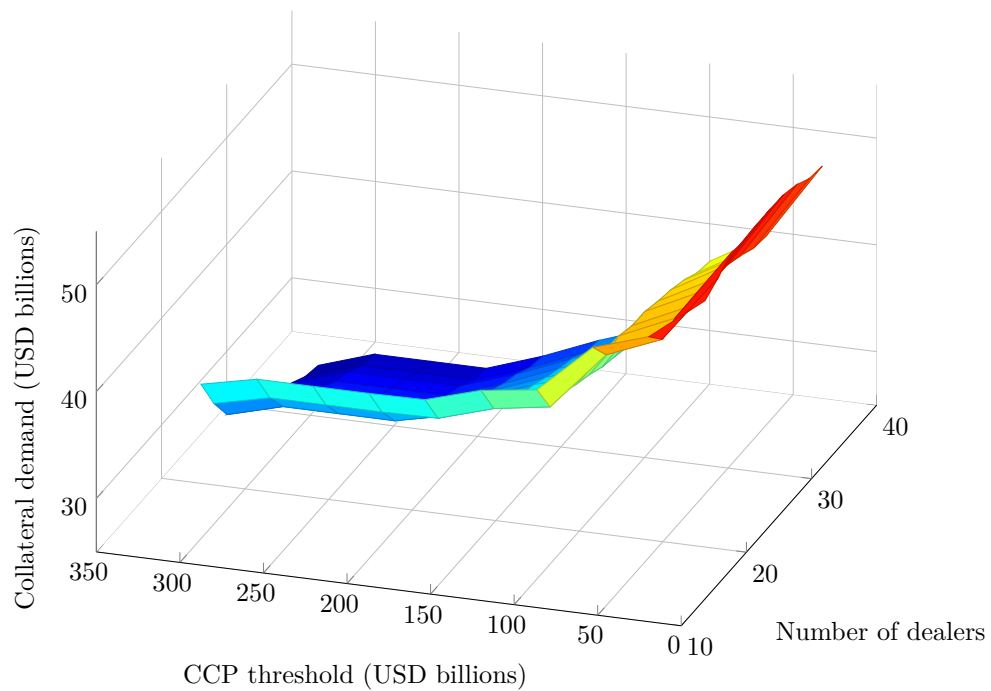
FIGURE 3.11: Collateral demand as a function of the number of clearing members and of $\bar{T}$. This surface chart plots total collateral demand as a function of both the number of clearing members (or dealers) and the CCP clearing threshold $\bar{T}$. The base case is with no dealer-to-dealer initial margins. Other calibrations are those of the baseline model. Results for $\bar{T} = 305$ bn USD correspond to the baseline case.
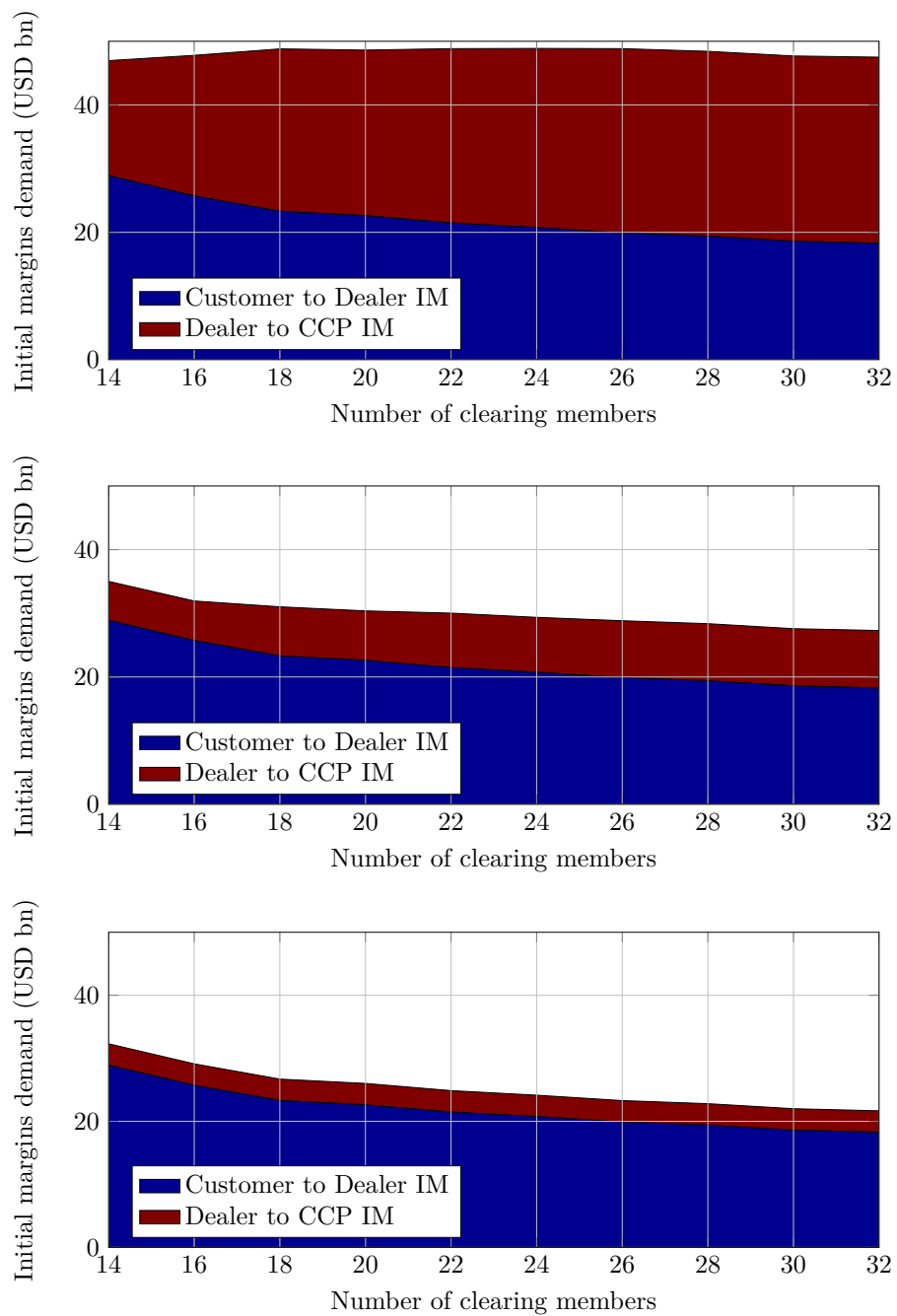
FIGURE 3.12: Decomposition of initial margins demand as a function of the number of clearing members. These chart decompose system-wide initial margins between customers and dealers initial margins. In the first chart, $\bar{T} = 1$ Bn USD; in the second $\bar{T} = 135$ Bn USD; in the third $\bar{T} = 305$ Bn USD. The base case is here with no dealer-to-dealer initial margins. Other calibrations are those of the baseline model.

effect is further illustrated in Figure 3.12, where initial margins (including the short charge) delivered by customers to dealers and by dealers to CCPs are decomposed for three values of $\bar{T}$ as the number of clearing members is varied. The increase in dealer-to-CCP initial margins is offset to a large extent by a shrinkage in customer-to-dealer initial margins, but the overall effect on collateral demand depends on $\bar{T}$.

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