Essays on Credit Markets and Banking

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Umeå 2012

Umeå Economic Studies No. 840
ISSN: 0348-1018
ISBN: 978-91-7459-384-6

Electronic version available at http://umu.diva-portal.org/

Printed by Print & Media at Umeå University
Umeå, Sweden 2012

To the memory of my grandparents

Abstract

This thesis consists of four self-contained papers related to banking, credit markets and financial stability.

Paper [I] presents a credit market model and finds, using an agent based modeling approach, that credit crunches have a tendency to occur; even when credit markets are almost entirely transparent in the absence of external shocks. We find evidence supporting the asset deterioration hypothesis and results that emphasize the importance of accurate firm quality estimates. In addition, we find that an increase in the debt's time to maturity, homogenous expected default rates and a conservative lending approach, reduces the probability of a credit crunch. Thus, our results suggest some up till now partially overlooked components contributing to the financial stability of an economy.

Paper [II] derives an econometric disequilibrium model for time series data. This is done by error correcting the supply of some good. The model separates between a continuously clearing market and a clearing market in the long-run such that we are able to obtain a novel test of clearing markets. We apply the model to the Swedish market for short-term business loans, and find that this market is characterized by a long-run non-market clearing equilibrium.

Paper [III] studies the risk-return profile of centralized and decentralized banks. We address the conditions that favor a particular lending regime while acknowledging the effects on lending and returns caused by the course of the business cycle. To analyze these issues, we develop a model which incorporates two stylized facts; (i) banks in which lending decisions are decentralized tend to have a lower cost associated with screening potential borrowers and (ii) decentralized decision-making may generate inefficient outcomes because of lack of coordination. Simulations are used to compare the two banking regimes. Among the results, it is found that even though a bank group where decisions are decentralized may end up with a portfolio of loans which is (relatively) poorly diversified between regions, the ability to effectively screen potential borrowers may nevertheless give a decentralized bank a lower overall risk in the lending portfolio than when decisions are centralized.

In **Paper [IV]**, we argue that the practice used in the valuation of a portfolio of assets is important for the calculation of the Value at Risk. In particular, a seller seeking to liquidate a large portfolio may not face horizontal demand curves. We propose a partially new approach for incorporating this fact in the Value at Risk and Expected Shortfall measures and in an empirical illustration, we compare it to a competing approach. We find substantial differences.

Keywords: financial stability, credit market, banking, agent based model, simulations, disequilibrium, clearing market, business cycle, risk, organization

Acknowledgements

Let me begin with expressing my deepest gratitude to my supervisor, Prof. Kurt Brännäs, who showed more confidence in my work than I initially deserved. This guy is a genius and he never fails to impress me with the widths of his knowledge. I would also like to thank my co-supervisor Prof. Jörgen Hellstöm for all the helpful comments (as well for teaming up with me in Uppsala so that we could beat the B-guys). Here, Prof. Tomas Sjögren deserves a special thanks for sharing my wide interest in economics, as well as for having (the most) awesome modeling skills. Working together with Tomas has been a pure pleasure!

I would like to thank Svenska Handelsbanken and the Graduate Industrial Research School at Umeå University for the financial support as well as for the opportunity to participate in a rather successful PhD student experiment that allowed me to have one foot in the "real world" (whatever that is) while keeping the other foot buried in sweet academic soil. I am grateful to Prof. Petter Gustafsson and Benkt Wiklund for organizing and managing the research school as well as for having the ambition and courage to try "something new". Here, I would also like to thank the Knut and Alice Wallenberg foundation for the travel grant.

Dr. Matias Eklöf at Svenska Handelsbanken deserves a thanks for introducing me to new (and complex) methods in economics as well as for giving me the opportunity to repeatedly present my work at the bank. The ideas that sprung from these meetings were most valuable. I am also grateful to the participants at the (sometimes wild) department seminars. I could not have done it without the comments from Prof. Karl-Gustaf Löfgren (who forced me to really understand what I was doing), Prof. Runar Brännlund (who gave me comments that I value almost as much as the occasional Belgian beer), Dr. Carl Lönnbark (who also deserves a thanks for the ease with which we have collaborated), Christian Lundström (who has a fresh businesslike take on the subject) and Emma Zetterdahl (who's comments tell a story about her in-depth understanding of the subject). In addition, I would like to thank Dr. Kenneth Backlund for his leadership and flexibility as well as Marie Hammarstedt for handling my employment with such ease. I would also like to thank my fellow PhD students as well as all the other researchers at the department for the awesome research environment as well as for giving the department a healthy mix between business and pleasure. I proudly consider the friends I have met here as my "pseudo family up north".

While on the subject, both the Holmbergs and Oldenburgs deserve a thanks for their support as well as for the wild discussions regarding my research. I now have a book on my side (even though I might have written it myself) and in the words of Henry Thoreau, "you should read the best books first...". Speaking of books, my brother Björn certainly deserves a thanks for dragging me into some random bookstore in Guilford a long time ago. I blame my interest in social sciences on this particular event and for that, he owes my gratitude. Finally, I would like thank the "skull loving" Anna Ternow for all the good times as well as for putting out with my lengthily monologs and variable mind.

Stockholm, March 2012
Ulf the wolf

This thesis consists of a summary and the following four papers:

[I] Holmberg, U. (2012): "The Credit Market and the Determinants of Credit Crunches: An Agent Based Modeling Approach", *Umeå Economic Studies No 836 (revised)*.

[II] Holmberg, U. (2012): "Error Corrected Disequilibrium", *Umeå Economic Studies No 837 (revised)*.

[III] Holmberg, U., T. Sjögren, and J. Hellström (2012): "Comparing Centralized and Decentralized Banking: A Study of the Risk-Return Profile of Banks" *Umeå Economic Studies No 838*.

[IV] Lönnbark, C., U. Holmberg, and K. Brännäs (2011): "Value at Risk and Expected Shortfall for Large Portfolios", *Financial Research Letters*, 8, 59-68 .

1 Introduction

When the United States real estate market collapsed in the end of 2006, most market participants failed to predict the scale and consequence of the coming unfolding of events. The collapse lead to a sudden liquidity crisis in the United States banking system that forced the eruption of a global financial crisis, unprecedented in scale since the 1930s' Great Depression.[1] The crisis forced the collapse of large financial institutions and a downturn in stock markets all around the world, while a stream of national bank bailouts and stimulus packages were implemented. Why the financial markets suddenly behaved in such a way quickly became a scholarly subject and, consequently, a wide range of theories emerged explaining the cause and nature of the recent unfolding of events. Among other things, government deregulation was targeted as a cause, as well as the practices of banks and investors on the unregulated collaterized debt obligation and credit default swap markets. However, the cause and nature of the crisis is still under debate and as discussed by Lo (2012), scholars have yet to agree on a single narrative.

Even though the specific nature of the crisis may be disputed, most scholars do agree on that the onset of the crisis was somewhat related to the expansion of bank credit; and as discussed in Fratianni and Marchionne (2009), the financial crisis of the late 2000s carries many features of a Credit-Boom-and-Bust (CBB) crisis. In short, a CBB crisis tends to begin with an economic shock that brightens the economic prospects of the market participants (e.g., an increase in housing prices). Credit from banks tend to feed the boom such that households accumulate debt while firms increase leverage in order to fund suddenly profitable new projects. Such credit booms are often correlated with monetary expansion, further increasing the credit supplied by banks (Kindleberger and Aliber, 2005). These events tend to force an increase in the value of assets, feeding the prevailing optimism about the firms' future investment opportunities, and so forth. However, the boom is fragile and the credit bubble tends to burst if a negative shock hits the system. Such a negative shock may for instance be the reach of some unforeseen threshold of acceptable liability structures (Minsky, 1977) or a sudden stream of defaults on debt. Whatever its nature, such a shock will inevitably reduce the value of firms' future stream of cash flows, reducing the value of assets such that investors tend to become more risk averse (Minsky, 1977). With a higher proportion of risk averse investors active on the market, an unloading of assets is sure to follow, forcing the value of assets to plummet while firms seek to deleverage, giving asset prices an extra push downhill. A consequence of such a large scale debt liquidation is an un-

[1] In Reinhart and Rogoff (2009), the recession that followed the financial crisis of the late 2000s is referred to as "the second great contraction" where the 1930s' Great Depression is referred to as the "first great contraction".

intended decrease in inflation such that inflation falls below expected levels. This in turn forces the real value of debt to increase while debtors suffer a decline in net worth (Fisher, 1933; Fratianni and Marchionne, 2009) and the quality of debt decreases. In addition, a drop in the value of assets lowers the value of collateral. Thus, borrowers need to put up even more security for a given value of nominal debt (Fratianni and Marchionne, 2009), further highlighting the importance of lenders within the CBB crisis framework.

As such, if one seeks to understand the nature of a financial crisis of this scale, one needs to understand the workings of credit markets as well as why banks suddenly reduce the amount of credit supplied (Paper I). It is also important to have the correct tools if one seeks to model credit markets empirically (Paper II) since empirical research may give new insights into the causes of a credit crisis. In addition, since banks tend to be at center of a financial crisis (Allen and Carletti, 2008), insights concerning the risk-return profile of banks during the course of the business cycle are equally important (Paper [III]). Further, since asset market liquidity tends to dry up during financial distress (Brunnermeier and Pedersen, 2009); investors need the means of accurately measuring financial risk while accounting for the liquidity risk of an investment (Paper [IV]).

2 Credit markets, banking and financial fragility

As so accurately put in Allen and Carletti (2008), "banks are always critical to the financial system". Banks act as delegated monitors and allow for various information problems to be solved, contribute to financial risk sharing as well as to economic growth (Allen and Carletti, 2008). However, due to the maturity differences between the banks' assets and liabilities, banks may cause fragility in the financial system due to the possibility of bank runs (Mitchell, 1941; Kindleberger and Aliber, 2005; Bryant, 1980; Diamond and Dybvig, 1983; Chen et al., 2010) as well as due to the the possibility of contamination (Allen and Gale, 2000; Freixas et al., 2000; Dasgupta, 2004; de Vries, 2005; Brusco and Castiglionesi, 2007) such that banks are often found to be at the very center of a financial crisis (Allen and Carletti, 2008). Thus if one seeks to understand the cause and nature of a financial crisis, one needs to begin with the practices of banks. In addition, since the financial crisis of the late 2000s originated from a liquidity crisis in the United States banking system, i.e. from a credit crunch; a natural starting point is to research the determinants of such sudden contractions of credit.

In general, a credit crunch is defined as "a significant contraction in the supply of credit reflected in a tightening of credit conditions" (Udell, 2009). What causes banks to simultaneously coordinate their actions in such a way? As discussed in the previous section, the recent crisis shares many features with a CBB crisis in the sense that the quality of debt was lowered by some external shock; darkening the economic prospects of the market participants. This explanation is well in line with the asset deterioration hypothesis (Sharpe, 1995), i.e. the hypothesis that banks tend to reduce their supply of credit due to unpredicted losses in bank capital. Pazarbasioglu (1996) found early evidence supporting this hypothesis after studying the Finnish credit crunch in the early 1990s, but this hypothesis alone does not explain why lenders tend to reduce credit since it relies on the occurrence of some exogenous shock. Thus, we turn to the theoretical literature for answers and in particular, to the model developed by Suárez and Sussman (1997, 2007). They developed a rational expectations model in which cyclical contractions of credit are driven endogenously by a moral hazard problem between firms and the providers of credit. As such, a credit crunch may manifest itself solely due to the inherent imperfections of a credit market. Kiyotaki and Moore (1997), on the other hand, developed a real business cycle model of a credit market of collateralized debt. They find that a recession is amplified with a reduction in the value of collateral during an economic downturn, fully in line with the timing of events seemingly inherent in a CBB crisis. Another explanation is given by the Risk-Based Capital (RBC) hypothesis. According to the RBC hypothesis, the implementation of new risk-based regulatory rules governing financial intermediaries allocation of internal resources may in itself cause the eruption of a credit crunch (Berger and Udell, 1994). If, for example, firm debt suddenly requires more cash reserves, banks may reallocate resources to less risky debt (e.g., governmental securities), forcing a decline in the supply of firm credit. However, no new risk-based regulatory rules were enforced in the United States in direct relation to the recent financial crisis; even though it is possible that previously implemented regulations may have contributed to the magnitude of credit reduction.

Given the above, one may be tempted to conclude that sudden credit contractions are either caused by some exogenous shock or by endogenous problems caused by information problems between the borrowers and lenders. This may be true, but as is found in Paper [I], contractions of credit may also emerge spontaneously, even if credit markets are almost entirely transparent. We find that credit booms and busts may evolve naturally when lenders have adaptive expectations about the credit risk in their debt portfolio. Since we also find evidence in line with previous theories, it may be that external shocks, such as a sudden reduction in the quality of debt, increases the probability of a credit crunch, even though the shock per se is not its cause.

However, it's not always obvious whether an observed reduction in credit is due to a contraction of the supply or demand for credit. Firms may have gloomy economic outlooks such that they need less credit for their future investments.

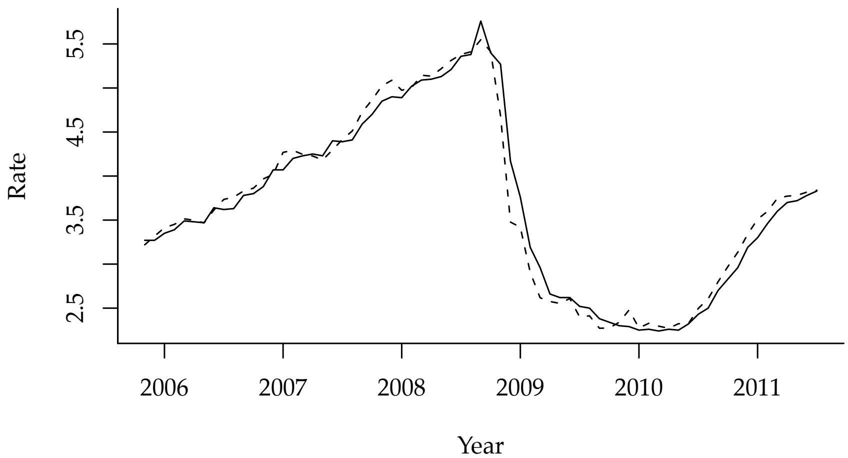

Figure 1: Actual average interest rate on short-term business loans in Sweden (solid line) and the long-run equilibrium interest rate (dashed line) as estimated as in Paper [II].

Thus, in order to determine if a credit market suffered from a credit crunch or not, one needs to use empirical models that separates between the demand and supply side of credit. In addition, since credit markets may be subject to some long-run excess demand for credit (Stiglitz and Weiss, 1981), one also needs to account for the possibility of a market in disequilibrium. Fortunately, a large bulk of literature have emerged, providing econometric methods for markets in disequilibrium (see Fair and Jaffee (1972); Amemiya (1974); Maddala and Nelson (1974); Goldfelfd and Quandt (1975); Quandt (1978); Bowden (1978); Gourieroux et al. (1980a,b); Maddala (1986) among others) and a recent stream of literature do in fact utilize the disequilibrium framework in credit market modeling (see Pazarbasioglu (1996); Perez (1998); Hurlin and Kierzenkowski (2003); Allain and Oulidi (2009) among others). However, the econometric methods used in these studies do not deal with the problems caused by spurious regressions in time series data, as first made explicit by Granger and Newbold (1974). Acknowledging this issue, Paper [II] derives a novel econometric model for markets in disequilibrium, suitable for time series data. Here, a distinction is made between a clearing market in the short and long-run while it is assumed that demand and supply of a good are co-integrated, i.e. the supply may not drift too far away from the demand and vice versa. By using the model on Swedish data, we find that the Swedish market for short-term business loans is subject to a long-run non-market clearing equilibrium; an equilibrium that determines the average interest rate on short-term business loans, as illustrated in

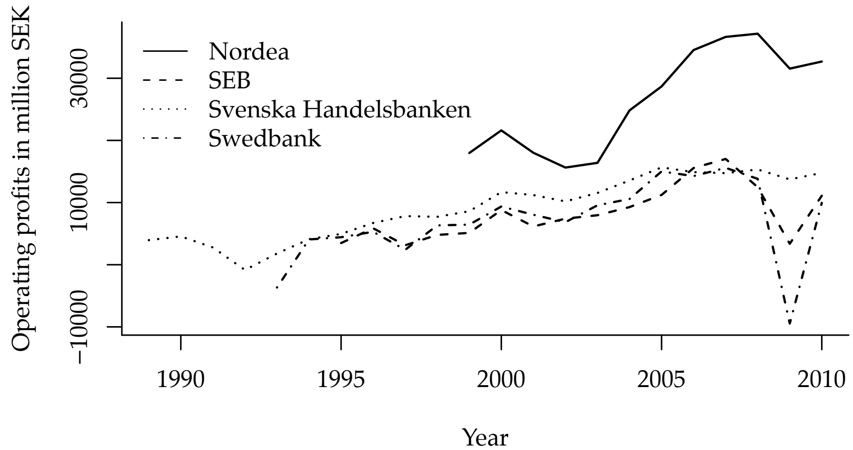

Figure 2: Operating profits for the four largest Swedish banks. Currency conversion based on the exchange rate on the last trading day of the year. Source: Annual reports.

Figure 1. In addition, we find a significant increase in the equilibrium interest rate, ceteris paribus, during the lowering of the Riksbanks prime rate during 2009. Since it is fairly unlikely that the lowering of the prime rate coincided with an increase in the demand for credit, this result implies that the supply of credit was reduced during this period. Thus, this result indicates that the Swedish market for short-term business loans suffered from a supply side driven credit crunch during 2009.

Even though lenders may suffer from credit losses during a crisis, it is important to note that there may be large differences in these losses as well as to the extent of which banks' balance sheets are exposed to risky credits/investments. For example, the reduction in operating profits, due to the recession of 2009, among the four largest Swedish banks (Nordea, SEB, Svenska Handelsbanken, Swedbank) varied from 10 percent (Svenska Handelsbanken) to 168 percent (Swedbank), as illustrated in Figure 2. Partially, these differences may reflect differences in risk culture between banks. However, since all banks are forced to deal with excessive asymmetry problems; such differences may also reflect the superiority of some banks in assessing the risk profile of their potential clients and investment opportunities.

One important factor within this context may be the lending technology used by banks. If, for instance, one bank engages heavily in transaction banking while another bank relies more heavily on relationship banking, the risks to which the two banks are exposed to are likely to differ (see Boot (2000) for an excellent review on relationship banking). Another potentially important factor is whether the lending/investment decisions are decentralized (meaning that the lending decisions are taken at a low level in the bank hierarchy) or centralized (meaning that the lending decisions are taken higher up in the organization). Hierarchical banks may be better at utilizing hard information (e.g., data from credit scoring models and balance sheet data) while small and decentralized banks may be better at processing soft information (e.g., ability, honesty, etc.), as implicitly argued by Stein (2002). However, the arguments laid out by Stein (2002) originate from the internal capital markets perspective of firms. In banking, a decentralized bank may lack the ability to achieve a well diversified debt portfolio and the raising of lendable funds may cause externalities within the bank group. As such, there may be a trade-of between being effective in terms of selecting high-quality clients (which is achieved by having a decentralized decision-making structure) and being effective in terms of ending up with a well diversified portfolio of loans at the aggregate level (which is achieved by having a more centralized decision-making structure). In addition, the advantages of a certain lending technology may vary during the course of the business cycle, since the probability of firm default is highly dependent on the phase of the business cycle (see Helwege and Kleiman (1997); Fridson et al. (1997); Carey (1998) among others).

We develop a stylized model (Paper [III]) to study the differences between a centralized and decentralized bank in the case of an economic downturn. We find that whether one of these specific lending technologies outperforms another, largely depends on whether the proportion of high ability entrepreneurs (i.e. the expected default rate) differs between regions. If banks lend funds to entrepreneurs in regions with a similar proportion of entrepreneur types (i.e. a similar risk structure), a decentralized bank tends to outperform its centralized counterpart; since a decentralized bank more accurately assesses the risks associated with each debt contract. On the other hand, if the proportion of high ability entrepreneurs differs between regions, a centralized bank's ability to effectively diversify its debt portfolio between the regional markets makes this lending technology superior in the case of an economic downturn. Thus, our research adds an extra dimension to the understanding of credit markets in distress by acknowledging that the credit losses suffered by banks in an economic downturn depend on a bank's lending technology, in combination with the risk structure of markets.

The view that a bank only functions as a financial intermediary may be a simplified view. A bank is exposed to a wide range of risks, unrelated to lending. In particular, banks are often engaged in frequent trading and thus, exposed to the risks associated with holding large portfolios of assets. As such, a correct assessment of such risks are equally important in banking. Two popular risk measures within this context are the Value at Risk (VaR) and Expected Shortfall (ES) measures; where VaR is the industry standard way of quantifying the risk of adverse price movements. It is defined as the maximum potential portfolio loss that will not be exceeded over a given time horizon with some probability (see Jorion (2007) for a survey). However, it is often assumed that the entire position can be sold at the market price, i.e. that the seller (buyer) of an asset face a horizontal demand (supply) curve. If this is not the case, such an assumption can be quite misleading, especially if the buyer (seller) is considering a large position of an illiquid asset. Thus, it is important to incorporate for price movements caused by illiquidity, i.e. liquidity risk, into industry standard risk measures (see Malz (2003) for a general discussion of liquidity risk). Within this strain of literature, Bangia et al. (1999) was the first to account for liquidity into the VaR measure using a spread based approach. In Paper [IV], we continue on their work and propose approaches of adjusting the VaR and ES measures for liquidity risk by using the average price per share, rather than the mid-price. Our proposed approaches for the VaR and ES measures rely on essentially the same idea as used for the VaR measure by Giot and Grammig (2006). They consider the average price per share that would be obtained upon immediate liquidation at the end of the horizon. Their VaR is volume dependent and it is based on the difference between the mid-price at the beginning of the horizon and the average price at the end of it. We argue that the relevant initial price is not the mid-price, but that the portfolio should be valued at the average price in the beginning of the period as well. By adjusting the risk measures with this insight, we find substantial differences.

3 Methodological approach

Since we use a wide range of tools to answer the research questions discussed above, many readers are likely to be unfamiliar with some of the methods. Thus, this section presents a brief introduction to the more unconventional methods used in the thesis, namely the methods used in order to answer the research questions in Paper [I] and Paper [II].

In Paper [I], we utilize a strain of computational economic simulation methods called Agent Based Models (ABMs) to find the determinants of credit crunches. To our knowledge, this method is new to the study of credit markets in economics and differs in essence from traditional analytical economic models. In traditional analytical economic methodologies, credit markets are often modeled as an economic system with equilibrium properties. Periodic patterns may then emerge around this equilibrium due to (say) some inherent imperfections of a credit market within a rational expectations framework (as in Suárez and Sussman (1997, 2007)). By adopting the ABM approach, the assumption that credit markets have some long-run equilibrium may be relaxed together with other assumptions.[2] Instead, within the ABM framework, agents are equipped with a set of decision rules governing their actions on an artificial market. The decision rules may vary in complexity and the agents may be given a varying degree of intelligence. By simulating the model, the researcher may observe the choices made by the agents as well as the aggregate outcomes of the agents' interactions (e.g., the total indebtedness of firms) that may arise as a consequence of their actions. Thus, ABMs may be thought of as belonging to a set of "out-of-equilibrium" models since such models allow for the behavior of a system (a market) to be a caused solely as a consequence of the decisions made by its parts (the agents). Any equilibrium that may evolve is "natural" in the sense that there is no rule that forces the market towards an equilibrium per se. In addition, ABMs allow for the modeling of markets even when equilibria are computationally intractable or nonexistent (Tesfatsion, 2006). Thus, the findings in Paper [I], that a credit market may naturally evolve into a credit crunch, may be viewed upon as a "punctuation" of one possible equilibrium in which bank credit is constantly expanding.

ABMs have some drawbacks compared to traditional equilibrium analysis that are important to highlight. Most notably, results obtained from simulations of ABMs tend to be rather path-dependent. Thus, the initial conditions may highly influence the obtained result. One obvious remedy for this drawback is to simulate the ABM in different "states of nature". Such a sensitivity analysis increases the understanding of the system while providing simulated data from which a version of comparative statics can be obtained by the use of standard statistical techniques. Another drawback is the difficulty to validate ABM outcomes against empirical data since simulations often suggest the nonexistence of an equilibrium or the existence of multiple equilibria. However, this is a drawback that ABMs share with other theoretical approaches.

In Paper [II], we explore the concept of disequilibrium in econometrics. In pervious literature, disequilibrium is often referred to as a state in which the supply of some good does not equate its demand, i.e. a market in which the observed price differs from the theoretical Walrasian equilibrium price. Thus, an economic equilibrium, as it is addressed in previous disequilibrium literature, is not to be confused with some long-run equilibrium of stationary prices (as often studied using error correction models), even though such a state may exist. Indeed, it is possible that some markets suffer from a long-run "out-of-equilibrium equilibrium" in the sense that the stationary price does not force the supply to equate the demand.

In Paper [II], we acknowledge these issues and divide the clearing market hypothesis into a continuously clearing market hypothesis (a market in which de-

[2]See Tesfatsion (2006) for a more detailed discussion about the advantages of ABMs in economics.

mand equals supply at every instant) and a long-run clearing market hypothesis (the hypothesis that a market will clear at the long-run stationary price). In addition, by assuming that the demand and supply are co-integrated (i.e. that the demand of some good may not drift too far away from its supply), we "error correct" for deviations from the long-run equilibrium and derive an error corrected disequilibrium model in price differences. Since the error corrected model in price differences implies a stationary price series, we also find an empirical model for the long-run equilibrium price.

4 Summary of the papers

Paper [I]: The Credit Market and the Determinants of Credit Crunches: An Agent Based Modeling Approach

In this paper, we derive an Agent Based Model (ABM) of a credit market, based on a simplified banking model in which banks screen applicants in order to reduce their exposure to credit risk. Here, we let banks decide their acceptable level of firm probability of default such that they truncate the distribution of firm quality at the highest acceptable default probability. We let banks have adaptive expectations about the risk in their debt portfolio and find that sudden reductions in lending may emerge spontaneously, even if credit markets are almost entirely transparent, since credit markets may evolve into periods in which banks acquire riskier debt than what is specified by their profit maximising conditions. Such periods are swiftly followed by periods in which banks try to cut back on risky debt, making credit difficult to obtain. If such cutbacks are coordinated across banks, the market may experience the eruption of a credit crunch.

We simulate the model in different "states of nature" and apply a standard logit model on the simulated data. From the maximum likelihood estimates obtained from the logit model, we find that credit crunches are seemingly spontaneous but highly dependent on the level of conservatism practiced when banks pursue their internal credit risk goals. If banks tend to react slowly to new credit risk goals, i.e. have a conservative approach to new risky ventures, the probability of a credit crunch is reduced.

We also find that an increase in the debts average time to maturity, reduces the probability of a credit crunch since such an increase tends to reduce the probability that banks lend to a sequence of firms associated with a profit reducing level of credit risk. In addition, we are able to find evidence in line with the asset deterioration hypothesis as well as to confirm the importance of accurate estimates in the banks' screening procedures. Thus, by adopting the ABM approach, we are able to find the determinants of credit crunches through a simple mechanism linked to the banks' own credit portfolio risk valuations while embracing the possibility of random spillover effects of counter party risk.

Paper [II]: Error Corrected Disequilibrium

In this paper, we relax the assumption of a clearing market and instead assume that the supply and demand for some good are co-integrated. In other words, we assume there is some process that drives the demand and supply towards a clearing market in the long-run, while relaxing the assumption that the markets clear at every instant. This assumption allows us to "error correct" the supply such that a model in price differences can be derived. This new "error corrected disequilibrium model" is suitable for economic time series data and it naturally separates between a clearing market in the short and long-run.

By studying the implications of the parameters of the model, we derive a test of the long-run clearing market hypothesis, related to a version of the augmented Dickey-Fuller test of a unit root with drift. In addition, we derive the implied long-run equilibrium (stationary) price from the error corrected disequilibrium model which allows us to estimate the effects on the long-run equilibrium price caused by changes in the exogenous parameters.

We apply the model on the Swedish market for short-term business loans and find that this market suffers from a long-run non-market clearing equilibrium. In addition, by estimating the long-run equilibrium effects, we find an increase in the equilibrium interest rate, ceteris paribus, during the lowering of the Riksbanks prime rate during 2009. Since it is fairly unlikely that the lowering of the prime rate coincided with an unexpected increase in the demand for credit, this result implies an unexpected reduction in the supply of credit; indicating that the Swedish credit market suffered from a supply-side driven credit crunch during 2009.

Paper [III]: Centralized or Decentralized Banking

In this paper, we argue that a potentially important factor contributing to the risk-return profile of a bank is whether the lending/investment decisions are decentralized (meaning that the lending decisions are decentralized) or centralized (meaning that the lending decisions are taken higher up in the organization). We derive a stylized theoretical model in which there is a trade-of between being cost effective in terms of selecting high-quality clients (which is achieved by having a decentralized decision-making structure) and being effective in terms of ending up with a well diversified portfolio of loans on the aggregate level (which is achieved by having a more centralized decision-making structure). In addition, we acknowledge that a possible consequence of decentralized decision-making is that the decision-maker in one local branch may not take into account that his/her choices may affect the situation for the other local branches. As such, local decision-making may generate “externalities” within the bank group. Here we focus on financing externalities, which occur if the decision on how many loans to grant in one local branch effects the cost of raising funds in other branches within the bank group.

By simulating the model while purifying each effect, we find (among other things) that, in the presence of only the cost efficiency effect, decentralized banks will lend more funds and have lower risks than their centralized counterparts. We also find that if the pure cost efficiency effect dominates, then centralized banks tend to react stronger, in terms of reducing the amount of issued loans, in the wake of a recession. Second, when only the financing externality is present, then decentralized banks over-provide loans at the expense of “proper screening”, in comparison with centralized banking. This implies that the pure financing externality produces lower profits and higher risks under decentralized banking. Third, the pure diversification effect also favors centralized banking in the sense that the client targeting is more efficient, the expected profit larger and risks lower, compared with decentralized banking.

We also simulate a model where the cost efficiency effect, the financing externality and the diversification effect are present simultaneously. This allows us to study how these three effects combine to jointly influence the comparison between the two banking regimes. Among the results, it is found that asymmetric markets (in terms of the proportion of high ability entrepreneurs) tend to favor centralized banking while decentralized banks seem better at lending in the wake of an economic downturn (high probability of a recession). In addition, we find that even though a bank group where decisions are decentralized may end up with a portfolio of loans which is (relatively) poorly diversified between regions, the ability to effectively screen potential borrowers may nevertheless give a decentralized bank a lower overall risk in the lending portfolio than when decisions are centralized.

Paper [IV]: Value at Risk and Expected Shortfall for Large Portfolios

In this paper we address the question of how to properly assess the risk in large financial portfolios. In risk assessment, it is usually assumed that the entire position can be sold at the market price (or mid-price), though one realizes that this can be a quite misleading valuation approach. The reason is that for large enough positions the seller (buyer) of an asset does not face a horizontal demand (supply) curve. Thus, there is an element of liquidity risk involved (see Malz (2003) for a general discussion of liquidity risk) and this should preferably be taken into account in risk assessment.

Here, the focus is on incorporating the liquidity risk in the Value at Risk (VaR) and the Expected Shortfall (ES) measures. VaR is the industry standard way of quantifying the risk of adverse price movements and it is defined as the maximum potential portfolio loss that will not be exceeded over a given time horizon for some small probability (see Jorion (2007) for a survey). However, as highlighted by Artzner et al. (1999) the VaR suffers from deficiencies such as non-sub-additivity. As an alternative, they propose the ES that gives the expected loss given that the VaR is exceeded. We emphasize, as argued by François-Heude and Wynendaele (2001) and others, that it is implicitly assumed that the liquidation occurs in one block at the end of the predefined holding period when assessing the portfolio risk. The question of how to incorporate the liquidity risk into the VaR is a relatively old one and several alternative approaches have been proposed. Bangia et al. (1999) were the first to account for it, with their spread based alternative. Ernst et al. (2009) evaluates some alternatives empirically.

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The Credit Market and the Determinants of Credit Crunches:

An Agent Based Modeling Approach

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Abstract

This paper presents a credit market model and finds, using an agent based modeling approach, that credit crunches have a tendency to occur; even when credit markets are almost entirely transparent in the absence of external shocks. We find evidence supporting the asset deterioration hypothesis and results that emphasize the importance of accurate firm quality estimates. In addition, we find that an increase in the debt's time to maturity, homogenous expected default rates and a conservative lending approach, reduces the probability of a credit crunch. Thus, our results suggest some up till now partially overlooked components contributing to the financial stability of an economy.

Keywords: financial stability, banking, lending, screening, truncation

JEL classification: C63, E51, G21

1 Introduction

During a time span of over twenty years, from the early nineties to present date, nearly all developed countries have experienced some form of supply side credit crunch in parts of their economies. Following Udell (2009), economists generally define a credit crunch as a "significant contraction in the supply of credit reflected in a tightening of credit conditions". Thus, during a crunch seemingly eligible borrowers find it hard to get credit under reasonable terms, forcing firms that rely on external capital to a halt. A recent example of such a tightening in the credit conditions is the financial crisis of 2008. During the crisis, new lending to large borrowers fell with almost 80 percent in the United States, a fall largely driven by a reduction in the supply of credit (Ivashina and Scharfstein, 2010).

Why do providers of credit suddenly mobilise their lending strategies in such a way? Existing theories provide a useful platform when building an understanding of the determinants of crunches. According to the Risk-Based Capital hypothesis (RBC), the implementation of new risk-based regulatory rules governing lenders' allocation of resources, may have a significant negative impact on the supply of credit. Berger and Udell (1994) tested the RBC hypothesis on the perceived crunch in the United States after the implementation of the first Basel Accord in the late eighties/early nineties. They found some support in favor of the RBC hypothesis but refrained from ruling out competing theories. Sharpe (1995), on the other hand, claimed that banks reduce credit supply due to unpredicted losses in bank capital. In analogy with the RBC hypothesis, he concluded that the reduction in credit coincides with banks having difficulties in meeting the minimum regulatory capital requirements. Pazarbasioglu (1996) found evidence in line with the asset deterioration hypothesis, suggesting that banks become less willing to supply credit during periods associated with a deterioration in asset quality. In addition, according to the financial instability hypothesis (Minsky, 1977, 1992) economies have a tendency to naturally evolve into a "Ponzi phase" in which firms are forced to borrow to meet their obligations on existing liabilities. Since lenders judge liability structures subjectively, sudden drops in the supply of credit may occur when corporate debt reaches some unforeseen threshold. Kiyotaki and Moore (1997), on the other hand, developed a real business cycle model of a credit market in which lending only occurs if the debt is collateralized. They found that a recession is amplified with the decrease in the value of collateral during an economic downturn. Further, the burdens of asymmetric information may in itself lead to cyclical credit and unexpected downturns in lending, a point that is emphasized by Suárez and Sussman (1997, 2007). They developed a dynamic rational expectations model in which business cycles are created endogenously. Their findings indicate that cyclical contractions of credit are driven by a moral hazard problem between firms and financial intermediaries. This implies that a credit crunch may manifest itself solely due to the inherent imperfections of the credit market. In addition, Lorenzoni (2008) presented a theoretical model of an financial market with friction and studied the welfare properties of a competitive equilibria hit by aggregate shocks. The author found that the first-best equilibrium always displays under-borrowing while the second-best solution may be characterized by excessive borrowing. Thus, sudden reductions in the supply of credit may simply originate from an adjustment away from the second-best solution. Further, a recent paper by Guerrieri and Lorenzoni (2011) studied the effects of a credit crunch on consumer spending in a heterogeneous-agent incomplete market model. They found that a tightening in the lending conditions forces some consumers to deleverage while others increase savings. Consequentially, a tightening in the lending conditions depresses interest rates while the economy experiences a drop in output.

Turning to the existing literature on banking and credit, it is well understood that lenders are forced to deal with excessive information asymmetry problems since borrowers have reason to withhold information in order to gain credit. Lenders seek to resolve this problem by practicing screening (Allen, 1990) and monitoring (Winton, 1995) thus reducing their exposure to counter party risk. If the estimates used in these procedures are based on subjective judgments of acceptable liability structures or fail to incorporate risks driven by exogenous shocks, such shocks may lead to a reduction in credit supply due to unforeseen losses.

Previous literature suggests that credit crunches are either driven by exogenous shocks (e.g., new risk based regulatory rules) or caused endogenously by problems springing from asymmetric information between the borrower and the lender or other types of market frictions. A natural conclusion is thus that credit markets grow "safer" with transparency, suggesting that policy makers concerned with sudden reductions in lending should concentrate their efforts to transparency increasing measures. However, in the light of the money market meltdown of 2008, one cannot avoid wondering if some other mechanism, inherent in the credit market, is equally to blame.

In this paper, we derive a simplified banking model in which banks screen applicants in order to pick suitable clients with an acceptable level of default risk. We use this model as a base on which we build an Agent Based Model (ABM) of a credit market. By adopting the ABM approach, we do not need to assume that some equilibrium condition drives the workings of the credit market. Instead, we are able to focus on the lending mechanism and study the credit market from an bottom-up approach. Through simulations of the ABM, we find that supply side driven credit crunches occur even if credit markets are almost entirely transparent. This result originates from the banks' expectations about future credit risk. If banks have adaptive expectations about the risk in their credit portfolios, the credit market may evolve into periods in which banks acquire riskier debt than what is specified by its profit maximizing condition. Such periods are swiftly followed by periods in which banks try to cut back on risky debt, making credit difficult to obtain. If such cutbacks are coordinated across banks, the market may experience the eruption of a credit crunch. These crunches are seemingly spontaneous but highly dependent on the level of conservatism practiced when banks pursue their internal credit risk goals. If banks tend to react slowly to new credit risk goals, i.e. have a conservative approach to new risky ventures or more risky debt, the probability of a credit crunch is reduced.

We also find that an increase in the debt's average time to maturity, reduces the probability of a credit crunch. This result is related to the arguments made in the work of Andreasen et al. (2011) but differs in terms of the nature of the result. In Andreasen et al. (2011), the authors argue that banks, by offering long-term credit to firms, attenuate firms' output responses to technological shocks. In this paper, we find that the mechanism causing a decrease in the probability of a credit crunch due to an increase in the maturity time of debt is far less complicated. An increase in the debts' time to maturity simply reduces the probability of sequential bad lending, i.e. it reduces the probability that banks lend to a sequence of firms associated with a profit reducing level of credit risk. In addition, we are able to find evidence in line with the asset deterioration hypothesis as well as to confirm the importance of accurate estimates in the banks' screening procedures. Thus, by adopting the ABM approach, we are able to find the determinants of credit crunches through a simple mechanism linked to the banks' credit risk valuation procedure while embracing the possible affects on lending caused by random spillover effects of counter party risk.

The outline of the paper is as follows. The next section discusses the theoretical underpinnings of the model. This is followed by a description of the artificial economy, its agents and the conditions driving the behavior of the agents. In the final sections we present and discuss the results derived from the simulations and conclude.

2 Theoretical underpinnings

We define a credit crunch as in Udell (2009), i.e. as a significant contraction in the supply of credit reflected in a tightening of credit conditions. Viewing banks as financial intermediators and providers of investment capital, this definition suggests that the onset of credit crunches are related to the banks' screening and monitoring procedures. The information production in imperfect screening and its effects have been previously studied by Broecker (1990), Chiesa (1998) and Gehrig (1998) among others. However, in this section, we seek a simple mechanism that can be linked to the onset of credit crunches. As such, we initially consider a perfectly transparent credit market such that banks practice costless and perfect screening in order to reduce their exposure to credit risk. In contrast to previous studies, we consider a continuum of firm qualities and view screening as a method of choosing suitable clients by truncating the distribution function defining firm quality.

Consider a two-period economy under the supervision of a financial authority. The economy is made up of a *finite* number of risk-neutral firms, $k = 1, ..., M$, and banks, $i = 1, 2, ..., N$, providing unsecured credit to firms. Firms are assumed to be heterogeneous in terms of quality summarised by $\theta_k \in [0, 1]$. At the initial date, firms are given the choice of carrying out a risky project lasting one time period. To undertake the project, firms need to raise external capital equivalent to l_k on the credit market. The gross return of the investment, $R(\theta_k) \in [0, \infty]$, is realized after one time period and retrieved with probability $1 - \theta_k$. Firm returns are increasing in θ_k such that firm quality also represents the riskiness of firm actions. A high quality firm is thus characterised by a low value of θ_k. The distribution of firm returns are binary and the success rate of the investment is firm size independent. For simplicity, it is assumed that in case of failure the firm defaults without liquidation value, allowing us to interpret θ_k as the firm's probability of default. Thus, firms are protected by limited liability such that they only care about the payoffs when the project succeeds. As such, the firms always implement their projects when granted a loan.

Banks act as information producers about the firms' investment projects and we let the banks observe the distribution of firm quality, $f(\theta)$, from which they make a noisy firm quality estimate $\theta^b_{k,i}$. We let the interest rate on external capital, r, and the deposit rate, ρ, be exogenous to the model and assume that lending is the banks' only source of profit. Given the above, the representative bank's *unconditional* expected profit function is:

$$\pi^e_b = \sum_{k}^{m \in M} \left[(1 + r)(1 - \theta^b_k) - 1 \right] l_k - \rho D, \tag{1}$$

where m is the subgroup of firms facing their demand towards the representative bank and D is the bank's deposits. To purely study the affects of lending while ignoring the bank's exposure to deposit risks, it is assumed that the bank finances lending using a stock of own capital, i.e. equity. The bank's equity is given by E such that $\sum_k^{\hat{m}\in M} l_k \leq E$ and $E - \sum_k^{\hat{m}\in M} l_k \geq \hat{E}$ where $\hat{E}$ is the minimum capital requirement as decided by the financial authorities and $\hat{m}$ is the number of firms granted credit. As such, the deposit costs in (1) can be ignored. Since banks observe the distribution of firm quality, the banks' beliefs about θ_k are taken on M. Using this, we rewrite the representative bank's unconditional expected profit function in (1) as:

$$\pi_b^e = [(1+r)(1-\theta^e) - 1] \sum_k^{m\in M} l_k, \tag{2}$$

where θ^e is the expected default rate (quality). From the bank's expected profit function in (2), it is fairly obvious that above some value of θ^e, expected bank-profit turns negative. More specifically, in the unconditional case the bank only participates on the credit market if:

$$\theta^e \leq r/(1+r). \tag{3}$$

However, as discussed by Gehrig (1998), when a contract is negotiated, banks may prefer to screen applicants in order to assess their credit risks. As such, it is assumed that the bank resolves the possibility of negative profits by screening applicants to identify risky firms which are removed from the bank's credit portfolio.

Since we seek a simple mechanism that can be linked to the banks' lending decisions, we assume for the remainder of this section that the credit market is perfectly transparent such that a bank has the ability to practice perfect and costless screening, i.e. $\theta_k^b = \theta_k$.[1] Recalling the participation constraint in (3), it may be tempting to argue that each bank lends to firms with $\theta_k \leq r/(1+r)$ up to the point when the bank runs out of equity, adjusted for the minimum capital requirements. However, the expected profit from a loan issued to a firm with high θ and a firm with a low θ is fundamentally different since a firm with a high θ is less likely to repay the debt. Recalling that the economy consists of a finite number of firms, the heterogeneity of firm quality leads to a trade-of between quality and quantity of credit. To see this, we acknowledge that the process of screening loan applicants ultimately aims to discriminate between firms and only picking applicants that live up to some minimum requirements for credit (given exogenous interests rates). Since the bank observes the distribution of firm quality,

[1] We will relax this assumption when we move over to the artificial economy in Section 3.

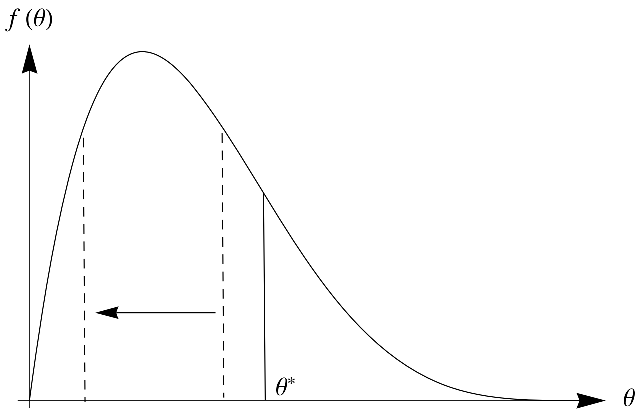

Figure 1: Screening reduces the expected default rate ($E[\theta|\theta_k \leq \theta^*]$).

$f(\theta)$, the screening procedure can be thought of as choosing a suitable value of a truncating function λ, constructed to be the function that solves:

$$E[\theta|\theta_k \leq \theta^*(\lambda)] = \lambda\theta^e, \quad 0 \leq \lambda \leq 1, \tag{4}$$

where $\theta^*(\lambda)$ is the truncation point on $f(\theta)$, monotonically increasing in λ. Thus, the criterion needed for credit is represented by $\theta^*(\lambda)$ and the expression in (4) states the expected default rate (quality) in the subpopulation of firms below the truncation point, i.e. the *conditional* expected default rate. The distribution of firm quality for some general distribution is displayed in Figure 1 in which we see that the bank, by screening applicants and truncating the distribution of firm quality, reduces its exposure to default risk.

To understand the trade-of between quality and quantity of credit, we move over to the supply of credit and acknowledge that a bank's *expected* credit supply function can be written as the product of the m firms' demand for credit and the probability that a firm meets the requirements of the bank:

$$L = \sum_{k}^{m \in M} l_k \int_0^{\theta^*} f(\theta)\, d\theta = \sum_{k}^{\hat{m}(\theta) \in m} l_k, \tag{5}$$

where $\hat{m}(\theta)$ is the number of firm's eligible for credit. For the analysis below, it is essential to know how screening affects the bank's expected credit supply. Thus, we consider a tightening in the criterion needed for credit, i.e. a reduction in θ^*. It follows that, for any probability density function of firm quality for $\theta_k \in [0,1]$ and a finite sample of firms (M), a decrease in θ^* will shrink the sample size of eligible firms. This in turn will reduce the bank's expected credit supply. Formally, since $\partial\hat{m}/\partial\theta^* > 0$ and since $\sum_k^{\hat{m}(\theta^*)\in m} l_k \leq \sum_k^{m\in M} l_k$, it follows that $\partial L/\partial\theta^* > 0$. This is summarised in the following Proposition;

Proposition 1: *A bank facing a finite number of applicants (firms) that tightens the criterion needed for credit will reduce the amount of supplied credit.*

A key result from Proposition 1 is that an there exists some profit maximizing value of θ^* implying some profit maximizing value of λ. Thus, the bank's optimization problem boils down to a decision between quality and quantity of credit. Hence, if the bank tightens the criterion needed for credit, i.e. it reduces θ^*, fewer firms will default on their loans but the supply of credit will drop, reducing the bank's *potential* profits. This crucial link between the bank's credit supply and the screening procedure of loan applicants provides a useful platform when forming a understanding of the determinants of credit crunches.

For tractability, let the expected credit supply function be based on the profit maximizing value of θ^*. This allows us to define a weight, ω, that scales the now constant probability in (5). Since θ^* is monotonically increasing in λ and since $E[\theta|\theta_k \leq \theta^*(\lambda)]$ is linear in λ, we solve the bank's expected credit supply function by scaling ω with λ, restricting the weight to positive values. This allows us to rewrite (5) as:

$$L(\lambda) = \lambda\omega \sum_k^{m\in M} l_k. \tag{6}$$

Combining (6) with the definition of the conditional expected default rate in (4) and the bank's expected profit function in (2) gives us the bank's *conditional* expected profit function:

$$E[\pi_b|\theta_k \leq \theta^*(\lambda)] = [(1+r)(1-\theta^e\lambda) - 1]\,\lambda\omega \sum_k^{m\in M} l_k. \tag{7}$$

Maximizing (7) with respect to λ and simplifying, results in the bank's first order condition[2]:

$$\partial E[\pi_b|\theta_k \leq \theta^*]/\partial\lambda = \omega\,[r - 2(1+r)\theta^e\lambda] \sum_k^{m\in M} l_k = 0, \tag{8}$$

[2]For illustrative reasons the regulatory bodies restriction is ignored.

such that $\lambda^* = \lambda^*(\theta^e, r)$ conditioned on the profit maximizing value of θ^*. More specifically, we use the first order condition in (8) and solve for the profit maximizing value of the truncating function:

$$\lambda^* = \frac{r}{2\theta^e(1+r)}. \tag{9}$$

Since $\partial\lambda^*/\partial\theta^e < 0$ and since θ^* is monotonically increasing in λ, it follows that $\partial\theta^*/\partial\theta^e < 0$, i.e. an increase in the unconditional expected default rate, reduces the bank's chosen truncation point. In addition, since $\partial\lambda^*/\partial r > 0$, it also follows that $\partial\theta^*/\partial r > 0$ such that the bank tends to accept a higher level of default risk when interest rates are increased. These results are summarised in Proposition 2;

Proposition 2: *A bank that screens applicants in order to maximize profits, tightens the criterion needed for credit if the unconditional default rate is increased or if the interest rate is decreased.*

Since a credit crunch is intrinsically related to the criterion needed for credit, Proposition 2 give some clues regarding the determinants of credit crunches.

We continue with some additional properties of the theoretical model, later to be used in the artificial credit market as defined in the next section. By combining (9) with the definition of the bank's conditional expected default rate in (4), we get the bank's profit maximizing conditional expected default rate; expressed only as a function of the interest rate:

$$E[\theta|\theta_k \leq \theta^*(\lambda^*)] = \frac{r}{2(1+r)}. \tag{10}$$

The expression in (10) highlights the importance of interest rates on the criterion needed for credit. Remembering the participation constraint in (3), we conclude that the optimal *conditional* expected default rate is simply half the *unconditional* expected default rate. In addition, since $\partial E[\theta|\theta_k \leq \theta^*(\lambda^*)]/\partial r > 0$, an increase in interest rates increases the amount of credit risk undertaken by banks, as previously implied in Proposition 2. By substituting for (9) and (10) in (7), we express the bank's profit maximizing conditional expected profit function in terms of the models exogenous variables:

$$E\left[\pi_b|\theta_k \leq \theta^*(\lambda^*)\right] = \omega \sum_{k}^{m\in M} l_k \frac{r^2}{4\theta^e(1+r)} > 0, \tag{11}$$

with $\partial E[\pi_b|\theta_k \leq \theta^*(\lambda^*)]/\partial r > 0$ and $\partial E[\pi_b|\theta_k \leq \theta^*(\lambda^*)]/\partial\theta^e < 0$. Studying the implications of (11), we see that the bank expects positive profits by screening out unwanted firms, conditioned on perfect estimates of firm quality; a result that follows from the bank's "monopoly" power in the screening procedure. However, by viewing the bank's expected profits as expected revenue, (11) also corresponds to the bank's expected deposit costs in a perfectly competitive economic environment.

Summing up our findings so far, in this section, we have derived a simple theoretical banking model in which banks maximize profits by removing risky firms from their credit portfolios. Despite its simplicity, the model is able to highlight the importance of firm quality and interest rates on the criterion needed for credit. Since a credit crunch relates to a period in time in which credit and investment capital are hard to obtain, we argue that a tightening of the criterion needed for credit, and its determinants, is intrinsically related to the onset of a credit crunch. Despite this, however, the theoretical model fails to capture the distinctive nature of credit crunches. Credit crunches are by definition dynamic phenomena since the tightening of the criterion needs to be coordinated across banks throughout a period of time. In addition, in a credit market with a finite number of participants, the decision made by a single bank may affect the pool of potential borrowers of its competitors and it is unlikely that banks face the full set of firms at every instant. To cope with these issues, we view the credit market as a complex adaptive system and proceed with constructing an artificial credit market based on the insights from the theoretical model.

3 An artificial credit market

Through the theoretical two-period model, we found variables that influence the representative bank's decision regarding the criterion needed for credit. However, the model fails to capture the dynamics of a credit market. In addition, in a credit market with a finite number of participants, the decision made by one bank may affect the pool of potential borrowers of its competitors. To cope with these issues, we view the credit market as a complex adaptive system as defined in Tesfatsion (2006). Thus, we construct an Agent Based Model (ABM) of a credit market based on repeated debt contracts. The theoretical model in the previous section is used as the base on which we build the ABM. This allows us to study the credit market in a dynamic framework, without imposing additional restrictive assumptions on the agents behavior. In addition, the ABM allows for random spillover affects of counter party risk. We begin by defining the details of the artificial economy and proceed by deriving the decision rules governing the agents' behavior.

3.1 The model

We first consider the matching process of firms and banks. In reality, this process is likely to be affected by some randomness making the initial match stochastic. In addition, as discussed in the large literature on relationship banking (see Sharpe (1990), Rajan (1992), Petersen and Rajan (1994), Petersen and Rajan (1995) among others), the initial lending may create some information advantage for the initial lender which then leads to some ex-post monopoly situation. However, since we view the interest rate on external capital as exogenous, we can safely ignore the potential ex-post monopoly effect since the lending standards of credit will remain unaffected in either case. Thus, we focus on the initial stochastic matching process and situate the ABM on a finite spaced torus populated with an initial number of firms ($k = 1, ..., M_0$) and banks ($i = 1, ..., N_0$) spread out on a grid at random. Time is discrete and represents new possible debt contracts and/or maturity dates. Following the arguments made in the previous section, firms need external capital in order to undertake a risky project. Firms search the torus for external capital through a 360^o random walk where the torus is of size b^2 and where $b \in \mathbb{Z}$ is divisible with remainder. Thus, by situating the agents on a finite spaced torus, the probability of a firm-bank encounter is partly given by the "density" of the credit market, $\mathbb{D}(M_t, N_t, b)$.

Banks are governed by a financial authority stipulating a regulatory rule requiring banks to hold own capital based on the Capital Adequacy Ratio (CAR) such that for any given bank and time:

$$\mathrm{CAR}_{i,t} \geq K, \quad 0 \leq K \leq 1, \tag{12}$$

where K represents the minimum capital requirements. All debt owned by the bank is unweighted and the sum of a bank's Tier-capital is equivalent to the bank's equity capital, henceforth referred to as the banks equity.

When a firm encounters a bank, the firm states its demand for credit which the bank evaluates according to the regulatory rule in (12). If the bank lives up to the requirement, it makes a noisy estimate of the firm's probability of default, $\theta^b_{k,i} = \theta_k + \phi_{k,i}$ with support $[0, \mathcal{T}]$ where $\phi_{k,i}$ is a random draw from a normal distribution with zero mean and standard deviation σ^f. Estimates outside of the support region are re-estimated. If the bank's estimate of firm quality is below the truncation point, i.e. if $\theta^b_{k,i} \leq \theta^*_{i,t}$, a debt contract is formed. If the bank rejects the firm's demand for credit, the firm continues its search for a debt contract. The debt lasts for a minimum of κ time periods and is only repaid upon a firm-bank encounter, making the maturity date of the contract stochastic. Thus, we allow for different maturity dates without specifying the details in the debt contract. Here, it is important to note that a large value of κ increases the *average* time to maturity. In addition, we limit the effect on credit crunches caused by a single firm's performance by prohibiting firms in debt from additional borrowing until the debt is repaid.

Given the above, the probability of a firm-bank encounter depends on the debt's minimum time to maturity (κ) as well as on the "density" of the credit market ($\mathbb{D}$). Since a firm in debt is restricted from signing a new debt contract until the previously acquired debt is repaid and since debt contracts are only formed when a firm encounters a bank; these variables implicitly define the agents' abilities to sign new debt contracts as well as the "flow of funds". Relating this to the market liquidity literature, in which market liquidity is defined as the ability to trade an assets at short notice (Nikolaou, 2009); we acknowledge that the debt's minimum time to maturity (κ) and the density of the credit market ($\mathbb{D}$), jointly determine something we may call "credit market liquidity" ($\psi(\kappa, \mathbb{D})$). When exploring the properties of credit market liquidity within the model context, we acknowledge that a sparsely populated credit market (relative to the size of the torus) may experience random demand-side drops in credit, reducing the overall indebtedness of firms. However, if $\mathbb{D}$ is large, sudden drops in the aggregate debt level only reflects the decisions made by the suppliers of credit. Thus, by keeping the density of the market high, we are able to study the effects on credit crunches caused by variations in credit market liquidity originating from variations in the minimum time to maturity (κ).

Following this line of reasoning, we state the probability of a debt contract being formed by bank i at any given date as:

$$\Pr(\text{Contract}_{i,t}) = h\left(\psi\left(\kappa, \mathbb{D}\right), \Pr(\theta_k \leq \theta^*_{i,t}), \Pr(\text{CAR}_{i,t} \geq K)\right). \tag{13}$$

The first term in (13) determines how the frequency (from the simulations) in the debt contract formation is affected by credit market liquidity. The second two terms determine how the probability of a debt contract is affected by the supply side of credit.

Using the definition of a credit crunch as a period in time in which credit and investment capital is hard to obtain, sudden reductions in the supply of credit can be tracked back to the speed by which new debt contracts are formed. Since the probability in (13) depends on the capital adequacy ratio as well as the acceptable level of credit risk, the model has the ability to capture effects on credit crunches caused by the implementation of new regulatory rules as well as the effects caused by a deterioration in firm quality. In addition, since reductions in credit supply needs to be coordinated across banks in order for a credit crunch to erupt, we state the probability of a debt contract being formed by any bank at time t as:

$$Pr\left(\text{Contract}_t\right) = Pr\left(\cup_{i=1}^{N_t}\text{Contract}_i\right). \qquad (14)$$

Hence, the complement of (14) defines the probability that no debt contract will be signed at time t, arguably an important component determining the probability of a credit crunch.

Since the probability that a contract will be signed at time t depends on $Pr(\text{CAR}_{i,t} \leq K)$, the probability in (14) relates to the bank's ability to build up capital; which in turn is effected by the bank's expected profit function and the criterion needed for credit. In addition, since the bank's choice of θ^* will depend on its previous encounters and since the market hosts a finite number of firms, the bank's debt portfolio is indirectly dependent on the debt portfolios of its competitors. This since lending reduces the pool of eligible firms. Returning to (13) and acknowledging that the probabilities by this reasoning are dependent, we see that the model allows for random spillover affects of counter party risk.

3.2 The Firms

We seek to keep the firms as simple as possible in order to make the simulations tractable. Thus, we assume that firms are "born" debt free with a pre-specified initial value of equity, E_0^f, identically distributed across firms. In addition, we let firms be defined by the balance sheet identity, allowing us to write the asset value of a representative firm as:

$$A_t^f = E_t^f + L_t^f, \quad t \geq 1,$$

where A_t^f is the firm's asset value, E_t^f is the firm's equity value and L_t^f is the value of firm liabilities at time t. As in the previous section, we let firms be protected by limited liability and assume a need for external capital to fund some risky project. Hence, by the same arguments as in Section 2, they always implement their projects when granted credit. We let the demand for credit vary between time periods to capture the randomness associated with investment opportunities. However, we limit the demand for credit to finite values and let the representative firm's demand for credit be given by a random draw from the firm's equity value:

$$l_t = \eta_t E_t^f,$$

where $\eta_t \sim U(0,1)$ resulting in $0 \leq l_t \leq E_t^f$.

Turning to the granting of credit, as previously mentioned, lending may only occur upon a firm-bank encounter at which the bank estimates the quality of the firm. If the bank's estimate of firm quality lies below the truncation point while the bank meets the requirements made by the model's regulatory body, the firm is granted credit from the bank to fund a risky project. The project lasts until the loan's maturity date on which the firm generates a gross return of R_{T^m} if the project succeeds, where $T^m = t + \tau(\kappa, \mathbb{D})$ denotes the loan's maturity date with $\partial\tau/\partial\kappa > 0$. Here, market density ($\mathbb{D}$) affects the debt't time to maturity since it determines the probability of a firm-bank encounter. Thus, as previously argued, the debt's maturity date is stochastic.

When determining the equation of motion defining the evolution of the firms' asset values, we seek a mechanism that links the performance of firms to their quality. We use the results in the work of Black and Scholes (1973) and Merton (1974) such that the probability that a firm defaults on its loan can be derived from its asset value. Assuming that the firm fails to meet its obligations to the bank if $A_t^f < L_t^f$, we write the equation of motion defining the representative firm's asset value as:[3]

$$A^f_{T^m} = A_{T^m-1} + \frac{E_{T^m-1}}{\Phi^{-1}(\theta)}\Delta W_{T^m}, \tag{15}$$

where $\Phi^{-1}(\theta)$ is the inverse of the standard normal distribution taken at firm quality and where $\Delta W_{T^m} \sim N(0,1)$. Firm quality is drawn from a truncated two parameter beta distribution, $\theta \sim \text{Beta}\,(\alpha, \beta)_{|\theta_k < \mathcal{T}}$, where the beta distribution is chosen for its ability to replicate bounded distributions of firm quality. Note that (15) requires $\mathcal{T} \leq 0.5$ such that $\theta \in [0, 0.5]$ due to the symmetry of the standard normal distribution.

Given (15), the asset value of the firm remains constant between maturity dates and the firm defaults with probability θ when the project's profit is realized. If the asset value of the firm drops below zero, the firm files for bankruptcy and fails to meet its obligations to the bank. Thus, we have a steady flow of firms exiting the credit market through bankruptcy forcing the need of a firm-entry process. The firm-entry process is defined by assuming a saturated market. Thus, we let the firm-entry process be governed by a simple rule requiring the number of firms active in the credit market at time t to be approximately equal to the constant and pre-specified finite number of firms, $M_t \approx M$. Hence, in every time period the model gives birth to d_{t-1} new firms, where d_{t-1} is the number of firm defaults in the previous time period. Such an entry process will in the long run affect the distribution of firm quality due to the resampling of θ from $f(\theta)$. This effect is summarised in the following Proposition;

[3] See Appendix A for details.

Proposition 3: *Consider an increase in t. If the market is saturated such that it supports a maximum of M firms at each time period, the resampling of firm quality from $f(\theta)$ reduces the unconditional expected default rate, θ_t^e.*

Proposition 3 states that since firms with a high value of θ_k have a high probability of default and since θ_k is drawn from the truncated beta distribution; a consequence of the firm-entry process is that the economic environment grows "safer" with time. Less risky firms will simply crowd-out the riskier ones. To see this, order firm quality such that $\theta_{1,t} < \theta_{2,t} < \cdots \theta_{M_t,t}$ and let S_l denote the state of firm $l < M_t$. Let the state of firm default be denoted Ω such that $\Pr(S_l = \Omega) < \Pr(S_{M_t} = \Omega)$. Since the sample estimate of the first central moment of θ is given by $\sum_{k=1}^{M_t} \theta_k / M_t$ it follows that $\Pr\left(\theta_t^e < \theta_{t-1}^e\right) > \Pr\left(\theta_t^e > \theta_{t-1}^e\right)$ such that $\partial\theta_t^e/\partial t < 0$.

3.3 The Banks

In analogy with the theoretical model in the previous section, banks use equity to provide firms with loans. The equity value of the banks at the initial date, E_0^b, is prespecified and identically distributed across banks. At the end of each time period, banks will have accumulated profits from matured loans, funded new projects using its equity and suffered from defaulted loans. Using this, we construct the equation of motion defining the representative bank's asset value from the balance sheet identity:

$$A_t^b = \left(E_{t-1}^b + \pi_t^b\right) + \left(L_{t-1}^b + \sum_k^{m_t^n \in m_t} l_k - \sum_k^{m_t^d \in \hat{m}_t} l_k\right), \quad t \geq 1,$$

where A_t^b is the bank's asset value, E_t^b is the bank's equity, L_t^b is the value of the bank's outstanding debt, $m_t \in M_t$ is the number of firms facing their demand towards the representative bank, $\hat{m}_t^n$ is the number of firms granted credit at time t, $\hat{m}_t$ is the number of firms in the bank's debt portfolio at time t and where m_t^d is the number of firms repaying their debt at time t.

As in the previous section, banks maximize profits by screening applicants in order to pick suitable clients with an acceptable level of default risk. This is done by truncating the distribution function defining firm quality. The functional form of the truncating function can be specified in various ways reflecting the decision making process within the bank (e.g., if the decisions are taken at the central or decentralized level). This makes the model flexible for variations in corporate structure. Here, we assume that the bank's management has absolute control over the truncating function allowing us to treat λ as the bank's decision variable. As such, the solution to the bank's optimization problem in the artificial economy bears obvious resemblance to the results derived in the previous section. To see this, define the value of the truncating function at time t as $\lambda_{i,t}$. Using the results in the previous section while acknowledging that the banks now rely on noisy estimates of firm quality, we rewrite the representative bank's objective function as:[4]

$$E[\pi_{b,t}|\theta_{k,t}^{b} \leq \theta_t^*] = [(1+r)(1-\theta_t^e\lambda_t)-1]\,\lambda_t\omega_t \sum_{k}^{m_t\in M_t} l_k. \tag{16}$$

We condition on the profit maximizing value of θ^* and maximize (16) with respect to λ_t, including the regulatory bodies constraint (12). This gives us the optimal value of the truncating function for the representative bank in the artificial economy:

$$\lambda_t^* = \begin{cases} \dfrac{r}{2\theta_t^e(1+r)} & \text{if } \mathrm{CAR}_t > K \\ 0 & \text{if } \mathrm{CAR}_t \leq K, \end{cases},$$

indicating that in an economic environment with fixed interest rates, the criterion needed for credit only varies with the estimate of θ_t^e. Recalling that $\partial\theta_t^e/\partial t < 0$ and that $\partial\lambda_t^*/\partial\theta_t^e < 0$, it follows that $\partial\theta_t^*/\partial t > 0$, using that θ_t^* is monotonically increasing in λ_t. In other words, a bank tends to decrease the criterion needed for credit with the passage of time.

Proposition 4: *Consider an increase in t. If the market is saturated such that it supports a maximum of M firms at each time period, a bank that screens applicants to maximize profits will tend to reduce the criterion needed for credit with time.*

From Proposition 4 it follows that banks tend to take on more risky debt as the economy evolves. However, the economy will suffer from short term fluctuations around the time path of the criterion needed for credit due to noisy estimates of firm quality. To see this, we acknowledge that $E[\theta|\theta_k \leq \theta_t^*(\lambda_t^*)] \neq E[\theta|\theta_k^b \leq \theta_t^*(\lambda_t^*)]$ where the inequality is due to imperfect estimates of firm quality.[5] It is reasonable to assume that banks learn about the quality of firms by interim information production, Besanko and Kanatas (1993) and Holmström and Tirole (1997). Thus, we assume that the bank observes the true quality of firms for the subpopulation of firms currently in

[4] Since $E[\theta^b] = E[\theta] + E[\phi] = \theta^e$.

[5] See Appendix B for details.

its debt portfolio. Using this, we let the bank have adaptive expectations of (4) such that $E[\theta|\theta_k^b \leq \theta_t^*(\lambda_t^*)] = \sum_k^{\hat{m}_{t-1}} \theta_{k,t-1}/\hat{m}_{t-1}$. Relating this to the profit maximizing conditional default rate in (10), we let the bank solve for the point of truncation by an iterative procedure stated as:

$$\theta_t^* = \begin{cases} \theta_{t-1}^* - c, & \text{if } E[\theta|\theta_k^b \leq \theta_t^*(\lambda_t^*)] > \dfrac{r}{2(1+r)} \\ \theta_{t-1}^*, & \text{if } E[\theta|\theta_k^b \leq \theta_t^*(\lambda_t^*)] = \dfrac{r}{2(1+r)} \\ \theta_{t-1}^* + c, & \text{if } E[\theta|\theta_k^b \leq \theta_t^*(\lambda_t^*)] < \dfrac{r}{2(1+r)} \end{cases},$$

where $0 \leq c \leq r/(2(1+r))$ is a parameter representing the speed by which banks move towards the optimal truncation point. In addition, the bank is refrained from lending if $\text{CAR}_t \leq K$, honouring the regulatory rule in (12).

Examining the iterative procedure defining θ_t^* above, we acknowledge four things. First, since the optimal truncation point, θ_t^*, represents the criterion needed for credit and since the truncation point determines the riskiness of the bank's credit portfolio; movements towards the optimal truncation point can be thought of as movements towards the bank's internal credit risk goal. Thus, c represents the speed of adjustment to the bank's internal credit risk goal. Second, given the parameter space of c, the bank may "overshoot" its own credit risk goal and acquire a debt portfolio characterized by more risky debt than in (10). This opens up for periods characterised by "over-lending" in which over-lending banks try to reduce their exposure to credit risk by tightening the criterion needed for credit. Third, if such a tightening occurs simultaneously across banks, the economy may move into a time period in which credit and investment capital is hard to obtain. Fourth, the bank's initial debt contracts may influence the bank's future decision regarding θ^*. To reduce this effect, we set $\theta_0^* = 0$ allowing the bank to steadily build up the riskiness of its credit portfolio using the iterative procedure as stated above.

Banks with a low value of c take small steps towards the optimal level of credit risk. Hence, the bank's speed of adjustment to its internal credit risk goal reflects the level of conservatism within the bank's organisational structure where conservative banks have a relatively low value of c. Relating c to the real world, the speed of adjustment to the bank's internal credit risk goal can be thought of as a parameter reflecting the bank's willingness to engage in new risky ventures or as its willingness to use new and unexplored debt instruments characterised by more unexplored risk. Since we are interested in the determinants of credit crunches, we study the case in which all banks are equally conservative. This allows us interpret c as a parameter reflecting the general level of conservatism in the economy.

4 Simulations

In order to find the determinants of credit crunches, we simulate the artificial economy in different economic states, implementing the framework discussed in the previous sections.[6] We first define a restrictive measure of a credit crunch within the context of the model and then explore the properties of the artificial economy through a selected simulation. The selected simulation is chosen as to illustrate the features of a progressive economy populated with many creditworthy firms.

When defining a restrictive and measurable variable of a credit crunch, we first recall the definition in Udell (2009), suggesting that a credit crunch is reflected in a tightening of credit conditions, here represented by a decrease in $\theta^*_{i,t}$. Thus, if the average truncation point drops below some threshold, investment capital becomes hard to obtain since only a small sample of firms are eligible for credit. Using this, in the absence of a stringent formal definition, we define an indicator variable of a credit crunch as:

$$\delta = \begin{cases} 1, & \text{if } \theta^*_{i,t} = 0,\ \forall i, \quad t > 0 \\ 0, & \text{if else} \end{cases}, \tag{17}$$

such that $\delta = 1$ in the case of a credit crunch which by all means of measurement, represents an increase in the criterion needed for credit. Arguably, the indicator variable in (17) relates to the probability in (14) since $\sum_i^N \theta^*_{i,t} \to 0 \Rightarrow \Pr(\text{Contract}_t) \to 0$. However, the definition above neglects the potential effects on the supply of credit caused by (i) the banks' potential inability to live up to the capital requirements, and (ii) the potential effects on crunches caused by risk based regulatory changes affecting (14) through $Pr(\text{CAR}_{i,t} \geq K)$. Remembering that all debt is unweighted in this version of the model, we neglect these issues.

4.1 Selected simulation

The properties of the model are illustrated through a selected simulation of a credit market in which banks have close to perfect firm quality estimates ($\sigma^f = 0.0001$) and where the unconditional expected default rate (θ^e_t) is lower than the banks' optimal

[6] The NetLogo environment is used for the simulations. The code is available on request.

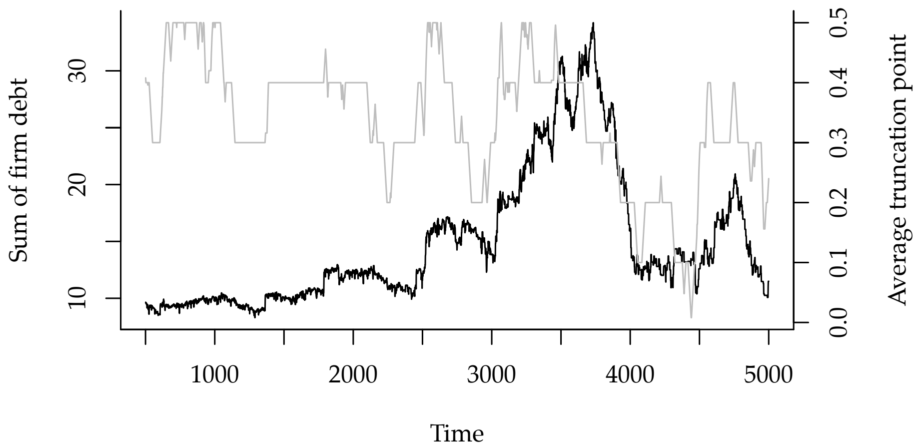

Figure 2: Sum of firm debt (L_t^f) (solid line) and the average truncation point (θ_t^*) (gray line).

expected default rate as stipulated in (10). Thus, since $\mathcal{T} = 0.5$, *ex-ante* we may expect banks with almost perfect firm quality estimates to set $\theta_{i,t}^* = 0.5$. However, since banks may oversample from the pool of risky firms, occasional decreases in the average truncation point is expected. The parameters of the beta distribution are chosen to be $\alpha = 2.6$ and $\beta = 150$ such that firm quality is distributed with a heavy tail to the right. Given this, the unconditional expected default rate at the initial time period is $\theta_0^e \approx 1.7$ percent. The interest rate on external capital is set to $r = 4$ percent such that the *optimal* conditional expected default rate is 1.92 percent, i.e. 22 basis points higher than the unconditional expected default rate. We set the minimum capital requirements at $K = 8$ percent, replicating the capital requirements enforced by the bank for international settlements in Basel, assuming that banks are refrained from holding capital to mitigate future risks. Figure 2 illustrates the evolution of debt and the average truncation point in an artificial economy lasting 5000 time periods where the first 500 observations have been removed in order to get rid of transients. The model is simulated with $M_0 = 2000$ firms, $N_0 = 5$ banks and the torus is constructed from $b = 11$. The initial equity of the banks is set to $E_0^b = 2$ and firms are born with $E_0^f = 1$. The level of conservatism in the economy, i.e. speed of adjustment to the banks' internal credit risk goals, is set to $c = 0.02$ and the debts minimum time to maturity is set to $\kappa = 10$.

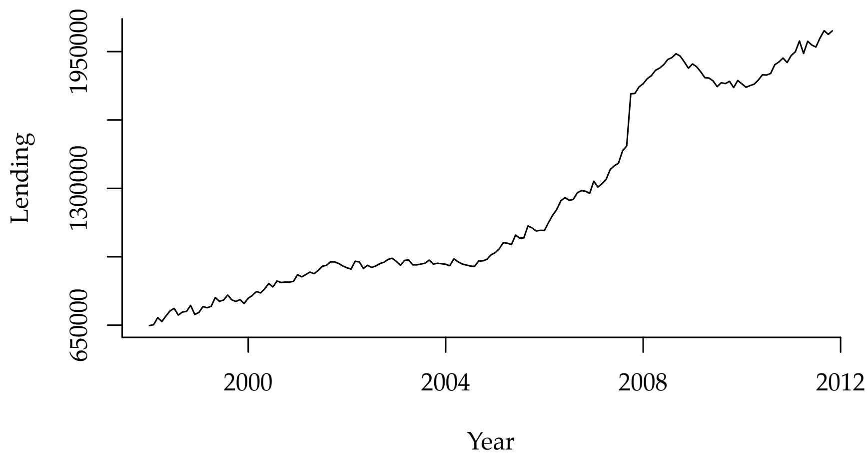

Figure 3: Value of lending to non-financial firms by Swedish banks in billion SEK. Source: Statistics Sweden.

From Figure 2 we see that the aggregated debt level has a positive trend, exhibiting cyclical tendencies. In addition, we acknowledge that firm debt is closely related to variations in the average truncation point (the criterion needed for credit). The average truncation point occasionally deviates from the profit maximizing solution and at $t = 4440$ the economy evolved into a two period credit crunch. The crunch, and the preceding decrease in the average truncation point, caused a 58.37 percent drop in debt compared to the aggregate debt's local maximum at $t = 3640$. Since all parameters are held constant during the simulation period, this indicates that crunches have a natural tendency to occur; this even if banks have near to perfect estimates of firm quality in the absence of new regulatory rules or sudden variations in firm quality.

During the time period preceding the credit crunch, the aggregate debt level experienced growth, despite occasional decreases in the average truncation point. The sudden downturn in debt due to the spontaneously coordinated tightening of the criterion needed for credit (reduced $\theta^*_{i,t}$), forced the onset of a credit crunch. Recalling the lending mechanism discussed in the previous section, this indicates that banks tend to engage in periodic over-lending, acquiring a debt portfolio characterised by more risk than the profit maximizing level of credit risk. When realized, the banks seek to "wash-out" previously acquired bad debt by tightening the criterion needed for credit. For comparison, Figure 3 exhibits the evolution of lending made by Swedish banks to

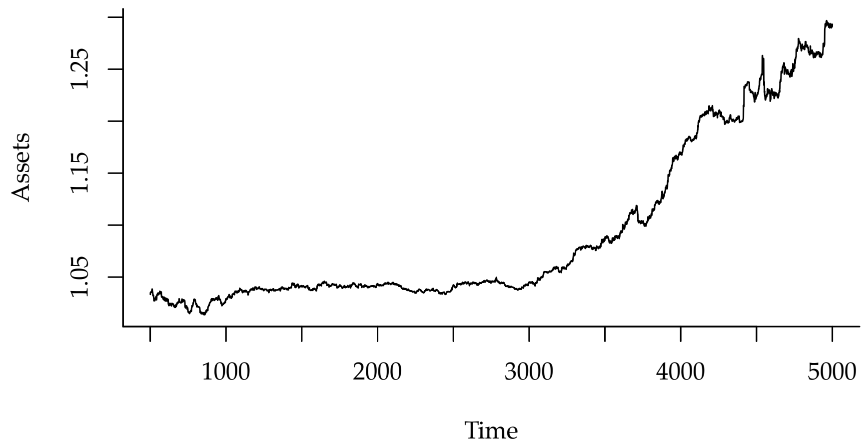

Figure 4: Average of firms' assets (A_t^f).

Swedish non-financial firms from January 1998 to November 2011. The series shows a reduced growth in lending after the internet bubble of 2001 and a sharp drop in lending during the aftermath of the financial crisis of 2008. By comparing the evolution of lending during the financial crisis and the evolution of debt in the artificial economy, we see an obvious resemblance.

The evolution of the average of firms' assets, on the other hand, is characterised by a positive trend as illustrated in Figure 4. On average, the firms' asset values grew with 5 basis points per time period.[7] The positive trend is frequently broken by sequential downturns due to reduced lending and sequential firm defaults. Such "busts" are highly dependent on the criterion needed for credit since the equation of motion defining the evolution of firms' asset values is defined by firm quality. Time periods characterised by little or no lending reduces the supply of investment capital. As such, firms have no means of funding potentially fruitful projects, reducing the aggregate growth level of firm assets. In addition, the series is characterised by seemingly random "booms" caused by an increase in project funding and numerous successful projects. Furthermore, we acknowledge that the series shows signs of increased volatility after the onset of the credit crunch at $t = 4440$ due to the small number of new debt contracts.

[7] We only measure firms active on the credit market, i.e. firms granted credit at least once, since non-participants have a constant asset value defined only by E_0^f.

4.2 The determinants of credit crunches

From the selected series, we acknowledge that the artificial credit market has a natural tendency to spontaneously evolve into a credit crunch. However, the determinants of crunches remain undetermined. In order to find the parameters of the model that can be held accountable for sudden supply side drops in credit, data is collected from simulations of the artificial credit market, limited to sequences of 5000 time periods. The experimental plan used in the study is presented in Table 1.

Since credit market liquidity, ψ, is jointly determined by the minimum time to maturity (κ) and the density of the market, $\mathbb{D}(M_t, N_t, b)$, we choose to hold the size of the torus (b^2) constant throughout the simulation periods since variations in this parameter only varies the density of the market. In addition, since all debt is unweighted in this version of the model, we deem it unlikely that regulatory changes between states will affect the criterion needed for credit. Thus, we keep the minimum capital requirements (K) constant at 8 percent in all simulations. Since the parameters of the beta distribution defines the evolution of firm assets as well the probability of firm default, these parameters represent the state of the economy. The parameters of the beta distribution are varied in two states such that θ_0^e takes on the same value for different values of α and β in a subset of the simulations.

Given the experimental plan in Table 1, we simulate the artificial economy in 256 different states with 100 replications resulting in a total of 25 600 observations. If the economy experiences a crunch during a simulation period, the result is documented and a new simulation is initiated. Thus, the onset of a credit crunch is defined as a dichotomous variable with one observation per simulation run. We acknowledge that the variable of interest is dependent on the vector of observables such that the probability of a crunch can be estimated using a standard logit model. To determine how the parameters of the beta distribution affect the probability of a credit crunch we estimate two models. The estimates from the logit models are displayed in Table 2 from which we only seek to interpret the signs of the estimates due to the theoretical nature of the model.

Examining Table 2, we conclude that an increase in the speed of adjustment to the banks' internal credit risk goals (c) has a positive effect on the probability of a credit crunch. This implies that a more conservative approach to lending reduces the probability of sudden supply side drops in credit, even in the absence of variations in the economic conditions; this being a partially overlooked component contributing to the financial stability of an economy. In addition, an increase in the debts' minimum time to maturity (κ) decreases the probability of a credit crunch. This result suggests that an

Table 1: Experimental plan used for the simulations.

Variables	Treatments	
Conservatism (c)	0.0001	0.01
Interest rate (r)	2%	4%
Initial number of firms (M_0)	1000	2000
Initial number of banks (N_0)	3	5
Minimum time to maturity (κ)	1	10
α, β	$1.67, 100$	$2.5, 150$
σ^f	0.0001	0.01
Constants	**Value**	
Minimum capital requirements (K)	8%	
Initial truncation point ($\theta^*_{i,0}$)	0	
Initial bank capital ($E^b_{i,0}$)	2	
Initial firm equity ($E^f_{j,0}$)	1	
Torus size parameter (b)	11	

increase in the average time to maturity *reduces* the probability of a credit crunch. We also see that an increase in market density, working through an increase in the initial numbers of firms (M_0) and banks (N_0), reduces the probability of a credit crunch.

To fully understand these findings, we need to view them in the light of how the artificial economy is constructed. Due to random movements of a finite number of firms on a torus, banks do not meet the full distribution of eligible firms at every instant. Since banks have adaptive expectations about the credit risk in their debt portfolio, they continue to increase $\theta^*_{i,t}$ until the credit risk in its debt portfolio equals/or overrides their profit maximizing level of credit risk. Acknowledging that firms are allowed to make repayments on matured debt in every time period, the risk associated with a bank's debt portfolio can increase rapidly if the bank grants credit to risky firms at the same instant as less risky firms meet their obligations to the bank. Thus, the faster a bank adjusts to its internal credit risk goal, i.e. the larger the c, the higher the probability of retrieving a debt portfolio defined by a suboptimal expected default rate. Simultaneous reductions in truncation points due to spontaneous wash-outs of bad debt may then lead to an absolute tightening of the criterion needed for credit, forcing the onset of a supply side credit crunch. As such, if the lending capacities of

Table 2: Maximum likelihood estimates from the logit models on credit crunches (δ). All parameter estimates are significant at the 0.001 level, $n = 25600$.

Variables	Model 1	Model 2
Intercept	2.8792	10.726
Conservatism (c)	540.31	527.28
Interest rate (r)	-383.66	-375.20
Initial number of firms (M_0)	-0.0004	-0.0004
Initial number of banks (N_0)	-0.6529	-0.6415
Initial unconditional expected default rate (θ_0^e)	505.65	
Minimum time to maturity (κ)	-0.0264	-0.0259
α		4.0634
β		-0.0643
σ^f	139.80	137.38
Nagelkerke R^2 index	0.8254	0.8213

banks are locked in contracts with long maturity dates, the probability of hastily increasing the bank's credit risk goal above the bank's optimal level is reduced. Thus, an increase in the minimum time to maturity (κ) decreases the probability of issuing credit to numerous risky firms at the same instant as less risky firms repay its debt, reducing the probability of a poorly diversified credit portfolio. This result indicates that an increase in the maturity time of debt may offset some of the negative side effects caused by rapid variations in the banks' truncation points.

The effects on crunches caused by the parameters of the beta distribution are more easily understood if we view them in the light of this new insight. If α is increased, the mode of the distribution defining firm quality is moved to the right, reducing the proportion of firms afflicted with an acceptable default risk. Hence, an increase of α can be thought of reducing the sample size of eligible firms. A rapid increase in the truncation point, conditioned on a relatively large value of α, may result in an oversampling of risky firms from the bank's perspective, forcing a tightening of the criterion needed for credit. This corresponds to an increase in the unconditional expected default rate (θ^e) since an increase in α moves the mode of the truncated beta distribution to the right. Thus, an increase in the unconditional expected default rate at the initial date (θ_0^e) increases the probability of a credit crunch, as previously suggested in the theoretical part of this paper. In contrast, an increase in β reduces the probability of a credit crunch. Such an increase centers the probability density mass around the mode of the distribution, increasing the "distance" to riskier loans. This can be thought of as homogenising firm quality which tends to reduce the probability of a crunch.

Since θ_k is drawn from the truncated beta distribution and since θ_k defines the evolution of firm assets, the results regarding the parameters of the beta distribution are fully in in line with predictions from the asset deterioration hypothesis. In addition, we find that an increase in interest rates (r) has a significant and negative impact on the probability of a crunch. Relating a credit crunch to the criterion needed for credit, this result is fully in line with the findings in the theoretical part of this paper. If the interest rate is lowered, the pool of firms that have the ability to bear a positive contribution to the banks' expected profits is reduced. The banks react to this by only granting credit to a subgroup of firms that add positive value to the banks' expected profits. Rapid variations in the banks' truncation points may then lead to an oversampling from the segment of value reducing firms with reduced lending as a direct consequence.

5 Concluding remarks

This paper analyses the determinants and causes of credit crunches. We start by deriving a simple theoretical banking model in which banks screen applicants in order to pick firms with an acceptable probability of default. We then use the mechanisms from the theoretical model and construct an Agent Based Model (ABM) of a credit market, allowing us to study the determinants of credit crunches without presuming that lending is driven by an equilibrium condition. Through simulations of the ABM, we show that crunches have a natural tendency to occur if banks have adaptive expectations about the risk in their credit portfolios. We also find that an increase in the speed by which banks adjust to their internal credit risk goals, increases the probability of a credit crunch. We link this parameter to the level of conservatism in the market and conclude that a more conservative approach to lending leads to fewer credit crunches; an up till now partially overlooked component contributing to the financial stability of an economy. In addition, we are able to show that the onset of crunches are affected by variations in the market conditions defining the evolution of firm assets. If the economy is in a state characterised by few creditworthy firms, the probability of a credit crunch is increased, fully in line with the asset deterioration hypothesis. In addition, we find that homogenous markets, in terms of firm quality, tends to be associated with a lower probability of a credit crunch. The simulations also show that an increase in the debts time to maturity reduces the probability of a credit crunch since the lending capacities of banks are locked in credit with long maturities. This, in turn, reduces the probability of a poorly diversified credit portfolio. Thus, this paper adds new insights to current theory as well as provides new perspectives on the nature of sudden reductions of credit. In addition, this paper highlights the importance of time to maturity and a conservative approach to lending if policy makers seek to reduce the probability of a credit crunch.

Acknowledgments

The financial support from Svenska Handelsbanken and the Graduate Industrial Research School at Umeå University is gratefully acknowledged. I am grateful for the comments from Kurt Brännäs, Matias Eklöf, Karl-Gustaf Löfgren and Jörgen Hellström, as well for the comments from the seminar participants at Svenska Handelsbanken, the Singapore Economic Review Conference of 2011 and the Department of Economics, Umeå School of Business and Economics, Umeå University.

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Appendix A: The firms' asset values

Assume that the representative firm has a calendar-time counterpart that acts on a credit market where the time horizon is represented by T^m. Fix a probability space $(\Omega, \mathcal{F}, P)$ on which there is a standard Brownian motion W. Let $(\mathcal{F}_t)_{t\in T^m}$ be a filtration on the probability space such that the σ-algebra $\mathcal{F}_t$ represents the collection of observable events up to time t. Given the above, it is assumed that the asset value of the firm's calendar-time counterpart follows a geometric Brownian motion:

$$dA_t^f = \mu A_t^f \, dt + \sigma A_t^f \, dW_t, \tag{A.1}$$

where W is a standard Brownian motion under the probability measure P. Moving over to the agent based model's sequential evolution of time, we rewrite (A.1) as:

$$\Delta A_t^f = A_t^f \left(\mu \Delta t + \sigma \Delta W_t \right). \tag{A.2}$$

Since the evolution is bounded by the endpoint, T^m we let $W_{t-\tau} = W_{t-1}$ such that the firm's asset value remains constant between maturity dates. Given this, we let time evolve in multiples of one such that $\Delta W_{T^m} = W_{T^m} - W_{T^m-1} \sim N(0,1)$. By rearranging (A.2) we get:

$$A_{T^m}^f = A_{T^m-1}^f + \sigma_{T^m}^* \Delta W_{T^m},$$

where $\sigma_{T^m}^* = A_{T^m}^f(\mu/\Delta W_{T^m} + \sigma)$. Since $\Delta W_{T^m} \sim N(0,1)$ it follows that $A_{T^m}^f \sim N(A_{T^m-1}^f, \sigma_{T^m}^*)$. Thus, the drift terms enter by asymmetric shocks. Acknowledge that $A_{T^m}^f = A_{T^m-1}^f + \sigma_{T^m}^* \Delta W_{T^m} = E_{T^m-1}^f + L_{T^m-1}^f + \sigma^* \Delta W_{T^m}$. Use that $L_{T^m-1}^f$ is constant between maturity dates and let the firm default if $A_{T^m}^f < L_{T^m-1}^f$ with probability θ. It follows that $Pr(A_{T^m}^f < L_{T^m-1}^f) = Pr(A_{T^m}^f - L_{T^m-1}^f < 0) = Pr(E_{T^m-1} + \sigma^* \Delta W_{T^m} < 0) = \theta$. Solve for the $\sigma_{T^m}^*$ that forces the firm to default with probability θ at the maturity date and it follows that $\sigma_{T_m}^* = E_{T^m-1}^f / \Phi^{-1}(\theta)$ where $\Phi^{-1}(\theta)$ is the inverse of the standard normal distribution taken at firm quality. Thus, we rewrite the representative firm's equation of motion as:

$$A_{T^m}^f = A_{T^m-1} + \frac{E_{T^m-1}}{\Phi^{-1}(\theta)} \Delta W_{T^m},$$

where $\theta \in [0, 0.5]$ due to the symmetry of the standard normal distribution.

Appendix B: Expected default rates

Let θ_k represent realizations of $f(\theta)$ and let ϕ_k represent realizations from $f(\phi)$. We seek the conditional expected default rate conditioned on a measurement error in expectations, i.e. $E[\theta|\theta^b \leq \theta^*] = E[\theta|\theta + \phi \leq \theta^*] = E[\theta|\theta \leq \theta^* - \phi] = E[\theta|\theta \leq \hat{\theta^*}]$. As such, we have a random truncation, selected out of a density $f(\hat{\theta}^*)$. Since $\phi \sim N(0, \sigma^f)$ it follows that $\hat{\theta^*} \sim N(\theta^*, \sigma^f)$. However, we truncate the distribution such that $\hat{\theta^*} \in [0, \mathcal{T}]$. Given this, the expected truncation point is:

$$E[\hat{\theta^*}|0 \leq \hat{\theta^*} \leq \mathcal{T}] = \frac{\int_0^{\mathcal{T}} \hat{\theta^*} f(\hat{\theta^*}) d\hat{\theta^*}}{F_{\hat{\theta^*}}(\mathcal{T}) - F_{\hat{\theta^*}}(0)},$$

where $F_{\hat{\theta}^*}(x)$ is the cumulative distribution function of $\hat{\theta}^*$. From this it follows that:

$$E[\theta|\theta_k \leq \theta^*] = \frac{\int_0^{\theta^*} \theta f(\theta)\, d\theta}{F_\theta(\theta^*)} \neq E[\theta|\theta_k^b \leq \theta^*] = \frac{\int_0^{E[\hat{\theta^*}|0 \leq \hat{\theta^*} \leq \mathcal{T}]} \theta f(\theta)\, d\theta}{F_\theta(\theta^*)},$$

where $F_\theta(x)$ is the cumulative distribution function of θ. Hence, the bank fails to find the optimal expected default rate.

Error Corrected Disequilibrium

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Abstract

We derive an econometric disequilibrium model for time series data. This is done by error correcting the supply of some good. The model separates between a continuously clearing market and a clearing market in the long-run such that we are able to obtain a novel test of clearing markets. We apply the model to the Swedish market for short-term business loans, and find that this market is characterized by a long-run non-market clearing equilibrium.

Keywords: disequilibrium econometrics, error correction, clearing market, interest rates, credit market

JEL classification: C12, C13, C51, D53, E43

1 Introduction

In economics, the concept of a clearing market is essential. As economists, we build theoretical models and draw inference from our empirical research using this concept but seldom, if ever, do we explicitly test for this hypothesis. Of course, the idea that some markets may not clear is not new in economics. Previous literature refers to such markets as markets in "disequilibrium" and, consequentially, previous attempts have been made to derive tests for the clearing market hypothesis. Indeed, the literature on disequilibrium econometrics is vast (see Fair and Jaffee, 1972; Amemiya, 1974; Maddala and Nelson, 1974; Goldfelfd and Quandt, 1975; Quandt, 1978; Bowden, 1978; Gourieroux et al., 1980a,b; Maddala, 1986, among others) but in spite of the large bulk of literature on the matter, relatively few empirical papers utilize the disequilibrium framework. In part, this may be due to the fact that estimation under disequilibrium specifications is considered complex and difficult (Srivastava and Rao, 1990). Another cause may be the discovery of spurious regression due to non-stationarity, as first made explicit by Granger and Newbold (1974) in their famous Monte Carlo study. Since many disequilibrium models rely heavily on time series data, spurious regressions may lead to false inference. Combining this insight with the importance of prior analysis of time series data as discussed by Granger (1981), and the discovery of methods that deal with the problems caused by non-stationary data, such as the Error Corrected Model (ECM) (Engle and Granger, 1987); it is easy to understand the current relative standstill in the disequilibrium econometrics literature.

Inference made on estimates from ECMs is based on the assumption of a long-run equilibrium. Notably, this equilibrium may be different from the market clearing equilibrium and it is more generally viewed as a steady state. Clearly, a steady state does not necessarily imply a clearing market. It is likely that many markets (e.g., the credit and labour markets) have excess demand (supply) in the long-run equilibrium, clearly violating the clearing market hypothesis. Thus, we acknowledge the need to separate the equilibrium concept from the concept of a clearing market. They need not be the same. Further, we acknowledge that the price mechanism in some markets may be flexible enough to equate supply and demand *in every instant* (continuously) while some markets may suffer from sticky prices, even though the market clears in the long-run. Armed with this insight, we split the clearing market hypothesis in two parts and provide the reader with the following two definitions:

Definition 1 *The continuously clearing market hypothesis: Prices are flexible enough to equate supply and demand at every instant.*

Definition 2 *The long-run clearing market hypothesis: The market mechanisms work in the direction of a clearing market, i.e. supply equates demand in the long-run.*

Examining the definitions above, clearly the long-run clearing market hypothesis is necessary but insufficient for the continuously clearing market hypothesis to hold true. As such, there is a need to derive methods that can be used to test the hypotheses stated in Definitions 1 and 2. Acknowledging this need, we derive a novel econometric model, capable of tackling the disequilibrium concept while embracing the issues caused by non-stationary data. The model naturally separates between a continuously clearing market and a clearing market in the long-run such that we are able to derive a novel test of the long-run clearing market hypothesis. We apply this test to the Swedish market for short-term business loans and find that this market suffers from a long-run non-market clearing equilibrium. In addition, we find results that indicate the occurrence of a supply side driven credit crunch in the Swedish market for short-term business loans during 2009.

The outline of the paper is as follows. The next section discusses the general idea and derives the disequilibrium model as well as a test for clearing markets. This is followed by a section in which we apply the model to the Swedish market for short-term business loans. The final section concludes.

2 The General Idea

Let D_t and S_t denote the demand and supply of some good, respectively, and let $Q_t = (D_t, S_t)$ be a bivariate quantity system of the latent quantities. It is reasonable to assume that the system is co-integrated, i.e. the supply may not drift too far away from the demand and vice versa. Thus, we relax the rather restrictive assumption of a continuously clearing market and consider the case when $D_t - S_t \sim I(0)$. Using this, while acknowledging the Granger representation theorem (Engle and Granger, 1987), we write a simple Error Corrected Model (ECM) for the supply function as:[1]

$$\Delta S_t = \psi_0 + \psi_1(S_{t-1} - D_{t-1}) + \gamma \Delta S_{t-1} + \lambda \Delta D_t + \epsilon_t, \tag{1}$$

where $E[\epsilon_t] = 0$. This model is related to the structural ECM by the inclusion of ΔD_t (Engle and Yoo, 1991) and if we examine the ECM above, while acknowledging that the continuously clearing market hypothesis requires $D_t = S_t, \forall t$; a necessary condition for a continuously clearing market is that $\psi_1 = 0$. This since ψ_1 is the speed of adjustment to the long-run equilibrium and since continuously

[1] Obviously, the arguments stated in this section also apply on the demand side of the market.

clearing markets, by definition, are liberated from occasional non-market clearing quantities. In addition, the ECM in (1) implies that:

$$0 = \psi_0 + \psi_1(S^* - D^*),$$

which we can rearrange to the long-run equilibrium:

$$D^* = S^* + \frac{\psi_0}{\psi_1}. \tag{2}$$

Hence, the difference between the long-run clearing market and the actual long-run equilibrium is represented by the ratio ψ_0/ψ_1. If this ratio is non-zero, the long-run clearing market hypothesis in Definition 2 can be falsified. We also note that any test of the long-run clearing market hypothesis requires $\psi_1 \neq 0$ due to the intangible nature of the two hypotheses.

Given the latent nature of Q_t, it is unlikely that we are able to measure the supply and demand of a good per se. If we are to test for the hypotheses in Definitions 1 and 2, we need to derive some measurable implications. Thus, we give functional forms to the demand and supply functions. In many cases economic theory may be of use. Just as often, the researcher may not know the appropriate functional form. Here, we consider the case when the demand and supply functions are linear in prices:

$$D_t = \alpha_C + \alpha_P P_t + \alpha_X X_t + u_t \tag{3}$$

$$S_t = \beta_C + \beta_P P_t + \beta_Z Z_t + v_t, \tag{4}$$

where X_t and Z_t are exogenous variables on the demand and supply side, respectively, P_t is the price of the good while u_t and v_t are random errors with zero means. If we substitute (3) and (4) into (1) we can rearrange (1) into a reduced form equation of the difference in prices:

$$\begin{aligned}\Delta P_t = \ & \theta \times [\psi_0 + \psi_1 (\beta_C - \alpha_C) + \psi_1 (\beta_P - \alpha_P) P_{t-1} + \psi_1 \beta_Z Z_{t-1} \\ & - \psi_1 \alpha_X X_{t-1} + \gamma \beta_P \Delta P_{t-1} - \beta_Z \Delta Z_t + \gamma \beta_Z \Delta Z_{t-1} + \lambda \alpha_X \Delta X_t \\ & + \psi_1 (v_{t-1} - u_{t-1}) - \Delta v_t + \gamma \Delta v_{t-1} + \lambda \Delta u_t + \epsilon_t],\end{aligned} \tag{5}$$

where $\theta = (\beta_P - \lambda \alpha_P)^{-1}$. For convenience we rewrite (5) as:

$$\begin{aligned}\Delta P_t = \ & \eta_0 + \eta_1 P_{t-1} + \mu_1 Z_{t-1} + \mu_2 X_{t-1} + \mu_3 \Delta P_{t-1} \\ & + \mu_4 \Delta Z_t + \mu_5 \Delta Z_{t-1} + \mu_6 \Delta X_t + \xi_t,\end{aligned} \tag{6}$$

where $E[\xi_t] = 0$, given the assumptions made on the error terms. Since the model in (6) is derived from the ECM in (1), we call this model the error corrected disequilibrium model.

In (6) we have an easy way of estimating the combined parameters. Unfortunately, all underlying parameters in (5) can not be uniquely recovered form the parameters of (6). In addition, the error term is serially correlated, i.e. $Cov[\xi_t, \xi_{t-1}] \neq 0$; a notable issue that needs to be tested for and dealt with in order for the parameters in (6) to be estimated consistently and efficiently. For now, however, the ability to estimate the combined parameters is enough and we proceed by deriving the implied long-run equilibrium (stationary) price from the error corrected disequilibrium model in (6):

$$P^* = \eta_1^{-1} \left(-\eta_0 - \mu_1 Z^* - \mu_2 X^*\right). \tag{7}$$

Thus, by estimating the combined parameters in (6) we can estimate the implied long-run affects in (7). We call this model the equilibrium price model. In addition, if we substitute for the underlying parameters of (5) in (7) while acknowledging that a clearing market in the long-run requires $\psi_0/\psi_1 = 0$; we can write the difference between the long-run equilibrium price (P^*) and the long-run clearing market price (P^C) as:

$$P^* - P^C = \frac{\psi_0}{\psi_1} \left(\alpha_P - \beta_P\right)^{-1}. \tag{8}$$

The above clearly highlights the importance of the price elasticity in markets subject to some long-run non-market clearing equilibrium. If the market participants are infinitely elastic, the long-run price difference in (8) is effectively nullified. In addition, the price difference in (8) also shows that the equilibrium price in (7) does not necessarily reflect the clearing market price. Thus, we acknowledge the need for a test of the long-run clearing market hypothesis if we seek to draw inference from the estimates in (7).

The long-run clearing market hypotheses requires $\psi_0/\psi_1 = 0$. If we are to test for this hypothesis, we need some measurable implication of this ratio. Since a clearing market in the long-run is a necessary condition for the continuously clearing market hypothesis, such a test would jointly test the two hypotheses. As it turns out, a simple statistical test on η_1 in (6) will suffice. In other words, if $\eta_1 \neq 0$ it follows that $\psi_0/\psi_1 \neq 0$ such that we may reject the long-run clearing market hypothesis as well as the continuously clearing market hypothesis. This result holds true regardless of the lag structure in (1) or if we include additional explanatory variables in (3) and (4). The arguments underlying these claims are presented at length in the Appendix. In addition, we acknowledge that such a test is based on the estimated lagged price affect on the difference in prices. Thus, the observant reader may have noticed the resemblance between the test of the long-run clearing market hypothesis and an augmented Dickey-Fuller test of a unit root with drift. Indeed, $\eta_1 \in [-1, 0]$ is required in order for the price series to be stationary.

3 An Empirical Application

We apply the error corrected disequilibrium model derived in the previous section to the Swedish credit market. More specifically, we test for the long-run clearing market hypothesis on the market for commercial bank loans in Sweden and estimate the implied effects on the equilibrium rate. We restrict the pool of borrowers to Swedish non-financial firms. Since lenders may limit the supply of loans (Stiglitz and Weiss, 1981), credit markets may suffer from some long-run non-market clearing equilibrium. Thus, the credit market is an ideal trial candidate. Indeed, some recent related studies do in fact embrace the disequilibrium framework in studies of credit markets (see Pazarbasioglu, 1996; Perez, 1998; Hurlin and Kierzenkowski, 2003; Allain and Oulidi, 2009, among others), even though the spurious regression problem caused by non-stationary data is widely ignored. Despite this we find it fruitful to borrow from previous research when selecting suitable determinants of the demand and supply for commercial bank loans. In particular, we are inspired by an early paper by Laffont and Garcia (1977), adjusting their suggested demand and supply functions to the Swedish credit market conditions.

The real demand and real supply of commercial bank loans are likely to share the interest rate, r, as a common determinant. Acknowledging that interest rates vary with maturity, we choose to study short-term debt such that r represents an interest rate on the short end of the yield curve. In order to incorporate the effects on real demand related to alternative funding schemes (e.g., commercial papers or long-term debt) we also choose to include an alternative funding rate, r^{alt}, as a determinant of the real demand. By doing so we control for potential substitution effects. In addition, it is likely that the real demand for commercial bank loans is strongly associated with economic activity. Thus, we include the industrial production index as our proxy for current economic activity, Ind. We acknowledge that an increase in prices may effect firm profits as well as the price of input factors used in banking and include inflation, $Infl$, as a common determinant of the real demand and the real supply for commercial bank loans. Continuing with the real supply, we include the real value of bank deposits, Dep, as one of its determinants. Since real supply is likely to be affected by regulatory rules, we also include the ratio between equity and invested capital, eic, as a proxy for capital requirements and state the real demand and real supply for short-term business loans as:

$$D_t = \alpha_c + \alpha_P r_t + \alpha_X r_t^{alt} + \sum_i a_{1,i} Infl_{t-i} + \sum_i a_{2,i} Ind_{t-i} + u_t \tag{9}$$

$$S_t = \beta_c + \beta_P r_t + \sum_j b_{1,j} Dep_{t-j} + \sum_j b_{2,j} eic_{t-j} + \sum_j b_{3,j} Infl_{t-j} + v_t, \tag{10}$$

where we have distributed lags of unspecified lengths and u_t and v_t are subject to the usual assumptions.

Inspecting the specified demand and supply functions above, one may argue that the the industry production index can be used as a proxy for firms' ability to repay debt. By this argument, the production index should be included as a determinant on the supply side of short-term business loans. However, such an argument is of little concern. The inclusion of demand specific variables on the supply side, or vice versa, does not alter the reduced form of the error corrected disequilibrium model per se; only the implied form of the μ parameters in the studied market's equivalence of (6). Since we can not uniquely solve for these parameters and since we primarily seek the equilibrium price effects while testing for the long-run clearing market hypothesis, we safely ignore such issues.

We use aggregate monthly data from November 2005 to July 2011, collected from Statistics Sweden and the Riksbank (Sweden's central bank). We use the seasonally adjusted Swedish production index and let r_t be the average interest rate on commercial bank loans. Thus, the price variable is averaged out over the yield curve. However, over 88 percent of all Swedish business loans provided to non-financial firms mature within one year after issue. Thus, it is unlikely that the averaging out effect has a significant impact on r_t. As regards the cost of alternative funding, we acknowledge that maturities on commercial paper are flexible and fixed by the issuer at the time of issue. Typically, maturities will range from one day up to two years where 1-3 months are the most common maturities in Sweden. Following this line of argument, we let r_t^{alt} be the average 3-month money market rate (3-month STIBOR).[2] In addition, since the Riksbank lowered the prime rate with historical proportions during the time period December 2008 to July of 2009, we choose to include an indicator variable, I_t, for the year 2009.

Implementing the framework derived in the previous section while acknowledging that $Cov[\xi_t, \xi_{t-s}] \neq 0$, we estimate a variety of error corrected models, choosing the model with the lowest Akaike Information Criterion value. Based on this method, the following error corrected disequilibrium model is estimated:

$$\begin{aligned}\Delta r_t = {} & \eta_0 + \eta_1 r_{t-1} + \mu_1 Dep_{t-1} + \mu_2 eic_{t-1} + \mu_3 r_{t-1}^{alt} + \mu_4 Infl_{t-1} \\ & + \mu_5 Ind_{t-1} + \mu_6 I_t + \mu_7 \Delta r_t^{alt} + \mu_8 \Delta Infl_t + \mu_9 \Delta Ind_t \\ & + \zeta_t + \phi_1 \zeta_{t-1} + \phi_2 \zeta_{t-2} + \phi_3 \zeta_{t-3},\end{aligned} \tag{11}$$

where $\{\zeta_t\}$ is a white noise error sequence. Due to the financial turmoil of the recession of 2008-2009, we split the sample in two, estimating a pre and post recession model using the full sample model structure. Notably, exactly when the

[2] Since the 3-month STIBOR is likely to be highly correlated with the average interest rate on short-term business loans, we check for the robustness of the results by replacing the 3-month STIBOR with a variety of interest rates higher up on the yield curve.

Table 1: Maximum likelihood estimates of the error corrected disequilibrium model applied to the Swedish market of short-term business loans. Conditional least squares estimates are used as starting values.

	Full sample	Nov 2005 - Dec 2008	Jan 2009 - Jul 2011
Intercept	1.718^{***}	0.607	1.235^{***}
r_{t-1}	-0.536^{***}	-0.264^{*}	-0.562^{***}
$Dep_{t-1}/10^6$	-0.153^{***}	-0.105	-0.106^{***}
eic_{t-1}	7.486^{***}	0.544	7.185^{***}
r_{t-1}^{alt}	0.346^{***}	0.162^{*}	0.431^{***}
$Infl_{t-1}$	0.055^{***}	0.040^{*}	-0.008^{**}
Ind_{t-1}	-0.006^{**}	0.002	-0.002^{***}
Δr_t^{alt}	0.425^{***}	0.461^{***}	0.438^{***}
$\Delta Infl_t$	-0.010	-0.008	-0.036^{***}
ΔInd_t	-0.014^{***}	-0.008	-0.009^{***}
I_t	0.086^{**}		
ζ_{t-1}	-0.909^{***}	-1.158^{***}	-2.831^{***}
ζ_{t-2}	0.337^{*}	0.532^{*}	2.739^{***}
ζ_{t-3}	-0.428^{**}	-0.375^{*}	-0.905^{***}
N	69	38	31

Note: Significance codes: 0.001 : "***", 0.01 : "**", 0.1 : "*"

crises came to affect the market for short-term business loans is hard to determine. However, it is likely that lending rates are affected by the cost of funding. Thus, we use the lowering of the Riksbank's prime rate as an indicator, splitting the sample at 2009.

Examining the full sample estimates in Table 1, the intercept as well as the lagged interest rate are clearly significant; implying non-zero values on ψ_0 and ψ_1. Thus, we reject the long-run clearing market hypothesis as well as the continuously clearing market hypothesis. As banks may ration credit, this result implies that the Swedish market for short-term business loans suffers from excess demand. This result is robust to the choice of alternative funding rates and is virtually unaffected by the number of lags in (9), (10) and (6). In addition, since the effect of r_{t-1} remains significant regardless of sample period, this result remains true even when the financial turmoil of the recent recession is excluded from the sample. The full sample model has a squared correlation between observed and in-sample forecast level values of 0.88 suggesting a good fit.

Based on the structure of the equilibrium price model in (7) and the estimated

Table 2: Implied estimates of the equilibrium price model applied to the Swedish market of short-term business loans.

Variables	Estimates
Intercept	3.207^{***}
Bank deposits $\left(Dep^{*}/10^{-6}\right)$	-0.286^{***}
Capital requirements (eic^{*})	13.971^{***}
3-month STIBOR $\left(r^{alt*}\right)$	0.646^{***}
Inflation $(Infl^{*})$	0.103
Economic activity (Ind^{*})	-0.011^{**}
2009 effect (I_t)	0.161^{**}

Note: Significance codes: 0.001 :"***", 0.01 : "**", 0.1 : "*"

error corrected disequilibrium model in (11); the long-run equilibrium interest rate is expressed as:

$$r^{*} = \eta_1^{-1}\left(-\eta_0 - \mu_1 Dep^{*} - \mu_2 eic^{*} - \mu_3 r^{alt*} - \mu_4 Infl^{*} - \mu_5 Ind^{*} - \mu_6 I_t\right).$$

The implied estimated equilibrium effects are presented in Table 2, where the significance tests are performed using the quotient determined standard errors by Fieller's theorem (Fieller, 1932). As can be seen, the sign of the estimated effects are largely in accordance with what we may expect from economic theory. The interest rate becomes smaller with "supply increasing" variables (Dep) and increases with quantity restrictions on the supply side (eic). In addition, an increase in the 3-month STIBOR, i.e. an increase in the cost of alternative funding (r^{alt}) forces an increase in the equilibrium interest rate. This effect can largely be traced back to the structure of yield curves and the covariance between interest rates. In addition, we note that the equilibrium rate does not fully absorb increases in inflation ($Infl$). A one percent increase in inflation implies a mere ten basis point increase in the equilibrium rate. However, since this estimate is non-significant, we do not dwell on this matter any further.

There is one variable that at first sight shows an unexpected impact. An increase in economic activity (Ind) reduces the equilibrium interest rate. One rational for this may be that an increase in economic activity increases the ability to repay debt. Possibly, this shifts the supply curve to such an extent that its effect on the equilibrium interest rate outweighs the effect caused by an increase in the demand for credit. Whatever its cause, our results indicate that the equilibrium interest rate is largely driven by the supply side of credit. In addition, we find an increase in the equilibrium interest rate, ceteris paribus, during the historical lowering of the Riksbank's prime rate during 2009. Since it is fairly unlikely that the lowering of

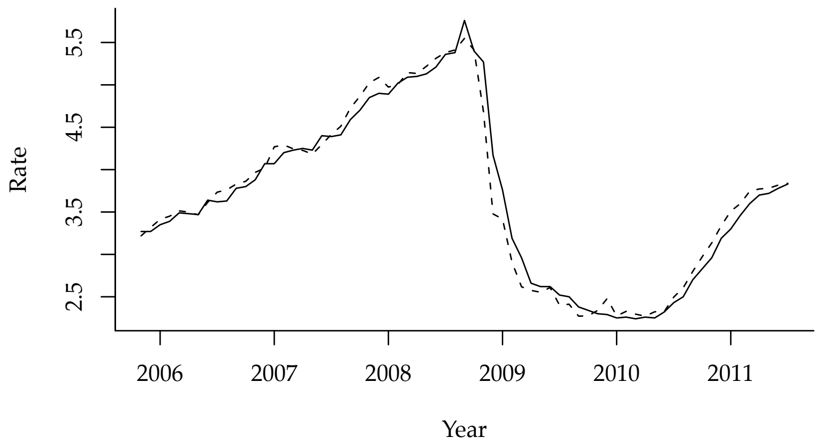

Figure 1: Actual interest rate (solid line) and the estimated equilibrium rate (dashed line).

the prime rate coincided with an unexpected increase in the demand for credit, this result implies an unexpected reduction in the supply of credit. Thus, we have found some evidence in support of a supply side driven credit crunch during 2009.

In Figure 1 we illustrate the equilibrium and actual interest rates for short-term business loans in Sweden. As can be noted, the actual interest rate moves sluggishly behind the equilibrium rate; possibly due to the stock variable of debt included due to the averaging out over the yield curve. As such, when the interest rate dropped in 2009, there was a huge temporary gap between the equilibrium and the actual average interest rate on short-term debt. Recalling the estimated reduction in the supply of credit during 2009 in Table 2; we acknowledge that the supply side driven credit crunch hindered a further drop of interest rates with, at least, 16 basis points.

4 Concluding Remarks

If we embrace the concept of co-integrated demand and supply of some good, there exists an error corrected model that corrects for short-term fluctuations around some long-run equilibrium supply (demand). Such a model implies a model in price differences, dependent on lagged variables of the demand and supply functions. We call this model the error corrected disequilibrium model from which we derive a model of the equilibrium price. Since the error corrected disequilibrium model allows for long-run non-market clearing equilibria, we derive a test of the long-run clearing market hypothesis and the continuously clearing market hypothesis. As it turns out, a simple statistical test on the parameter estimates from the error corrected disequilibrium model suffices.

We use the error corrected disequilibrium model on the Swedish market for short-term business loans and find that this market suffers from a long-run non-market clearing equilibrium. Acknowledging that banks may ration credit, this result indicates that the Swedish market for short-term business loans suffers from excess demand for credit. In addition, by including an indicator variable for the year 2009, we are able to capture an unexpected supply shift. By this method, we find evidence in support for a supply side driven credit crunch during 2009.

Acknowledgments

The financial support from Svenska Handelsbanken and the Graduate Industrial Research School at Umeå University is gratefully acknowledged. I am grateful for the comments from Kurt Brännäs, Runar Brännlund and Christian Lundström as well as for the comments form the seminar participants at the Department of Economics, Umeå School of Business and Economics, Umeå University.

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Appendix: A Test of Clearing Markets

Consider a test of the long-run clearing market hypothesis of Definition 2. To derive a test that is robust to functional form, we base it on the parameters η_0 and η_1 from the error corrected disequilibrium model in (6). These parameters are confined to the same basic structure, regardless of the lag structure in (1) or if we include additional explanatory variables in (3) and (4).[3] When deriving such a test, we first consider the combined parameter η_1 from (6):

$$\eta_1 = \psi_1 \left(\frac{\beta_P - \alpha_P}{\beta_P - \lambda \alpha_P} \right). \tag{A.1}$$

If we assume that the price elasticity differs between the demand and supply side, i.e. that $\alpha_P \neq \beta_P$, it follows from (A.1) that a non-zero value on η_1 implies a non-zero value on ψ_1. Thus, if $\eta_1 \neq 0$ we may reject the continuously clearing market hypothesis, as defined in Definition 1.

Recalling that the long-run clearing market hypothesis of Definition 2 requires $\psi_0/\psi_1 = 0$, we acknowledge the need of deriving some measurable implication of this ratio. As it turns out, a non-zero value on η_1 implies a non-zero value of the ratio ψ_0/ψ_1. To see this, we first use the intercept in the error corrected disequilibrium model in (6):

$$\eta_0 = \frac{\psi_0 + \psi_1(\beta_C - \alpha_C)}{\beta_P - \lambda \alpha_P}. \tag{A.2}$$

Now, consider the case when $\eta_0 = 0$ and solve for ψ_0 in (A.2):

$$\psi_0 = \psi_1(\alpha_C - \beta_C). \tag{A.3}$$

By inspection of the above we see that if $\eta_1 \neq 0$ such that $\psi_1 \neq 0$ when $\eta_0 = 0$, the long-run clearing market hypothesis only holds true when $\alpha_C = \beta_C$. Clearly, such cases are irrelevant. The same conclusion arrises if we let $\eta_0 \neq 0$. To see this assume, for the sake of argument, that $\psi_0 = 0$. Solve for ψ_1 in (A.2) and we get:

$$\psi_1 = \eta_0 \left(\frac{\beta_P - \lambda \alpha_P}{\beta_C - \alpha_C} \right). \tag{A.4}$$

Solve for ψ_1 in (A.1), recalling that we have assumed that the price elasticity differs between the demand and supply side ($\alpha_P \neq \beta_P$):

$$\psi_1 = \eta_1 \left(\frac{\beta_P - \lambda \alpha_P}{\beta_P - \alpha_P} \right). \tag{A.5}$$

[3] Strictly speaking, the removal of ΔD_t in (1) reduces the denominators in (A.1) and (A.2) into β_P.

Substitute for (A.5) in (A.4) and solve for λ:

$$\lambda = \frac{\beta_P}{\alpha_P},$$

which we substitute back to either (A.3) or (A.5) such that $\psi_1 = 0$. Returning to (A.1), it follows that $\eta_1 = 0$ if $\psi_0 = 0$ when $\eta_0 \neq 0$. Thus, if $\eta_1 \neq 0$ and $\eta_0 \neq 0$ it follows that ψ_0 is non-zero such that we may reject the long-run clearing market hypothesis.

Given the above, a simple statistical test on η_1 in (6) is sufficient for testing the long-run clearing market hypothesis as defined in Definition 2. Since a clearing market in the long-run is a necessary condition for the continuously clearing market hypothesis, as defined in Definition 1, such a test jointly tests the two hypotheses.

Comparing Centralized and Decentralized Banking

A Study of the Risk-Return Profiles of Banks

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Abstract

This paper studies the risk-return profile of centralized and decentralized banks. We address the conditions that favor a particular lending regime while acknowledging the effects on lending and returns caused by the course of the business cycle. To analyze these issues, we develop a model which incorporates two stylized facts; (i) banks in which lending decisions are decentralized tend to have a lower cost associated with screening potential borrowers and (ii) decentralized decision-making may generate inefficient outcomes because of lack of coordination. Simulations are used to compare the two banking regimes. Among the results, it is found that asymmetric markets (in terms of the proportion of high ability entrepreneurs) tend to favor centralized banking while decentralized banks seem better at lending in the wake of an economic downturn (high probability of a recession). In addition, we find that even though a bank group where decisions are decentralized may end up with a portfolio of loans which is (relatively) poorly diversified between regions, the ability to effectively screen potential borrowers may nevertheless give a decentralized bank a lower overall risk in the lending portfolio than when decisions are centralized.

Keywords: lending, screening, business cycle, portfolio diversification, risk, organization, simulations

JEL classification: C63, E30, G01, G11, G21, G32

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1 Introduction

An important aspect of a bank's lending activity is the ability to assess the risk-return profile of its investments. Failure to do so may result in substantial credit losses in the case of an unanticipated event. A recent example is the subprime crisis of 2008 where the five largest U.S. investment banks either went bankrupt, were taken over by other companies or were bailed out by the U.S. government. Although nearly all banks suffered from reduced profitability during this period, there was a large variation between banks in terms of how exposed their balance sheets were to risky credits/investments and how large losses they actually experienced during the crisis. Partly, these differences may reflect differences in corporate culture and different attitudes towards risk but since banks are forced to deal with excessive information asymmetry problems, such differences may also reflect the superiority of some banks in assessing the risk profiles and probabilities of default within their respective pools of potential clients and investment opportunities.

A natural question is then why some banks seem to be more effective than others in limiting their credit losses when hit by a negative shock. In this paper we argue that a potentially important factor is whether lending/investment decisions are decentralized (meaning that the lending decisions are taken at the local branch level) or centralized (meaning that the lending decisions are taken higher up in the organization). The purpose of this paper is to develop a stylized theoretical model to analyze this issue.

Our paper relates to the relatively new strand in the corporate finance literature dealing with organizational structure. In this field, an important question is how effective different organizational structures are in terms of handling intangible "soft information" (e.g., ability, honesty, etc.) and "hard information" (e.g., data form credit scoring models and balance sheet data).[1] However, the effects of organizational structure on a bank's risk-return profile have not yet been studied and this is the focus of this paper. To address this issue, we develop a model that allows us to study the potential trade-off that a bank may face between (i) being effective in terms of selecting high-quality clients (which is achieved by having a decentralized decision-making structure) and (ii) being effective in terms of ending up with a well diversified portfolio of loans on the aggregate level (which is achieved by having a more centralized decision-making structure). We also take into account

[1]Stein (2002) contrasted decentralized and centralized (hierarchical) firms from an internal capital markets perspective. He found that hierarchical firms are better suited to deal with hard information since such information is easily handed upwards in the hierarchy whereas decentralized firms handle soft information more effectively. Takáts (2004), in turn, focused exclusively on the difference between centralized and decentralized banks in terms of their abilities to handle soft information and he found (among other things) that information asymmetries are especially important in small business lending.

that a possible consequence of decentralized decision-making is that the decision-maker in one local branch may not recognize that his/her choices may affect the situation for the other local branches. As such, local decision-making may generate "externalities" within the bank group. Here we will focus on (iii) financing externalities, which occur if the decision on how many loans to grant in one local branch affects the cost of raising funds in other branches within the bank group.

Point (i) can be motivated from two perspectives. On one hand, it is well known that banks screen and monitor potential borrowers (Allen, 1990; Winton, 1995) in order to reduce their exposure to counter party risk. In this context, the concept of relationship banking has been put forward as an effective strategy (at least in the longer term) to harvest the information needed to attain high-quality clients (see Boot, 2000, for an excellent review on relationship banking). The underlying concept in relationship banking is to develop comprehensive working relations with each client by assessing his/her individual situation. This means that a bank practicing relationship banking has the ability to collect intangible soft information about the potential client which may improve the bank's client quality estimates (Petersen, 2004), thereby increasing the bank's ability to discriminate between good and bad clients. We will refer to this discrimination procedure as client targeting. Typically, relationship banking is associated with small banks, or large banks that have a decentralized decision-making structure. One rationale for this is that managers of small banks, and branch managers of decentralized banks, have a greater autonomy over adjudication and lending decisions (Stein, 2002). As such, branch managers in decentralized banks have a strong incentive to act on soft information. In contrast, branch managers in centralized banks tend to rely more on hard information (Canales and Nanda, 2011) which means that their incentive to act on soft information may be less strong compared with their decentralized counterparts.

Another explanation for why decentralized banks tend to rely more on relationship banking than centralized banks is that soft information is hard to quantify (Petersen, 2004). This implies that soft information gathered through a relationship with a client may not easily be communicated along the chain of command within a centralized bank, especially if the communication relies on formalized procedures such as score sheets, etc. We will refer to this as information erosion and a consequence of this potential failure to communicate effectively is that a multi-layered centralized bank needs to put in more effort to maintain the quality of the soft information that has been gathered. This adds an extra cost to the client targeting activity in a centralized organizational structure.

A consequence of the arguments presented above is that decentralized banks are likely to put in more effort into screening their potential customers than do centralized banks and this is supported by empirical findings. Liberti (2009) found that the transmission and reliance of soft information is larger in a decentralized organizational structure, whereas Berger et al. (2005) found that small banks tend to have a comparative advantage in processing soft information. As such, small and decentralized banks may be better at alleviating credit constraints for small businesses (Stein, 2002) and they are likely to lend more heavily to small and opaque firms, as previously suggested by Berger et al. (2001, 2005). Further, a recent study by Uchida et al. (2008) on Japanese data, confirmed the findings of Berger et al. (2005), suggesting that the comparative advantage in relationship lending experienced by small banks, is likely to be universal.

Point (ii) is related to portfolio diversification (in the spirit of Markowitz, 1952) whereby large banks are able to finance a wider range of firms (Takáts, 2004) than small banks. Here the argument is that under decentralized decision-making, the aggregate portfolio of clients that the bank group as a whole ends up with (which is the sum of the portfolios of loans over all local branches in the bank group) need not be as well diversified between regions as it might have been if the lending decisions where made at the central level. For example, if the local branch in one region ends up with a small portfolio of clients (because the local bank office predicts that the overall quality of the potential borrowers in that region is low) whereas the local branch in another region ends up with a large portfolio of clients (because the local bank office predicts that the overall quality of the potential borrowers in that region is high), then the bank's aggregate portfolio has a heavy weight on lending in the other region. Depending on how the bank profit in the first region correlates with the bank profit in the other region, the bank group's aggregate portfolio of clients/investment projects need not be "optimal" in terms of risk diversification between the two regions. By referring to this as aggregate portfolio risk, it follows that a bank which has a decentralized decision-making structure may lack the ability to diversify effectively between regions. However, this problem need not arise in a bank with a centralized decision-making structure since centralized lending decisions makes it possible for the central management to take the aggregate portfolio risk into account.

Turning to point (iii), a financing externality may arise if the bank group's cost of financing is an increasing function of the total amount of funds that needs to be raised within the bank group. For example, this may reflect that the supply of deposits is an increasing function of the interest paid by the bank group. Under decentralized decision-making, each local branch may fail to recognize that its need to raise funds will affect the borrowing cost for the other branches. This creates an externality within the bank group which will lead to a too high borrowing cost from the perspective of the bank group as a whole.

The arguments underpinning points (i) - (iii) suggests a potential trade-off between, on one hand, effective client targeting and on the other hand aggregate portfolio risk and financing externalities. These trade-offs are likely to be intrinsically

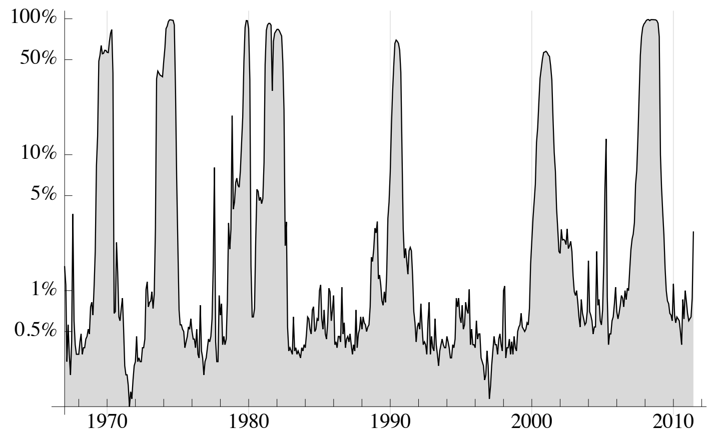


Figure 1: Logarithmic scaled plot of the historical U.S. recession probabilities from a dynamic-factor markov-switching model as in Chauvet and Piger (2008).

related to the organizational structure of a bank. Acknowledging this, we develop a theoretical banking model which incorporates the specific characteristics that are unique for a centralized and a decentralized bank respectively. Due to the complexity of the model, we use simulations to determine under what circumstances, and to what extent, the trade-offs presented in points (i) - (iii) work in favor of a centralized or a decentralized organizational structure.

The key issue that we focus on is which type of organizational structure that tends to perform better in terms of producing lower risk and higher profits (or lower losses) when the economy is hit by a recession. Since the probability of a recession varies over the business cycle, as illustrated in Figure 1, and since the probability of firm default is highly dependent on which phase of the business cycle the economy is in (see Helwege and Kleiman (1997), Fridson et al. (1997) and Carey (1998) among others), the risk associated with a given credit portfolio will change over the course of the business cycle, thereby influencing the bank's lending decisions.

In the simulations, we acknowledge the business cycle and calculate the actual profits/losses if a recession or a boom actually occurs. This allows us to study whether a bank which has chosen a lending strategy which will produce high expected profits if the economy is expected to boom, will suffer relatively larger losses if this prediction turns on its head and the actual outcome is a recession.

The outline of the paper is as follows. In Section 2, we briefly present the outline of the model. This is followed by a characterization of the borrowers in Section 3 and a characterization of the bank's problem in Section 4. The simulation results are presented in Section 5 and the paper is concluded in Section 6.

2 Outline of the Model

Consider an economy (country) that is made up of two regions, 1 and 2. Each region is populated by a large number of entrepreneurs who need to borrow funds to finance risky projects. At the national level there is a bank group which has a local branch in each region that supplies funds to a selected group of entrepreneurs in each region.

The timing of events is as follows. In period 1, each entrepreneur contacts the regional (local) bank office and applies for a loan. At the same instant, the bank evaluates the quality of the potential borrowers and, based on this evaluation, decides on the number of applicants eligible for credit. In period 2, the rates of returns of the entrepreneurs projects are realized which, in turn, determines the performance of the debt and the bank's profit.[2]

3 The Entrepreneurs

Each entrepreneur has a project which requires an initial and indivisible investment of one dollar. Entrepreneurs differ in terms of ability and there are two ability types; high-ability (h) and low-ability (l) entrepreneurs. The proportions of h- and l-types in the population of entrepreneurs in region $k = 1, 2$ are θ_k (high-ability) and $1 - \theta_k$ (low-ability). Ability is not known before (ex ante) the enterprise is set up which means that in period 1, when an entrepreneur applies for funds to make the investment, neither the entrepreneur nor the bank knows the true ability of the entrepreneur.[3] This uncertainty will be referred to as ability risk. Ability is revealed (ex post) in period 2 when the rate of return on the investment is realized.

We let the projects' rate of return depend on whether the business cycle in period 2 features a boom, a recession or is somewhere in between these two extremes (henceforth referred to as a "normal" state). To model this market risk, we assume

[2]This means that our model abstracts from the possible information advantages associated with repeated lending, see Sharpe (1990); Rajan (1992); Petersen and Rajan (1994, 1995) among others.

[3]From an entrepreneur's perspective this uncertainty reflects that before the enterprise is set up, the entrepreneur does not know exactly what qualities are required to be successful in the business. Hence, even though each entrepreneur potentially knows his/her skills, the entrepreneur does not know which skills are important for being successful in the business. The bank, in turn, can be viewed as having had prior experience with firms in the business. As such, the bank knows what qualities are required to be successful but the bank's problem is that some of these qualities are intangible (e.g., social competence, self confidence, effectiveness in handling stress, etc.) which cannot be determined without putting in some effort to learn more about the potential client.

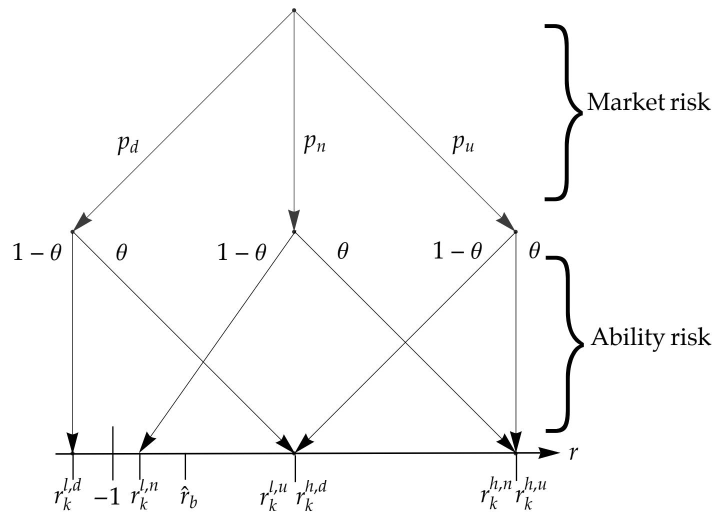


Figure 2: The projects' rate of return.

that with probabilities p_u, p_n and p_d the economy is in a boom (or upstate, u), in a normal state (n) or in a recession (or downstate, d), such that $p_u + p_n + p_d = 1$. Conditional on market condition j ($j = u, n, d$) realized in period 2, the project rate of return, $r_k^{i,j}$, for an entrepreneur of ability type i ($i = h, l$) in region k is illustrated in Figure 2.

There are two basic assumptions underlying this pay-off tree; high-ability entrepreneurs will never default on their loans whereas low-ability entrepreneurs will not be able to pay back the loan with full interest unless the economy is booming. This is illustrated in Figure 2 by incorporating the interest rate, $\hat{r}_k^b$, which is the interest rate charged by the bank that causes the entrepreneur's expected profit to be zero (see below). Thus, the first assumption implies $r_k^{h,u}, r_k^{h,n}, r_k^{h,d} \geq \hat{r}_k^b$ whereas the second implies $r_k^{l,u} \geq \hat{r}_k^b$ and $\hat{r}_k^b > r_k^{l,n}, r_k^{l,d}$. These two assumptions capture the essence of the empirically observed relationship between firm defaults and the phase of the business (see Helwege and Kleiman, 1997; Fridson et al., 1997; Carey, 1998, among others).

Note here that the rate of return is negative for l-entrepreneurs if the market condition is n or d. More specifically, if market condition n occurs, then the rate of low ability entrepreneur is $r_k^{l,n}$. Since $\hat{r}_k^b > r_k^{l,n} > -1$ (as illustrated in Figure 2), the bank has first priority on the rest value of an l-entrepreneur's firm, which is given by $1 + r_k^{n,l}$. On the other hand, if market condition d occurs, then the rate of low ability entrepreneur is $-1 > r_k^{l,d}$, in which case the bank's loss on the loan provided to an l-entrepreneur is 100 percent.

We normalize each entrepreneur's initial endowment of resources to zero which means that each entrepreneur needs to finance his/her investment by borrowing from the bank. Since each entrepreneur is oblivious about his/her ability type, and acknowledging that each entrepreneur needs one dollar to undertake the investment, the expected profit, $E(\pi_k)$, evaluated in period 1 for an arbitrary entrepreneur in region k is given by:

$$E(\pi_k) = [1 + E(r_k)] - \left(1 + r_k^b\right) = E(r_k) - r_k^b, \tag{1}$$

where:

$$\begin{aligned}
E(r_k) &= p_u \cdot E^u(r_k) + p_n \cdot E^n(r_k) + p_d \cdot E^d(r_k) \\
E^u(r_k) &= \theta_k \cdot r_k^{h,u} + (1 - \theta_k) \cdot r_k^{l,u} \\
E^n(r_k) &= \theta_k \cdot r_k^{h,n} + (1 - \theta_k) \cdot r_k^{l,n} \\
E^d(r_k) &= \theta_k \cdot r_k^{h,d} + (1 - \theta_k) \cdot r_k^{l,d}.
\end{aligned}$$

Here, $E(r_k)$ is the unconditional expected rate of return of investing one dollar in an arbitrary entrepreneur's enterprise before ability and market condition have been revealed, whereas $E^i(r_k)$ is the expected value of r_k conditional on the economy being is in state i. As such, the upper branch in the pay-off tree in Figure 2 reflects the market risk associated with investing one dollar in the enterprise whereas the lower branch captures the ability risk.

From equation (1), it follows that potential entrepreneurs will apply for loans as long as $E(r_k) - r_k^b \geq 0$ which means that this condition can be viewed as a *participation constraint* on behalf of the entrepreneurs. The interest rate which makes the entrepreneur's expected profit in equation (1) equal to zero is denoted $\hat{r}_k^b$. As such, $\hat{r}_k^b$ is exogenously determined by the parameters appearing in equation (1). In the simulations we set the parameter values in accordance with the pay-off tree in Figure 2 such that $\hat{r}_k^b$ satisfies the inequality:

$$r_k^{l,u}, r_k^{h,d}, r_k^{h,n}, r_k^{h,u} > \hat{r}_k^b > r_k^{l,n}, r_k^{l,d}.$$

4 The Bank

As mentioned above, the entrepreneurs contact the bank in period 1 to apply for loans. Since the bank cannot observe the true ability of an individual entrepreneur, it will screen the applicants to obtain an estimate of their ability. In this process potential h-entrepreneurs are sorted into the pool of borrowers whereas potential l-entrepreneurs are discarded. If the bank would not collect any background information about the applicants, this process would be a random draw where the expected proportion of h-entrepreneurs in the pool of borrowers in region k would be given by θ_k. However, by putting in some effort, e_k, to collect information about an applicant, the bank can detect and sort away some l-entrepreneurs, thereby increasing the proportion of h-entrepreneurs in the pool of borrowers. Here, the characteristics of an individual applicant can be used as predictors of ability, and the more information that is collected about an applicant, the better the prediction. Hence, the more effort that is put into the screening process, the larger will be the proportion, $z_k = z(e_k)$, of true h-entrepreneurs in the pool of borrowers in region k. The proportion of l-entrepreneurs who are incorrectly sorted into this pool is then given by $1 - z(e_k)$. Observe that the bank does not know the true ability of any given entrepreneur in the pool of borrowers. The sorting just increases the probability that any given entrepreneur in the pool is of high-ability. As such, the possibility to eliminate some l-entrepreneurs from the list of applicants can be viewed as changing the distribution of entrepreneurs from which the bank draws a sample when it lend funds. We require that the function $z_k = z(e_k)$ satisfies the following conditions:

$$z'(e_k) > 0, \quad z(0) = \theta_k, \quad \lim_{e_k \to \infty} z(e_k) = 1.$$

The first two properties follow from the discussion above, whereas the third reflects that for finite levels of effort, there will always be a random element in the sorting of agents into the pool of borrowers. A functional form that satisfies the criteria laid out above, and which will be used in the simulations, is:

$$z(e_k) = \theta_k + q(e_k) \cdot (1 - \theta_k),$$

where:

$$q(e_k) = 1 - \exp(-e_k).$$

We let $0 \leq e_k < \infty$ such that the function $q(e_k)$ lies in the interval $[0, 1]$.

To determine how many applicants, M_k, that needs to be screened in region k to obtain a pool of borrowers in which the expected proportion of h-entrepreneurs is $z(e_k)$, observe first that, conditional on the level of $z(e_k)$, the expected number of true h-entrepreneurs within the pool of N_k borrowers is given by $z(e_k) \cdot N_k$. We now ask the following question: from the population of entrepreneurs in region k, where the proportion of high-ability entrepreneurs is θ_k, how many applicants must be screened in order to obtain $z(e_k) \cdot N_k$ high-ability entrepreneurs? The answer[4] is obtained by setting $z(e_k) \cdot N_k$ equal to $\theta_k \cdot M_k$. Solving for M_k from this equality

[4] Recall that the screening process detects and eliminates l-entrepreneurs from the pool of borrowers. Therefore, among the M_k agents who are screened, no h-entrepreneurs are lost which means that the expected number of h-entrepreneurs, $\theta_k \cdot M_k$, is unchanged in the screening process.

produces:

$$M_k = \frac{z\left(e_k\right) \cdot N_k}{\theta_k}. \tag{2}$$

Equation (2) shows that (i) the larger the bank requires the proportion of high ability entrepreneurs (z_k) to be within the pool of borrowers, (ii) the lower the proportion of high-ability entrepreneurs (θ_k) is within the population and (iii) the more loans (N_k) the bank wants to provide, the larger will be the number of persons that needs to be screened.

Since the effort put into screening a potential borrower in region k is e_k, it follows that the total screening effort made by the bank in region k is given by $e_k \cdot M_k$. The cost of this screening effort in region k is an increasing and (weakly) convex function $S_k\left(\cdot\right)$, where $S_k'\left(\cdot\right) > 0$ and $S_k''\left(\cdot\right) \geq 0$. In the simulations, we use a quadratic functional form:

$$S_k\left(e_k \cdot M_k\right) = \alpha_{k,1} \cdot \left(e_k \cdot M_k\right) + \alpha_{k,2} \cdot \left(e_k \cdot M_k\right)^2, \tag{3}$$

where $\alpha_{k,1} > 0$ and $\alpha_{k,2} \geq 0$ are parameters which capture the regional bank's cost effectiveness of handling intangible soft information. Since empirical studies have found that small and decentralized banks rely more heavily on soft information (Liberti, 2009) and since soft information may be hard to quantify (Petersen, 2004), it is reasonable to assume that centralized banks are subject to an additional screening cost when they move the information upwards in the hierarchy. In terms of our model framework, this indicates that the marginal cost of effort is lower under decentralized banking such that decentralized banks will but more effort into building relationships than do their centralized counterparts. This assumption basically reflects that, the shorter the chain of command is within the bank, the lower the cost of obtaining and transmitting information through the bank hierarchy. As such, we assume that $S_k'\left(\cdot\right)$ is lower for a decentralized bank (working through lower values of $\alpha_{k,1}$ and $\alpha_{k,2}$) than in a bank where the decisions are centralized. In the discussions below, we will refer to this as decentralized banks being more cost efficient with respect to screening than centralized banks.

We now characterize the bank's pay-off, R_k, of lending one dollar to an entrepreneur in region k. The pay-off of the loan is the amount the bank actually receives in period 2 when borrower default is taken into account. From Figure 2, it follows that if the bank charges the interest rate $\hat{r}_k^b$, then the set of possible pay-offs are given by:

$$\begin{gathered} R_k^{h,u} = R_k^{h,n} = R_k^{h,d} = R_k^{l,u} = 1 + \hat{r}_k^b \\ R_k^{l,n} = 1 + r_k^{l,n} < 1 + \hat{r}_k^b, \quad R_k^{l,d} = 0. \end{gathered}$$

Given this pay-off structure, and conditional on e_k, the expected pay-off of lending one dollar is given by:

$$E\left(R_k\right) = \left(1+\hat{r}_k^b\right) - \left[1 - z\left(e_k\right)\right] \cdot \left[p_n \cdot \left(\hat{r}_k^b - r_k^{l,n}\right) + p_d \cdot \left(1+\hat{r}_k^b\right)\right].$$

Let us now turn to the bank's profit. Since we focus on the effects of organizational structure, we keep the model as simple as possible and assume that the accounting identity for the bank at the national level is written:

$$D + E = N. \tag{4}$$

Equation (4) shows that the bank group's total liabilities are made up of private equity, E, and total deposits, D, whereas total assets are made up of the amount of loans issued in the two regions, $N = N_1 + N_2$. Cash reserves are normalized to zero. Private equity is exogenously given and in the following, we will normalize E to be zero, which means that $D = N_1 + N_2$. The supply of deposits are an increasing function of the interest rate paid by the bank, ρ, henceforth referred to as the bank's financing rate. The positive relationship between ρ and D reflects that the bank has to pay a larger interest rate to attract more depositors. Hence $\rho'\left(D\right) > 0$, and in the simulations we use a quadratic form for this function:

$$\rho\left(D\right) = b_1 \cdot D + b_2 \cdot D^2,$$

where $b_1 > 0$ and $b_2 \geq 0$ are two exogenously given parameters that determine the bank's financing cost. The bank group's profit, $\mathit{\Pi}$, can then be written as:

$$\mathit{\Pi} = \sum_{k=1}^{2} \left[N_k \cdot \bar{R}_k - S_k\left(e_k \cdot M_k\right)\right] - \left[1 + \rho\left(D\right)\right] \cdot D,$$

where:

$$\bar{R}_k = \frac{1}{N_k} \cdot \sum_{m=1}^{N_k} R_{k,m} \quad \text{for } k = 1, 2.$$

We can use equations (2) and (5) to write the expected profit as:

$$E\left(\mathit{\Pi}\right) = E\left(\mathit{\Pi}_1\right) + E\left(\mathit{\Pi}_2\right),$$

where:

$$E\left(\mathit{\Pi}_1\right) = N_1 \cdot E\left(\bar{R}_1\right) - S_1\left(\frac{e_1 \cdot z\left(e_1\right) \cdot N_1}{\theta_1}\right) - \left[1 + \rho\left(N_1 + N_2\right)\right] \cdot N_1$$
$$E\left(\mathit{\Pi}_2\right) = N_2 \cdot E\left(\bar{R}_2\right) - S_2\left(\frac{e_2 \cdot z\left(e_2\right) \cdot N_2}{\theta_2}\right) - \left[1 + \rho\left(N_1 + N_2\right)\right] \cdot N_2.$$

4.1 Objective Function and Measures of Risk

We allow the bank to care both about the expected profit and the volatility of profit, where the latter is a measure of the risk associated with lending. The question is what measure of volatility to use to capture risk? One approach is to follow the bulk of the finance literature and use the variance of the profit. This implies that we can write the bank group's risk-adjusted expected profit as:

$$\Omega = E\left(\Pi_1\right) + E\left(\Pi_2\right) - \frac{1}{2} \cdot A \cdot Var\left(\Pi\right), \tag{5}$$

where:

$$\begin{aligned} Var\left(\Pi\right) &= Var\left(\Pi_1\right) + Var\left(\Pi_2\right) + 2 \cdot Cov\left(\Pi_1, \Pi_2\right) \\ Var\left(\Pi_k\right) &= E\left[\Pi_k - E\left(\Pi_k\right)\right]^2 \text{ for } k = 1,2 \\ Cov\left(\Pi_1, \Pi_2\right) &= E\left[\left(\Pi_1 - E\left(\Pi_1\right)\right) \cdot \left(\Pi_2 - E\left(\Pi_2\right)\right)\right], \end{aligned} \tag{6}$$

and where $A \geq 0$ reflects the degree of risk-aversion. If $A = 0$, the bank is risk-neutral whereas a level of $A > 0$ indicates risk aversion. As such, the parameter A can be viewed as reflecting the risk culture within the bank group. The measure $Var\left(\Pi_k\right)$ will be referred to as the total risk in region k whereas $Var\left(\Pi\right)$ is the total risk within the bank group. These risk measures can be decomposed according to:

$$\begin{aligned} &\text{total risk} = \text{market risk} + \text{ability risk} \\ &Var\left(\Pi_k\right) = Var_m\left(\Pi_k\right) + Var_a\left(\Pi_k\right), \end{aligned}$$

where the market risk $Var_m\left(\Pi_k\right)$ is the variance associated with the first leg in Figure 2 in region k whereas the ability risk $Var_a\left(\Pi_k\right)$ is the variance associated with the second leg in Figure 2 in region k.

Another approach frequently used in the finance literature is to incorporate the downside variance (also referred to as the semivariance) as a measure of risk. In the simulations, we have used both the variance and various semivariance measures as indicators of risk and they produce the same qualitative results. Therefore, when we present the results from the simulations, we only show the results associated with the variance of profits as a measure of risk.

4.2 Organizational Structure

Let us now characterize the choices made within the bank group. As mentioned earlier, we will consider two different organizational structures; centralized and decentralized banking.

4.2.1 Centralized Banking

In terms of this model, centralized banking implies that all decisions are taken at the national level. This means that the objective function coincides with equation (5). Thus, by using equation (5) and (6), we can write the centralized bank's objective function as:

$$\Omega^C = \Omega_1 + \Omega_2 - A \cdot Cov\left(\Pi_1, \Pi_2\right), \tag{7}$$

where super-index C stands for "centralized" and where:

$$\Omega_k = E\left(\Pi_k\right) - \frac{1}{2} \cdot A \cdot Var\left(\Pi_k\right) \text{ for } k = 1, 2, \tag{8}$$

is the risk-adjusted profit associated with region k. The decision variables are given by the vector $\left(r_1^b, e_1, N_1, r_2^b, e_2, N_2\right)$. However, from the entrepreneurial participation constraint in equation (1) it follows that r_k^b cannot exceed $E\left(r_k\right)$ and this constraint will be binding, i.e. $\hat{r}_k^b = E\left(r_k\right)$. This means that the actual decision variables are $\left(e_1, N_1\right)$ and $\left(e_2, N_2\right)$. This also applies under decentralized banking.

4.2.2 Decentralized Banking

Under decentralized banking, all decisions are taken at the regional level which means that the local bank in region k chooses the policy vector $\left(e_k, N_k\right)$ while it treats the choices made by the local bank in the other region as exogenous. From this perspective, the two local banks play a non-cooperative Nash game vis-a-vis each other. The only thing that takes place at the central level is the financing. This is assumed to work as follows. Once the local bank has determined N_k, the local bank office requests the central level of the bank to arrange the funds that are needed to lend the required amount. Hence, the funds that the bank at the central level needs to raise is $N = N_1 + N_2$.

The objective function for the local bank in region k is the local risk-adjusted profit defined in equation (8) which means that:

$$\Omega_k^{DC} = E\left(\Pi_k\right) - \frac{1}{2} \cdot A \cdot Var\left(\Pi_k\right), \tag{9}$$

where super-index DC stands for "decentralized". Since the bank group's risk culture may be the same regardless of organizational structure, we assume that the parameter A takes the same value in both banking regimes.

4.2.3 Centralized vs Decentralized Decision-Making

The decisions regarding lending and screening effort will differ between centralized and decentralized banks and there are three basic reasons for this;

(i). Decentralized banks may be more cost efficient with respect to screening than their centralized counterparts. We call this the *cost efficiency effect*.
(ii). A centralized bank may be more efficient in diversifying the lending portfolio between regions. We call this the *diversification effect*.
(iIi). Decentralized decision-making may give rise to *financing externalities* within the bank group.

To see clearly how the cost efficiency effect, the diversification effect and the financing externality cause the choices made by the bank in a centralized regime to differ from those made by the bank in the decentralized regime, let us consider the bank's optimal choice of N_k in the two regimes. When the decisions are centralized and the bank's objective function is Ω^C, the first order condition with respect to N_1 becomes (the first-order condition for N_2 is analogous):

$$\begin{aligned}\frac{\partial \Omega^C}{\partial N_1} = 0 = & E\left(\bar{R}_1\right) - \frac{\partial S_1^C}{\partial N_1} - A \cdot \left[\frac{1}{2} \cdot \frac{\partial Var\left(\Pi_1\right)}{\partial N_1} + \frac{\partial Cov\left(\Pi_1, \Pi_2\right)}{\partial N_1}\right] \\ & - \left[1 + \rho\left(D\right)\right] - \left[1 + \rho'\left(D\right)\right] \cdot \left(N_1 + N_2\right). \end{aligned} \tag{10}$$

On the other hand, when decisions are decentralized, then the local bank's objective function is given by Ω_k^{DC}. The first-order condition with respect to N_1 then becomes (the first-order condition for N_2 is analogous):

$$\begin{aligned}\frac{\partial \Omega_1^{DC}}{\partial N_1} = 0 = & E\left(\bar{R}_1\right) - \frac{\partial S_1^{DC}}{\partial N_1} - A \cdot \frac{1}{2} \cdot \frac{\partial Var\left(\Pi_1\right)}{\partial N_1} \\ & - \left[1 + \rho\left(D\right)\right] - \left[1 + \rho'\left(D\right)\right] \cdot N_1. \end{aligned} \tag{11}$$

In equation (10), the function S_1^C is the cost function associated with screening under centralized banking whereas S_1^{DC} in equation (11) is the cost function associated with screening under decentralized banking. These cost functions differ because decentralized banks may be more cost efficient with respect to screening than their centralized counterparts. As mentioned earlier, the cost efficiency effect is incorporated into the model by setting lower values of the parameters $\alpha_{k,1}$ and $\alpha_{k,2}$ in equation (3) for a decentralized bank than for a bank where the decisions are centralized. As such, for given levels of e and N, it follows that $\partial S_1^C / \partial N_1 > \partial S_1^{DC} / \partial N_1$. All else equal, this cost efficiency effect provides the bank in the decentralized regime with an incentive to provide more loans than the bank in the centralized regime.

Second, comparing the last term in the first row of equation (10) with the corresponding term in equation (11), we see that the effect of N_1 on $Cov\left(\Pi_1, \Pi_2\right)$ is present in equation (10) but absent in equation (11). The reason is that the risk-adjusted objective function differs between the two banking regimes. Recall that when the decisions are centralized, then the risk-adjusted profit is given by equation (7), whereas when the decisions are decentralized, then each regional bank maximizes Ω_k^{DC} which means that the risk-adjusted profit summed over both regions becomes:

$$\Omega^{DC} = \Omega_1^{DC} + \Omega_2^{DC}. \tag{12}$$

As can be seen, equations (7) and (12) do not coincide and the difference lies in the fact that when decisions are decentralized, the regional banks do not take into account the covariation between Π_1 and Π_2 when they make their decisions. If $\partial Cov\left(\Pi_1, \Pi_2\right)/\partial N_1 > 0$ (as one would normally expect) then this term will, all else equal, provide the bank in the centralized regime with an incentive to provide fewer loans than the bank in the decentralized regime (see equation (10)). This is the diversification effect.

Third, equations (10) and (11) also differ with respect to the final term in the second row in each equation. In these equations, the final term reflects that an increase in the number of loans will lead to a higher cost per loan via a higher financing rate (ρ). The difference between the two banking regimes is that under decentralized decision-making, the local bank only recognizes the effect of a higher financing rate on its loans, N_1, whereas under centralized decision-making, the bank takes into account the effects of a higher financing rate in both regions. Since the local bank in each region fails to recognize how its decision affects the cost of lending in the other region, the local banks effectively impose an externality upon each other when decisions are decentralized. All else equal, this failure in coordination under decentralized decision-making will induce each local bank to provide more loans than is optimal from the perspective of the bank group as a whole. This is the financing externality.

5 Simulations

Because of the difficulties associated with obtaining analytical solutions from the theoretical model, we simulate outcomes using constrained numerical optimization.[5] The presentation of our results will be divided into four parts. As for the first three parts, we know from the analysis above that the cost efficiency effect, the financing externality and the diversification effect will influence decentralized (DC) decision-makers to choose different levels of e and N than centralized (C) decision-makers. Therefore, in Section 5.1 we analyze the difference in outcomes between centralized and decentralized banking when only the cost efficiency effect applies while the financing externality and the diversification effect are made redundant. In Section 5.2, we instead analyze the behavior when only the financing externality is present while the cost efficiency effect and the diversification effect are made redundant and in Section 5.3, we look at the diversification effect when

[5]Mathematica is used in the simulations. See the Appendix for details.

the cost efficiency effect and the financing externality are made redundant. The parameter values used in the simulations are presented in the Appendix.

Having worked out these isolated effects, we continue in Section 5.4 by analyzing the full model, where the cost efficiency effect, the financing externality and the diversification effect simultaneously influence the choices made under centralized and decentralized decision-making, respectively.

In all simulations, a key question is how the outcome in the two banking regimes differ when the probability of a deep recession (which in this model corresponds to market condition downstate) is increased. In the full model, we also analyze how the profits in the two banking regimes are affected if a "black swan" hits the economy. By that we mean that a recession unexpectedly hits the economy, even though the initial probability for such an event was low.

5.1 The Pure Cost Efficiency Effect

To isolate the cost efficiency effect we need to eliminate the diversification effect and the financing externality from the model. To eliminate the former we set the degree of risk aversion (A) equal to zero in equations (7) and (9). This means that the bank effectively becomes risk-neutral in which case the incentive to diversify away risk is absent. To eliminate the financing externality from the model, we allow each local branch in the bank group to have a separate financing function which is independent of the other branch's amount of borrowing. As a consequence, the financing function in region k is given by $\rho\left(N_k\right)$ (instead of $\rho\left(N_1 + N_2\right)$). Having made these adjustments, only the cost efficiency effect (i.e. that $\alpha_k^C > \alpha_k^{DC}$ in the screening cost function defined in equation (3)) remains in the model.

In Table 1, we summarize the results in the presence of the pure cost efficiency effect. As can be seen in Table 1(a), the bank in the DC-regime chooses a higher screening effort than the (less cost efficient) bank in the C-regime which implies that the proportion of h-entrepreneurs among the borrowers will be larger in the former regime ($z\left(e^{DC}\right) > z\left(e^{C}\right)$). A consequence of this is that the expected marginal revenue of an increase in N will (from any given initial level) be larger under decentralized banking. This will induce the decentralized bank to lend more funds ($N^{DC} > N^C$) than the centralized bank which causes the expected profit to be larger in the DC-regime ($E(\Pi^{DC}) > (E(\Pi^C))$. Observe, however, that even though the portfolio of loans is larger under decentralized banking, the ability to be more effective in terms of sorting out poor clients means that the risk (measured both in terms of market risk and total risk) in the bank's portfolio of loans is smaller under decentralized banking than under centralized banking.

Next, recall from the introduction that the probability of a recession changes over the course of the business cycle (see Figure 1). Let us therefore take a closer

Table 1: Summarized effects; pure cost efficiency effect.

(a) Implied relationships.

$e^{DC} > e^{C}$	$N^{DC} > N^{C}$	$E(\Pi^{DC}) > E(\Pi^{C})$
$Var\left(\Pi^{DC}\right) < Var\left(\Pi^{C}\right)$	$Var_m\left(\Pi^{DC}\right) < Var_m\left(\Pi^{C}\right)$	

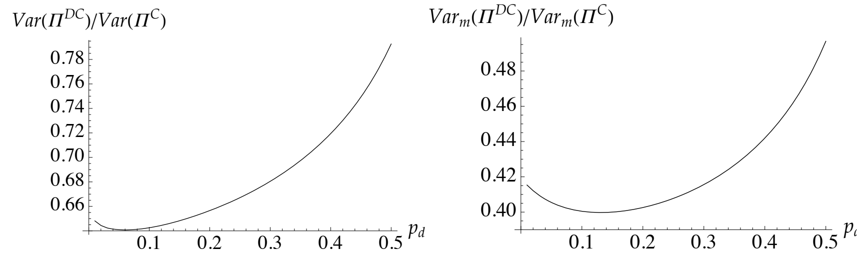
(b) Summarized effects; increase in the probability of a recession.

$\overset{(+)}{e^{DC}}$	$\overset{(+)}{e^{C}}$	$\overset{(-)}{N^{DC}}$	$\overset{(-)}{N^{C}}$	$\overset{(-)}{\left(\frac{e_{DC}}{e_{C}}\right)}$	$\overset{(+)}{\left(\frac{N^{DC}}{N^{C}}\right)}$
$\overset{(+)}{\left(\frac{E(\Pi^{DC})}{E(\Pi^{C})}\right)}$	$\overset{(-\text{ then }+)}{\left(\frac{Var(\Pi^{DC})}{Var(\Pi^{C})}\right)}$	$\overset{(-\text{ then }+)}{\left(\frac{Var_m(\Pi^{DC})}{Var_m(\Pi^{C})}\right)}$			

look at how the two banking regimes' optimal choices of e and N, and the resulting profit and risk levels, are affected by an increase in the probability that a recession will occur (p_d). In our simulations, the increase in p_d is matched by a corresponding reduction in p_u while p_n is unchanged. The effects are summarized in Table 1(b) and the direction of change in each variable is indicated by the sign above the variable at hand. From Table 1(b), we see that when the probability of a recession increases, then the screening effort increases in both regimes because it is now more important than before to eliminate "rotten eggs" from the portfolio of loans. The increase in e is proportionally larger under centralized banking which causes the ratio e^{DC}/e^{C} to decrease, but our simulations show that e^{DC} will nevertheless exceed e^{C}. In addition, the increase in p_d has a negative effect on the number of loans granted in both regimes. Here, N^{C} is reduced proportionally more than N^{DC} which causes the ratio N^{DC}/N^{C} to increase but N^{DC} will still exceed N^{C}.

These results indicate that in the presence of the pure cost efficiency effect, the preventive response to an *expected* recession is stronger under centralized banking than under decentralized banking. The explanation is straightforward. Since the client targeting activity is less efficient under centralized banking, such a bank tends to be more exposed to credit losses if a recession actually occurs. Hence, it is this type of bank which is in greater need to cut its lending portfolio, if a recession becomes more likely to happen. Stretching our argument a bit, we may say that banks under centralized decision-making may be more inclined to "push the panic button" when the prospect of a recession looms large.

Let us now take a look at how these responses affect the profit and risk levels in the two banking regimes. From Table 1(b) it follows that the ratio of expected prof-



(a) Ratio of total risk (b) Ratio of market risk

Figure 3: The ratio of total risk (left) and the ratio of market risk (right) when the proportion of high ability entrepreneurs is equal between regions; pure cost efficiency effect.

its increases. This basically reflects that when a recession is more likely to occur, it becomes more important than before to have a large proportion of h-entrepreneurs in the pool of borrowers. Since the client targeting activity is more effective under decentralized banking, this favors the decentralized banking system when the likelihood of a recession is increased.

Turning to the risk levels, the indicator "$-$ then $+$" above the ratio of the total risk and the ratio of the market risks means that the ratio first decreases but after some level of p_d, the ratio instead increases. This is illustrated in Figure 3.

To explain the U-shaped effect on the risk ratios, observe that two opposite effects are at work here. On the one hand, the client targeting is more effective under decentralized banking, which means that for given levels of e and N, the increase in the market risk and the total risk following a larger value of p_d is relatively smaller under decentralized banking than under centralized banking. For given levels of e and N, this *conditional effect* works in the direction of reducing the risk ratios $Var\left(\Pi^{DC}\right)/Var\left(\Pi^{C}\right)$ and $Var_m\left(\Pi^{DC}\right)/Var_m\left(\Pi^{C}\right)$. On the other hand, when e and N change in response to the increase in p_d, then the simulations indicate that it is the bank in the centralized regime which adjusts its choices of e and N relatively more than the bank in the decentralized regime. This *response effect* works in the direction of increasing the market risk ($Var_m\left(\Pi\right)$) and the total risk ($Var\left(\Pi\right)$) but these increases are smaller under centralized banking than under decentralized banking. Hence, the response effect works in the direction of increasing the risk ratios $Var(\Pi^{DC})/Var(\Pi^{C})$ and $Var(\Pi_m^{DC})/Var_m(\Pi^{C})$. As such, the total effect on the market risk and the total risk in the two banking regimes is ambiguous and our simulations indicate that the conditional effect dominates for low levels of p_d whereas the response effect dominates for larger levels of p_d.

Table 2: Summarized effects; pure finance externality.

(a) Implied relationships.

$e^{DC} < e^{C}$	$N^{DC} > N^{C}$	$E(\Pi^{DC}) < E(\Pi^{C})$
$Var\left(\Pi^{DC}\right) >< Var\left(\Pi^{C}\right)$	$Var_m\left(\Pi^{DC}\right) >< Var_m\left(\Pi^{C}\right)$	

(b) Summarized effects; increase in the probability of a recession.

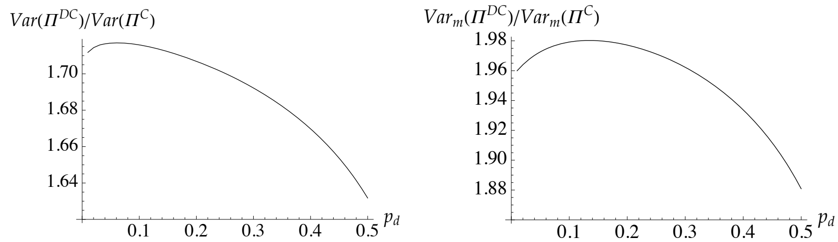
$\overset{(+)}{e^{DC}}$	$\overset{(+)}{e^{C}}$	$\overset{(-)}{N^{DC}}$	$\overset{(-)}{N^{C}}$	$\overset{(+)\text{ or }(+\text{ then }-)}{\left(\dfrac{e_{DC}}{e_C}\right)}$	$\overset{(-)}{\left(\dfrac{N^{DC}}{N^{C}}\right)}$
$\overset{(+)\text{ or }(+\text{ then }-\text{ then }+)}{\left(\dfrac{E(\Pi^{DC})}{E(\Pi^{C})}\right)}$	$\overset{(+\text{ then }-)}{\left(\dfrac{Var(\Pi^{DC})}{Var(\Pi^{C})}\right)}$	$\overset{(+\text{ then }-)}{\left(\dfrac{Var_m(\Pi^{DC})}{Var_m(\Pi^{C})}\right)}$			

5.2 The Pure Financing Externality

Let us now turn to the financing externality. To eliminate the diversification effect, the degree of risk aversion (A) is set equal to zero and to eliminate the cost efficiency effect, we set the parameters $\alpha_{k,1}$ and $\alpha_{k,2}$ in the screening cost function (equation (3)) at the same levels in the two banking regimes.

The simulation results are summarized in Table 2. As we argued earlier in the paper, the financing externality provides the bank in the decentralized regime with an incentive to over-provide the number of loans, and this is verified in the simulations where $N^{DC} > N^{C}$. As a consequence, the expected profit is lower under decentralized banking than under centralized banking. Another effect of the over-provision of loans is that it reduces the decentralized bank's screening effort ($e^{DC} < e^{C}$) because the screening cost is increasing in N. Even though this implies that the client targeting activity is more efficient in the centralized regime, this need not imply that the total risk and the market risk are lower compared with the decentralized regime. Rather, our simulations indicate that when the two regions are symmetric in terms of having the same proportion of h-entrepreneurs in the population (i.e., $\theta_1 = \theta_2$), then the risks are lower in the centralized regime. On the other hand, when $\theta_1 \neq \theta_2$, then the risks may be lower in the decentralized regime. This latter result can be explained by acknowledging that the centralized bank tends to focus its resources on the less risky region. By doing so, the centralized bank increases the variance of the profit associated with the less risky region by more than it reduces the variance in the profit associated with the riskier region.

Let us now turn to the effects of an increase in the probability that a recession



(a) Ratio of total risk (b) Ratio of market risk

Figure 4: The ratio of total risk (left) and the ratio of market risk (right) when the proportion of high ability entrepreneurs is equal between regions; pure financing externality.

will occur. These results are summarized in Table 2(b) from which we see that when the risk of a (deep) recession increases, then e increases and N decreases in both banking regimes (as they did in Section 5.1). However, the net effect on the ratios e^{DC}/e^{C} and $E(\Pi^{DC})/E(\Pi^{C})$ depends on whether the two regions in which the bank group is active have similar ($\theta_1 = \theta_2$) or different proportions ($\theta_1 \neq \theta_2$) of h-entrepreneurs in their respective populations. If the two regions are symmetric ($\theta_1 = \theta_2$) then the effect of an increase in p_d on e^{DC}/e^{C} is positive, but if the two regions are asymmetric ($\theta_1 \neq \theta_2$) then the ratio e^{DC}/e^{C} may be increasing in p_d for low levels of p_d but after some critical value of p_d, the ratio instead decreases. As for the ratios N^{DC}/N^{C}, $Var\left(\Pi^{DC}\right)/Var\left(\Pi^{C}\right)$ and $Var_m\left(\Pi^{DC}\right)/Var_m\left(\Pi^{C}\right)$, the signs in Table 2(b) are opposite to those presented in Table 1(b) in Section 5.1. The explanation is that (in contrast to the situation in Section 5.1) it is now the bank in the decentralized regime which is less effective in its client targeting activity. Hence, it is the decentralized bank that adjusts more strongly if the probability of a recession increases. By using the same type of arguments as in Section 5.1, we can explain why the ratios e^{DC}/e^{C}, N^{DC}/N^{C}, $Var\left(\Pi^{DC}\right)/Var\left(\Pi^{C}\right)$ and $Var_m\left(\Pi^{DC}\right)/Var_m\left(\Pi^{C}\right)$ in Table 2(b) have opposite signs compared with those presented in Section 5.1. As consequence, the relationship between the risk ratios and the probability of a recession are now featuring an inverted U-shape, as illustrated in Figure 4.

Another result is that an increase in p_d has an ambiguous effect on the ratio of expected profits, $E(\Pi^{DC})/E(\Pi^{C})$. This is related to whether the two regions are symmetric ($\theta_1 = \theta_2$) or asymmetric ($\theta_1 \neq \theta_2$). Since it is the bank in the decentralized regime which increases its screening activity relatively more than the bank in the centralized regime when $\theta_1 = \theta_2$, it follows that the subsequent increase in the proportion of h-entrepreneurs that accompanies the increase in e tends to

Table 3: Summarized effects; pure diversification effect.

(a) Implied relationships.

$e^{DC} < e^{C}$	$N^{DC} > N^{C}$	$E(\Pi^{DC}) > E(\Pi^{C})$
$Var\left(\Pi^{DC}\right) > Var\left(\Pi^{C}\right)$	$Var_m\left(\Pi^{DC}\right) > Var_m\left(\Pi^{C}\right)$	

(b) Summarized effects; increase in the probability of a recession.

$\overset{(+)}{e^{DC}}$	$\overset{(+)}{e^{C}}$	$\overset{(-)}{N^{DC}}$	$\overset{(-)}{N^{C}}$	$\overset{(-\text{ then }+)}{\left(\frac{e_{DC}}{e_{C}}\right)}$	$\overset{(+\text{ then }-)}{\left(\frac{N^{DC}}{N^{C}}\right)}$
$\overset{(+\text{ then }-)}{\left(\frac{E(\Pi^{DC})}{E(\Pi^{C})}\right)}$	$\overset{(+\text{ then }-)}{\left(\frac{Var(\Pi^{DC})}{Var(\Pi^{C})}\right)}$	$\overset{(+\text{ then }-)}{\left(\frac{Var_m(\Pi^{DC})}{Var_m(\Pi^{C})}\right)}$			

be larger in the decentralized regime than in the centralized regime. As a consequence, $E(\Pi^{DC})$ will be reduced by a relatively smaller amount than $E(\Pi^{C})$ following an increase in p_d. This explains why $E(\Pi^{DC})/E(\Pi^{C})$ is increasing in p_d when $\theta_1 = \theta_2$. On the other hand, if $\theta_1 \neq \theta_2$, this result need not hold because when the probability of a recession becomes sufficiently large, the bank in the centralized regime tends to cut back on lending altogether in the risky region whereas the bank in the decentralized regime continues to lend. As a consequence, $E(\Pi^{C})$ is reduced "faster" than $E(\Pi^{DC})$, resulting in an increase in the ratio $E(\Pi^{DC})/E(\Pi^{C})$.

5.3 The Pure Diversification Effect

Let us now turn to the pure diversification effect. To eliminate the financing externality, the financing function in region k is written $\rho\left(N_k\right)$ and to eliminate the cost efficiency effect, the parameters in equation (3) (i.e. the screening cost function) are set at the same levels in the two banking regimes.

The simulation results are summarized in Table 3. From Table 3(a) we see that in the presence of only the diversification effect, the market risk and the total risk will be smaller for the bank in the centralized regime. The reason is that when decisions are centralized, the bank in the centralized regime has an opportunity to obtain a better diversified portfolio of loans between the two regions than the bank in the decentralized regime. As can be seen in Table 3(a), the possibility to effectively diversify between regions gives the bank in the centralized regime an incentive to provide fewer loans compared with when the lending decisions are uncoordinated, which is in line with the discussion in Section 4.2.3. Another result is that since the screening cost is increasing in N, it follows that a bank in the centralized regime will put in a larger screening effort than a bank in the decentralized regime ($e^C > e^{DC}$). This means that the ability to be more effective in diversifying the lending portfolio between regions leads to a more efficient client targeting activity in the centralized regime. Finally, observe that since the bank in the decentralized regime tends to over-provide the number of loans in the presence of the pure diversification effect, both the expected profit levels and the risk levels will be larger under decentralized banking than under centralized banking (i.e. $E(\Pi^{DC}) > E(\Pi^C)$ and $Var\left(\Pi^{DC}\right) > Var\left(\Pi^C\right)$). However, the bank group's risk-adjusted expected profit in the centralized regime will, nevertheless, exceed that in the centralized regime ($\Omega^C > \Omega^{DC}$).

As for the effects of an increase in the probability that a recession will occur (p_d), they are summarized in Table 3(b). The intuition for these results are the same as for the corresponding outcomes in Section 5.2.

5.4 The Full Model

Let us now turn to the full model where the cost efficiency effect, the financing externality and the diversification effect are all present simultaneously. Observe that the full model is more than just the sum of the three effects in Section 5.1 - 5.3 because we kept the degree of risk aversion (A) equal to zero when we analyzed the cost efficiency effect and the finance externality effect in isolation. Therefore, when all three effects are included in a full model experiment where $A > 0$, we add an extra dimension to the analysis.

To achieve an easy overview of how centralized and decentralized banking may differ when all above mentioned effects are added together, we simulate the optimal choices of e and N using the experimental plan presented in Table 4. As can be seen, we vary five key parameters in two levels producing a total of $2^5 = 32$ data points. This, in turn, makes it possible to calculate the expected profit, $E(\Pi)$, the total risk, $Var\,(\Pi)$, the market risk, $Var_m\,(\Pi)$, and the expected value of the risk-adjusted profit, Ω, within the bank group for each of the 32 data points. We also calculate the actual profit levels if the market condition turns out to be "upstate", "normal" or "downstate" (i.e., Π_u, Π_n and Π_d) for each of the 32 data points.

We begin the analysis by calculating the "sample average" of the 32 data points for each variable mentioned above in the experiment. The first two rows in Table 5 show that the "average" value of e is larger in the decentralized regime than in the centralized regime whereas the number of loans provided in the decentralized regime exceeds the amount provided in the centralized regime. Since this outcome is qualitatively the same as the one that arose in the presence of only the pure cost efficiency effect, it indicates that with our choice of parameter values, the cost

Table 4: Experimental plan used for the simulations of the full model.

Variables	Treatments	
Risk aversion (A)	0.01	0.1
Probability of recession (p_d)	0.01	0.49
Market asymmetry (θ_1/θ_2)	1	1.5
Relative cost efficiency (α^C/α^{DC})	2	3
Financing cost (b)	10^{-5}	10^{-6}
Constants	**Value**	
Cost efficiency, centralized bank (α_C)	10^{-7}	
Proportion of high-ability entrepreneurs in region 2 (θ_2)	0.1	
Probability of a normal state (p_n)	0.5	

efficiency effect dominates over the financing externality and the diversification effect.

Let us now take a look at how these differences in behavior affect profit and risk levels in the two banking regimes. As can be seen in Table 5, the expected profit ($E(\Pi)$) tends to be larger in the centralized regime than in the decentralized regime. Although the difference is small, our simulations indicate that the negative effect on the expected profit in the decentralized regime, generated by the financing externality and the diversification effect, outweighs the decentralized regime's comparative advantage in terms of being more efficient in its client targeting activity. However, this is only half the story since the total risk ($Var\,(\Pi)$) and the market risk ($Var_m\,(\Pi)$) are considerably smaller in the decentralized regime. Since the size of the market risk and the total risk depends on (i) how effective the bank group is in its client targeting activity and (ii) how effective the bank group is in terms of diversifying the portfolio of loans between regions, our simulations show that it is possible for the client targeting effect to outperform the diversification effect in terms of achieving a portfolio of loans where the market risk and the total risk are low. Hence, our results show that even if a portfolio of loans in the decentralized regime appears to be poorly diversified in the "classical" sense, this portfolio may nevertheless contain less risk than a portfolio in the centralized regime which appears to be well diversified in the "classical" sense.

Since $E(\Pi)$ and $Var\,(\Pi)$ both tend to be larger in the centralized regime, our simulation results indicate that the centralized regime may deliver higher profits at the expense of higher risk. The question is then in which regime the trade-off between profit and risk is most efficient. To evaluate this, we look at the simulated levels of the risk-adjusted expected profits and as can be seen in Table 5, the cen-

Table 5: Sample averages from the experiment.

	Centralized	Decentralized
e	10.11	10.41
N	154.94	195.87
$E(\Pi)$	26.15	25.26
Ω	25.61	24.83
$Var(\Pi)$	35.49	26.45
$Var_m(\Pi)$	0.60	0.29
Π_u	26.68	26.68
Π_n	25.96	25.12
Π_d	22.26	22.45

tralized regime, "on average", produces a larger risk-adjusted expected profit than the decentralized regime.

However, since the full model results are highly dependent on our choice of parameter values, the results should be interpreted with some caution. Acknowledging this, we now proceed to fit a curve to the optimized values. Right-hand side variables in this curve fitting are p_d, A, θ_1/θ_2, α^C/α^{DC} and b (as before, the increase in p_d is matched by a corresponding reduction in p_u while p_n is unchanged). This enables us to take a closer look at how the two banking regimes' respective choices of e and N, and the resulting profit and risk levels, are affected by a change in each of these exogenous variables. The results from the curve fitting are presented in Table 6 and a summary of the effects due to an increase in the probability of a recession is given in Table 7.

We would like to emphasize the following general points. First, an increase in p_d tends to favor the decentralized banking regime in comparison with the centralized regime. Reading off the second row in Table 6, we see that when p_d increases, both the expected profit and the risk-adjusted profit improves in the decentralized regime relative to the centralized regime. Also the actual profit ratios, Π_j^{DC}/Π_j^C, for $j = u, n, d$, increase with p_d. Second, if the banks become more risk-averse (i.e. A increases), this tends to favor the decentralized banking regime because both the expected, risk-adjusted and actual profit ratios increase with A. Third, if the asymmetry increases between the two regions (i.e. the ratio θ_1/θ_2 goes up), then it is more important than before to achieve an efficient allocation of lending portfolios between the two regions. This favors the centralized banking regime.

Finally, let us consider the possibility of a "black swan" hitting the economy. By that we mean that the actual outcome turns out to be a recession (i.e. market condition downstate) even if the probability p_d was initially low. Calculating the

Table 6: Fitted curve parameters on ratios of the full model outcomes. We use standardized values of the variables such that the magnitude of the changes can be compared between variables.

	$\frac{e^{DC}}{e^{C}}$	$\frac{N^{DC}}{N^{C}}$	$\frac{E(\Pi^{DC})}{E(\Pi^{C})}$	$\frac{\Omega^{DC}}{\Omega^{C}}$	$\frac{Var(\Pi^{DC})}{Var(\Pi^{C})}$	$\frac{Var_m(\Pi^{DC})}{Var_m(\Pi^{C})}$	$\frac{\Pi_u^{DC}}{\Pi_u^{C}}$	$\frac{\Pi_n^{DC}}{\Pi_n^{C}}$	$\frac{\Pi_d^{DC}}{\Pi_d^{C}}$
Intercept	5.60	24.63	13.46	12.39	7.93	7.12	14.03	14.46	14.00
Recession prob. (p_d)	0.13	0.51	0.53	0.55	0.11	−0.02	0.52	0.48	0.30
Riskaversion (A)	0.28	0.24	0.20	0.22	0.20	0.18	0.25	0.23	0.04
Asymmetry (θ_1/θ_2)	−0.23	−0.37	−0.41	−0.36	−0.62	−0.32	−0.40	−0.42	−0.56
Rel. screening cost (α^C/α^{DC})	0.34	0.26	0.10	0.13	−0.35	−0.62	0.08	0.09	0.21
Financing cost (b)	−0.40	−0.45	−0.53	−0.53	−0.44	−0.40	−0.53	−0.54	−0.56

Table 7: Summarized effects of an increase in the probability of a recession; full model.

+	+	−	−	+	+	+	+
$\bar{e}^{DC}$	$\bar{e}^{C}$	$\bar{N}^{DC}$	$\bar{N}^{C}$	$\left(\frac{\bar{e}^{DC}}{\bar{e}^{C}}\right)$	$\left(\frac{\bar{N}^{DC}}{\bar{N}^{C}}\right)$	$\left(\frac{E(\bar{\Pi}^{DC}}{E(\bar{\Pi})^{C}}\right)$	$\left(\frac{\bar{\Omega}^{DC}}{\bar{\Omega}^{C}}\right)$
+	−	+	+	+			
$\left(\frac{\bar{Var}(\Pi^{DC})}{\bar{Var}(\Pi^{C})}\right)$	$\left(\frac{\bar{Var}_m(\Pi^{DC})}{\bar{Var}_m(\Pi^{C})}\right)$	$\left(\frac{\bar{\Pi}_u^{DC}}{\bar{\Pi}_u^{C}}\right)$	$\left(\frac{\bar{\Pi}_n^{DC}}{\bar{\Pi}_n^{C}}\right)$	$\left(\frac{\bar{\Pi}_d^{DC}}{\bar{\Pi}_d C}\right)$			

mean ratio of the actual profit, $\bar{\Pi}_d^{DC}/\bar{\Pi}_d^{C}$, when market downstate actually occurs shows that if $p_d = 0.01$ and $\theta_1 = \theta_2$, then $\bar{\Pi}_d^{DC}/\bar{\Pi}_d^{C} = 1.03$ whereas if $p_d = 0.01$ and $\theta_1 \neq \theta_2$, then $\bar{\Pi}_d^{DC}/\bar{\Pi}_d^{C} = 0.96$. As such, we conclude that when the economy enters a recession (downstate) then the decentralized bank, "on average", performs better if the markets are similar (when the cost efficiency effect dominates). However, if the markets differ in terms of the proportion of high ability entrepreneurs, then the centralized bank's ability to target the less risky market makes this bank better suited to handle an unexpected downturn in the economy. Recall that this result appears when the risk of a deep recession is very low ($p_d = 0.01$). On the other hand, if the probability of a recession becomes sufficiently large, then our simulations indicate that, "on average", the decentralized bank outperforms the centralized bank when a recession hits the economy ($\bar{\Pi}_d^{DC}/\bar{\Pi}_d^{C} = 1.042$), regardless of whether the markets are similar or not.

We end with some stylized facts about the Swedish banking sector and calculate the yearly growth in operating profits for the four main Swedish banks (Nordea, SEB, Svenska Handelsbanken and Swedbank) during the years 2006-2010. Since Svenska Handelsbanken (SHB) is the only major Swedish bank operating under a decentralized structure, we calculate the difference in growth rates, where a positive value indicates that the decentralized bank outperformed its centralized counterparts. By doing so, we are able to relate the results in Table 6 to the effects on operating profits caused by an actual recession as well as the effects caused by an increase in the probability of recession during the next coming fiscal year.

In Table 8, we present the mean difference in growth rates for three different cases. The mean difference in growth rates when the probability of recession was high the forthcoming fiscal year (2009) while the Swedish economy was in an actual recession (2008 and 2009) is presented in the upper left quadrant of the table. As can be seen, the mean difference in grow rates is positive, indicating that the decentralized bank performed better during these circumstances. Revisiting Table 6, while acknowledging that an increase in p_d affects the ratio Π_d^{DC}/Π_d^{C} positively,

Table 8: Mean difference in growth rates in operating profits from 2006-2010 for the four major Swedish banks. Source: Datastream.

		Probability of a recession	
		High	Low
Actual recession	Yes	0.47	0.63
	No	-	-0.03

this finding is fully in line with the predictions from our theoretical model. Turning to the lower right quadrant of Table 8, we find that this difference is negative, indicating that the centralized banks (Nordea, SEB, Swedbank) tends to have a larger growth in operating profits, compared the decentralized bank (SHB), when the probability of a recession is low in the case of economic growth. Since our model predicts that a decrease in p_d tends to decrease the ratio $\bar{\Pi}_u^{DC}/\bar{\Pi}_u^{C}$, also this result is predicted by the theoretical model.

Finally, we turn to the case of when a "black swan" hits an economy, i.e. the case when the probability of a recession was low the forthcoming fiscal year but when the economy, nonetheless, entered a recession during the year of operations. As previously discussed, our theoretical findings concerning such a case are rather ambiguous and highly dependent on if the proportion of high ability entrepreneurs are equal across regions or not. If $\theta_1 = \theta_2$, our results indicate that the decentralized bank tends to handle a "black swan" more efficiently while if $\theta_1 \neq \theta_2$, a bank operating under a centralized regime tends to outperform its decentralized counterpart. Returning to Table 8, and acknowledging that the mean difference in growth rates displayed in the upper right quadrant represents such a case, we find this mean difference to be positive. Since this suggests that the decentralized bank (SHB) tends to outperform its competitors, in relative terms, when an unexpected recession hits the economy; this finding suggests that SHB operates in markets characterized by a similar proportion of high performing entrepreneurs.

6 Concluding Remarks

To our knowledge, this is the first paper that attempts to simultaneously address the question of how screening and lending decisions differ between banks having a centralized and decentralized decision-making structure. To analyze this issue, we develop a model where centralized and decentralized banks differ in three aspects; (i) the cost efficiency related to the screening of potential borrowers, (ii) the presence of a financing externality which arises because of lack of coordination when the lending decisions are decentralized and (iii) the inability to effectively diversifying the portfolio of loans between regions under decentralized decision-making.

We emphasize three main conclusions. First, in the presence of only the cost efficiency effect, decentralized banks will lend more funds and have lower risks than their centralized counterparts. It is also shown that in the presence of the pure cost efficiency effect, the bank in the centralized regime tend to react stronger than the bank in the decentralized regime, in terms of reducing the lending portfolio, in the wake of a recession. Second, when only the financing externality is present, then decentralized banks tend to over-provide loans while reducing the amount of effort put into the screening procedure, in comparison with centralized banking. This implies that the pure financing externality produces lower profits and higher risks under decentralized banking. Third, the pure diversification effect also favors centralized banking in the sense that the client targeting is more efficient, the expected profit larger and risks lower, compared with decentralized banking.

We also simulate a model where the cost efficiency effect, the financing externality and the diversification effect are present simultaneously. This allows us to study how these three effects combine to jointly influence the comparison between the two banking regimes. Here, we would like to emphasize that our results show that the client targeting effect may outperform the diversification effect in terms of achieving a portfolio of loans where the market risk and the total risk is low. As such, a portfolio of loans that appears to be poorly diversified under decentralized banking may actually contain less risk than a portfolio chosen by the bank in the centralized regime under the same conditions.

However, there are conditions that, in relative terms, are favorable to a particular lending regime's risk-return profile. Asymmetric markets (in terms of the proportion of high ability entrepreneurs) tend to favor centralized banking while decentralized banks are favored by an increase in the probability of a recession. In addition, our results indicate that decentralized banks are favored by an increase in risk aversion.

Future research may take several directions. For example, an interesting avenue would be to analyze how centralized and decentralized banking perform under different market forms. What are the profit and risk levels under oligopoly and in a perfectly competitive banking market? Another question that would be interesting to address is what the outcome would be in an duopoly where one bank has a centralized organizational structure whereas the other uses a decentralized decision-making. Will the aggregate risks in this duopoly be higher or lower compared to a duopoly made of two centralized or two decentralized banks?

Acknowledgments

Ulf Holmberg gratefully acknowledges the financial support from Svenska Handelsbanken and the Graduate Industrial Research School at Umeå University. We are grateful for the comments from Kurt Brännäs, Carl Lönnbark and Emma Zetterdahl as well as the comments from the seminar participants at the Department of Economics, Umeå School of Business and Economics, Umeå University.

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Appendix: Simulation procedure

We use the Mathematica function FindMaximum for the simulations presented in Section 5, using algorithms suitable for constrained numerical optimization (Nelder and Mead, 1965; Mehrotra, 1992). We proceed as follows.

First, we define the necessary functions from Section 3 and 4 and give the exogenous parameters of the model some suitable value. For the centralized bank, we then solve for optimal values of e_k^C and N_k^C by calling on the FindMaximum command on equation (5). This gives us the numerical global optimum of Ω^C as well as $E(\Pi^C)$, $Var(\Pi^C)$, $Var_m(\Pi^C)$. We then let the actual outcome of high ability entrepreneurs in region k be $Z(e_k^C)$. By doing so, we are able to call on the functions from Section 4 in order to calculate the actual profit for each market condition (Π_j^C).

Turning to the constrained numerical optimization problem for the decentralized bank, we acknowledge that the regional banks play a non-cooperative Nash game vis-a-vis each other. Thus, we start with the bank in region 1 and call on the FindMaximum command on equation (9), solving for the optimal levels of e_1^{DC} and N_1^{DC}, using given start values for e_2^{DC} and N_2^{DC}. We then apply the FindMaximum command on equation (9) for the local bank in region 2, while using the (conditionally) optimal values of e_1^{DC} and N_1^{DC} as given. This is followed by new numerical solution of the the bank in region 1's maximization problem, using the (conditionally) optimal values of e_2^{DC} and N_2^{DC} as given. This procedure is iterated until a stable solution is found, defining the global optimal values of $e_1^{DC}, e_2^{DC}, N_1^{DC}$ and N_2^{DC}. We then calculate the risk adjusted profits using equation (12) and call on the functions from Section 4 in order to calculate $E(\Pi^{DC}), Var(\Pi^{DC}), Var_m(\Pi^{DC})$. The same procedure as for the centralized bank is then used in order to derive the actual outcome in each market condition (Π_j^{DC}).

In Table A.1, we present the parameter values used for the simulations in Sections 5.1 - 5.3. Here, we solve for the optimal values using the method discussed above, over the span $p_d \in [0.01, 0.49]$ in increments of 0.01. We let an increase in p_d correspond to a decrease in p_u such that $p_u = 1 - (p_n + p_d)$. In addition to the parameter values presented in Table A.1, we have checked for robustness of the results by using a wide range of parameters in the simulations, all yielding the same qualitative results.

Table A.1: Parameter values used for the simulations in Sections 5.1 - 5.3.

Variables	Value
Risk aversion (A)	0 or 0.01
Proportion of high-ability entrepreneurs in region 1 (θ_1)	0.1 and 0.2
Proportion of high-ability entrepreneurs in region 2 (θ_2)	0.1
Cost efficiency, centralized bank (α^C)	10^{-7}
Cost efficiency, decentralized bank (α^{DC})	10^{-7} or 5×10^{-8}
Financing cost (b)	10^{-5} and 10^{-6}
Probability of a normal state (p_n)	0.5
Project rate of returns	**Value**
$r_k^{h,u}$	0.6
$r_k^{h,l}$	0.5
$r_k^{n,u}$	0.6
$r_k^{n,l}$	0.6
$r_k^{d,u}$	0.5
$r_k^{d,l}$	0

Finance Research Letters 8 (2011) 59–68

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Value at Risk and Expected Shortfall for large portfolios

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A R T I C L E I N F O

Article history:
Received 2 July 2010
Accepted 5 October 2010
Available online 10 October 2010

JEL classification:
C22
C51
C53
D40
G00
G10

Keywords:
Demand
Supply
Liquidity risk
Limit order book
Bank
Sweden

A B S T R A C T

We argue that the practise of valuing the portfolio is important for the calculation of the Value at Risk and the Expected Shortfall. In particular, the seller (buyer) of an asset does not face a horizontal demand (supply) curve. We propose a new approach for incorporating this fact into the risk measures and in an empirical illustration we compare it to a competing approach. We find substantial differences.

1. Introduction

In this paper we address the question of how to properly assess the risk in large financial portfolios. In risk assessment it is usually assumed that the entire position can be sold at the market price (or mid-price), though one realizes that this can be a quite misleading valuation approach. The reason is that for large enough positions the seller (buyer) of an asset does not face a horizontal demand (supply) curve. Thus, there is an element of liquidity risk involved (see Malz (2003) for a general discussion of liquidity risk) and this should preferably be taken into account in risk assessment.

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1544-6123/$ - see front matter
doi:10.1016/j.frl.2010.10.002

Here, the focus is on incorporating the liquidity risk in the Value at Risk (*VaR*) and the Expected Shortfall (*ES*) measures. *VaR* is the industry standard way of quantifying the risk of adverse price movements and it is defined as the maximum potential portfolio loss that will not be exceeded over a given time horizon for some small probability (see Jorion (2007) for a survey). However, as highlighted by Artzner et al. (1999) the *VaR* suffers from deficiencies such as non-sub-additivity. As an alternative they propose the *ES*, that gives the expected loss given that the *VaR* is exceeded. We emphasize, as argued by François-Heude and Van Wynendaele (2001) and others, that it is implicitly assumed that the liquidation occurs in one block at the end of the predefined holding period when assessing the portfolio risk. The question of how to incorporate the liquidity risk into the *VaR* is a relatively old one and several alternative approaches have been proposed. Bangia et al. (1999) were the first to account for it, with their spread based alternative. Ernst et al. (2009) evaluates some alternatives empirically.

Our proposed approaches for the *VaR* and *ES* measures rely on essentially the same idea as used for the *VaR* measure by Giot and Grammig (2006) (GG hereafter). They consider the average price per share, rather than the mid-price, that would be obtained upon immediate liquidation at the end of the horizon. Their *VaR* is volume dependent and it is based on the difference between the mid-price at the beginning of the horizon and the average price at the end of it. We argue that the relevant initial price is not the mid-price, but that the portfolio should be valued at the average price in the beginning of the period as well. We have assets traded on an order driven markets with a visible limit order book (LOB) (e.g., Gourieroux and Jasiak, 2001, chapter 14) in mind and the context is intra-day. Though frequently used on a (at least) daily basis, intra-day risk measures are of interest as well. For example, Dionne et al. (2009) argue that the investment horizon for very active agents on the market is typically less then one day.

When it comes to the modelling of the dynamics of the average prices the literature is quite scarce. The model employed in GG is of AR-GARCH type and it is essentially univariate (see Bali and Theodossiou (2007, 2008) for an extensive evaluation of AR-GARCH based (daily) *VaR* and *ES* measures). Other previous attempts include Gourieroux et al. (1998) and Bowsher (2004). The former consider a factor model in transaction time, while the latter proposes a functional signal plus noise time series model in calender time. Our framework shares features with all three approaches and the resulting multivariate model allows for spatial (in the volume dimension) as well as serial correlation in the time dimension.

The paper is organized as follows. In Section 2 our framework is presented. Section 3 gives some descriptive statistics of our data set consisting of high-frequency observations on the limit order books of Swedish banking stocks. In Section 4 we propose a time series model for the dynamics of the limit order book. Section 5 contains some empirical results including a comparison with the competing approach of GG.

2. Liquidity adjusted risk measures

The objects of interest are the conditional *VaR* and *ES* for the horizon T to $T + h$ for a univariate portfolio consisting of v_T shares of a financial asset. We will consider measures for both long and short portfolios. For the latter we borrow shares today and agree to return them at some future date. Thus, in that case v_T is negative. We do not allow for portfolio updating, so that $v_T = v_{T+i}$, $i = 1, \ldots, h$, and we denote the value of the portfolio at time point $t = T, \ldots, T + h$ by V_t. Following Gourieroux and Jasiak (2001, chapter 16), the *VaR* for the position v_T satisfies

$$\Pr\left\{V_{T+h} - V_T < -VaR^{1-\alpha}_{T,h} | \mathscr{F}_T\right\} = \alpha, \tag{1}$$

where $\mathscr{F}_T$ is the information available at time T. That is, with (the small) probability α the change in the value of the portfolio is less than $-VaR^{1-\alpha}_{T,h}$. The corresponding *ES* is defined by

$$ES^{1-\alpha}_{T,h} = -E_T\left(V_{T+h} - V_T | V_{T+h} - V_T < -VaR^{1-\alpha}_{T,h}\right), \tag{2}$$

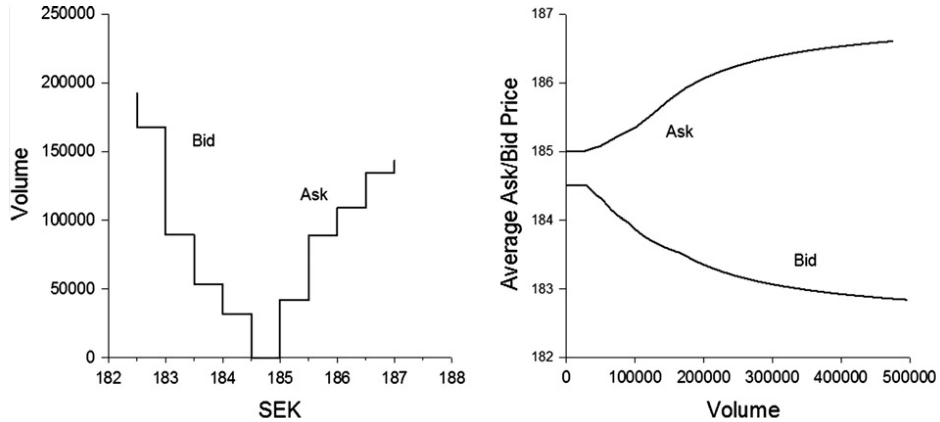

Fig. 1. Supply and demand schedules (left) and average price curves (right) in *SWB*, August 1 at 10 AM.

where E_T denotes expectation conditional on $\mathscr{F}_T$. Thus, the *ES* gives the expected loss given that the loss exceeds the *VaR*.

We give our way of incorporating liquidity risk in terms of the *VaR*. The derivation for the *ES* follows analogously and the corresponding measures are presented at the end of this section. We note that the *VaR* depends on how we compute the values V_{T+h} and V_T (2). The approach typically adopted in the literature is to assume that the entire portfolio can be sold at one and the same price, e.g., the mid-price, $\widetilde{P}_t, t = T, \ldots, T+h$ (say). This implies that the portfolio values V_T and V_{T+h} in (1) are approximated by $\widetilde{V}_T = \widetilde{P}_T v_T$ and $\widetilde{V}_{T+h} = \widetilde{P}_{T+h} v_T$, respectively. The corresponding approximative *VaR* for a long position then satisfies

$$\Pr\left\{\widetilde{V}_{T+h} - \widetilde{V}_T < -\widetilde{VaR}^{1-\alpha}_{T,h} | \mathscr{F}_T\right\} = \Pr\left\{(\widetilde{P}_{T+h} - \widetilde{P}_T) v_T < -\widetilde{VaR}^{1-\alpha}_{T,h} | \mathscr{F}_T\right\} \tag{3}$$

For a short position the expression becomes $\Pr\left[(\widetilde{P}_{T+h} - \widetilde{P}_T) v_T > \widetilde{VaR}^{1-\alpha}_{T,h} | \mathscr{F}_T\right]$. The discussion below is for a long position, but it applies analogously for a short one. Now, for relatively small positions we expect the *VaR* as defined by (3) to provide a reasonable approximation. However, as argued in the introduction $\widetilde{V}_T$ does not in general give the correct value of the portfolio. For example, assume that our position consists of 1000 shares and that at time $T+h$, 500 shares are demanded at the price 2 at the first level of the bid-side of the LOB, and that 1000 shares are demanded at price 1 at the second level. Whereas a marking to the mid-price approach would assign a value of, at least, 2000 we would actually obtain $500 \times 2 + (1000 - 500) \times 1 = 1500$ upon immediate liquidation. The average price per unit of sold volume for this transaction is 1.5 and it appears that this is the fair price to replace for $\widetilde{P}_{T+h}$ in (3).

Generalizing, we define the average price, $\overline{P}_t(v)$, as a function of the volume, i.e. the average price per unit of volume that would result from immediately executing a market order of v shares. In the sequel we let superscripts a and b indicate whether the average price is for the ask or the bid-side of the LOB. Fig. 1 shows demand and supply schedules along with the corresponding average price curves for an observation of one of the stocks (SWB) in our data set.

The question is then how to properly use $\overline{P}_t(v)$ to compute the relevant change in value and this is where we differ from GG. They consider a one-period setting and in their view the relevant change in the value of a (long) position of size v_T is given by $\overline{P}^b_{T+1}(v_T)v_T - \widetilde{P}_T v_T$, where $\widetilde{P}_T = \left[\overline{P}^a_T(1) + \overline{P}^b_T(1)\right]/2$. They specify the dynamics of the log-returns, $p^{GG,v}_t = \ln\left(\overline{P}_t(v_T)/\widetilde{P}_{t-1}\right)$, on the location-scale form $p^{GG,v}_t = \mu^{GG,v}_t + \sigma^{GG,v}_t \varepsilon^{GG,v}_t$, where μ^{GG}_t and σ^{GG}_t are the conditional mean and standard deviation of $p^{GG,v}_t$, respectively, and $\varepsilon^{GG,v}_t$ is an iid random variable with zero mean and unit variance. Their *VaR* is[1]

$$VaR^{GG,1-\alpha}_{T,1} = -\widetilde{P}_T v_T(\exp(\mu^{GG,v}_{T+1} + \sigma^{GG,v}_{T+1} q^{\eta}_{\alpha}) - 1), \tag{4}$$

[1] Actually, their *VaR* is the quantile of the distribution of the log-returns, but this is the implication for the *VaR* definition we use.

where q_α^η is the αth quantile in the Student's t distribution with η degrees of freedom.

We argue that with the same motivation as we value the portfolio at the average price at the end of the period, we should also value it at the average price in the beginning of it. Thus the relevant one-period change in value is $\overline{P}_{T+1}^b(v_T)v_T - \overline{P}_T^b(v_T)v_T$. With the corresponding log-return dynamics

$$p_t^v = \mu_t^v + \sigma_t^v \varepsilon_t^v, \tag{5}$$

our *VaR* alternative for a long position is

$$VaR_{T,1}^{1-\alpha} = -\overline{P}_T^b(v_T)v_T\left(\exp(\mu_{T+1}^v + \sigma_{T+1}^v q_\alpha) - 1\right), \tag{6}$$

where q_α is the αth quantile of some suitable distribution.

For a horizon of h periods the *VaR* satisfies $\Pr\left\{\left[\overline{P}_{T+h}(v_T) - \overline{P}_T(v_T)\right]v_T \leqslant -VaR_{T,h}^{1-\alpha}|\mathscr{F}_T\right\}$. However, the dynamics of the h-period returns do not follow easily from that of the one-period returns (cf. Lönnbark, 2009) . Note also that our *VaR* and the *VaR* in Giot and Grammig (2006) are related by

$$VaR_{T,h}^{1-\alpha} = VaR_{T,h}^{GG,1-\alpha} + v_T\left(\overline{P}_T(v_T) - \widetilde{P}_T\right).$$

Hence, given one of the *VaR*'s it is possible to obtain the other through an additive transformation that is known at time T. Note also that the difference between the two measures grows with an increasing volume.

The *VaR* in (6) implicitly assumes that we own the portfolio at T. If it is to be purchased at T we use $\overline{P}_T^a(v_T)$ for the initial price and the *VaR* becomes

$$VaR_{T,1}^{1-\alpha} = \overline{P}_T^a(v_T)v_T - \overline{P}_T^b(v_T)v_T \exp\left(\mu_{T+1}^v + \sigma_{T+1}^v q_\alpha\right). \tag{7}$$

The corresponding *VaR*'s for a short position are given, respectively, by

$$VaR_{T,1}^{1-\alpha} = -\overline{P}_T^a(v_T)v_T\left(\exp\left(\mu_{T+1}^v + \sigma_{T+1}^v q_{1-\alpha}\right) - 1\right), \tag{8}$$

$$VaR_{T,1}^{1-\alpha} = \overline{P}_T^b(v_T)v_T - \overline{P}_T^a(v_T)v_T \exp\left(\mu_{T+1}^v + \sigma_{T+1}^v q_{1-\alpha}\right). \tag{9}$$

Note that $q_{1-\alpha}$ instead of q_α appears in (8) and (9).

When it comes to defining the corresponding liquidity adjusted *ES* measures we note that the *VaR* for a long (short) position is exceeded when $\varepsilon_{T+1}^v < q_\alpha(\varepsilon_{T+1}^v > q_{1-\alpha})$. Hence, the *ES* corresponding to (6) and (7) are given, respectively, by

$$ES_{T,1}^{1-\alpha} = -\overline{P}_T^b(v_T)v_T(e_\alpha^l - 1),$$
$$ES_{T,1}^{1-\alpha} = \overline{P}_T^a(v_T)v_T - \overline{P}_T^b(v_T)v_T e_\alpha^l,$$

where $e_\alpha^l = E_T(\exp(\mu_{T+1}^v + \sigma_{T+1}^v\varepsilon_{T+1}^v)|\varepsilon_{T+1}^v < q_\alpha)$. The *ES* for short positions are given accordingly by

$$ES_{T,1}^{1-\alpha} = -\overline{P}_T^a(v_T)v_T(e_{1-\alpha}^s - 1),$$
$$ES_{T,1}^{1-\alpha} = \overline{P}_T^b(v_T)v_T - \overline{P}_T^a(v_T)v_T e_{1-\alpha}^s,$$

where $e_{1-\alpha}^s = E_T(\exp(\mu_{T+1}^v + \sigma_{T+1}^v\varepsilon_{T+1}^v)|\varepsilon_{T+1}^v > q_{1-\alpha})$. In practice the expected values e_α^l and e_α^s may be obtained through first order approximations or by means of simulations.

3. Data and descriptives

Our dataset consists of time series for the four largest banks in Sweden (Nordea NRD, Skandinaviska Enskilda Banken SEB, Handelsbanken SHB, Swedbank SWB[2]) and covers the period May 3–August 8, 2005.[3] Table 1 gives a few descriptive statistics for the trading patterns in the four banking stocks for the first trading month (21 days) of the data. The number of traded shares distributions are quite skewed with a long upper tail and the largest transactions in each month are quite large. The largest transaction

[2] Föreningssparbanken in the sample period.

[3] For technical reasons the period June 7–10 is missing for all banks, and additionally May 27–June 1 for SWB and NRD.

Table 1
Descriptive statistics for the number of traded shares and closing prices in individual transactions for the four banks in the first trading month.

Bank	No. of traded shares			Closing price		n
	Mean	StDev	Max	Mean	StDev	
NRD	9921.6	95424.5	7,383,816	67.7	0.42	19,026
SEB	5341.5	1.12×10^5	12,946,377	127.7	1.81	14,325
SHB	3963.1	33227.2	1,831,705	161.1	2.40	10,445
SWB	3644.2	22917.7	1,299,919	171.4	2.56	11,468

was in SEB and amounted to about 1653 million SEK using the average price. This corresponds to about 17% of total transactions during the month. For the other stocks the corresponding percentages are about 4%. Trading is most frequent in NRD with about 900 daily transactions or about 2 per minute.

The sampling frequency is chosen to be 30 min, such that the records immediately preceding the given half-hour are chosen. The daily records cover 1000–1700, i.e. there are 15 observations during the day and the total time series length is $T = 936$ for SEB and SHB and $T = 861$ for NRD and SWB.

For the empirical modelling we can obtain time series of average prices for any chosen volume level. For the analyses reported later we have chosen five volume levels $v = 1, 100{,}000(50{,}000)300{,}000$ and all results are based on log-returns $p_t^v = \ln(\overline{P}_t^v) - \ln(\overline{P}_{t-1}^v)$. As an illustration of the spatial/volume correlations within stocks we consider log-returns for the ask side of SHB, cf. Table 2. As expected from the smoothness of the average curve in Fig. 1, we find that correlations between log-returns at the different volume levels are close to 1. Obviously, the correlations are weaker for lagged log-returns. The autocorrelation function closely matches the cross correlation, except for the first volume level.

Based on the SWB series the autocorrelation functions suggest that MA(1) models will account for most of the serial correlation in the time series. Table 3 gives estimated models and some descriptive statistics for the residuals of the models. In all but one case there is significant autocorrelation in squared residuals, suggesting that ARCH effects are of major importance. For the ask series there is positive skewness and weak but negative for the bid series. For most series there is substantial kurtosis.

4. A time series model for the average price curves

We specify the dynamics of the average price curves in terms of log returns. Stock prices are widely taken to be random walks with drift and for returns various autoregressive and/or moving average extensions of the basic model seem to empirically surface. Based on some initial specification searches on the SWB stock we take as a reasonable model

$$\begin{aligned} p_t^{v_1} &= \alpha_{v_1} + \boldsymbol{\beta}'\mathbf{d}_t + \varepsilon_t^{v_1} + \theta_0\varepsilon_{t-1}^{v_1} \\ p_t^{v_i} &= \alpha_{v_i} + \boldsymbol{\beta}'\mathbf{d}_t + \gamma_{v_i}p_{t-1}^{v_{i-1}} + \varepsilon_t^{v_i} + \theta_{v_i}\varepsilon_{t-1}^{v_i}, \quad i = 2, \ldots, m, \end{aligned}$$

where $p_t^{v_i} = \ln[\overline{P}_t(v_i)] - \ln[\overline{P}_{t-1}(v_i)]$. The parameters γ_{v_i} and θ_{v_i} are volume dependent; $\gamma_{v_i} = \gamma_0 + \gamma_1 v_{i-1}$ and $\theta_{v_i} = \theta_0 + \theta_1 v_i, i = 2, \ldots, m$. The $\mathbf{d}_t$ is a vector of dummy variables to catch overnight impacts on

Table 2
Cross correlations for log-returns (ask) in SHB across volume levels with $v = 200{,}000$ as a base.

Lag	Volumes (thousands)					
	1×10^{-3}	100	150	200	250	300
0	0.77	0.94	0.99	1.00	0.99	0.97
1	−0.01	−0.00	−0.03	−0.04	−0.04	−0.04
2	−0.02	−0.13	−0.13	−0.13	−0.13	−0.13
3	−0.07	−0.05	−0.06	−0.07	−0.07	−0.07
4	−0.03	0.00	0.00	0.01	0.01	0.01

Table 3
Parameter estimates and descriptive statistics for MA(1) models and their residuals of the ask/bid (a and b) average log-return series of the four banks at volume level v = 200,000. p-Values are used for the Ljung–Box statistics, LB.

Bank		MA(1)	t	LB_{10}	LB^2_{10}	Skew	Kurt
NRD	a	0.088	2.59	0.86	0.02	0.26	3.60
	b	0.141	4.15	0.95	0.03	−0.04	3.58
SEB	a	−0.030	−0.90	0.83	0.00	2.10	7.97
	b	−0.010	−0.32	0.82	0.00	−0.38	15.7
SHB	a	0.044	1.34	0.05	0.00	0.76	6.73
	b	0.063	1.94	0.60	0.00	−0.08	5.56
SWB	a	0.088	2.60	0.31	0.63	1.11	8.39
	b	0.018	0.54	0.63	0.00	−0.64	14.0

the first observation of the day and time of day effects. In addition, the models of different volume levels may be correlated such that $E(\varepsilon_t^{v_i}\varepsilon_s^{v_j}) \neq 0$, for all v_i, v_j and also for $t \neq s$.

For all volume levels, $\mathbf{v} = \{v_1, v_2, \ldots, v_m\}$, we write

$$\begin{pmatrix} p_t^{v_1} \\ \vdots \\ p_t^{v_m} \end{pmatrix} = \begin{pmatrix} \alpha_{v_1} \\ \vdots \\ \alpha_{v_m} \end{pmatrix} + (\boldsymbol{\beta}'\mathbf{d}_t)\boldsymbol{\iota} + \begin{pmatrix} 0 & & \ldots & & 0 \\ \gamma_{v_2} & & & & \\ 0 & \gamma_{v3} & \ddots & & \vdots \\ \vdots & \ddots & \ddots & & \\ 0 & \ldots & 0 & \gamma_{v_m} & 0 \end{pmatrix} \begin{pmatrix} p_{t-1}^{v_1} \\ \vdots \\ p_{t-1}^{v_m} \end{pmatrix} + \begin{pmatrix} \varepsilon_t^{v_1} \\ \vdots \\ \varepsilon_t^{v_m} \end{pmatrix}$$
$$+ \begin{pmatrix} \theta_{v_1} & 0 & \ldots & 0 \\ 0 & \theta_{v_2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \ldots & 0 & \theta_{v_m} \end{pmatrix} \begin{pmatrix} \varepsilon_{t-1}^{v_1} \\ \vdots \\ \varepsilon_{t-1}^{v_m} \end{pmatrix}$$

or compactly

$$\mathbf{p}_t^{\mathbf{v}} = \boldsymbol{\alpha} + (\boldsymbol{\beta}'\mathbf{d}_t)\boldsymbol{\iota} + \boldsymbol{\Gamma}_{\mathbf{v}}\mathbf{p}_{t-1}^{\mathbf{v}} + \boldsymbol{\varepsilon}_t + \boldsymbol{\Theta}_{\mathbf{v}}\boldsymbol{\varepsilon}_{t-1}, \tag{10}$$

where $\boldsymbol{\iota}$ is a vector of ones and $\boldsymbol{\varepsilon}_t$ has zero mean and conditional covariance matrix $\boldsymbol{\Sigma}_t$. Thus, the model is of VARMAX type and has both a time series and volume/spatial dimension. The $\boldsymbol{\Sigma}_t$ may contain non-zero off-diagonal elements and is also indexed by t to allow for ARCH-effects. For the conditional variances we employ a version of the asymmetric GARCH specification of Glosten et al. (1993)

$$h_t^{v_i} = \omega_{v_i} + \delta h_{t-1}^{v_i} + \eta(\varepsilon_{t-1}^{v_i})^2 + \lambda(\varepsilon_{t-1}^{v_i})^2\mathbf{1}(\varepsilon_{t-1}^{v_i} < 0), \tag{11}$$

where $\mathbf{1}(\cdot)$ is the indicator function. Note that ω_{v_i} is the only parameter that changes across v_i. As a full baseline model for $\boldsymbol{\Sigma}_t$ we consider (11) together with constant off-diagonal elements

$$\boldsymbol{\Sigma}_t = \boldsymbol{\Omega} + \delta\ \mathrm{diag}\left(\mathbf{h}_t^{\mathbf{v}}\right) + \eta\ \mathrm{diag}\left(\boldsymbol{\varepsilon}_{t-1}^{2,\mathbf{v}}\right) + \lambda\ \mathrm{diag}\left(\boldsymbol{\varepsilon}_{t-1}^{2-,\mathbf{v}}\right),$$

where $\mathbf{h}_t^{\mathbf{v}}$, $\boldsymbol{\varepsilon}_t^{2,\mathbf{v}}$ and $\boldsymbol{\varepsilon}_t^{2-,\mathbf{v}}$ have elements $h_t^{v_i}$, $(\varepsilon_t^{v_i})^2$ and $(\varepsilon_t^{v_i})^2\mathbf{1}(\varepsilon_t^{v_i} < 0)$, $i = 1, \ldots, m$, respectively. The diag$(\cdot)$ operator returns a matrix with the vector argument on the diagonal and zeros elsewhere. Hence, the conditional expectation and the conditional variance of the log-returns are, respectively, given by

$$\begin{aligned} E(\mathbf{p}_t^{\mathbf{v}}|\mathscr{F}_{t-1}) &= \boldsymbol{\alpha} + (\boldsymbol{\beta}'\mathbf{d}_t)\boldsymbol{\iota} + \boldsymbol{\Gamma}_{\mathbf{v}}\mathbf{p}_{t-1}^{\mathbf{v}} + \boldsymbol{\Theta}_{\mathbf{v}}\boldsymbol{\varepsilon}_{t-1} \\ V(\mathbf{p}_t^{\mathbf{v}}|\mathscr{F}_{t-1}) &= \boldsymbol{\Sigma}_t. \end{aligned} \tag{12}$$

These expression are useful both for estimation and forecasting over time. From (10) it is straightforward to obtain the corresponding price levels as $\overline{P}_t^{v_i} = \overline{P}_{t-1}^{v_i}\exp(p_t^{v_i}),\ \ i = 1,\ldots,m$. The conditional expectation and variance of $\overline{P}_t^{v_i}$ may be obtained by taking first order expansions of the exponential function and (12).

With respect to the spatial aspects of the model note that this is an unusual context of observation availability for all volume levels. However, for low levels the volume curves are typically flat and for very large levels linear. Therefore, it appears reasonable to focus the modelling exercise on the intermediate levels, where the curvature is most pronounced. The way we choose v and m in the estimation phase impacts the precision of the estimates, but as our model is not able to predict in the volume direction, the choice is also practically related to the model's end use for *VaR* calculations.

4.1. Estimation

When it comes to predicting the risk measures we use a multivariate version of a popular methodology known as filtered historical simulation (FHS) in the literature (e.g., Christoffersen, 2009). To explain the approach we first collect all model parameters in the vector $\boldsymbol{\psi}$ and consider the prediction error $\mathbf{e}_t = \mathbf{p}_t^{\mathbf{v}} - E_\psi(\mathbf{p}_t^{\mathbf{v}}|\mathscr{F}_{t-1})$, where we subindex the expectation operator to emphasize that it is to be taken under $\boldsymbol{\psi}$. Assuming that the standardized prediction errors $\tilde{e}_t = (\boldsymbol{\Sigma}_t^{1/2})^{-1}\mathbf{e}_t,\ \ t = 1,\ldots,T$, is an iid sequence we may approximate the conditional distribution of $\mathbf{p}_{T+1}^{\mathbf{v}}$ with the sequence $\mathbf{p}_{T+1,j}^{\mathbf{v},*} = E_\psi(\mathbf{p}_{T+1}^{\mathbf{v}}|\mathscr{F}_T) + \boldsymbol{\Sigma}_{T+1}^{1/2}\tilde{\mathbf{e}}_j,\ \ j = 1,\ldots,T$. The predictors of the one-period *VaR*'s and *ES*'s are then trivially obtained from suitable empirical counterparts.

The FHS is a two-step procedure that in the first step estimates the underlying model parameters employing some estimator, $\hat{\boldsymbol{\psi}}$. In the second step it filters out the $\tilde{\mathbf{e}}_t$ sequence.

A natural choice for $\hat{\boldsymbol{\psi}}$ is the quasi maximum likelihood estimator. Given observations up til time T it involves finding the $\boldsymbol{\psi}$ that maximizes the log-likelihood function

$$\ln L = -\frac{1}{2}\sum_{t=2}^{T}\left(\ln|\boldsymbol{\Sigma}_t| - \mathbf{e}_t'\boldsymbol{\Sigma}_t^{-1}\mathbf{e}_t\right).$$

For practical estimation we use the RATS 6.0 package and employ robust standard errors.

5. Empirical results

The empirical results are summarized in terms of *ES* and *VaR* measures in Table 4 for the case when we own the portfolio at the horizon origin. Parameter estimates may be found in Table 5. The mea-

Table 4
ES and *VaR* estimates for $\alpha = 0.01$.

Volume	NRD		SEB		SHB		SWB	
	Short	Long	Short	Long	Short	Long	Short	Long
VaR								
1	0.59	0.29	1.29	1.41	1.30	0.53	1.63	0.86
100,000	57,698	30,147	136,107	98,702	125,733	74,944	175,379	92,403
150,000	86,138	44,404	225,120	140,387	198,631	116,893	281,068	174,078
200,000	113,910	59,725	307,464	207,619	313,717	182,451	416,784	222,729
250,000	139,688	72,506	414,339	261,063	463,808	248,137	528,713	299,420
300,000	166,669	88,144	517,234	311,448	591,360	341,902	606,274	382,042
ES								
1	0.89	0.42	1.59	1.84	1.51	0.90	1.93	1.12
100,000	85,107	43,355	161,435	140,785	155,173	114,156	215,154	145,084
150,000	125,889	67,226	256,700	207,176	261,855	175,300	342,465	269,497
200,000	165,274	94,523	342,069	302,197	399,855	256,292	483,341	381,425
250,000	202,544	122,589	443,519	394,702	597,406	355,849	613,566	485,682
300,000	241,818	151,206	561,074	478,579	779,317	487,990	740,240	596,578

Table 5
Estimates (bold facing indicates significance at 5% level). The Ljung–Box statistics are evaluated at the volume $v = 200{,}000$ level.

Param	NRD		SEB		SHB		SWB	
	Ask	Bid	Ask	Bid	Ask	Bid	Ask	Bid
α_0	-2.75×10^{-5}	-2.53×10^{-5}	3.84×10^{-6}	$\mathbf{3.01 \times 10^{-4}}$	-1.68×10^{-5}	4.72×10^{-5}	-6.72×10^{-5}	5.43×10^{-5}
α_1	-2.97×10^{-5}	-2.70×10^{-5}	1.10×10^{-4}	$\mathbf{2.92 \times 10^{-4}}$	-3.88×10^{-5}	4.43×10^{-5}	-9.19×10^{-5}	1.42×10^{-5}
α_2	-3.27×10^{-5}	-3.07×10^{-5}	1.31×10^{-4}	$\mathbf{3.12 \times 10^{-4}}$	-3.47×10^{-5}	3.89×10^{-5}	-7.96×10^{-5}	-1.70×10^{-5}
α_3	-3.49×10^{-5}	-3.29×10^{-5}	1.40×10^{-4}	$\mathbf{3.01 \times 10^{-4}}$	-3.05×10^{-5}	3.73×10^{-5}	-6.93×10^{-5}	$\mathbf{-3.84 \times 10^{-5}}$
α_4	-3.74×10^{-5}	-3.43×10^{-5}	1.58×10^{-4}	$\mathbf{2.98 \times 10^{-4}}$	-2.95×10^{-5}	3.03×10^{-5}	-6.21×10^{-5}	$\mathbf{-5.48 \times 10^{-5}}$
α_5	-4.06×10^{-5}	-3.35×10^{-5}	1.76×10^{-4}	$\mathbf{2.90 \times 10^{-4}}$	-2.97×10^{-5}	2.45×10^{-5}	-5.79×10^{-5}	$\mathbf{-6.95 \times 10^{-5}}$
β_0	$\mathbf{2.27 \times 10^{-3}}$	$\mathbf{2.13 \times 10^{-3}}$	$\mathbf{1.96 \times 10^{-3}}$	-6.13×10^{-4}	$\mathbf{2.70 \times 10^{-3}}$	5.55×10^{-4}	$\mathbf{4.13 \times 10^{-3}}$	7.36×10^{-5}
β_{on}	1.67×10^{-6}	-3.16×10^{-5}	-3.88×10^{-4}	-2.58×10^{-4}	$\mathbf{-3.68 \times 10^{-4}}$	-1.59×10^{-5}	$\mathbf{-4.25 \times 10^{-4}}$	1.09×10^{-4}
β_m	-9.76×10^{-5}	-8.44×10^{-6}	-7.18×10^{-5}	-2.65×10^{-4}	7.44×10^{-5}	3.51×10^{-6}	1.39×10^{-4}	$\mathbf{1.59 \times 10^{-4}}$
γ_0	0.0407	−0.0109	−0.0136	0.1011	0.0217	**0.1867**	0.0331	**0.2763**
γ_1	2.22×10^{-7}	-1.53×10^{-7}	-7.88×10^{-7}	-1.68×10^{-7}	$\mathbf{6.92 \times 10^{-7}}$	$\mathbf{1.01 \times 10^{-6}}$	-4.08×10^{-7}	$\mathbf{2.55 \times 10^{-6}}$
θ_0	**−0.1178**	**−0.163**	−0.0612	**−0.1167**	0.0520	**−0.1818**	**−0.1440**	**−0.0818**
θ_1	$\mathbf{-1.13 \times 10^{-7}}$	3.49×10^{-7}	8.32×10^{-7}	-4.81×10^{-9}	$\mathbf{-1.41 \times 10^{-6}}$	$\mathbf{-1.26 \times 10^{-6}}$	$\mathbf{3.21 \times 10^{-7}}$	$\mathbf{-2.80 \times 10^{-6}}$
ω_0	$\mathbf{5.35 \times 10^{-6}}$	$\mathbf{5.82 \times 10^{-6}}$	$\mathbf{3.84 \times 10^{-6}}$	$\mathbf{3.42 \times 10^{-6}}$	$\mathbf{3.47 \times 10^{-6}}$	$\mathbf{3.39 \times 10^{-6}}$	$\mathbf{3.74 \times 10^{-6}}$	$\mathbf{3.72 \times 10^{-6}}$
ω_1	$\mathbf{4.91 \times 10^{-6}}$	$\mathbf{5.83 \times 10^{-6}}$	$\mathbf{3.71 \times 10^{-6}}$	$\mathbf{2.80 \times 10^{-6}}$	$\mathbf{2.98 \times 10^{-6}}$	$\mathbf{2.78 \times 10^{-6}}$	$\mathbf{3.67 \times 10^{-6}}$	$\mathbf{3.38 \times 10^{-6}}$
ω_2	$\mathbf{4.80 \times 10^{-6}}$	$\mathbf{5.90 \times 10^{-6}}$	$\mathbf{3.83 \times 10^{-6}}$	$\mathbf{2.85 \times 10^{-6}}$	$\mathbf{3.23 \times 10^{-6}}$	$\mathbf{2.92 \times 10^{-6}}$	$\mathbf{4.25 \times 10^{-6}}$	$\mathbf{3.79 \times 10^{-6}}$
ω_3	$\mathbf{4.72 \times 10^{-6}}$	$\mathbf{5.95 \times 10^{-6}}$	$\mathbf{4.19 \times 10^{-6}}$	$\mathbf{3.15 \times 10^{-6}}$	$\mathbf{3.57 \times 10^{-6}}$	$\mathbf{3.10 \times 10^{-6}}$	$\mathbf{4.83 \times 10^{-6}}$	$\mathbf{4.45 \times 10^{-6}}$
ω_4	$\mathbf{4.63 \times 10^{-6}}$	$\mathbf{5.98 \times 10^{-6}}$	$\mathbf{4.50 \times 10^{-6}}$	$\mathbf{3.40 \times 10^{-6}}$	$\mathbf{3.84 \times 10^{-6}}$	$\mathbf{3.39 \times 10^{-6}}$	$\mathbf{5.03 \times 10^{-6}}$	$\mathbf{5.01 \times 10^{-6}}$
ω_5	$\mathbf{4.55 \times 10^{-6}}$	$\mathbf{5.99 \times 10^{-6}}$	$\mathbf{4.81 \times 10^{-6}}$	$\mathbf{3.68 \times 10^{-6}}$	$\mathbf{4.06 \times 10^{-6}}$	$\mathbf{3.71 \times 10^{-6}}$	$\mathbf{5.03 \times 10^{-6}}$	$\mathbf{5.34 \times 10^{-6}}$
δ	1.75×10^{-4}	-6.11×10^{-5}	**0.3108**	**0.4136**	$\mathbf{1.94 \times 10^{-3}}$	-1.02×10^{-4}	$\mathbf{1.51 \times 10^{-3}}$	-6.27×10^{-5}
η	0.0348	0.0655	0.1507	−0.0124	**0.1421**	0.0786	**0.1488**	0.1576
λ	0.0335	−0.0157	0.0935	**0.5249**	-5.07×10^{-3}	0.1801	−0.0996	0.0877
LB_{10}	6.01	2.94	4.39	7.61	20.3	3.90	11.6	18.8
LB^2_{10}	2.53	3.27	7.56	8.53	10.1	44.8	6.0	3.50
T	861	861	936	936	936	936	861	861

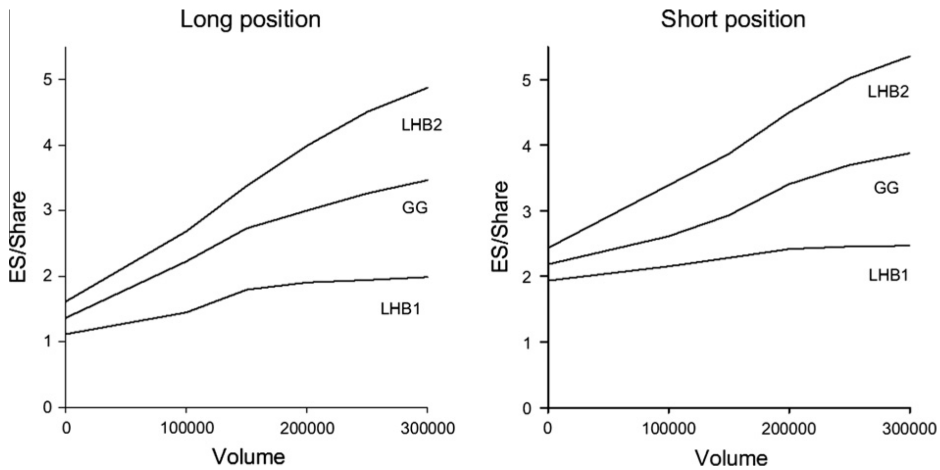

Fig. 2. *ES* per share vs volume for long and short positions in the SWB stock. LHB1 and LHB2 are our *ES*'s for a portfolio owned and purchased at *T*, respectively. GG refers to the *ES* as given by the approach in Giot and Grammig (2006).

sures are calculated for the first post sample time period, i.e. 5 PM of August 8 to 10 AM of August 9, 2005. The numbers reported for a short position are, with one exception, throughout larger than the ones for the corresponding long position. This is a consequence of, at least, the asymmetry in average price curves. Noteworthy is also that the *ES* measures are considerably higher than the *VaR* measures in most cases.

Fig. 2 gives the *ES*'s per share for SWB (the corresponding picture for *VaR* shows a similar pattern). With some exceptions, there is a modest growth in all measures. If we take the view that we own the portfolio at the horizon origin, our *ES*'s are smaller than those as calculated according to the view in GG. If the portfolio is to be purchased, they are larger. Noteworthy is also that for the latter view our *ES*'s rise more sharply with volume. There is a growing difference between our *ES*'s and the ones implied by the view in GG, starting from one half of a tick (0.25 SEK) at volume 1 to exceeding two ticks for the largest position of $v = 300{,}000$ shares. Obviously, these differences will have substantial consequences for how to set the required capital for large financial institutions.

Acknowledgement

We thank an anonymous reviewer for helpful comments and suggestions. The financial support from the Browald and Wallander–Hedelius Foundations is gratefully acknowledged.

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