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Risk-taking and uncertainty: do contingent convertible (CoCo) bonds increase the risk appetite of banks?

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Abstract

We assess the impact of contingent convertible (CoCo) bonds 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 try to maintain risk-taking incentives by issuing CoCo bonds, when regulators reduce them through higher capitalisation ratios? 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 economic volatility amplifies the impact of CoCo bonds on risk-taking.

Key words: Contingent convertible bonds, risk-taking, bank capital structure, selection bias.

JEL classification: G01, G11, G21, G32.

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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 some banks. Contingent convertible (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 regulators' focus 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.

In this paper we show that CoCo bonds in their present form can substantially increase risk-taking incentives, and this effect is amplified if the original shareholders are less diluted upon conversion/write-down. Even though we do not find evidence of selection bias in the decision to issue CoCo bonds, banks do increase their risk-profile after issuance. 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: trigger level, trigger type and conversion type. The trigger level is the pre-specified capitalisation level at which the conversion would take place, and the trigger type indicates whether the trigger is evaluated at market or book-based indicators.[1] Under Basel III capital requirements the trigger level has to be specified as a ratio of Common Equity Tier 1 capital (CET1) to risk weighted assets and has to be 5.125 % or higher for CoCos to be admissible as Tier 1 (T1) capital. The last component is the conversion type, which specifies 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 balance sheet, or conversion to equity (CE), where the bonds are converted into equity shares at a pre-specified price which

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

may depend on market indicators. These securities became prominent in the post-2008 European financial system, as banks can cover up to 25% of their minimum (risk-based) Tier 1 capital requirements with CoCo bonds.[2]

There is an open empirical debate concerning the impact of CoCo bonds on bank risk-taking behaviour, and the extent to which this behaviour is dependent on the conversion type selected by issuing banks. CoCo bonds can also be classified based on the direction of the wealth transfer in case of conversion: if conversion would make shareholders gain wealth, then the CoCo bonds are non-dilutive for existing shareholders, and dilutive otherwise. In the empirical literature so far, authors use accounting values of shares to determine the conversion price, or compared between PWD CoCo bonds and CE bonds without incorporating the heterogeneity 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 dilutive/ non-dilutive CoCo distinction is the meaningful one from a risk-taking incentive point of view. 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 (non-dilutive) and reduce risk-taking incentives when the wealth transfer goes from existing shareholders to the CoCo holders (dilutive). 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 predicts.

We focus on the potential effects of CoCo bonds on banks' risk-taking profile.

[2]To qualify, CoCos 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.

The research aims are three fold. First, we explicitly test for sample selection bias: are banks with a greater risk appetite more inclined to issue Coco bonds? Second, we test the impact of CoCo bonds and their dilution on risk-taking, by constructing a measure for the market price of equity at conversion, and the respective size of dilution upon conversion. Lastly, we compare whether results differ based on market or accounting-based measures of riskiness.

We empirically test whether having CoCo bonds on the banks' balance sheet changes the risk-taking behaviour. This analysis potentially suffers from a sample selection bias: if banks that issue CoCo bonds do so because of other characteristics driving risk-taking, a simple regression analysis would not be enough. For example Chan and van Wijnbergen (2017) suggested a regulatory arbitrage hypothesis. They hypothesize that institutions issue certain types of CoCo bonds to circumvent the risk-taking incentives which arise from regulatory capital requirements. Hence, if banks aim to take on more risk, they have incentives to issue non-dilutive CoCo bonds as opposed to dilutive ones. To the best of our knowledge, we are the first to test empirically for such a selection bias.

Second, we study how the size of expected dilution/gain for shareholders from a CoCo conversion relates to banks' risk-taking behaviour. For that we use in our empirical analysis a proxy for market-based prices of equity at conversion. 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 (Berg and Kaserer, 2015). 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 more accurately than a simple distinction between PWD and

CE CoCo bonds allows. We also 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 on market-based risk measures of risk-taking with the results derived from analysing an accounting-based proxy. We find that the market-based measures conform to the theory predictions but the results based on the accounting based measure do not.

In terms of our sample, we focus on the UK, the largest CoCo bond market in Europe, with 35% of all going-concern (Additional Tier 1) CoCo bond issuances.[3] 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 42 out of the 46 CoCo bonds in our UK sample are conversion-to-equity.

When analysing our results, we do not find enough evidence to support the regulatory arbitrage hypothesis. More precisely, the choice of CoCo bond issuance does not seem to be driven by firms' risk-taking behaviour. 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.

We do find that the issuance of CoCo bonds has a positive and significant impact on asset risk of the issuing banks. So even though we find that firms do not self-select in CoCo issuance based on their risk profile (regulatory arbitrage hypothesis), *ex-post* the issuance will lead to a positive relationship to asset risk. 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,

[3] At the end of 2018, UK banks had CoCo bonds worth EUR 54.208 billion, out of EUR 158.2 billion in total in Europe.

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 estimations which use market measures of risk as dependent variable, and not for book-based measures. A potential interpretation is that markets react faster or perceive differently firm decisions which may not be fully reflected in accounting measures. The results also show that the interaction between higher macroeconomic uncertainty and CoCo bonds increases asset risk.

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 be able to 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 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 includes 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.

In the theoretical CoCo literature several authors focus on the relation between risk-shifting incentives and CoCo bond issuance. This impact depends on the direction of the wealth transfer between CoCo holders and existing shareholders conditional on conversion(Hilscher and Raviv, 2014; Song and Yang, 2016; Chan and van Wijnbergen, 2017; Martynova and Perotti, 2018; 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.[4] If shareholders stand to lose from a conversion, the impact on risk-taking is actually negative (cf Chan and van Wijnbergen (2017)). They point out that the risk-shifting problem can be addressed through an improved 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 a cap, setting a maximum price to guarantee sufficient dilution.[5] Derksen et al. (2018) construct and calibrate an asset pricing model which captures the link between debt overhang and the decision to choose CoCo bonds to meet capital requirements.

Despite the extensive body of theoretical literature on the impact of CoCo bonds on ex-post risk-taking incentives, there is as of yet little empirical investigation of this issue. Previous empirical 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

[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 (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.

banks with less risky profiles are more likely to issue CoCo bonds, while riskier banks prefer to issue equity instead. We also analyse a similar issue, although for a different reason: we want to test for sample selection bias. Sample selection bias might appear if ex-ante risk characteristics influence the decision to issue CoCo bonds rather than equity potentially 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.

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. The classification of CoCo bonds in existing studies mainly relies into the PWD and CE split.[6] The only empirical paper to classify CoCo bonds into dilutive and non-dilutive at time of issuance is Berg and Kaserer (2015). They find that the majority of CoCo bonds considered are non-dilutive, based on a sample size of 24 CoCo issuances. In our work, we analyse 46 CoCo bonds, and construct a measure for expected dilution which takes into account the expected number of shares issued at the time of a CoCo conversion, and the probability of conversion.

Other empirical CoCo work deals with the market response/market perception of CoCo bonds. Hesse (2018) analyse market reactions to increased risk-taking incentives,Fiordelisi et al. (2019) study the fear of conversion and Ammann et al. (2017) focus on announcement effects of CoCo issuances. They distinguish between PWD CoCos and CE CoCos without recognizing the dilutive heterogeneity within the class of CE CoCos.

Finally, the past decade, during which all existing CoCo bonds have been issued,

[6] 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.

has also seen changes in market volatility and 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 competition 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 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). There is mixed evidence on the link, and most importantly, causality between competition and risk-taking. de Ramon et al. (2020) show that the effects of competition on risk-taking are not uniform: UK banks and building societies which are close to insolvency exhibit a positive relationship - more competition suggests a decrease in risk, while the opposite holds true for foreign (non-UK) owned banks and healthy building societies. 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.

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.

2.1 Data

Our focus is on U.K. banks and building societies. Building societies offer a much more limited range of services compared to traditional commercial banks,focusing on mortgages. They are not listed at the stock market, but they have Credit Default Swaps. We have a sample of 15 firms, 10 of which issued CoCo bonds between 2013 to 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, but the number of observations varies per bank.[9] We combine proprietary data from Bank of England with publicly available data. A summary of the data collection is in Table 1.

We capture the universe of Additional Tier 1 (AT1) UK CoCo issuances between 2013-2018, which comprises of 46 issuances. They have been issued in four different currencies - Pound Sterling, Euro, US Dollar and Singaporean Dollar. We transform all non-GBP data into GBP by using the average exchange rate against the sterling on a semi-annual basis. We obtain daily FX rates against the sterling from the Bank

[7]The 10 CoCo issuing banks are: HSBC Holdings PLC, Barclays PLC, Santander UK Group Holding PLC, Standard Chartered PLC, One Savings Bank PLC, CYBG PLC, RBS PLC, Lloyds Banking group PLC, Nationwide Building Society, Coventry 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 1: Data sources

Variable	Nr of firms	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	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
Macroeconomic uncertainty	-	Semi-annual	2000-2018	Bank of England internal measurement
GPD growth	-	Quarterly	2000-2018	Office for National Statistics

of England exchange rate statistics Database. The number of issuances varies widely across banks, from HSBC which is the biggest issuer with 13, to only one issuance for banks such as One Savings or Coventry Building Society.

We retrieve from Yahoo Finance the daily adjusted close stock prices for the 10 listed banks in our sample at London Stock Exchange. FTSE100 is our benchmark for market returns, and the 10Y UK gilt rate is the risk free measure. We retrieve daily values of CDS spreads on 5 year subordinated debt for 9 firms 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 are retrieved from SNL, and from annual bank reports when SNL data was not available. All book-based measures are reported end-period. The banking competition level, and the measure for macroeconomic uncertainty in the U.K. are sourced from internal Bank of England measurements.

Table 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.

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). The bank type implies a classification in commercial banks, mixed or investment banks. Commercial banks take on more deposits, thus the ratio of deposits to liabilities is very high. By 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 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 to total assets (NPL ratio) 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 Returns on Assets (ROA) plus the fraction of equity to total assets, and the volatility of ROA (accounting based insolvency risk). This book measure suffers from a similar problem as the NPL ratio one.

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 firms. From the listed firms, 9 are CoCo issuers, and there is large heterogenity in the timing of their first CoCo issuance, which we exploit in our analysis.

We derive the asset beta from the equity beta by taking into account leverage. Specifically we estimate β_{asset} per bank by regressing $\frac{\text{total assets}}{\text{common equity}}$ on equity beta : $\beta_{\text{equity}} = \frac{Assets}{TotEquity}\beta_{\text{asset}}$, where L are total liabilities and TE total common 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 out of the 15 firms, from which 7 are CoCo issuers. Here we also exploit the timing heterogeneity of issuance. 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

[10]e.g. The asset beta starts in 2001 H2, as it uses values from 2000H1 up to and including 2001 H2.

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 - all measures are annualized and retrieved from SNL. We compute the standard deviation of ROA using the past three semi-annual observations up to and including the current half-year.

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 one of our key contributions to the CoCo bond literature. 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 at time t of bank i.

A measure which incorporates the degree of share dilution after conversion comes

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

[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, so those would be time dependent.

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:

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

where R is the value of asset returns, D_d are deposits, D_s is the total value of CoCo debt (D_s + D_d- total liabilities) , N is the total number of shares per unit of CoCo (conversion rate) and $N = P_0/P_c$: initial price/conversion price stipulated in the contract. More generally, C[R, D] is a call option with current value R and strike price D - outstanding liabilities. Extrapolating from this method, our simplified measure of wealth transfer is:

$$MarginalWT_{i,t} = \frac{\text{Mrktcap}_{i,t} + CoCo_{i,t}}{a_{i,t} + N \cdot CoCo_{i,t}} - \frac{\text{Mrktcap}_{i,t}}{a_{i,t}} \tag{2}$$

where $a_{i,t}$ is the total number of ordinary shares of bank i at time t [13], $\text{Mrktcap}_{i,t}$ is the market capitalisation, calculated as the number of existing shares multiplied with the estimated price of a share at conversion, and $CoCo_{i,t}$ is the total CoCo amount converted. The first term denotes the value per share in case the CoCo bonds are 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

[13] Note that Chan and van Wijnbergen (2017) assume that the total number of shares is 1, so their second term is, in fact, divided by 1.

issuance per bank at time t. We find that in our sample none of the issuing firms called a CoCo bond and replaced it with a new issuance.[14]

We use two different estimates for the share 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),

[14] A CoCo bond has a minimum 5 year maturity. Our earliest issuance is from November 2013 (Barclays), so the earliest date for them to call the CoCo would have been November 2018. The last CoCo issued by Barclays in our sample is from August 2018. None of the CoCos issued from 2014 onwards would have been eligible to be called.

where instead of considering default as the threshold conversion point, we use the CoCo conversion trigger requirement stipulated in the prospectus. The 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.[15] Using it, we calculate the distance to conversion and probability of conversion using the asset value and asset volatility. The distance to conversion is the distance between the expected value of the asset and the conversion point. Thus,

$$DC(t) = \frac{log(\frac{V_A}{\lambda D}) + (r - \frac{1}{2}\sigma_A^2)(T - t)}{\sigma_A \sqrt{T - t}} \tag{3}$$

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 $T = 1$.

The expected wealth transfer: the wealth transfer and the distance to conversion

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,

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

$$TotalWTCoCo_{i,t} = \phi(-DC_{i,t}) \cdot MarginalWT_{i,t} \cdot a_{i,t} \tag{4}$$

[15]See Appendix for the derivation.

where $\phi(.)$ is the normal inverse cumulative distribution function.

Macroeconomic uncertainty, competition and other variables

The level of competition (Comp) is measured using the Boone indicator calculated by de Ramon and Straughan (2016), and based on Boone (2008). This measures competition in the UK banking sector alone, while we have in our sample also large institutions which are active in international markets. Hence, we caveat that this variable would not necessarily apply to all the firms in our sample. The correlation we find between risk-taking and competition would therefore be an imperfect measure for capturing the link. Generally, 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.

The level of uncertainty (Uncty) is measured using the quarterly uncertainty indicator produced by the Bank of England's Monetary Analysis Directorate. 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 inspired by Agoraki et al. (2011) and Avdijev et al. (2020) 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.

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. 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, and 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.

2.3.1 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 total assets ratio - the "Debt" variable, which measures the main source of financing for the bank, and is a measure of leverage. 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 security issuance variable is most likely a better instrument than the Debt ratio, and this is why we later on keep only the security issuance variable for the semi-parametric Cosslett (1991) selection method.

The selection equation (first stage) is:

$$\text{CoCobank}_i = \beta_0 + \beta_1 Dep/Liab_{i,t} + \beta_2 Debt_{i,t} + \beta_3 \text{SecurityIssuance}_{i,t} + \eta_{i,t} \tag{5}$$

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 - $Dep/Liab$ - deposits to liabilities, $Debt$ -total liabilities to total assets ratio and $SecurityIssuance$ - number of security issuances. The debt ratio is a measure for leverage ratio, and indicates the main source of funding for a firm: if the value is > 0.5, then debt is the main source of financing. The deposits to liabilities ratio indirectly captures the business model of a bank. Investment banks have a low deposits to liabilities ratio, while retail-oriented have a higher ratio. Note that all 15 firms in our sample are part of the selection equation.

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 response (second stage) equation is:

$$\begin{aligned} r_{i,t} =& \beta_4 + \beta_5 \text{GDPgrowth}_{t-1} + \beta_6 Size_{i,t-1} + \beta_7 \text{CoCoDummy}_{i,t-1} + \beta_8 \text{TotalWTCoCo}_{i,t} \\ & + \beta_9 Dep/Liab_{i,t} + \beta_{10} Uncty_{t-1} + \beta_{11} Comp_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

and the macro variables are GDPgrowth - GDP growth, $Uncty$ - macroeconomic uncertainty, and $Comp$ is the measure of UK 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 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 (5), but the estimation method is semiparametric. Based on these estimates, we predict the scalar outcome for a bank to be CoCo issuing $v_{i,t} = (\hat{\gamma}Z) = \hat{\gamma}Z$, 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.[16] If the value $v_{i,t} = (\hat{\gamma}Z)$ falls in section M_j, then the dummy variable $D_{i,j}$ takes a value of 1, and 0 otherwise. The dummy variables are then inserted in the response/ second stage

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

equation, which we estimate with 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 for a firm to be a CoCo issuer 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. By 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 (6).

2.3.2 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 a lack of instruments, and it has a distribution-free estimator. The 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, the assumption would be 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 a plausible 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.

2.3.3 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 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:

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

$$\beta_4 \mathrm{Dep/Liab}_{i,t-1} + \beta_5 \mathrm{CoCoDummy}_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

We augment the specification to test for the impact of uncertainty and competition, and the wealth transfer measure:

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

$$+\beta_5 Uncty_t + \beta_6 \text{Dep/Liab}_{i,t-1} + \beta_7 \text{CoCoDummy}_{i,t-1} + \beta_8 \text{TotalWTCoCo}_{i,t} + \varepsilon_{i,t} \quad (8)$$

Adding the wealth transfer measure, we test the secondary effect: does dilution size also impact risk-taking, or issuance alone matters? We additionally incorporate the competition and macroeconomic uncertainty to test whether they play a role on risk-taking. Finally, we augment the model with interaction terms: Inter Uncty = uncertainty $*$ CoCo dummy, Inter Comp = competition $*$ CoCo dummy. These are meant to capture whether having CoCos on the balance sheet amplifies the risk-taking behaviour in the presence of high uncertainty or high competition.

2.3.4 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:

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

$$\beta_4 \text{Dep/Liab}_{i,t-1} + \beta_5 \text{CoCoDummy}_{i,t-1} + \beta_6 \text{TotalWTCoCo}_{i,t} + \varepsilon_{i,t} \quad (9)$$

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

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

$$+\beta_5 Uncty_t + \beta_6 \text{Dep/Liab}_{i,t-1} + \beta_7 \text{CoCoDummy}_{i,t-1} + \beta_8 \text{TotalWTCoCo}_{i,t} + \varepsilon_{i,t} \tag{10}$$

Lastly, we also add interaction terms in this specification.

3 Descriptive statistics and empirical results

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.

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

Table 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

Table 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

issuers both in number of issuances and amount outstanding, with U.K. having issued 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 between 2013 to 2018, 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 in our sample. 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 after the end of our sample 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. In the UK, the supervisory expectation for AT1 CoCo bonds is that they are issued at a trigger level above or equal to 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 2.

We report on the key descriptive statistics of our derived CoCo variables in Table 4.[17] 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 GBP 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. The two wealth transfer measures only exist for listed banks, so we cannot generalise the result for Building Societies. We still use the issuance information for the CDS and z-score analysis, and in the selection equation in the selection bias analysis.

Lastly, we present descriptive statistics for macroeconomic variables and bank control variables in Table 12. We report all values in GBP, unless otherwise stated.

3.2 Selection bias results

Full Information Maximum Likelihood

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

The first two columns in Table 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 (bottom part of Table 5) 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 ratio, 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.[18] 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 Table 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.

[18] 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 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)
Nfirst stage	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.

Columns (3) and (4) in Table 5 illustrate the results of the two-step Heckman estimator. The selectivity effect is summarised by *lambda*.[19] 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 6, and the full estimation results can be found in Table 13.

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.

Table 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 13.

Semiparametric two step selection models

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

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 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.

Exteme 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 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.

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 9 and 14. The coefficient of the lagged dependent variable is positive and statistically significant at a 1% level for all four risk measures [20], and so we accept the dynamic model instead of the static specification. We did not explicitly choose instruments for the GMM estimation, but the statistical algorithm we employed automatically selected them.

[20] See Tables 15, 17, 19.

Table 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	semiparametric	semiparametric
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 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***]

Table 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

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

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. This only applies for banks, as building societies do not have a wealth transfer measure. 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 shareholders 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 specification. Macroeconomic uncertainty and competition have a small, but significant positive economic impact on asset risk - they increase the value of asset beta with 0.000384, and 0.000253 respectively (column (2) of Table 9).

In the model specification with interaction terms (Table 14) 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. By 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 CoCo bonds on their balance sheet do not self-select into CoCo issuance based on their risk profile. We test this using various selection bias specification models. Nonetheless, even though we lack evidence for a selection effect at issuance, we find that firms with CoCo bonds on their balance sheet take more asset risk. This result is consistent for both the static and dynamic econometric specification. 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[21] Both banking competition and macroeconomic uncertainty have a positive and statistically significant association with asset beta and CDS spreads in the dynamic model, and they also bring on an additional positive association on CoCo impact on bank risk-taking decisions.

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.

We perform additional robustness checks in terms of model specification [22]. 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

[21] 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

[22] Additional robustness tables are available upon request

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.

4 Conclusion

In this paper we assess the impact of CoCo bonds on risk-taking. We add three novelties to the existing literature. Firstly, we explicitly test for sample selection bias: are banks with a greater risk appetite more inclined to issue CoCo bonds? Secondly, we include the extent to which CoCo bonds will dilute shareholders upon conversion and assess its impact on risk-taking. Lastly, we explicitly distinguish between market- and accounting based measures of riskiness when assessing the CoCo bond impact.

We test the regulatory arbitrage hypothesis in a CoCo setting, which argues that a bank's decision to issue is determined by incentives to ex-post increase their risk-taking behaviour, but we find no compelling evidence for this hypothesis. In a wide range of tests we either find no statistical significance of selection bias, or when we do, it has a negligible economic impact. Our analysis covered the United Kingdom, as they are by far the largest CoCo bond market in Europe, which accounts for 60% of all conversion to equity at the end of 2018.

We find that the decision to issue CoCo bonds has a positive and statistically 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. Our tests controlled for a host of factors shown to be associated with risk, which include competition and macroeconomic uncertainty. We find a positive and statistically significant association between competition and risk, but the economic impact seems to be small. There was no clear direction on the association between macro uncertainty and risk in our setup, as results were ambiguous 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 relationship between CoCo bonds and risk-taking.

Our results have several limitations. Building societies are not listed at the stock exchange, so we could not compute the market dilution parameter for them. They still feed in the selection bias first stage regression, and in the CDS analysis with their choice to issue. Recent work on competition shows that the relationship between competition and risk-taking is not uniform across banks and building societies (de Ramon et al., 2020). We do not control for this, so our results for the link between the two is potentially not robust. Additionally, we find that our results are not robust across all measures of risk - a potential explanation could be that markets react faster than book-based measures. Our sample takes into account only UK firms, so we cannot generalise to other countries or periods outside our sample. In that light, our sample covers a relatively small number of firms, so the power of the tests and any inferences has to be carefully weighted.

Summing up, our empirical results confirm earlier CoCo theories (Chan and van Wijnbergen, 2017; Fatouh and McCunn, 2019), according to which the size of the dilution matters for risk-taking incentives. We obtain evidence to support that less dilutive CoCo bonds increase banks' risk-taking incentives, as existing shareholders can potentially gain from CoCo conversion.

These results suggest that policymakers would be well advised to consider elements beyond the level of capital requirements or the share which can be met by issuing CoCo bonds, when they want to control the risk-taking incentives for banks. 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 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.

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A 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):

$$E_t = A_t\theta(d) - De^{-r_f T}\theta_t(d - \sigma_a\sqrt{T}) \tag{11}$$

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 (11) also implies a relation between the two volatilities, which gives us a second equation for the two unknowns in

$$\frac{dE_t}{E_t} = \frac{\theta dA_t}{E_t} = \theta\frac{A_t}{E_t}\frac{dA_t}{A_t} \tag{12}$$

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 (11) and (12).

B Variable description

C Descriptive statistics

Table 10: 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 total assets 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

Table 11: 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 12: 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 13: 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 14: Dynamic panel data specification with interaction terms, and robust std errors. Bank risk measure: Asset beta

	(1)	(2)	(3)	(4)	(5)
	Asset beta	Asset beta	Asset beta	Asset_beta	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

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

D Robustness tables

Table 15: Dynamic panel data specification with robust std errors. Risk measure: Equity beta

	(1) Equity beta	(2) Equity beta	(3) Equity beta	(4) Equity beta	(5) Equity beta	(6) 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 16: Dynamic panel data specification with robust std errors and interaction terms. Risk measure: Equity beta

	(1) Equity beta	(2) Equity beta	(3) Equity beta	(4) Equity beta	(5) 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 17: 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 18: 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 19: 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 20: Dynamic panel data specification with robust std errors and interaction terms. Risk measure: Z-score

	(1) Z-score	(2) Z-score	(3) Z-score	(4) Z-score	(5) Z-score	(6) 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

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

Table 21: Static panel data specification with bank fixed effects and interaction terms. Bank risk measure: Asset beta

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asset_beta	Asset_beta	Asset_beta	Asset_beta	Asset_beta	Asset_beta	Asset_beta	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 22: Static panel data specification with bank fixed effects and interaction terms. Bank risk measure: Equity beta

	(1) Equity beta	(2) Equity beta	(3) Equity beta	(4) Equity beta	(5) Equity beta	(6) Equity beta	(7) Equity beta	(8) 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 23: 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 24: 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

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