The stabilizing effects of risk-sensitive bank capital

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Abstract

The aim of the present paper is to assess the pro-cyclical impact of risk-sensitive bank capital. We develop a theoretical model where banks may apply two capital management rules: (i) either keep a constant, time-invariant, capital to loan ratio for all loans ("flat" capital ratio), (ii) or hold distinct, time-variant, capital to loan ratios depending on the measured riskiness of the loans ("risk-based" capital ratio). Despite its inherent cyclicality we show that the risk-sensitive capital rule may work to stabilize banks' supply of credit over the business cycle when the credit market is characterised by over-investment, i.e. credit standards are loose and resources are inefficiently allocated to risky projects. In this case the decrease in the capital-to-high-quality-loan ratio in good times provides banks with more leeway to lend to high quality borrowers, limits the search for higher but riskier yields, reduces over-investment, and ultimately smoothes the credit cycle.

We test the relevance of this stabilizing effect using quarterly balance sheet data from a panel of US banks over the period 2003-2007. This period, characterized by easy access to credit and –presumably– over-investment, is particularly well suited for our test. We start by partitioning our sample of banks into two groups: banks whose capital to asset ratio has been observationally counter-cyclical, and banks whose capital has been either flat or pro-cyclical over our sample. We then compare the elasticities of credit to GDP across the two groups. Although such partitioning works to biase our statistical test against finding stabilizing effects, we find that banks with counter-cyclical, risk-sensitive, capital ratios have been the least sensitive to the business cycle. This paper thus provides both theoretical support for and empirical evidence of the stabilizing effects of risk-sensitive bank capital management.

JEL classification: G28, E32, D82

Key words: Basel II accord, pro-cyclicality, risk management incentives.

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1 Introduction

In the discussion on the impact of the revised regulatory framework for capital adequacy (Basel II), the potential for amplified pro-cyclicality in the financial system and the economy as a whole has been a major source of concern (see among many others Kashyap and Stein, 2004; Taylor and Goodhart, 2006). In bad times, credit risk, measured by the borrower's probability of default, would be high, as would capital requirements (now more closely tied to risk than under a "flat-rate" capital requirements framework such as Basel I). Banks would therefore face much higher capital needs, while finding it more difficult to increase their capital because their profits and, hence, their capacity to build up reserves diminishes. The combination of higher capital requirements and the difficulty of raising new capital could lead banks to reduce credit to firms and households and could aggravate the recession. Conversely, during an economic upturn, banks would face much lower capital needs with excess capital holdings, allowing them to expand credit further and potentially fuel a credit-led boom. These concerns have not gone unnoticed by policy makers and academics. A large number of studies have examined the potential for amplifying pro-cyclical effects arising in the context of the implementation of Basel II. Under the assumption that bank lending has an effect on the business cycle, risk-based capital requirements would work to amplify the business cycle if two conditions are met. First, capital requirements would need to increase in downturns and decline in upturns by more than what would be observed under a flat-rate regulatory framework. Second, credit supply would need to be inversely related to capital requirements. Hitherto, the pro-cyclicality literature has mainly focused on the first condition and tested whether capital requirements will be more cyclical under risk-based capital adequacy rules. Most of these studies have tended to confirm that more risk-sensitive capital requirements will produce more volatility in minimum required capital (see, among many others, Catarineau-Rabell et al., 2003; Kashyap and Stein, 2004). In contrast, the second condition has largely been taken for granted, notably because most studies have assumed banks' risk management and credit supply behaviours would not change with the new rule set.

The present paper revisits the literature on the pro-cyclicality of risk-sensitive bank capital. We build upon the existing literature by assuming that risk-sensitive bank capital management is likely to produce more (counter-)cyclicality in capital. However, we identify a particular theoretical mechanism that makes cyclical capital ratios have counter-cyclical effects on banks' lending, thus drawing attention on a potential stabilizing effect risk-sensitive capital management. We provide empirical evidence of the relevance of this mechanism by documenting that – for a large sample of US banks – the supply of credit from banks whose capital is the most sensitive to the business cycle behaves smoother over the business cycle. Our analysis is twofold.

First, we present a theoretical model in which we analyse the effects of two alternative capital rules: (i) either banks keep a constant capital to loan ratio for all loans ("flat" capital ratio), (ii) or they hold distinct capital to loan ratios depending on the measured riskiness of the loans ("risk-based" capital ratio). Although such simple rules cannot account for the complexity of Basel II's capital adequacy framework, the analysis of their respective cyclical effects brings some insights into the on-going debate on the pro-cyclical impact of risk-sensitive capital. We find that risk-sensitive capital management may smooth the fluctuations in the supply of credit while increasing the cyclicality of the capital ratio. Our model builds upon the textbook model of De Meza and Webb (1987), which provides a simple framework to analyse banks' lending behaviour in the presence of heterogeneous entrepreneurs and credit market frictions. In this model, the existence of asymmetries of information between banks and heterogeneous entrepreneurs gives rise to a free-rider problem whereby low quality entrepreneurs obtain the same financing conditions as high quality entrepreneurs. In other words, high-quality entrepreneurs "cross-subsidize" low-quality entrepreneurs. This generates "too much" investment in the economy because low quality entrepreneurs, with negative net present value projects, invest more than they would in the first-best case.[1] We introduce into De Meza and Webb's original model the possibility for banks to rate borrowers as well as two types of *ad hoc* capital management rules: a flat-rate rule and a risk-sensitive rule. Rating is costly but it reduces the asymmetry of information in the credit market. In this setup the credit market features both rated and unrated loans in equilibrium, and the scope of over-investment depends on the proportion of unrated entrepreneurs in the economy. The higher the proportion of rated entrepreneurs, the lower the degree of information asymmetry, and the lower over-investment. In addition, which entrepreneur is rated depends on quality. The comparison of the effects of the two capital rules shows that banks have a less cyclical credit supply with the risk-sensitive capital management rule. The key mechanism is based on the feature that the capital ratio is constant for unrated loans, whereas for rated loans it varies inversely with the business cycle.[2] By making the opportunity cost of rating lower in good times than in bad times, such a rule gives banks an incentive to extend (reduce) their rating to more borrowers in good (bad) times, which works to resorb (amplify) the free-rider problem, diminish (increase) over-investment, and ultimately smooths the credit cycle. Our model thus points to a channel through which risk-sensitive capital management has counter-cyclical effects. This finding goes against the majority of papers in the pro-cyclicality literature. In particular, Estrella (2004), Zhu (2008), Repullo and Suarez (2008), and Jokivuolle and Vesala (2008) present dynamic models in which banks build up counter-cyclical capital buffers to fulfil capital requirements at each point in time through the business cycle. Although such buffers somewhat mitigate the otherwise pro-cyclical effects of the risk-based capital adequacy framework, they find that Basel II overall works to magnify the credit cycle.

In the second step, we test the cyclical effects of risk-based capital management. The main obstacle to the empirical work on Basel II is the lack of data under a risk-sensitive capital requirement regime. Most of the previous papers circumvented this obstacle by inferring from past bank loan portfolios what would have been banks' regulatory capital had Basel II been implemented earlier, and showed that indeed required capital is more volatile within the new framework. However, this approach by simulations is typically subject to Lucas' critique to the extent that banks' lending behaviour may change under the new rules. In the present paper we take another route. We have in mind that even under Basel I some banks might have already managed their leverage based on their credit risk. Under this conjecture, the comparison of the lending behaviour of banks with historically counter-cyclical capital ratios (which we will refer to as "risk-sensitive capital" banks) with that of other banks (which we will call "flat capital" banks) makes it possible to assess the potential impact of risk sensitive capital management on lending. If the counter-cyclicality of bank capital ratios works to amplify the credit cycle, as argued by the pro-cyclicality literature, then we should observe, *ceteris paribus*, that banks with historically counter-cyclical capital ratios have had a particularly pro-cyclical lending behaviour. In contrast, if we do not observe more pro-cyclical lending from these types of banks, then we would conclude that some counter-cyclical forces of the type described in our theoretical model are at work.

[1] This mechanism stands in contrast to another strand of the financial frictions literature; namely the notion of credit rationing (see e.g. Stiglitz and Weiss, 1981), which predict a problem of under-investment. However, we would argue that the recent period leading up to the finanicial turmoil starting in mid-2007 has rather been characterised by loose credit standards and possibly over-investment.

[2] This aspect is somewhat similar to Basel II's standardized aproach, in which the risk weight for unrated corporate claims is fixed and equal to 100%, while it goes from 20% to 150% for rated claims, depending on the underlying risk (Basel Committee on Banking Supervision, 2006, p. 19).

The aim of our empirical analysis is therefore to answer the following question: Have the banks with a historically risk-sensitive capital to asset ratio had a particularly more cyclical credit supply than the other banks? Although this question seems a natural step in the analysis of the procyclical impact of risk-sensitive capital requirements, it has not been answered yet. Our data set is a quarterly panel of more than 200 US banks for the period 2003-2007. Like Adrian and Shin (2007), we start documenting the heterogeneity of capital management behaviours among US financial institutions, with notably some institutions clearly displaying counter-cyclical capital ratios. Then we use this heterogeneity to separate the "risk-sensitive capital" from "flat capital" banks, on the basis of the serial correlations between banks' total assets and Tier one capital ratios. Based on this partition, we compare the elasticities of credit to GDP across the two groups and test whether "risk-sensitive" banks have had particularly higher elasticities. Note that our test strategy is likely to be biased against finding stabilizing effects. Indeed, we select as "risk-sensitive capital" those banks whose assets rise the most when bank capital increases (i.e. whose capital to assets ratio decreases the most). Since bank capital increases during booms when GDP is rising fastest, one would expect, everything being equal, the supply of credit from those banks to be rising faster than the supply of credit from the "flat capital" banks. Despite this bias, we do not find any evidence in favour of the procyclical impact of risk-sensitive capital management. On the contrary, if anything, lending from "risk-sensitive" banks appears to have been the least sensitive to the business cycle. Overall, we conclude that risk-based capital management characterised by a counter-cyclical capital ratio works to stabilize the credit cycle. Our theoretical model provides one plausible explanation for this somewhat surprising empirical finding.

The rest of the paper is structured as follows: the theoretical model is presented in Section 2, the data and empirical analysis are presented in Section 3, and Section 4 concludes.

2 Theory

Our model is an adaptation of the textbook model of De Meza and Webb (1987), which shows how credit market frictions generate over-investment. As in the original model, we assume that borrowers have a fixed size project, are heterogeneous, differ in their project's success probability, and that the information about these probabilities is private. To compare banks' risk analysis behaviours and discuss the cyclicality of credit under flat-rate and risk-based capital requirements, respectively, we introduce endogenous screening by banks and regulatory capital requirements into the original model.

We consider an economy peopled with a continuum of risk neutral, one-period lived agents, which have access to an investment project, and with banks, which have access to a rating technology. Each agent is endowed with one unit of labour, which he may supply at the exogenous wage rate 1. A given agent cannot both undertake his project and work. Agents who undertake their project are called "entrepreneurs", while the others are called "workers". Each worker can supply his labour to one entrepreneur only. We do not model the labour market in detail and assume, for simplicity, that workers find a job with probability λ, so that λ is also the opportunity cost of running the project.

Technology We index entrepreneurs according to the probability that their project is successful, π. Entrepreneur π's project consists in producing, with probability π, R consumption goods at the end of the period with one unit of labour hired at the beginning of the period, with $R > 1$. When the project fails, with probability $1 - \pi$, it yields γR only, with $0 \leqslant \gamma < 1$. We will assume R large enough so that there is some investment in the equilibrium, but also low enough so that the project is risky to external financiers (see Section 2.2). The success probabilities differ across entrepreneurs and are private information, so that there is an information asymmetry between entrepreneurs on the one hand, and workers and banks on the other hand. The distribution of success probabilities is assumed Uniform over the interval $[0, 1]$.

Preferences Agents are risk neutral and their utility is a linear function of their end-of-period consumption. Their objective is to maximise their expected utility. They take two types of decisions. First they decide whether to undertake their project or instead supply their labour. Second, if they invest, they choose the debt contract that maximises their expected utility.

Banks and Capital Management Rule In the paper we do not justify why the banking system exists, as this is irrelevant for the question we are addressing. We rule out the potential autarkic, non-banking, equilibrium where the agents would deal directly with each others by assuming that workers do not have the possibility to force entrepreneurs to pay their debt (wages) at the end of the period, while banks do. However, workers have the possibility to force banks to pay their debt at the end of the period. Banks thus have the ability to facilitate transactions between workers and entrepreneurs. They do so by issuing at the beginning of the period bank notes (or "cash") that give their holders the right to obtain one unit of consumption good from the bank at the end at the period. Each entrepreneur can borrow one unit of cash from the banks and use it to pay the wages at the beginning of the period. In exchange, the entrepreneur promises to deliver the banks with consumption goods at end of the period.

To analyse the effects of bank risk management on lending, we first assume that banks have access to a rating technology. With this technology they are able to analyse the information provided by borrowers, perfectly infer the quality of the projects from this information, and rate the loans accordingly. This technology costs $s > 0$ per loan at the end of the period.[3] When the bank using the technology for a given borrower, we will say that the loan of this borrower is "rated". Next, we assume that banks follow an *ad hoc*, exogenous, capital management rule, which banks take as given and comply with. It consists in providing for unexpected liquidity shocks by retaining earnings as capital reserves, that is a proportion κ^r (κ^u) of their returns on the rated (unrated) loans as capital buffer.[4] (The upperscripts r and u stand for "rated" and "unrated", respectively.) The banking sector is competitive and banks offer a set of debt contracts that maximises their expected profit, under the constraint that they comply with the capital management rule.

Definition of the Credit Market Equilibrium The competitive credit market equilibrium is defined as a Nash equilibrium where banks offer a set of debt contracts $\{r(\pi)\}_{\pi\in[\underline{\pi},1]}$ to the borrowers and do not make any additional expected profit, beyond the one required under the capital management rule, with any of these contracts,[5] with $\underline{\pi}$ being the probability of success of the marginal, lowest quality,

[3] Notice the two possible interpretations of the cost s here. In the model there will be no fundamental difference between a case where it is the bank that decides whether to analsyse and rate (with cost s) the information provided by the borrowers (at no cost), and a case where it is the borrower who decides whether to provide enough information (with cost s) to the banks in order to be rated (at no cost). See also Section 2.4.

[4] Such a rule may have several interpretations and rationales, which we do not model here. Either it can be viewed as capital requirements imposed by the banking authorities. Or it can be viewed as a minimum equity requirement constraint imposed by the depositors or market investors, in order the bank to have the right incentives to monitor the loans (as in, for example, Holmström and Tirole (1997).

[5] If they did so, then it would be possible for a given bank to lower its lending rate, gain market shares, and increase its expected profit.

entrepreneur.

2.1 Debt Contracts

In the typical debt contract the bank lends one unit of cash to entrepreneur π at the beginning of the period against the promise of the entrepreneur to deliver consumption goods to the bank at the end of the period. Banks may offer two types of debt contracts. First, they may offer a unique "pooling" contract independent of borrowers' quality where they require a payment of $r(\underline{\pi})$ consumption goods at the end of the period if the project is successful, and γR otherwise. In this case the interest is the same for all borrowers, and therefore the bank neither does not need to screen the borrowers. Since the bank does not observe the quality of the borrower if it does not rate, and would not pool a rated borrower, we will interchangeably use the terms "pooled" and "unrated" in the rest of the paper. Second, banks may offer a "screening" contract specific to each borrower π where they require the payment of $r(\pi)$ consumption goods at the end of the period if the project is successful, and γR otherwise. Since the interest is differentiated across borrowers banks need to use their rating technology prior to lending in this case. In the rest of the paper, we will interchangeably refer to the borrowers who sign such a contract as "screened" or "rated".

2.1.1 Screening Contract

In the competitive equilibrium, a bank that screens borrower π charges the break-even rate $r(\pi)$ that satisfies the following condition:

$$\pi r(\pi) + (1-\pi)\gamma R = 1 + s + \kappa^r \quad \forall \pi \tag{1}$$

The term on the left hand side is the expected payment made to the bank at the end of the period per unit of loan. The bank receives the full payment of the loan with probability π, or seizes the outcome of the unsuccessful project γR with probability $1-\pi$. The term on the right hand side is the bank's cost of funds. The bank has to pay one unit of consumption goods at the end of the period and the screening cost s, and has to make enough profit κ^r to comply with the capital management rule. Relation (1) implies that the break-even rate decreases with the probability of success: the better the entrepreneur, the lower the interest rate. This negative relationship between the interest rate and the quality of rated loans is crucial because it implies that rating is more valuable to high quality than to low quality borrowers. As a consequence, only the best borrowers are willing to provide enough information to the banks and be rated.

2.1.2 Pooling Contract

Banks can also offer a debt contract common to a pool of borrowers. To derive such pooling contract, we start by identifying the pool of the entrepreneurs that are potentially interested in it. On the one hand, relation (1) implies that those can only be the low quality borrowers. We denote by $\overline{\pi}$ the success probability of the best entrepreneur in the pool. Entrepreneur $\overline{\pi}$ is such that the interest rates of the pooling and screening contracts are equal:

$$r(\underline{\pi}) = r(\overline{\pi}) \tag{2}$$

where $r(.)$ is defined by relation (1). On the other hand, only the agents with a probability of success that is high enough are willing to undertake their project. The other agents prefer to supply labour. Hence, entrepreneur $\underline{\pi}$ is indifferent between undertaking his project and supplying labour:

$$\underline{\pi}\left(R - r\left(\underline{\pi}\right)\right) = \lambda \tag{3}$$

The left hand side of relation (3) is the expected utility derived from the project. When it is successful (with probability $\underline{\pi}$) the entrepreneur produces R and reimburses $r\left(\underline{\pi}\right)$ to the bank. When the project fails, the entrepreneur gets zero. The right hand side of relation (3) is the expected gain from being a worker, who gets one unit of consumption good at the end of the period with probability λ and is unemployed otherwise.

Only the borrowers in interval $[\underline{\pi}, \overline{\pi})$ opt for the pooling contract. Borrowers in interval $[\overline{\pi}, 1]$ prefer to be screened, while the other agents, in interval $[0, \underline{\pi})$, supply labour. Given the quality of the pool, the equilibrium break-even interest rate on the pooling contract $r\left(\underline{\pi}\right)$ satisfies relation (4):

$$\int_{\underline{\pi}}^{\overline{\pi}} \left[\pi r\left(\underline{\pi}\right) + (1-\pi)\,\gamma R\right] d\pi = \int_{\underline{\pi}}^{\overline{\pi}} (1+\kappa^u) d\pi \tag{4}$$

where the left hand side corresponds the payment expected from the pool, and the right hand side corresponds to the bank's cost of funding the pool (including the minimum required capital κ^u).

2.2 Credit Market Equilibrium

In order to have investment in the equilibrium, we set parameters such that at least the best entrepreneur ($\pi = 1$) is willing to run his project (Assumption 1).

Assumption 1 *(Rated borrowers participation condition)*: $R > 1 + s + \kappa^r + \lambda$

The above participation condition means that the net return of entrepreneur $\pi = 1$'s project is higher than the opportunity cost λ. In addition, we set the parameters in order to have rated loans in the equilibrium (Assumption 2).

Assumption 2 *(The best entrepreneur prefers to be rated)*: $R > 1 + s + \kappa^r + \lambda \frac{(1-\gamma)(1+s+\kappa^r)}{1+2\kappa^u - s - \kappa^r - \gamma R + \gamma\lambda}$

Assumption 2 means that entrepreneur $\pi = 1$ prefers to be rated than unrated. Together with Assumption 1, it ensures that there is some screening in the equilibrium. The intuition is the following. A high return R gives incentive to low quality entrepreneurs to undertake their project. While entering the credit market, these entrepreneurs lower the quality of the pool of unrated borrowers, which works to increase the risk premium and the interest rate on the unrated contract, and pushes the best entrepreneurs toward the screening contract. Thus, the screening contracts are all the more attractive to the best entrepreneurs than R is high. To obtain an equilibrium with unrated loans, we also assume that the screening cost is high enough so that unrated contracts are competitive against rated contracts (Assumption 3).

Assumption 3 *(Screening contracts do not dominate the pooling contract)*: $s > \kappa^u - \kappa^r$

Finally, we rule out the cases where all agents undertake their project by assuming that the opportunity cost of running the project is high enough so that at least agent $\pi = 0$ prefers to supply labour (Assumption 4).

Assumption 4 *(Strictly positive labour supply)*: $\lambda > s + \kappa^r + \gamma R - 1 - 2\kappa^u$

Altogether, Assumptions 1 to 4 rule out the uninteresting corner solutions with either no investment, or no screening, or no pooling, or no labour supply in the equilibrium, so that a non-trivial credit market equilibrium exists.[6] It is easy to check that the set of parameters that satisfies these assumptions is not empty (see Table 1 in Section 2.3). Under these assumptions, the equilibrium of the credit market can be described by Proposition 1.

Proposition 1: *In the presence of asymmetric information, under Assumptions 1-4, a non-trivial credit market equilibrium exists and is characterized by:*

$$\begin{cases} r^*(\pi) & = \begin{cases} \frac{1+2\kappa^u-s-\kappa^r-\gamma R+\gamma\lambda}{1+2\kappa^u-s-\kappa^r-\gamma R+\lambda} R & \forall \pi \in [\underline{\pi}^*, \overline{\pi}^*) \\ \\ \frac{1+s+\kappa^r}{\pi} - \frac{(1-\pi)\gamma R}{\pi} & \forall \pi \in [\overline{\pi}^*, 1] \end{cases} \\ \\ \underline{\pi}^* & = \frac{1+2\kappa^u-s-\kappa^r-\gamma R+\lambda}{(1-\gamma)R} \\ \\ \overline{\pi}^* & = \frac{1+s+\kappa^r-\gamma R}{1+2\kappa^u-s-\kappa^r-\gamma R} \frac{1+2\kappa^u-s-\kappa^r-\gamma R+\lambda}{(1-\gamma)R} \end{cases}$$

Proof: Follows directly from relations (1) to (4).

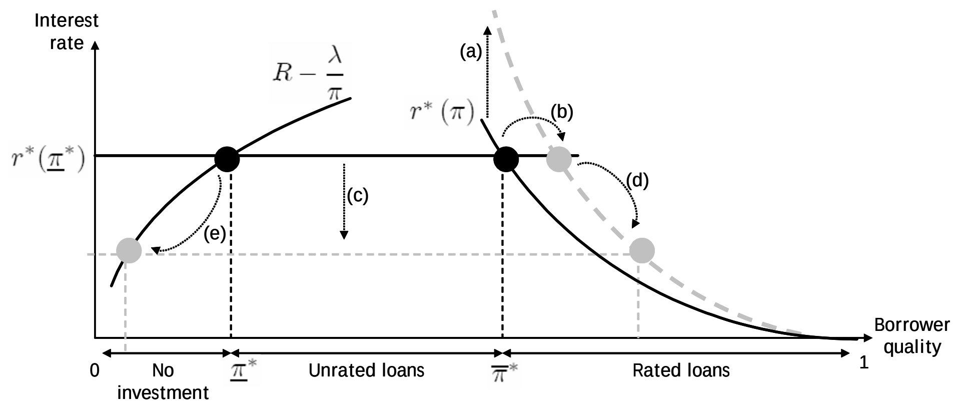
Corollary 1: *In the equilibrium, the aggregate amount of credit is equal to:*

$$L^*(R) = 1 - \underline{\pi}^* = \frac{R + s + \kappa^r - 1 - 2\kappa^u - \lambda}{(1-\gamma)R}$$

Not surprisingly, aggregate credit increases with the return of the project R and diminishes with the amount of capital required on unrated loans (κ^u). The key, non trivial, result of our simple model is the positive effect of the capital required on rated loans (κ^r) on aggregate credit. In line with De Meza and Webb (1987), the presence of information asymmetries gives low quality entrepreneurs the opportunity to free ride on higher quality entrepreneurs, to obtain the same financing conditions as the latter, and to invest despite low net present value projects. This generates over-investment in equilibrium. In contrast with De Meza and Webb, however, banks have the ability to limit these information asymmetries by screening their borrowers. The lower the cost of screening, the less stringent the free riding problem, and the lower over-investment. The capital required on rated loan contracts κ^r can be interpreted, *ceteris paribus*, as an additional screening cost. Proposition 1 shows that it affects banks' incentive to rate borrowers or, equivalently, borrowers' incentive to be rated the same way as the screening cost s. (What matters is $\kappa^r + s$.) To understand the mechanics of the model, we describe in Figure 1 the impact of a rise in κ^r (for example, owing to an increase in loss-given-default, LGD). It first implies a rise in the interest rate on rated loans $r^*(\pi)$ (a), which then become less attractive to borrowers in general, and to the best borrowers in particular. Given the equilibrium interest rate on the unrated loans $r^*(\underline{\pi})$, some high quality borrowers are willing to switch from the rated to the unrated loan (b). As these borrowers enter the pool of unrated borrowers, the quality of the pool increases, which in turn works to diminish the interest rate on the unrated loan (c). It follows not only a further inflow of high quality borrowers (d), but also the entry of new, low quality borrowers, which could not previously invest, into the credit market (e). Ultimately, the aggregate amount of lending to the economy increases.

[6] Assumptions 1-4 respectively imply that (i) $R - r^*(1) > \lambda$, (ii) $r^*(1) < \widehat{r}^*$, (iii) $\underline{\pi}^* < \overline{\pi}^*$, and (iv) $\underline{\pi}^* > 0$ in the equilibrium (see Proposition 1).

Figure 1: Effect of an increase in κ^r



2.3 Cyclical Effects of Flat-rate versus Risk-based Capital Rules

We now turn to the discussion on the cyclical effects of flat-rate versus risk-based capital ratios, and consider the two distinct capital management rules defined in Assumption 5.

Assumption 5 *(Capital management rules)*: $\kappa^r = \kappa^u = \kappa > 0$ under the flat-rate rule, and $\kappa^u = \frac{\kappa}{3-\mu}$ and $\kappa^r = \left[\mu - \frac{1+s-\gamma\overline{R}}{1+s-\gamma R}\right]\frac{\kappa}{3-\mu}$ under the risk-sensitive rule, with $1 < \mu < 2$

Assumption 5 states that under the flat-rate rule the capital ratio is constant over the business cycle, with no distinction between rated and unrated loans. In contrast, under the risk-sensitive rule the capital ratio is time-invariant for unrated loans but increases with risk for rated loans. In our model, risk is reflected through the bank's loss given default, defined as the difference between the cost of the rated loan and what the bank gets when the project fails, $1 + s - \gamma R$ (see the denominator in the expression of κ^r). We model the risk sensitivity of capital as a negative relationship between capital and the loss given default. As defined, the risk-sensitive rule satisfies two convenient properties. First, for comparability purpose, it is normalised in such a way that the aggregate amount of credit is the same under the risk-sensitive rule as under the flat-rate rule when $R = \overline{R}$.[7] By construction, the productivity level $\overline{R}$ corresponds to the point in the business cycle where the capital management rule does not have any effect on output. Second, the condition $1 < \mu < 2$ ensures that the level of capital required on rated loans is positive and lower than the one required on unrated loans when $R = \overline{R}$. We now discuss the cyclical behaviour of the economy by analysing the response of aggregate credit to a positive deviation of productivity R from the reference level $\overline{R}$. Denoting this deviation by $\Delta R = R - \overline{R} > 0$ and the response of aggregate credit by ΔL, Corollary 2 follows directly from Corollary 1 and Assumption 5.

Corollary 2: *Credit is less cyclical under the risk-sensitive capital rule than under the risk-insensitive*

[7] It is easy to check that under both rules, $2\kappa^u - \kappa^r = \kappa$ when $R = \overline{R}$, which implies the same equilibrium levels of credit in this case (see Corollary 1).

capital rule:

$$\begin{cases} \Delta L_{|\text{risk-sens.}} & = \frac{1+\kappa+\lambda-s}{(1-\gamma)R\overline{R}}\Delta R + \frac{1}{(1-\gamma)R}\Delta\kappa^r \quad \textit{(semi-reduced form)} \\ & = \frac{1+\kappa+\lambda-s}{(1-\gamma)R\overline{R}}\Delta R - \frac{\gamma\kappa}{(1+s-\gamma R)(3-\mu)(1-\gamma)R}\Delta R \quad \textit{(reduced form)} \\ \Delta L_{|\text{risk-insens.}} & = \frac{1+\kappa+\lambda-s}{(1-\gamma)R\overline{R}}\Delta R > \frac{\Delta L}{\Delta R}_{|\text{risk-sens.}} \end{cases}$$

Credit is less cyclical under the risk-sensitive rule than under the flat-rate rule. The key mechanism behind Corollary 2 relies on the notion that, under a risk-sensitive rule, banks' opportunity cost of screening is positively related to the capital required on rated loans and, therefore, counter-cyclical. It is lower in good times than in bad times. In contrast, banks' opportunity cost of pooling borrowers is constant throughout the business cycle. The rest of the mechanism follows directly from Proposition 1. For the sake of completeness, it is interesting to compare the responses of the economy to exogenous oscillations of the productivity parameter R around its reference level $\overline{R}$. To do so, we parameterize the model such that Assumptions 1-4 hold throughout the productivity cycle (see Table 1), and take the equilibrium of the economy when $R = \overline{R}$ as baseline (see Table 2).[8]

Table 1. Parameters

$\overline{R}$	s	γ	λ	κ	μ
1.5	0.1	0.5	0.1	0.08	1.8

In our parameterization the screening costs amounts to 10% of the loan, unsuccessful projects yield half of the gross return of successful projects, and workers' probability to find a job is equal to 10%. Banks are required to retain earnings equal to 8% of the amount of the loans under the flat-rate rule. Finally, we arbitrarily set the parameter μ of the risk-sensitive rule to 1.8. The corresponding baseline equilibrium is described in Table 2. In this economy, 56% of the agents undertake their project. The other agents do not invest because the 27% interest rate of the pooling loan contract is too high to make it worth investing, rather than supplying labour. Notice that in the baseline, capital requirements are lower under risk-sensitive rule than under the flat-rate rule, for both rated and unrated loans (5% and 7% against 8%, respectively): the capital required on unrated loans is lower under risk-sensitive rule in order to exactly compensate for the negative effect of having lower capital requirements on rated loans under risk-sensitive rule. Finally, since in risk-sensitive rule the capital required is lower on rated loans than on unrated loans, there are relatively more rated loans under this rule (i.e. 41% of total loans against 32% under the flat-rate rule).

Table 2. Baseline equilibrium (when $R = \overline{R}$)

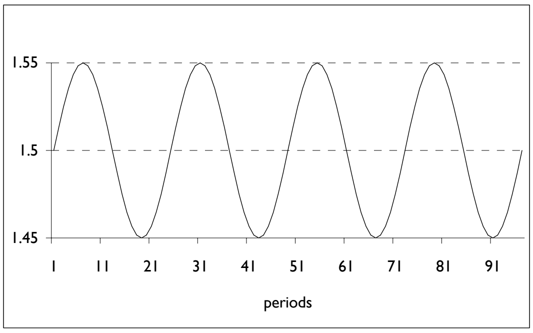
Both		Flat-rate			Risk-based		
$\underline{\pi}^*$	$r(\underline{\pi})^*$	κ^u	κ^r	$\overline{\pi}^*$	κ^u	κ^r	$\overline{\pi}^*$
44%	1.27	8%	8%	82%	7%	5%	77%

The response of the economies under the flat-rate rule and the risk-sensitive rule, respectively, to the productivity cycle are described in Figure 2a-e. By assumption, the productivity R oscillates between 1.45 and 1.55 over time, with a reference level at $\overline{R} = 1.5$ (Figure 2a). In line with the conventional wisdom, minimum capital required on rated loans under the risk-sensitive rule has a counter-cyclical

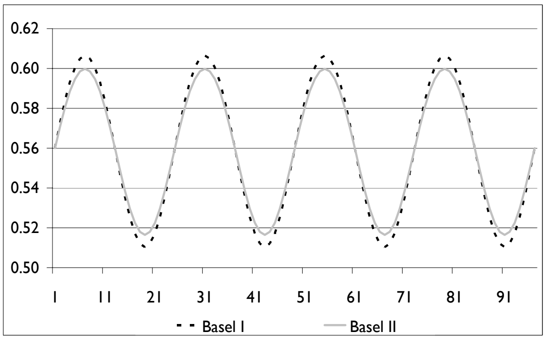
[8] Remember that in this case the two rules imply the same level of aggregate credit.

behaviour and is always below that on unrated loans throughout the productivity cycle, whereas in the flat-rate rule required capital remains constant at 8% (see Figure 2c). Under the risk-sensitive rule, the decrease in the level of capital required on rated loans diminishes the cost of rated loans with respect to unrated loans, which attracts unrated borrowers toward the rated loans. As a result, the proportion of rated to unrated loans increases disproportionately in the economy under the risk-sensitive rule (compare the dotted black lines with the plain grey lines in Figure 2e),[9] the pool of unrated loans becomes riskier, and the cost of borrowing to the marginal entrepreneur rises above that of the economy under the flat-rate rule (plain grey versus dotted black lines in Figure 2d). The key result of our model is the impact of required capital on aggregate credit (Figure 2b): ultimately, the increase in the marginal lending rate deters the entry of new entrepreneurs and limits the initial effect of the productivity rise on aggregate credit

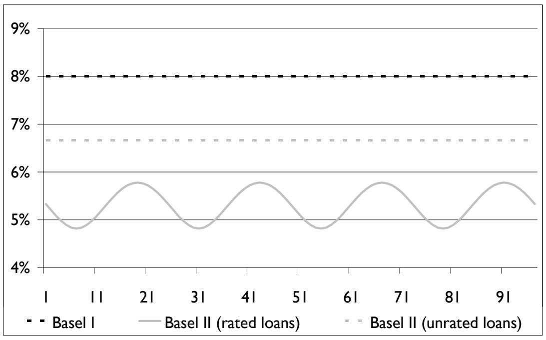
Figure 2: Responses of financing conditions to the productivity cycle



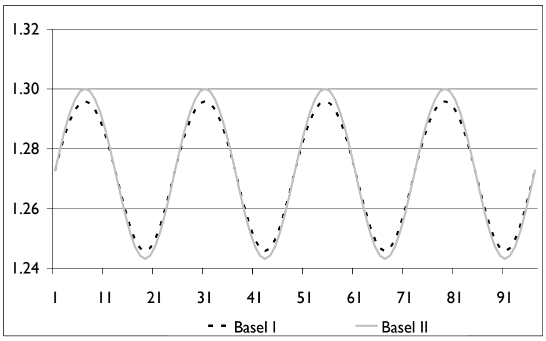
(a) Exogenous productivity cycle (R)



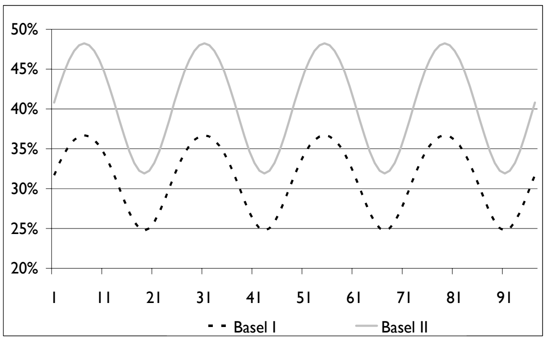
(b) Credit (L)



(c) Minimum required capital (κ^p, κ^s)



(d) Marginal lending rate ($r(\underline{\pi})$)



(e) Proportion of rated loans

[9] The proportion of rated loans is defined as $\frac{1-\overline{\pi}^*}{1-\underline{\pi}^*}$.

2.4 Discussion

As is well known, frictions on the credit market generate inefficiencies in the allocation of resources. On the one hand, they generate under-investment due to credit rationing, as in Stiglitz and Weiss (1981). On the other hand, they generate over-investment in the sense that borrowers undertake negative net present value projects, as in De Meza and Webb (1987). Overall, the consequences of credit market frictions on the level, but also the dynamics, of aggregate lending are unclear: they may have either a financial accelerator effect (Bernanke and Gertler, 1989), or a stabilizer effect (House, 2006). In general, two conditions are required for stabilization or acceleration. First, in both cases, credit market frictions must be counter-cyclical, i.e. decrease in good times and increase in bad times. Second, these frictions must also be able to cause either over-investment (for stabilization) or under-investment (for acceleration). In our theoretical framework a risk-based capital rule exerts a counter-cyclical effect on credit market frictions: it lowers (raises) banks' opportunity cost of rating borrowers in good (bad) times. While a model of credit rationing would make a risk-based capital rule have pro-cyclical effects on lending, we chose to focus on a model à la De Meza and Webb, with over-investment. This choice serves two purposes. On the one hand, we are able to describe one theoretical mechanism through which a risk-based capital rule generates a stabilizing effect, and therefore to propose an alternative view with respect to the existing literature. On the other hand, we believe the over-investment model fits better the recent period than the credit rationing model, insofar as the loosening of credit standards is often put forward as one of the major factors underlying the current financial crisis (Financial Stability Forum, 2008).

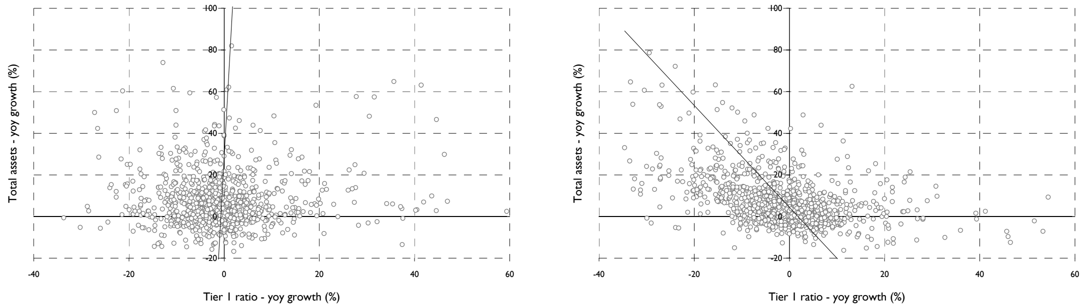
3 Empirical Analysis

The aim of this section is to document the relationship between the risk-sensitivity of bank capital and the sensitivity of bank lending to the business cycle. We test directly whether credit supply is more elastic to GDP for banks with a counter-cyclical capital ratio than for other banks. We use a quarterly balance sheet data set for a panel of 206 US banks over the period 2003-2007. Our test strategy is twofold.

In a first step, we separate the banks whose capital has been observationally the most negatively correlated with total assets ("risk-sensitive" banks) from the banks whose capital has been the least negatively correlated ("risk-insensitive" banks). We rank banks based on their elasticity of Tier one capital ratio to total assets. We compute this elasticity for each bank and assign to the "risk-sensitive" ("risk-insensitive") group those banks in the bottom (top) half of the cross-sectional distribution of elasticities.[10] The cross-sectional dispersion shows large disparities across banks (see Figure 3). By construction, for the risk-sensitive banks the growth rate of the Tier one ratio is significantly and negatively related to the growth rate of total assets, while for risk-insensitive banks there is no such clear pattern (see also Table 3.1.3).

[10] Those are banks whose elasticity is below (above) the median of the sample -0.28. Bank i's elasticity corresponds to the estimates of β_i in the model: $(tier_{it} - tier_{it-4})/tier_{it-4} = \alpha_i + \beta_i(assets_{it} - assets_{it-4})/assets_{it-4} + \varepsilon_{it}$ where $(tier_{it} - tier_{it-4})/tier_{it-4}$ is bank i's year-on-year growth rate of Tier 1 capital ratio, and $(assets_{it} - assets_{it-4})/assets_{it-4}$ is bank i's year-on-year growth rate of total assets. We computed the elasticities using on average 13 quarterly observations per bank. Our results do not change when we use simple correlations between the growth rate of the Tier one ratio and the growth rate of assets.

Figure 3: Total assets and Tier one ratios of US bank holdings (2003-2007)



Basel-I group Basel-II group

The above figure is a scatter chart of the year-on-year change in Tier one ratio (x-axis) against the year-on-year change in total assets (y-axis) for the two groups of banks. The observations correspond to the bank-quarter observations in our panel data set. The lines correspond to the fitted values of the growth rate of the Tier one ratio projected on the growth rate of total assets.

In the second step, we estimate a standard credit growth model, which relates credit growth to past GDP growth, and test the difference in the credit to GDP elasticities across the two groups of banks. Our empirical model is based on the reduced form in Corollary 2:

$$\begin{aligned} \Delta_1 Loans_{i,t} = \quad & \alpha_0 + \alpha_1 B1_i * \Delta_4 GDP_{s_i,t-1} + \alpha_2 B2_i * \Delta_4 GDP_{s_i,t-1} \\ & + \beta_1 B1_i + \beta_2 lnassets_i + \beta_3 \epsilon_{si} + \beta_4 e_t + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where $B1_i$ is a dummy variable equal to 1 if bank i is a "risk-insensitive" bank, and to zero otherwise, $B2_i = 1 - B1_i$, Δ_j is the growth rate operator[11], $\Delta_1 Loans_{i,t}$ is the growth rate of bank i's real customer loans between quarters $t-1$ and t, and $\Delta_4 GDP_{s_i t-1}$ is the year-on-year growth rate of real GDP in bank i's state s_i between quarters $t-5$ and $t-1$. In our baseline model, we also include the logarithm of the sample average of real total assets of bank i, $lnassets_i$, as well as state and (quarterly) time fixed effects, ϵ_{si} and e_t, respectively, in order to control for bank characteristics. All variables are in volume, that is, deflated using the US national GDP deflator.

Test Strategy Our theory's prediction concerns the change in customer loans in response to GDP, captured by the coefficients α_1 and α_2. We test the null hypothesis:

$$H0 : \alpha_1 - \alpha_2 > 0$$

and would conclude that risk-based capital management has a pro-cyclical effect on the credit cycle if we reject $H0$. The logic behind this test is the following. If the counter-cyclicality of capital to asset ratio implied by a risk-sensitive capital management indeed works to amplify the credit cycle, as argued by the pro-cyclicality literature, then we should observe, *ceteris paribus*, that banks with historically counter-cyclical capital ratios (risk-sensitive banks) have had a particularly more pro-cyclical supply of credit than the other banks, and so: $\alpha_2 > \alpha_1$. In contrast, if we do not observe more pro-cyclical lending from risk-sensitive banks (i.e. $\alpha_2 \leqslant \alpha_1$), then we would conclude that some counter-cyclical forces of the type described in our theoretical model are at work.

[11] By definition: $\Delta_j x_{it} = 100 * (x_{it} - x_{it-j})/x_{it-j}$

Direction of the Potential Bias Our results may potentially be affected by two types of bias. First, the partitioning of our sample into risk-sensitive and risk-insensitive banks is likely to affect our statistical test. In which direction would this bias go? Consider an economic boom, where the level of bank capital increases. Since we classify as risk-sensitive those banks whose assets rise the most when bank capital increases (i.e. whose capital to assets ratio decreases the most during booms), one would expect, everything being equal and by construction, that lending from those banks rise faster than lending from the banks classified as risk insensitive. In other terms, in line with the pro-cyclical literature and in the absence of counter-balancing forces, we would expect to reject our null hypothesis. Accepting H0 would suggest that some forces, for example due to the change in banks' portfolio composition over the business cycle (see section 2.3) counter-balance the positive effect of the decrease in bank capital on the credit supply. The second source of bias is related to the endogeneity of GDP. As is well known, the coefficients the coefficients α_1 and α_2 might be biased upward due to the potential endogeneity of GDP. While the lagged GDP that we use may to some extent help resorb this endogeneity bias, we do not expect the remaining endogeneity bias to affect our test in a material way. The reason is that our test is based on the difference between coefficient α_2 and α_1, and not on their levels. Our test could be affected if GDP were systematically more sensitive to the expected variations in credit supply from one of our two groups of banks. For example, if a one dollar loan originated with a flat capital banks generated more output than a one dollar loan originated with a risk-sensitive capital bank. This situation is however unlikely to the extent that the two groups are comparable in terms of asset size, Tier one ratio, and loans to assets ratio, as we report in Table 3.1.3. For the sake of completeness, we will control for potential reverse causality in the robustness checks (Table 3.2.4).

3.1 Data

Our data set includes quarterly balance sheet information for 206 US bank holdings from Thomson Financial Datastream (Worldscope) and Bureau Van Dijk (Bankscope) over the period 2003-2007. Quarterly bank level data are more appropriate than annual data to analyse the reaction of lending to the business cycle. Hence we restrict our analysis to the banks that provide quarterly balance sheets and to the recent period. Although our sample includes more observations for the years 2006 and 2007, Table 3.1.1 shows it is still overall reasonably well balanced over time.

Table 3.1.1: Sample distribution across time

	N	%
2003	453	14.90
2004	570	18.74
2005	560	18.41
2006	740	24.33
2007	718	23.61
Total	3,041	100.00

For the identification of the business cycle, we used the variations of GDP both over time and across US States. We prefer regional GDP to national GDP because our sample is too short to capture enough business cycle variations. Using the cross-sectional heterogeneity of GDP growth among US States helps identify more of those variations. ECB (2006) provides evidence that the variation across US states in real GDP growth is relatively large, or at least not significantly different from the cross-country variation within the euro area. Furthermore, despite the removal of barriers to inter-state banking in the US, the US banking sector remains relatively fragmented along regional lines (see e.g. Berger et al., 1995; and Heffernan, 2005). Another valuable advantage of regional GDP is that it helps disentangle the effects of banks' financing conditions (e.g. from the Federal Reserve or on the interbank market), which are the same across States, from the effects of the business cycle, which may differ across States. The distribution of our sample across States is reported in Table 3.1.2.

Table 3.1.2: Sample distribution across US States

States	Observations		Banks	
	N	%	N	%
California	319	10.5	19	9.2
New York	285	9.4	19	9.2
Pennsylvania	202	6.6	11	5.3
Illinois	201	6.6	16	7.8
Indiana	141	4.6	9	4.4
North Carolina	139	4.6	9	4.4
Texas	139	4.6	10	4.9
Michigan	133	4.4	7	3.4
Ohio	125	4.1	7	3.4
Georgia	115	3.8	6	2.9
Washington	102	3.4	7	3.4
Mississippi	99	3.3	6	2.9
New Jersey	82	2.7	6	2.9
Florida	77	2.5	6	2.9
Maryland	76	2.5	4	1.9
Kentucky	75	2.5	4	1.9
Others	731	23.9	60	29.1
Total	3,041	100	206	100

The partitioning of our sample based on the elasticity of the tier one ratio to total assets interestingly results in relatively similar groupings in terms of size, customer loan to asset ratio, and Tier one ratios; see Table 3.1.3.[12] While the slight difference in total assets (risk-insensitive banks being slightly larger) may reflect that it is primarily the larger banks that may have already adopted advanced credit risk management systems, this difference is not statistically significant. Only the average elasticity of the Tier one ratio to total assets differs, by construction, between the two groups. It is strictly negative for risk-sensitive banks and close to zero for risk-insensitive banks. For instance, a 1% decrease in total assets would be accompanied with an increase of the Tier one capital ratio by 0.6% for the median risk-senstive bank, whereas it would hardly affect the median risk-insensitive bank's capital position.

[12] Our sample is winsorized at 1%. Due to missing observations, the total number of observations for the Tier one ratio is smaller than the sample size.

Table 3.1.3: Descriptive statistics of key variables

	Total assets (millions, 2000$)	Customer loans to assets ratio (%)	Tier 1 ratio (%)	Elasticity of Tier 1 ratio to total assets
Risk-insensitive				
1%	603	29.2	6.14	-0.28
median	2,805	67.2	10.5	0.05
mean	32,780	65.6	11.4	0.16
99%	1,141,415	90.1	29.3	1.54
N	1,446	1,446	1,244	1,446
Risk-sensitive				
1%	704	36.0	7.1	-2.44
median	2,320	66.8	10.6	-0.60
mean	40,486	65.9	11.1	-0.76
99%	1,218,022	88.1	17.6	-0.29
N	1,595	1,595	1,345	1,595
All				
1%	693	31.7	7.0	-2.20
median	2,681	67.0	10.6	-0.33
mean	36,822	65.7	11.2	-0.32
99%	1,143,359	89.4	24.3	1.28
N	3,041	3,041	2,589	3,041

3.2 Results

We now turn to the estimation of our empirical model (5). Since regional GDP is not available at the quarterly frequency we interpolate the annual regional data with a geometric trend to obtain a quarterly series.[13] The results are reported in Table 3.2.1. We find in Model 1, our baseline, that the elasticity of credit supply to GDP is higher for risk-insensitive than for risk-sensitive banks. Although the difference between the two groups is not statistically significant, the elasticity of credit to GDP is significantly positive for risk-insensitive banks, whereas it is not different from zero for risk-sensitive banks. Note that a zero elasticity of credit to regional GDP does not mean that credit is not sensitive to the business cycle, since the model includes time fixed effects. In other terms, the coefficients α_1 and α_2 must be interpreted as the effects of regional GDP on bank lending, net of the effects of national GDP. The result is robust to including bank fixed effects into the model (Model 2): the elasticity of credit to GDP remains significantly positive for risk-insensitive banks and null for risk-sensitive banks.

In Model 3, we furthermore interact the time fixed effects together with the group dummies, i.e. re-estimate the model with the interaction terms $B1_i * e_t$. We do this in order to control for banks' financing conditions. The rationale behind this check is the following. While the time fixed effects control both for national GDP growth and banks' general financing conditions, it might still be that the cyclical evolution of banks' financing conditions differs across the two groups of banks. This might potentialy bias $\alpha_1 - \alpha_2$ in two opposite directions. Assume first that risk-sensitive banks get a relatively cheaper access to external funds in good times than risk-insensitive banks. Other things equal, one

[13] The way we interpolate does not materially affect the results (e.g. using quarterly real disposable income or employment data).

would then expect lending from risk-sensitive banks to be more sensitive to the business cycle and so $\alpha_1 - \alpha_2$ to be biased downward. On the contrary, one could equally assume that the external financing conditions deteriorate relatively more in bad times for risk-insensitive banks than for risk-sensitive banks, reflecting some "flight-to-quality" effect. In this case, we would expect a higher elasticity of lending for risk-insensitive banks and $\alpha_1 - \alpha_2$ would be biased upward. The interaction of the time fixed effects with the capital rule dummies controls for such effects. The results from this model extension are essentially similar to those of Model 2, but now the elasticity of credit to GDP for risk-insensitive banks is significantly larger than for risk-sensitive banks (at the 5% threshold). Notice that the widening of the elasticity gap between the two groups of banks in the presence of interaction terms suggests that $\alpha_1 - \alpha_2$ was biased downward in Models 1 and 2, and goes against a flight-to-quality type of mechanism.

Since our sample overlaps with the first two quarters of the financial turmoil, which started in July-August 2007, in Model 4 we interact the group-specific credit elasticities with dummies defined as "pre-turmoil" and "turmoil" dummies. The results indicate that our analysis is robust to the structural changes that might have occurred in the second half of 2007, in the sense that lending by risk-insensitive banks is still found to display significantly larger sensitivity to GDP than lending by risk-sensitive banks, irrespective of the turmoil.

Table 3.2.1 Results

Dependent variable: Customer loan growth (i,t)	Model 1	Model 2	Model 3	Model 4
Independent variables:	Baseline	Model 1 + fixed effects	Model 2 + group-specific time dummies	Model 3 + turmoil interactions
Constant	1.89 (1.59)	2.24^{**} (2.44)	2.47^{**} (2.34)	0.27 (0.22)
GDP(State i,t)				
Risk-insensitive banks (I)	0.31^{**} (2.03)	0.37^{**} (2.48)	0.45^{**} (2.87)	-
pre-turmoil (pre-I)	-	-	-	0.48^{**} (2.82)
turmoil (turm-I)	-	-	-	0.39^{*} (1.78)
Risk-sensitive banks (II)	0.17 (1.17)	0.11 (0.67)	0.06 (0.37)	-
pre-turmoil (pre-II)	-	-	-	0.11 (0.67)
turmoil (turm-II)	-	-	-	-0.08 (-0.30)
Flat-rate rule dummy (i)	-0.13 (-0.26)	-	-	-
log assets (i)	-0.17^{*} (-1.70)	-	-	-
p-value H0: (I)>(II)	0.22	0.12	0.05^{**}	-
p-value H0: (pre-I)>(pre-II)	-	-	-	0.07^{*}
p-value H0: (turm-I)>(turm-II)	-	-	-	0.09^{*}
N	3,041	3,041	3,041	3,041
R^2	0.14	0.10	0.11	0.06

The endogenous variable is the growth rate of real customer loans of bank i in quarter t. GDP(State i,t) is the year-on-year growth rate of real GDP in the state of bank i in quarter t, interacted with the group dummies. The (risk-insensitive) group *dummy is equal to one if the elasticity of Tier one ratio to total assets for bank i is above -0.28, and to zero otherwise. Model 1 includes 39 state dummies and 19 quarterly dummies. Model 2-4 include 19 quarterly time dummies and bank fixed effects. In Model 3, the group dummy is interacted with the 19 quarterly dummies. In model 4, the interaction term GDP*group dummy is further interacted with the turmoil dummy, which is equal to one in 2007Q3 and 2007Q4, and to zero otherwise. The t-statistics (in parentheses) are calculated using robust standard errors adjusted for clustering at the bank level. **, * : significant at the 5% and 10% level, respectively.*

Next, we perform a first series of robustness checks, starting with three alternative schemes of partitioning the sample (see Table 3.2.3). In Model 5 we classify banks on the basis of their reliance on non-deposit funding. We rank bank/quarter observations based on the customer loan to deposit ratio and assign to the risk-sensitive group in a given quarter those banks in the top half of the distribution. The reasoning behind this scheme is that banks that to a large extent fund themselves in the public debt markets are more subject to market discipline than are traditional banks relying predominantly on core deposits. We conjecture that market disciplined banks are more likely to be risk-sensitive, to the extent that the market is more likely to force them actively manage their capital in line with their credit risk. Our second alternative partitioning scheme consists in simply dividing banks by size (Model 6). We rank bank/quarter observations based on asset size and assign to the risk-sensitive group in a given quarter those banks in the top half of the distribution. In this case, the classification is based on the idea that bigger and more sophisticated banks are more likely to have already introduced advanced credit risk models, and one would expect capital management in those banks to be relatively more sensitive to credit risk.[14] Table 3.2.2 compares these two classification schemes with our baseline partition. While the two alternative schemes are quite correlated, our baseline scheme based on the elasticities of Tier one ratio to total assets yields a specific partition of the sample. In particular, the majority of the banks classified as risk-sensitive with the baseline scheme are classified as "risk-insensitive" with the two other schemes, and vice versa.

Table 3.2.2: Cross-classification criteria

	Tier one elasticity		Loans to deposit		Asset size	
	insens.	sens.	insens.	sens.	insens.	sens.
1. Elasticity of Tier one ratio to assets						
insensitive	1,446		727	719	661	785
sensitive		1,595	818	777	855	740
2. Customer loans to deposit ratio						
insensitive			1,545		833	712
sensitive				1,496	683	813
3. Asset size						
insensitive					1,516	
sensitive						1,525

Reading: The first classification scheme, based on the elasticity of the Tier one ratio to total assets, partitions the sample into 1,446 bank-quarter observations related to risk-insensitive banks, and 1,595 observations related to risk-sensitive banks. Among the latter, 818 are classified as related to risk-insensitive banks with the second classification scheme (based on the loan to deposit ratio).

[14] As there are most likely threshold fixed costs of introducing such models and systems.

For the results of the estimations see Table 3.2.3. Models 5 and 6 do not show any significant differences between risk-insensitive and risk-sensitive banks. The elasticity of credit to GDP is still slightly higher for risk-insensitive than for risk-sensitive banks in Model 5, and there is no difference at all in Model 6. These results do not point to a pro-cyclical effect of a risk sensitive capital management. Finally, we consider a third partition based on the geographical zone. In Model 7 we add to our sample the European banks for which quarterly balance sheets were available over the sample period, and assign the US and the European banks to the "risk-insensitive" and "risk-sensitive" groups, respectively. This partition relies on the idea that Basel II's implementation process is more advanced for EU banks than for US banks, and that European banks are therefore a priori more likely to already manage their capital in line with their credit risk.[15] Due to the scarcity of quarterly balance sheet data for European banks, we included in the sample both bank holdings and commercial banks. Ultimately, the "risk-sensitive" group includes 34 European banks against 236 US banks for the "risk-insensitive" group.[16] The results confirm our previous finding: European banks have had a significantly less cyclical lending behaviour than US banks at the 10% threshold.

Table 3.2.3: Alternative partition schemes

Dependent variable: Customer loan growth (i,t)	Model 5	Model 6	Model 7
Independent variables:	Model 3 with partition based on market discip.	Model 3 with partition based on asset size	Model 3 with EU vs US partition
Constant	2.14^{**} (3.75)	2.61^{**} (2.79)	2.26^{**} (2.46)
GDP(State i,t)			
insensitive banks (I)	0.24 (1.27)	0.22 (1.34)	0.15 (1.20)
sensitive banks (II)	0.19 (1.33)	0.24 (1.44)	-0.49 (-0.98)
Real personal income(State i,t)			
insensitive banks (I)	-	-	-
sensitive banks (II)	-	-	-
p-value H0: (I)>(II)	0.41	0.54	0.10^{*}
N	3,041	3,041	3,649
R^2	0.08	0.10	0.14

The endogenous variable is the growth rate of real customer loans of bank i in quarter t. GDP(State i,t) is the year-on-year growth rate of real GDP in the state of bank i in quarter t, interacted with the group dummies. Here the definition of the flat-rate rule dummies depends on which classification scheme is considered. In Model 5, this dummy is equal to one if the loan-to-deposit ratio of bank i in quarter t is below the sample median (67%) and to zero otherwise. In Model 6, it is equal to one if the total assets of bank i in quarter t is below the sample median ($2,681 million in 2000 dollars), and to zero otherwise. In Model 7, it is equal to one for the US banks, and to zero for the European banks. All models include 19

[15] In the EU, the Capital Adequacy Directive implementing the Basel II framework was introduced as of 2007, whereas in the US the implementation of Basel II is still pending.

[16] We could obtain quarterly data for only 5 European bank holdings, which represent only 2% of the total number of observations. When we include commercial banks, this proportion goes up to 10%. Although one may argue that commercial banks may behave in a very different way from bank holdings, we prefered to present the results based on this larger sample. We however checked that our results still hold with the shorter sample of bank holdings only.

*quarterly time dummies and bank fixed effects. The t-statistics (in parentheses) are calculated using robust standard errors adjusted for clustering at the bank level. **, * : significant at the 5% and 10% level, respectively.*

Finally, we complement the robustness checks with Models 8-11 (Table 3.2.4). In Model 8 we replace the growth rate of regional GDP with the growth rate of the regional real personal income, which is available at the quarterly frequency for US States. The results still hold. The difference between risk-insensitive and risk-sensitive banks continues to be statistically significant. To make sure that our results are not driven by reverse causality, we use instruments in Model 9. For each state, we first estimate the year-on-year growth rate of regional GDP as a function of national GDP growth lagged by one to four quarters as well as a time trend. Then, we use the fitted value as explanatory variable in the model. Lagged national GDP is a licit instrument to the extent that it is not correlated with the error terms in the model. Note that the error terms are cleansed of time and bank fixed effects and therefore only capture random shocks to a given bank in a given quarter. Under the reasonable assumption that most banks are small enough to have a limited regional scope, and by virtue of atomicity, such random shocks are unlikely to affect the aggregate national GDP. We therefore expect the potential endogeneity problem, if any, to be less severe with the fitted regional GDP growth than with regional GDP itself. The comparison between Models 3 and 9 shows that the results are hardly affected by the instruments: the elasticity of credit to GDP is still significantly positive in the case of risk-insensitive banks, while not different from zero in the case of risk-sensitive banks. We take this result as evidence that our model indeed captures the effects of GDP on bank lending, and not the reverse effect of bank loans on regional GDP. In Models 10 and 11 we further control for potential reverse causality by splitting the sample into small and large banks. The classification is based on banks' size with respect to regional GDP: the group of small banks includes banks whose loan-to-state GDP ratio is below 2% (i.e. the sample median), whereas the group of large banks includes banks above 2%. The contention here is that one would expect an increase in lending by banks with a large market share (large banks) to affect regional GDP by far more than the same increase in lending by small banks. If the positive elasticity gap that we find between risk-insensitive and risk-sensitive banks is due to such reverse causality, then we would find that the elasticity of credit to GDP is higher for the banks with a larger market share. However, we do not find such an effect when comparing Models 10 and 11.

Table 3.2.4: Control for reverse causality

Dependent variable: Customer loan growth (i,t)	Model 8	Model 9	Model 10	Model 11
	Model 3 with real	Model 3 with	Model 3 with sample of	
Independent variables:	personal income	instrumental variables	small banks	large banks
Constant	1.76 (1.58)	2.10^* (1.91)	-0.20 (0.75)	2.65^{**} (2.04)
GDP(State i,t)				
Risk-insensitive banks (I)	0.24^* (1.65)	0.49^{**} (2.38)	0.51^{**} (2.31)	0.49^{**} (2.09)
Risk-sensitive banks (II)	-0.06 (1.17)	0.18 (0.79)	0.05 (0.23)	0.07 (0.26)
p-value H0: (I)>(II)	0.09^*	0.15	0.08^*	0.12
N	3,041	3,041	1,520	1,521
R^2	0.14	0.11	0.09	0.14

The endogenous variable is the growth rate of real customer loans of bank i in quarter t. In Model 8 GDP(State i,t) is defined as the year-on-year growth rate of real disposable income in the state of bank i in quarter t, interacted with the group *dummy. In Model 9, it is defined as the fitted value of the first stage OLS regression of the year-on-year growth rate of real GDP in the state of bank i in quarter t on the lagged values of the real national GDP growth and a time trend, interacted with the group dummies. In Model 10 and 11, it is defined as the year-on-year growth rate of real GDP in the state of bank i in quarter t, interacted with the group dummies. In all cases, the (insensitive) group dummy is equal to one if the elasticity of Tier one ratio to total assets for bank i is above -0.28, and to zero otherwise. In Models 10 and 11, the sample of small (large) banks includes the banks whose customer loans represent less (more) than 2% of the regional GDP. All models include 19 quarterly time dummies and bank fixed effects. The t-statistics (in parentheses) are calculated using robust standard errors adjusted for clustering at the bank level. **, * : significant at the 5% and 10% level, respectively.*

Overall, we do not find any evidence that lending by risk-sensitive banks is more sensitive to the business cycle than lending by risk-insensitive banks. On the contrary, lending from risk-sensitive banks appears if anything less sensitive to the business cycle than lending from risk-insensitive banks. These results lead us to conclude that banks whose capital to asset ratio is sensitive to risk have a lower elasticity of credit supply to GDP. In other words, risk-sensitive capital management may work to stabilise the credit cycle.

4 Conclusion

The aim of the present paper was to assess the pro-cyclical impact of risk-sensitive bank capital management. We developed a theoretical model that shows banks with risk-sensitive capital ratio may have a less cyclical supply of credit than banks with a flat capital ratio. This theory is particularly relevant when the credit market is characterised by over-investment, i.e. credit standards are loose and resources inefficiently allocated to risky projects. We show that in this case the decrease in capital requirements on high-quality loans in good times provides banks with more leeway to lend to high-quality borrowers, gives them incentive to monitor risks, limits the search for high but risky yields, reduces over-investment, and ultimately smooths the business cycle. Then we tested the relevance of this stabilizing effect using quarterly balance sheet data from a panel of US banks over the period 2003-2007. This period, characterized by easy access to credit and –presumably– over-investment, is particularly well suited for our test. We partitioned our sample of banks into two groups: the risk-insensitive banks, whose capital has been observationally the least counter-cyclical, and the risk-sensitive banks, whose capital has been the most counter-cyclical over our sample. Based on this partition, we compared the elasticities of credit to GDP across the two groups.

We could not find any evidence that lending by risk-sensitive banks have been more sensitive to the business cycle than lending by risk-insensitive banks over our sample period. If anything, "risk-sensitive" banks have been on the contrary the least sensitive to the business cycle. Our work thus provides both theoretical support and empirical evidence of the some potential stabilizing effects of a risk-sensitive capital management. More generally, our findings can be viewed as supporting a risk-based capital adequacy framework, such as Basel II, and therefore provides new insight into the on-going and vivid debate on the pro-cyclicality of banking regulation. In contrast with the views that challenge the usefulness of the new accord (e.g. Benink and Kaufmann, 2008), we would argue that Basel II may create the right incentives to deter risk-taking when it is needed the most, i.e. in periods of easy money and over-investment.

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