Unintended consequences of post-crisis banking reforms

Neamțu, I.

Publication date
2021

Document Version
Final published version

License
Other

Link to publication

Citation for published version (APA):
Neamțu, I. (2021). *Unintended consequences of post-crisis banking reforms*. [Thesis, fully internal, Universiteit van Amsterdam]. Tinbergen Institute.

The post 2007 - 2009 financial crisis reforms in banking were meant to increase the resilience and capitalisation of the financial system, but they might have also lead to unintended consequences. This thesis focuses on two of these reforms: the introduction of contingent convertible bonds (CoCos), and the introduction of the leverage ratio requirement. CoCos are meant to act as a bail-in mechanism for banks, but as I show in this thesis, they can also lead to internal contagion or increase banks' risk-taking depending on their design features. The first paper is a theoretical analysis on the financial stability of a bank with CoCos that trigger at different capitalisation levels, and the second paper is an empirical analysis on the risk-taking determinants and implications for UK banks of having CoCos on their balance sheet. The introduction of the leverage ratio requirement is meant to stop excessive leverage, but it might incentivise some banks to invest more in their high risk, high margin businesses rather than in their low margin, low risk activities, leading to an overall increase in banks' risk-taking. In this thesis, we assess in a theoretical model and numerical calibration on UK banks the risk-taking effects when a bank applies its capital requirements at a consolidated level compared to applying them at each business unit.

Ioana Neamţu (1993) holds a *summa cum laude* BA degree in Liberal Arts and Sciences (2015) from Amsterdam University College, The Netherlands. She obtained her MPhil degree (2017) with a specialisation in finance from Tinbergen Institute, and joined the Macro and International Economics department of University of Amsterdam as a PhD candidate under the guidance of Prof. Sweder van Wijnbergen. During her PhD she was twice a PhD intern at the Bank of England.

Unintended consequences of post-crisis banking reforms   Ioana Neamţu

772

tinbergen institute

Unintended consequences of post-crisis banking reforms

Ioana Neamţu

University of Amsterdam

(This page is intentionally left blank)

Unintended consequences of post-crisis banking reforms

Ioana Neamțu

ISBN: 978-90-361-0638-2

Cover: Artist - *Pollock Jackson*, Title - *Convergence*, *1952* ©The Pollock-Krasner Foundation ARS, NY and DACS, London 2021

Tinbergen cover design: *Crasborn Graphic Designers bno, Valkenburg a.d. Geul*

This book is no. **772** of the Tinbergen Institute Research Series, established through cooperation between Rozenberg Publishers and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.

Unintended consequences of post-crisis banking reforms

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad van doctor

aan de Universiteit van Amsterdam

op gezag van de Rector Magnificus

prof. dr. ir. K.I.J Maex

ten overstaan van een door het College voor Promoties ingestelde

commissie, in het openbaar te verdedigen

op maandag 15 maart 2021, te 14.00 uur

door Ioana Neamțu

geboren te Piatra Neamț, Roemenië

Promotiecommissie:

Promotor:	Prof. Dr. S.J.G. van Wijnbergen	*University of Amsterdam*
Co-promotor:	Prof. Dr. E.C. Perotti	*University of Amsterdam*
Overige leden:	Prof. Dr. N. van Horen	*University of Amsterdam*
	Prof. Dr. A.W.A. Boot	*University of Amsterdam*
	Prof. Dr. R.M.W.J. Beetsma	*University of Amsterdam*
	Dr. R.E. Vlahu	*De Nederlandsche Bank*
	Dr. J. Schnitzler	*Grenoble Ecole de Management*
	Prof. Dr. S. Gryglewicz	*Erasmus University Rotterdam*
Faculteit:	Economie en Bedrijfskunde	

Acknowledgments

I thought of so many different ways to start this section, and I realised, as some friends told me that they were all ‘a mountain of clichès’. But what can you do if indeed writing a PhD thesis feels so relatable with the saying “ You need a village to raise a child”? I can sincerely say that I do not think I could have written this thesis without the help, support, confidence, trust or friendship of so many people around me.

Firstly, I am very grateful to my supervisor Sweder van Wijnbergen for guiding me through this journey, and for pushing me to go beyond what I thought at times were my limits. When I met him during the Macro IV course at TI, I was electrified by his enthusiasm towards research. I always appreciated his passion and curiosity towards big questions, and I hope to be able to carry on with me at least a part of the drive I saw in Sweder. Without his support I would never dared to embark on the empirical chapter of my thesis, which opened a new path for me towards empirics. I learned a lot in the past three and a half years from his “get things done” mindset, and I am sure I would not have finished my PhD on time if it wasn’t for him.

I am very lucky to have started my research career by co-authoring with two people from whom I had a lot to learn. Anh taught me how to think better of corporate finance modelling, and the nitty-gritty of developing a model, that you can only learn by practice. Her dedication and desire to get the best possible version of our work were contagious, and I hope that I managed to live up to the expectations. Mahmoud supported me and gave me a lot of freedom, and I learned from him to think more intuitively and how to work more efficiently with data. Without his early persuasion early in the job market, I would most likely not be moving to London in 2020 to start a new very exciting chapter of my life there.

I want to thank my professors from whom I learned so much, who trusted and listened to me at key moments that defined and shaped my path as an economist so far. At AUC I was very fortunate to have as mentors Roland Luttens, Coen Teulings and my thesis advisor Jose Luis Moraga-Gonzalez, and later on at TI I learned how to think about banking from Enrico Perotti and Tanju Yorulmazer. I cannot emphasize enough how much it meant for me to learn beyond textbook knowledge from such extraordinary professors.

I am not a linear person, and as in almost every other aspect of my life, my time at the UvA was often a roller-coaster. I had the joy of going through the PhD journey with the fellow MInt PhDs Stephanie, Egle, Gabrielle, Oana, Merve, Stan, Daniel, Stefan, Eva, Josha, Andras, Pim, Rui and Jante. Early in my PhD I got valuable tips and tricks to navigate the PhD life from Egle and Stephanie, and later on I laughed, talked about Dutch language, football and peculiarities in Eastern Europe with Stan, Daniel and Merve in our office. I bonded with Daniel over our Balkan background which captures a certain futility of life, and I will miss my talks with Pim about obscure movies. I will for sure miss teaching, and I am glad I taught for 3 years under the guidance of Franc, and in a great team alongside Rui, Kees, Elisabeth and Albert-Jan. I am grateful to all my colleagues at MInt for showing me a glimpse of academic life, for the advice I got at times for my papers and for our lunch talks. I want to thank Lucy, Kees, Andra, Răzvan, Simon, Peter, my office mates and the Medium-term Strategy and Research team at the Bank of England for reading through my work and giving me timely feedback. Support came also from the amazing UvA and TI staff, especially Wilma and Arianne who were a rock for me with their wisdom and help.

There are people who shaped you as a professional, and people who help define who you are as a person. I want to thank especially my middle school Romanian teacher Doina Budescu, and my former dean Marijk van der Wende who were some of my leading examples of strong women, next to my mother and grandmother. I thank Jan, Darja, Daisy for their personal support during the PhD, and to my dearest friends who kept me alert to the world outside economics: Adi, Andreea, Dana, Emma, Maria, Ruxi, Simon, Sonya, Tasneem. It seems apparent that a defining characteristic of a PhD student is complaining, and I am glad I could do it while drinking a glass of wine, or on a trip with my dear friends Bouke, Leonard, Tolga, Magda, Benjamin and Domenico. I hope our paths will bring us to together again.

My parents allowed me to be whatever I wanted to be, and here I am. I cannot imagine how difficult it must have been to let their only child leave when she was only 18, but they always supported and encouraged me to pursue my dreams. My father pushed me constantly and told me not to give up, making it sound like everything can be fixed, and my mom was and will continue to be my emotional support who lets me call her at whatever hour in night and day and listen to all my challenges and insecurities. My grandma is contagious with her positivity, always ready to come visit wherever I am and learn how to work with Skype or Whatsapp for our late night talks. I hope to continue to go with her in any possible adventure. Most importantly, the best thing that happened to me during the PhD was meeting Arjan. He is complementing me in every single way, and without his support I would not have been able to be where I am today. I want to build a life with him, and I am sure that many decades of adventure and joy await us.

List of authors

Multiple buffer CoCos and their impact on financial stability

This paper is single-authored and based on my Tinbergen MPhil thesis. The paper circulated under the name of 'Instabilities of two-layered CoCo capital structures', which was further changed into the current title.

Risk-taking, competition and uncertainty: Do CoCo bonds increase the risk appetite of banks?*

This paper is co-authored with Mahmoud Fatouh and Sweder van Wijnbergen. I partially worked for this thesis during my second internship at the Bank of England in 2019. I gratefully acknowledge the financial support and the data access from the Bank of England.

Capital allocation, leverage ratio requirement and banks' risk-taking*

This paper is co-authored with Quynh-Anh Vo. I started my work for this paper during my first internship at the Bank of England in 2018. I gratefully acknowledge the financial support and the data access from the Bank of England.

* The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its Committees.

Contents

Chapter 1

Introduction

The post 2007 – 2009 financial crisis reforms in banking were meant to increase the resilience and capitalisation of the financial system, but they potentially created unforeseen consequences in other bank decisions which would counterbalance the initial purpose for which they were created. In the aftermath of the financial crisis, critics targeted poor bank capitalisations and the need for tax-funded bail-outs. To solve these problems, Basel III introduced more stringent capital requirements and additional instruments that qualify as bank capital. Another critique on the pre-2008 banking regimes was the excessive leverage endemic in the system. Hence, the Basel III reforms introduced minimum requirements on banks' leverage ratio to complement the risk-based capital requirements. The changes in banking regulation extend much beyond these two examples, but this thesis aims to address in particular one new financial instrument which counts towards Basel III capital requirements - contingent convertible bonds (CoCos), and the risk-insensitive leverage ratio requirement.

Contingent convertible bonds are a security that acts as a bond and converts into equity when the bank is in a bad enough state as defined by a certain capitalisation ratio. CoCos became a popular instrument issued by banks in Europe, as they are relatively cheap to issue, they have tax benefits (Goncharenko et al., 2020), and they are a high-yield investment for investors. CoCos are effectively meant to act as a bail-in mechanism (internal recapitalisation) and are eligible to qualify as either Additional Tier 1 (AT1) capital, or Tier 2 (T2) capital [1]. The distinct difference between the two is that AT1 CoCos are meant to recapitalise the bank on a going-concern basis – when the bank is still solvent – while T2 CoCos act on a gone-concern basis – when the bank is already 'failing or likely to fail' [2]. In this thesis I focus exclusively on going-concern CoCos.

Even though they have existed for almost 10 years at the moment of this writing, there has been only one conversion and that was not done under regular circumstances. Banco Popular, a Spanish bank, was declared bankrupt and was sold for €1 to Banco Santader (Buck, 2017). Subsequently, the Spanish regulator announced CoCo holders that their debt has been erased, even though it was supposed to be triggered while the bank was still solvent (Smith, 2017). Hence there is little evidence of implications of CoCo conversions on any market mechanisms on banks' financial stability, although this topic has been explored by a large body of theoretical research.

The second chapter of this thesis focuses in a theoretical setup on the banks' financial stability effects of CoCo conversion when a bank holds two CoCo buffers at different capitalisation levels. Timely bank recapitalisation without the need of bail-outs is a very appealing feature of CoCos, but some regulators fear that the Basel III minimum trigger at which recapitalisation is meant to take place (5.125% of CET1 to Risk Weighted Assets (RWA)) is too low for CoCos to fulfil their primary aim. As a consequence, in countries such as Switzerland or United Kingdom, the regulators either imposed higher minimum triggers on top of Basel III requirements (for instance UK requires a minimum trigger level of 7% CET1 to RWA), or required certain financial institutions to hold multiple buffers of CoCos at different capitalisation levels (for example Switzerland requires Systemically Important Financial Institutions (SIFIs) to hold both 5.125% trigger and 7% trigger CoCos). In the second chapter I find that this two-layered of CoCo buffer structure can negatively affect a banks' stability, as it can lead to market panic and subsequent CoCo

[1] Tier I Capital is the core capital of the bank, and its main absorption mechanism, and it is split into Core Equity Tier 1 (CET1) (common equity) and Additional Tier 1 capital (AT1). Tier 2 capital is supplementary capital, and includes undisclosed reserves, subordinated term debt and hybrid instruments.

[2] Art. 51 et seq. and Art. 62 et seq. from the Capital Requirements Regulation (CRR) EU NO 575/2013 of the European Council define a series of conditions. Some of the key features are: both needs to have a Point of Non-Viability (PONV) clause and a mechanical trigger, can be either conversion to equity or principal write-down, and the first call must be at least 5 years after issuance. The AT1 CoCos are ranked before equity capital, and T2 CoCos ahead of AT1 CoCos. The AT1 CoCos must be perpetual with a call feature, while T2 CoCos have fixed maturity.

conversions. This issue can be mitigated through certain CoCo designs, and I argue towards an optimal CoCo structure in this setting.

The third chapter deals with the implications of CoCos on bank risk-taking, which is another crucial discussion, both in academic literature and for the regulators. Theoretical literature argues that banks strategically issue certain types of CoCos to increase their risk-taking behaviour, or that different CoCo features lead to different risk taking implications. In the third chapter, I empirically test these theoretical results. This chapter is co-authored with Mahmoud Fatouh and Sweder van Wijnbergen. We find no effect of an issuing bias on a UK banks sample, but we confirm the theoretical prediction that the potential gains or losses of existing shareholders upon conversion influence the risk-taking behaviour of banks. We argue that CoCos can create unintended consequences on risk-taking behaviour, and that the regulator should distinguish between different CoCo designs in order to mitigate increased risk-taking behaviours.

Unforeseen risk-taking consequences are not unique to CoCos. Another debate regards to the now mandatory leverage ratio requirement (LRR). The LRR is meant to complement the risk-sensitive RWA requirement, but it also creates unintended consequences in terms of risk-taking implications. A bank will diversify its portfolio across different business activities based on the relative profitability and capital requirement impact on the two regulatory requirements. An early question was whether the most binding constraint changes banks' risk-taking incentives. Both theoretical and empirical literature find evidence that banks which are more likely to be bound by LRR will increase their share in high-margin, high-risk assets (Acosta-Smith et al., 2018; Choi et al., 2018).

The LRR is only required at banks' consolidated (group) level, but there is evidence that bank groups instead require that each business unit meets the requirement as well. In the fourth chapter we go a step further and ask if and how the impact on asset risk differs if a bank applies their regulatory constraints exclusively at the group level, compared to requiring each business unit to comply with them. In joint work with Quynh-Anh Vo we find, both in a theoretical model and a numerical calibration and simulation on UK banks that the most binding constraint plays a crucial role in the asset risk impact. Intuitively, the LRR negatively affects businesses with very low margin, but high impact on a banks' leverage ratio, such as repurchase agreements (repos). The current evidence for the impact of LRR on repo transactions is mixed, so we use confidential transactional data on the UK repo market to calibrate our model to bring additional insights on the matter. In this chapter we bring further illuminate how different bank business models influence the asset risk impact. We furthermore argue that regulators should distinguish between them if they consider changing the level at which the LRR is applied, as one size does not fit all.

I described in very general terms the matters discussed in this thesis, and further I elaborate over key features of CoCos and their regulatory landscape, the thesis outline and the chapter break-down.

1.1 CoCo primer

Contingent convertible bonds were first proposed by Flannery (2002) in the academic literature, and were first issued by the UK commercial bank Lloyds Bank group in 2009. Even though they were issued as early as 2009, CoCos have only qualified as Additional Tier 1 capital under Basel III regulation since 2013. Although they have been issued in various forms around the world, but they can be defined by a number of key features.

CoCo key features

Contingent convertible bonds have two key features: the conversion type and the trigger. CoCos can either convert to equity at a fixed or variable ratio dependent on the share price at the time of conversion, or have a write-down function. Current CRR regulation does not distinguish between the two types of conversion for CoCos to qualify as regulatory capital. The type of conversion and the ratio for which CoCo debt converts into common shares implies a wealth transfer between CoCo holders and equity holders. For instance, a principal write-down CoCo bond implies that in case of conversion the equity holders have a wealth transfer gain of the entire CoCo sum. At the other extreme we find CoCo debt which converts to equity at such a high rate that existing equity holders are infinitely diluted, hence leading to a negative wealth transfer from CoCo bond holders to equity holders. A neutral conversion implies that there is a zero wealth transfer between CoCo and equity holders.

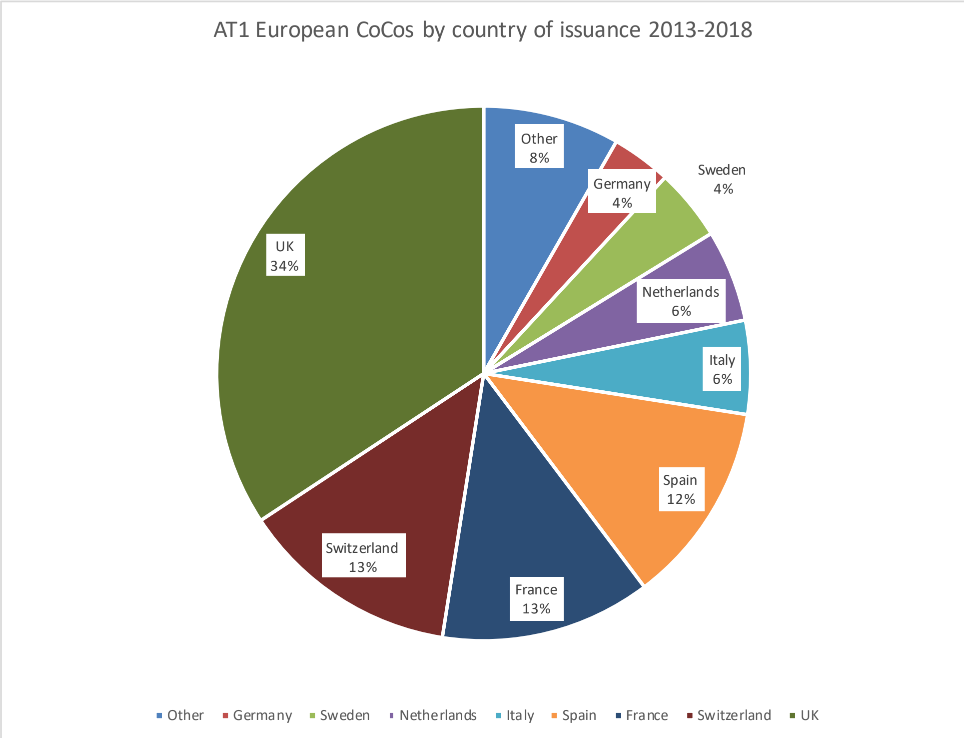
The second key feature is the trigger type, which can be either mechanical or at the discretion of the regulator (Point of Non-Viability - PONV). In terms of mechanical triggers, CoCos can convert at either market-based or book-based triggers. It implies that the soundness of a bank is evaluated at market capitalisation indicators, or at accounting-based ones. There have been debates in the literature whether market or book-based triggers are more suited (for example see Calomiris and Herring (2013); Sundaresan and Wang (2015)), and the impact of the regulators' decision whether to convert or not (see Chan and van Wijnbergen (2015)).

AT1 European issuances and regulatory regime

The national regulatory landscape greatly influence the amount and type of CoCos issued. The first important inclusion was the qualification of CoCos as capital under Basel III, followed by Total Loss-Absorbing Capacity (TLAC) requirements for Global Systemically Important Banks (G-SIBs). The Financial Stability Board imposed TLAC requirements of at least 16% until January 2019, and at least 18% until January 2022 of the G-SIBs group's Risk-Weighted Assets (RWAs), which can be partially filled with CoCos (Financial Stability Board, 2015). More recently, in the Bank Recovery and Resolution Directive (BRRD), banks need to hold bail-in-able debt: CoCos qualify as such under Write-down or Conversion of Capital (WDCC) instruments (World Bank, 2017). The European Banking Authority in the Capital Requirements Regulation (CRR) requires that mechanical triggers are exclusively accounting-based, thus rendering the debate on the favourability of market triggers purely theoretical for the time being.[3] Additionally Europe made them an attractive security to issue as the coupon payments are tax deductible. The three primary reasons for CoCo issuance are summarised in a Bundesbank report as: inclusion as regulatory capital, advantageous tax treatment, and lower costs of issuance compared to pure equity (Deutsche Bundesbank, 2018).

[3] CRR EU 575/2013 Art. 54. et seq.

Figure 1.1: AT1 CoCos country of issuance. Data source: Bloomberg



The CoCo rules have changed over time and the banks adjust their issuances to national regulation. Germany had no tax deductibility on coupons until 2014 which led to a limited issuance up until that point (Deutsche Bundesbank, 2018), and the Netherlands removed the tax benefits on CoCos in January 2019.[4] United Kingdom and Denmark require that CoCos have a trigger level of at least 7%, compared to the minimum 5.125% from Basel III, and Switzerland requires Systemically Important Financial Institutions (SIFIs) to hold both low- and high-trigger CoCos.

In early years, from 2009 to 2015 the world-wide CoCo market saw total issuances of $ 521 bn., spread across 731 CoCo issuances, from which only slightly less than half (55%) qualified as AT1 capital (Avdijev et al., 2020). At a country level, issuers from China, UK, Switzerland and Australia had the largest aggregate CoCo issuance between 2009 to 2015 (Avdijev et al., 2020). Comprehensive overviews of the international CoCo market up to 2015 can be found in Avdijev et al. (2020) and Greene (2016).[5]

[4]See government announcement `https://bit.ly/2Sedxpm`.

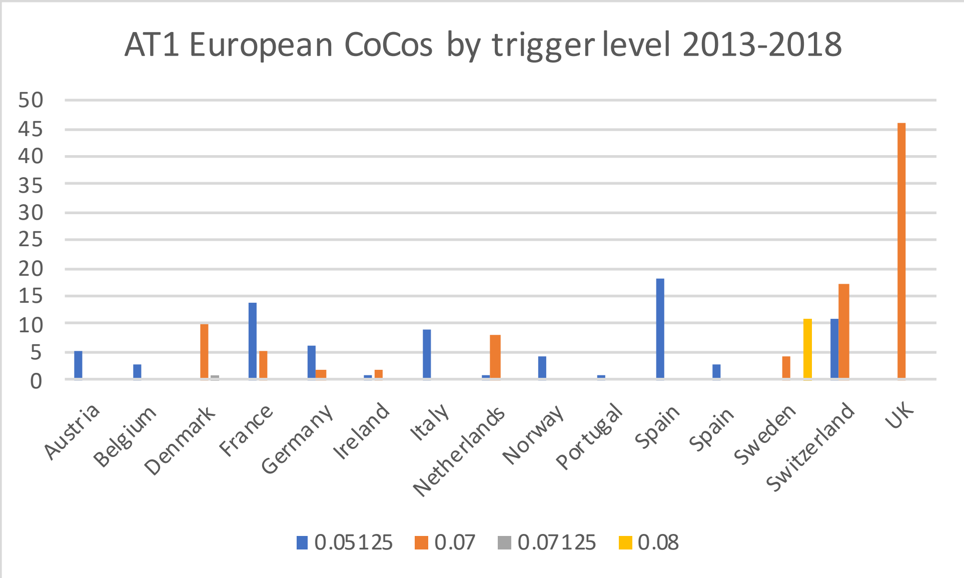
[5]See the 2017 Working Paper version of Avdijev et al. (2020) for a more elaborate summary.

This thesis focuses exclusively on characteristics of AT1 European CoCos, which up to August 2020 had almost 200 issuances with a cumulative worth of €180 bn. ($212 bn.) (Gledhill, 2020). Our sample retrieved from Bloomberg comprises of 182 AT1 European contingent convertible bonds, issued between 2013 to end of 2018, worth almost €158 bn. ($ 184 bn.). The European market has four large issuers in terms of country of origin: UK (34% of total issuances by volume in €bn.), followed by Switzerland, France and Spain, each holding 12-13% of the market. A summary of issuances by country of origin based on amount issued (€bn.) is found in Figure 1.1. As previously discussed, the minimum CoCo trigger level is sometimes set at country-level in addition to the Basel III recommendations, and almost all banks issue at the minimum regulatory requirement imposed by the country of issuance with very few exceptions - see Figure 1.2. For example Crédit Agricole is the only French bank which issued at a high trigger level (7%), but only at the bank's group - the conversion trigger for the individual bank entity is still at 5.125%. The feature where the bank sets a different trigger event for the group (high trigger) compared to the solo entity (low trigger) is seen for almost all Dutch and Swedish issuances. The conversion type is left at the latitude of each issuer. There is no obvious pattern in the data (see Figure 1.3) besides that almost all issuances within a certain country indicate to follow the same type of issuance, whether it is conversion to equity (such as Spain and the UK), or principal write-down (like in France and Switzerland).

We can observe that banks with large CoCo issuances keep their portfolio diversified by issuing in different currencies and even changing the type of conversion. Banks that issue conversion to equity CoCo bonds in different currencies tend to keep the same price of conversion as calculated in their national currency at the time of every new CoCo issuance, even if issuances are done at different points in time.[6] Outside the UK (where issuances in GBP dominate the market), the two most common currencies of issuance in Europe are EUR and USD. Except for Spain which issued almost exclusively EUR-denominated CoCo bonds, local banks tend to diversify the currency in which they issue, while keeping their own currency as majority currency, with a notable exception being

[6] To exemplify, if a Spanish bank issues at a conversion rate of 1 EUR in 2019, in September 2020 the new issuance in GBP will insure that the conversion rate translates into 1 EUR per share, so the conversion rate would be 0.91 GBP.

Figure 1.2: AT1 CoCos mechanical trigger. Data source: Bloomberg



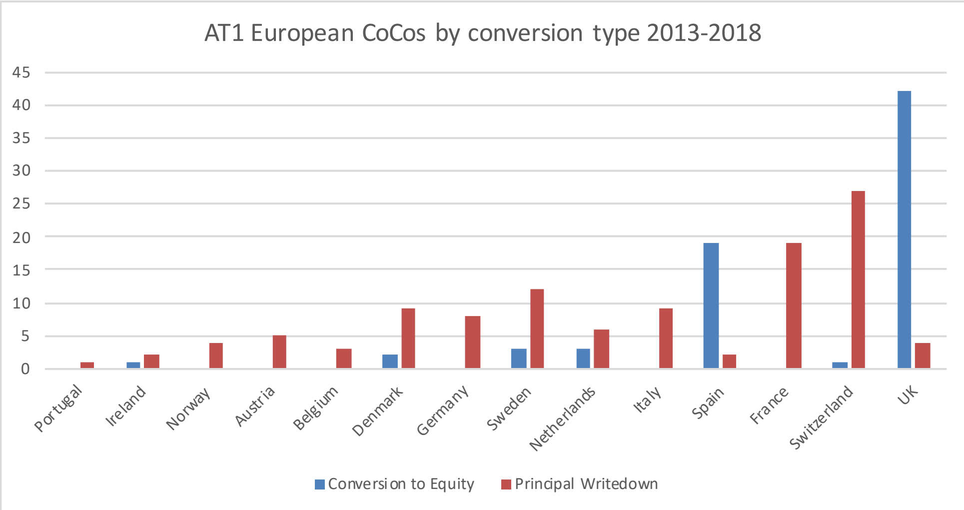
France who's banks almost exclusively issued in USD.

Evolution and challenges

There have been few, but significant events in the CoCo world. The first one was in February 2016, when Deutsche Bank had a negative profit warning, led by commotion in the markets at potential information that the bank might not be able to meet their CoCo coupon payments. The event led to a market panic in CoCo secondary markets, with prices falling sharply. A seemingly unimportant event affecting one bank led to contagion, leading to the natural question whether CoCos can fulfill their preventive purpose and make the financial system safer (Kiewiet et al., 2017; Glasserman and Perotti, 2017). The second event was the first (and only) CoCo conversion when the Spanish bank Banco Popular was declared insolvent in 2017, and subsequently all the CoCo debt worth €1.25 bn. was erased. Unlike the Deutsche Bank announcement, the Banco Popular CoCo conversion led to no spillovers in the CoCo market.

Standard CoCo issuances have a callable option at 5 years, even if the bonds are perpetual. Since the CoCo market became more mature, banks call their previous CoCo issuances, and they re-issue at lower coupon levels. So far, only Santander and Deutsche Bank did not use their call option in 2019, followed by the London based Lloyds bank

Figure 1.3: AT1 CoCos conversion type. Data source: Bloomberg



in June 2020. Even if the expected gains are lower now than they were a few years ago, the CoCos issued in 2020 had coupons in the range of 3.375% and 7.5%, which represent more than double the value of senior debt coupons (Gledhill, 2020).

The year 2020 proved eventful for all financial markets, and the CoCo market was no exception. The first market turmoil was in March 2020, when yields reached 15.4% and slowly recovered after major government and central bank intervention around the world (Gledhill, 2020). The CoCo issuance market effectively halted from March until beginning of May 2020, but in September 2020 the level of issuance reached pre-Covid levels. Also in March 2020, the European Central Bank announced that AT1 CoCos can be used to meet Pillar 2 capital requirements as part of their temporary Covid-19 package relief.[7] This decision is expected to lead to an increase in CoCo issuances. Moreover, investors still indicate to have a strong appetite for CoCos (Baker, 2020), and banks started diversifying their issuances with respect to social corporate responsibility, with BBVA's first green CoCo issuance in July 2020.[8] Hence, early evidence indicates that CoCos proved robust in the face of the virus, but we did not yet witness any pause in coupon payments, and banks' capitalisation levels are high enough for investors not to be afraid of a potential conversion.

[7] The full announcement: `https://bit.ly/2S96oX7`.

[8] The 2020 BBVA €1 bn. green CoCo issuance was three times oversubscribed - `https://bbva.info/2S7fpjA`.

The current challenge that lies ahead is the medium-term impact of Covid-19 on CoCos. As the virus still creates excessive uncertainty, and the winter 2020 prospects are gloomy, CoCo bonds are more likely to be affected in terms of coupon payments, and the banks might not exercise their right to call the CoCos amid fear of lack of new investors and decreasing their Tier 1 capital. There are early signs that banks enter a signaling game - some want to signal to the market that they are strong enough to repay their CoCo debt, and confident that there is enough demand for a new issuance, such as Dutch ING and Swedish Swedbank did earlier this year (Ramnarayan and Nikolaeva, 2020). Would banks call their CoCos just to prevent reputational damage, or is the signal strong enough to not be able to be faked by 'lemons'? We should soon be prepared to experience the effects of missed coupon payments. Will it lead to market contagion, or will the investors have learned from the Deutsche Bank event of 2016? These are questions worth exploring, and I aim to do so in future research.

1.2 Thesis outline and summary

The thesis proceeds as follows. Chapters 2 and 3 focus on CoCos, and Chapter 4 on the leverage ratio implications on risk-taking.

In Chapter 2 I develop a theoretical model to investigate the effect on a bank's financial stability of having multiple CoCo buffers on the same bank balance sheet, using cash-in-the-market pricing (Allen and Gale, 1994) and global games (Goldstein and Pauzner, 2005) methodologies. I analyse CoCo buffers with triggers at different capitalisation levels, and I find that they can be detrimental for the CoCo bail-in capacity. Market-based triggers lead to premature conversion and fire-sales of equity. I compare the key features of CoCos in terms of wealth transfer and type of mechanical trigger for banks with two-layered CoCo structures, and argue that book-based triggers can be the most beneficial from a stability perspective, as long as they incorporate expected credit losses.

In Chapter 3 we assess the impact of CoCos and the wealth transfers they imply conditional on conversion on the risk-taking behaviour of the issuing bank. We also test for regulatory arbitrage: do banks by issuing CoCo bonds try to maintain risk-taking incentives when regulators reduce through higher capitalization ratios? We test it on the

UK sample, who's banks account for the largest share of CoCo issuers in Europe. Our dataset combines bank balance sheet data with internal Bank of England measurements of banking competition and macroeconomic uncertainty in the UK. Almost all CoCo bonds that we consider are conversion to equity, and we calculate the expected wealth transfer they will impose on conversion based on historical observed declines of share prices in times of crisis. We use parametric (Heckman, 1976), semi-parametric (Cosslett, 1991; Ahn and Powell, 1993) and non-parametric (Lee, 2009; d'Haultfoeuille et al., 2019) methodologies that evaluate selection effects, and further we evaluate the CoCo impact on risk-taking using static (pooled OLS) and dynamic (Arellano-Bond) model specifications. While we test for and reject sample selection bias, we show that CoCo bonds issuance has a strong positive effect on risk-taking behaviour, and so do conversion parameters that reduce dilution of existing shareholders upon conversion. Higher volatility amplifies the impact of CoCo bonds on risk-taking.

In Chapter 4 we examine how the level at which banks apply regulatory constraints affects their investment and their asset risk. We develop a theoretical model and calibrate it to UK banks. The bank can choose a portfolio mix between a high-risk, high-margin investment, which we capture via lending, and a low-risk, low-margin investment which we proxy with the UK gilt repo market. We use bank balance sheet data and a confidential Bank of England dataset on UK gilt repo transactions for our calibration. Our main finding is that the impact differs significantly depending on which of regulatory constraints matter at the group consolidated level. As long as at the consolidated level, only the leverage constraint matters, the allocation of constraints to business units does not imply any negative impact on banks' resilience. However, it could bring about an increase in banks' asset risk in the case where only Value-at-Risk constraint matters at the group level. We also find that banks' business model matter for this issue. We divide our sample in capital-oriented, wholesale and retail banks using the methodology of Roengpitya et al. (2014), and find that the retail group has similar risk-taking results as the average bank, while the wholesale and capital-orientated group calibration yields opposite results.

Chapter 2

Multiple buffer CoCos and their impact on financial stability[1]

2.1 Introduction and related literature

In 2013, the Swiss National Bank (SNB) imposed additional requirements on bank capitalisation for Systemically Important Financial Institutions (SIFIs) in addition to Basel III regulation. Besides increased minimum levels of capitalisation, a distinct element of Basel III compared to past regulation is the introduction of Contingent Convertible bonds (CoCos), a security which is meant to act as a bail-in mechanism for banks in times of distress. CoCos are a hybrid security which act as a bond, but convert immediately into equity or are (partially) written down if the bank reaches, or is below, a pre-specified threshold which signals a poor financial state of the issuing body. In the 'Swiss finish', SNB imposes a higher capitalisation level of going-concern CoCos and unlike Basel III, a higher minimum trigger level. The CoCo IPOs of the two SIFI Swiss banks – Credit Suisse AG and UBS AG – indicate that the banks still work towards filling in the minimum requirements on high trigger CoCos (in end 2017), but they still hold, or even issue new low trigger CoCos on their balance sheet. To the best of our knowledge, these two groups are the only two banks world-wide to hold a two-layered going-concern CoCo structure

[1]I am grateful to my supervisor Sweder van Wijnbergen for his suggestions and support throughout the process. In particular I thank Giorgia Piacentino, Tanju Yorulmazer, Vladimir Vladimirov and Simon Mayer for early feedback. I am grateful to the discussants and seminar participants from various conferences and seminars for their valuable feedback and suggestions.

on the same set of assets, which indicates to us that they only exist to meet regulatory requirements, and do not necessarily arise as part of an optimal banks' capital structure (Avdjiev et al., 2015). The novelty of a bank having two different going-concern trigger levels in the capital structure has not yet been discussed in the literature, but their treatment in case of conversion has been incorporated in the European Banking Authority report (EBA Report, 2016).[2]

To the best of our knowledge, the effects of this multiple buffer strategy on financial stability have not yet been researched, even though it is implemented and advocated as a safe bail-in mechanism. The aim of this paper is two-fold. Our overarching research question is to analyse the effects of CoCo conversion on subsequent CoCo bail-in capacity in case of multiple buffer CoCo bank capital structures. Secondly, we aim to find an optimal CoCo design which minimises inefficient conversion, for a given capital structure. By 'inefficient' we understand that conversion occurs above the bank fundamentals trigger threshold.

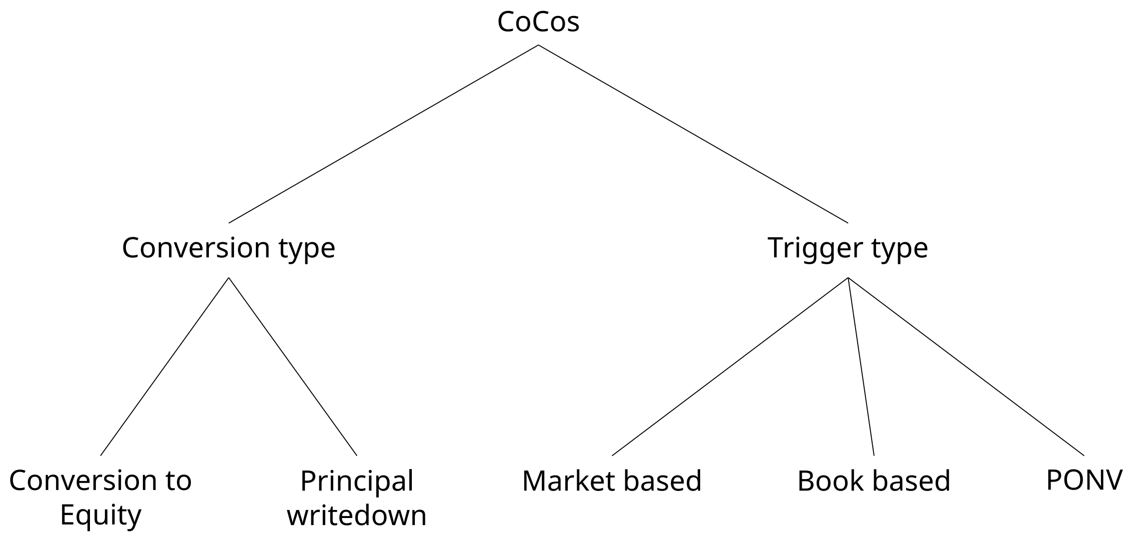
In this paper we argue that there is a key trade-off in the two-layered structure of CoCo bonds. Multiple trigger levels effectively translate in multiple recapitalisation buffers on a going-concern basis, which increase bank resilience. Nonetheless, the triggering of the first buffer can be perceived as a strong market signal that the bank is in financial distress, leading to further market panic, which can artificially trigger subsequent CoCo buffers. Hence, the trade-off of several CoCo buffers that we aim to capture is increased bank resilience versus the possibility of fire sales of equity.

We show how CoCo design matters when a bank has to comply with regulatory requirements on an equity ratio, as it is currently stipulated in the Basel III regulations. To that end, we model decisions that are taken in industry, but have not yet been accounted for in the CoCos literature. We incorporate the pro-cyclicity of limited cash with the returns on assets, and assess how this co-movement affects equity. This paper falls under the banking literature that deals with unintended post-crisis regulation, and more specifically with the one of CoCo regulation in Basel III and beyond. Firstly, in order to

[2]The report stipulates the possibility that both CoCos are hit simultaneously.The sequencing is as follows: " losses corresponding to the amount required to go back to 5.125% should be absorbed by both the low trigger and the high trigger instruments on a pro rata basis. Losses above 5.125% will only be supported by the high trigger instrument" (Art. 96).

maintain a particular equity to assets ratio, banks can either increase their equity base or decrease their asset side. Empirical evidence indicates that shrinking the balance sheet through asset liquidation is commonly done (Association for Financial Markets in Europe, 2016), aspect which we incorporate in the paper. De-leveraging is often observed as opposed to raising new capital in face of negative shocks to existing positions (Classens, 2014), as in times of distress equity is expensive to issue. We model the banks' choices as a constrained maximisation problem, in which the bank maximises the equity value while maintaining a minimum level of equity to assets ratio. Secondly, equity holders are affected by initial CoCo issuance and later on by asset pricing volatility due to the news impact that CoCos can create. Insofar, the focus in the literature has been placed on depositor bank runs (Chan and van Wijnbergen, 2015), but we argue that the signaling value of CoCos can create a downward spiral on equity as well, aspect which was previously modeled in continuous time by Sundaresan and Wang (2015). They show multiplicity of equilibria in the presence of market triggers in discrete time, but they were further ruled out in continuous time (Glassserman and Nouri, 2016), and corrected by Pennacchi and Tchistyi (2019). Lastly, we introduce cash-in-the-market pricing in the CoCos literature: in times of distress there is not enough cash available in the market which in turn will depress the market prices of equity. We find that a two-layered CoCo capital structure leads to multiplicity of equilibria, no equilibrium or a unique (inefficient) equilibrium for CoCo conversion in times of distress. We further compare the optimality of different types of CoCo designs and show which one minimises the inefficient conversion space, for a fixed capital structure. We find that market based triggers, even though very popular in academic literature, harm the issuing bank either directly, through inefficient conversion of CoCos, or indirectly through an artificial speculative attack on forcing conversion by equity holders. In this context we show that a capital structure with two different types of CoCos is detrimental to the financial health of the bank, as the second (low trigger) CoCo will not successfully act as an additional buffer. Instead, the high trigger one can induce a negative externality of converting the low one as well through the equity holders reaction. In contrast, we argue that book based triggers can be an effective bail-in mechanisms as long as the value of assets is evaluated accurately by the issuing bank, and it incorporates expected losses. If the accounting value only accounts for occurred losses, as

Figure 2.1



it is was stipulated in the International Financial Reporting Standards (IFRS) until 2018, then going concern CoCos do not fulfil any function on loss absorbing capacities before it is too late in our model. Nonetheless, this problem is mitigated with the incorporation of expected credit losses.

The paper is structured as follows. Firstly, we present a primer on CoCos and how this paper is embedded in the existent literature. In section 2 we define and solve the baseline model and economy. In section 3 we analyse the extended model of having two CoCo buffers and draw comparisons with the baseline model. Lastly, in section 4 a comparison between different types of CoCos follows, and the paper concludes.

2.1.1 CoCo primer

Contingent Convertible bonds have two key characteristics: the trigger which determines the conversion, and the type of conversion they will incur. A summary can be found in Figure 2.1. The loss absorption mechanism can be either conversion to equity (CE hereafter) or a principal write-down (PWD hereafter). To generalize, let the conversion rate be $\psi \in [0, \infty)$, per unit of CoCo, with conversion price $\frac{1}{\psi}$(Chan and van Wijnbergen, 2017). The PWD CoCos are a limiting case, with conversion rate $\psi = 0$.

The trigger can be mechanical and/or discretionary. The discretionary trigger is activated at the point of non-viability of a bank (PONV). This feature allows the supervisor to force conversion if it considers it as a necessary step in preventing insolvency.[3]. The mechanical trigger imposes conversion at a pre-specified ratio of core capital to risk weighted assets (RWA). The key distinction between market and book based triggers is in measuring the value of core capital and RWA. Book value can be effective in terms of timely recapitalisation if it is measured correctly, and at a high frequency, while market value could capture inconsistent accounting valuations. We understand by correct measurement an accurate evaluation of asset value, which incorporates tail-risk events.

Under Basel III, CoCos can qualify as Additional Tier 1 (AT1 hereafter) or Tier 2 (T2) capital. To qualify as AT1 under European Law, the CoCos need to, among others: have a PONV clause, absorb losses on a going-concern basis, be perpetual instruments and have a minimum trigger level of 5.125% of Core equity tier 1 (CET1) to RWA. Countries can stipulate additional conditions to the European Law minimum requirements. For instance, Denmark and UK imposed a minimum trigger level of 7% for AT1 instruments. The Swiss national supervisors request at least 6 percent of 'low-trigger' AT1 or T2 CoCos and an additional 4.3 percent of 'high-trigger' AT1 CoCos (Swiss Financial Market Supervisory Authority, 2015). Tier 2 CoCos and further regulatory requirements are beyond the scope of this paper, but a more comprehensive analysis can be found in Avdjiev et al. (2013), Avdijev et al. (2020) and Kiewiet et al. (2017).

[3]Effects of conversion on equity holders or market prices are unclear, as the very first conversion happened only in June 2017 at Banco Popular, a Spanish bank which was taken over by Santander (Smith, 2017) The decision of a full write-down was made under PONV and imposed by the Single Resolution Board, part of the EU Banking Union. Financial Times argued that the conversion had little spillovers in the market, and some CoCo holders already accused the authority of lack of transparency and valuation of the resolution (Beardsworth, 2017). In this paper we abstract from a PONV clause, and do not model its additional effects on conversion prices.

Related literature

The dominant views on the CoCo issuance are either for meeting regulatory requirements (Avdjiev et al., 2013) or emerging as an optimal capital structure of a bank for risk shifting incentives. Our paper belongs to the former strain, where banks issue them only to meet regulatory requirements, and have additional bail-in buffers.

There has been an extensive theoretical literature on CoCos after their introduction after the financial crisis. The focus in the literature has been on depositor runs (see Chan and van Wijnbergen (2015)), managerial risk shifting incentives (see Glasserman and Nouri (2012), Zeng (2014), Martynova and Perotti (2018) and Chan and van Wijnbergen (2017)). The closest models to our framework are the ones by Avdijev et al. (2020) and Chan and van Wijnbergen (2015).

If market participants have noisy information about the true state of nature, methodologies on self-fulfilling crisis use global strategic complementarities or adverse selection (impatient and patient agents with need to withdraw) (Morris and Shin, 1998; Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005). We employ the bank-run methodology of Goldstein and Pauzner (2005) to prove uniqueness of the inefficient equilibrium, below which crises are self-fulfilling. A similar approach based on global games has been done by Chan and van Wijnbergen (2015) on depositor runs, but our focus is on equity. To the best of our knowledge, we are the first to introduce limited cash availability in the market in a CoCos model. We exemplify the impact of market liquidity on pricing stocks using the liquidity shocks from the seminal paper of Allen and Gale (1994).

The existent debate in the literature on CoCo trigger levels focuses almost exclusively on market based triggers. Glasserman and Nouri (2012) and Derksen et al. (2018) develop valuation models in continuous time for CoCos based on book value. Nonetheless, in industry all financial institutions have a book-based trigger. In Europe market based triggers are outlawed by the Capital Requirements Regulation (CRR). The downward equity spiral aspect was previously modeled in continuous time by Sundaresan and Wang (2015). They argue against regulation which uses a CoCo trigger based on market value, because it can create instability in the market and lead to multiplicity of equillibria in pricing the assets. Their multiple equillibria were obtained using discrete time, and were further ruled out in continuous time (Glassserman and Nouri, 2016). Albul et al. (2015) find closed form solutions of CoCo prices in continuous time of optimal capital structure when market trigger CoCos are a choice variable. Their objective function is maximizing equity value, and show how different structures affect leverage, bankruptcy costs and tax benefits.

2.2 Baseline model and equilibrium analysis

The framework is based on a theoretical three period model $t = \{1,\ 2,\ 3\}$, with a bank, and three types of agents: private investors, passive bank debt holders, a bank manager, and two main frictions: fire sales of equity (cash-in-the-market) pricing of equity and an unexpected shock to asset returns. The economy is described by its fundamentals $\theta \sim Unif[0, 1]$, where a low value of θ indicates a bad state of the world. θ is realised at $t = 2$, but each market participant $i \in \{1, 2, 3, ..., n\}$ only obtains a noisy signal $\theta_i = \theta + \varepsilon_i$ about its true value, where the noise is drawn from a uniform distribution $\varepsilon_i \in Unif[-\varepsilon, \varepsilon]$.

Baseline model

We start with the most general case, where the bank has only one layer of CoCo debt, and it faces a strong informational shock in the intermediate period which alerts the market about the possibility of CoCo conversion.

Bank capital structure

We assume an exogenous bank capital structure, in place before $t = 1$, consisting of a risky asset, and liabilities in the form of senior debt, CoCo debt and equity. We justify this simplifying case of exogeneity based on CoCo regulation being introduced on existing capital structures. The bank invests ex-ante an amount A in a risky investment[4] - see Table 2.1. The risky investment has returns at $t = 3$, and depend on the initial asset riskiness - determined by the variance of returns, and the state of economic fundamentals

[4]We assume that the bank does not hold any cash ex-ante. We solved the model with cash on the balance sheet of the bank as well, but the main results do not change and just add additional notation.

θ. The returns follow a general probability distribution function $f_A(\theta)$, with a cumulative distribution function $F_A(\theta)$, and a corresponding standard deviation σ_A [5]. The expected value from the investment decision perspective is $E_{t=0}[A] = \int_{\theta=0}^{\theta=1} A\theta f_A(\theta)d\theta = R > 1$. The long term risky asset can be liquidated early in the intermediate period $t = 2$. Early liquidation is costly, and the entire asset can be liquidated for a value l, where $l < E[A]$.

To fund its investment, the bank raises a total amount outstanding of senior debt D, CoCo debt C, and equity e_0.[6] CoCo debt has a conversion rate of ψ and a trigger level τ. The conversion is dependent on the ratio of equity to risk weighted assets. If the ratio is below τ, then the CoCo debt will convert. All debt is repaid at $t = 3$ and equity holders $e_0 = A - D - C$ receive dividends. Further, let e_t^m denote the market equity capitalisation evaluated at $t = \{1, 2, 3\}$, and e_t^b the corresponding book capitalisation at time t.

Capital requirement for CoCos

The bank is subject to a risk-based capital requirement (RWA) at each time period. The regulatory requirement imposes a minimum level of equity to be held against the total value of risk weighted assets.In case this ratio falls below the minimum requirement τ, then CoCo debt converts and acts as an internal bail-in mechanism. If equity is book-based evaluated, then the requirement reads:

$$RWA_{book} = \frac{E[A] - D - C}{\sigma_A E[A]} > \tau \tag{2.1}$$

Alternatively, if equity is evaluated on the market, the numerator is given by the market capitalisation $e^m = P_m\, n_{max}$, where P_m is the market price per share, and $n_{max}$is the number of shares. In this case, the constraint reads:

$$RWA_{market} = \frac{P_m\, n_{max}}{\sigma_A E[A]} > \tau \tag{2.2}$$

[5]For the purpose of this setup the shape of the distribution function does not affect the results.

[6]We assume throughout deposit insurance, and so we do not consider depositor runs. We abstract from this matter by completely excluding demandable debt in the capital structure of the bank. For a global games analysis of potential CoCo impact on depositor runs, see Chan and van Wijnbergen (2015).

If the bank is priced at fair value, then the book and market based requirements coincide - equations (2.1) and (2.2) are equivalent. In case of distress, the ratio can be maintained either through costly liquidation of long term assets, or by CoCo conversion. The other alternative is issuing new equity, but we argue that this is the least appealing for the bank in times of crisis, due to underpricing and dilution of existing shareholders.

Table 2.1: Initial balance sheet baseline model

Assets	**Liabilities**
A - initial investment	D -senior debt
	C - CoCo debt
	e_0 - initial equity

Agents

There are three types agents of in the economy: active investors, bank manager and passive debt holders.

Investors

There is a unit mass risk-neutral investors with wealth $W = c + e_0$ divided ex-ante between cash c and equity e_0. These investors know ex-ante the existence of the idiosyncratic shock, but they do not know the magnitude (as it is dependent on yet unknown θ), hence they self-insure by holding both cash and equity. They are the only ones to hold bank equity, and their decisions are going to determine the (fire sale) share price in the market at $t = 2$. At $t = 2$ fraction $\lambda(\theta) \in (0, 1)$ of investors is hit by a liquidity shock. Each investor $i \in \{1, 2, ...n\}$ and the bank manager B obtain a noisy signal $\theta_i = \theta + \varepsilon_i$, $\theta_B = \theta + \varepsilon_B$ respectively, where ε_i is the information noise drawn from a uniform distribution $Unif[-\varepsilon, \varepsilon]$.

The fraction of investors $\lambda(\theta)$ hit by the liquidity shock sell their equity. The investors $1 - \lambda(\theta)$ not hit by the shock decide whether to sell or not their stake in the bank. The consumption decision of the late investors depends on the market price of equity today versus the expected dividend payments of tomorrow, which depend on own signal θ_i, and how many other market participants sell at $t = 2$. We denote the fraction of late investors which sell by $\lambda_{panic}(\theta) \in (0, 1-\lambda(\theta))$. This framework which will further drive our cash-in-the-market pricing results is based on the seminal work of Allen and Gale (1994). The investor decisions to sell or buy bank equity at the intermediate stage determine the equilibrium share price on the market P^m.

Bank manager

The bank manager has no initial wealth, and their aim is to maximise banks' share value while meeting the risk-sensitive capital requirements at $t = \{1, 2\}$. In case of recapitalisation needs, the bank's choice is between asset substitution or Coco conversion. In the baseline model, the manager faces a decision only at the intermediate time $t = 2$ after the price of equity is pinpointed in the market.

The decision of the manager is to maximise shareholders' value, by choosing the optimal liquidation fraction and conversion, conditional on meeting the risk-based capital requirement. In case of market based requirements, the banks' manager problem reads:

$$\begin{aligned} \max_{\beta, \mathbb{1}_{conv}} \quad & \frac{e^b}{n_{max}} = \frac{(1-\mathbb{1}_{conv}\beta)E[A] + \mathbb{1}_{conv}\beta l - \mathbb{1}_{conv}C - D}{n_{max}} \qquad \text{s.t.} \\ RWA = \; & \frac{P^m n_{max}}{\sigma_A(1-\mathbb{1}_{conv}\beta)E[A]} \geq \tau \end{aligned} \tag{2.3}$$

where $\beta \in [0, 1]$ is the liquidation fraction of long term assets, $l < 1$ liquidation value per unit of investment and $\mathbb{1}_{conv}$ is an indicator function for conversion:

$$\mathbb{1}_{conv} = \begin{cases} 0 & \text{if conversion of low CoCo} \\ 1 & \text{otherwise} \end{cases}$$

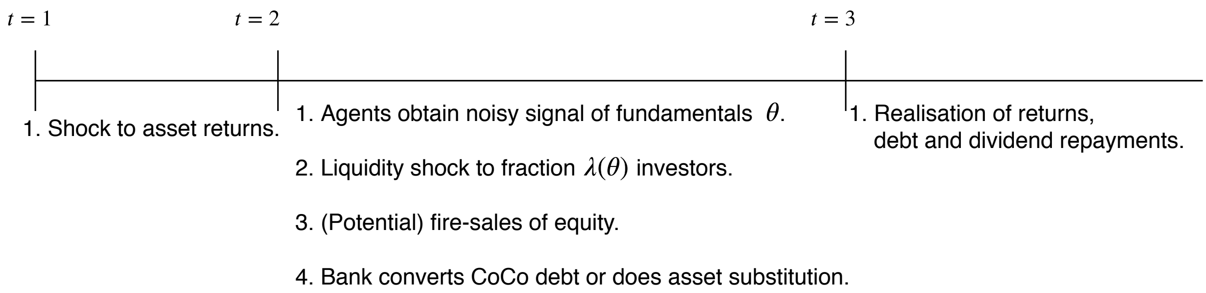
The maximum number of shares, $n_{max} = 1 + (1 - \mathbb{1}_{conv})\psi C$ Alternatively, when the requirement is book based, the numerator $P^m n_{max}$ is replaced with the book value of equity.

Passive debt holders

The third type of agents are passive bond holders, which hold debt in the bank either in the form of senior or CoCo debt. They do not play an active role in the subsequent analysis, as their behavior on the secondary market does not influence equilibrium out-comes in this setting.

Timeline

Figure 2.2: Timeline baseline model



Ex-ante, the bank raises funds, and investors allocate their portfolio $W = c + e_0$.

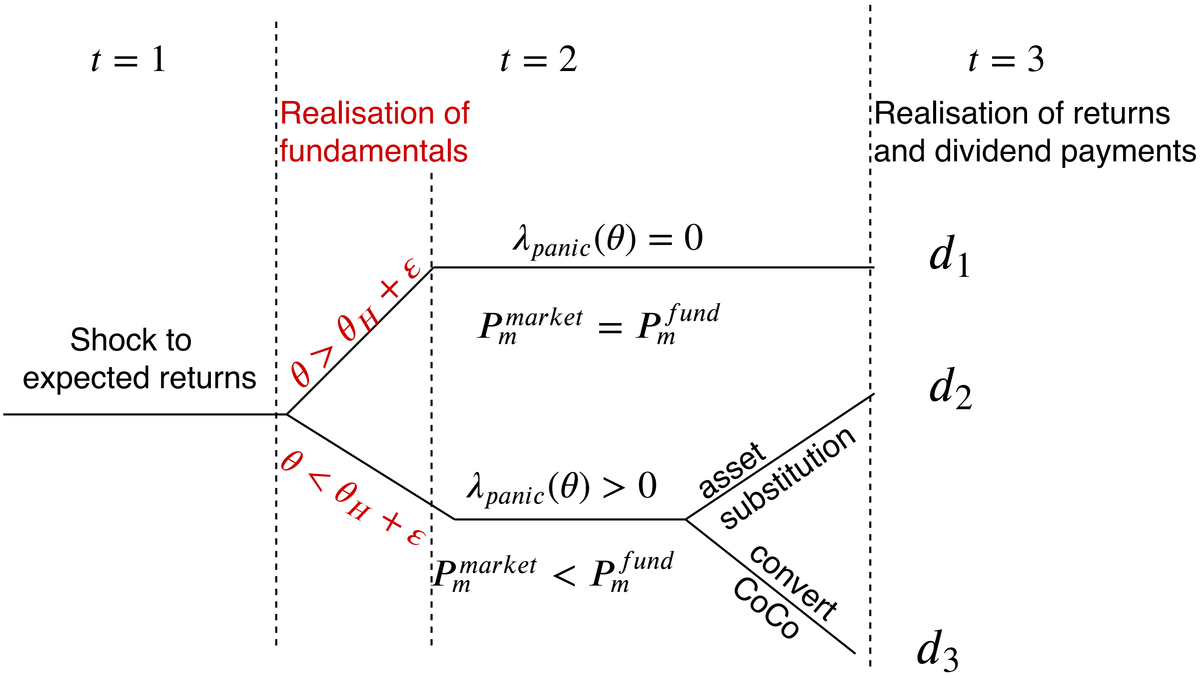
At $t = 1$ there is new private information revealed about the risky assets, which decreases the expected value of returns to the risky asset from R to R_L. We model this new information as a first order stochastic dominance shift in the probability distribution of returns of the long term asset from $f_A(\theta)$ to $f_L(\theta)$: $E_1[A|f_L] = R_L < R$, thus maintaining the same standard deviation σ_A. The bank manager incorporates this information at time $t = 1$ in the capitalisation requirement, which becomes:

$$RWA_1 = \frac{E_1[A|f_L] - D - C}{\sigma_A E_1[A|f_L]} > \tau$$

The new ratio is still higher than the minimum capital requirement, but the shock is large enough to be observed in the market. This signals to the market that returns are lower than initially expected which potentially influence the behaviour of equity holders at $t = 2$.

At $t = 2$, the true state of fundamentals θ is realized. Each investor $i \in \{1, 2, ...n\}$ and the bank B obtain noisy signals $\theta_i = \theta + \varepsilon_i$, where ε_i is the information noise drawn from a uniform distribution $Unif[-\varepsilon, \varepsilon]$. A fraction $\lambda(\theta)$ of investors are hit by a liquidity shock and sell their equity. Due to the asset shock at $t = 1$ existing equity holders expect lower returns, but also a potential CoCo conversion or asset substitution. If the fundamentals are perceived as good enough, so the worst signal that an investor obtains is θ_H, and so

Figure 2.3: Decision tree baseline model



the fundamentals are higher than $\theta_H + \varepsilon$, then the expected returns are high enough to have no investors which sell equity without having a liquidity need. Otherwise, there is a fraction of investors $\lambda_{panic}(\theta)$ who sell their equity in light of these potential effects, and we refer to them as panic investors.

After markets clear, and the price of equity is determined, the bank manager re-evaluates the RWA requirement. The manager maximises share value, while meeting the capitalisation requirements. They re-establish the capitalisation ratio either by asset substitution or high CoCo conversion.

At $t = 3$ returns on the long term asset are realized and debt and dividend payments are made.

To summarise, there are two signals in the economy. At $t = 1$ the manager obtains new private information about the distribution of returns to the long term asset. The second signal is represented by the noisy information about the state of fundamentals θ at $t = 2$. The shock to assets and the state of the fundamentals are uncorrelated.

If fundamentals are good enough: $\theta > \theta_H + \varepsilon$, then there are no panicked investors, and equity trades at book/fundamental prices: $P^m = P^{book}$. Otherwise, there are panicked investors and equity trades below book value. We depict this decision tree mechanism in Figure 2.3. The possible dividend payoffs at $t = 3$ are (d_1, d_2, d_3) corresponding to the three states of the world.

2.2.1 Equilibrium analysis

We solve for equilibrium using backward induction, and derive the optimal strategy of the bank manager, and of late investors $\lambda^*_{panic}(\theta)$ at $t = 2$. The most interesting case is the one when the ratio is evaluated in the market, and so we solve for equilibrium for the baseline model only for that case. In the extension with two CoCo buffers we treat also the book ratio case. We start by deriving the market clearing price of equity, followed by banks' best response to it, and the investors' decision.

Market clearing price of equity

At $t = 1$, the bank manager received additional information that the expected returns on the risky asset are lower than expected. They incorporate it in the value of risk weighted assets. As there is too little information about the state of the world - θ is unknown, and none of the investors is hit by a shock yet, we assume that equity is traded at fundamental value.

At $t = 2$ the market clearing price of shares is endogenously determined by the cash availability in the market. Let P^m be the market clearing price per share at time $t = 2$, and n_{max} is the total number of shares the bank has, and is defined as

$$n_{max} = \begin{cases} 1 & \text{if no conversion} \\ 1 + \psi C & \text{if CoCo debt converts} \end{cases} \tag{2.4}$$

Proportion $\lambda(\theta)$ of initial investors face at $t = 2$ a liquidity shock, and they have to consume. The function $\lambda(\theta) : [0, 1] \rightarrow [0, 1]$ is continuous and monotonically decreasing in θ. This captures that more investors require liquidity as the economic state worsens. All investors hit by the shock sell their stake in the bank, regardless of the market price. There are $0 < \lambda_{panic}(\theta) < 1 - \lambda(\theta)$ fraction of panic investors which are not hit by the liquidity shock, but they still decide to sell equity at $t = 2$. Thus, there are three types of investors at $t = 2$: $\lambda(\theta)$ of early investors who are hit by a shock and have to sell, $\lambda_{panic}(\theta)$ late investors who are not hit by a shock but still decide to sell (panicked agents), and $1 - \lambda(\theta) - \lambda_{panic}(\theta)$ who are not hit by a shock and do not sell, but instead buy all the equity in the market. The available cash in the market is determined by the late investors which wait for dividend payments: $[1 - \lambda_{panic}(\theta) - \lambda(\theta)]c$. Their preference of buying equity is trivially satisfied, as in case the equity sells at fundamental value they are indifferent, and if it sells at a depressed price then they are better-off buying, given their beliefs. The market capitalisation must be lower then or equal to the available cash in the market. Thus, the market clearing condition at $t = 2$ satisfies:

$$P^m(\theta)[\lambda(\theta) + \lambda_{panic}(\theta)]e_0 \leq [1 - \lambda(\theta) - \lambda_{panic}(\theta)]c \tag{2.5}$$

Corollary 2.1. *At $t = 2$, shares are either traded at fundamental value, or below it. The market clearing price in the stock market is:*

$$P^m(\lambda(\theta), \lambda_{panic}(\theta)) = \min\left[\frac{e_1^b}{n_{max}}, \frac{[1 - \lambda(\theta) - \lambda_{panic}(\theta)]c}{[\lambda(\theta) + \lambda_{panic}(\theta)]e_0 \cdot n_{max}}\right] \tag{2.6}$$

where n_{max} is the initial number of shares, and e_1^b represents the book value of equity at $t = 1$.

Banks' best response

Once the equilibrium price $P^m(\lambda(\theta), \lambda_{panic}(\theta))$ is determined on the market, the bank manager best response is:

$$\max_{\beta, \mathbb{1}_{conv}} \frac{e_1^b}{n_{max}} = \frac{(1 - \mathbb{1}_{conv}\beta)E_1[A|f_L] + \mathbb{1}_{conv}\beta l - \mathbb{1}_{conv}C - D}{n_{max}} \quad \text{s.t.} \tag{2.7}$$

$$RWA_1(\theta) = \frac{P_1^m(\lambda(\theta), \lambda_{panic}(\theta)) \cdot n_{max}}{(1 - \mathbb{1}_{conv}\beta)\sigma_A E_1[A|f_L]} \geq \tau \tag{2.8}$$

Liquidation is a form of asset substitution, which allows the bank to diminish the overall value of risk weighted assets, which in turn will increase the RWA ratio. *Ceteris paribus*, we assume that the bank has a preference towards liquidating assets first, as it permits the low trigger CoCo buffer to be used in case of *force majeure* in the future (in a multi-period model). Another explanation for delaying conversion is high reputational costs for the bank.

If the size of the shock is big enough, and the expected returns are below gains from liquidation $E_1[A|f_L] < l$ it can readily be seen that the value of equity is maximised if the bank liquidates all risky assets.[7] This is a corner solution which brings little insight and so we will not treat this case further.

If $E_1[A|f_L] > l$, the value of equity is decreasing in the liquidation fraction β and increasing in the value of fundamentals θ. Thus the overall costs of bank to maintain $RWA_1 \geq \tau$ increase as $\lambda_{panic}(\theta)$ increases, because the bank has to liquidate more of the long-term assets. The bank will maximise the value of equity by minimizing the fraction of risky assets that it has to liquidate. Conditional on liquidation, the share value will be maximised when the constraint will be minimised, and hence binding.

Proposition 2.1. *The bank prefers asset substitution over CoCo conversion, and liquidates a fraction $\beta^*(\lambda(\theta), \lambda_{panic}(\theta))$ of long term risky assets as long the proportion of panic investors is below $\lambda^*_{panic}(\theta)$, and otherwise prefers CoCo debt conversion, and further liquidation $\beta^*_{conv}(\lambda(\theta), \lambda_{panic}(\theta))$ if needed.*

The banks' best response liquidation fraction of long term risky assets is given by

$$\beta^*(\lambda(\theta), \lambda_{panic}(\theta)) = 1 - \frac{[1 - \lambda(\theta) - \lambda_{panic}(\theta)]\ c}{\tau \sigma_A e_0 E[A|f_L][\lambda(\theta) + \lambda_{panic}(\theta)]} \tag{2.9}$$

The bank's indifference point between asset substitution and CoCo conversion is given by:

$$\lambda^*_{panic}(\theta) = \frac{c(1 - \lambda(\theta)) + \lambda(\theta))(B-1)e_0 \tau \sigma_A E[A|f_L]}{c - (B-1)e_0 \tau \sigma_A E[A|f_L]} \tag{2.10}$$

where $B = \underbrace{\frac{E[A|f_L] - C - D}{E[A|f_L] - l}}_{liquidation} - \underbrace{\frac{(E[A|f_L] - D)}{(E[A|f_L] - l)(1 + \psi C)}}_{conversion}$.

[7] If the bank could further shift the distribution of returns, a moral hazard problem could arise as banks have incentives to 'gamble' and continue with their long term assets due to limited liability (see Martynova and Perotti (2018); Chan and van Wijnbergen (2017)).

The derivations can be found in the appendix. Intuitively, the optimal $\lambda^*_{panic}(\theta)$ depends on the initial capital structure, and dilution size after conversion. There are three possible cases.

We can eliminate the cases where $\lambda^*_{panic}(\theta)$ is not an interior solution based on economically sensible arguments. Firstly, if the optimal threshold between conversion and liquidation $\lambda^*_{panic}(\theta)$ has a negative value, then liquidating all assets always yields a lower value than CoCo conversion. In this case, bank converts first and share value always increases if conversion occurs. This case can happen if CoCos are principal write-down. Otherwise, if $\lambda^*_{panic}(\theta) > 1 - \lambda(\theta)$, then liquidating all assets is always preferred to CoCo conversion. An interpretation could be that dilution is so large for shareholders, that conversion becomes a solution of last resort. This can be interpreted as CoCos having a very large dilution size ψ for existing shareholders.

The interior solution $\lambda^*_{panic}(\theta) \in [0, 1 - \lambda_{panic}(\theta)]$ guarantees that the bank liquidates first, and converts if $\lambda_{panic}(\theta) > \lambda^*_{panic}(\theta)$. In this case, the trade-off between dilution and costly liquidation depends on market price of shares, and dilution size ψ. After conversion, if the ratio still falls below τ_L bank manager liquidates

$$\beta^*_{conv} = 1 - \frac{P^m_1(\lambda(\theta), \lambda_{panic}(\theta))[1 + \psi C]}{\tau \sigma_A E[A|f_L]} \tag{2.11}$$

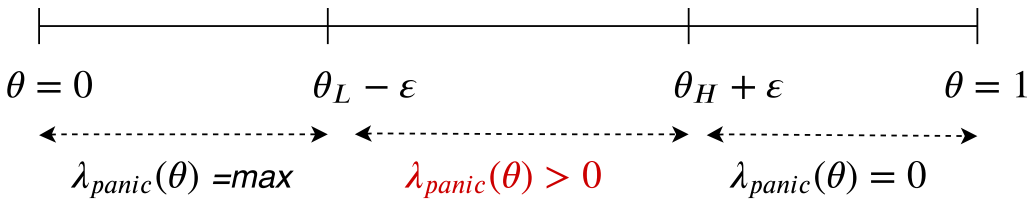
Let $\bar{\psi}$ be the "neutral conversion" at which there is a zero wealth transfer from CoCo holders to equity holders (Chan and van Wijnbergen, 2017). For $\psi_L < \bar{\psi}_L$ shareholders benefit from conversion, and for $\psi_L > \bar{\psi}_L$ the wealth transfer from CoCo holders to equity is negative.

The neutral conversion, with a zero wealth transfer between low trigger CoCo holders to equity holders is

$$\bar{\psi}_L = \frac{(\beta^* - \beta^*_{conv})(E[A|f_L] - l) - C}{C(1 - \beta^*_1)E[A|f_L] + \beta^* l - C - D} \tag{2.12}$$

A derivation of the parameter can be found in the appendix. The existence of an interior solution, where the bank prefers first to do asset substitution depends on the maximum available cash in the market, and the size of the shock to assets. Intuitively,

Figure 2.4: Investors decision to sell and fundamentals



if there is more cash available, equity will trade at fundamental value. Alternatively, if returns are high enough in expectation, there is no need to liquidate any assets to begin with. The proof and full solution of the following proposition can be found in the Appendix.

Proposition 2.2. *The bank's best response to liquidate fraction $\beta^*(\lambda(\theta))$ is an interior solution* [8]*, up to a maximum amount of cash in the market $(1 - \lambda(\theta) - \lambda_{panic}(\theta))c$, and a maximum value of expected returns $E[A|f_L]$.*

Investors' behavior

The investors which are not hit by a liquidity shock decide whether to sell or not based on their expected payoffs. If they expect that waiting yields a higher payoff compared to selling equity at current market price, then they will not sell.The bank best responds to the decision of equity holders. If the fundamentals are good enough, and so $\theta > \theta_H + \varepsilon$, the incentive compatibility constraint of equity holders to wait until $t = 3$ is always met, and the shares trade at fundamental price. The number of equity holders not hit by a liquidity shock that sell in equilibrium is $\lambda_{panic}(\theta) = 0$.

If the fundamentals are bad enough, and so $\theta < \theta_L - \varepsilon$, equity holders will sell regardless of the beliefs about the behavior of other equity holders, because conversion is imminent and returns will be very low. Thus, in this region the fraction of late investors who sell is $\lambda_{panic}(\theta) = 1 - \lambda(\theta)$. The three regions are summarised in Figure 2.4.

We build further on the methodology of Goldstein and Pauzner (2005) and we stay close to their notation.

[8]defined as $0 < \beta^*(\lambda_{panic}(\theta)) < 1$ $0 < \lambda^*_{panic}(\theta) < 1 - \lambda(\theta)$

In the intermediate region of fundamentals $\theta_L - \varepsilon < \theta < \theta_H + \varepsilon$, the expected payoffs for each share are summarised in Table 2.2,where β^*, β^*_{conv} are the bank's best response functions derived earlier.

Table 2.2: Investors' waiting versus selling payoffs

Sell in	$t = 2$	$t = 3$
$\lambda_{panic}(\theta) < \lambda^*_{panic}(\theta)$	$P^m(\lambda(\theta), \lambda_{panic}(\theta))$	$d_2 = (1 - \beta^*)E[A\|f_L] + \beta^* l - C - D$
$\lambda_{panic}(\theta) > \lambda^*_{panic}(\theta)$	$P^m(\lambda(\theta), \lambda_{panic}(\theta))$	$d_3 = \frac{(1-\beta^*_{conv})E[A\|f_L]+\beta^*_{conv} l - D}{1+\psi C}$

Following Goldstein and Pauzner (2005), we denote by $v(\lambda_{panic}(\theta)) : (0, 1 - \lambda(\theta)) \rightarrow \mathbf{R}$ the function that captures the value of waiting until $t = 3$ minus value of selling at $t = 2$ for equity holders:

$$v(\lambda_{panic}(\theta)) = \begin{cases} d_2(\beta^*) - P^m_1(\lambda_{panic}(\theta)) & \text{if } \lambda_{panic}(\theta) < \lambda^*_{panic}(\theta) \\ d_3(\beta^*_{conv}) - P^m_1(\lambda_{panic}(\theta)) & \text{otherwise.} \end{cases} \tag{2.13}$$

The proofs of unique equilibrium in Morris and Shin (1998); Goldstein and Pauzner (2005) relate to how agents interact with each other. The decisions are global strategic complementarities if the incentive to take a specific action is monotonically increasing with the number of agents who take the same action (Goldstein and Pauzner, 2005). In contrast, strategic substitutes are when the action incentives of an agent are monotonically decreasing with the number of agents who take that decision.

Depending on the initial capital and CoCo design, there can be one, multiple or no indifference points in investors' value of waiting minus value of selling: $v(\lambda(\theta)) = 0$. More precisely, if it is always better to wait, so $v(\lambda_{panic}(\theta)) > 0 \ \forall \ \lambda_{panic}(\theta) \in [0, 1-\lambda(\theta)]$, then in equilibrium $\lambda_{panic}(\theta) = 0$, as all late investors prefer to wait. Multiple equilibria arise if $\exists$ at least $\lambda_{11}(\theta), \lambda_{12}(\theta) \in [0, 1-\lambda(\theta)]$, $\lambda_{11}(\theta) \neq \lambda_{12}(\theta)$ such that $v(\lambda_{11}(\theta)) = v(\lambda_{12}(\theta)) = 0$. We guarantee a unique equilibrium if $\exists^* \lambda_{panic}(\theta) \in (0, 1 - \lambda(\theta))$ s.t. $v(\lambda_{panic}(\theta)) = 0$. We further assume a capital structure that allows for a unique equilibrium. Our model does not allow for closed form solutions, but we are able to provide numerical solutions or confidence intervals which have only a single crossing.

Table 2.3: Indifference points between waiting and selling for investors

	$\lambda_2(\theta) - \lambda^*_{panic}(\theta) \geq 0$	$\lambda_2(\theta) - \lambda^*_{panic}(\theta) < 0$
$\lambda_1(\theta) - \lambda^*_{panic}(\theta) \geq 0$	Single crossing after conversion	No crossing
$\lambda_1(\theta) - \lambda^*_{panic}(\theta) < 0$	Double crossing	Single crossing before conversion

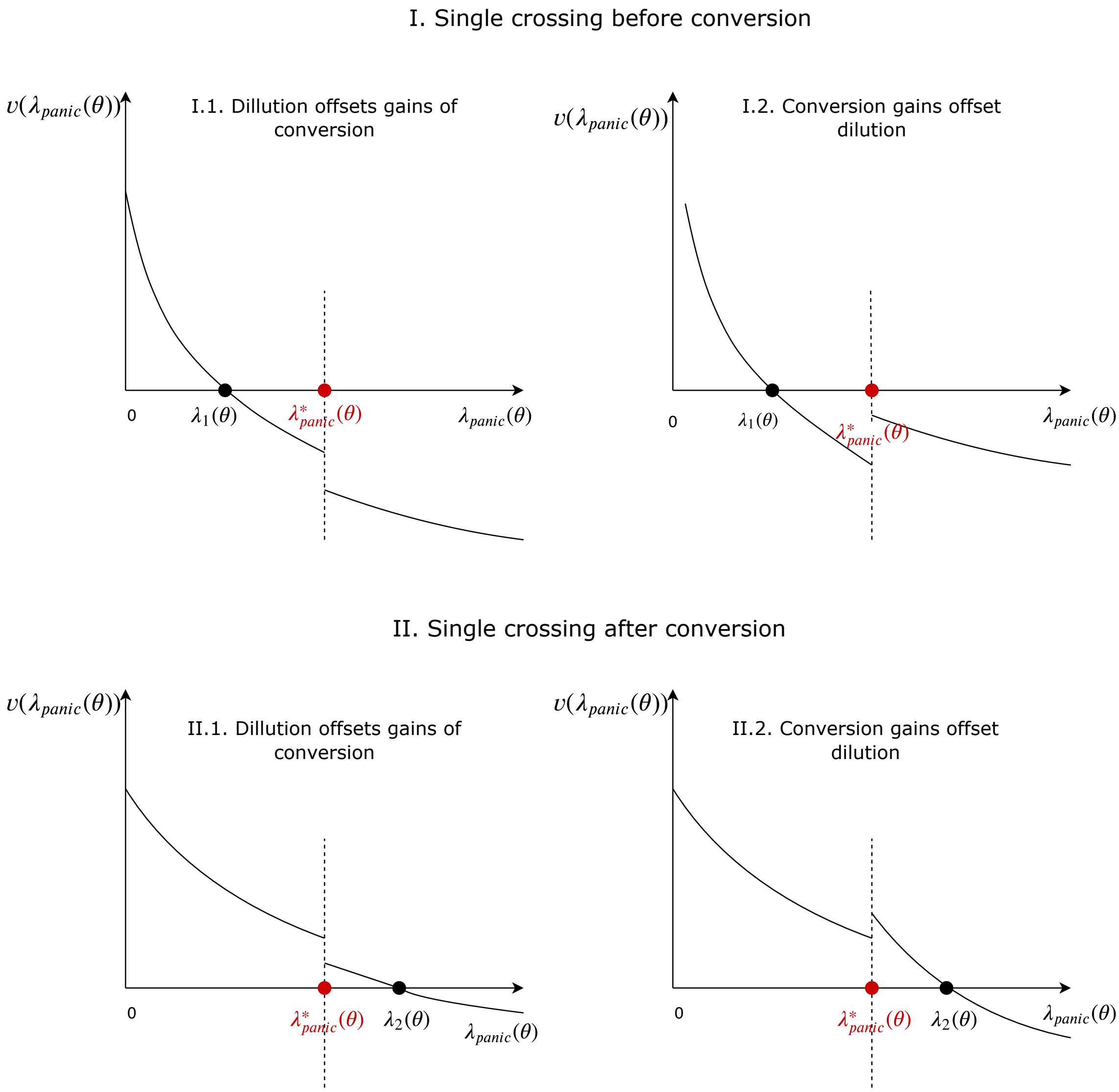
Lemma 2.1. *For dilutive CoCos $\psi > \bar{\psi}$, the necessary and sufficient condition for late investor decisions to be **strategic complementarities** is that $v(\lambda_{panic}(\theta))$ is piece-wise monotonically decreasing on the intervals $(0, \lambda^*_{panic}(\theta))$ and $[\lambda^*_{panic}(\theta), 1 - \lambda(\theta))$*

Condition under lemma 2.1 is achieved as long as the fraction $1 - \tau_L$ of expected returns on long term assets is larger than the liquidation value: $l < E_1[A|f_L](1 - \tau)$.

We further proceed to derive the unique equilibrium threshold θ^* above which all agents with a signal $\theta_i > \theta^*$ decide to wait for payoff payments at $t = 2$ and sell if $\theta_i < \theta^*$. Following the uniqueness proof of Goldstein and Pauzner (2005), a unique θ^* exists if $v(\lambda_{panic}(\theta))$ crosses zero only once. Due to the discontinuity of $v(\lambda_{panic}(\theta))$ point $\lambda^*(\theta)$, we cannot apply one-to-one their methodology, and we state additional restrictions on the capital structure of the bank to guarantee uniqueness. As a consequence, we can argue that under specific initial capital structures the model can have multiplicity of fire sales of equity equilibria, or none.

Figure 2.5 displays the four possible cases of single crossing: before (I), or after conversion (II), which further depend on whether dilution offsets gains of conversion (I.1 and II.1) or not(I.2 and II.2). Yet again, the relationship will be uniquely determined by the parameters of the initial capital structure, and how the conversion rate of ψ compares to the "neutral conversion" $\bar{\psi}$ from Chan and van Wijnbergen (2017). At this stage it is worth noting that for the single crossing the dilutive power of CoCos does not matter. Intuitively, in cases I.1 and I.2 from figure 2.5, even under the most optimistic scenario (I.2) the dilution gains cannot offset the losses from the decrease in current market price. Additionally, if the single crossing happens after conversion, then the dilution vs. conversion gains will only swift $\lambda_2(\theta)$: in II.1 the indifference point will be achieved for a lower λ_{panic} than under II.2. Hence we do not distinguish further between $I.1 \wedge I.2$ and $II.1 \wedge II.2$ as we argue that it does not bring any additional economic insight.

Figure 2.5: Single crossing cases



Let $\lambda_1(\theta)$ be the solution of: $d_2(\theta) - P^m = 0$ and $\lambda_2(\theta)$ the value which solves: $d_3(\theta) - P^m = 0$. In other words, $\lambda_1(\theta), \lambda_2(\theta)$ are the threshold values at which equity holders are indifferent between selling or waiting before, or after conversion respectively.

Proposition 2.3. *The necessary and sufficient conditions for the existence of a unique point at which equity holders are indifferent between waiting until $t = 2$ or selling their equity are:*

(i) ***before conversion*** –

$$\begin{cases} 0 < \lambda_1(\theta) \leq \lambda^*_{panic}(\theta) \\ 0 < \lambda_2(\theta) < \lambda^*_{panic}(\theta) \end{cases}$$

(ii) ***after conversion*** –

$$\begin{cases} \lambda_1(\theta) > \lambda^*_{panic}(\theta) \\ \lambda_2(\theta) \geq \lambda^*_{panic}(\theta) \end{cases}$$

Intuitively, these conditions capture a simultaneity issue: the indifference condition $v(\lambda_{panic}(\theta)) = 0$ has to co-exist in the same variable space as the bank's best response. We construct a proof by contradiction in the Appendix.

Lower and upper dominance regions

Outside the intermediate region, there is a range of extremely good or extremely bad fundamentals, where the behavior of equity holders is independent on the others decision.

We guarantee that the *lower dominance region* is nonempty if $\theta_L > 2\varepsilon$. The lower bound for θ_L is established if even for the lowest possible returns today, the equity holder is not willing to wait for payoffs: $P^m(\theta_L) \geq d_2(\theta_L)$. The lowest possible market price is obtained if all equity holders sell: $\lambda_{panic}(\theta) = 1 - \lambda(\theta)$. A complete proof can be found in the Appendix.

The condition for a non-empty lower dominance region is implicitly defined from the following inequality, which can be trivially solved for any monotonically increasing functional form of $F_{R_L}(.)$:

$$F(\theta_L - \varepsilon) - F(\theta_L + \varepsilon) = D > 0 \tag{2.14}$$

Let $\theta_U \leq \theta_H$ be the upper bound of fundamentals, above which the expected utility of waiting for residual payments is always at least as large as the expected utility of selling equity at $t = 1$, regardless of how many shares are traded in the market. This condition is trivially satisfied, due to our earlier assumption that for $\theta > \theta_H + \varepsilon$ shares trade at fundamental value, independent on how many shares are sold. In the upper dominance region $RWA(\theta|f_L) \geq RWA(\theta_H|f_L) > \tau_H$ fundamentals are strong enough that the bank will be able to pay back the debt without further asset substitution or conversion and the equity holders will make a positive profit at $t = 3$.

Corollary 2.2. *A late investor always sells if she observes a signal $\theta_i \leq \theta_L - \varepsilon$. A late investor never sells if she observes a signal $\theta_i \geq \theta_U + \varepsilon$.*

When $\theta < \theta_L - 2\varepsilon$, all agents are guaranteed to obtain a signal $\theta_i < \theta_L - \varepsilon$, and thus all equity holders sell their shares at $t = 2$: $\lambda^*(\theta) = 1 - \lambda(\theta)$, independent on the actions of others. Symmetrically, for $\theta > \theta_H + 2\varepsilon$, all agents obtain a signal $\theta_i > \theta_H + \varepsilon$ and thus no equity holder sells at $t = 2$.

The distribution of ε is uniform over $[0, 1]$ and in the interval $[\theta_L - 2\varepsilon, \theta_L]$ the fraction of equity holders which observe signals below $\theta_L - \varepsilon$ decreases linearly at a rate of $\frac{1}{2\varepsilon}$[9] - see Figure 2.6. Similarly, in the region $[\theta_U, \theta_U + 2\varepsilon]$, the proportion of agents who receive signals $\theta_i > \theta_U + \varepsilon$ increases at rate $\frac{1}{2\varepsilon}$.Figure 2.6 follows the same format of Goldstein and Pauzner (2005). The solid line represents the upper bound from the upper dominance region: the maximum number of equity holders that sell. The dotted line denotes the lower bound of equity holders which sell. On the intervals $[0, \theta_L - 2\varepsilon]$ and $[\theta_U + 2\varepsilon, 1]$, the segments fully overlap.

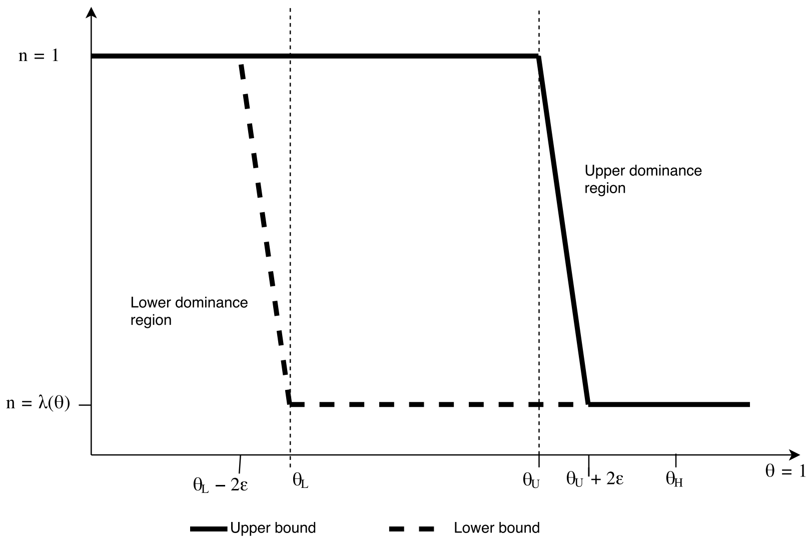
Unique equilibrium

Theorem 2.1. *Under single crossing conditions for $v(\lambda_{panic}(\theta)) = 0$, there is a unique equilibrium θ^* below which a late investor with signal $\theta_i < \theta^*$ sells all her shares at $t = 2$, and otherwise waits for residual payments at $t = 3$.*

A sketch of the proof based on Goldstein and Pauzner (2005) is presented in the Appendix. Their proof uses the continuity property of $v(\lambda_{panic}(\theta))$, which does not generally hold in our case. We can prove that the unique equilibrium exists if $v(\lambda_{panic}(\theta)) = 0$ only once.

[9] Which is derived from the corresponding probability density function.

Figure 2.6: Proportion of equity holders that sell



The equilibrium value θ^* is defined such that an equity holder with signal θ^* is indifferent between selling at $t = 2$ or waiting for dividend payments over all possible values of $\lambda_{panic}(\theta^*)$. The threshold θ^* is implicitly defined from:

$$\int_0^{\lambda^*(\theta^*)} (d_2(\theta^*) - P^m(\lambda_{panic}(\theta^*))d\lambda_{panic} + \int_{\lambda_1^*(\theta^*)}^{1-\lambda(\theta)} (d_3(\theta^*) - P^m(\lambda_{panic}(\theta^*)))d\lambda_{panic} = 0 \tag{2.15}$$

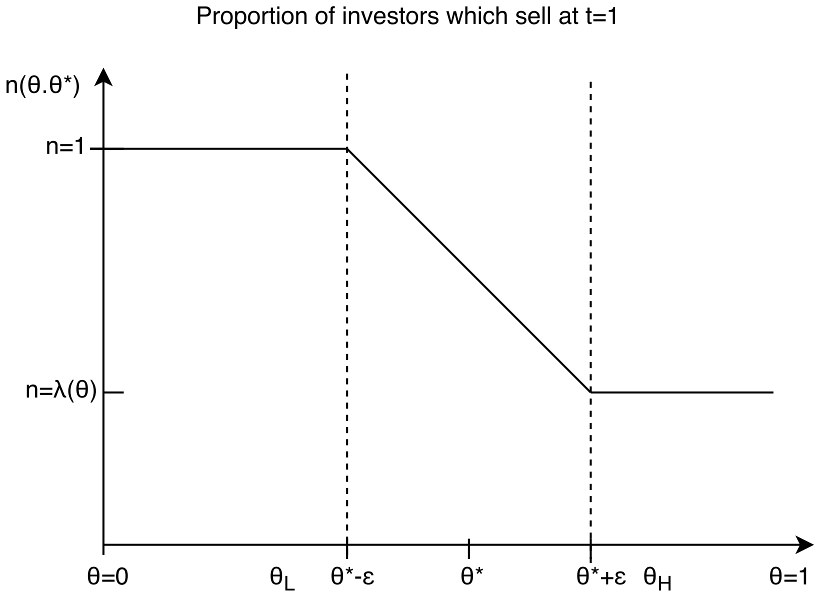
Corollary 2.3. *The proportion of total equity holders that sell, as a function of fundamentals is given by:*

$$n(\theta, \theta^*) = \begin{cases} 1 & \theta < \theta^* - \varepsilon \\ \lambda(\theta) + (1 - \lambda(\theta))\frac{\theta^* - \theta + \varepsilon}{2\varepsilon} & \theta^* - \varepsilon \leq \theta \leq \theta^* + \varepsilon \\ \lambda(\theta) & \theta > \theta^* + \varepsilon \end{cases} \tag{2.16}$$

Goldstein and Pauzner (2005) call the corresponding intermediate region from Figure 2.6: $\theta \in (\theta_L - 2\varepsilon, \theta_U + 2\varepsilon)$ as the panic based runs region. In our model this is the critical region which leads to multiple inefficiencies.

In case of uniformly distributed errors, the proportion of equity which sell in equilibrium is depicted in Figure 2.7.

Figure 2.7



if $\lambda_{panic}(\theta)$ is high enough, the bank converts when in fact the book value of $RWA > \tau$. This conversion is inefficient for CoCo holders, and the effect is ambiguous for equity holders. If dilution offsets the gains of conversion, then it has a negative effect for equity holders. Otherwise, if $\lambda_{panic}(\theta) < \lambda^*_{panic}(\theta)$ then it leads to inefficient asset substitution which decreases overall payoffs, which is harmful for existing equity holders.

If CoCos are non-dilutive $\psi_L < \bar{\psi_L}$, then the decisions to sell of late investors are **strategic substitutes**. In this case, the CoCos are not artificially triggered, as long as shareholders cannot sort sell their equity. The possibility of re-purchasing, combined with limited cash in the market pricing, CoCos with dilution $\psi_L < \bar{\psi_L}$ are not a good loss absorption mechanism, as it creates incentives for shareholders to force CoCo conversion by short-selling their equity. Note that an extreme case of non-dilution is given by principal write-down CoCos.

Proposition 2.4. *Under the assumption that equity holders cannot re-buy their shares and CoCos are non-dilutive $\psi_L < \bar{\psi_L}$, the threshold equilibrium θ^*_{nd} below which all equity holders sell is $\theta^*_{nd} = \theta_L - \varepsilon$. The number of equity holders who sell as a function of* *fundamentals is:*

$$n_{nd}(\theta, \theta^*) = \begin{cases} 1 & \theta \leq \theta^* - \varepsilon \\ \frac{\theta^* - \theta + \varepsilon}{2\varepsilon} & \theta^* - \varepsilon < \theta < \theta^* + \varepsilon \\ 0 & \theta > \theta^* + \varepsilon \end{cases} \tag{2.17}$$

2.3 Two CoCo buffers model and analysis

2.3.1 Model extension

In this case, the bank has two CoCo buffers compared to the baseline model - see timeline with changes in red compared to the baseline in Figure 2.4. The bank raises a total amount of outstanding CoCo debt C_H, with a trigger level τ_H, and a conversion ratio ψ_H, and C_L CoCo debt, with trigger level τ_L, and ratio ψ_L. By construction, $\tau_H > \tau_L$. In this case, total equity amounts to $e_0 = A - D - C_H - C_L$.

Table 2.4: Initial balance sheet two CoCo buffers model

Assets	**Liabilities**
A - initial investment	D -senior debt C_H - high trigger CoCo C_L - low trigger CoCo e_0 - initial equity

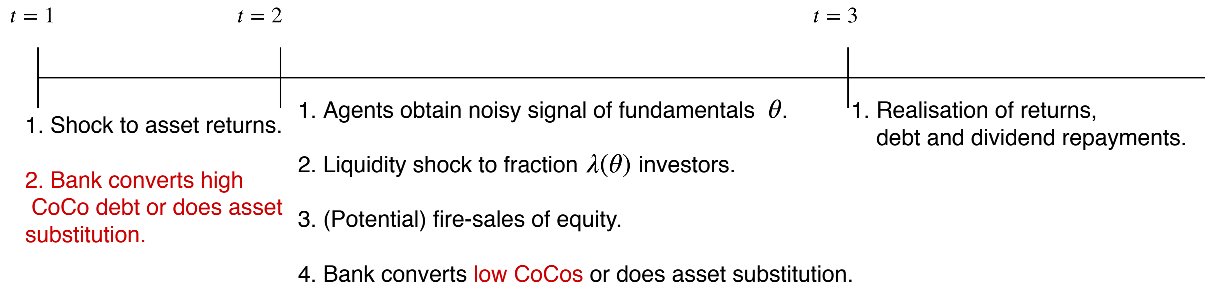
The bank has to comply with the capital requirement in both time periods $t = 1$ and $t = 2$. We assume that the shock to the expected asset returns is high enough such that the RWA_1 falls below the high CoCo trigger τ_H, but it is higher than the low trigger τ_L:

$$\tau_L < RWA_1 = \frac{E_1[A|\tau_L] - D - C_L - C_H}{\sigma_A E_1[A|f_L]} < \tau_H$$

After the manager incorporates the shock, the bank has to decide between asset substitution or high CoCo conversion. The trade-off is between lower returns at $t = 3$ versus possible fire sales of equity at $t = 2$. CoCo conversion signals to the market that returns are lower than initially expected which subsequently influence the behaviour of equity holders at $t = 2$. We denote by $\theta_H \in (0, 1)$ the corresponding values of fundamentals such that conditional on a high CoCo initial conversion, at $t = 1$ is:

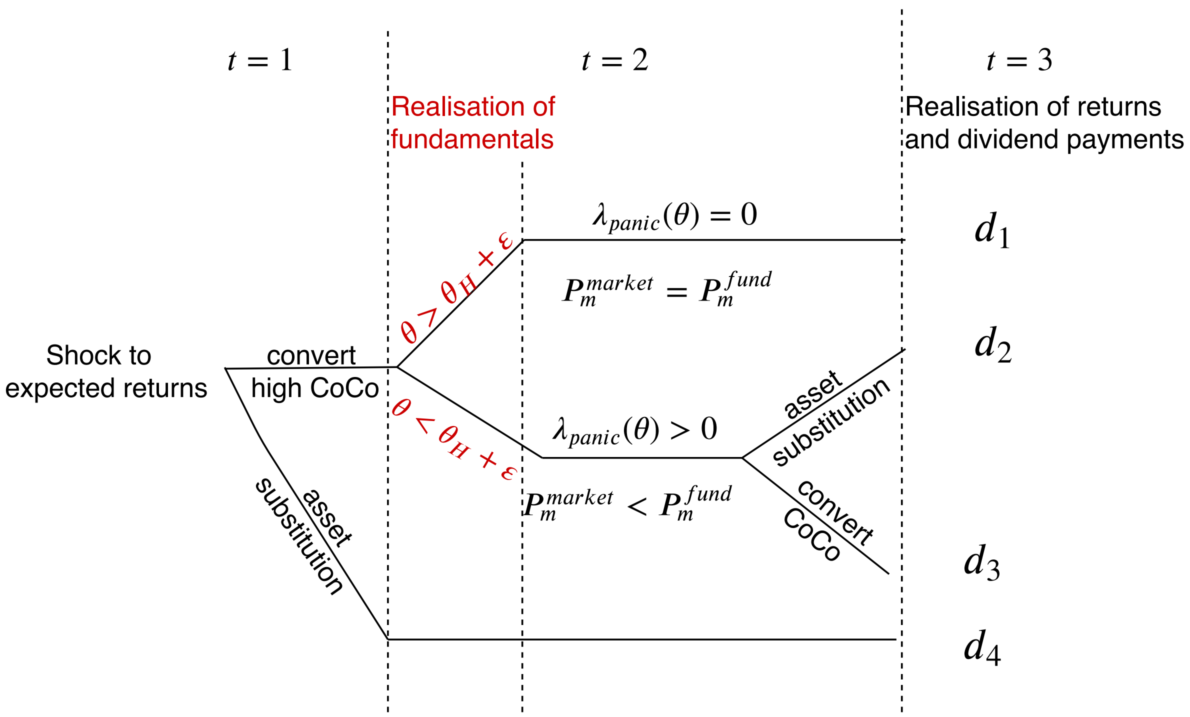
$$RWA_1(\theta_H|f_L) = \frac{e_1^b}{\sigma_A \int_{\theta-\varepsilon}^{\theta+\varepsilon} Af_{R_L}(\theta)\theta d\theta} > \tau_L$$

Figure 2.8: Timeline two CoCo buffers



The bank manager decision at $t = 1$ is similar now to the one at $t = 2$. We summarise the extended decision tree in Figure 2.9. The key difference compared to the baseline model is that, depending on the high CoCo design features, the bank manager might have incentives to prevent the high CoCo conversion via initial asset substitution.

Figure 2.9: Bank manager decision tree



The market clearing price at $t = 2$ is determined in the same way as before, with the difference that the maximum number of shares in the market changes now to:

$$n_{max}(\theta) = \begin{cases} 1 & \text{if no conversion} \\ 1 + \psi_H C_H & \text{if high CoCo converts} \\ 1 + \psi_H C_H + \psi_L C_L & \text{if both CoCos convert} \end{cases}$$

2.3.2 Equilibrium analysis

We solve for equilibrium using backward induction, but unlike the baseline model, now the bank has to take an additional decision at $t = 1$ which is whether to convert the high CoCo or do asset substitution instead - see Figure 2.9. Moreover, we further distinguish between the case where the ratio is evaluated at market value, and the case when the market capitalisation is book based, as it is done in practice.

Market based trigger

Decision at $t = 2$

In this case the capitalisation ratio RWA_2 is evaluated in the market. The decision of the bank manager and investors' behaviour is identical with the baseline case.

In case the bank converted the high CoCo at $t = 1$, the bank's best response liquidation fraction changes compared to the benchmark case. Now, the indifference point between conversion of the low trigger CoCo and asset liquidation is given by:

$$\lambda^*_{panic}(\theta) = \frac{c(1 - \lambda(\theta)) + \lambda(\theta)(G - 1)e_0\tau_L E[G|f_L]}{c - (G - 1)e_0\tau_L E[G|f_L]} \tag{2.18}$$

where $G = \frac{E[A|f_L] - C_L - B}{E[A|f_L] - l} - \frac{(E[A|f_L] - B)(1 + \psi_H C_H)}{(E[A|f_L] - l)(1 + \psi_H C_H + \psi_L C_L)}$.

The proof can be found in the appendix.

We previously defined $\bar{\psi}_L$ as the zero wealth transfer point between equity holders and CoCo holders. The neutral conversion in this case incorporates the previous high CoCo conversion.

Corollary 2.4. *The neutral conversion, with a zero wealth transfer between low trigger CoCo holders to equity holders is*

$$\bar{\psi_L} = \frac{(\beta_1^* - \beta_{1,C}^*)(E[A|f_L] - l) - C_L \cdot (1 + \psi_H C_H)}{C_L(1 - \beta_1^*)E[A|f_L] + \beta_1^* l - C_L - D} \tag{2.19}$$

A derivation of the parameter can be found in the appendix. We compare how the CoCo structure depends on optimal liquidation and conversion, and we find the following intuitive results. More cash is available in the market leads to a lower optimal liquidation fraction, as equity is traded closer to the fundamental value ($\frac{\partial \beta_1^*}{\partial c} < 0$). The size of the shock is inversely proportional with the optimal size of liquidation. The bank manager is more likely to convert the CoCo debt faster if the trigger is higher.

Corollary 2.5. *If $\theta < \theta_H + \varepsilon$ and the long term risky asset faces a negative shock to returns at $t = 1$, then the optimal fraction of asset substitution β_1^* at $t = 2$ depends in the following way on the CoCo structure:*

(i) If the high CoCo debt was highly dilutive for existing shareholders, then there is less need for other forms of recapitalisation at a later stage ($\frac{\partial \beta_1^*}{\partial \psi_H} < 0$)

(ii) The bank manager postpones conversion as the size of expected dilution increases ($\frac{\partial \lambda^*_{panic}}{\partial \psi_L} > 0$).

(iii) Wealth transfer and conversion

- *If the low CoCo debt is non-dilutive for existing shareholders, then the bank manager prefers conversion over asset liquidation, and this decision is increasing with the size of CoCo debt C_L ($\frac{\partial \lambda^*_{panic}}{\partial C_L} < 0$).*
- *If the CoCo debt is dilutive, then the bank postpones conversion, and opts for asset substitution instead.*

Investors' behavior

In a similar manner with the baseline model, the investors decide between selling and waiting. Compared to the first case, now the pay-off structure is different, which in turn might change their decisions. The crucial difference is the increase in the number of shares after the first conversion, but the functions only change by a scalar, making the function of waiting or selling shift by a scalar, and the solution method equivalent with the baseline case. In this case, the value function that investors face, based on the payoffs in Table 2.5.

$$v(\lambda_{panic}(\theta)) = \begin{cases} d_2(\beta_2^*) - P_2^m(\lambda_{panic}(\theta)) & \text{if } \lambda_{panic}(\theta) < \lambda_{panic}^*(\theta) \\ d_3(\beta_{2,conv}^*) - P_2^m(\lambda_{panic}(\theta)) & \lambda_{panic}(\theta) \geq \lambda_{panic}^*(\theta) \end{cases} \tag{2.20}$$

Table 2.5: Investors' waiting versus selling payoffs after first CoCo conversion

Sell in	$t = 2$	$t = 3$
$\lambda_{panic}(\theta) < \lambda_{panic}^*(\theta)$	$P^m(\lambda(\theta), \lambda_{panic}(\theta))$	$d_2 = \frac{(1-\beta_2^*)E[A\|f_L]+\beta_2^* l-C-D}{1+\psi_H C_H}$
$\lambda_{panic}(\theta) > \lambda_{panic}^*(\theta)$	$P^m(\lambda(\theta), \lambda_{panic}(\theta))$	$d_3 = \frac{(1-\beta_{2,conv}^*)E[A\|f_L]+\beta_{2,conv}^* l-D}{1+\psi_H C+H+\psi_L C_L}$

Based on this function specification, there is a unique θ^*, below which investors with signal $\theta_i < \theta^*$ sell their equity, and otherwise wait for residual payments. This result is formalised under Theorem 2.1. The threshold equilibrium θ^* is determined implicitly by:

$$\int_{\lambda_{panic}(\theta^*)=0}^{\lambda_{panic}(\theta^*)=\lambda^*(\theta^*)} (d_1(\theta^*) - P_2^m(\lambda_{panic}(\theta^*))d\lambda_{panic} + \tag{2.21}$$

$$+ \int_{\lambda_{panic}(\theta^*)=\lambda^*(\theta^*)}^{1-\lambda(\theta)} (d_2(\theta^*) - P_2^m(\lambda_{panic}(\theta^*)))d\lambda_{panic} = 0 \tag{2.22}$$

Compared to the benchmark case, the threshold $\lambda^*(\theta)$ is either larger or smaller depending on the conversion ratio ψ_H, and the size of CoCo debt C_H.

To summarise, in case of high CoCo conversion at $t = 0$, the equilibrium expected dividend payments at $t = 1$ are given by:

$$d_1(\theta) = \frac{E[A|f_L] - C_L - B}{1 + \psi_H C_H} \text{ if } \theta > \theta_H + \varepsilon \tag{2.23}$$

$$d_2(\theta) = \frac{(1 - \beta_1^*)E[A|f_L] + \beta_1^* l - C_L - B}{1 + \psi_H C_H} \text{ if } \theta_H + \varepsilon > \theta > \theta^* \tag{2.24}$$

$$d_3(\theta) = \frac{(1 - \beta_{1,conv}^*)E[A|f_L] + \beta_{1,conv}^* l - B}{1 + \psi_H C_H + \psi_L C_L} \text{ if } \theta^* > \theta > \theta_L - \varepsilon \tag{2.25}$$

$$d_4(\theta) = 0 \text{ if } \theta < \theta_L - \varepsilon \tag{2.26}$$

Decision at $t = 2$ in case of initial asset substitution

Insofar we treated the case where the high trigger CoCo has been converted at $t = 1$, which signaled to the market bad asset quality, which in turn led to inefficient conversion. In case of initial asset substitution at $t = 1$, now there are two CoCos which can convert. We assume that unlike CoCo conversion, asset substitution is not perceived as such as a strong signal by the market. This is in line with the industry observation of the coupon payment interruption on CoCo debt by Deutsche bank in 2016, which led to strong negative market reactions.

There will be no panic based agents who intend to sell, and so $\lambda_{panic}(\theta) = 0$. This simplifying assumption does not chance the key results, but rather provides a more intuitive perspective on the trade-off between asset substitution and conversion. Nonetheless, this asset substitution is in place before the market and the bank has any signal regarding the state of fundamentals.

Corollary 2.6. *Regardless of the state of fundamentals, there is never a need for CoCo conversion or further asset substitution at $t = 1$ if the bank manager liquidates at $t = 0$ a minimum of:*

$$\beta_1^* = \frac{C_H + C_L + D - \delta(1 - \tau_H)}{l - \delta(1 - \tau_H)} \tag{2.27}$$

where δ is an infinitesimally positive value, close to 0.

In the case where the bank tries to self-insure against conversion, by the large asset substitution towards safe assets described in Corollary 2.6, then the dividend payments are lower in expectation compared to an initial conversion of the high trigger CoCo.

Bank manager decision at $t = 1$

Once the shock to asset returns is observed by the bank manager, they will have to report the value of risk weighted assets and the risk weighted capital requirement. The trade-off that he faces is between reporting truthfully, which leads to immediate conversion of the high CoCo $RWA_1 < \tau_H$, or engaging in asset substitution which will lead to a higher RWA ratio, due to the decrease in the riskiness of asset portfolio.

The bank manager must liquidate a minimum fraction of β_1, described by:

$$\beta_1 = \frac{E[A|f_L](1-\tau_H) - C_L - D - C_H}{E[A|f_L](1-\tau_H) - l}$$

such that the risk based capital ratio is above τ_H:

$$RWA_1 = \frac{(1-\beta_2)E[A|f_L] + \beta_1 l - C_L - C_H - D}{(1-\beta_0))E[A|f_L]} > \tau_H$$

This insures that at $t = 2$ only fraction $\lambda(\theta)$ of investors sell and there are no panicked agents in the market: $\lambda_{panic}(\theta) = 0$. For this value of β_1, the value of fundamentals at $t = 2$ can lead to further CoCo conversion but shares will still be traded at fundamental value.

To further restrict the case space at $t = 2$ we assume a liquidation of β_1^*, as described in Corollary 2.6[10].

In case of initial asset substitution, expected dividends at $t = 3$ are:

$$d_4(\theta) = (1-\beta_1^*)E[A|f_L] + \beta_1^* l - C_L - C_H - D \quad \forall\, \theta \in (0,1] \tag{2.28}$$

[10]For completeness we should re-derive the cases for conversion $RWA_1 > \tau_H$; $\tau_L < RWA_1 < \tau_H$; $RWA_1 < \tau_L$ and calculate dividend payments. Nonetheless, the key intuition and results for this paper will not change, so we abstract from this matter and keep it in a simpler format.

At $t = 1$, the overall expected dividend payments in case of conversion is:

$$e_1^{\text{conv}} = \int_{\theta_H+\varepsilon}^{1} Pr(\theta > \theta_H + \varepsilon) d_0(\theta) d\theta + \int_{\theta^*}^{\theta_H+\varepsilon} Pr(\theta^* < \theta < \theta_H + \varepsilon) d_1(\theta) d\theta +$$
$$\int_{\theta_L-\varepsilon}^{\theta^*} Pr(\theta_L - \varepsilon < \theta < \theta^*) d_2(\theta) d\theta + \int_{0}^{\theta_L-\varepsilon} Pr(\theta < \theta_L - \varepsilon) d_3(\theta) d\theta$$

and in case of asset substitution:

$$e_1^{\text{subst}} = \int_{\theta=0}^{\theta=1} d_4(\theta) d\theta$$

The manager prefers conversion if $e_0^{\text{conv}} > e_0^{\text{subst}}$. This time, the trade-off is driven by the functional form of expected returns, and the distance between θ^* and θ_H, θ_L. The most efficient conversion space from an optimal bail-in perspective is achieved for $\lambda_{panic}(\theta) = 0$, thus if $\theta^* = \theta_L - \varepsilon$. For a distribution of returns with fat tails, conversion dominates initial asset substitution, due to the limited liability property of the bank. In contrast, for a uniform distribution of returns, we find that the driver of results is θ^*: a lower value of θ^* leads to an increasing value of e_0^{conv}.

2.3.3 Book value trigger

The equity holders behavior crucially depends on the type of conversion, as shown in the market case. Nonetheless, the market price behavior is not reflected in the book value CET ratio. Under equal issuance costs, if the bank tries to protect existent equity holders it should issue non-dilutive CoCos.

Although all CoCos issued so far are book-value based, there is very little research on book value RWA ratio. Glasserman and Nouri (2012) and Derksen et al. (2018) develop a valuation model for CoCos, when the RWA ratio is book based. Due to the lack of existing stylized equations in discrete time of what constitutes the book value of equity, for the scope of this paper we inspire from current regulation. The International Financial Reporting Standard (IFRS) makes a distinction between occurred and expected credit loss. The regulation which was in place until 1st of January 2018 states that only occurred losses should be incorporated in the balance sheets of banks. Nonetheless, under the new

IFRS 9 rules with effect from 2018 firms have to incorporate expected credit loss in their balances (IFRS 9, 2014). More precisely, they have to change the accounting value if "the credit risk increases significantly and the resulting credit quality is not considered to be low credit risk" (IFRS 9, 2014). For brevity and consistency with the earlier section, we further incorporate the expected credit loss as expected lower returns in the book value of equity.

Based on existing practice, we define the book value of equity as the (discounted) expected value of long term assets minus liabilities.

Occurred credit loss

In this case, $RWA_1 = RWA_2 = \frac{E[A|f_L]-D-C_L-C_H}{\sigma_A E[A|f_L]}$, as the bank does not readjust its expectations regarding the returns of long term risky assets. Even though the bank can observe a negative idiosyncratic shock to asset distribution f_{R_L} and/or bad state of fundamentals, the expected losses in long term returns have not yet incurred and thus not accounted for in the book value. In these circumstances, bad fundamentals will not reflect in the accounting value, and so the CoCos will never be converted before low returns are incurred at $t = 3$.

In this case, the risk associated with CoCos is much lower than the one priced for, as only in case of bankruptcy $E[A|f_L] < D + C_L + C_H$ the CoCo holders will not recover at least part of their investment.

Expected credit loss

We incorporate the expected credit loss by defining the book value as expected returns on assets minus liabilities. At $t = 1$, the bank manager incorporates the new expected returns in the capital ratio.

In case of an idiosyncratic shock to the asset distribution, the new book value is: $RWA_1 = 1 - \frac{C_H+C_L+D}{\int_0^1 A\theta f_L(\theta)d\theta} < \tau_H$. High CoCos are converted. At $t = 2$ the bank manager with signal θ_B readjusts the RWA value to: $RWA_2(\theta_B) = 1 - \frac{C_H+C_L+D}{\int_{\theta_B-\varepsilon}^{\theta_B+\varepsilon} A\theta f_L(\theta)d\theta}$. Note that in the market case the ratio was evaluated at θ which was the market average, but here only θ_B matters in evaluation. Any fluctuation in $P_2^m(\lambda(\theta), \lambda_{panic}(\theta))$ will not change the RWA ratio, as it is book based, so investor behavior does not change the manager's response.

The bank's manager optimization problem at $t = 2$ is to maximise share value while maintaining the RWA ratio above τ_L:

$$\max_{\beta_2, \mathbb{1}_{conv}} \quad \frac{e_2^b}{n_{max}} = \frac{(1 - \mathbb{1}_{conv}\beta_1)E_2[A|f_L \wedge \theta_B] + \mathbb{1}_{conv}\beta_2 l - \mathbb{1}_{conv}C_L - D}{n_{max}} \quad \text{s.t.} \tag{2.29}$$

$$RWA_2(\theta) = \frac{e_2^b}{(1 - \mathbb{1}_{conv}\beta_2)E_2[A|f_L \wedge \theta_B]} \geq \tau_L \tag{2.30}$$

Corollary 2.7. *The bank's best response is independent on the number of equity holders which sell, and is given by an optimal liquidation fraction $\beta^*_{2,BV}$*[11]*, if the risk based ratio is below τ_L $RWA_1 < \tau_L$.*

In the intermediate region: $\theta_L - \varepsilon < \theta < \theta_H + \varepsilon$ the value of waiting minus selling for an investor not hit by liquidity shock is:

$$v(\lambda_{panic}(\theta)) = \Big[\frac{E[A|f_L] - D - C_L}{n_{max}} - P_1^m(\lambda_{panic}(\theta))e_0\Big] \tag{2.31}$$

Lemma 2.2. *The decision of equity holders are global strategic substitutes regardless of the type of conversion, as the value of waiting always increases with the share of panicked investors ($\frac{\partial v(\lambda_{panic}(\theta))}{\partial \lambda_{panic}} > 0$).*

As a consequence, equity holders have no incentive to sell at the intermediate stage, so $\lambda_{panic}(\theta) = 0 \; \forall \theta \in (\theta_L + \varepsilon, \theta_H - \varepsilon)$.

Proposition 2.5. *In case of a book value trigger, the threshold equilibrium θ^*_{BV} below which all equity holders sell is $\theta^*_{BV} = \theta_L - \varepsilon$. The number of equity holders who sell as a function of fundamentals reported by the bank is:*

$$n_{BV}(\theta_B, \theta^*) = \begin{cases} 1 & \theta_B \leq \theta^* - \varepsilon \\ \frac{\theta^* - \theta_B + \varepsilon}{2\varepsilon} & \theta^* - \varepsilon < \theta_B < \theta^* + \varepsilon \\ 0 & \theta_B > \theta^* + \varepsilon \end{cases} \tag{2.32}$$

Now the fundamental value of equity, and thus the RWA ratio relies heavily on θ_B, the bank's signal. If this is significantly different than the true θ, then CoCos are not a

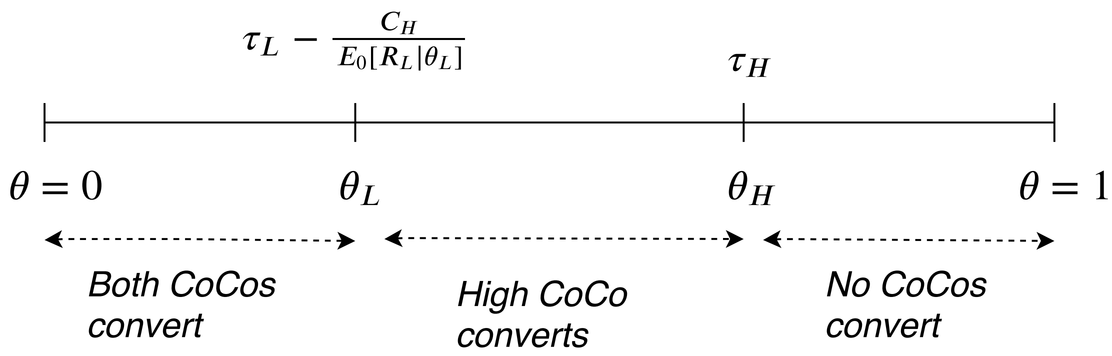
[11] $\beta^*_{1,BV} = \min\Big((\frac{D - E[A|f_L \wedge \theta_B](1-\tau_L)}{l - E[A|f_L \wedge \theta_B](1-\tau_L)})^+, 1\Big)$

successful bail-in mechanism. A CoCo conversion provides a negative signal to market participants and depositors about the asset quality of the bank. Banks have incentives to avoid this stage, and thus they might overstate θ_B. It is not incentive compatible for the bank to state their true observed value of the fundamentals. An advantage of this structure is limited market volatility due to lack of excessive trading, as compared to the market based case.

2.4 Discussion and Conclusion

2.4.1 CoCo structure comparison

Figure 2.10: Book value conversion space



To summarise, in case of a book based trigger with occurred credit losses, the conversion space is given in 2.10. In contrast, the conversion space when both CoCos convert increases when CoCos are dilutive and the trigger is based on market indicators - as depicted in Figure 2.11.

We further draw a comparison between the four types of CoCos we analysed: market based trigger- dilutive or non-dilutive; occurred losses book value and expected losses book value, conditional on the high trigger CoCo conversion at $t = 1$. Throughout the paper we assume deposit insurance, and going concern situations, hence when the bank is still solvent. Thus, it is guaranteed that depositors and senior debt will be repayed. Hence, only CoCo and equity holders are affected on the bank's side. From a policy perspective, we are concerned with the bail-in capacity of CoCos.

Figure 2.11: Market value conversion space

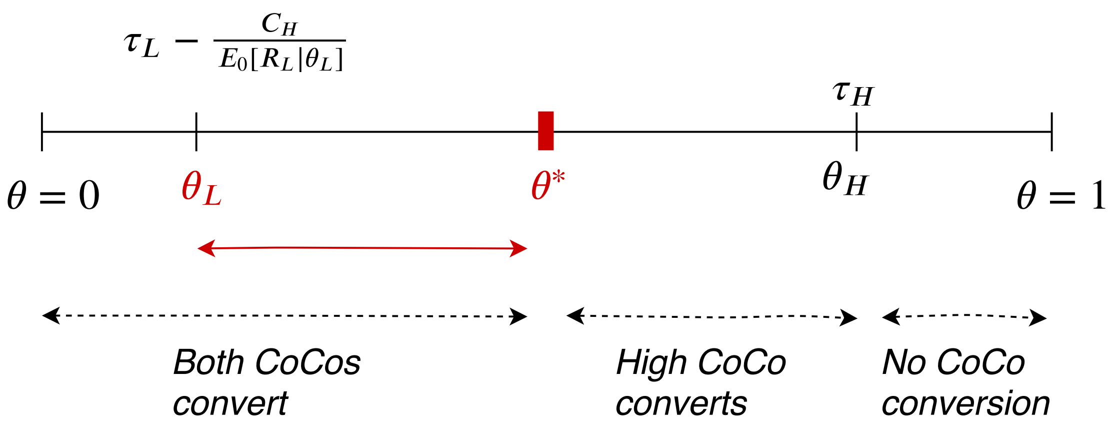


Table 2.6: Comparison CoCo design

	Market based trigger CoCo		Book based trigger CoCo	
	Dilutive for existing shareholders	Non-dilutive for shareholders	Expected credit loss	Occurred credit loss
Inefficient conversion	Yes	No	Depends	Yes
Relies heavily on bank's valuation	No	No	Yes	Yes
Shareholder strategic behaviour	Strategic complements	Strategic substitutes	No	No
Initial capital structure matters for outcome	Yes	Yes	No	No

As long as equity holders cannot re-buy their shares, and the wealth transfer benefits shareholders $\psi_L < \bar{\psi}_L$, market based triggers are an effective bail-in mechanism, in the sense that they are converted when the bank needs them the most. In this case, the investors decisions are strategic substitutes. Nevertheless, this is under the unrealistic assumption that equity cannot re-buy their shares. The same effect can be reached with book value triggers which account for expected losses, as long as the bank correctly assesses the value of its assets. Moreover, this case can bring more flexibility in issuance, as both conversion to equity and principal write-down would reach the same effect from a loss absorption perspective. The wealth effect is ambiguous for equity and CoCo holders, and depends on the dilutive properties of CoCos.

In matter of effectiveness, the conversion to equity market trigger CoCos are second to last. We show that they have the highest range of inefficient conversion and early liquidation of long term risky assets, which is dependent on the initial bank capital structure. The CoCo holders have a higher probability of loss due to the *strategic complementarities* decision of equity holders. Existent shareholders can benefit if face value of conversion offsets its dilutive effects.

The least effective loss absorption mechanism is the book value occurred losses trigger, as it does not have the capacity to absorb losses ex-ante. It is the most beneficial type of CoCos for both equity holders and CoCo holders, as they do not incur losses before the realization of returns or insolvency. An example to support this claim is the write-down of Banco Popular's CoCos in 2017, which was imposed by the regulator once the bank was already insolvent. One can argue that if the conversion would have taken place earlier, the bank could have maintained solvency.

2.4.2 Conclusion

The Swiss government is the first to introduce more stringent capital requirements for systemically important banks, and this is reflected through a mandatory quota on high trigger AT1 CoCos (Swiss Financial Market Supervisory Authority, 2015). In this context, this paper focuses on the signalling function of CoCos on the financial state of the issuing ank, and analyses the effects of multiple trigger CoCos on market participants and loss absorption capacities. The most obvious advantage of this structure is the creation of multiple bail-in buffers in case of distress. In contrast, once a conversion is observed, it will subsequently create tensions in the market. An example in that sense is the high share price volatility of Deutsche Bank in 2016, after it was speculated that it cannot meet its CoCo coupons payments. In this paper we argue that there is a trade-off between increased bank resilience and possible fire sales of equity. This damage on a banks' financial stability is a potential unintended consequence of CoCo regulation.

Insofar, CoCo research focused on depositor bank runs, but we argue that equity holder behaviour can influence conversion or asset substitution as well. We develop a model combines cash-in-the-market pricing of equity, noisy market signals about fundamentals, and an idiosyncratic asset shock observed initially only by the bank. We assume a fixed capital structure, and postulate that the bank‘s aim is to maximise individual value of shares, while meeting the risk based capital regulatory requirements. We evaluate possible CoCo structures, and employ a backward induction equilibrium concept. We solve for the minimum number of equity sellers needed for automatic conversion, and for the unique threshold equilibrium of fundamentals below which shareholders decide to sell. To do so, we draw from the bank run methodology of Goldstein and Pauzner (2005), and modify it to account for the special discontinuity feature created by conversion.

We find that the initial capital structure matters for the scope of inefficient conversions in the market based case triggers. From a social planner perspective, we conclude that market triggers are the least effective. If conversion benefits shareholders, they would have incentives to force inefficient conversion. The dilutive CoCos case ($\psi_L > \bar{\psi_L}$) could lead to 'panic-based' conversions. In contrast, for the book value case, the role of shareholders is limited, and CoCos can act as an effective bail-in mechanism if the bank assesses accurately the asset value and incorporates expected losses in their evaluation. Due to possible underpricing of equity in times of distress or very early inefficient asset substitution, we conclude that the bank has an ex-ante incentive not to issue market based CoCos.

We use the high trigger CoCo conversion as a signalling mechanism, but we argue that similar conclusions are achieved with other types of strong market signals that alert the market on the bank's solvency. For that we refer to the benchmark model. The example has a high degree of generality, and the comparison between the four types of CoCos would still be the same regardless of the type of shock which alerts the market on expected low bank returns. More generally, we provide a formal argument against market based triggers.

Throughout the paper we assume the bank capital structure as fixed, consider simplified types of CoCos and impose additional restrictions for uniqueness of equilibrium. A major point for further research is to determine the optimal capital structure which will minimise the scope of market inefficiencies, and implicitly maximise the capacity of CoCos to act as effective loss absorbing buffers. We talk throughout the paper about low and high triggers, which in practice are very close to each other (5.125% and 7% ratio). We aim to further provide a simulation of the model and find a minimum distance between the two triggers that would resolve, or diminish, the panic-runs discussed in this paper. Moreover, there is a current debate on the pricing equilibrium of equity, as conversion creates a simultaneity issue which can lead to multiple equilibria. In this paper we simplify the pricing issue through cash in the market pricing and fixed conversion rates, but there is scope for a continuous time analysis in this framework which endogenizes the market price and issuance costs even further.

Appendices

Appendix A

Proofs of lemmas and propositions

A.1 Proof of Proposition 2.1

It can trivially be seen that the value of equity is decreasing in liquidation value β. Thus, the max problem is obtained for binding constraint in (2.7):

$$\frac{P^m(\lambda(\theta), \lambda_{panic}(\theta)) \cdot n_{max}}{(1-\beta)E_{t=1}[A|f_L]} = \tau_L \iff$$
$$\frac{\frac{[1-\lambda(\theta)-\lambda_{panic}(\theta)]c}{[\lambda(\theta)+\lambda_{panic}(\theta)]e_0 \cdot n_{max}} \cdot n_{max}}{(1-\beta)E_{t=1}[A|f_L]} = \tau_L \iff$$
$$\beta^*(\lambda(\theta), \lambda(\theta_1)) = 1 - \frac{[1-\lambda(\theta)-\lambda_{panic}(\theta)]\ c}{\tau_L[\lambda(\theta)+\lambda_{panic}(\theta)]e_0 E_1[A|f_L]}$$

From the bank manager perspective, the indifference point between conversion and liquidation is at:

$$\frac{(1-\beta^*)E_1[A|f_L] + \beta^* l - C_L - D}{1+\psi_H C_H} = \frac{E_1[A|f_L] - D}{1+\psi_H C_H + \psi_L C_L}$$

Plugging in $\beta^*(\lambda(\theta), \lambda(\theta_1))$ and solving for $\lambda_{panic}(\theta)$ immediately yields the threshold $\lambda^*_{panic}(\theta)$ from proposition 2.1.

A.2 Derivation of Corollary 2.4

The neutral conversion, with a zero wealth transfer between equity holders and CoCo holders is given at the point where the share value in case of conversion is the same as under optimal liquidation:

$$\frac{(1-\beta_C^*)E_1[A|f_L]+\beta_C^* l - D}{1+\psi_H C_H+\psi_L C_L}=\frac{(1-\beta^*)E_1[A|f_L]+\beta^* l - C_L - D}{1+\psi_H C_H}$$

Rewriting the function in terms of ψ_L yields the result from the corollary.

A.3 Solution of Proposition 2.2

The condition for an interior solution is given by the following system of equations:

$$\begin{cases} 0<\frac{(1-\lambda(\theta)-\lambda_{panic}(\theta)c}{(\lambda(\theta)+\lambda_{panic}(\theta)e_0\tau_L E_1[A|f_L]}<1 \\ 0<\lambda_{panic}(\theta)<1-\lambda(\theta) \end{cases} \tag{A.1}$$

This system of inequalities, alongside with economic sensible assumptions, such as $E_1[A|f_L]>0$ and $0<\tau_L<1$ is solved for:

$$\left(e_0>0\wedge E_1[A|f_L]>0\wedge 0<\lambda_{panic}(\theta)<1-\lambda(\theta)\wedge 0<c<\frac{e_0E_1[A|f_L]\tau_L(\lambda(\theta)+\lambda_{panic}(\theta))}{1-\lambda(\theta)-\lambda_1(\theta)}\right)$$

Note that $e_0+c=W$ from the initial portfolio allocation. Thus, the maximum amount of cash in the market, as a function of expected returns is given by:

$$c=\frac{E_1[A|f_L]\tau_L W(\lambda(\theta)+\lambda_1(\theta))}{1-\lambda(\theta)-\lambda_{panic}(\theta)+(\lambda(\theta)+\lambda_1(\theta))E_{t=1}[A|f_L]\tau_L}$$

Alternatively, we can write the solution to the system as:

$$
\begin{aligned}
&0 < E_1[A|f_L] \leq \frac{(1-\lambda(\theta))c}{\lambda(\theta)\tau_L(W-c)} \wedge \frac{c\lambda(\theta) - c\lambda(\theta)E_1[I|R_L]\tau_L - c + \lambda(\theta)E_1[A|f_L]\tau_L W}{cE_1[A|f_L]\tau_L - cE_1[A|f_L]\tau W} \\
&< \lambda_1 < 1-\lambda \vee \\
&E_1[A|f_L] > \frac{c\lambda - c}{c\lambda\tau_L - \lambda\tau_L W} \wedge 0 < \lambda_1 < 1-\lambda
\end{aligned}
$$

A.4 Existence conditions for Lemma 2.1

By inserting β^*, β_C^* and P^m in the value of waiting versus selling function, we re-written as:

$$
v(\lambda_{panic}(\theta)) = \begin{cases} -\dfrac{\frac{c\left(D-\frac{1}{\lambda+\lambda_1}-l+1\right)+W(r-D)}{c-W} - \frac{c(\lambda+\lambda_1-1)(l-R)}{e_0 R\tau_L(\lambda+\lambda_1)} + C_L}{C_H\psi_H+1} & \text{if } \lambda_{panic}(\theta) < \lambda^*_{panic}(\theta) \\ -\dfrac{D-l\left(\frac{c(\lambda+\lambda_1-1)}{e_0 R\tau_L(\lambda+\lambda_1)}+1\right)+\frac{c(\lambda+\lambda_1-1)}{e_0\tau_L(\lambda+\lambda_1)}+\frac{c(\lambda+\lambda_1-1)}{(\lambda+\lambda_1)(c-W)}}{C_H\psi_H+C_L\psi_L+1} & \lambda_{panic}(\theta) \geq \lambda^*_{panic}(\theta) \end{cases}
$$

Which further simplify in:

$$
v(\lambda_{panic}(\theta)) = \begin{cases} \dfrac{\frac{c\left(D-\frac{1}{\lambda+\lambda_1}+1-l\right)+W(r-D)}{e_0} + \frac{c(1-\lambda-\lambda_1)(l-R)}{e_0 R\tau_L(\lambda+\lambda_1)} - C_L}{1+C_H\psi_H} & \text{if } \lambda_{panic}(\theta) < \lambda^*_{panic}(\theta) \\ \dfrac{\frac{lc\left(1-\lambda-\lambda_{panic}\right)}{\left(\lambda+\lambda_{panic}\right)e_0 E_2[A|f_L]\tau_L} - D + l}{1+C_H\psi_H+C_L\psi_L} & \lambda_{panic}(\theta) \geq \lambda^*_{panic}(\theta) \end{cases}
$$

To evaluate the condition for monotonically decreasing piecewise function, we take the partial derivatives in respect to $\lambda_{panic}(\theta)$, and obtain:

$$
\frac{\partial v(\lambda_{panic}(\theta))}{\partial\lambda_{panic}} = \begin{cases} c\dfrac{\frac{1}{\left(\lambda+\lambda_{panic}\right)^2 e_0 - \frac{(E_0[A]-l)\tau_L(\lambda+\lambda_1)}{e_0 E_0[A]\tau_L\left(\lambda+\lambda_{panic}\right)^2}}}{1+C_H\psi_H} & \text{if } \lambda_{panic}(\theta) < \lambda^*_{panic}(\theta) \\ c\dfrac{\frac{1}{\left(\lambda+\lambda_{panic}\right)^2 e_0 - \frac{(E_0[A]-l)\tau_L(\lambda+\lambda_1)}{e_0 E_0[A]\tau_L(\lambda+\lambda_1)^2}}}{1+C_H\psi_H+C_L\psi_L} & \lambda_{panic}(\theta) \geq \lambda^*_{panic}(\theta) \end{cases}
$$

The derivatives have to be negative on both intervals, which simplifies on the entire domain to the following condition:

$$
\begin{aligned}
&\frac{1}{(\lambda+\lambda_1)^2 e_0} - \frac{(E_0[A]-l)\tau_L(\lambda+\lambda_1)}{e_0 E_1[A|f_L]\tau_L(\lambda+\lambda_1)^2} < 0 \iff \\
&1 - \frac{(E_1[A|f_L]-l)(\lambda_{panic}+\lambda)}{E_0[A|f_L]} < 0 \iff \\
&E_1[A|f_L] < \frac{l(\lambda_{panic}+\lambda)}{1+\lambda_{panic}+\lambda}
\end{aligned}
$$

Note that the restriction for strategic complementarities depends on very few parameters: expected value of returns, liquidation value of total assets, and equity sold in the market.

A.5 Condition for non-empty lower dominance region - section 3

Under the worst circumstances, all equity holders sell. Thus,the indifference condition between waiting for dividend payments or selling is:

$$
\frac{\int_{\theta_L-\varepsilon}^{\theta_L+\varepsilon} \theta dF_{R_L}(\theta) - D}{1+\psi_H C_H + \psi_L C_L} = \frac{[1-\lambda(\theta)-\lambda_{panic}(\theta)]c}{(\lambda(\theta)+\lambda_{panic}(\theta)e_0(1+\psi_H C_H+\psi_L C_L)}
$$

In the worst case, $\lambda(\theta)+\lambda_{panic}(\theta)=1$. The integral on the left hand side is a standard Riemann-Stieltjes integral,. Thus we can evaluate it as:

$$
\begin{aligned}
&F(\theta_L-\varepsilon) - F(\theta_L+\varepsilon) - D = 0 \iff \\
&F(\theta_L-\varepsilon) - F(\theta_L+\varepsilon) = D
\end{aligned}
$$

Given that the senior debt $D>0$, the region is trivially non-empty.

A.6 Proof of Theorem 2.1

Here we briefly reconstruct the two part proof of uniqueness of equilibrium from Goldstein and Pauzner (2005), which uses the single crossing condition. The conditions and the proof follows largely the same structure, except for the discontinuity point between the value of waiting versus selling at the CoCo conversion trigger. Further we modify the proof presented in Goldstein and Pauzner (2005) pp 1311 to allow for this discontinuity. Please see the complete 3 part proof with the adjoint lemma's in Goldstein and Pauzner (2005) pp 1311-1314

Part I. If there is an equilibrium, then it is a threshold equilibrium.

Strategy profiles

Let $n(\theta, \theta')$ be a function that denotes the proportion of agents who sell their equity at signals below θ', and wait for payoffs at $t = 2$ otherwise when the true state of nature is θ

$$n(\theta, \theta') = \begin{cases} 1 & \theta > \theta^* + 2\varepsilon \\ \frac{1}{2} + \frac{\theta}{2\varepsilon} & \theta^* - \varepsilon \leq \theta \leq \theta^* + \varepsilon \\ 0 & \theta < \theta^* - 2\varepsilon \end{cases}$$

Let $\Delta(\theta_i, \tilde{n}(n))$ be the utility differential from waiting for payoffs at $t = 2$ or selling in $t = 1$, when an equity holders observes signal θ_i and holds beliefs $\tilde{n}$. The posterior distribution of θ is Unif $[\theta_i - \varepsilon, \theta_i + \varepsilon]$. By treating $\tilde{n}$ as a number, we can write the utility differential as:

$$\Delta(\theta_i, n(\theta)) = \frac{1}{2\varepsilon} \int_{\theta_i - \varepsilon}^{\theta_i + \varepsilon} v(n(\theta)) d\theta$$

where

$$F_\theta(n) = prob[\tilde{n}(\theta) \leq n]$$

This utility differential is the average of the value of waiting over the uncertainty range $[\theta_i - \varepsilon, \theta_i + \varepsilon]$. $\Delta(\theta_i, n())$ is always negative in the lower dominance region $\theta' < \theta_L - \varepsilon$, and always non-negative in the upper dominance region $\theta' > \theta_U + \varepsilon$. θ' is an equilibrium is any value below θ' gives a negative utility differential, and any value above gives a larger utility differential than the indifference point. Note that unlike global strategic complementarities, the utility differential after the single crossing does not necessarily have to be positive.

At a discontinuity point caused by conversion, the utility differential will be the sum of the region before conversion, and the region after.

Lemma 1: (i) $\Delta(\theta_i, n())$ is piecewise continuous in θ_i for intervals $(\lambda(\theta), \lambda^*(\theta))$ and $(\lambda^*(\theta)), 1]$ where $\lambda^*(\theta)$ is the threshold at which the bank is indifferent between converting and liquidating. (ii) Monotonic transformations make the function continuous and nondecreasing. (iii) Function $\Delta(\theta_i, n())$ is strictly increasing is $\theta_i < \theta_H + \varepsilon$ and $\tilde{n}(\theta) < n^*(\theta)$.

The solution concept is a Bayesian equilibrium, where an agent sells at $t = 1$ if $\Delta(\theta_i, \tilde{n}()) < 0$ and waits otherwise.

Part II. There exists a unique threshold equilibrium.

A threshold equilibrium at θ^* is a unique equilibrium if conditional on all equity holders using the same threshold θ^*, it is optimal for the agent to sell its shares if he observes a signal $\theta_i < \theta^*$, and otherwise wait for residual payments at $t = 2$.

At this stage Goldstein and Pauzner (2005) show that there is exactly one threshold equilibrium by continuity of $\Delta(\theta_i, n())$. We escape the lack of continuity in our model, by imposing the additional conditions from Proposition 2.3, which ensure single crossing of the utility differential. The proof of uniqueness follows the steps presented in Goldstein and Pauzner (2005), and we redirect further the interested reader to pages 1313-1324.

A.7 Derivation of Corollary 2.6

There is never a conversion choice at $t = 2$ if and only if $RWA_1 > \tau_H$ $\forall\theta \in (0, 1]$. Let δ be the admissible lower bound of expected returns on long term assets, with a direct correspondence to θ, through $\int_{\theta-\varepsilon}^{\theta+\varepsilon} \theta f_{R_L}(\theta) d\theta = \delta$. The condition must hold even for the worst case of fundamentals, thus also for δ. At θ, the condition reads:

$$\frac{(1-\beta_0)\delta + \beta_0 l - C_L - C_H - D}{(1-\beta_0)\delta} > \tau_H \iff$$
$$\beta_0 > \frac{C_H + C_L + D - \delta(1-\tau_H)}{l - \delta(1-\tau_H)}$$

A.8 Proof of Proposition 2.3

We succinctly present a proof by contradiction which simultaneously shows part (i) and (ii) of the proposition.

I. Let us assume that there is a unique $\lambda^s_{panic}(\theta) \in (0, 1-\lambda(\theta))$ such that $v(\lambda^s_{panic}(\theta)) = 0$ if $\lambda_1(\theta) < \lambda^*_{panic}(\theta)$ and $\lambda_2(\theta) > \lambda^*_{panic}$. By definition, there are only two candidate solutions for $\lambda^s_{panic} : \{\lambda_1, \lambda_2\}$. Thus, the first condition insures that $v(\lambda_1(\theta)) = 0$ exists in the admissible space, for any given θ:

$$\frac{(1-\beta^*)E_1[A|f_L] + \beta^* l - C_L - D}{1+\psi_H C_H} - \frac{[1-\lambda(\theta) - \lambda_1(\theta)c]}{[\lambda(\theta) + \lambda_1(\theta)e(1+\psi_H C_H)} = 0$$

Similarly, the second condition reads that $v(\lambda_2(\theta)) = 0$ is well-defined for any given θ:

$$\frac{(1-\beta^*_{conv})E_1[A|f_L] + \beta^*_{conv} l - D}{1+\psi_H C_H + \psi_L C_L} - \frac{[1-\lambda(\theta) - \lambda_2(\theta)c]}{[\lambda(\theta) + \lambda_2(\theta)e(1+\psi_H C_H + \psi_L C_L)} = 0$$

Hence, there are two points $\lambda^s_{panic}(\theta) \in (0, 1-\lambda(\theta))$ such that $v(\lambda^s_{panic}(\theta)) = 0$, for a given θ. But this contradicts our initial assumption that single crossing holds under the above mentioned conditions. Thus, at least one of them cannot hold true.

II. Alternatively, let us assume that we have one unique$\lambda^s_{panic}(\theta)$ if $\lambda_1(\theta) > \lambda^*_{panic}(\theta)$ and $\lambda_2(\theta) < \lambda^*_{panic}(\theta)$. Both conditions guarantee that $\lambda_1(\theta), \lambda_2(\theta)$ are not in the admissable space where $v(\lambda_{panic}(\theta)$ is defined. Thus, neither one of the candidate solutions is viable, so $\lambda^s_{panic}(\theta) = \emptyset$. This result again contradicts our assumption. Hence at least one of the two conditions does not hold.

Combining the results from *I* and *II*, we have only two possible admissible sets which permit single crossing:

$$\begin{cases} \lambda_1(\theta) \leq \lambda^*_{panic}(\theta) \\ \lambda_2(\theta) < \lambda^*_{panic}(\theta) \end{cases}$$

or

$$\begin{cases} \lambda_1(\theta) > \lambda^*_{panic}(\theta) \\ \lambda_2(\theta) \geq \lambda^*_{panic}(\theta) \end{cases}$$

The first one gives the single crossing condition before conversion, and the second one insures that the single crossing happens after conversion.

Chapter 3

Risk-Taking, Competition and Uncertainty: Do CoCo Bonds Increase the Risk Appetite of Banks?[1]

3.1 Introduction and related literature

The capital ratios of major banks were too low to withstand the great financial crisis, forcing governments in many countries to bail-out banks. Contingent convertible bonds (CoCo bonds), first suggested by Flannery (2002), seemed an attractive way to involve creditors in a recapitalisation before the taxpayer funded bail-outs would have to come in. These bonds convert into equity shares, or have their principal written-down, when a certain trigger is hit. The focus of regulators was on the automatic recapitalisation feature of Coco bonds; little thought was paid to the risk-taking incentives CoCos themselves would lead to, or how they should be designed to minimize that risk-taking effect. European regulators permit banks to cover up to 25% of their minimum (risk-based)

[1]We are grateful for the early feedback and interest we received at a Bank of England internal seminar.

capital requirements CoCo bonds.[2] In this paper we show that CoCo bonds as they are commonly structured can substantially increase risk-taking incentives and the more so the less the original equity holders are diluted upon conversion/write-down. This works at cross-purposes of the tighter recapitalisation requirements they were allowed to be used for.

The structure of CoCo bonds is determined by three components: (i) trigger type - is the trigger level evaluated at market or book-based indicators[3]; (ii) trigger level - the pre-specified level of the trigger indicator, at which the conversion/write-down is triggered. Under Basel III capital requirements the trigger level has to be specified as a ratio of Core equity Tier 1 capital to risk weighted assets and has to be 5.125 % or higher for CoCos to be admissible as Tier 1 (T1) capital; and (iii) type of conversion, which is the loss-absorption mechanism and defines the CoCo bond transformation upon conversion. The type of conversion is either principal write-down (PWD), where the entire/ part of CoCo debt is erased (temporarily or permanently) from a bank's balance sheet, or conversion to equity (CE), where the bonds are converted into equity shares at a pre-specified price which may or may not depend on market indicators.

Empirically, the debate on whether these securities have an impact on bank risk-taking behavior, and to what extent this behavior is dependent on the conversion type selected by issuing banks is still going on. If CoCo bonds distort risk-taking incentives, then the benefits that they bring from a societal perspective might be out-weighted by the costs associated with an increase in the risk profile of the banks issuing them. The loss-absorbing mechanism of CoCo bonds induces wealth transfers between CoCo holders and the existing shareholders, depending on the conversion price. This leads to potential unintended impact on the risk-taking incentive of existing shareholders of the issuing bank. A number of papers (Koziol and Lawrenz, 2012; Hilscher and Raviv, 2014; Berg and Kaserer, 2015; Albul et al., 2015; Chen et al., 2017; Chan and van Wijnbergen, 2017;

[2]But they need to meet certain conditions; Article 52 of the European Capital Requirements Regulation (CRR) states that, to qualify as AT1 capital, CoCo bonds have to be perpetual, have a predetermined trigger not below 5.125% of Common Equity Tier 1 (CET1) capital, and have cancelable coupon payments at the full discretion of the issuer, where cancellation is not subject to any restriction on the institution and cannot bring it into default. There are no requirements in terms of the conversion type. Hence, banks can freely choose the loss absorption mechanism.

[3]All CoCo bonds issued to this date trigger at book-based indicators.

Fatouh and McCunn, 2019) have focused on the impact of CoCo bonds on risk-taking but with mixed, incomplete and sometimes contradictory results. The empirical literature has not yet addressed the impact of the degree and sign of dilution of existing shareholders implied by the conversion parameters on risk-taking, a key focal point of our paper. Hilscher and Raviv (2014), Song and Yang (2016) and Chan and van Wijnbergen (2017) argue that CoCo bonds that dilute the wealth of current shareholders upon conversion reduce risk-taking incentives.[4] They point out that therefore the risk-shifting problem can be addressed through a proper design of CoCo bonds contracts: a low enough conversion price would eliminate this problem. Somewhat contradictory, Basel III requirements and their EU implementation (CRR) stipulate the presence of a minimum conversion price rather than requiring a cap, setting a maximum price to guarantee sufficient dilution. [5]

In the empirical literature so far, authors have assumed that accounting values are to be used to determine the conversion price, or simply distinguished PWD CoCo bonds and CE bonds without paying any attention to the heterogeneity within the second class in terms of implied dilution. Nonetheless, theoretical papers classify CoCo bonds in terms of their impact on risk-taking incentives based on dilution size, where they link the conversion price to market values. The theoretical literature generally argues that CoCo bonds increase risk-taking incentives if their loss-absorption mechanism implies a wealth transfer from CoCo holders to the existing shareholders and reduce risk-taking incentives when the wealth transfer goes from existing shareholders to the CoCo holders. One of this paper's contributions is that we proxy what market prices would be in a crisis environment, which we can plausibly assume to be necessary to trigger conversion. This allows us to assess the implied wealth transfer and subsequent dilution embedded in the particular design of a given CoCo bond. This in turn allows our econometric tests of risk-taking incentives to test the theory predictions much more accurately than a simple distinction between PWD and equity converter CoCo bonds allows.

[4]Martynova and Perotti (2018) argue that the principal write-down CoCo bonds (which imply wealth transfers from CoCo holders to the existing shareholders) reduce risk incentives, but they did not take into account the endogeneity of conversion; doing so would have reversed their results (cf Chan and van Wijnbergen (2017)).

[5]Art. 54 part c (i) of CRR (575/2013/EU) stipulates that the issuance provisions shall specify "(i) the rate of such conversion and a limit on the permitted amount of conversion". The way to limit the permitted amount of conversion for non-fixed conversion prices is via a floor.

This paper focuses on the potential effects of CoCo bonds on banks' risk-taking profile. The research aims are three-fold. Like others before us, we want to empirically test whether having CoCo bonds on a bank's balance sheet changes that bank's risk-taking behaviour. But if banks that have issued CoCo bonds do so because of other characteristics driving risk-taking, a simple regression linking risk-taking to the presence of CoCo bonds could suffer from sample selection bias. For example Chan and van Wijnbergen (2017) suggested a regulatory arbitrage hypothesis, according to which banks issue certain types of CoCo bonds structured to increase their risk-taking incentives in an attempt to offset the impact on risk-taking that regulators had when stipulating higher capital requirements. This potentially introduces a selection bias in regressions tracing the impact of CoCo bonds on risk-taking by the issuing bank. This issue has to the best of our knowledge not received attention in the empirical CoCo bond literature, but we do test for such a bias explicitly.

Second, we study the ex-ante impact on risk-taking of the conversion price and its impact on the expected wealth transfer conditional on conversion from CoCo holders to existing shareholders (note that that transfer can be negative if the conversion price is low enough). We use in our empirical analysis a proxy for market-based conversion prices. The assumption of basing the conversion on market prices is in line with the conditions embedded in most CoCo bonds issued so far. The stipulated conversion price of CoCo bonds, combined with the market price of equity at time of conversion determines the wealth transfer. This allows us to classify CoCo bonds based on their dilutive nature, which has been done before only on a much smaller sample. Finally we add control variables for the degree of banking competition and the extent of macroeconomic uncertainty in our analysis of the impact of the presence and structure of CoCo bonds on bank risk-taking.

A third novelty of this paper is that we explicitly compare results based market based risk measures of risk-taking with the results derived from analyzing an accounting based proxy and find that the market based measures conform to the theory predictions but the results based on the accounting based measure do not.

To sum up, new in this paper is that we explicitly test for sample selection bias (are banks with a greater risk appetite more inclined to issue Coco bonds?), that we include the extent to which CoCo bonds will dilute shareholders upon conversion and assess its impact on risk-taking, and that we explicitly distinguish between market- and accounting based measures of riskiness.

We focus on the UK, the largest CoCo bond market in Europe, with 35% of all going-concern (Additional Tier 1) CoCo bond issuances.[6] The UK market has also the largest share of conversion-to-equity CoCo bond issuances. Almost 60% out of all conversion-to-equity CoCo bonds in Europe were issued in the UK. Moreover (covered in our sample) 42 out of the 46 CoCo bonds issues in the UK are conversion-to-equity.

When analysing our results, we do not find enough evidence to support the regulatory arbitrage hypothesis. When we compare parametric and semiparametric selection models with the pooled OLS results, we find no significant difference, and where we find a statistically significant selection bias effect the economic impact is minimal. Our tests for sample selection bias thus come out negative: as a consequence we do not need to control for the endogenous decision to issue when assessing the risk-taking impact of CoCo bonds. But we do find that the issuance of CoCo bonds have a positive and significant impact on asset risk of the issuing banks. As predicted, the direction and the size of wealth transfer affect the magnitude of this impact. An increase in the wealth transfer from the CoCo holders to shareholders leads to an increase in asset risk. We find that based on our measures of price at conversion, the conversion to equity CoCo bonds on aggregate per bank are non-dilutive for existing shareholders. The impact of the wealth transfer on risk-taking is only robust across market measures of risk, and not for book-based measures. The results also show that macroeconomic uncertainty and banking competition increases asset risk chosen by CoCo-issuing banks.

Our findings have obvious policy implications. We show that the risk-taking implications of CoCo bonds are affected by the size and the direction of the wealth transfer between CoCo holders and the existing shareholders. Wealth transfer can be controlled through the conversion price. Hence, regulators may limit the risk-shifting incentives of CoCo-issuing banks either by imposing some restrictions on the contractual features that determine the size of the wealth transfer, such as the conversion price or by not counting

[6] In the end of 2018, UK banks had CoCo bonds worth EUR54.208 billion, out of EUR158.2 billion in total in Europe.

them one-for-one as capital (cf Chan and van Wijnbergen (2017) for such a proposal). Additionally, since certain types of banks tend to issue certain types of CoCo bonds, the type of CoCo bonds issued by a bank could be used as a warning indicator for its future risk profile.

The reminder of the paper is organised as follows. In the remainder of Section 1 we discuss the related literature. Section 2 describes our methodological choices for the empirical analysis and describes the data. Section 3 focuses on descriptive statistics and discusses the estimation results, whereas Section 4 has concluding remarks.

Related literature

Since CoCos are a relatively recent phenomenon, the CoCo bonds literature has initially largely been dominated by theoretical analyses. However, due to increasing data availability, empirical CoCo papers have emerged. Our paper contributes to this growing empirical CoCo bonds literature.

Several authors focus on the relation between risk-shifting incentives and CoCo bond issuance. As we already discussed, this impact depends on the direction of the wealth transfer between CoCo holders and existing shareholders conditional on conversion (Berg and Kaserer, 2015; Chan and van Wijnbergen, 2017; Fatouh and McCunn, 2019). That is, if shareholders are expected to gain from a CoCo conversion they have reasons to increase their risk-taking since that will increase the chance that a conversion will in fact take place. Obviously if shareholders stand to lose from a conversion, the impact on risk-taking is actually negative (cf Chan and van Wijnbergen (2017)). To test this prediction, we construct a measure which takes into account the number of shares issued at the time of a CoCo conversion (or, equivalently, the expected market share price at conversion, and the probability of conversion. This classification of CoCo bonds has received little attention in the empirical literature, which relies mainly on the classification into conversion to equity and principal write-down bonds without distinguishing within the class of CE CoCos between high and low price conversion contracts. The only empirical paper to classify CoCo bonds into dilutive and non-dilutive at time of issuance is Berg and Kaserer (2015), who, based on a sample size of 24 CoCo issuances, find that the majority of CoCo bonds considered are non-dilutive.

Other empirical work deals with the market response/market perception of CoCo bonds, such as market reactions to increased risk-taking incentives (Hesse, 2018), fear of conversion (Fiordelisi et al., 2019) or announcement effects of CoCo issuance (Ammann et al., 2017), simply distinguishing PWD CoCos and CE CoCos without recognizing heterogeneity within the class of CE CoCos. But PWD CoCos are just a limiting case of CE conversion, where the CoCo holder gets zero shares (equivalently has to pay an infinite share price) upon conversion. From a risk-taking incentive point of view this is not a meaningful distinction, the distinction should be between dilutive and non-dilutive CoCos. To the best of our knowledge we are the first to measure the conditional wealth transfer for a large number of CoCo bond issuances; this allows us to assess the impact of the size and sign of that variable on risk-taking and verify whether that impact is in line with what theory has predicted or not.

Additionally, for robustness we use four different measures for the level risk-taking (three market-based and one book-based). The benchmark measure is asset risk measured by asset beta. The other two market-based indicators are market risk (equity beta), and bankruptcy risk (CDS spreads on 5 year subordinated debt). The book-based measure of risk is the z-score, a measure of insolvency risk widely used in the literature.

Despite the extensive body of theoretical literature on the impact of CoCo bonds on ex-post risk-taking incentives, there is as yet little empirical investigation of this issue. Previous papers (Avdijev et al., 2020; Goncharenko et al., 2020) concentrate more on ex-ante determinants of CoCo issuance. They analyse the choice of issuance from a debt overhang perspective, where the bank's ex-ante risk profile (Goncharenko et al., 2020) or capital structure characteristics (Avdijev et al., 2020) determine whether it will issue CoCo bonds. Goncharenko et al. (2020) argue that banks with less risky profiles are more likely to issue CoCo bonds, while riskier banks prefer to issue equity instead. See also Derksen et al. (2018) for a discussion of the link between debt overhang and the decision to choose CoCo bonds to meet capital requirements. We also analyse this issue, although for a different reason: we want to test for sample selection bias. Sample selection bias might result if ex ante risk characteristics influence the decision to issue CoCo bonds rather than equity in response to higher capital requirements. A subsequent test for the impact of CoCos on risk-taking behavior would then suffer from sample selection bias. A similar theory of regulatory arbitrage has been tested using trust preferred securities (TPS) (Boyson et al., 2016), who found that more financially constrained banks are more likely to issue TPS. We test for selection bias, using both parametric and non-parametric selection models and instrument-free estimates.

Finally, the past decade, during which all existing CoCo bonds have been issued, has also seen increasing market volatility and reduced competition in the banking sector. To avoid finding spurious correlations, a comprehensive analysis of the effects of CoCo bonds on risk-taking incentive should account for these trends. We do so by including proxies for market volatility and the degree of banking comnpetition as controls.

The interaction between market uncertainty and risk-taking preferences has received much attention since beginning of the 1990s. Authors try to explain the implication of uncertainty for optimal portfolio choice (Dow and da Costa Werlang, 1992), and the interaction between uncertainty and risk in the context of monetary policy (Greenspan, 2004; Bekaert et al., 2013). More recent papers attempt to quantify the impact of different sources of uncertainty (economic, political, etc.) on the riskiness of banks' assets (Francis et al., 2014). The consensus is that higher levels of uncertainty lead to higher bank operating costs, and as a consequence more risk-taking (see Brock and Suarez (2000) for an example).

A number of authors point out to an overall reduction in the level of competition in the banking system in the UK (de Ramon and Straughan, 2016), and in Europe in general (Maudos and Vives, 2019). The literature on risk-taking bases its analysis of the impact of the degree of competition on risk-taking mostly on the franchise value theory: the argument is that an increase in competition increases the insolvency probability of banks which in itself can lead to more risk-taking in an attempt to increase the value of downside risk insurance provided by limited liability (the so called Merton put (Merton, 1974)). Moreover, more competition diminishes franchise value, and since the latter act as a break on risk-taking, competition and more risky bank asset portfolio's tend to go together. A low franchise value has been identified as a predictor for regulatory arbitrage and risk-taking by Boyson et al. (2016). We use an aggregate index of banking competition to test the franchise value argument.

3.2 Data and empirical methodology

In this section we introduce the data which we use for our analysis. We further discuss model specifications, variable descriptions and the methods used to construct the key variables in our study.

3.2.1 Data

Our focus is on U.K. banks. We have a sample of 15 banks, of which 10 of them issued CoCos at some time until the end of 2018.[7] This sample represents approximately 84% of the entire UK banking industry in terms of total assets.[8] We use semi-annual data from 2000 to 2018. The maximum numbers of observations per bank for each variable is 38, but it can vary per bank.[9] We combine proprietary data from Bank of England with publicly available data. A summary of the data collection is in Table 3.1.

We capture the universe of UK CoCo issuances that qualify as Additional Tier 1, which comprises of 46 issuances from a total of 10 banks between 2013 to the end of 2018. They have been issued in 4 different currencies - pound sterling, euro, US dollar and Singaporean dollar. We transform all non-GBP data in GBP by using the average exchange rate against the sterling on a semi-annual basis. We obtain daily FX rates against the pound from the Bank of England exchange rate statistics Database. The number of issuances varies widely per bank, from HSBC which is the biggest issuer with 13, to only one issuance for banks such as One Savings or Coventry Building Society.

The daily adjusted close stock prices for the listed banks in our sample size at London Stock Exchange are from Yahoo Finance. The data is from H12000 until H22018.

[7]The 10 CoCo issuing banks are: HSBC Holdings PLC, Barclays PLC, Santander UK Group Holding PLC, Standard Chartered PLC, OneSavings Bank PLC, CYBG PLC, RBS PLC, Lloyds Banking group PLC, Nationwide Building Society.

[8]At the end of June 2018, the total assets of our sample were £6,097,642 million out of a total reported value of £7,336,381 million for all UK banks – `https://bit.ly/2QFWmxs`

[9]We have the least amount of observations for Metro bank which only started operating in 2010.

Table 3.1: Data sources

Variable	Nr of banks	Frequency	Timespan	Source
Adjusted close stock price	10	Daily	2000-2018	Yahoo Finance
CDS spreads	9	Daily	2000-2018	Eikon Thomson One
Market capitalisation/ share numbers	10	Semi-annual	2006-2018	Factset
FX rates	-	Daily	2000-2018	Bank of England Exchange rate statistics Database
AT1 CoCo issuance data	10	-	2013-2018	Bloomberg
Bank balance sheet	15	Semi-annual	2000-2018	SNL + directly from annual reports
Number of security issuances	15	Quarterly	2000-2018	Refinitive Eikon
Banking competition level	-	Semi-annual	2000-2018	Bank of England internal measurement
Macro-economic uncertainty	-	Semi-annual	2000-2018	Bank of England internal measurement

FTSE100 is our benchmark for market returns, and the 10Y UK gilt rate is the risk free measure. Daily values of CDS spreads on 5 year subordinated debt of 9 banks are retrieved from Eikon Thomson One, from which we derive semi-annual CDS averages per bank. Data on market capitalisation and total number of shares on a half annual basis are retrieved from Factset, with the earliest value from 2006.

Bank specific characteristics for our 15 banks are retrieved from SNL, and when data was not available we retrieved them directly from the annual bank reports. All book based measures are reported end period. The banking competition level, and the measure for macro-economic uncertainty in the U.K. are sourced from internal Bank of England measurements.

3.2.2 Concepts and Variables

We use standard bank control variables, such as size (natural log of book value total assets), debt ratio (total liabilities to total assets) and bank type (deposits to liabilities). By bank type we mean a bank classification in commercial banks, mixed or investment banks. Commercial banks take on more deposits, thus the ratio of deposits to liabilities is very high. In contrast, the ratio is very low for investment banks. We control for GDP growth as well. We further augment the analysis to incorporate competition level and

Table 3.2: CoCo issuances UK

Year	Amount EUR mn	N (from which CE)*	GBP	EUR	USD	SGD
2013	2753	2 (2)	0	1	1	0
2014	15936	15 (15)	8	3	4	0
2015	10128	8(7)	3	1	4	0
2016	7401	5(5)	1	0	4	0
2017	9246	10(7)	6	1	2	1
2018	8744	6(6)	1	0	4	1
Total UK	**54208**	**46(42)**	**19**	**6**	**19**	**2**
Total Europe	*158200*	*182(71)***	*21*	*66*	*67*	*5*

* Total number of issuances, from which number of conversion to equity in brackets.
** The total number of issuances stated here is larger than the sum of issuances in the 4 currencies summarised after. This is because in Europe there were issuances in other currencies as well, which we do not cover in our summary table, given our UK focus.

macro economic uncertainty in both the dynamic and static specifications. A full list of variables names and description can be found in the appendix.

Bank risk measures

We use four different measures measures for bank risk-taking, three market-based and one book-based measure. The most common ones in the literature are the ratio of non-performing loans and z-score. Both of them are book-based. The credit risk (NPL ratio) only captures past risk-taking behaviour, while we want to capture changes in risk-tasking post CoCo issuance. We think that market-based measures would better (more rapidly) reflect the level of risk-taking. The market-base measures are asset beta (asset risk), equity beta (market risk), and CDS spreads on 5 year subordinated debt (bankruptcy risk). The book-based measure is the z-score, defined as the ratio between ROA (returns on assets) plus the fraction of equity to total assets, and the volatility of ROA (accounting based insolvency risk).

To derive our benchmark measure of asset risk, the asset beta, we first calculate the equity beta on a semi-annual basis. We use the standard CAPM methodology, where $\beta_{X,equity} = \frac{COV(r_X - r_f, r_m - r_f)}{VAR(r_m - r_f)}$. COV denotes the covariance, VAR the variance, and r_X are returns on asset, r_f is the risk free rate, and r_m is the market return. To calculate it, we derive the returns for each listed bank (r_X) and FTSE1000 (r_m), and we calculate a daily measure for equity beta based on a rolling window, which we aggregate on a semi-annual basis. Equity beta is only possible to calculate for listed banks, and so our sample restricts to 10 banks, out of the initial 15 we had in our sample.

We derive the asset beta from the equity beta by taking into account leverage. Specifically we estimate β_{asset} per bank by regressing $\frac{\text{total assets}}{\text{core equity}}$ on equity beta :
$\beta_{\text{equity}} = \frac{Assets}{TotEquity}\beta_{\text{asset}}$, where L are total liabilities and TE total core equity. We estimate it using a 24 month rolling window, where the value for the first half year is computed using the past 2 years including the current half.[10]

We retrieve daily CDS spreads for five year subordinated debt, and we use the semi-annual average for our analysis. This covers 9 of our 15 banks. The advantage of this measure compared to the previous two market based ones is that it includes some financial institutions (Building Societies) which are not listed at the London Stock Exchange.

We calculate the z-score from 2006 onwards, following the methodology used by the Federal Reserve[11]:

$$\text{z-score}_{i,t} = \frac{\text{ROA}_{i,t} + \frac{TE_{i,t}}{TA_{i,t}}}{\sigma_{ROA}}$$

where $TE_{i,t}$ represents the total amount of equity of bank i at time t, and $TA_{i,t}$ denotes the total amount of assets on banks' i balance sheet at time t. We use bank balance sheet values for ROA, total assets and total equity. We compute the standard deviation of return on assets (ROA) using the past three semi-annual observations up to and including the current half-year.

[10]e.g. The asset beta for first half of 2000 (H1- 2000) uses values from H2-1998 up to and including H1 - 2000.

[11]For more details please see Fred Economic research St. Luis bank z-score.

CoCo variables

Let $CoCo_{i,t}$ be the total amount outstanding in pound sterling of CoCo bonds on a semi-annual basis at time t for bank i, and $P_{c,i}$ be the conversion price per CoCo bond of bank i (sold initially at price P_0).[12] Moreover, we denote by $P^m_{i,t}$ the expected market price at conversion per share of bank i at time t. We compute the number of shares received for each CoCo bond (with initial price 100), and convert the amount outstanding and prices in pound sterling.

The wealth transfer measure

The wealth transfer measure is a key contribution to the CoCo bond literature, which we further use in our analysis. We define $TotalWTCoCos_{i,t}$ as the total expected wealth transfer in case of conversion at time t for bank i, multiplied with the probability of a CoCo conversion for bank i at time t.

A measure which incorporates the degree of share dilution after conversion comes from the wealth transfer measure developed in Chan and van Wijnbergen (2017). This paper mimics a CoCo by setting up an equivalent pair of call options. The resulting measure for the wealth transfer at conversion is:

$$MarginalWT_{i,t} = \frac{C[R, D_d]}{1 + N \cdot D_s} - C[R, D_d + D_s] \tag{3.1}$$

where N is the total number of shares per unit of coco (conversion rate),
$N = P_0/P_c$: initial price (100 usually)/ conversion price stipulated in the contract. Based on this method, our simplified measure of wealth transfer is:

$$MarginalWT_{i,t} = \frac{\text{Mrktcap}_{i,t} + CoCo_{i,t}}{a_{i,t} + N \cdot CoCo_{i,t}} - \frac{\text{Mrktcap}_{i,t}}{a_{i,t}} \tag{3.2}$$

[12]Notice that the conversion price does not have a time dimension - in the U.K. all CoCo bonds have a fixed pre-specified conversion price. In the rest of Europe, conversion prices sometimes depend on various market indicators at the time of conversion.

where $a_{i,t}$ is the total number of ordinary shares of bank i at time t, Mrktcap$_{i,t}$ is the market capitalisation and $CoCo_{i,t}$ is the total CoCo amount converted. The first term denotes the value per share in case the CoCo bonds get converted - the new number of shares is $a_{i,t} + N \cdot CoCo_{i,t}$, and the total wealth is the CoCo debt which is converted $CoCo_{i,t}$ and the market capitalisation pre-conversion. The second term denotes the share price in case of non-conversion. If $MarginalWT_{i,t} > 0$, then the wealth transfer from CoCo holders to shareholders is positive, so CoCo bonds are non-dilutive for existent shareholders, and shareholders have to gain from conversion. The total impact on wealth transfer to existing shareholders in case of conversion is $WT_{i,t} = MarginalWT_{i,t}a_{i,t}$. We calculate the total amount outstanding of CoCo bonds on a semi-annual basis, by aggregating the CoCo issuance per bank at time t.

$Mrktcap_{i,t}$ is the market capitalisation in case of conversion. We calculate it as the number of existing shares multiplied with the estimated price of a share at conversion.

We use two different estimates for the price at conversion. The first one is inspired by Baron et al. (2020). They study the relationship between equity prices and banking crises between 1870 to 2016 in 46 countries, and find that bank equity prices decline on average by 30% nine months before a panic. One month before, the decline is estimated at 35% compared to the previous peak. Hence, to simulate price levels in times of crisis, we define the estimated share price at conversion as a 30% drop in the share price at the end of each half year, and we refer to the corresponding measure of wealth transfer as *wealth transfer 30%*. In robustness checks we vary the price drop from 5% to 25%.

Our second proxy for the estimated price per share at conversion is based on a stress testing approach. We derive the maximum observed price drop per bank since 2006 using semi-annual prices, using SNL data on semi-annual reported values of market capitalisation. The maximum drop varies from 20% for HSBC to close to 50% for Lloyds and RBS. Thus, the expected price at conversion is the maximum historical decline (fixed per bank), multiplied with the current share price at each half-year end. We further denote this price estimate as *empirical wealth transfer*. Under both the empirical wealth transfer based, and the 30% drop, the CoCos turn out to be non-dilutive for existing shareholders at the average conversion price.

Distance to conversion / Probability of conversion

We define the expected wealth transfer as probability of conversion multiplied with the wealth transfer in case of conversion. To derive the probability of conversion, we first compute the distance to conversion. The distance to conversion is similar to the distance to default from the Kealhofer Merton Vasicek model (Vasicek, 1977), where instead of considering default as the threshold conversion point, we use the CoCo conversion trigger requirement stipulated in the prospectus. Whether a conversion is likely to take place or notThe conversion depends on the capitalisation level of the issuing bank and on the CoCo trigger level.

Using the Black-Scholes formula for an European call option, we derive numerically the asset value and asset volatility for each bank i from the equity value and the equity return volatility.[13] That allows us to calculate the distance to conversion and probability of conversion using the asset value and asset volatility. More precisely, the distance to conversion is the distance between the expected value of the asset and the conversion point. Thus,

$$DC(t) = \frac{log(\frac{V_A}{\lambda D}) + (r - \frac{1}{2}\sigma_A^2)(T - t)}{\sigma_A \sqrt{T - t}} \tag{3.3}$$

where V_A is the asset value, σ_A is the asset volatility, and $\lambda = \frac{1}{1-TRC}$ and TRC is the stipulated trigger level for each CoCo. In the U.K. all banks issue at the minimum regulatory requirement of 7% , and so TRC is 7% throughout the sample. We numerically solve for distance to conversion and probability of conversion for a one year horizon $T = 1$.

Combining the wealth transfer measure and the distance to conversion indicator: the expected wealth transfer

The probability of conversion is derived based on the distance to conversion measure defined above. This is the final measure that we use in our estimation. Thus,

[13] See Appendix for the derivation.

$$TotalWTCoCo_{i,t} = Pr(conversion_{i,t}) \cdot MarginalWT_{i,t} \cdot a_{i,t}$$

$$TotalWTCoCo_{i,t} = \phi(-DC_{i,t}) \cdot MarginalWT_{i,t} \cdot a_{i,t} \tag{3.4}$$

The degree of competition, the measure of general uncertainty and other variables

The level of competition (Comp) is measured using the Boone indicator calculated by de Ramon and Straughan (2016). Introduced by Boone (2008) and increasingly popular, this indicator only uses easily available firm-level data and does not require observations for all firms. Originally, the Boone indicator is negative, and higher values (movement towards zero) represent a reduction in competition. To avoid misinterpretation of the coefficients, we multiply the values of the indicator by -1. Hence, smaller values of our competition variable indicate lower levels of competition. We expect higher competition to increase risk-taking.

The level of uncertainty (Uncty) is measured using the quarterly uncertainty indicator produced by the Bank of England's Monetary Analysis Division. This indicator is computed as the principal component of a set of indicators. The uncertainty indicators they use combine information from the whole economy, such as the option implied volatility of FTSE and of the Pound Sterling, with firm and household information. The Bank of England indicator incorporates the standard deviation of observed dispersion of company earning forecasts, and of annual growth forecasts based on financial market or survey information. On the firm side, they use survey data from the Confederation of British Industry (CBI) in the score of 'demand uncertainty limiting investment'. The measure also incorporates information such as unemployment expectations from the household perspective, and the number of newspaper articles that mention 'economic uncertainty'. Haddow et al. (2013) in a Bank of England Quarterly bulletin present more detailed information on this measure.

For the reasons discussed earlier, we add a set of industry-level and bank-level control variables. These industry-level variables include determinants of risk-taking common to all banks. We use GDP growth to proxy fluctuations in economic activity (Agoraki et al., 2011). The bank-level variables are used to control for the differences in size, technical efficiency and business models across banks. They include debt ratio (total liabilities divided by total capital), ratio of deposits to liabilities, and the natural logarithm of total assets. Given that higher debt levels (debt ratio) imply higher bankruptcy risks, we would expect a negative impact of the debt ratio on the dependent variable.

3.2.3 Empirical model specifications

We test for sample selection bias using three different approaches. The first class involves two-step selection parametric and semiparametric models which need at least one instrumental variable (Heckman, 1976; Cosslett, 1991; Ahn and Powell, 1993). The second one is non-parametric, and is based on extreme quantile regression and can be performed in the absence of an instrument (D'Haultfœuille et al., 2018; d'Haultfoeuille et al., 2019). The last method gives bound estimates of the treatment effect, assuming that the treatment was random, and we use it in order to check the robustness of our previous results (Lee, 2009).

We further use a dynamic GMM model specification of the Arellano-Bond estimator with robust standard errors (Arellano and Bond, 1991), because of evidence in the literature (cf Agoraki et al. (2011); Delis and Kouretas (2011); Jiménez et al. (2013)) that risk-taking behaviour is time-persistent. Use of the Arellano-Bond estimator is then called for because persistence is captured by including a lagged endogenous variable. For further robustness we compare results of a specification that includes respectively excludes the Heckman selection estimate (inverse Mills ratio), and test for sample selection bias using a Hausman test. Even though we find evidence that risk-taking is time persistent, we also perform a pooled OLS for completeness of results and comparability with the selection bias method estimates.

Two stage selection models

If banks that want to increase their risk profile are the ones most likely to issue CoCo bonds, a test of the hypothesis that having issued CoCos leads to additional risk-taking incentives is likely to suffer from sample selection bias. We set up the basic model in line with the well-known two-step selection model of Heckman (1976) by formulating a selection equation and a response equation, with potentially correlated error terms. The selection equation assesses the likelihood of banks selecting CoCos as part of their capital structure. And the response equation tests our hypothesis of the impact of CoCos and their design on risk-taking behavior. In the first approach we use a full information maximum likelihood (FIML) estimator and test explicitly whether the relevant correlation parameter is different from zero. But FIML estimators may lead to misspecification in one equation biasing the other equation. We therefore also try in our second approach a single equation estimator, the well-known Heckman estimator relying on the inverse Mills ratio.

The Heckman (1976) selection model relies heavily on the assumption of joint normality of the error terms. We relax this assumption using two semiparametric two stage selection models. The first one is proposed by Cosslett (1991), and the selection effect is captured by N dummies which are derived from the first stage selection equation. The second method we employ is Ahn and Powell (1993), which is less restrictive than Cosslett (1991), as it does not rely on the correct parametric specification of the single index variable which captures selection bias. In this setup, the selection effect is captured via a weighted matrix from the first stage equation.

The selection equation is based on known bank characteristics which are expected to predict CoCo issuance, such as bank type and capitalisation level (Goncharenko et al., 2020; Avdijev et al., 2020). We define a new time-invariant variable CoCobank_i, which has a value of 1 if the bank ever issued CoCos, and 0 if they never did. As mentioned in the data subsection already, we have 10 CoCo issuing banks and 5 which did not issue any CoCos in our sample. So the selection equation applies to all banks, both issuers or non-issuers.

We use two exclusion variables that we incorporate in the selection equation, but not in the response equation. Hence, variables that we consider have a strong impact on whether a bank issues CoCo bonds or not, but does not predict risk-taking. The first exclusion variable that we use is the total number of securities issued by a bank - "SecurityIssuance". We argue that banks which are more familiar with issuing securities in general are also more likely to issue CoCos, but this has no effect on bank risk-taking as we do not define either the size or the type of security issued. Hence we expect a positive coefficient of this variable for CoCo issuing banks. The second one is the size of total liabilities to capital ratio - the "Debt" variable, which is in fact a measure for the leverage ratio. In theory, the debt ratio is a predictor of risk appetite. Nonetheless, the banks are subject to minimum regulatory requirements, which were found to play an important role in costs of capital (Baker and Wurgler, 2015). The capital structure is affected by such regulations, and does not permit banks to reach their optimal allocation of debt and equity, and the standard link between leverage and risk(Baker and Wurgler, 2015). Moreover, we argue that this ratio is a good predictor as to whether a bank is an issuer. A higher debt ratio indicates a low value of CET1, and so a CoCo issuance would be more expensive to issue as the distance to the CoCo trigger would be small, and hence unattractive for the issuer. In this sense, we expect a negative coefficient of the debt ratio for predicting CoCo issuance.

The selection equation (first stage) is:

$$\text{CoCobank}_{i,t} = \beta_0 + \beta_1 DepLiab_{i,t} + \beta_2 Debt_{i,t} + \beta_3 \text{SecurityIssuance}_{i,t} + \eta_{i,t} \tag{3.5}$$

The dependent variable in this case "CoCobank" is a time-invariant dummy variable with a value of 1 if the bank ever issued CoCos, and 0 if not. Bank specific variables are - $DepLiab$ - deposits to liabilities, $Debt$ -debt to total capital ratio and $SecurityIssuance$ - number of security issuances. Deposits to liabilities indirectly captures the business model of a bank. Investment banks (so low deposits to liabilities ratio) are more likely to issue CoCos, while retail-oriented banks are less likely to do so.

In the response equation, the dependent variable captures bank risk-taking, and is computed using one of the four bank risk-taking measures discussed above. $CoCoDummy$

is a dummy variable indicating whether the bank has CoCo bonds in the capital structure, and $TotalWTCoCo$ measures the expected wealth transfer in case of CoCo conversion to existing shareholders: the total amount of wealth transfer multiplied with the probability of conversion.

The response (second stage) equation is:

$$\begin{aligned} r_{i,t} =& \beta_4 + \beta_5 \text{GDPgrowth}_{t-1} + \beta_6 Size_{i,t-1} + \beta_7 \text{CoCoDummy}_{i,t-1} + \beta_8 \text{TotalWTCoCo}_{i,t} \\ & + \beta_9 DepLiab + \beta_{10} Uncty_{t-1} + \beta_{11} Comp_t + \varepsilon_{i,t} \end{aligned} \quad (3.6)$$

and the macro variables are GDPgrowth - GDP growth, $Uncty$ - macroeconomic uncertainty, and $Comp$ measure of competition in the banking industry.

Based on this set of equations - selection and response equations, the null hypothesis H_0 is no selection bias, or $Var(r|\mathbf{x}, \text{CoCobank} = 1) = Var(r|\mathbf{x})$, where $\mathbf{x}$ is the vector of independent variables and so homoskedasticity holds under H_0. If we reject this hypothesis, we can construct a consistent estimate for the impact of CoCo bonds on risk-taking.

In a third test, we use the Hausman-Wu test to we compare the model estimation which incorporates the CoCo selection bias with the variant where we do not incorporate it. We denote by $\hat{\theta_1}$ the vector of parameter estimates from the Arellano-Bond estimator which do not incorporate selection bias, and by $\hat{\theta}_{Mills}$ the one which incorporates the Mills ratio. The null hypothesis in this case is: H_0*:* $\hat{\theta_1}$ *is efficient and consistent, and* $\hat{\theta}_{Mills}$ *is inefficient and consistent.* Alternatively, H_A*:* $\hat{\theta_1}$ *is inconsistent, and* $\hat{\theta}_{Mills}$ *is consistent.*

Two stage semiparametric selection methods

The Heckman (1976) selection model relies on strong assumptions: joint normality of error terms, and valid instruments for the selection equation. For robustness, we relax both of these assumptions using four different methods, and compare the effect of CoCo bonds on risk-taking taking into account the possibility of selection bias.

The first method is based on Cosslett (1991) which relaxes the joint normality assumption, but still requires valid instruments. The author proposes a two-step semiparametric method, which imposes no restrictions on the functional form of the selection equation. The suggestion for the semiparametric estimation in the original version of Cosslett (1991) is the Cosslett (1983) estimator for the first stage, but we use an improved version on it which is the semiparametric maximum likelihood estimator of Klein and Spady (1993), which is proven to be efficient and consistent. The first stage equation is the same as in Heckman (1976) and as described in equation (3.5), but the estimation method is semiparametric. Based on these estimates, we predict the scalar outcome $v_{i,t} = (\hat{\gamma}Z) = \hat{\gamma}Z$, where Z are the variables used in the first stage. The predicted values $v_{i,t} = (\hat{\gamma}Z)$ from the first stage equation are divided and ordered into M equal sized sections.[14] If the value $v_{i,t} = (\hat{\gamma}Z)$ falls in section Mj, then the dummy variable Di,j takes a value of 1, and 0 otherwise. The dummy variables are then inserted in the second stage, and we estimate the equation using OLS:

$$\text{Asset beta}_{i,t} = X_{i,t}\beta + \sum_{j=1}^{M} b_j D_{j,i,t}\left(\hat{\gamma}Z\right)$$

In that sense, the selection correction term is $\phi\left(v_{i,t}\left(\hat{\gamma}Z\right)\right) = \sum_{j=1}^{M} b_j D_{j,i,t}\left(\hat{\gamma}Z\right)$.

The second method that we use to test for selection bias is the Ahn and Powell (1993) semiparametric two-stage estimation. In contrast to Cosslett (1991), this method is less restrictive, as they assume that the selection effect only depends on the conditional mean of an observable selection variable. Hence this estimator does not rely on the correct parametric specification of the single index variable which captures the selection bias as we defined it in the first stage equations above. We choose as an observable selection variable the number of security issuances, as we argue it is the best instrument we have in terms of lack of correlation with the risk-taking measures. The first stage estimation ofAhn and Powell (1993) generates a weighted matrix which we subsequently use in the second stage equation as the one described in equation (3.6).

Extreme quantile regression and bounds of treatment effect

This method is very different from the ones presented so far, as it uses extreme quantile regression, it is based on no instruments, and it has a distribution-free estimator. The

[14]We heuristically choose a number of 10 sections due to the size of our sample

estimator coined in D'Haultfœuille et al. (2018); d'Haultfoeuille et al. (2019) is based on the assumption that selection is independent of covariates when the outcome takes large values. In our case, this would translate that banks issue CoCos regardless of debt level or number of securities issued in the past, as long as they exhibit high risk-taking. We argue that this would be an appropriate assumption for our model as well, as it is more costly for high risk banks to raise equity, and so the bank has higher incentives to orientate towards cheaper sources of funding such as different type of debt, including CoCo debt.

We perform one last check for selection bias using the Lee (2009) bounds. This technique gives estimated bounds of the treatment effect, making no assumptions on the selection instruments, but assumes a random treatment effect. If we argue that there is no clear driver in self-selection for banks which issue CoCos, then the size of the effect of CoCo debt on risk-taking from previous regressions should be the same as if we were to assume that banks randomly self-select into issuing CoCos.

Dynamic model specification and testing for persistence

We test for persistence by assessing the significance of the lagged endogenous variable among the explanatory variables. The Arellano-Bond model is designed for such a dynamic panel data structure with a lagged endogenous variable on the right hand side of the equation. We test for auto-correlation of order 1 and 2 (AR(1) and AR(2)) using the Arellano-Bond test (Arellano and Bond, 1991). We first test only for the impact of the presence of CoCo bonds, and then we add the contemporaneous effects of possible wealth transfer in case of conversion. We use contemporaneous instead of lagged effects when we analyse market values as markets react faster compared to book values. When we use the z-score as a measure of risk we incorporate instead only lagged values.

The first test is for the impact of CoCo bonds presence on risk-taking in a dynamic setting:

$$r_{i,t} = \beta_0 + \rho r_{i,t-1} + \beta_1 \text{GDPgrowth}_{t-1} + \beta_2 Size_{i,t-1} + \beta_3 Debt_{i,t-1} +$$

$$\beta_4 \text{Dep/Liab}_{i,t-1} + \beta_5 \text{CoCoDummy}_{i,t-1} + \varepsilon_{i,t} \tag{3.7}$$

We augment the specification to test for the impact of uncertainty and competition:

$$r_{i,t} = \beta_0 + \rho r_{i,t-1} + \beta_1 \text{GDPgrowth}_{t-1} + \beta_2 Size_{i,t-1} + \beta_3 Debt_{i,t-1} + \beta_4 Comp_{t-1} +$$

$$+\beta_5 Uncty_t + \beta_6 \text{DepLiab}_{i,t-1} + \beta_7 \text{CoCoDummy}_{i,t-1} + \beta_8 \text{TotalWTCoCo}_{i,t} + \varepsilon_{i,t} \tag{3.8}$$

Finally, we augment the model with interaction terms: Inter Uncty = uncertainty $*$ CoCo dummy, Inter Comp = competition $*$ CoCo dummy.

Static model specification

Although our estimates confirm the need to use a dynamic specification, for comparability with the literature we also show the results of a pooled OLS. The first variant of the static version is simply the dynamic version but with the lagged endogenous variable left out:

$$r_{i,t} = \beta_0 + \beta_1 \text{GDPgrowth}_{t-1} + \beta_2 Size_{i,t-1} + \beta_3 Debt_{i,t-1} +$$

$$\beta_4 \text{Dep/Liab}_{i,t-1} + \beta_5 \text{CoCoDummy}_{i,t-1} + \beta_6 \text{TotalWTCoCo}_{i,t} + \varepsilon_{i,t} \tag{3.9}$$

The initial model specification is then also extended to test for CoCo effects in the presence of macroeconomic uncertainty and banking competition, like was done for the dynamic setup:

$$r_{i,t} = \beta_0 + \beta_1 \text{GDPgrowth}_{t-1} + \beta_2 Size_{i,t-1} + \beta_3 Debt_{i,t-1} + \beta_4 Comp_{t-1} +$$

$$+\beta_5 Uncty_t + \beta_6 \text{DepLiab}_{i,t-1} + \beta_7 \text{CoCoDummy}_{i,t-1} + \beta_8 \text{TotalWTCoCo}_{i,t} + \varepsilon_{i,t} \tag{3.10}$$

3.3 Descriptive statistics and empirical results

3.3.1 Descriptive Statistics

Bank risk measures

We derive equity and asset beta measures for the ten out of the fifteen banks in our sample which are listed at London Stock Exchange. The first reported measure is equity beta, with a mean value of -0.0109, indicating that our sample has almost no correlation with the FTSE100. We find that asset beta, which takes into account bankruptcy risk, has both a smaller mean value and a smaller standard deviation, as expected. We further report the CDS 5 year subordinated debt on 9 banks. The reported values are in basis points, which shows an average CDS spread of 2,015%, with a variation between 0,555% to 5,964%. The accounting measure z-score is reported for all banks in our sample. We find that the z-score has the highest volatility from all measures. Summary statistics for our four measures of bank risk-taking are listed in Table 3.3.

Table 3.3: Bank Risk measures

Variable		**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Equity beta	overall	258	-.0109	.1302	-.4733	.4389
	between	10		.0592	-.1058	.0502
	within	25.8		.1211	-.4293	.3776
Asset beta	overall	226	-.0008	.0065	-.0154	.0225
	between	9		.0047	-.0097	.0028
	within	25.1		.0052	-.0160	.0190
CDS	overall	141	201.476	110.121	55.487	596.454
	between	9		48.316	116.480	248.139
	within	15.67		102.1	39.428	561.374
Z-score	overall	270	6.742	11.635	-5.746	99.1368
	between	15		5.809	-.823	20.915
	within	18		9.992	-12.480	84.964

The CoCo market

The total amount of CoCo bonds issued in Europe between Jan 2013 and November 2018 was approximately 158.2 bn EUR. U.K. and Switzerland are by far the largest issuers both in number of issuances and amount outstanding, with U.K. having issued

Table 3.4: CoCo descriptive statistics

Variable		**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
CoCo bonds to overall capital ratio	overall	69	.1233	.0891	.0272	.4310
	between	10		.0778	.0552	.3092
	within	6.9		.0387	.0168	.2452
Prob of CoCo conversion	overall	69	8.27e-06	.0000417	3.47e-51	.00026
Total CoCo shares mn	overall	78	19.387	27.620	0	83.171
	between	11		25.880	0	83.171
Marginal wealth transfer per share (empirical decline)	overall	57	.3288	.27027	0	1.1509
Total expected WT at conversion £mn (empirical decline)	overall	57	3979.367	3280.7	0	13272.63

CoCo bonds worth 54.2 bn EUR, so more than a third of the entire market in terms of size.

We analyse the 46 AT1 U.K. CoCo issuances, from which almost all are conversion to equity, with a fixed conversion price. The U.K. has by far the largest European issuance in terms of CE CoCo bonds, both in terms of size and number of issuances. CoCo bonds represent an average of 12.3% relative to total bank capital. The market issues at a constant pace every year, with occasional spikes. A standard feature of CoCo IPO's is that banks can call the CoCo bonds every 5 years. We observe that banks call the CoCo bonds, and they subsequently reissue, leading to a five year cycle. A possible explanation for this behaviour is cheaper financing costs, as CoCo bonds are no longer an exotic instrument to the market, as it was in the early 2010's. Under Bank of England regulation, AT1 CoCo bonds must have a trigger level of minimum 7%. Very few other countries (Switzerland) impose a higher trigger level compared to the Basel regulation of 5.125%, which leads to a 'cluster' of CoCo issuances at the minimum regulatory requirement of a 5.125% CET1 to RWA trigger. A brief market overview for AT1 U.K. CoCo bonds can be found in Table 3.2.

We report on the key descriptive statistics of our derived CoCo variables in Table 3.4.[15] The probability of CoCo conversion is on average very small, due to the current high level of bank capitalisation in terms of CET1 to RWA ratio. The marginal wealth transfer, under the assumption of a share price drop equal to the historical price drop per bank, implies a gain of 0.329 sterling per share for existing shareholders. We obtain a similar value for the marginal wealth transfer gain when we assume a 30% share drop. Based on our two measures of price at conversion, we find that the aggregate conversion to equity CoCos per bank are non-dilutive for existing shareholders.

Lastly, in Table B.3 we present descriptive statistics for macroeconomic variables and bank control variables which we use. We report all values in GBP, unless otherwise stated.

3.3.2 Selection bias results

Full Information Maximum Likelihood

The first two columns in Table 3.5 report the full information maximum likelihood estimation results of the selection and response equation simultaneously, where column (1) assumes a static response equation, and column (2) refers to a dynamic model specification with a lagged endogenous variable. In the selection equation we find all variables to have a statistically significant effect on whether a bank ever issued CoCos or not. The more deposits a bank has as part of their total liabilities, the less likely they are to issue CoCos, and the same applies for debt level as anticipated. The number of security issuances has a positive effect on banks issuing CoCos. We find no statistically significant evidence of selection bias as indicated by the reported estimate (*athrho*) which captures the correlation in the error terms of the selection and response equation.[16] We report the LR test test of no selection bias ($\rho = 0$) and find that in both model specifications (1) and (2) we cannot reject the null hypothesis that the two equations are independent. The results and corresponding probabilities are reported in the LR test and $Prob > chi2$ in

[15]The full table of descriptive statistics can be found in the appendix.

[16]The correlation between the error terms of the selection and response equation is ρ, and the reported estimate *athrho* denotes the inverse hyperbolic tangent of ρ, or the Fisher z-transform : $atanh\rho = \frac{1}{2}ln(\frac{1+\rho}{1-\rho})$. In this setup, the estimates in the response function do not correct for the Mills ratio, and so the coefficients are different compared to the two step variant. Let σ denote the standard error of the residuals in the response equation. The lnsigma coefficient reports the log transform of σ.

Table 3.5.

Two step Heckman correction model

In the Heckman two step correction model, the first stage is the selection equation, a probit model which determines the probability that a bank is a CoCo issuing bank based on key capital structure characteristics documented in the literature. The second stage is the response equation, and incorporates other variables that affect asset beta, while taking into account the selection bias of a bank issuing CoCo bonds from the first stage. This selection bias is calculated via the inverse Mills ratio, which captures the probability that a bank issues CoCo bonds given ex-ante characteristics. Columns (3) and (4) in Table 3.5 illustrate the results of the two-step Heckman estimator. The selectivity effect is summarised by *lambda*.[17] The test did not detect selection bias, as the inverse Mills ratio is not statistically significant in either static or dynamic case.

As an additional test, we incorporate the inverse Mills ratio from the first stage Heckman as an additional variable in the static model estimated via pooled OLS and in the dynamic version of our model estimated via the Arellano-Bond estimator, and we find that the coefficients are statistically insignificant in both cases, providing further indication of no selection bias. We report the coefficients for the inverse Mills ratio in Table 3.6, and the full estimation results can be found in Table B.4.

Hausman test

The Hausman test for the χ^2 test with 8 degrees of freedom is 0.80, and has a corresponding p-value of 0.99. These results show that the difference in coefficients is not systematic, providing further evidence against the presence of selection bias in our model specification.

[17] This value captures $\lambda = \rho\sigma$ from the maximum likelihood estimation variant described in the previous footnote

Table 3.5: Heckman correction model. Bank risk measure: Asset beta

	(1) Asset beta	(2) Asset beta	(3) Asset beta	(4) Asset beta
Asset beta				
GDP growth (-1)	0.0950*	-0.0301	0.0966*	-0.0301
	(1.72)	(-1.02)	(1.73)	(-1.02)
Size(-1)	0.00120**	-0.0000602	0.00154*	-0.0000636
	(2.13)	(-0.21)	(1.86)	(-0.14)
Dep/Liab	0.0144***	0.000277	0.0107	0.000313
	(2.86)	(0.11)	(1.25)	(0.07)
Uncty (-1)	0.00300***	0.000309	0.00298***	0.000309
	(5.45)	(1.00)	(5.38)	(1.00)
CoCo dummy	0.00888***	0.00363***	0.00879***	0.00363***
	(6.69)	(4.93)	(6.62)	(4.90)
Comp	0.00215***	0.000532***	0.00221***	0.000531**
	(6.11)	(2.66)	(6.06)	(2.55)
Asset beta (-1)		0.848***		0.848***
		(23.66)		(23.63)
Const.	-0.0334***	-0.00138	-0.0372***	-0.00134
	(-3.57)	(-0.28)	(-3.24)	(-0.22)
CoCo bank				
Dep/Liab	-3.799***	-4.096***	-3.857***	-4.096***
	(-4.97)	(-5.64)	(-5.49)	(-5.66)
Debt	-0.441*	-0.448*	-0.429*	-0.448*
	(-1.74)	(-1.81)	(-1.75)	(-1.81)
Security Issuances	0.00759*	0.00705*	0.00734**	0.00705*
	(1.94)	(1.90)	(1.99)	(1.91)
Const.	3.114***	3.302***	3.148***	3.302***
	(4.93)	(5.32)	(5.20)	(5.33)
athrho	0.0735	-0.000984		
	(0.20)	(-0.00)		
lnsigma	-5.240***	-5.915***		
	(-101.74)	(-116.51)		
LR test(rho=0)	chi2(1)=0.04	chi2(1)=0.00		
$Prob > chi2$	0.84	0.99		
Inv. Mills ratio				
lambda			0.00332	-0.0000296
			(0.58)	(-0.01)
N	301	296	301	296

t statistics in parentheses

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

The first two columns use the maximum likelihood estimation. Column (1) assumes a static model specification and column (2) incorporates the first lag of asset beta in the response equation. The variables of interest are *athrho*- correlation in the error terms of selection and response equation, and the *LR chi2* test.
Columns (3) and (4) report the two step Heckman correction, where column (3) uses the static response, and column (4) the dynamic response equation. The selection effect coefficient is captured by the *lambda* under the Mills ratio.

Table 3.6: Estimated coefficients for Mills ratio

Dependent variable: Asset beta	Pooled OLS	Arellano-bond
Inv Mills ratio	-0.00132	-0.00155
	(-0.29)	(-0.90)
N	223	208

t statistics in parentheses

First column reports the coefficient of the Inverse Mills ratio in the pooled OLS estimation, with a static model specification. The second column reports the coefficient in the Arellano-Bond estimation for the dynamic model specification. See the full regression estimations in Table B.4.

Semiparametric two step selection models

The Heckman correction model is very restrictive in terms of assumptions of both the error terms (joint normally distributed) and of correct model specifications. We summarize the three two-step selection estimator results in Table 3.7, and we compare it to the OLS benchmark. We first relax the joint normality assumption using the two-step semiparametric estimator of Cosslett (1991). We find that the ten dummy variables which capture the selection effect are statistically significant at either 1% or 10%. The risk-taking impact of having CoCos on the balance sheet increases from 0.0081 (under OLS), to 0.00905 when we correct for the selection effect using the Cosslett (1991) semiparametric method. This evidence suggests that if there was selection bias, the economic impact in terms of risk-taking magnitude is fairly small.

The second relaxation of assumptions is the correct model specification of the selection equation. The Ahn and Powell (1993) method is less restrictive than Cosslett (1991) as it makes no assumption on the error term and moreover, requires only one valid instrument for the selection equation. We use the number of security issuances as our instrument, and based on it we derive a weight matrix for the response equation which implicitly incorporates the selection effect. Our results indicate that when we account for selection bias in this manner, the CoCo impact on risk-taking is almost the same as the outcome from the simple OLS regression: 0.00845 compared to 0.00811, but the 95% confidence intervals are much smaller. This method does not capture a clear variable which can be interpreted as a selection bias effect, but compared to the OLS results we have further evidence against the selection bias hypothesis.

Extreme quantile regression and Lee bounds

One of the least restrictive selection methods that we use is based on d'Haultfoeuille et al. (2019). The estimator does not need a valid instrument, nor makes any assumptions on the distribution of the variable of interest, but requires that the selection is independent of covariates when the outcome (asset beta in our case) takes large values. We obtain an almost identical size of the effect of CoCo bonds on bank risk-taking as using the Ahn and Powell (1993) weighted-matrix semiparametric estimation technique, and still very similar to the effect from the OLS.

So far the results indicate a lack of selection bias. We perform one last check using the Lee (2009) bounds, which measures the size of the treatment effect assuming that the treatment (whether a bank issues CoCos or not) is random. The Lee bounds on the size of the impact of CoCo bonds on risk-taking has as upper bound of 0.0086, which encompasses all our previous estimates except for the Cosslett (1991) estimator.

To summarize, we tested two semiparametric two stage estimation techniques, one using dummy values for the selection equation (Cosslett, 1991) and one using a weighted-matrix (Ahn and Powell, 1993), and two techniques which use no instruments, one using extreme quantile regression (d'Haultfoeuille et al., 2019) and one which gives bounds on the size of the effect assuming random self-selection in CoCo issuance (Lee, 2009). The comparison between the different methods, and the CoCo bond effect effects on risk-taking alongside their respective confidence intervals are summarized in Table 3.8. The parameter estimates for the effects of CoCo debt on risk-taking are very similar to each other and to the simple OLS results, and the corresponding confidence intervals also widely overlap. In spite of a statistically significant effect of the Cosslett (1991) selection bias estimators, we obtain robust evidence against selection bias in CoCo issuance for our UK sample.

Table 3.7: Two step correction models. Bank risk measure: Asset beta

	OLS Asset beta	Heckman (1976) Asset beta	Cosslett (1991) Asset beta	Ahn and Powell (1993) Asset beta
GDP growth (-1)	.098*	0.096*	0.100**	0.15***
	(0.0521)	(1.73)	(2.08)	(0.003)
Size (-1)	0.0019***	0.0015*	0.0006	.0012***
	(0.0003)	(1.86)	(1.17)	(0.00002)
Dep/Liab	0.0155***	0.010*	0.019***	.0139***
	(0.0039)	(1.25)	(5.08)	(0.00024)
Uncty (-1)	.0024***	0.0029***	0.0029***	0.0034***
	(0.0005)	(5.38)	(6.20)	(0.00003)
CoCo dummy	**0.00811***	**0.0087***	**0.00905***	**0.00845***
	(.0012)	(6.62)	(7.59)	(0.00)
Comp	0.0018***	0.0022***	0.00184***	.0021***
	(0.00001)	(6.06)	(5.82)	(0.00)
Const	-.0426***	-0.037***	-0.0426***	-0.0335***
	(0.006)	(-3.24)	(-6.04)	(0.0004)
Selection+	NO	Parametric	Semi-parametric	Semi-parametric
Inv. Mills ratio	NO	0.0033	NO	NO
		(0.58)		
Dummy selection bins	NO	NO	YES‡	NO
Weight Matrix	NO	NO	NO	YES†
CoCo bank selection		Heckman (1976)	Klein and Spady (1993)	
Dep/Liab		-3.857***	-4.093***	
		(-5.49)	(1.27)	
Debt		-0.429*	1.543***	
		(-1.75)	(.418)	
Security Issuances		0.007*	0.096 ***	
		(1.99)	(0.025)	
Const.		3.148***		
		(5.20)		
N(selected)	223	223	223	233

t statistics in parentheses

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

+ This indicates if and how the selection effect has been incorporated in the regression.

‡All 10 dummies are statistically significant at either 1% or 10% sig.

† The weight matrix captures the selection effect based on the instrument of nr. of security issuances. There is no separate selection equation.

Table 3.8: Selection bias testing summary

Variable	Key features	CoCo dummy impact on risk taking	95% CI interval
OLS	-	0.0081***	[0.0056, 0.0105]
Heckman (1976)	1. Parametric two step selection. 2. Joint normality of errors. 3. Selection effect: Inv. Mills Ratio. 4. Relies on correct model specification.	0.0088***	[0.0062, 0.0114]
Cosslett (1991)	1. Semiparametric two stage. 2. No assumption on error terms. 3.Selection effect: N ordered dummies/bins derived from first stage.	0.00905***	[0.0066, 0.0114]
Ahn and Powell (1993)	1. Semiparametric two stage. 2. No assumption on error terms. 3. Selection effect: depends only on the conditional mean of an observable selection variable. 4. Less restrictive than Cosslett: does not rely on the correct parametric specification of the single index variable which captures the selection effect.	0.00845***	[0.0083,0.0085]
d'Haultfoeuille et al. (2019)	1. Extreme quantile regression. 2. Absence of instrument. 3. Distribution-free estimator. 4. Selection assumption: selection is independent of covariates when the outcome takes large values.	0.00844***	[0.0047, 0.0121]
Lee (2009)	1. Measures bounds of 'treatment' effect. 2. No assumption on instrument. 3. Assumes randomly assigned treatment.	/	[-0.0003, 0.0086***]

3.3.3 Dynamic specification results

Our main results stem from the dynamic model specification with the asset beta as LHS variable, and are presented in Tables 3.9 and B.5. The coefficient of the lagged dependent variable is positive and statistically significant at a 1% level for all four risk measures, and so we accept the dynamic model instead of the static specification.

We find that CoCo bonds on the balance sheet have a positive and significant effect on asset risk, and moreover this impact depends on the size of wealth transfer, regardless on whether we measure it via the empirical, or the 30 % price drop. The size of expected dilution for existing shareholders has a lower economic impact than the presence of CoCos. Our results confirm our hypotheses and the results in theoretical literature that less dilutive CoCos have a higher impact on bank risk-taking behaviour. We find that the size of dilution has a positive impact on asset risk. The more equity holders have to gain from a possible CoCo conversion (so higher value of the Wealth Transfer variable), the more risk the bank will take. The coefficients for both the CoCo dummy and the wealth transfer are statistically significant at a 1% or 5% depending on the model specifi-

Table 3.9: Dynamic panel data specification with robust std errors. Bank risk measure: Asset beta

	(1) Asset beta	(2) Asset beta	(3) Asset beta	(4) Asset beta	(5) Asset beta	(6) Asset beta
Asset beta (-1)	0.813***	0.788***	0.815***	0.792***	0.815***	0.792***
	(30.03)	(26.50)	(29.66)	(26.76)	(29.65)	(26.76)
GDP growth (-1)	-0.0414***	-0.0241**	-0.0404***	-0.0243**	-0.0404***	-0.0243**
	(-3.23)	(-2.23)	(-3.12)	(-2.27)	(-3.12)	(-2.27)
Size (-1)	-0.00102***	-0.000803***	-0.000975***	-0.000727**	-0.000975***	-0.000727**
	(-3.30)	(-2.60)	(-3.16)	(-2.36)	(-3.16)	(-2.36)
Dep/Liab	-0.00372*	-0.00308	-0.00352	-0.00297	-0.00352	-0.00297
	(-1.75)	(-1.26)	(-1.61)	(-1.21)	(-1.61)	(-1.21)
CoCo dummy (-1)	0.00288***	0.00359***	0.00274***	0.00346***	0.00274***	0.00346***
	(4.64)	(5.66)	(4.20)	(5.28)	(4.20)	(5.28)
Comp		0.000253**		0.000269**		0.000269**
		(2.30)		(2.39)		(2.39)
Uncty		0.000384***		0.000364***		0.000364***
		(3.02)		(3.04)		(3.04)
Wealth transfer empirical			0.00257***	0.00243***		
			(3.29)	(3.36)		
Wealth transfer 30%					0.00260***	0.00245***
					(3.28)	(3.36)
Const.	0.0148***	0.0107***	0.0142***	0.00963**	0.0142***	0.00963**
	(3.25)	(2.72)	(3.07)	(2.38)	(3.07)	(2.38)
N	208	208	208	208	208	208

t statistics in parentheses

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

cation. Macroeconomic uncertainty and competition have a small, but significant positive economic impact on asset risk, and it strengthens the effects of having CoCo bonds on balance sheet, while diminishing the impact of the wealth transfer on asset risk.

In the model specification with interaction terms (Table B.5) Inter uncty and Inter Comp measure the relative impact of CoCo bonds on risk-taking in the presence of macroeconomic uncertainty, and competition respectively. Both interaction of uncertainty or competition in the presence of CoCo bonds have a statistically significant effect on asset risk, so the effects of these two variables is enhanced by the presence of CoCo bonds. Nonetheless, under some model specifications with interaction terms the dilution size seems to no longer impact asset risk, while having CoCo bonds on the balance sheet continues to play a positive and statistically significant role.

Our results in a dynamic setting reinforce our hypotheses when looking at the other two market measures of risk, equity beta and CDS spreads respectively. Equity beta, one of our proxies for market risk, is positively affected by CoCo bonds on a banks' balance sheet, but the size of the wealth transfer does not seem to affect it. Past levels of higher inter-bank competition increase market risk, but the interaction effects with the CoCo bonds variable do not seem to play a role.

CDS spreads are a measure of the riskiness of debt (in all cases we use CDS on 5 year subordinated debt). CoCo bonds are an additional capitalisation buffer which protects debt-holders, which in turn makes the subordinated debt less risky. In this model specification we include the debt ratio as an independent variable, as it one of the key determinants of CDS spreads. The presence of CoCo bonds on the balance sheet has a negative and significant impact at 5% or 10%, which is what one would expect. In contrast, the wealth transfer has a positive impact on CDS spreads. If gains from conversion are expected, then the bank is expected to take more risk, which in turn will decrease the probability of subordinated debt to be repaid, which leads to higher CDS spreads.

Overall, the results for the three market based risk measures (the asset beta, the equity beta and CDS spreads) are very similar, but the results based on the accounting based risk measure are very different. In both the dynamic and static panel, CoCo issuance has no effect on the z-score, and the only determinant of it appears to be the banking competition level from the last half year and the uncertainty measure. Again, under all cases for both asset and equity beta we find a positive significant effect of past CoCo issuance. The dynamic specification gives more robust results, but the accounting based measure of risk (z-score) does not capture the impact of CoCo bonds on risk-taking.

Summing up, our empirical results indicate that banks with CoCos on their balance sheet do not self-select in CoCo issuance with the purpose of changing their risk profile, as we showed under various selection bias specification models. Nonetheless, even though we lack evidence for a selection effect at issuance, we find that banks with CoCo bonds take more asset risk, both in the static and dynamic model specifications. The expected wealth transfer has a statistically significant effect when we use the asset beta and CDS spread risk measure. If the shareholders expect a negative wealth transfer, they are less likely to increase their asset risk.[18] Both banking competition and macroeconomic uncertainty have a positive and statistically significant effect on asset beta and CDS spreads in the dynamic model, and they also bring on an additional positive effect on CoCo impact on bank risk-taking decisions. This suggests that CoCo bonds are pro-cyclical and the increased asset risk which they cause is reinforced by uncertain economic states or increased competition.

3.3.4 Model misspecifications and robustness checks

In the selection bias analysis we specify a selection equation involving deposits to liabilities, number of security issuances and the debt ratio. From all our selection models, only the semiparametric two-stage Cosslett (1991) one indicates the presence of selection bias, which might indicate that our selection equation is misspecified. As such, we use other key determinants of CoCo issuance documented in the literature such as asset size in alternative selection equations and we find no selection effect under the two-stage selection models employed. Nonetheless, asset size is a very strong predictor of CoCo issuance, and it creates a statistically insignificant effect of other CoCo issuance predictors.

Consider next the Arellano-Bond estimator results which eliminate potential problems related to the presence of lagged endogenous variables. We test for auto-correlation of order 1 and 2 AR(1), AR(2) in the dynamic panel using the Arellano-Bond test. We

[18] In the static setup this variable is insignificant, but note that the static equation suffers from omitted variable bias. It is included only for comparability with the literature.

reject the null hypothesis of no auto-correlation in error terms for AR(1), and accept it for AR(2). This is further evidence that our dynamic model with one lag is well-specified.

We perform additional robustness checks in terms of model specification. We argue in the selection bias subsection that the debt ratio is not a good predictor for asset risk. We include the debt ratio variable as an independent variable for asset and equity beta, and we find that indeed it has no effect on the dependent variables. Moreover, we use few bank specific characteristics in our analysis which might lead to omitted variable bias. As such, we add up to three more control variables such as capital ratio, leverage or income to capital ratios for robustness. The main effects we are capturing do not change, but the new controls and some of the pre-existing control variables such as deposits to liabilities are no longer statistically significant. Hence we conclude that the additional controls do not add explanatory power and their potential correlation with other control variables introduces some bias, while the variables of interest are unaffected in terms of both size and statistical significance.

We re-run the analysis with market price of shares evaluated at assumed drops in the market price at conversion time varying from 5 to 25 percent, and we obtain similar values compared to the empirical and 30% price drop that we considered. Secondly, a change in one or two lags from when the CoCo was issued does not significantly change our main results. Thirdly, we test for a static panel models with fixed, and random effects as well, and results are consistent for CoCo presence, macroeconomic uncertainty and banking competition. The impact of wealth transfer on risk measures is positive, but not significant. Fourthly, we calculate the wealth transfer only using the marginal impact per shareholder in case of conversion. Results are not robust for the wealth transfer when assessing the impact on CDS, as we obtain contradicting results. Moreover, the wealth transfer for the marginal shareholder is no longer statistically significant for asset beta. In light of these results, we argue that the marginal impact is too small to be able to affect the risk measures, and the aggregate is a more economically relevant measure to inspect.

3.4 Conclusion

In this paper we add to the empirical literature assessing the impact of CoCos on risk-taking. New is that we explicitly test for sample selection bias (are banks with a greater risk appetite more inclined to issue Coco bonds?), that we include the extent to which CoCo bonds will dilute shareholders upon conversion and assess its impact on risk-taking, and that we explicitly distinguish between market- and accounting based measures of riskiness.

Further we test the regulatory arbitrage hypothesis in a CoCo setting, which argues that banks' decision to issue is determined by incentives to ex-post increase their risk-taking behaviour, but we find no compelling evidence for this hypothesis. We analyse the impact in the U.K., as the United Kingdom is by far the largest CoCo issuer in Europe, and it accounts for 60% of all conversion to equity CoCo issuances.

We find that the decision to issue CoCo bonds has a positive and significantly significant effect when looking at market-based measures of bank risk-taking, but no effect with respect to book-based measures. Taking into account that risk-taking is persistent, we find that the total amount of expected dilution to current shareholders has a significant effect on asset risk. More precisely, less dilutive CoCo bonds from last period predict an increase in current risk-taking. The impact of wealth transfer on risk is only robust across market measures of risk, and not for the book based measure. Banking competition has a positive and significant impact on current risk-taking, as expected, but the economic impact seems to be small. Macroeconomic uncertainty has an ambiguous effect on bank risk-taking, depending on whether we analyse it on market or book based measures. Looking at market based measures of risk-taking, we find that higher uncertainty amplifies the positive impact of CoCo bonds on risk-taking.

Summing up, our empirical results confirm earlier CoCo theories (Chan and van Wijnbergen, 2017), according to which the size of the dilution matters for risk-taking incentives. More precisely, we obtain evidence to support that less dilutive CoCo bonds increase banks' risk-taking incentives, as existing shareholders can potentially gain from a CoCo conversion.

These results suggest that policymakers would be well advised, when they want to control the risk-taking incentives for banks, to not just consider the level of capital requirements or the share which can be met by issuing CoCos; The specific design features of the CoCos should be considered as well if overall risk-taking incentives are to be lowered. In particular regulators may well want to insist on a sufficiently high degree of dilution for existing shareholders in the event CoCo triggers are set off and conversion will take place.

Appendices

Appendix B

B.1 Probability of conversion

The Merton credit risk model states that equity under limited liability is equivalent to a call option on the assets of the firm with strike price the debt of the firm:

$$E_{t+T} = max(A_{t+T}, 0)$$

We use the Black-Scholes formula for a European call option to value E (note that the exercise time equals the maturity of the debt):

$$E_t = A_t\theta(d) - De^{-r_f T}\theta_t(d - \sigma_a\sqrt{T}) \tag{B.1}$$

Note also that r_f is the risk free rate. This gives us one equation in two unknowns: we know E_t but we do not know A_t and σ_A. But (B.1) also implies a relation between the two volatilities, which gives us a second equation for the two unknowns in

$$\frac{dE_t}{E_t} = \frac{\theta dA_t}{E_t} = \theta\frac{A_t}{E_t}\frac{dA_t}{A_t} \tag{B.2}$$

Combining the two, $E_t\sigma_E = \theta(d)A_t\sigma_A$. Using the standard stochastic process definition for Brownian motion asset price dynamics. So we derive numerically the asset value A and asset volatility σ_A from the equity value E_t and the equity return volatility $sigma_E$ using equations (B.1) and (B.2).

B.2 Variable description

Table B.1: Variable description

Variable	Description
$r_{i,t}$	risk measure of bank i at time t
Equity beta	Equity beta of bank i at time t
Asset beta	Asset beta of bank i at time t
CDS	CDS spread in basis points on 5 year subordinated debt
Z-score	Z-score of bank i at time t
$GDPgrowth_t$	GDP growth at time t
$Size_{i,t}$	log total assets
$Debt_{i,t}$	Total liabilities to capital ratio
$Comp_t$	Banking competition - Boone indicator for UK
$Uncty_t$	UK Macroeconomic Uncertainty indicator
$Dep/Liab_{i,t}$	Deposits to liabilities ratio
$SecurityIssuance_{i,t}$	Number of securities issued
$\text{CoCoDummy}_{i,t}$	1 if the bank had CoCo bonds on their balance sheet last time period
CoCoBank_i	1 if the bank ever issued CoCo bonds in our sample
$\text{TotalWTCoCo}_{i,t}$	probability of CoCo conversion times expected WT to shareholders
Wealth transfer 30%	Total wealth transfer for an expected 30% price drop of equity
Wealth transfer emp.	Total wealth transfer for an expected maximum historical price drop of equity
$CoCo_{i,t}$	the total amount of CoCo bonds outstanding at time t for bank i
N_i	total number of shares obtained per unit of CoCo in case of conversion
$TE_{i,t}$	Total amount of Tier 1 capital (equity) of bank i at time t
$TA_{i,t}$	Total assets of bank i at time t
$a_{i,t}$	total number of shares before conversion
$Mrktcap_{i,t}$	Market capitalisation
$MarginalWT_{i,t}$	Marginal wealth transfer (per share) in case of conversion
$WT_{i,t}$	Total wealth transfer to existing shareholders in case of conversion
$P_{c,i}$	Conversion price per coco stipulated in contract
$P_{0,i}$	Price of CoCo bond at issuance
$P^m_{i,t}$	price per share of bank i at time t
v_A	Asset value
σ_A	Asset volatility
$DC(t)$	Distance to conversion at time t
TRC	Stipulated trigger level

B.3 Descriptive statistics

Table B.2: CoCo descriptive statistics

Variable		N	Mean	Std. Dev.	Min	Max
CoCo bonds to overall capital ratio	overall	69	.1233	.0891	.0272	.4310
	between	10		.0778	.0552	.3092
	within	6.9		.0387	.0168	.2452
Prob of CoCo conversion	overall	69	8.27e-06	.0000417	3.47e-51	.0002638
	between	10		.0000184	4.97e-12	.0000496
	within	6.9		.0000382	-.0000413	.0002226
Total CoCo shares mn	overall	78	19.387	27.620	0	83.171
	between	11		25.880	0	83.171
Total CoCo issued £mn	overall	80	3019.308	3154.22	60	13297.87
	between	11		2862.67	60	8434.63
Total expected WT at conversion £mn (30% decline)	overall	57	3890.012	3195.58	0	12997
Total expected WT at conversion £mn (empirical decline)	overall	57	3979.367	3280.7	0	13272.63
Wealth transfer per share (30% decline)	overall	57	.3234	.2675	0	1.141
	between	10		.2513	0	.778
	within	5.7		.1381	-.0581	.6867
Marginal wealth transfer per share (empirical decline)	overall	57	.3288	.2702	0	1.1509
	between	10		.2536	0	.7839
	within	5.7		.1402	-0.0564	.6959

Table B.3: Descriptive statistics

Variable		**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
GDP growth	overall	37	.0087	.0103	-.0311	.0231
Comp	overall	34	3.561	1.453	1.119	6.361
Uncty	overall	37	.0775	1.1672	-1.421	3.753
Size (ln assets)	overall	471	11.772	1.827	6.647	14.691
	between	15		1.960	8.47	13.924
	within	31.4		.5317	9.917	13.128
Debt ratio	overall	439	.9877	.2608	.4013	3.820
	between	15		.0788	.8753	1.174
	within	29.266		.2485	.4387	3.6338
Dep Liab (deposits to liab)	overall	439	.6471	.1752	.1084	.9907
	between	15		.1572	.4207	.9550
	within	29.266		.1059	.0838	.9483

Table B.4: Dynamic and static panel specifications with the inverse Mills ratio

	(1) Asset beta	(2) Asset beta
GDP growth (-1)	0.0890*	-0.0251
	(1.96)	(-1.41)
Size (-1)	-0.00357***	-0.000772*
	(-3.26)	(-1.84)
Dep/Liab	0.00700	-0.00282
	(0.93)	(-1.00)
Uncty (-1)	0.00270***	0.000383**
	(5.96)	(2.05)
CoCo dummy	0.00765***	0.00398***
	(6.40)	(8.47)
Comp	0.000586	0.000447***
	(1.57)	(3.16)
Inv. Mills ratio	-0.00132	-0.00155
	(-0.29)	(-0.90)
Asset beta (-1)		0.813***
		(31.52)
Const.	0.0363**	0.0102*
	(2.39)	(1.77)
N	223	208

t statistics in parentheses

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

Table B.5: Dynamic panel specification with interaction terms, and robust std errors. Bank risk measure: Asset beta

	(1) Asset beta	(2) Asset beta	(3) Asset beta	(4) Asset_beta	(5) Asset beta
Asset beta (-1)	0.818***	0.820***	0.820***	0.788***	0.826***
	(43.38)	(42.38)	(42.37)	(24.72)	(33.86)
GDP growth (-1)	-0.0310**	-0.0309**	-0.0309**	-0.0204*	-0.0455***
	(-2.54)	(-2.54)	(-2.54)	(-1.88)	(-2.98)
Size (-1)	-0.000580	-0.000544	-0.000544	-0.00103***	-0.000366
	(-1.58)	(-1.49)	(-1.49)	(-2.92)	(-1.46)
Dep/Liab	-0.00375*	-0.00367*	-0.00367*	-0.00220	-0.00449**
	(-1.75)	(-1.70)	(-1.70)	(-0.87)	(-2.52)
CoCo dummy (-1)	0.00241***	0.00237***	0.00237***	0.00314***	0.00288***
	(4.78)	(4.50)	(4.50)	(5.22)	(3.99)
Comp	0.000307***	0.000315***	0.000315***		0.000396***
	(2.88)	(2.95)	(2.95)		(4.16)
Uncty	0.000198	0.000192	0.000192	0.000300*	
	(1.26)	(1.24)	(1.24)	(1.71)	
Inter Uncty	0.00194**	0.00190**	0.00190**		0.000776
	(2.18)	(2.12)	(2.12)		(0.64)
Inter Comp	0.00244***	0.00237***	0.00237***	0.00156**	
	(4.42)	(4.19)	(4.19)	(2.11)	
Wealth transfer empirical		0.00135		0.00168*	0.00267***
		(1.60)		(1.89)	(3.66)
Wealth transfer 30%			0.00136		
			(1.60)		
Const.	0.00822*	0.00770*	0.00770*	0.0139***	0.00584
	(1.78)	(1.66)	(1.66)	(3.04)	(1.58)
N	208	208	208	208	208

t statistics in parentheses

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

Table B.6: Dynamic panel data specification with robust std errors. Risk measure: Equity beta

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta
Equity beta (-1)	0.540***	0.536***	0.540***	0.536***	0.540***	0.536***
	(11.77)	(11.88)	(11.83)	(11.95)	(11.83)	(11.95)
GDP growth (-1)	-0.961	-1.006	-0.957	-1.007	-0.957	-1.007
	(-1.20)	(-1.25)	(-1.20)	(-1.25)	(-1.20)	(-1.25)
Size (-1)	-0.0214***	-0.00312	-0.0212***	-0.00254	-0.0212***	-0.00254
	(-3.45)	(-0.36)	(-3.35)	(-0.30)	(-3.35)	(-0.30)
Dep/Liab	-0.0638	-0.0701	-0.0621	-0.0684	-0.0621	-0.0684
	(-0.79)	(-0.84)	(-0.76)	(-0.81)	(-0.76)	(-0.81)
CoCo dummy (-1)	0.0694***	0.0868***	0.0685***	0.0858***	0.0685***	0.0858***
	(3.84)	(3.44)	(3.64)	(3.31)	(3.64)	(3.31)
Comp		0.00991		0.0100		0.0100
		(1.59)		(1.62)		(1.62)
Uncty		0.000488		0.000376		0.000376
		(0.21)		(0.16)		(0.16)
Wealth transfer empirical			0.0179	0.0228		
			(0.98)	(1.49)		
Wealth transfer 30%					0.0181	0.0230
					(0.98)	(1.49)
Const.	0.295***	0.0401	0.291***	0.0316	0.291***	0.0316
	(3.52)	(0.39)	(3.37)	(0.31)	(3.37)	(0.31)
N	228	228	228	228	228	228

t statistics in parentheses

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

Table B.7: Dynamic panel specification with robust std errors and interaction terms. Risk measure: Equity beta

	(1)	(2)	(3)	(4)	(5)
	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta
Equity beta (-1)	0.548***	0.548***	0.548***	0.540***	0.552***
	(13.35)	(13.40)	(13.40)	(12.78)	(13.71)
GDP growth (-1)	-1.105	-1.104	-1.104	-0.779	-1.191
	(-1.37)	(-1.37)	(-1.37)	(-0.88)	(-1.46)
Size (-1)	-0.00652	-0.00626	-0.00626	-0.0234***	-0.00452
	(-0.57)	(-0.55)	(-0.55)	(-2.83)	(-0.45)
Dep/Liab	-0.0880	-0.0871	-0.0871	-0.0536	-0.0926
	(-1.15)	(-1.12)	(-1.12)	(-0.72)	(-1.18)
CoCo dummy (-1)	0.0558*	0.0555*	0.0555*	0.0689***	0.0561*
	(1.90)	(1.86)	(1.86)	(3.33)	(1.69)
Comp	0.0111*	0.0112*	0.0112*		0.0117*
	(1.86)	(1.89)	(1.89)		(1.88)
Uncty	0.00163	0.00160	0.00160	0.00409	
	(0.70)	(0.69)	(0.69)	(1.38)	
Inter Comp	0.0507**	0.0503**	0.0503**		0.0477
	(2.02)	(2.01)	(2.01)		(1.41)
Inter uncty	0.00547	0.00497	0.00497	-0.0140	
	(0.19)	(0.17)	(0.17)	(-0.42)	
Wealth transfer empirical		0.0115		0.0216	0.0151
		(0.58)		(0.83)	(1.13)
Wealth transfer 30%			0.0116		
			(0.58)		
Const.	0.0879	0.0840	0.0840	0.311***	0.0654
	(0.64)	(0.63)	(0.63)	(3.27)	(0.54)
N	228	228	228	228	228

t statistics in parentheses

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

Table B.8: Dynamic panel data specification with robust std errors. Risk measure: CDS

	(1) CDS	(2) CDS	(3) CDS	(4) CDS	(5) CDS	(6) CDS	(7) CDS
CDS (-1)	0.706***	0.706***	0.693***	0.631***	0.622***	0.706***	0.622***
	(18.61)	(18.88)	(17.71)	(21.34)	(21.23)	(18.88)	(21.23)
GDPgrowth	-598.5***	-598.7***	108.6	2159.0***	2695.7***	-598.7***	2695.7***
	(-2.59)	(-2.59)	(0.27)	(4.68)	(4.90)	(-2.59)	(4.90)
Size	1.345	3.508	10.07	-5.380	-2.272	3.508	-2.272
	(0.04)	(0.11)	(0.33)	(-0.28)	(-0.11)	(0.11)	(-0.11)
Debt	54.78***	55.64***	58.86***	49.12***	51.95***	55.64***	51.95***
	(3.08)	(3.25)	(3.36)	(3.64)	(3.15)	(3.25)	(3.15)
Dep/Liab	-365.0***	-356.2***	-335.6***	-263.3***	-237.3***	-356.2***	-237.3***
	(-6.54)	(-6.71)	(-4.99)	(-3.40)	(-2.83)	(-6.71)	(-2.83)
CoCo Dummy (-1)	-11.12*	-12.78**	-1.654	2.620	11.72	-12.78**	11.72
	(-1.77)	(-2.21)	(-0.20)	(0.58)	(1.61)	(-2.21)	(1.61)
Wealth Transfer Empirical		167.7***	158.7***	198.8***	192.1***		
		(18.12)	(10.57)	(8.87)	(7.98)		
Comp (-1)			10.82**		9.464**		9.464**
			(2.08)		(2.48)		(2.48)
Uncertainty				35.58***	35.27***		35.27***
				(5.33)	(5.27)		(5.27)
Wealth Transfer 30%						167.7***	192.1***
						(18.12)	(7.98)
Const.	209.8	175.0	46.27	220.1	138.2	175.0	138.2
	(0.44)	(0.39)	(0.11)	(0.83)	(0.45)	(0.39)	(0.45)
N	124	124	124	124	124	124	124

t statistics in parentheses

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

Table B.9: Dynamic panel data specification with robust std errors and interaction terms. Risk measure: CDS

	(1) CDS	(2) CDS	(3) CDS	(4) CDS	(5) CDS	(6) CDS
CDS (-1)	0.699***	0.639***	0.633***	0.699***	0.639***	0.633***
	(16.91)	(18.59)	(17.69)	(16.91)	(18.59)	(17.69)
GDP growth	-252.2	2417.4***	2411.3***	-252.2	2417.4***	2411.3***
	(-0.50)	(4.21)	(3.81)	(-0.50)	(4.21)	(3.81)
Size	10.86	-7.234	-2.971	10.86	-7.234	-2.971
	(0.38)	(-0.37)	(-0.14)	(0.38)	(-0.37)	(-0.14)
Debt	56.73***	50.63***	49.85***	56.73***	50.63***	49.85***
	(3.13)	(3.72)	(2.88)	(3.13)	(3.72)	(2.88)
Dep/Liab	-350.4***	-247.1***	-246.3**	-350.4***	-247.1***	-246.3**
	(-4.96)	(-2.95)	(-2.49)	(-4.96)	(-2.95)	(-2.49)
Comp (-1)	5.612		2.177	5.612		2.177
	(0.85)		(0.35)	(0.85)		(0.35)
Inter comp (-1)	32.48**		38.15***	32.48**		38.15***
	(2.20)		(3.58)	(2.20)		(3.58)
CoCo Dummy (-1)	-38.67**	5.197	-31.04*	-38.67**	5.197	-31.04*
	(-2.01)	(1.22)	(-1.86)	(-2.01)	(1.22)	(-1.86)
Wealth Transfer Empirical	122.9***	179.9***	139.8***			
	(5.79)	(8.19)	(5.30)			
Uncty		40.35***	38.85***		40.35***	38.85***
		(4.92)	(4.67)		(4.92)	(4.67)
Inter Uncty		-16.50	-10.20		-16.50	-10.20
		(-1.23)	(-0.68)		(-1.23)	(-0.68)
Wealth Transfer 30%				122.9***	179.9***	139.8***
				(5.79)	(8.19)	(5.30)
Const.	59.16	225.6	167.0	59.16	225.6	167.0
	(0.15)	(0.86)	(0.53)	(0.15)	(0.86)	(0.53)
N	124	124	124	124	124	124

t statistics in parentheses

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

Table B.10: Dynamic panel data specification with robust std errors. Risk measure: Z-score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score
Z-score (-1)	0.768***	0.768***	0.748***	0.766***	0.746***	0.768***	0.746***
	(34.50)	(34.62)	(75.77)	(38.14)	(54.37)	(34.62)	(54.37)
GDP growth (-1)	-9.233	-9.118	-36.15	-42.58	-74.95	-9.118	-74.95
	(-0.25)	(-0.25)	(-1.00)	(-0.65)	(-0.87)	(-0.25)	(-0.87)
Size (-1)	3.154	3.205	0.359	3.603	0.781	3.205	0.781
	(1.46)	(1.45)	(0.20)	(1.12)	(0.33)	(1.45)	(0.33)
Debt (-1)	-0.159	-0.167	-2.790	-0.0887	-2.717	-0.167	-2.717
	(-0.09)	(-0.09)	(-1.11)	(-0.05)	(-1.10)	(-0.09)	(-1.10)
Dep/Liab (-1)	1.943	1.963	-5.871	2.768	-5.075	1.963	-5.075
	(0.32)	(0.32)	(-0.62)	(0.55)	(-0.62)	(0.32)	(-0.62)
CoCo Dummy (-1)	0.701	0.649	-1.216	0.297	-1.629	0.649	-1.629
	(1.20)	(1.13)	(-1.01)	(0.37)	(-0.88)	(1.13)	(-0.88)
Wealth Transfer Empirical (-1)		1.283	0.483	1.666	0.917		
		(0.90)	(0.41)	(0.71)	(0.45)		
Comp (-1)			-1.573*		-1.586*		-1.586*
			(-1.83)		(-1.82)		(-1.82)
Uncty (-1)				-0.426	-0.485		-0.485
				(-0.39)	(-0.43)		(-0.43)
Wealth Transfer 30% (-1)						1.283	0.917
						(0.90)	(0.45)
Const.	-37.78	-38.40	7.602	-43.30	2.529	-38.40	2.529
	(-1.58)	(-1.57)	(0.28)	(-1.19)	(0.08)	(-1.57)	(0.08)
N	238	238	238	238	238	238	238

t statistics in parentheses

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

Table B.11: Dynamic panel data specification with robust std errors and interaction terms. Risk measure: Z-score

	(1)	(2)	(3)	(4)	(5)	(6)
	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score
Z-score (-1)	0.750***	0.766***	0.747***	0.750***	0.766***	0.747***
	(90.51)	(41.66)	(50.96)	(90.51)	(41.66)	(50.96)
GDP growth (-1)	-41.41	-42.42	-75.71	-41.41	-42.42	-75.71
	(-1.14)	(-0.57)	(-0.81)	(-1.14)	(-0.57)	(-0.81)
Size (-1)	0.429	3.601	0.818	0.429	3.601	0.818
	(0.24)	(1.09)	(0.33)	(0.24)	(1.09)	(0.33)
Debt (-1)	-2.872	-0.0882	-2.810	-2.872	-0.0882	-2.810
	(-1.16)	(-0.05)	(-1.15)	(-1.16)	(-0.05)	(-1.15)
Dep/Liab (-1)	-5.402	2.766	-4.622	-5.402	2.766	-4.622
	(-0.57)	(0.55)	(-0.57)	(-0.57)	(0.55)	(-0.57)
Comp (-1)	-1.644*		-1.645*	-1.644*		-1.645*
	(-1.92)		(-1.92)	(-1.92)		(-1.92)
Inter comp (-1)	2.966		3.178	2.966		3.178
	(1.24)		(1.25)	(1.24)		(1.25)
CoCo Dummy (-1)	-4.166*	0.295	-4.596	-4.166*	0.295	-4.596
	(-1.73)	(0.43)	(-1.56)	(-1.73)	(0.43)	(-1.56)
Wealth Transfer Empirical (-1)	0.781	1.672	0.919			
	(0.63)	(0.84)	(0.52)			
Uncty (-1)		-0.424	-0.441		-0.424	-0.441
		(-0.34)	(-0.35)		(-0.34)	(-0.35)
Inter uncty (-1)		-0.0159	0.534		-0.0159	0.534
		(-0.01)	(0.48)		(-0.01)	(0.48)
Wealth Transfer 30% (-1)				0.781	1.672	0.919
				(0.63)	(0.84)	(0.52)
Const.	6.745	-43.28	1.999	6.745	-43.28	1.999
	(0.25)	(-1.16)	(0.06)	(0.25)	(-1.16)	(0.06)
N	238	238	238	238	238	238

t statistics in parentheses

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

B.4 Robustness tables

Table B.12: Static panel data specification with bank fixed effects and interaction terms. Bank risk measure: Asset beta

	(1) Asset_beta	(2) Asset_beta	(3) Asset_beta	(4) Asset_beta	(5) Asset_beta	(6) Asset_beta	(7) Asset_beta	(8) Asset_beta
GDP growth (-1)	-0.0983***	-0.0983***	-0.0926***	-0.0800**	-0.00888	-0.0104	-0.00820	-0.00308
	(-3.00)	(-2.99)	(-2.78)	(-2.52)	(-0.25)	(-0.29)	(-0.23)	(-0.09)
Size (-1)	-0.00259***	-0.00260***	-0.00185	-0.00138	-0.00345***	-0.00324***	-0.00397***	-0.00324***
	(-2.86)	(-2.84)	(-1.60)	(-1.25)	(-3.92)	(-3.62)	(-3.39)	(-2.85)
Debt (-1)	0.00174	0.00174	0.00196	0.00203	0.00159	0.00173	0.00144	0.00163
	(0.76)	(0.76)	(0.86)	(0.93)	(0.74)	(0.80)	(0.67)	(0.79)
Dep/Liab (-1)	0.00643	0.00640	0.00584	0.00372	0.00825	0.00851	0.00870	0.00670
	(1.08)	(1.06)	(0.96)	(0.65)	(1.44)	(1.49)	(1.51)	(1.22)
CoCo Dummy (-1)	0.00586***	0.00587***	0.00651***	0.0164***	0.00677***	0.00684***	0.00641***	0.0155***
	(6.28)	(6.09)	(5.73)	(7.19)	(7.30)	(7.36)	(5.96)	(7.15)
Wealth transfer Empirical		-0.000127	0.0000603	0.000910	-0.000952	-0.00145	-0.00111	-0.000536
		(-0.03)	(0.01)	(0.23)	(-0.25)	(-0.37)	(-0.29)	(-0.14)
Comp (-1)			0.000395	0.000651*			-0.000252	0.0000430
			(1.06)	(1.83)			(-0.67)	(0.12)
Inter comp (-1)				-0.0101***				-0.00926***
				(-4.91)				(-4.70)
Uncty					0.00171***	0.00158***	0.00179***	0.00159***
					(5.11)	(4.50)	(5.02)	(4.46)
Inter uncty						0.00141		0.000823
						(1.21)		(0.74)
Const.	0.0261*	0.0261*	0.0155	0.00979	0.0347**	0.0319**	0.0419**	0.0329*
	(1.73)	(1.71)	(0.85)	(0.56)	(2.39)	(2.17)	(2.32)	(1.88)
N	223	223	223	223	223	223	223	223

t statistics in parentheses

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

Table B.13: Static panel data specification with bank fixed effects and interaction terms. Bank risk measure: Equity beta

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta	Equity beta
GDP growth (-1)	-2.007***	-1.998***	-1.661**	-1.525**	-1.051	-1.074	-1.114	-1.061
	(-2.64)	(-2.62)	(-2.18)	(-2.01)	(-1.20)	(-1.22)	(-1.28)	(-1.22)
Size (-1)	-0.0601***	-0.0594***	-0.0153	-0.0109	-0.0673***	-0.0654***	-0.0280	-0.0202
	(-3.33)	(-3.27)	(-0.63)	(-0.45)	(-3.65)	(-3.48)	(-1.07)	(-0.76)
Dep/Liab (-1)	-0.0710	-0.0646	-0.0857	-0.104	-0.0345	-0.0344	-0.0627	-0.0826
	(-0.55)	(-0.50)	(-0.67)	(-0.82)	(-0.27)	(-0.27)	(-0.49)	(-0.64)
CoCo dummy (-1)	0.136***	0.134***	0.171***	0.278***	0.143***	0.144***	0.170***	0.273***
	(5.98)	(5.71)	(6.35)	(5.16)	(6.04)	(6.05)	(6.34)	(5.06)
Wealth transfer empirical		0.0349	0.0465	0.0562	0.0273	0.0215	0.0396	0.0443
		(0.35)	(0.47)	(0.58)	(0.28)	(0.22)	(0.40)	(0.45)
Comp (-1)			0.0230***	0.0254***			0.0189**	0.0220**
			(2.70)	(2.99)			(2.09)	(2.42)
Inter comp (-1)				-0.111**				-0.105**
				(-2.29)				(-2.16)
Uncty					0.0176**	0.0162*	0.0113	0.00873
					(2.12)	(1.86)	(1.29)	(0.95)
Inter Uncty						0.0157		0.0147
						(0.55)		(0.52)
Const.	0.771***	0.759***	0.144	0.0910	0.826***	0.803***	0.295	0.199
	(2.87)	(2.80)	(0.41)	(0.26)	(3.05)	(2.93)	(0.80)	(0.53)
N	243	243	243	243	243	243	243	243

t statistics in parentheses

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

Table B.14: Static panel data specification with bank fixed effects and interaction terms. Bank risk measure: CDS

	(1) CDS	(2) CDS	(3) CDS	(4) CDS	(5) CDS	(6) CDS	(7) CDS	(8) CDS
GDP growth (-1)	-689.5	-680.8	-499.8	-569.0	1177.8	1108.7	1145.5	1000.0
	(-1.00)	(-0.98)	(-0.70)	(-0.78)	(1.63)	(1.53)	(1.58)	(1.39)
Size (-1)	158.3***	159.1***	180.5***	181.3***	220.7***	217.1***	209.4***	214.7***
	(3.46)	(3.47)	(3.58)	(3.58)	(5.10)	(5.02)	(4.53)	(4.69)
Debt (-1)	36.12	35.96	53.04	51.57	82.52	78.12	73.38	69.06
	(0.50)	(0.50)	(0.72)	(0.70)	(1.25)	(1.19)	(1.09)	(1.04)
Dep/Liab (-1)	-324.0**	-319.9**	-235.1	-233.8	6.221	-21.27	-34.70	-29.92
	(-2.42)	(-2.38)	(-1.49)	(-1.47)	(0.05)	(-0.15)	(-0.23)	(-0.20)
CoCo Dummy (-1)	-78.97***	-80.44***	-70.50***	-95.99**	-63.84***	-64.80***	-69.66***	-146.7***
	(-4.29)	(-4.30)	(-3.34)	(-2.02)	(-3.70)	(-3.76)	(-3.63)	(-3.37)
Wealth Transfer Empirical		148.3	139.7	113.1	211.2	240.0	219.9	174.8
		(0.50)	(0.47)	(0.38)	(0.79)	(0.89)	(0.82)	(0.65)
Competition (-1)			9.870	8.814			-6.553	-8.506
			(1.02)	(0.89)			(-0.70)	(-0.88)
Inter comp (-1)				24.29				74.68**
				(0.60)				(1.99)
Uncty					41.47***	36.88***	43.43***	40.84***
					(5.29)	(4.21)	(5.20)	(4.30)
Inter uncty						23.84		27.87
						(1.17)		(1.34)
Const.	-1718.6**	-1730.5**	-2105.4***	-2112.8***	-2824.3***	-2750.3***	-2627.1***	-2686.1***
	(-2.56)	(-2.57)	(-2.74)	(-2.74)	(-4.37)	(-4.24)	(-3.72)	(-3.85)
N	141	141	141	141	141	141	141	141

t statistics in parentheses

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

Table B.15: Static panel data specification with bank fixed effects and interaction terms. Bank risk measure: Z-score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score
GDP growth (-1)	81.16	81.05	56.60	56.27	25.38	18.21	30.85	23.42
	(1.41)	(1.41)	(0.98)	(0.97)	(0.38)	(0.27)	(0.46)	(0.35)
Size (-1)	0.559	0.500	-1.886	-1.884	0.624	1.037	-1.592	-1.101
	(0.23)	(0.20)	(-0.73)	(-0.72)	(0.25)	(0.42)	(-0.61)	(-0.42)
Debt (-1)	-0.000476	0.0110	-1.371	-1.372	-0.418	-0.732	-1.453	-1.692
	(-0.00)	(0.00)	(-0.17)	(-0.17)	(-0.05)	(-0.09)	(-0.18)	(-0.21)
Dep/Liab (-1)	1.087	0.924	-7.183	-7.156	0.785	0.910	-6.466	-5.929
	(0.14)	(0.12)	(-0.87)	(-0.87)	(0.10)	(0.12)	(-0.78)	(-0.71)
CoCo Dummy (-1)	-0.799	-0.726	-3.101	-3.317	-1.339	-1.290	-3.180	-3.657
	(-0.45)	(-0.40)	(-1.56)	(-0.79)	(-0.73)	(-0.70)	(-1.60)	(-0.87)
Wealth Transfer Empirical		-1.721	-2.723	-2.742	-1.244	-2.452	-2.385	-3.493
		(-0.20)	(-0.32)	(-0.32)	(-0.14)	(-0.28)	(-0.28)	(-0.40)
Comp (-1)			-1.771***	-1.776***			-1.599**	-1.535**
			(-2.75)	(-2.73)			(-2.35)	(-2.23)
Inter comp (-1)				0.222				0.631
				(0.06)				(0.16)
Uncty					-1.017	-1.391**	-0.514	-0.874
					(-1.61)	(-2.09)	(-0.78)	(-1.25)
Inter uncty						3.681*		3.371
						(1.72)		(1.57)
Const.	-1.025	-0.216	39.61	39.57	-0.295	-4.590	35.70	29.95
	(-0.03)	(-0.01)	(1.08)	(1.07)	(-0.01)	(-0.13)	(0.96)	(0.80)
N	270	270	270	270	270	270	270	270

t statistics in parentheses

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

Chapter 4

Capital Allocation, Leverage Ratio Requirement and Banks' Risk-Taking[1]

4.1 Introduction

In the aftermath of the 2007 – 2009 financial crisis, the global regulatory capital framework has undergone substantial reform to address shortcomings in the pre-crisis framework and deliver a resilient banking system that can support the real economy. One of the prominent changes is the introduction of a leverage ratio requirement to complement the risk-based capital requirements and thus, to make the whole regulatory capital framework more robust to different types of uncertainties. This introduction however brings about significant challenges for banks to efficiently manage their limited financial resources. These challenges include issues on how to incorporate multiple regulatory constraints within their capital allocation framework. Banks are therefore developing new

[1]We are grateful for helpful comments from Matthew Willison, Arzu Uluc, Aakriti Mathur, Ieva Sakalauskaite and seminar participants at the Bank of England. All remaining errors are of our own.

approaches to allocating capital to their businesses. The evolution of banks' practices in turn may have implications for the effectiveness of regulatory measures. One important question, as highlighted in Bajaj et al. (2018), that requires further analysis is how the banks' riskiness depends on the way they treat the leverage ratio requirement within their capital allocation process.

This paper aims to shed light on this question. We examine how banks' asset risk is affected by the level at which they apply the regulatory constraints. To do that, we construct a two-period model where there is a bank that runs two business units. One has higher non-risk adjusted returns but it is also riskier, while the other has lower returns and it is less risky. We model the two businesses as the lending business as the riskier one, and the repo business as the safer one. The bank is subject to two main regulatory constraints - the risk-weighted capital requirements formulated using the Value-at-Risk (VaR) constraint and the leverage ratio requirement. Those constraints are legally applied at the bank's group consolidated level but the bank can choose to require each of their business units to comply with both constraints - hereafter referred to as the bank allocating the two constraints to their businesses. Further we measure the change in the bank's optimal investment in the case when the constraints are exclusively applied at the group level to when they constraints are allocated to the respective business units. We interpret the change in investment through a risk-taking perspective: the change in bank's asset risk is measured through the fraction of investment in lending of the total bank's balance sheet.

One of the key insight we get is that the impact differs significantly depending on which of the two constraints matter at the group consolidated level. If the bank is constrained by the leverage ratio at the group level, we show analytically that the impact on risk-taking depends on the relationship between the average risk weights at group and business unit levels and the ratio of two regulatory requirements. If both the bank's group and business units on a stand-alone basis have average risk weights below a certain threshold, then the allocation of constraints does not change the bank's investment decisions. In contrast, if the stand-alone average risk weights for the business units are higher than a threshold, which in turn is higher than the aggregate average risk weight at the group level, then applying both regulatory constraints at the business unit level will lead to a decrease in the bank's asset risk. The intuition behind this result relates to the most binding constraint. If the stand-alone business units are bound also by the leverage ratio, then the bank's asset risk does not change. If the stand-alone business units are bound by the risk-weighted capital requirement, then we observe a decrease in asset risk when constraints are applied at the business unit level.

However, the allocation of constraints could bring about an increase in the bank's asset risk if at the group level, the risk-weighted constraint is the only binding constraint. One of the necessary conditions for this result is that the riskier business unit is bound by the risk-weighted capital requirement, while the less risky business unit is bound by the leverage ratio on a stand-alone basis. This implies that the bank has incentives to reallocate capital from the less risky unit to the riskier unit to increase marginal profitability, leading to an overall change in asset risk. We also point out to a diversification benefit in terms of required capital of applying the risk-weighted capital requirement at group level, compared to applying it on a stand-alone basis which further plays a role in the necessary conditions to observe an increase in asset risk. Given that it is not possible to obtain closed-form solutions for the analytical analysis, we complement it with the numerical simulations. We calibrate the model using data on large UK banks. In our numerical results, we indeed find that the allocation of constraints leads to an increase of asset risk of the average bank in our sample when at the group level the bank is bound by the risk-weighted constraint only.

To understand the role of the business model, we examine whether the impact of the allocation of the constraints differ across banks with different business models. For this purpose, we first classify the UK banks in our sample into two types of banks, namely retails banks and wholesale and capital market-oriented banks. Intuitively, retail banks are more likely to be bounded by leverage ratio, while wholesale and capital market-oriented are more likely to be constrained by the risk-weighted assets requirement. We recalibrate the model to each type of bank and run the numerical simulations. The most interesting finding is that there is a stark difference in the impact of the allocation of constraints on the banks' asset risk between the two types. Especially, in the case where only the risk-weighted constraint matters at the group level, while the allocation of constraints results in an increase in asset risk of retail banks, it leads to a decrease in the asset risk of wholesale and capital market-oriented banks.

The organisation of the paper is as follows. After discussing the related literature in the next section, we set out in Section 4.3 our theoretical setup. Section 4.4 presents our main analytical insights. Then in Section 4.5 we calibrate our model to the UK banks and explain our numerical simulations in Section 4.6. In Section 4.7 we further break down our UK bank sample in two bank business model groups: retail orientated, and wholesale and capital-markets orientated banks, and discuss our new simulation results in this context. Finally Section 4.8 concludes and suggests further research.

4.2 Related Literature

This research adds to three strands of existing literature. We add to the literature on capital allocation under constraints, where we assess the impact of leverage ratio on internal capital allocation between different business units. Secondly, our research is related to the broader literature on unintended consequences of post-crisis financial regulation, more specifically on the leverage ratio requirement impact on bank risk-taking. Lastly, we apply our theoretical model to the repo and lending market, and substantiate with our theory the observed decrease in repo transactions since the introduction of leverage ratio.

The literature on the allocation of capital within complex financial institutions is still very limited. Capital allocation is a method used to determine the notional amount of equity capital needed to support a business. The performance of a business unit, and it's respective capital allocation can be assessed and done in a large variety of ways.[2] An important factor in capital allocation among different business units is the marginal profitability relative to the costs of capital associated with that business. The allocation relies on the relative profitability of each business unit in relation to the minimum marginal amount of capital required to perform operations. Among the most common are the Risk Adjusted Returns on Capital (RAROC) and Economic Value Added (EVA) which relate to economic capital, or measures that take into account the regulatory capital

[2] For a recent primer on capital allocation methods implemented in practice see Ita (2017).

requirements (Ita, 2017). Economic capital is a measure of calculating a minimum amount of equity needed to cover unexpected shortfalls measured via Value-at-Risk (VaR) or Expected Shortfall (ES), and regulatory capital allocation relates to the minimum Basel III requirements on equity to risk-weighted assets, and more recently to the leverage ratio requirements.[3] An Oliver Wyman report finds that the minimum capital requirements started playing a much more central role in banks' capital allocation after the financial crisis of 2008 (Khaykin et al., 2017). The reason behind it is that the banks attach the highest weight to the most binding constraint of capital requirements, and regulatory capital took that role compared to other measures such as economic capital. Criticism on different methods of capital allocation relates to calculating the cost of capital at an aggregate value of the firm, and not per project. In early work on the topic, Stein (1997) provides a rationale for the establishment of internal capital markets, which enable firms' headquarter to shift resources across business units according to their profitability. Graham and Harvey (2001) find that banks traditionally use aggregate risk, via the weighted average cost of capital (WACC) when evaluating projects, and not project-specific risk. This finding is supported by Krüger et al. (2015), which argue that the aggregate allocation type leads to under-investment in safer businesses, and over-investment in relatively riskier ones. The link between costs of capital and regulation is made also in Baker and Wurgler (2015), which argue that an increase in regulation that makes banks less risky lead to an increase in cost of capital, and substantiate their hypothesis by an analysis of US bank returns. Moreover, it has been shown that accounting for diversification benefits between different units can reduce banks' capital needs (Perold, 2005). He suggests that banks should evaluate business activities based on their marginal contribution to expected operating profits and to the bank's required risk capital.

In our paper the minimum amount of capital required depends on the leverage ratio and the risk-sensitive regulatory requirement, as it is the most commonly used measure at the time when this paper is written. Additionally, we take into account the criticism of the average capital charge, by assessing both the cases when the regulatory capital constraints are applied at group level and at separate business unit levels. For instance,

[3] For more methodological details, Dhaene et al. (2012) analyse the existing literature and practice on different capital allocation methods and their rationale, and construct a unified capital allocation framework, which encompasses a large majority of these cases.

the low-risk, low-margin activities have a low risk-based capital charge, but the risk insensitive leverage ratio has a relatively higher capital charge compared to the risk-based one. This effect is amplified for low margin and high balance sheet intensity activities such as repo transactions. In contrast, the high-risk, high-margin businesses derive the highest capital charge from risk-based requirements, while the leverage ratio requirement is less likely to be binding. In that sense, the most relevant paper related to our work is Goel et al. (2019) which analyses the allocation of capital across two business units (i.e. lending and market making) by banks that face multiple constraints, namely risk-based capital and leverage ratio requirements. They develop a theoretical model and calibrate it to US data, and show how shocks to one unit lead to spillover effects to other units in terms of allocated capital. Although our model is in similar spirit with the one from Goel et al. (2019), they formally analyse the impact of tightening constraints on capital allocation and business unit investments, while we focus on the risk-taking implications of applying the same constraints at different levels of a bank holding.

The impact of leverage ratio requirement (LRR) on the banking portfolio composition is a relatively new research topic. Blum (2008) is the first one to advocate for the importance of introducing this risk-insensitive measure as an incentive for truthful risk reporting in an adverse selection model. The Basel Committee provides three reasons for the introduction of the LRR: help against excessive leverage build up, help against banks trying to circumvent the risk-based capital requirements and lastly, help against model risk (Basel Committee, 2009). In more recent work, both Kiema and Jokivuolle (2014) and Acosta-Smith et al. (2018) find in theoretical setups that the leverage ratio introduction leads to an increase in risk-taking under certain conditions. Kiema and Jokivuolle (2014) focus on the model risk argument, and find that this shift does not affect the aggregate risk profile and banking stability, as banks re-shuffle the loans: banks focused on low-risk lending will shift towards more high-risk lending, while the high-risk lending banks will reallocate part of their portfolio to low-risk investments.Acosta-Smith et al. (2018) focus on the complementing risk-based capital requirements argument, and find an increase in risk-taking if equity is sufficiently costly, or banks are bound by the leverage ratio. They confirm these results empirically on a large panel of European banks. Choi et al. (2018) find similar empirical results for the US, where banks shift towards riskier investments (higher asset risk), but the shift is counterbalanced by increased capital leading to no change in overall bank risk. Our paper focuses on the asset risk implications of the leverage ratio introduction as a complement to risk-based capital requirements. Nonetheless unlike previous literature we do not assess how the introduction of LRR changes the portfolio composition, but rather how the allocation of the constraint at different business levels impacts asset risk. Other work assessing the leverage ratio requirement introduction focuses on business cycle and long-run interaction with risk-based requirements (Gambacorta and Karmakarb, 2018), or moral hazard and debt absorption capacity(Barth and Seckinger, 2018). The most likely operations to be negatively affected by the leverage ratio requirement introduction are operations with a low expected return, but a high capital charge, such as repurchase agreements (repos). Early evidence shows that the repo markets have been hit by the LR requirement both in Europe and the US (BIS CGFS, 2017; Allahrakha et al., 2018; Duffie, 2018). Nonetheless, disentangling the causation or the persistency of the interaction between repo markets and leverage ratio has mixed evidence. In a recent study on market liquidity of the UK gilt, Bicu-Lieb et al. (2020) find that the occurrence of a decrease in the repo liquidity occurred simultaneously with the introduction of the leverage ratio requirement, but there is no clear evidence on the existence of a causal relationship between the two. Kotidis and Van Horen (2019) also analyse the UK gilt repo market, and conclude that the leverage ratio introduction has no impact on bilateral repo transactions. They find that repo dealers constrained by the leverage ratio decrease initially the transacted volumes with smaller clients, but this effect was temporary. The repo dealers who were not affected by the LRR took over the smaller clients, and later on the affected dealers increased haircuts on reverse repo transactions, as a passthrough mechanism of increased costs of regulation. We do not perform an empirical analysis akin the previous two studies, but rather we emulate some of the (UK gilt) repo characteristics in our theoretical model and simulation. We consider the two types of balance sheet charges that repo transactions have, and estimate UK gilt repo market returns which we later use to simulate banks' investment decisions.

4.3 The model

We consider a bank that runs two business units, one yields higher non-risk adjusted returns but is riskier than the other. Although our results will hold for any combination of two businesses that have those characteristics, in this paper, we model the riskier business as a lending business and the safer business as a repo business.

Two business units The lending unit grants loans to customers. We denote the bank's ex-ante gross interest income from loans by $G(L)$ where L is the total value of granted loans. We capture the fact that granting loans is a risky business by assuming that ex-post some loans do not pay back. Denote by $\tilde{Z}$ the random variable that represents the losses per unit of total loans. Therefore, the bank's ex-post lending revenue is equal to $G(L) - ZL$ where Z is the realised value of $\tilde{Z}$. We assume that $\tilde{Z}$ is distributed according to the distribution H_Z, h_Z with expected value equal to μ_Z.

The repo unit owns a stock of government bonds of value X with coupon c. It uses this government bonds inventory to raise collateralised fundings to finance bond trading activities or to act as an intermediary entering into repo transaction with some counterparties and offsetting reverse repo with others. We assume that the ex-ante income from repo activities is equal to $F(X)$. We capture the risk of the repo business by assuming that ex-post the bank could suffer losses $\tilde{\varepsilon}X$ due to, for example, unpaid payments by reverse repo counterparties or losses from trading activities. Distribution of $\tilde{\varepsilon}$ is characterised by $H_\varepsilon, h_\varepsilon$ with expected value μ_ε.

We make the following assumptions on the profitability and riskiness of the two business units.

Assumption 4.1. *Functions $G(.)$ and $F(.)$ satisfy the following conditions:*

$$G(0) = 0; \quad G'(.) > 0 \quad and \quad G''(.) < 0 \tag{4.1}$$

$$F(0) = 0; \quad F'(.) > 0 \quad and \quad F''(.) < 0 \tag{4.2}$$

Assumption 4.1 implies that both lending and repo businesses have diminishing marginal returns. For lending business, this property could be explained by the fact that the loan interest rate is a decreasing function of loan size. For repo business, this could be due to the fact that interest rate on reverse repo is less sensitive to the transactional amount than the repo rate.

Assumption 4.2. *The rank between the two functions $G(.)$ and $F(.)$ is as follows:*

$$G'(y) - \mu_Z > F'(y) + c - \mu_\varepsilon \quad \textit{for all} \quad y \leq max(X^*, L^*) \tag{4.3}$$

where

$$X^* = \underset{y}{\text{argmax}}\,[F(y) + cy - \mu_\varepsilon y - Ry] \quad \textit{and} \quad L^* = \underset{y}{\text{argmax}}\,[G(y) - \mu_Z y - Ry] \tag{4.4}$$

Assumption 4.2 indicates that lending business is more profitable than repo business on a non risk-adjusted basis. Note that X^* and L^* defined in this assumption represent the size of, respectively, the repo and lending businesses so that expected profits from those activities are maximised when their costs of funding is R. The banks will never grant more loans than L^* and never hold an inventory of government bonds of value higher than X^*.

Assumption 4.3. *Two random variables $\tilde{Z}$ and $\tilde{\varepsilon}$ are ranked as follows:*

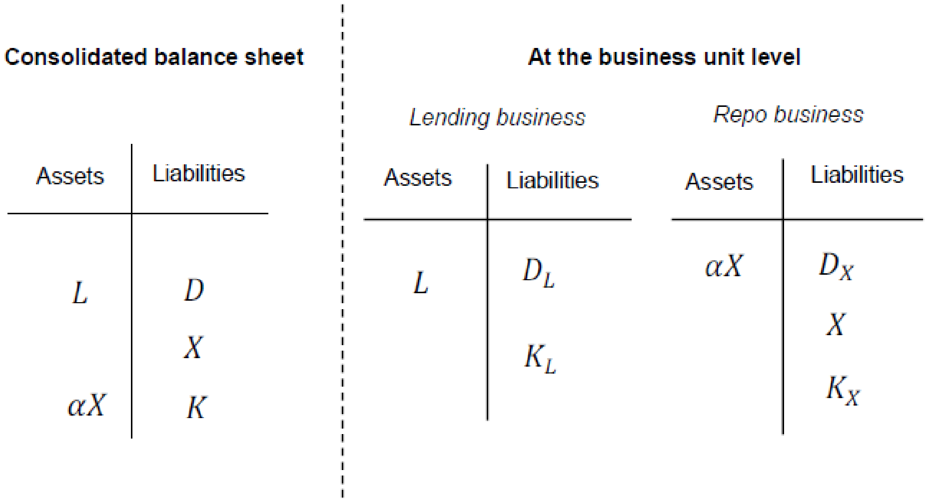
$$VaR_{1-q}(\tilde{Z}) \geq VaR_{1-q}(\tilde{\varepsilon}) \tag{4.5}$$

Therefore, lending business is riskier on a stand-alone basis than repos business.

Funding structure and capital allocation We assume that the bank finances their assets with equity of amount K and the remaining is debt with gross interest rate R. Among the total capital resources K the bank has, K_L will be allocated to support lending business while K_X is allocated to the repo business. Figure 4.1 illustrates the balance sheet of the bank at the consolidated level and at the business unit level. Note that the size of the balance sheet of the repo business is recorded as a multiple $\alpha \in [1, 2]$ of X to take into account the different regulatory treatment between netted reverse repos and unetted ones.

We denote by $\tilde{\Pi}_L$ and $\tilde{\Pi}_X$ the profit of, respectively, lending and repo business units. Therefore, $\tilde{\Pi}_L$ and $\tilde{\Pi}_X$ could be written as follows:

Figure 4.1: Bank's balance sheet



$$\tilde{\Pi}_L = G(L) - \tilde{Z}L - R(L - K_L) \tag{4.6}$$

and

$$\tilde{\Pi}_X = F(X) + cX - \tilde{\varepsilon}X - R(X - K_X) \tag{4.7}$$

The overall profit of the bank at the consolidated level is thus equal to $\tilde{\Pi}_L + \tilde{\Pi}_X$

Regulatory constraints The bank is subject to the two regulatory constraints, namely the leverage ratio (LR) requirement and the risk-weighted capital requirement. These two constraints are legally imposed at the consolidated level but the bank could choose to apply them at the group level or at the business unit level.

In line with the principle underlying the Basel requirements, we formulate the risk-weighted capital requirement using the Value-at-Risk (VaR) constraint. Given the bank's balance sheet as described in Figure 4.1, the two regulatory constraints can be written at the consolidated level as follows:

$$\mathbb{P}\left(\tilde{\Pi}_L + \tilde{\Pi}_X \leq 0\right) \leq a \tag{4.8}$$

and

$$K \geq \chi(L + \alpha X) \tag{4.9}$$

where χ is the required minimum LR. After some algebra, VaR Constraint (4.8) can be rewritten as:

$$K \geq \frac{VaR_{1-a}(\tilde{Z}L + \tilde{\varepsilon}X) - \Pi(L, X)}{R} \tag{4.10}$$

where

$$\Pi(L, X) = \underbrace{G(L) - RL}_{\equiv \Pi_L(L)} + \underbrace{F(X) + cX - RX}_{\equiv \Pi_X(X)}$$

In the form of the Basel III framework, the right hand side (RHS) of Constraint (4.10) is equivalent to the product of the minimum risk-weighted (RW) capital requirements and the risk-weighted assets (RWAs) of the bank at the group level. We denote the former by γ and the latter by RWA^G. RWA^G can thus be proxied in our model by:

$$RWA^G = \frac{VaR_{1-a}(\tilde{Z}L + \tilde{\varepsilon}X) - \Pi(L, X)}{\gamma R}$$

If the bank chooses to require both business units to comply with both constraints individually, then the lending business has to satisfy:

$$\mathbb{P}\left(\tilde{\Pi}_L \leq 0\right) \leq a \quad \text{and} \quad K_L \geq \chi L$$

while the repo business has to satisfy:

$$\mathbb{P}\left(\tilde{\Pi}_X \leq 0\right) \leq a \quad \text{and} \quad K_X \geq \chi \alpha X$$

The two individual VaR constraints can similarly be expressed in terms of RWA^L and RWA^X - the RWAs of, respectively, the lending and repo businesses on a stand-alone basis - as follows:

$$K_L \geq \gamma RWA^L \quad \text{where} \quad RWA^L = \frac{VaR_{1-a}(\tilde{Z}L) - \Pi_L(L)}{\gamma R} \tag{4.11}$$

and

$$K_X \geq \gamma RWA^X \quad \text{where} \quad RWA^X = \frac{VaR_{1-a}(\tilde{\varepsilon}X) - \Pi_X(X)}{\gamma R} \tag{4.12}$$

4.4 Analysis

We now analyse the bank's optimal investments. Our main objective is to investigate how the bank's asset risk is affected by the level at which it applies the two regulatory constraints. To do so, we will compare the bank's optimal investments in each business between the case where it applies the two constraints at the group level and the case in which it requires both business units to individually comply with both regulatory constraints. In the following, we first formulate the bank's problem for each of these two cases. Then, we examine how the bank's decision differs between them.

4.4.1 Bank's optimisation problems

Optimisation problem with constraints applied at the group's level When the bank applies all constraints at the group level, its optimisation problem, denoted as $\wp^G$, can be written as follows:

$$\underset{L,X}{\text{Max}} \quad \mathbb{E}\left[\tilde{\Pi}_L + \tilde{\Pi}_X\right]$$

subject to Constraints (4.9) and (4.10).

Our focus is on how the level at which the bank applies its regulatory constraints affects its asset risk. Given that the bank runs two businesses with one riskier than the other, the bank's asset risk in our model can be measured by the fraction of the bank's total balance sheet devoted to lending business - the riskier one. We denote by w this fraction, i.e.

$$w = \frac{L}{L+X} \tag{4.13}$$

To facilitate the examination of how w would change depending on the application level of the two regulatory constraints, we reformulate Problem $\wp^G$ by changing the bank's decision variables from (L, X) to w and the bank's total balance sheet size $S = L + X$. After expressing L and X via S and w, Problem $\wp^G$ could be written as:

$$\underset{S,w}{\text{Max}} \quad \{\Pi(w,S) - \mu_Z wS - \mu_\varepsilon(1-w)S + RK)\}$$

subject to

$$K \geq \gamma RWA^G = \frac{VaR_{1-a}(\tilde{Z}w + (1-w)\tilde{\varepsilon})S - \Pi(w,S)}{R} \tag{4.14}$$

$$K \geq \chi\,(wS + \alpha(1-w)S) \tag{4.15}$$

Optimisation problem with constraints applied at the business unit's level When the bank applies all constraints at the business unit level, its problem, denoted as $\wp^B$, is as follows:

$$\underset{L,X}{\text{Max}} \quad \mathbb{E}\left[\tilde{\Pi}_L + \tilde{\Pi}_X\right]$$

subject to Constraints (4.11), (4.12) as well as the following two LR requirements

$$K_L \geq \chi L \quad \text{and} \quad K_X \geq \chi\alpha X$$

and the capital allocation constraint

$$K \geq K_L + K_X$$

After reformulating Problem $\wp^B$ in terms of w and S, we get:

$$\underset{S,w}{\text{Max}} \quad \{\Pi(w,S) - \mu_Z wS - \mu_\varepsilon(1-w)S + RK)\}$$

subject to

$$K_L \geq \gamma RWA^L = \frac{VaR_{1-a}(\tilde{Z}w)S - \Pi_L(w,S)}{R} \tag{4.16}$$

$$K_X \geq \gamma RWA^X = \frac{VaR_{1-a}((1-w)\tilde{\varepsilon})S - \Pi_X(w,S)}{R} \tag{4.17}$$

$$K_L \geq \chi wS \tag{4.18}$$

$$K_X \geq \chi\alpha(1-w)S \tag{4.19}$$

$$K \geq K_L + K_X \tag{4.20}$$

4.4.2 Bank's optimal investments

We are now equipped to compare the bank's investment policy, especially the bank's asset risk, between the two above scenarios. Denote by (w^G, S^G) and (w^B, S^B) the solutions of, respectively, Problem $\wp^G$ and $\wp^B$.

To get first intuitions on how investment decision of the bank could change, let us compare constraints of Problem $\wp^G$ to the ones of Problem $\wp^B$. Clearly, we see that the group-level LR constraint is weakly looser than business unit-level LR constraints. The group-level RW constraint is also looser than the business unit-level RW ones and the gap denoted by Div is equal to

$$Div = VaR_{1-a}(\tilde{Z}w) + VaR_{1-a}((1-w)\tilde{\varepsilon}) - VaR_{1-a}(\tilde{Z}w + (1-w)\tilde{\varepsilon}) \tag{4.21}$$

Div represents the diversification benefit that the bank will profit from if it applies the RW constraint at the consolidated level.

These first observations imply that applying regulatory constraints at the business unit level will reduce the set of investment opportunities available to the bank. The following proposition highlights the efficiency losses resulting from allocating both constraints down to business units.

Proposition 4.1. *Efficiency losses:*

$$S^B \leq S^G$$

Proof. It is the direct consequence of the fact that constraints of Problem $\wp^B$ are weakly tighter than the ones of Problem $\wp^G$ $\square$

Turning to the impact on the bank's asset risk of allocating constraints down to business units, for the purpose of characterising this impact, it is useful to define the average risk weight (ARW) of the bank's group as

$$ARW^G = \frac{RWA^G}{[w + \alpha(1-w)]S}$$

and of each business unit as

$$ARW^L = \frac{RWA^L}{wS} \quad \text{and} \quad ARW^X = \frac{RWA^X}{\alpha(1-w)S}$$

We state in the following proposition our first result

Proposition 4.2. *When the bank is bound by the LR requirement at the group level (i.e. $ARW^G \leq \frac{\chi}{\gamma}$), we have:*

1. $w_B = w_G$ *if*
$$ARW^L \leq \frac{\chi}{\gamma} \quad \textit{and} \quad ARW^X \leq \frac{\chi}{\gamma}$$

2. $w_B < w_G$ *if*
$$ARW^L \geq \frac{\chi}{\gamma} \quad \textit{and} \quad ARW^X \geq \frac{\chi}{\gamma}$$

Proof. See Appendix. □

Proposition 4.2 states conditions under which allocating down regulatory constraints to business units will either not affect the bank's asset risk or lead to its decrease if the bank is bound by the LR requirements at the group level. The two conditions in the first part of the proposition imply that both business units will be constrained by the LR when the two requirements are allocated down. The bank's investment does not change in this case since the optimal investment at the group level already allows two business units to comply with the relevant constraint - the LR.

In relation to the second part of Proposition 4.2, the two conditions imply that both businesses will be bound by the RW constraint in the case of applying regulatory requirements down to business units. To understand why there is a decrease in the bank's asset risk in this case, it is useful to compare the two first order conditions (FOC) that determine w^G and w^B. Indeed, w^G is determined by

$$\big(G'(w^G S^G) - \mu_Z\big) - \big(F'((1 - w^G)S^G) + c - \mu_\varepsilon\big) = \underbrace{\lambda_{LR}\chi(1 - \alpha)}_{\leq 0} \tag{4.22}$$

while w^B is determined by

$$\begin{aligned}\big(G'(w^B S^B) - \mu_Z\big) - \big(F'((1 - w^B)S^B) + c - \mu_\varepsilon\big) = \lambda^L_{VaR} \Bigg[& \underbrace{\frac{VaR_{1-a}(\tilde{Z}) - G'(w^B S^B) + R}{R}}_{\frac{\partial(\gamma RWA^L)}{\partial L}} \\ & - \underbrace{\frac{VaR_{1-a}(\tilde{\varepsilon}) - (F'((1 - w^B)S^B) + c) + R}{R}}_{\frac{\partial(\gamma RWA^X)}{\partial X}} \Bigg]\end{aligned} \tag{4.23}$$

The left hand side (LHS) of both Equations (4.22) and (4.23) represent the marginal benefit of moving on unit of investment from repo business to lending business. It is the increase in the bank's marginal expected profit since marginal profitability of lending business is higher than the one of repo business. The right hand side (RHS) of the two equations represent the marginal cost of that action in terms of marginal changes in required capital resources. Two remarks are in order here.

First, when the two constraints apply at the group level (i.e. Equation (4.22)), the required capital resources are determined by the constraint relevant at the group level which is the LR. Since leverage cost per unit of investment in repo business is weakly higher than the leverage cost per unit of investment in lending business (i.e. $\alpha \geq 1$), moving one unit of investment from repo business to lending business will lead to a non positive change in required capital.

When the two constraints apply at the business unit level (i.e. Equation (4.23)), the required capital resources are now determined by two individual RW constraints since business units are bound by those constraints. The marginal change in required capital, when moving one unit of investment from repo business to lending business, is now determined by the difference between marginal change in RWAs of lending business and marginal change in RWAs of repo business. Since lending business is riskier than repo business, this difference is positive.

Therefore, the marginal cost of moving one unit of investment from repo business to lending business is higher in the case of applying constraints down to business unit level than in the case where constraints are applied at the group level. This in turn implies that that action is less beneficial in the former case than in the latter one and so the bank's asset risk decrease in the former case.

We turn to the case where the RW constraint binds at the group consolidated level.

Proposition 4.3. *When the banks is bound by the RW constraint at the group level (i.e.* $ARW^G \geq \frac{\chi}{\gamma}$*), it can happen that* $w^B > w^G$ *if the following conditions are satisfied:*

1. $ARW^L \geq \frac{\chi}{\gamma}$ *and* $ARW^X \leq \frac{\chi}{\gamma}$
2. $\chi\alpha \geq \frac{\partial(\gamma RWA^X)}{\partial X}$
3. $VaR_{1-a}(\tilde{Z}) - VaR_{1-a}(\tilde{\varepsilon}) - \frac{\partial VaR_{1-a}(\tilde{Z}w+\tilde{\varepsilon}(1-w))}{\partial w} < 0$

Proof. See Appendix. □

In Proposition 4.3, the first condition implies that when allocating regulatory constraints down to business units, the lending unit will be bounded by risk-weighted capital requirements while the repo unit bounded by the leverage constraint. The second condition means that for repo business, the required capital per unit of investment generated by the LR constraint is greater than the required capital per unit of investment generated by the RW constraint. Finally the third condition implies that the diversification benefit is decreasing with the share of the lending business in the bank's total balance sheet.

To understand the intuition underlying Proposition 4.3, it is again useful to compare two FOCs that determine w^G and w^B in this situation. They are as follows:

$$\begin{aligned}\left(G'(w^G S^G) - \mu_Z\right) - \left(F'((1-w^G)S^G) + c - \mu_\varepsilon\right) &= \lambda_{VaR}\left[\frac{\partial(\gamma RWA^L)}{\partial L} - \frac{\partial(\gamma RWA^X)}{\partial X}\right] \\ &- \frac{\lambda_{VaR}}{R}\underbrace{\left(VaR_{1-a}(\tilde{Z}) - VaR_{1-a}(\tilde{\varepsilon}) - \frac{\partial VaR_{1-a}(\tilde{Z}w+\tilde{\varepsilon}(1-w))}{\partial w}\right)}_{\text{marginal diversification benefit}} \quad (4.24)\end{aligned}$$

for w^G and

$$\big(G'(w^B S^B) - \mu_Z\big) - \big(F'((1-w^B)S^B) + c - \mu_\varepsilon\big) = \lambda^L_{VaR}\left(\frac{\partial(\gamma RWA^L)}{\partial L} - \chi\alpha\right) \quad (4.25)$$

for w^B

We can see that if the three conditions in Proposition 3 is satisfied, then the marginal cost of moving one unit of investment from repo business to lending business in the case where two constraints apply at the group level will be higher than in the case where constraints are allocated down.

4.5 Model calibration

In the previous analysis, we intentionally kept our theoretical setup very general to emphasise the generality of our analytical insights. That generality however implies that we cannot characterise analytically all the possible changes in the bank's investments following the allocation of regulatory constraints to its business units. In this section we complement those analytical insights by calibrating our model on data of banks in the UK to conduct numerical simulations. We first make additional assumptions on the specific functional forms for the lending and repo incomes to identify further parameters to be calibrated. Then, we describes the data used for the calibration and explain our calibration methods.

Parameters to be calibrated The bank's ex-ante gross interest income from loans $G(L)$ is naturally the product of the loan volume L and the gross interest rate charged on loans. We assume that the interest rate is a decreasing function of the loan volume: $g_1 + g_2 L$ where $g_1 > 0$ and $g_2 < 0$. Therefore, we have:

$$G(L) = (g_1 + g_2 L)L$$

In line with the literature, we also assume that the loan losses are log-normally distributed with parameter μ_Z^{log} and σ_Z^{log}.

In relation to the repo income, we focus here on the role of the repo unit as market maker in the repo market. Therfore, $F(X)$ is the revenue from reverse repo activities net of the repo cost. We assume that the interest rates charged on both repo and reverse repo depend on the borrowing amount, which implies that

$$F(X) = \underbrace{(d_1 + \varepsilon_1 X)X}_{\text{reverse repo revenue}} - \underbrace{(d_2 + \varepsilon_2 X)X}_{\text{repo cost}}.$$

We further define $\gamma_1 = d_1 - d_2$ and $\gamma_2 = \varepsilon_1 - \varepsilon_2$ as the spreads between the two transactions, where $\gamma_1 > 0$ and $\gamma_2 < 0$. Due to limitations on the data as explained below, in this part, we assume that repo is riskless, i.e. repo losses $\tilde{\varepsilon}$ is equal to zero with probability 1.

We summarise the set of parameters that need to be calibrated in Table 4.1.

Table 4.1: Parameters to be calibrated

Parameters	Description
a	VaR confidence level
χ	Leverage requirement
c	Coupon of government bond
R	Bank's borrowing cost
g_1	Marginal return on loan
g_2	Curvature of loan return
μ_Z^{log}	Lognormal parameter of loan losses
σ_Z^{log}	Lognormal parameter of loan losses
γ_1	Marginal return on repo
γ_2	Curvature of return on repo

Data In calibrating the model, we use three main data sources. First, we collect information on performance analysis, asset quality and balance sheet for 15 UK banks for which semi-annual data is available in SNL from 2015 to 2018. Our second source of data is the confidential Sterling Money Market Data (SMMD) of the Bank of England. This dataset is daily, transactional-level data. It contains repo and reverse repo transactions with maturity of up to one year that are denominated in Sterling and secured against UK government-issues securities. The repo and reverse repo transactions reported in this dataset cover 95% of total turnover of the market. They are executed by institutions with significant proportion of total activity in the market among which there are 5 UK banks. Finally, the third dataset is daily yield rates for the 15 year UK government bond retrieved from Factset. Table 4.2 report the variables we use in these datasets for our calibration.

Table 4.2: Data sources

Variable description	**Timespan**	**Frequency**	**Data source**
Gross loans to customers	2015-2018	Semi annual	SNL
Impaired loans	2015-2018	Semi annual	SNL
Net interest margin	2015-2018	Semi annual	SNL
Cost of funds	2015-2018	Semi annual	SNL
Yield 15Y UK gilt	2015-2018	Daily	Factset
Repo Transaction Nominal Amount	2017-2019	Daily	SMMD
Repo interest rate	2017-2019	Daily	SMMD
Reverse repo Transaction Nominal Amount	2017-2019	Daily	SMMD
Reverse repo interest rate	2017-2019	Daily	SMMD

Calibration methods We set a series of parameters individually. In line with the Basel III risk-weighted capital requirements and leverage ratio requirement, we set the VaR confidence level a to be equal to 0.001 and the minimum leverage ratio χ equal 3%. For the coupon on government bonds, we proxy it by the 15Y UK gilt yield retrieved from Factset, as the average of daily yields over the entire period. We set the bank's borrowing cost R to be the average cost of funds of all banks in our sample.

To estimate the distribution parameters μ_Z^{log} and σ_Z^{log} of the loan loss Z, we proxy Z by the amount of impaired loans per unit of total loans. Then we use the maximum likelihood estimation to fit the lognormal distribution of Z with the distribution of impaired loans.

We employ the least square fitting method to derive parameters g_1 and g_2 that underlies the function of gross lending returns from net interest margin reported in our datasets. To do so, we first express the net interest margin of bank i at time t - denoted by $IM_{i,t}$ - via g_1 and g_2 as follows:

$$IM_{i,t} = g_1 + g_2 L_{i,t} - Z_{i,t} - R_{i,t}$$

where $L_{i,t}$ is gross loans to customers; $Z_{i,t}$ is the realised impaired loans and $R_{i,t}$ is the cost of funds - all variables are observed in the data. g_1 and g_2 then can be obtained by estimating the following regression equation:

$$y_{i,t} = g_1 + g_2 L_{i,t} + \eta_{i,t}$$

where $y_{i,t} = IM_{i,t} + Z_{i,t} + R_{i,t}$ and $\eta_{i,t}$ is error term. Both coefficients g_1, g_2 derived from the regression are statistically significant at, respectively, 1% and 5% level.

Similarly, to estimate the repo returns, we regress the repo and reverse repo interest rate reported for each transaction on the borrowing amount of that transaction using the equations:

$$f_{i,t}^{reverse} = d_1 + \varepsilon_1 X_{i,t}^{reverse} + \nu_{i,t} \quad \text{and} \quad f_{i,t}^{repo} = d_2 + \varepsilon_2 X_{i,t}^{repo} + \upsilon_{i,t}$$

Both regressions give statistically significant coefficients at 1% level. Afterward, we calculate the marginal return on repo γ_1 as equal to $d_1 - d_2$ and the curvature of repo return γ_2 as $\varepsilon_1 - \varepsilon_2$.

Table 4.3 report the calibrated value for all parameters.[4]

Table 4.3: Calibration UK

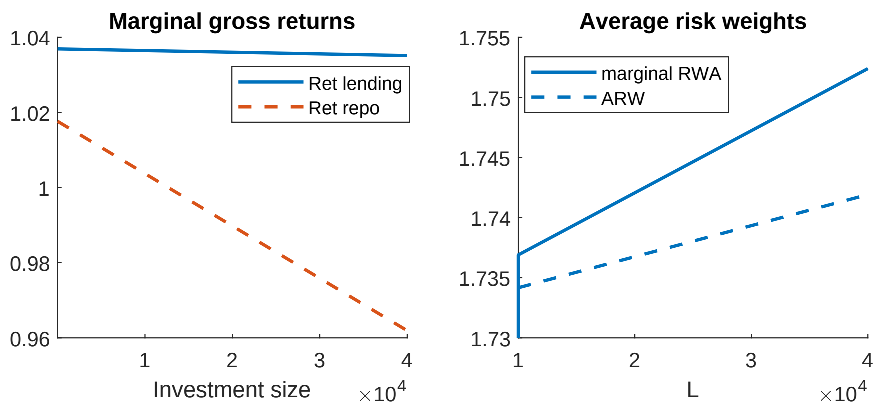
Description	Parameters	Calibrated Value
VaR confidence level	a	0.001
Leverage requirement	χ	0.03
Coupon on government bond	c	1.0172
Bank's borrowing cost	R	1.0114
Lending unit		
Marginal return on loan	g_1	1.0369
Curvature of loan return	g_2	$-2.22 \cdot 10^{-5}$
Log-normal parameter of Z	μ_Z^{log}	-4.568
(Mean Z)		(0.015)
Log-normal parameter of Z	σ_Z^{log}	0.913
(Standard deviation Z)		(0.018
Repo unit		
Return on reverse repo - repo	γ_1	0.000427
Diminishing return parameter	γ_2	$-6.943 \cdot 10^{-4}$

In Figure 4.2 we exemplify the characteristics of our calibrated bank. As seen in the left panel, the marginal gross returns on lending are higher compared to the repo returns,

[4] Values of parameters are reported, when appropriate, in terms of billion GBP.

and also they decrease at a much slower rate compared to the repo ones as the investment size increases, making it relatively more profitable to invest in lending. We also observe from the bottom left panel that the average risk weights of our calibrated lending business are higher than $\frac{\chi}{\gamma} = 0.35$.

Figure 4.2: Bank's characteristics full sample



Note: This figure displays main characteristics of the calibrated values for the full sample. The left panel captures the marginal gross returns of repo (Ret repo) and lending (Ret lending) as a function of investment. The right panel shows the marginal RWA of lending business and its average risk weights of lending (ARW).

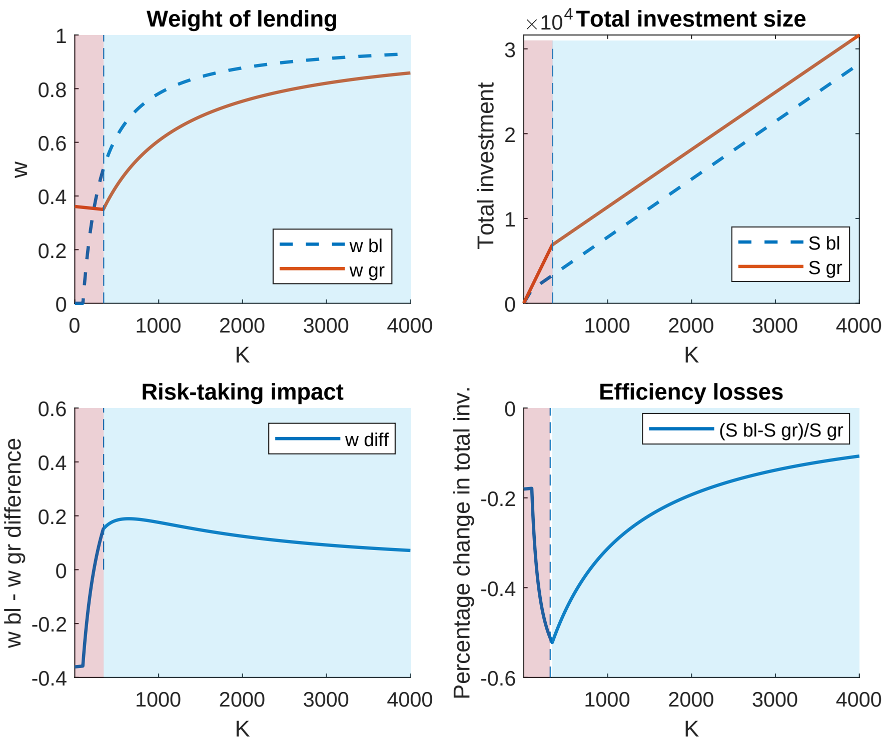
4.6 Numerical simulations

Using the calibrated values, we solve numerically, for different values of the bank's initial equity K, the two optimisation problems $\wp^G$ and $\wp^B$ as defined in Section 4.4.1.

Solving for optimal investment decisions, note that depending on the value of K, the bank can be bounded at the group level by either both leverage and VaR constraints (dark pink area) or only the VaR constraint (light blue area). Figure 4.3 compares the bank's optimal investments between the case where all constraints are applied at the group level and the case in which the bank chooses to allocate both constraints to its business units.

We can see that the allocation of constraints leads to efficiency losses since the total investments are reduced (see bottom right panel). As explained in the Section 4.4, these losses are due to the fact that, when allocating regulatory constraints to its business units,

Figure 4.3: Bank's optimal investments



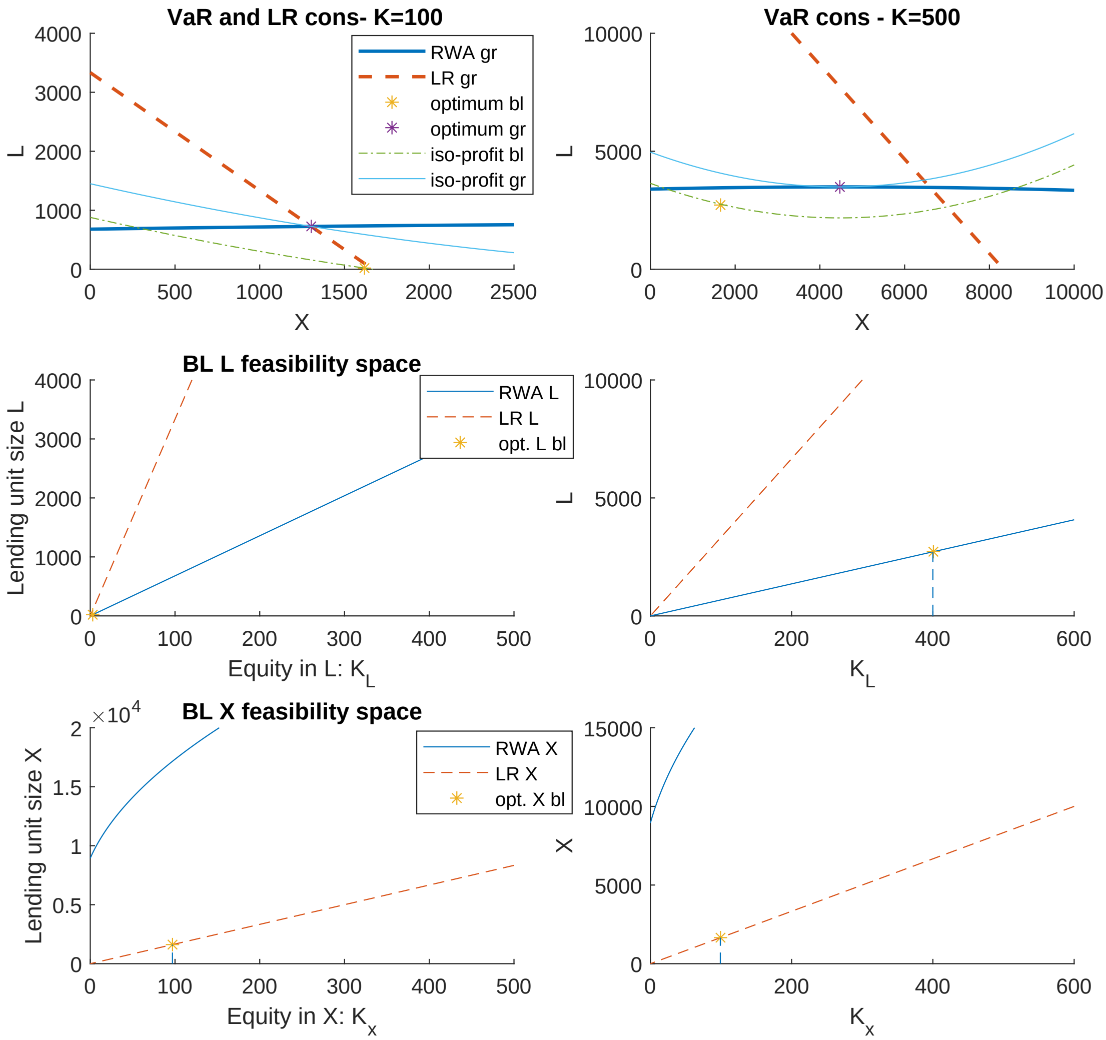
Note: This figure compares the bank's optimal investments in two cases:(i) when both regulatory constraints are applied at the group consolidated level and (ii) when the bank allocates both constraints to its business units. In the top two panels, the red solid lines represent bank's choices in the first case while the blue dashed lines stand for bank's choices in the second case. The two bottom panels represent the difference in the total size of the bank's balance sheet (bottom right panel) and in the fraction of the balance sheet invested in lending business (bottom left panel) between the two cases. For all panels, the dark pink area corresponds to the situation where both leverage and RW constrains bind at the group level while in the light blue area, only RW constrain matters at the group level.

the bank cannot exploit the diversification of its investment portfolio to increase the total size of the portfolio for each level of capital resource.

In term of the impact of the allocation on the bank's asset risk, from the top left panel, we can see that this impact depends on whether the bank is constrained only by the RW constrains at the group level (light blue area) or by both (dark pink area). In line with Proposition 4.3, when only the RW constraint matters at the consolidated level, the fact that the bank requires all its business units to comply with both regulatory constraints will lead to a distortion of investment policy in the sense that the bank will invest relatively more into riskier business - lending - and reduce the size of less risky business - repo. This in turn will increase the overall asset risk of the bank. When both constraints matter at the consolidated level, the impact on the bank's asset risk is somehow ambiguous. When K is very small, the asset risk is decreasing but when K is above some level, the bank's asset risk increases following the allocation of constraints.

For additional insights in terms of feasibility sets, we further breakdown the effect in terms of optimal allocation and binding constraints for two values of K in Figure 4.4, which correspond to the cases when the firm is both VaR and leverage ratio constrained at optimum (K=100), and the VaR constrained bank (K=500). For K=100, cascading constraints leads to an increase in the repo size, and a decrease in lending, which corresponds to an overall lower level of profits (see iso-profit curves in the corresponding Figure). The most binding constraint will determine the feasibility set for each business unit. We find that the feasibility set for L is determined by the VaR requirement, while the repo unit will be bound by the leverage ratio requirement, and these will be the two constraints that will bind at the optimum investment. For K=500, the bank is bounded by the VaR requirement at the optimum investment level. Applying constraints leads to a decrease in both lending and repo investment, and the effect of which constraint is most binding is preserved as in the previous case. The most binding constraint result (VaR for lending and leverage ratio for repo) corresponds to the first condition of proposition 4.3.

Figure 4.4: Optimal allocation and binding constraints - overall UK sample example



Note: The 3 subplots: (i) on the left hand side capture an example for an initial value of capital (K=100) when the bank is bounded at the group level by both the leverage ratio (LR gr dotted red line) and the value at risk constraint (RWA gr blue solid line), (ii) on the right hand side capture the example for K=500 where the bank is exclusively VaR constrained at optimum. In the top left and right figures, the x-axis captures the investment in repo (X) and the y-axis the investment in lending (L). The optimum investment at the group optimisation problem is denoted via the purple star (optimum gr), and the optimum investment for business line application of constraints is the yellow star (optimum bl). The thin lines depict the iso-profit curves at the optimal level of investment for group (iso-profit gr solid light blue line), and for business line optimum (iso-profit bl dotted green line). The middle row shows the feasibility set and optimal investment of lending (opt L bl), when constraints - VaR (RWA L) and leverage ratio (LR L) are applied at business line level in the case when K=100 (left middle) and K=500 (right middle) respectively. The last row captures the feasibility set and optimal investment of repo (opt X bl), when constraints - VaR (RWA X) and leverage ratio (LR X) are applied at business line level in the case when K=100 (left bottom) and K=500 (right bottom). As we assume repo riskless, the RWA constraint for repo is just the condition that profits are positive. The legend of the curves per each row corresponds to both the LHS and RHS graph.

4.7 Role of business model

As highlighted in the analytical part, the impact of the allocation of constraints on banks' investment decisions depends on the diversification benefits, which in turn depends on the specific characteristics, such as riskiness, of their investments. We therefore expect that this impact will vary with banks' business model. In this section, we examine this potential effect of business model. We first classify the 15 UK banks in our SNL dataset into different business models. Then we recalibrate the model to each type and run the numerical simulations. Note that since the limited number of UK banks in the SMMD database that we use to calibrate the repo unit does not allow us to have a meaningful business model classification, we focus here on the consequences of the difference in lending business characteristics and funding structure between business models.

4.7.1 Business model classification and calibration

We classify our sample in three types of banks: capital market oriented, wholesale and retail-funded banks using a bank business classification methodology proposed in the seminal paper of Roengpitya et al. (2014). Roengpitya et al. (2014) use a statistical clustering method based on various ratios of banks' balance sheet which are informative on the bank business model. They find that retail-funded banks have a high share of gross loans and rely more on stable sources of funding, such as deposits. The wholesale-funded banks have a lower percentage of funding coming from deposits, but a higher share of inter-bank liabilities compared to retail banks. Lastly, the capital markets-orientated banks have a much higher percentage in trading assets and liabilities compared to the previous two types. The last type of banks has the highest ratio of inter-bank borrowing as percentage of total assets and also display a lower reliance on stable funding. The paper reports average values of these ratios to total assets, and we use them as a benchmark to construct the selection criteria for our sample.

Due to limited data availability compared to the Roengpitya et al. (2014), we use a restricted version of their selected ratios, and we adjust downwards the threshold criteria to match our sample. Our criteria include: the ratio of customer deposits to total liabilities for the stable source of funding ratio, the ratio of assets held for trading to total assets as a measure of tradable assets, loans to banks as fraction of total assets for our interbank lending measure, and bank deposits to total liabilities as the bank deposit ratio. Classifying these ratios based on observed bank characteristics from the Roengpitya et al. (2014), we group our sample into 9 retail-funded, 5 wholesale-funded, and one capital markets-orientated bank. Table 4.4 reports some characteristics of each business model

Table 4.4: Business model descriptives

Description	Variable	Values		
		Retail	**Wholesale**	**Capital oriented**
Interest rate unsecured debt	R	0.0129 (47)	0.0094 (27)	0.0065 (4)
Leverage ratio	LR	0.0549 (55)	0.0537 (39)	0.0457 (4)
Fully loaded risk weighted capital ratio		0.2528 (43)	0.184 (24)	0.187 (8)
Loans to total assets	L/total assets	0.7649 (63)	0.6601 (37)	0.3653 (6)
Percentage of impaired loans to total loan size		1.11% (53)	1.99% (26)	2.74% (2)

The number of observations is in brackets, unless otherwise stated.

We recalibrate the model to the different categories of banks. In this step, we combine the last two groups and split our sample in 'Retail banks' and 'Wholesale and capital markets orientated' since with only one capital market-oriented banks, the regression analysis would not have enough observations to be reliable. We report the calibrated values of different parameters for each types of banks in Table 4.5.

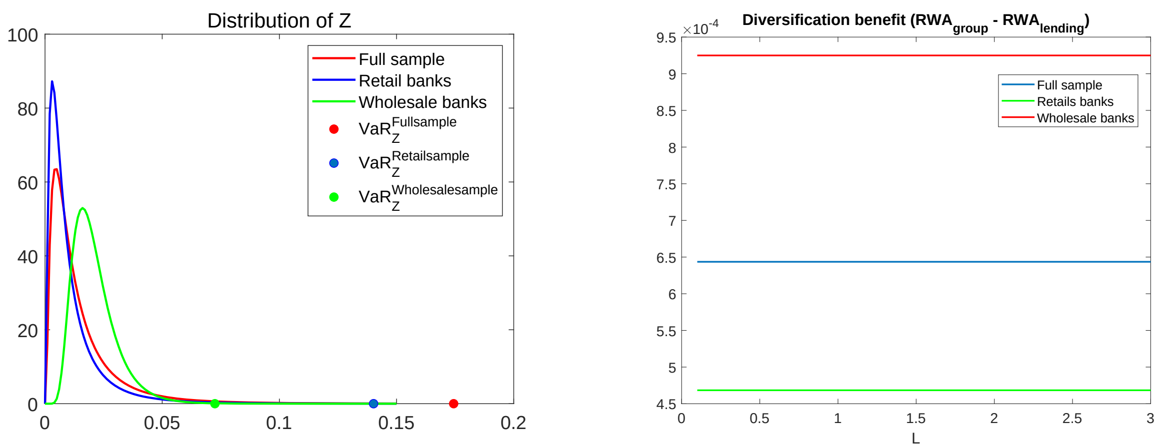
Comparing the borrowing cost R between retail banks, wholesale and capital markets-oriented banks and our full sample, we see that the capital markets-oriented banks have lowest cost of funding while retail banks have highest cost. To compare the risk characteristics between these samples, we present the distribution of impaired loans and the diversification benefits in Figure 4.5. We observe that wholesale and capital markets-oriented banks have lowest level of risk in lending business and highest diversification benefits in their investment portfolio.

Further, in Figure 4.6, we compare the two calibrated sets in terms of returns and risk weights. The marginal returns of lending are higher for the retail bank group, and decrease at a higher speed compared to the wholesale and capital market-oriented banks

Table 4.5: Calibration UK business models

Description	Parameters	**Retail banks**	**Wholesale and cap.**
Bank's borrowing cost	R	0.0129	0.009
		Lending	
Marginal return on loan	g_1	1.0369	1.03081
Curvature of loan return	g_2	$-3.15 \cdot 10^{-5}$	$-1.03 \cdot 10^{-5}$
Log-normal parameter of Z (Mean Z)	μ_Z^{log}	-4.885 (0.0118)	-3.97 (0.0207)
Log-normal parameter of Z (Standard deviation Z)	σ_Z^{log}	0.945 (0.0142)	0.429 (0.0093)

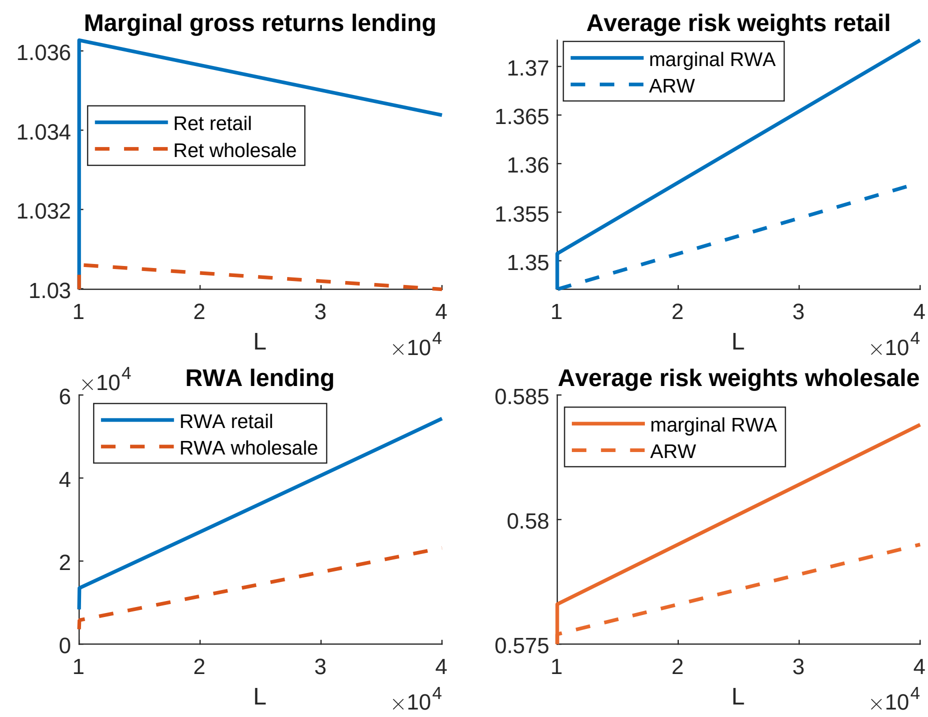
Figure 4.5: Risk characteristics and diversification benefits across business models



Note: The left panel displays the different distributions of nonperforming loans to total loans (Z) based on the calibrated values for the full sample, retail banks and wholesale and capital oriented banks (denoted by wholesale in graph). The right panel captures the diversification benefits, defined as the RWA at group level minus the RWAs of lending.

as seen in top left panel. The retail group has a higher variation in losses compared to second group, and that can be seen via a higher value of Risk Weighted Assets in the bottom left panel. The ARWs for retail are larger in absolute terms compared to the wholesale and capital-markets oriented group (dotted blue line from top right panel compared to dotted orange line from bottom right panel), but they are both above the threshold $\frac{\chi}{\gamma} = 35\%$. The difference between the two groups indicates that lending is a more profitable investment relatively to repo for the retail banks compared to the second

Figure 4.6: Bank's characteristics business model comparison



Note: This figure compares main characteristics of banks across business models. The top left panel captures the marginal gross returns of lending, where the blue filled line is the marginal return of the retail group (Ret retail), and the orange dotted one of the wholesale and capital orientated group (Ret wholesale). The bottom left panel captures the total value of risk weighted assets of lending for the two groups as a function of lending. In the two right panels we exemplify the average risk weights (ARW) and the marginal RWA as a function of investment in lending for retail, and wholesale and capital oriented banks respectively.

group, aspect which is later confirmed in the optimal investment solutions. Moreover, given the stronger diminishing marginal returns in the retail group, we expect the overall retail bank size to be smaller compared to the wholesale and capital bank size for equal initial capital.

4.7.2 Numerical simulations for different business models

We now run the simulations for each of the two types of banks. Figure 4.7 compares the optimal investments of both retail and wholesale and capital markets-oriented banks between the case where all constraints are applied at the group level and the case in which the bank chooses to allocate both constraints to its business units.

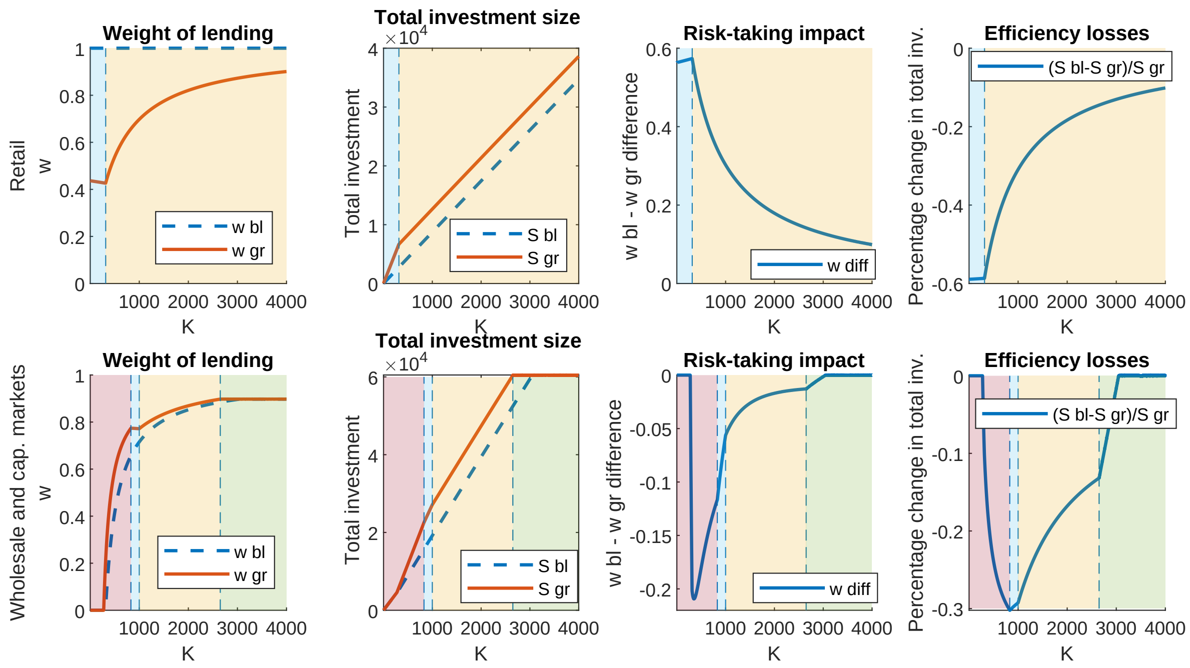
We break down examples to exemplify how investment decisions and binding constraints change for different values of initial capital (K) that make the bank be either leverage ratio constrained, VaR constrained, or both in Figure 4.8 for the retail group, and in Figure 4.9 for the wholesale and capital-oriented group. In all cases we observe a decrease in total investment from the group optimisation problem (purple star in top row) compared to the optimisation solution when constraints are applied at business line level (yellow star in top row). The feasibility sets and binding constraints at business unit depicted in the middle and bottom rows relate to the conditions from Proposition 4.2 and 4.3 in terms of the average risk weight relationship to $\frac{\chi}{\gamma}$. In all cases, the leverage ratio binds the repo unit, and the VaR binds the lending unit

Three main observations are in order here. First the situation in which the leverage constraint binds at the group consolidated level happens only with wholesale and capital market-oriented banks but not for retail banks. Note also that since in this simulation, we assume that repo business is riskless, the average risk weight of repo business for both types of banks is lower than 35%. This difference can therefore be explained by the fact that the average risk weight of the lending business for both types of banks is higher than $\frac{\chi}{\gamma} = 35\%$ but the diversification benefits of the wholesale banks would be higher than retail banks as shown in Figure 4.5.

Second, there is a stark difference in the impact of the allocation of constraints on the banks' asset risk between retail type and wholesale and capital markets-oriented type in the case where only VaR constraint matters at the group level (beige area in Figure 4.7). Precisely, in this case, while the allocation of constraints results in an increase in asset risk of retail banks, it brings about a decrease in asset risk of wholesale banks.

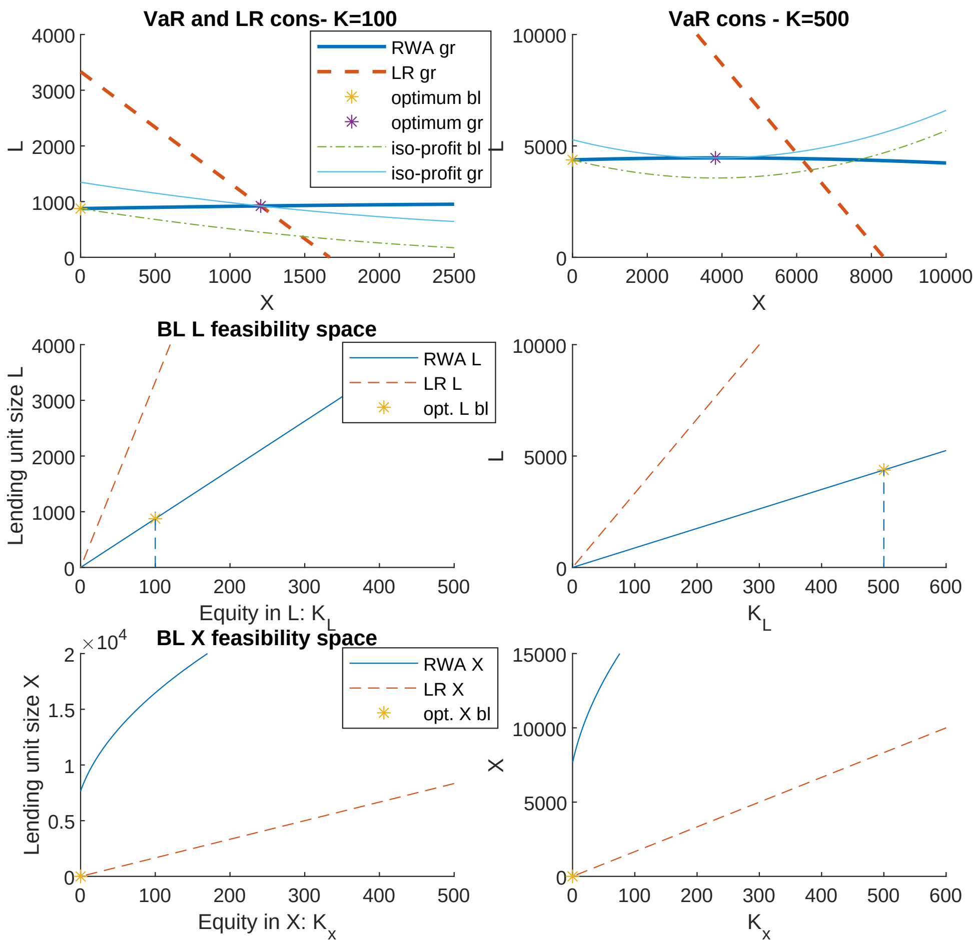
Finally, when comparing the simulation results of each type of banks with the ones of our full sample, we could see that the average bank in our full sample behave in a very similar way with retail banks.

Figure 4.7: Optimal investment comparison



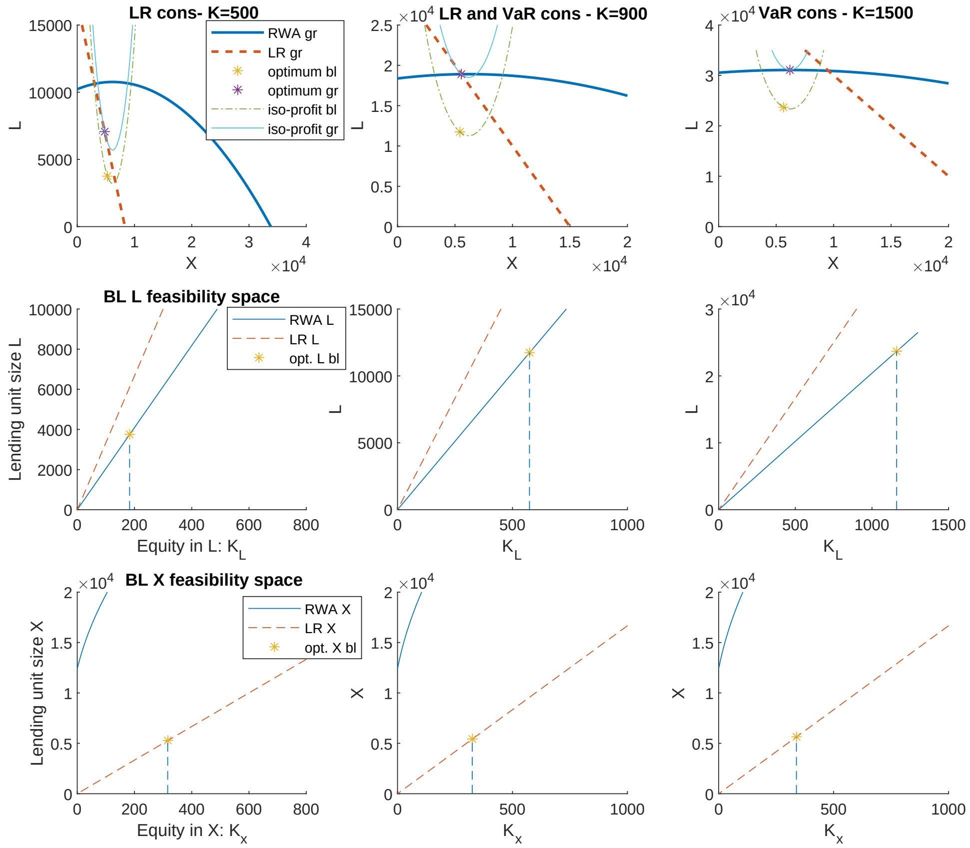
Note: This figure compares the optimal investments of retail and wholesale and capital markets-oriented banks in two cases:(i) when both regulatory constraints are applied at the group consolidated level and (ii) when the bank allocates both constraints to its business units. In the 4 top panels, the red solid lines represent bank's choices in the first case while the blue dashed lines stand for bank's choices in the second case. The first row of panels shows the retail banks group results, while the second row displays the results of the wholesale and capital orientated markets bank group. The panels in the third and 4th column represent the difference in the total size of the bank's balance sheet (forth top and bottom panels) and in the fraction of the balance sheet invested in lending business (third top and bottom panel) between the two cases. For all panels, the dark pink area corresponds to the situation where the leverage constraint binds at the group level; the light blue area to the case in which both leverage and RW constrains bind; the beige are to the case only RW constraint matters and finally the green area is when no constraints bind. Notice how for retail we have only the case when either both RW constraint and LR bind at group level, or when only the RW constraint binds.

Figure 4.8: Optimal allocation and binding constraints - retail banks example



Note: For the retail group calibration: First column exemplifies the case when the bank is both leverage ratio and RW bounded at optimum group level. The second column shows an RW only bounded bank (for K=500). The top row displays the feasibility set at group level determined by the RW constraint (RWA gr) and the leverage ratio (LR gr), the optimal levels of investment at group (optimum gr) and business line optimization (optimum bl), and the corresponding iso-profit curves for group (iso-profit gr) and business line allocation (iso-profit bl). The middle and bottom rows show the feasibility sets and their respective optimal investments and capital allocation for lending (middle row) and repo (bottom row) for the case when constraints are allocated at business unit level. As we assume repo riskless, the RW constraint for repo is just the condition that profits are positive.

Figure 4.9: Optimal allocation and binding constraints example - wholesale and capital-orientated firms



Note: For the wholesale and capital-orientated group calibration: First column exemplifies the case when the bank is leverage ratio bounded at optimum (K=500). Second column shows the situation when the bank is both RW and leverage ratio constrained (K=900), and the third column exemplifies an RW bounded bank (K=1500). The top row displays the feasibility set at group level determined by the RW constraint (RWA gr) and the leverage ratio (LR gr), the optimal levels of investment at group (optimum gr) and business line optimization (optimum bl), and the corresponding iso-profit curves for group (iso-profit gr) and business line allocation (iso-profit bl). The middle and bottom rows show the feasibility sets and their respective optimal investments and capital allocation for lending (middle row) and repo (bottom row) for the case when constraints are allocated at business unit level. As we assume repo riskless, the RW constraint for repo is just the condition that profits are positive.

4.8 Conclusion

In this paper we evaluate the risk-taking implications of introducing the leverage ratio requirement. More precisely, we assess how banks' asset risk depends on whether the bank applies the leverage ratio requirement at the consolidated level alone, or at each individual business line. We construct a two-period theoretical model where the bank has two business units defined by two investment opportunities: a riskier one which yields a higher margin, and a less risky one which has low returns. We refer to these units as lending and repo business. We further calibrate the model to UK banks, which yields additional insights into the effects of applying the constraint at the group level alone, or at the individual business lines, and how do these effects depend on the business model of the banks.

We find that the effects on asset risk depend on the most binding constraint at the banks' consolidated level, on the average risk weights of each unit, and on the diversification gains from applying the risk-weighted requirement exclusively at the consolidated level or at the business unit level. Firstly, when requirements are applied exclusively at consolidated level, the bank has diversification benefits to its investment portfolio as the two units can complement each other: the leverage ratio has a relatively higher capital impact on the repo unit, while the risk-weighted asset requirement penalizes more the lending unit. Hence, allocating constraints at business units instead can lead to a loss of the diversification benefit. We find that this leads to either the same, or a decrease in total investment.

In terms of most binding constraints, when the bank is bounded by the leverage ratio at the group level, we find that allocating requirements to business units leads to no increase in risk taking. As long as both business units have average risk weights below a certain threshold on a stand-alone basis, then optimal investment is not affected by the level at which the regulatory requirements are applied. If the average risk weights are higher than the threshold, then requiring each of the business units to comply to the leverage ratio requirement will lead to a decrease of investment in the lending unit. In the case when the bank is bounded by the VaR requirement at a group level, allocating constraints to business units leads to a distorted investment decision. If allocating constraints leads to a VaR constrained lending unit, and a leverage ratio constrained repo unit, and the bank has decreasing diversification benefits from applying the risk-weighted capital requirement at the consolidated level, then allocating requirements at business units most likely leads to an increase in the relative investment in lending as compared to the total investment.

We capture additional insights when we calibrate the model to UK banks in terms of efficiency losses and the impact on asset risk of allocating constraints to business units. If only the risk-weighted requirement matters at the consolidated level, we find that the investment is distorted, leading to a higher relative investment in the riskier unit. Both the efficiency loss and risk taking effects diminish as the overall investment size increases. If the bank is bounded by the VaR and leverage ratio requirement, the results are ambiguous in terms of asset risk.

We find that allocating constraints to business units generally lead to higher bank asset risk, and efficiency losses in terms of total investment. The only case when investment decisions are not distorted is when the bank is bounded by the leverage ratio at group level, and the average risk weights on a stand-alone basis are below 35% for UK. The decrease in total investment size is observed for banks which are bounded either by the risk-weighted requirement, or by both the VaR and the leverage ratio requirement at consolidated level. The effect on risk-taking is ambiguous, and depends on the risk profile and marginal returns and costs of the different bank groups. When we calibrate the model based on different business models, we find that applying constraints at business units leads to an increase in risk taking for retail banks, while we obtain the opposite effect for wholesale and capital-orientated banks. These results depend on the different factors explained above.

From a policy perspective, our paper generates useful insights on the current debate on what is the appropriate level of application of the leverage ratio requirement. We highlight the potential cost when applying this requirement at the business unit level since it can induce banks to increase their asset risk and to decrease their overall investment, generating inefficiency losses. A key insight is that the impact on risk-taking differs across bank types, depending on which regulatory requirement (RWA or leverage ratio) matters most for the bank at group level. Hence we argue that any new policy should be tailored to bank business models which in turn relates to the most binding constraint, as it otherwise leads to distorted asset risk decisions.

In further work we aim to expand the model to cross-lending, where one of the two business units funds the other. The cash generated in the repo transaction can be used as a source of cheap funding for the banks' lending unit. Moreover, at the moment we analyse the extreme case when banks cascade down completely their requirements at business line levels. What we observe in practice is that banks also attach specific weights to the two requirements when they apply the constraints at business unit levels, with the highest weight given to the most binding constraint. We aim to further enhance this research work by analysing the effects of attaching different weights to each of the two requirements.

Appendices

Appendix C

C.1 Maximisation problem at group and business line level

Maximisation problem at group

We define the lending profit as:

$$\tilde{\Pi}_L = G(L) - \tilde{Z}L - R(L - K_L) \tag{C.1}$$

$$\mathbb{E}\left[\tilde{\Pi}_L\right] = G(L) - \mu_Z L - R(L - K_L) \tag{C.2}$$

and the repo unit profit as:

$$\tilde{\Pi}_X = F(X) + c(X) - \tilde{\varepsilon}L - R(L - K_X) \tag{C.3}$$

$$\mathbb{E}\left[\tilde{\Pi}_X\right] = F(X) - \mu_\varepsilon X - R(L - K_X) \tag{C.4}$$

We further combine equations (C.2) and (C.4) and write the joint expected profit as:

$$\mathbb{E}\left[\tilde{\Pi}\right] = G(L) + F(X) + cX - \mu_Z L - \mu_\varepsilon X - R(X + L - K)$$

Hence, the optimization problem at the group level can be written as:

$$\underset{L,X}{\text{Max}} \quad G(L) + F(X) + cX - \mu_Z L - \mu_\varepsilon X - R(X + L - K)$$

s.t.

$$\mathbb{P}\left(\tilde{\Pi} \leq 0\right) \leq a$$

$$\frac{K}{L+\alpha X} \geq \chi$$

We can re-write the first constraint as

$$\begin{aligned}
\mathbb{P}\Big(G(L)+F(X)+cX-R(X+L-K) \leq \mu_Z L+\mu_\varepsilon X\Big) &\leq a && \Longrightarrow \\
1-\mathbb{P}\Big(G(L)+F(X)+cX-R(X+L-K) \leq \mu_Z L+\mu_\varepsilon X\Big) &\geq 1-a && \Longleftrightarrow \\
\mathbb{P}\Big(G(L)+F(X)+cX-R(X+L-K) \geq \mu_Z L+\mu_\varepsilon X\Big) &\geq 1-a && \Longleftrightarrow \\
\mathbb{P}\Big(\mu_Z L+\mu_\varepsilon X \leq G(L)+F(X)+cX-R(X+L-K)\Big) &\geq 1-a
\end{aligned}$$

Define $VaR_\alpha(Y)$ of a Random Variable Y at confidence level α as:

$$VaR_\alpha \equiv inf\{y : \mathbb{P}(Y \leq y) \geq \alpha\}$$

This implies that the first constraint can be interpreted in terms of VaR as:

$$\begin{aligned}
VaR_{1-a}(\tilde{Z}L+\tilde{\varepsilon}X) &\leq G(L)+F(X)+cX-R(X+L-K) \Longrightarrow \\
VaR_{1-a}(\tilde{Z}L+\tilde{\varepsilon}X) &\leq G(L)+F(X)+cX-R(X+L)+RK \Longrightarrow \\
K &\geq \frac{VaR_{1-a}(\tilde{Z}L+\tilde{\varepsilon}X)-G(L)+F(X)+cX-R(X+L)}{R}
\end{aligned}$$

The optimization problem at the group's level becomes:

$$\underset{L,X}{\text{Max}} \quad G(L)+F(X)+cX-\mu_Z L-\mu_\varepsilon X-R(X+L-K)$$

s.t.

$$K \geq \frac{VaR_{1-a}(\tilde{Z}L+\tilde{\varepsilon}X)-G(L)+F(X)+cX-R(X+L)}{R}$$

$$K \geq \chi(L+\alpha X)$$

We further define the following variables:

$$\Pi(L, X) = G(L) + F(X) + cX - R(L + X)$$
$$S = L + X$$
$$w = \frac{L}{S}$$
$$1 - w = \frac{X}{S}$$
$$\tilde{Z}L + \tilde{\varepsilon}X = \tilde{Z}wS + \tilde{\varepsilon}(1 - w)S = \big(\tilde{Z}w + \tilde{\varepsilon}(1 - w)\big)S$$

Moreover, we show that the VaR requirement satisfies positive homogeneity:
For a Random Variable $\tilde{L}$, and every $\lambda > 0$:

$$VaR_\alpha(Y) = inf\{y : \mathbb{P}(Y \leq y) \geq \alpha\}$$
$$VaR_\alpha(\lambda Y) = inf\{y' : \mathbb{P}(\lambda Y \leq y') \geq \alpha\} \implies$$

$$\mathbb{P}(\lambda Y \leq y') \geq \alpha \iff \mathbb{P}(\lambda Y \leq y') \geq \alpha(\text{ since } \lambda > 0) \implies$$
$$\frac{y'}{\lambda} = inf\{t : \mathbb{P}(\lambda Y \leq t) \geq \alpha\} \implies \frac{y'}{\lambda} = y \implies VaR_\alpha(\lambda Y) = \lambda VaR_\alpha(Y)$$

We further apply the positive homogeneity property of VaR to the first constraint in our maximisation problem, and rewrite the VaR using the new notation as:

$$VaR_{1-a}\Big[\big(\tilde{Z}w + \tilde{\varepsilon}(1 - w)\big)S\Big] = SVaR_{1-a}\Big[\tilde{Z}w + \tilde{\varepsilon}(1 - w)\Big]$$

Hence, the optimization problem at group level can be summarized in:

$$\underset{S,w}{\text{Max}} \quad \{G(wS) + F((1 - w)S) + c(1 - w)S - RS + RK)\} \tag{C.5}$$

subject to

$$K \geq \frac{VaR_{1-a}(Zw + (1 - w)\varepsilon)S - \Pi(w, S)}{R} \tag{C.6}$$

$$K \geq \chi\,(wS + \alpha(1 - w)S) \tag{C.7}$$

Maximisation problem at business unit level

At business unit level, the optimization problem reads:

$$\underset{L,X}{\text{Max}} \quad G(L) + F(X) + cX - \mu_Z L - \mu_\varepsilon X - R(X + L - K)$$

s.t.

$$\mathbb{P}\left(G(L) - R(L - K_L) \leq \tilde{Z}L\right) \leq a$$
$$\mathbb{P}\left(F(X) + cX - R(X - K_X) \leq \tilde{\varepsilon}\right) \leq a$$

$$K_L \geq \chi L$$
$$K_X \geq \chi \alpha X$$
$$K_{\geq} K_L + K_X$$

In a similar fashion as for the group VaR constraint, we can re-write the VaR constraints of lending and repo unit. The VaR of lending is:

$$\begin{aligned}
&\mathbb{P}\big(G(L) - R(L - K_L) \leq \tilde{Z}L\big) \leq a \iff \\
&\mathbb{P}\big(\tilde{Z}L \leq G(L) - R(L - K_L)\big) \geq 1 - a \iff \\
&VaR_{1-a}(\tilde{Z}L) \leq G(L) - RL + RK_L \iff \\
&K_L \geq \frac{VaR_{1-a}(\tilde{Z}L) - (G(L) - RL)}{R} \iff \\
&K_L \geq \frac{SVaR_{1-a}(\tilde{Z}w) - (G(wS) - RwS)}{R}
\end{aligned}$$

In a similar way we can rewrite the VaR constraint of repo:

$$K_X \geq \frac{SVaR_{1-a}(\tilde{\varepsilon}(1-w)) - \Big(F[(1-w)S] + c(1-w)S - R(1-w)S)\Big)}{R}$$

This implies that we can rewrite the optimization problem at business unit level with constraints (4.16), (4.17), re-written below:

$$\operatorname*{Max}_{S,w} \quad \{G(wS) + F((1-w)S) + c(1-w)S - RS + RK)\}$$

s.t.

$$K_L \geq \frac{VaR_{1-a}(Zw)S - \Pi_L(w,S)}{R} \tag{C.8}$$

$$K_X \geq \frac{VaR_{1-a}((1-w)\varepsilon)S - \Pi_X(w,S)}{R} \tag{C.9}$$

$$K_L \geq \chi w S \tag{C.10}$$

$$K_X \geq \chi\alpha(1-w)S \tag{C.11}$$

$$K_L + K_X \leq K \tag{C.12}$$

C.2 Lagrangian and FOC's for group level maximisation problem

For reference, we define only once the corresponding Lagrangian and first order conditions for the group level maximisation problem, and in further subsections of the appendix we will refer to parameters of shadow values as described in this subsection.

The Lagrangian reads:

$$\begin{aligned}\Lambda_g =& \Pi(S,w) - \mu_Z wS - \mu_\varepsilon(1-w)S + RK \\ &+ \lambda_{VaR}\Big(K - \frac{VaR_{1-a}(\tilde{Z}w + (1-w)\tilde{\varepsilon})S - \Pi(w,S)}{R}\Big) \\ &+ \lambda_{LR}(K - \chi\big(w + \alpha(1-w)\big)S)\end{aligned}$$

The FOC's are:

$$\begin{aligned}\frac{\partial\Lambda_g}{\partial S} =& \frac{\partial\Pi(S,w)}{\partial S} - \mu_Z w - \mu_\varepsilon(1-w) - \lambda_{VaR}\frac{VaR_{1-a}(\tilde{Z}w + (1-w)\tilde{\varepsilon})}{R} + \frac{\lambda_{VaR}}{R}\frac{\partial\Pi(w,S)}{\partial S} \\ &- \lambda_{LR}\chi\big(w + \alpha(1-w)\big) = 0\end{aligned}$$

$$
\begin{aligned}
\frac{\partial \Lambda_g}{\partial w} =& \frac{\partial \Pi(S,w)}{\partial w} - \mu_Z S + \mu_\varepsilon S - \frac{S\lambda_{VaR}}{R}\frac{\partial VaR_{1-a}(\tilde{Z}w + (1-w)\tilde{\varepsilon})}{\partial w} \\
&+ \frac{\lambda_{VaR}}{R}\frac{\partial \Pi(w,S)}{\partial w} - \lambda_{LR}\chi(1-\alpha)S = 0
\end{aligned}
$$

From now on, when we denote $\lambda_{LR}, \lambda_{VaR}$ we refer to the shadow values of the two constraints as described above.

C.3 Lagrangian and FOC's for business units maximisation problem

Hereby we define the corresponding Lagrangian and the FOC's for the business unit maximisation problem.

$$
\begin{aligned}
\Lambda_b =& \Pi(S,w) - \mu_Z wS - \mu_\varepsilon(1-w)S + RK + \lambda_{VaR}^L\Big(K_L - \frac{VaR_{1-a}(\tilde{Z}w)S - G(wS) + RwS}{R}\Big) \\
&+ \lambda_{VaR}^X\Big(K_X - \frac{VaR_{1-a}(\tilde{\varepsilon}(1-w))S - F\big((1-w)S\big) - c(1-w)S + R(1-w)S}{R}\Big) \\
&+ \lambda_{LR}^L(K_L - \chi wS) + \lambda_L R^X(K_X - \chi\alpha(1-w)S + \lambda_K(K - K_L - K_X)
\end{aligned}
$$

The FOC's are:

$$
\begin{aligned}
\frac{\partial \Lambda_b}{\partial S} =& \frac{\partial \Pi(S,w)}{\partial S} - \mu_Z w - \mu_\varepsilon(1-w) - \lambda_{VaR}^L\frac{VaR_{1-a}(\tilde{Z}w)}{R} + \frac{\lambda_{VaR}^L}{R}\Big(\frac{\partial G(wS}{\partial S} - Rw\Big) \\
&+ \frac{\lambda_{VaR}^X}{R}\Big(\frac{\partial F((1-w)S}{\partial S} + c(1-w) - R(1-w)\Big) - \lambda_{VaR}^X\frac{VaR_{1-a}(\tilde{\varepsilon}(1-w)}{R} \\
&- \lambda_{LR}^L\chi w - \lambda_{LR}^X\chi\alpha(1-w) = 0
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial \Lambda_b}{\partial w} =& \frac{\partial \Pi(S,w)}{\partial w} - \mu_Z S + \mu_\varepsilon S - \frac{S\lambda_{VaR}^L}{R}\frac{\partial VaR_{1-a}(\tilde{Z}w)}{\partial w} + \frac{\lambda_{VaR}^L}{R}\Big(\frac{\partial G(wS}{\partial w} - RS\Big) \\
&- \frac{S\lambda_{VaR}^X}{R}\frac{\partial VaR_{1-a}(\tilde{\varepsilon}(1-w)}{\partial w} + \frac{\lambda_{VaR}^X}{R}\Big(\frac{\partial F((1-w)S}{\partial w} - Cs + RS\Big) \\
&- \lambda_{LR}^L\chi S + \lambda_{LR}^X\chi\alpha S = 0
\end{aligned}
$$

$$\frac{\partial \Lambda_b}{\partial K_L} = \lambda^L_{VaR} + \lambda^L_{LR} - \lambda_K = 0$$

$$\frac{\partial \Lambda_b}{\partial K_X} = \lambda^X_{VaR} + \lambda^X_{LR} - \lambda_K = 0$$

From now on, when we denote $\lambda^X_{LR}, \lambda^X_{VaR}, \lambda^L_{LR}, \lambda^L_{VaR}, \lambda_K$ we refer to the shadow values of the constraints as described above.

C.4 Proof of Proposition 4.2

Here the prove the results for when the bank is bounded by the leverage ratio (LR) at the group level. We start by restating the bank's maximisation problem at consolidated level:

$$\underset{S,w}{\text{Max}} \quad \{G(wS) + F((1-w)S) + c(1-w)S - RS + RK)\}$$

subject to

$$K \geq \frac{VaR_{1-a}(Zw + (1-w)\varepsilon)S - \Pi(w,S)}{R} \tag{C.13}$$

$$K \geq \chi\,(wS + \alpha(1-w)S) \tag{C.14}$$

where the first constraint is the VaR at group level - equation (C.13), and the second captures the leverage constraint - equation (C.14).

The problem at business line level reads:

$$\underset{S,w}{\text{Max}} \quad \{G(wS) + F((1-w)S) + c(1-w)S - RS + RK)\}$$

s.t.

$$K_L \geq \frac{VaR_{1-a}(Zw)S - \Pi_L(w,S)}{R} \tag{C.15}$$

$$K_X \geq \frac{VaR_{1-a}((1-w)\varepsilon)S - \Pi_X(w,S)}{R} \tag{C.16}$$

$$K_L \geq \chi w S \tag{C.17}$$

$$K_X \geq \chi \alpha (1-w) S \tag{C.18}$$

$$K_L + K_X \leq K \tag{C.19}$$

where

$$\Pi_L(w,S) = G(wS) - RwS \quad \text{and} \quad \Pi_X(w,S) = F((1-w)S) + c(1-w)S - R(1-w)S$$

where the first two constraints are the VaR equations for lending and repo respectively (C.15), and (C.16), followed by the business line leverage constraint equations (C.17) and (C.18), and the maximum capital available for each business unit - equation (C.19).

Proof of first bullet of proposition 2

Proof. Denote by (w^G, S^G) the solution to the problem at consolidated level when the leverage constraint is binding, that means: (w^G, S^G) satisfy constraints (C.14) and (C.13), and (C.14) is satisfied with equality:

$$\begin{aligned} K =& \chi(w^G S^G + \alpha(1-w^G)S^G) \\ K >& \frac{VaR_{1-a}(Zw^G + (1-w^G)\varepsilon)S^G - \Pi(w^G, S^G)}{R} \end{aligned}$$

Note that (w^G, S^G) will satisfy all constraints from the business line level -equations (C.15) – (C.19) if and only if:

$$\begin{cases} \text{RHS of } (C.17) & \geq \text{RHS of } (C.15) \\ \text{RHS of } (C.18) & \geq \text{RHS of } (C.16) \end{cases}$$

The condition translates to:

$$\begin{cases} \chi w S \geq \frac{SVaR_{1-a}(\tilde{Z}w) - \Big(G(wS) - RwS\Big)}{R} \\ \chi\alpha(1-w)S \geq \frac{SVaR_{1-a}((1-w)\tilde{\varepsilon}) - \Bigg(F[(1-w)S] + c(1-w)S - R(1-w)S\Bigg)}{R} \end{cases}$$

This is equivalent with:

$$\begin{cases} \chi w S & \geq \gamma RWA_S(L) \\ \chi(1-w)S & \geq \gamma RWA_S(X) \end{cases} \iff \begin{cases} \frac{RWA_S(L)}{wS} & \leq \frac{\chi}{\gamma} \\ \frac{RWA_S(X)}{(1-w)S} & \leq \frac{\chi}{\gamma} \end{cases}$$

Hence, when the conditions stated above are satisfied, then (w^G, S^G) satisfy all constraints of the bank's problem at business line level, which implies that:

1. (w^G, S^G) belong to the feasible set of the bank's problem at business unit level.
2. The feasible set of the problem at business unit level is smaller than the feasible set of the problem at consolidated level.

From the two points above, we conclude that (w^G, S^G) are also the solution to the bank's problem at the business unit level.

□

Proof of second bullet of proposition 2

Proof. In a similar fashion, we can show that if both business units have average risk weights above $\frac{\chi}{\gamma}$ on a stand-alone basis, then by requiring each of its two business units to satisfy the two regulatory constraints, the bank reduces the share of its lending business as compared to the case in which all the constraints are applied at the group's level.

The condition for which the solution (w^G, S^G) is also a solution for the business line level problem is stated above in terms of average risk weights. Hence, if

$$\begin{cases} \chi w S < \frac{SVaR_{1-a}(\tilde{Z}w) - \Big(G(wS) - RwS\Big)}{R} \\ \chi\alpha(1-w)S < \frac{SVaR_{1-a}((1-w)\tilde{\varepsilon}) - \Bigg(F[(1-w)S] + c(1-w)S - R(1-w)S\Bigg)}{R} \end{cases} \tag{C.20}$$

then (w^G, S^G) is no longer a solution for the business line level problem, and S^G is larger than the maximum feasible level of total investment in this case. The system of equations above implies that

$$\chi\big(w + (1-w)\alpha\big)S < \frac{S\Big(VaR_{1-a}(\tilde{Z}w) + VaR_{1-a}((1-w)\tilde{\varepsilon}) - \Pi(w,S)\Big)}{R}$$

In terms of risk weights, we can interpret the system C.20 as:

$$\begin{cases} \text{average risk weights of lending} > \frac{\chi}{\gamma} \\ \text{average risk weights of repo} > \frac{\chi}{\gamma} \end{cases}$$

In this case, both businesses are quite risky, but diversification benefit is large, which leads to the situation in which

$$\begin{cases} \text{business unit level: VaR constraint more important} \\ \text{but at the group level: LR is more important} \end{cases}$$

At the group level, LR is binding, and in terms of shadow values of the Lagrangian, we can write:

$$\begin{cases} \lambda_{VaR} = 0 \\ \lambda_{LR} \geq 0 \end{cases}$$

This implies that the solution at the group level (w^G, S^G) is characterized by:

$$\begin{cases} \frac{\partial \Pi(S^G, w^G)}{\partial S} - \mu_Z w^G - \mu_\varepsilon(1-w^G) - \lambda_L R^X \chi\big(w + \alpha(1-w)\big) & = 0 \\ \\ \frac{\partial \Pi(S^G, w^G)}{\partial w} - \mu_Z w^G - \mu_\varepsilon(1-w^G) - \lambda_{LR}\chi(1-\alpha)S^G & = 0 \end{cases} \tag{C.21}$$

Let (w^B, S^B) be the solution for the bank's maximisation problem at business unit level. At the business unit level, if condition C.20 is satisfied, then if there is a binding constraint, if should be VaR constraints. In terms of shadow values, this reads as:

$$\begin{cases} \lambda^L_{LR} = 0; \quad \lambda^X_{LR} = 0 \\ \lambda^L_{LR} \geq 0; \quad \lambda^X_{VaR} \geq 0 \end{cases}$$

Moreover, from the two FOC's for K_L and K_X, combining the equations above, it implies that $\lambda^L_{VaR} = \lambda^X_{VaR}$. The solution (w^B, S^B) at the business unit level satisfies the following 2 equalities:

$$\frac{\partial \Pi(S^B, w^B)}{\partial S} - \mu_Z w^B - \mu_\varepsilon (1 - w^B) - \frac{\lambda^L_{VaR}}{R}\Big(VaR_{1-a}(\tilde{Z} w^B) + VaR_{1-a}((1 - w^B)\tilde{\varepsilon})\Big) \\ + \frac{\lambda^L_{VaR}}{R}\frac{\partial \Pi(w^B, S^B)}{\partial S} = 0 \tag{C.22}$$

$$\frac{\partial \Pi(S^B, w^B)}{\partial w} - \mu_Z S^B + \mu_\varepsilon S^B - \frac{S^B \lambda^L_{VaR}}{R}\Big(\frac{\partial VaR_{1-a}(\tilde{Z} w^B)}{\partial w} + \frac{\partial VaR_{1-a}((1 - w^B)\tilde{\varepsilon})}{\partial w}\Big) \\ + \frac{\lambda^L_{VaR}}{R}\frac{\partial \Pi(w^B, S^B)}{\partial S} = 0 \qquad \Longleftrightarrow$$

$$\frac{\partial \Pi(S^B, w^B)}{\partial w}\Big(1 + \frac{\lambda^L_{VaR}}{R}\Big) - \mu_Z S + \mu_\varepsilon S^B = \frac{S^B \lambda^L_{VaR}}{R}\Big(VaR_{1-a}(\tilde{Z}) - VaR_{1-a}(\tilde{\varepsilon})\Big) \tag{C.23}$$

Hence, to compare (w^G, S^G) and (w^B, S^B) we know that (w^G, S^G) satisfies (C.21) i.e.

$$\frac{\partial \Pi(S^G, w^G)}{\partial w} - \mu_Z S^G + \mu_\varepsilon S^G = \underbrace{\lambda_{LR}\chi(1 - \alpha)S^G}_{\leq 0}$$

In contrast, (w^B, S^B) satisfies (C.23), i.e.

$$\frac{\partial \Pi(S^B, w^B)}{\partial w}\Big(1 + \frac{\lambda^L_{VaR}}{R}\Big) - \mu_Z S^B + \mu_\varepsilon S^B = \underbrace{\frac{\lambda^L_{VaR}}{R} S^B \Big(VaR_{1-a}(\tilde{Z}) - VaR_{1-a}(\tilde{\varepsilon})\Big)}_{\geq 0}$$

Combining the two, it implies that $w^B < w^G$, which is the second result in proposition 2. $\square$

C.5 Proof of Proposition 4.3

Let w^G, S^G be the solution at the group level. In this case, in terms of constraints at optimum:

$$\begin{aligned} K =& \frac{S^G VaR_{1-a}\big(\tilde{Z}w^G + (1-w^G)\tilde{\varepsilon}\big) - \Pi(w^G, S^G)}{R} \\ K >& \chi\big(w^G + \alpha(1-w^G)\big)S^G \end{aligned}$$

Remark 1. w^G, S^G can **not** be a solution to the problem at business unit level since w^G, S^G cannot satisfy VaR constraints at business level.

Proof. Indeed, since

$$\frac{S^G VaR_{1-a}\big(\tilde{Z}w^G + (1-w^G)\tilde{\varepsilon}\big) - \Pi(w^G, S^G)}{R} < \frac{S^G VaR_{1-a}\big(\tilde{Z}w^G\big) - \big(G(w^G S^G) - R w^G S^G\big)}{R}$$
$$+ \frac{S^G VaR_{1-a}((1-w^G)\tilde{\varepsilon}) - \big[F((1-w^G)S^G) + c(1-w^G)S^G - R(1-w^G)S^G\big]}{R}$$

This inequality implies that $K \leq K_L + K_X$: contradiction with the condition that $K \geq K_L + K_X$.

Remark 2. In the case where banks are bounded by VaR constraint at the group level, when constraints are cascaded down, it can **not** happen that:

$$\begin{cases} \text{RHS of (C.18)} \geq \text{RHS of (C.16)} \\ \text{RHS of (C.17)} \geq \text{RHS of (C.15)} \end{cases}$$

Remark 3. For the optimization problem at the business unit level, it can **not** happen that one business is bounded by some constraint while the other is not bounded by any constraint.

Remarks 1,2, and 3 imply that when the bank is bounded by VaR constraint at the group level, when the constraint is cascaded down, there are 4 possible cases:

$$A. \begin{cases} \text{only VaR is binding for lending} \\ \text{only VaR is binding for Repo} \end{cases} \iff \begin{cases} \lambda^L_{VaR} = \lambda^X_{VaR} > 0 \\ \lambda^L_{LR} = 0; \lambda^X_{LR} = 0 \end{cases} \tag{C.24}$$

$$B. \begin{cases} \text{only VaR is binding for lending} \\ \text{only LR is binding for Repo} \end{cases} \iff \begin{cases} \lambda^L_{LR} = \lambda^X_{VaR} = 0 \\ \lambda^L_{VaR} = \lambda^X_{LR} = 0 \end{cases} \tag{C.25}$$

$$C. \begin{cases} \text{only LR is binding for lending} \\ \text{only VaR is binding for Repo} \end{cases} \iff \begin{cases} \lambda^L_{VaR} = \lambda^X_{LR} = 0 \\ \lambda^L_{LR} = \lambda^X_{VaR} > 0 \end{cases} \tag{C.26}$$

$$D. \text{ All 4 constraints are binding} \tag{C.27}$$

We will consider case B. At the business unit level, (w^B, S^B) is defined by :

$$G'(w^B S^B) + F'((1-w^B)S^B)(1-w^B) + c(1-w^B) - R =$$

$$\mu_Z w^B + \mu_\varepsilon(1-w^B) + \frac{\lambda^L_{VaR}}{R}\big(VaR_{1-a}(\tilde{Z}w^B) - G'(w^B S^B)w^B + Rw^B\big) \tag{C.28}$$

$$G'(w^B S^B) - F'((1-w^B)S^B) - c = \mu_Z - \mu_\varepsilon + \frac{\lambda^L_{VaR}}{R}\big(VaR_{1-a}(\tilde{Z} - G'(w^B S^B) + R) - \lambda^L_{VaR}\chi\alpha \tag{C.29}$$

At the group level, the solution w^G, S^G is defined by:

$$G'(w^G S^G)w^G + F'((1-w^G)S^G)(1-w^G) + c(1-w^G) - R =$$
$$\mu_Z w^G + \mu_\varepsilon(1-w^G) + \frac{\lambda_{VaR}}{R}\Big(VaR_{1-a}(\tilde{Z}w^G + (1-w^G)\tilde{\varepsilon} - G'(w^G S^G)w^G + Rw^G\Big) \tag{C.30}$$

$$\begin{aligned} G'(w^G S^G) - F'((1-w^G)S^G) - c &= \mu_Z - \mu_\varepsilon \\ &+ \frac{\lambda_{VaR}}{R}\Big(\frac{\partial VaR_{1-a}(\tilde{Z}w^G + (1-w^G)\tilde{\varepsilon})}{\partial w} - G'(w^G S^G) + R\Big) \\ &+ \frac{\lambda_{VaR}}{R}\big(F'((1-w^G)S^G) + c - R\big) \end{aligned} \tag{C.31}$$

The second equation from (C.29) can be written as:

$$G'(w^B S^B) - F'((1-w^B)S^B) - c = \mu_Z - \mu_\varepsilon + \lambda^L_{VaR}\underbrace{\big(\frac{VaR_{1-a}(\tilde{Z} - G'(w^B S^B) + R}{R}\big)}_{\text{marginal RWA L}}$$
$$- \lambda^L_{VaR}\chi\alpha$$

The second equation from (C.31) can be written as:

$$G'(w^G S^G) - F'((1-w^G)S^G) - c = \mu_Z - \mu_\varepsilon + \lambda^L_{VaR}\underbrace{\Big(\frac{VaR_{1-a}(\tilde{Z} - G'(w^G S^G) + R}{R}\Big)}_{\text{marginal RWA L}}$$
$$- \lambda_{VaR}\underbrace{\frac{VaR_{1-a}(\tilde{\varepsilon}) - F'((1-w^G)S^G) - c + R}{R}}_{\text{marginal RWA X}}$$
$$- \frac{\lambda_{VaR}}{R}\underbrace{\Big(-\frac{\partial VaR_{1-a}(\tilde{Z}w^G + (1-w^G)\tilde{\varepsilon}}{\partial w} + VaR_{1-a}(\tilde{Z} - VaR_{1-a}(\tilde{\varepsilon})\Big)}_{\text{marginal diversification benefit}}$$

Hence, combining the two,

$$G'(w^B S^B) - F'((1-w^B)S^B) - c < G'(w^G S^G) - F'((1-w^G)S^G) - c$$

if

$$\begin{cases} \chi\alpha > \frac{VaR_{1-a}(\tilde{\varepsilon}) - F'((1-w^G)S^G) - c + R}{R} \\ VaR_{1-a}(\tilde{Z}) - VaR_{1-a}(\tilde{\varepsilon}) - \frac{\partial VaR_{1-a}(\tilde{Z}w^G + (1-w^G)\tilde{\varepsilon})}{\partial w} \leq 0 \end{cases} \tag{C.32}$$

The first equation from the system above means that for the repo business, the marginal required capital from leverage constraint > marginal required capital from risk-weighted constraint. The second equation can be interpreted as diversification benefits decrease with w. Using Taylor approximation:

$$\begin{aligned} G'(w^B S^B) - F'((1-w^B)S^B) - c = {} & G'(w^G S^G) - F'((1-w^G)S^G) - c \\ & + \Big(\underbrace{\frac{\partial G'}{\partial w}(w^G, S^G) - \frac{\partial F'}{\partial w}(w^G, S^G)}_{<0}\Big)(w^B - w^G) \\ & + \Big(\frac{\partial G'}{\partial S}(w^G, S^G) - \frac{\partial F'}{\partial S}(w^G, S^G)\Big)(S^B - S^G) \end{aligned}$$

Therefore, $w^B > w^G$ if

$$\begin{aligned} & \Big[G'(w^B S^B) - F'((1-w^B)S^B) - c - (G'(w^G S^G) - F'((1-w^G)S^G) - c)\Big] \\ & \quad - \Big(\underbrace{\frac{\partial G'}{\partial S}(w^G, S^G) - \frac{\partial F'}{\partial S}(w^G, S^G)}_{>0 \text{ if w is not too high}}\Big)\underbrace{(S^B - S^G)}_{<0} < 0 \iff \end{aligned}$$

$$\begin{aligned} & G'(w^B S^B) - F'((1-w^B)S^B) - c - (G'(w^G S^G) - F'((1-w^G)S^G) - c) \text{ is low enough } \iff \\ & \underbrace{(G'(w^G S^G) - F'((1-w^G)S^G) - c)}_{\text{marginal benefit at the group optimum}} - \underbrace{(G'(w^B S^B) - F'((1-w^B)S^B) - c)}_{\text{marginal benefit at the business level optimum}} \text{ is high enough.} \end{aligned}$$

$\square$

Bibliography

Acosta-Smith, J., M. Grill, and J. H. Lang (2018). The leverage ratio, risk-taking and bank stability. *Bank of England Staff Working Paper No. 766*.

Agoraki, M.-E. K., M. D. Delis, and F. Pasiouras (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability 7*(1), 38–48.

Ahn, H. and J. L. Powell (1993). Semiparametric estimation of censored selection models with a nonparametric selection mechanism. *Journal of Econometrics 58*(1-2), 3–29.

Albul, B., D. M. Jaffee, and A. Tchistyi (2015). Contingent convertible bonds and capital structure decisions. *Center for Risk Management Research UC Berkeley*.

Allahrakha, M., J. Cetina, and B. Munyan (2018). Do higher capital standards always reduce bank risk? the impact of the basel leverage ratio on the us triparty repo market. *Journal of Financial Intermediation 34*, 3–16.

Allen, F. and D. Gale (1994). Limited market participation and volatility of asset prices. *The American Economic Review*, 933–955.

Ammann, M., K. Blickle, and C. Ehmann (2017). Announcement effects of contingent convertible securities: Evidence from the global banking industry. *European Financial Management 23*(1), 127–152.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Association for Financial Markets in Europe (2016). Prudential data report. EU GSIBs prudential capital and liquidity.

Avdijev, S., B. Bogdanova, P. Bolton, W. Jiang, and A. Kartasheva (2020). CoCo issuance and bank fragility. *Journal of Financial Economics*.

Avdjiev, S., P. Bolton, W. Jiang, A. Kartasheva, and B. Bogdanova (2015). CoCo bond issuance and bank funding costs. *BIS and Columbia University working paper*.

Avdjiev, S., A. V. Kartasheva, and B. Bogdanova (2013). Cocos: a primer. *Available at SSRN 2326334*.

Bajaj, R., A. Binmore, R. Dasgupta, and Q.-A. Vo (2018). Banks' internal capital markets: how do banks allocate capital internally? *Bank of England Quarterly Bulletin*, Q2.

Baker, M. and J. Wurgler (2015). Do strict capital requirements raise the cost of capital? bank regulation, capital structure, and the low-risk anomaly. *American Economic Review 105*(5), 315–20.

Baker, S. (2020, 07/09). Contingent convertible debt survives rocky ride. *Pensions and Investments*. `https://bit.ly/3jcKle3`.

Baron, M., E. Verner, and W. Xiong (2020). Banking crises without panics. *NBER Working Paper No. 26908*.

Barth, A. and C. Seckinger (2018). Capital regulation with heterogeneous banks–unintended consequences of a too strict leverage ratio. *Journal of Banking & Finance 88*, 455–465.

Basel Committee (2009). Strengthening the resilience of the banking sector. *Basel Committee*.

Beardsworth, T. (2017, 11/07). Wiped out Banco Popular creditors question EU on resolution. `https://bloom.bg/2u4rUBV`.

Bekaert, G., M. Hoerova, and M. L. Duca (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics 60*(7), 771–788.

Berg, T. and C. Kaserer (2015). Does contingent capital induce excessive risk-taking? *Journal of Financial Intermediation 24*(3), 356–385.

Bicu-Lieb, A., L. Chen, and D. Elliott (2020). The leverage ratio and liquidity in the gilt and gilt repo markets. *Journal of Financial Markets*, 100510.

BIS CGFS (2017). Repo market functioning report. *Committee on the Global Financial System Papers no 59*.

Blum, J. M. (2008). Why Basel II may need a leverage ratio restriction. *Journal of Banking & Finance 32*(8), 1699–1707.

Boone, J. (2008). A new way to measure competition. *The Economic Journal 118*(531), 1245–1261.

Boyson, N. M., R. Fahlenbrach, and R. M. Stulz (2016). Why don't all banks practice regulatory arbitrage? Evidence from usage of trust-preferred securities. *The Review of Financial Studies 29*(7), 1821–1859.

Brock, P. L. and L. R. Suarez (2000). Understanding the behavior of bank spreads in Latin America. *Journal of Development Economics 63*(1), 113–134.

Buck, T. (2017, 07/06). Santander takes over 'failing' rival Banco Popular after EU steps in. *Financial Times*. `https://on.ft.com/2E1Hfd4`.

Calomiris, C. W. and R. J. Herring (2013). How to design a contingent convertible debt requirement that helps solve our too-big-to-fail problem. *Journal of Applied Corporate Finance 25*(2), 39–62.

Chan, S. and S. van Wijnbergen (2015). Cocos, contagion and systemic risk. *Tinbergen Institute Discussion Paper* (No. 14-110/VI/DSF79).

Chan, S. and S. van Wijnbergen (2017). CoCo design, risk shifting incentives and financial fragility. *CEPR Discussion Paper No. DP11099*.

Chen, N., P. Glasserman, B. Nouri, and M. Pelger (2017). Contingent capital, tail risk, and debt-induced collapse. *The Review of Financial Studies 30*(11), 3921–3969.

Choi, D. B., M. R. Holcomb, and D. P. Morgan (2018). Leverage limits and bank risk: New evidence on an old question. Technical Report No. 856, Staff Report Federal Reserve Bank of New York, New York NY.

Classens, S. (2014). Capital and liquidity requirements: a review of the issues and literature. *Yale Journal on Regulation 31*, 735.

Cosslett, S. R. (1983). Distribution-free maximum likelihood estimator of the binary choice model. *Econometrica: Journal of the Econometric Society*, 765–782.

Cosslett, S. R. (1991). Distribution-free estimator of a regression model with sample selectivity. *Nonparametric and semiparametric methods in econometrics and statistics*.

de Ramon, S. and M. Straughan (2016). Measuring competition in the UK deposit-taking sector. *Bank of England Working Paper No. 631.*.

Delis, M. D. and G. P. Kouretas (2011). Interest rates and bank risk-taking. *Journal of Banking & Finance 35*(4), 840–855.

Derksen, M., P. Spreij, and S. van Wijnbergen (2018). Accounting noise and the pricing of CoCo's. *CEPR DP no 12869*.

Deutsche Bundesbank (2018, March). Monthly report vol 70 nr 3. , Deutsche Bundesbank.

Dhaene, J., A. Tsanakas, E. A. Valdez, and S. Vanduffel (2012). Optimal capital allocation principles. *Journal of Risk and Insurance 79*(1), 1–28.

d'Haultfoeuille, X., A. Maurel, X. Qiu, and Y. Zhang (2019). Estimating selection models without instrument with Stata. Technical report, National Bureau of Economic Research.

Diamond, D. W. and P. H. Dybvig (1983). Bank runs, deposit insurance, and liquidity. *The Journal of Political Economy*, 401–419.

Dow, J. and S. R. da Costa Werlang (1992). Uncertainty aversion, risk aversion, and the optimal choice of portfolio. *Econometrica: Journal of the Econometric Society*, 197–204.

Duffie, D. (2018). Financial regulatory reform after the crisis: An assessment. *Management Science 64*(10), 4835–4857.

D'Haultfœuille, X., A. Maurel, and Y. Zhang (2018). Extremal quantile regressions for selection models and the black–white wage gap. *Journal of Econometrics 203*(1), 129–142.

EBA Report (2016, October). On the monitoring of Additional Tier 1 (AT1) instruments of European Union institutions. , European Banking Authority.

Fatouh, M. and A. McCunn (2019). Shareholder risk-taking incentives in the presence of contingent capital. *Bank of England Working Paper No. 775*.

Financial Stability Board (2015, November). Total loss-absorbing capacity (tlac) term sheet. , Financial Stability Board.

Fiordelisi, F., G. Pennacchi, and O. Ricci (2019). Are contingent convertibles going-concern capital? *Journal of Financial Intermediation*, 100822.

Flannery, M. J. (2002). No pain, no gain? Effecting market discipline via 'reverse convertible debentures'.

Francis, B. B., I. Hasan, and Y. Zhu (2014). Political uncertainty and bank loan contracting. *Journal of Empirical Finance 29*, 281–286.

Gambacorta, L. and S. Karmakarb (2018). Leverage and risk-weighted capital requirements. *International Journal of Central Banking*.

Glasserman, P. and B. Nouri (2012). Contingent capital with a capital-ratio trigger. *Management Science 58*(10), 1816–1833.

Glasserman, P. and E. Perotti (2017). The unconvertible CoCo bonds. *Achieving Financial Stability: Challenges to Prudential Regulation*.

Glassserman, P. and B. Nouri (2016). Demand–deposit contracts and the probability of bank runs. *Econometrica 84*(6), 2113 – 2153.

Gledhill, A. (2020, 12/08). Contingent convertibles. *Bloomberg*. `https://www.bloomberg.com/quicktake/contingent-convertible-bonds`.

Goel, T., U. Lewrick, and N. Tarashev (2019). Bank capital allocation under multiple constraints. *Journal of Financial Intermediation*, 100844.

Goldstein, I. and A. Pauzner (2005). Demand–deposit contracts and the probability of bank runs. *The Journal of Finance 60*(3), 1293–1327.

Goncharenko, R., S. Ongena, and A. Rauf (2020). The agency of cocos: Why contingent convertible bonds aren't for everyone. *Journal of Financial Intermediation*, 100882.

Graham, J. R. and C. R. Harvey (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics 60*(2-3), 187–243.

Greene, R. (2016). Understanding cocos: What operational concerns & global trends mean for us policymakers. *Harvard University, John F. Kennedy School of Government, M-RCBG Associate Working Paper* (62).

Greenspan, A. (2004). Risk and uncertainty in monetary policy. *American Economic Review 94*(2), 33–40.

Haddow, A., C. Hare, J. Hooley, and T. Shakir (2013). Macroeconomic uncertainty: what is it, how can we measure it and why does it matter? *Quarterly Bulletin Bank of England Q2*.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of Economic and Social Measurement, volume 5, number 4*, pp. 475–492. NBER.

Hesse, H. (2018). Incentive effects from write-down CoCo bonds: An empirical analysis.

Hilscher, J. and A. Raviv (2014). Bank stability and market discipline: The effect of contingent capital on risk taking and default probability. *Journal of Corporate Finance 29*, 542–560.

IFRS 9 (2014, July). IFRS 9 financial instruments. Project summary. Technical report, IFRS.

Ita, A. (2017). Capital allocation in large banks - a renewed look at practice. *Available at SSRN 2726165*.

Jiménez, G., J. A. Lopez, and J. Saurina (2013). How does competition affect bank risk-taking? *Journal of Financial Stability 9*(2), 185–195.

Khaykin, I., U. Koyluoglu, D. Elliott, and C. Spicer (2017). Balancing complex and competing constraints on capital, liquidity and funding. Technical report.

Kiema, I. and E. Jokivuolle (2014). Does a leverage ratio requirement increase bank stability? *Journal of Banking & Finance 39*, 240–254.

Kiewiet, G., I. Van Lelyveld, and S. Van Wijnbergen (2017). Contingent convertibles: Can the market handle them? *De Nederlandsche Bank Working Paper*.

Klein, R. W. and R. H. Spady (1993). An efficient semiparametric estimator for binary response models. *Econometrica: Journal of the Econometric Society*, 387–421.

Kotidis, A. and N. Van Horen (2019). Repo market functioning: The role of capital regulation. *CEPR Discussion Paper No. DP13090*.

Koziol, C. and J. Lawrenz (2012). Contingent convertibles. solving or seeding the next banking crisis? *Journal of Banking & Finance 36*(1), 90–104.

Krüger, P., A. Landier, and D. Thesmar (2015). The WACC fallacy: The real effects of using a unique discount rate. *The Journal of Finance 70*(3), 1253–1285.

Lee, D. S. (2009). Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *The Review of Economic Studies 76*(3), 1071–1102.

Martynova, N. and E. Perotti (2018). Convertible bonds and bank risk-taking. *Journal of Financial Intermediation 35*, 61–80.

Maudos, J. and X. Vives (2019). Competition policy in banking in the European Union. *Review of Industrial Organization*, 1–20.

Merton, R. C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance 29*, 449–470.

Morris, S. and H. S. Shin (1998). Unique equilibrium in a model of self-fulfilling currency attacks. *American Economic Review*, 587–597.

Pennacchi, G. and A. Tchistyi (2019). On equilibrium when contingent capital has a market trigger: A correction to Sundaresan and Wang Journal of Finance (2015). *The Journal of Finance 74*(3), 1559–1576.

Perold, A. F. (2005). Capital allocation in financial firms. *Journal of Applied Corporate Finance 17*(3), 110–118.

Ramnarayan, A. and M. Nikolaeva (2020, 20/04). AXA to repay CoCo bond, but investors worry others may not follow. `https://reut.rs/338Iz88`.

Roengpitya, R., N. A. Tarashev, and K. Tsatsaronis (2014). Bank business models. *BIS Quarterly Review December*.

Smith, R. (2017, 7/07). Coco bond contagion contained after Banco Popular wipeout. *Financial Times*. `http://on.ft.com/2uy2igA`.

Song, D. and Z. Yang (2016). Contingent capital, real options, and agency costs. *International Review of Finance 16*(1), 3–40.

Stein, J. C. (1997). Internal capital markets and the competition for corporate resources. *The Journal of Finance 52*(1), 111–133.

Sundaresan, S. M. and Z. Wang (2015). Bank liability structure. *Kelley School of Business Research Paper*, 14–41.

Swiss Financial Market Supervisory Authority, F. (2015, October). New “too big to fail” capital requirements for global systemically important banks in Switzerland. , Swiss Financial Market Suervisory Authority.

Vasicek, O. (1977). An equilibrium characterization of the term structure. *Journal of Financial Economics 5*(2), 177–188.

World Bank (2017). Understanding Bank Recovery and Resolution in the EU: a Guidebook to the BRRD. , Financial Sector Advisory Center.

Zeng, J. (2014). Contingent capital structure. Technical report, Working Paper.

Nederlandse Samenvatting (Summary in Dutch)

Dit proefschrift richt zich op twee bancaire instrumenten die bedoeld zijn om de bankkapitalisatie te vergroten en de excessieve die zijn ontstaan sinds de financiële crisis van 2008 te verminderen. De eerste twee hoofdstukken bespreken Contingent Convertible Capital, en het derde hoofdstuk gaat in op de leverage ratio-eisen en de repomarkt. Contingent Convertible Capital (CoCo's) zijn effecten die als schuld fungeren en worden omgezet in eigen vermogen of (gedeeltelijk) afgeschreven wanneer het kapitalisatieniveau van de bank lager is dan een bepaalde vooraf bepaalde ratio van Core Equity Tier 1 (CET1) ten opzichte van Risico-gewogen activa. In hoofdstuk 2 ontwikkel ik een theoretisch model om het effect van een bank met meerdere CoCo's op de bankbalans op de financiële stabiliteit te onderzoeken, aan de hand van cash-in-the-market pricing (Allen and Gale, 1994) en global games (Goldstein and Pauzner, 2005) methodologieën. Ik analyseer CoCo-buffers met triggers op verschillende kapitalisatieniveaus, en ik concludeer dat deze een negatief effect hebben voor de bail-in-capaciteit van CoCo's. Market-based triggers leiden tot voortijdige conversie en overhaast verkoop van eigen vermogen. Ik vergelijk de belangrijkste kenmerken van CoCo's in termen van vermogensoverdracht en het type mechanische trigger voor banken met tweelagige CoCo-structuren, en beargumenteer dat book-based triggers vanuit stabiliteitsperspectief het meest voordelig kunnen zijn, zolang ze de verwachte kredietverliezen in acht nemen. In hoofdstuk 3, geschreven met Sweder van Wijnbergen en Mahmoud Fatouh, bekeken wij of de impact van CoCo's en de vermogensoverdrachten die daardoor ontstaan, afhankelijk is van het risicogedrag van de bank die ze uitgeeft. We bekijken ook regelgevingsarbitrage: proberen banken door het uitgeven van CoCo-obligaties risicovolle prikkels om risico te nemen in stand te houden wanneer toezichthouders deze verminderen door hogere kapitalisatieratio's? We testen het op een dataset van Britse banken, die samen de meeste CoCo- uitgaven in Europa hebben. Onze dataset combineert bankbalansgegevens met interne metingen van de Bank of England op bankconcurrentie en macro-economische onzekerheid in het VK. Bijna alle CoCo-obligaties die we bestuderen converteren naar aandelen, en we berekenen de verwachte vermogensoverdracht die zal ontstaan bij de conversie, op basis van historisch waargenomen dalingen van aandelenkoersen in tijden van crisis. We gebruiken parametrische (Heckman, 1976), semi-parametrische (Cosslett, 1991; Ahn and Powell, 1993) en niet-parametrische (Lee, 2009; d'Haultfoeuille et al., 2019) schattingen die de selectie-effecten bepalen, en daarnaast evalueren we de impact van CoCo's met behulp van statisch- (gepoolde OLS) en dynamisch- (Arellano-Bond) gespecificeerde modellen. Hoewel we op selection bias testen en deze afwijzen, laten we zien dat de uitgifte van CoCo-obligaties een sterk positief effect heeft op risico-nemend gedrag, wat ook geldt voor conversieparameters die de verwatering voor bestaande aandeelhouders bij conversie verminderen. Een hogere volatiliteit versterkt de impact van CoCo-obligaties op het risico-nemend gedrag. In hoofdstuk 4, dat in samenwerking met Quynh-Anh Vo is geschreven, onderzoeken we hoe het niveau waarop banken regelgevingsbeperkingen toepassen van invloed is op hun investeringen en hun activarisico . We ontwikkelen een theoretisch model en kalibreren dit voor Britse banken. De bank kan een portefeuillemix kiezen van een belegging met een hoog risico en een hoge marge, die we modelleren als kredietverlening, en een belegging met een laag risico en een lage marge waarvoor we de Britse goudrepomarkt gebruiken. We gebruiken bankbalansgegevens en een vertrouwelijke gegevensset van de Bank of England over Britse gilt repotransacties voor onze kalibratie. Onze belangrijkste bevinding is dat de impact aanzienlijk verschilt afhankelijk van welke regelgevende beperkingen op het geconsolideerde niveau van de groep belangrijk zijn. Zolang op geconsolideerd niveau alleen de leverage constraint van belang is, heeft de allocatie van restricties geen negatieve impact op de veerkracht van banken. Het zou echter kunnen leiden tot een toename van het activarisico van banken in het geval dat alleen de Value-at-Risk-beperking op groepsniveau van belang is. We constateren ook dat het bedrijfsmodel van banken van belang is voor deze kwestie. We splitsen onze steekproef met behulp van de methodologie van beschreven door Roengpitya et al. (2014) op in kapitaalgeoriënteerde wholesalebanken en retailbanken, en stellen vast dat de retailgroep vergelijkbare resultaten heeft wat betreft het nemen van risico's als de gemiddelde bank, terwijl de wholesale- en kapitaalgeoriënteerde groep tegenovergestelde resultaten opleveren.

The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus University Rotterdam, University of Amsterdam and VU University Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. The following books recently appeared in the Tinbergen Institute Research Series:

721. M. LI, *Essays on Time Series Models with Unobserved Components and Their Applications*
722. N. CIURILĂ, *Risk Sharing Properties and Labor Supply Disincentives of Pay-As-You-Go Pension Systems*
723. N.M. BOSCH, *Empirical Studies on Tax Incentives and Labour Market Behaviour*
724. S.D. JAGAU, *Listen to the Sirens: Understanding Psychological Mechanisms with Theory and Experimental Tests*
725. S. ALBRECHT, *Empirical Studies in Labour and Migration Economics*
726. Y.ZHU, *On the Effects of CEO Compensation*
727. S. XIA, *Essays on Markets for CEOs and Financial Analysts*
728. I. SAKALAUSKAITE, *Essays on Malpractice in Finance*
729. M.M. GARDBERG, *Financial Integration and Global Imbalances*
730. U. THUMMEL, *Of Machines and Men: Optimal Redistributive Policies under Technological Change,*
731. B.J.L. KEIJSERS, *Essays in Applied Time Series Analysis*
732. G. CIMINELLI, *Essays on Macroeconomic Policies after the Crisis*
733. Z.M. LI, *Econometric Analysis of High-Frequency Market Microstructure*
734. C.M. OOSTERVEEN, *Education Design Matters*
735. S.C. BARENDSE, *In and Outside the Tails: Making and Evaluating Forecasts*
736. S. SÓVÁGÓ, *Where to Go Next? Essays on the Economics of School Choice*
737. M. HENNEQUIN, *Expectations and Bubbles in Asset Market Experiments*
738. M.W. ADLER, *The Economics of Roads: Congestion, Public Transit and Accident Management*
739. R.J. DÖTTLING, *Essays in Financial Economics*

740. E.S. ZWIERS, *About Family and Fate: Childhood Circumstances and Human Capital Formation*
741. M. KUTLUAY, *The Value of (Avoiding) Malaria*
742. A. BOROWSKA, *Methods for Accurate and Efficient Bayesian Analysis of Time Series*
743. B. HU, *The Amazon Business Model, the Platform Economy and Executive Compensation: Three Essays in Search Theory*
744. R.C. SPERNA WEILAND, *Essays on Macro-Financial Risks*
745. P.M. GOLEC, *Essays in Financial Economics*
746. M. SOUVERIJN, *Incentives at Work*
747. M.H. COVENEY, *Modern Imperatives: Essays on Education and Health Policy*
748. P. VAN BRUGGEN, *On Measuring Preferences*
749. M.H.C. NIENTKER, *On the Stability of Stochastic Dynamic Systems and Their Use in Econometrics*
750. S. GARCIA-MANDICÓ, *Social Insurance, Labor Supply and Intra-Household Spillovers*
751. Y. SUN, *Consumer Search and Quality*
752. I. KERKEMEZOS, *On the Dynamics of (Anti) Competitive Behaviour in the Airline Industry*
753. G.W. GOY, *Modern Challenges to Monetary Policy*
754. A.C. VAN VLODROP, *Essays on Modeling Time-Varying Parameters*
755. J. SUN, *Tell Me How To Vote: Understanding the Role of Media in Modern Elections*
756. J.H. THIEL, *Competition, Dynamic Pricing and Advice in Frictional Markets: Theory and Evidence from the Dutch Market for Mortgages*
757. A. NEGRIU, *On the Economics of Institutions and Technology: a Computational Approach*
758. F. GRESNIGT, *Identifying and Predicting Financial Earth Quakes using Hawkes Processes*
759. A. EMIRMAHMUTOGLU, *Misperceptions of Uncertainty and Their Applications to Prevention*
760. A. RUSU, *Essays in Public Economics*

761. M.A. COȚOFAN, *Essays in Applied Microeconomics: Non-Monetary Incentives, Skill Formation, and Work Preferences*
762. B.P.J. ANDRÉE, *Theory and Application of Dynamic Spatial Time Series Models*
763. P. PELZL, *Macro Questions, Micro Data: The Effects of External Shocks on Firms*
764. D.M. KUNST, *Essays on Technological Change, Skill Premia and Development*
765. A.J. HUMMEL, *Tax Policy in Imperfect Labor Markets*
766. T. KLEIN, *Essays in Competition Economics*
767. M. VIGH, *Climbing the Socioeconomic Ladder: Essays on Sanitation and Schooling*
768. YAN XU, *Eliciting Preferences and Private Information: Tell Me What You Like and What You Think*
769. S. RELLSTAB, *Balancing Paid Work and Unpaid Care over the Life-Cycle*
770. Z. DENG, *Empirical Studies in Health and Development Economics*
771. L. KONG, *Identification Robust Testing in Linear Factor Models*