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## **Bank Liquidity Regulation and Risk\***

Foly Ananou<sup>a,1</sup> Dimitris Chronopoulos<sup>b</sup> Amine Tarazi<sup>a,c</sup> John O.S. Wilson<sup>b</sup>

<sup>a</sup> Université de Limoges, LAPE, 5 rue Félix Eboué, 87031 Limoges Cedex 1, France

<sup>b</sup> University of St Andrews, Centre for Responsible Banking & Finance, Gateway Building, St Andrews, Fife KY16 9RJ, UK

<sup>c</sup> Institut Universitaire de France (IUF), 1 rue Descartes, 75231 Paris Cedex 05, France

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#### **Abstract**

We investigate the impact of liquidity requirements on bank risk. Using the Netherlands as a setting, we investigate the impact of the 2003 liquidity balance rule (LBR) on individual bank default risk and systemic risk. Using the differential regulatory treatment of Dutch and other Eurozone banks (that were not subject to the LBR) to overcome identification concerns, we find that following the introduction of the LBR, the individual risk and systemic risk of Dutch banks declines relative to unaffected counterparts. The observed decline in risk is at the expense of lower profitability (driven by a decline in interest income), which is not offset by the lower funding costs of treated banks following the enactment of the LBR. Our findings also suggest that better financing conditions allow Dutch banks to increase the balance sheet shares of deposits and capital.

JEL Classification: G21, G28

**Keywords:** Banking; liquidity regulation; Netherlands; propensity score matching; quasi-natural

experiment; risk; stability; systemic risk.

Email addresses: foly.ananou@etu.unilim.fr (F. Ananou), dc45@st-andrews.ac.uk (D. Chronopoulos), amine.tarazi@unilim.fr (T. Amine), jsw7@st-andrews.ac.uk (J.O.S. Wilson).

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<sup>&</sup>lt;sup>1</sup> Corresponding author.

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We investigate the impact of liquidity requirements on bank risk. Using the Netherlands as a setting, we investigate the impact of the 2003 liquidity balance rule (LBR) on individual bank default risk and systemic risk. Using the differential regulatory treatment of Dutch and other Eurozone banks (that were not subject to the LBR) to overcome identification concerns, we find that following the introduction of the LBR, the individual risk and systemic risk of Dutch banks declines relative to unaffected counterparts. The observed decline in risk is at the expense of lower profitability (driven by a decline in interest income), which is not offset by the lower funding costs of treated banks following the enactment of the LBR. Our findings also suggest that better financing conditions allow Dutch banks to increase the balance sheet shares of deposits and capital.

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#### 1. Introduction

Until the liquidity shortages that occurred upon the onset of the global financial crisis (GFC) of 2007-2009, empirical research paid scant attention to the importance of liquidity for bank risk. Since then, coordinated international agreements under the auspices of the Basel Committee on Banking Supervision (Basel III standards) have required banks to enhance liquidity via adherence to a liquidity coverage ratio (LCR), which requires banks to hold sufficient high-quality liquid assets to survive a stress scenario spanning one month. The standards also include a net stable funding ratio (NSFR), which requires banks hold a minimum amount of stable funding to withstand a closure of wholesale funding markets (Basel Committee on Banking Supervision, 2009, 2013). Given the importance of liquidity for individual banks, the banking industry, the broader financial system and the real economy, this study investigates the impact of liquidity regulation on bank risk.

Given that banks have myriad of ways to manage liquidity, it is unclear whether liquidity regulations aimed at reducing the maturity mismatch between illiquid assets and liquid liabilities affects individual bank risk (DeYoung and Jang, 2016) and systemic risk (Ibragimov et al. 2011).<sup>2</sup> On the one hand, liquidity regulations mandating higher levels of liquid assets as a buffer against liquidity shocks leads to a subsequent decrease in bank risk and the likelihood of bank runs (Diamond and Kashyap, 2016). Liquidity regulations akin to Basel III enable banks to meet regulatory standards by increasing their capital (Hartlage 2012; Ananou et al. 2021). Thus enhancing their resilience to unexpected adverse balance sheet shocks (Hoerova et al., 2018). In order to comply with liquidity regulations, banks also have the flexibility to shift from wholesale funding to retail deposits. In doing so, banks can reduce the cost of capital, increase profitability, and accumulate capital buffers to withstand negative balance sheet shocks. Moreover, through the mitigation of banks' individual (liquidity) risk, the implementation of liquidity requirements may provide wider benefits by reducing systemic risk.

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<sup>&</sup>lt;sup>2</sup> Bonner et al. (2015) use data from 30 countries and find that the correlation among bank liquidity, market concentration, and bank size is weaker in countries with formal liquidity regulation. The authors contend that liquidity regulations act as substitutes for active liquidity management and limit excessive risk-taking by banks.

On the other hand, holding more retail deposits may increase bank risk in the presence of safety-net guarantees, such as deposit insurance schemes (Lambert et al. 2017; Wagner 2017). The introduction of liquidity regulation may also lead banks to increase investments in more liquid, but lower-yielding assets, leading to a subsequent decline in profitability. Faced with declining profitability, banks may invest remaining funds in riskier investments in order to boost returns (Hoerova et al., 2018; Bosshardt et al. 2021). Prior evidence suggests that when faced with additional liquidity requirements, banks increase lending to households, small and medium-sized enterprises, and corporates (Ananou et al. 2021). Consequently, the introduction of liquidity regulation can increase bank risk. Additionally, banks may respond to liquidity requirements by pursuing similar investment and funding strategies, leading to increased interconnectedness, and increased systemic risk (Lagunof and Schreft, 2001; de Vries 2005; Wagner 2010; Ibragimov et al. 2011). Given that the tools banks use to respond to liquidity constraints can affect risk positively or negatively, the impact of liquidity regulation on individual bank default risk and systemic risk is unclear and remains an open question – one we investigate, and answer is the present study.<sup>3</sup>

Assessing the impact of liquidity regulations on bank risk is not straightforward, given that such rules are often introduced and phased in alongside other forms of safety and soundness regulation. In this study, we overcome these challenges via a research design that uses an unanticipated policy change as a quasi-natural experiment to investigate the impact of liquidity regulation on bank risk. Specifically, we consider the liquidity balance rule (LBR) introduced in the Netherlands in 2003. Under the terms of the LBR, banks are required to hold sufficient high-quality liquid assets to withstand net cash outflows over a 30-day stress period. The LBR is similar to the more recent Basel III liquidity coverage ratio (LCR). However, contrary to the LCR, which was enacted following the global financial crisis, the introduction of the LBR did not occur following a period of financial instability. Thus, it was unlikely that banks and other industry stakeholders (such as shareholders, bondholders, depositors) anticipated the change. Moreover, the LBR applies to Dutch banks only, and not to banks in

<sup>&</sup>lt;sup>3</sup> In common with capital regulation, the extent to which liquidity regulation affects bank risk is closely linked to profitability. An essential feature of Basel III is the addition of liquidity requirements. While there is an extensive literature which investigates the impact of capital regulation on bank risk (Koehn and Santomero, 1980; Kim and Santomero, 1988; Gjerde and Semmen, 1995; Fegatelli 2010; Anginer et al., 2021, among others), to our knowledge this study is among the first to investigate empirically how liquidity regulation affects bank risk.

other Benelux countries (Belgium, Luxembourg) or the rest of the Eurozone. To overcome identification concerns, we use this differential regulatory treatment and investigate how liquidity regulation affects individual bank default risk and systemic risk.

We use a difference-in-differences approach where we estimate the change in the risk of affected banks (subject to LBR requirements) between the pre-LBR and post-LBR period, with the same difference in the risk of a control group of banks (not subject to LBR requirements). To avoid potential selection bias, we follow prior literature (Schepens, 2016; Ananou et al., 2021) and use propensity score matching to construct a control group of similar banks based in Eurozone countries where the LBR does not apply. In further testing, we restrict the control group to: banks from other Benelux countries; and banks from Belgium only. Our baseline model includes bank-level characteristics and country timevarying controls that prior literature considers important determinants of bank risk. We use accounting-based measures of individual bank risk comprising: the standard deviation of the return on assets (which provides insights into the volatility of bank profitability); and a bankdefault risk (Z-score) measure, along with its asset and leverage risk subcomponents is also used to assess the overall risk of bank failure. For the listed banks in our sample, we construct market-based indicators using the standard deviation of daily bank stock returns over a calendar year, (offering a perspective on investor views of bank risk), as well as a market-based version of bank default risk (to capture the likelihood of default as perceived by the market). The marginal expected shortfall (MES) is also used as a measure of systemic risk. The sample period, which spans 1998 to 2008, straddles the introduction of the LBR. Our data set comprises unconsolidated balance sheet, off-balance-sheet, and income statement data for commercial banks from 12 Eurozone member countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain).

Our baseline results show that following the introduction of the LBR, both the individual default risk and systemic risk of Dutch banks decreases relative to counterparts not subject to the LBR. These findings are consistent across both accounting and market-based measures of risk. The observed decrease in risk is more pronounced for banks with relatively lower levels of liquidity in the pre-treatment period. The decline in bank default risk occurs primarily via reduced leverage, as banks become better capitalized. We also find that the enactment of liquidity regulation leads to a decreased contribution to systemic risk. This

suggests that liquidity regulation not only reduces individual bank risk, but also improves financial stability via a decline in systemic risk.

We conduct an impulse-response function analysis to examine the dynamic effects (if any) of liquidity regulation on individual bank default risk and systemic risk. The results of this analysis suggest that the impact of liquidity regulation on bank risk diminishes over a five-year period. Its effect on systemic risk is more transient and diminishes following by the fourth year following the introduction of the LBR.

In a series of additional tests, we investigate how the introduction of the LBR affects bank profitability, interest margins, and the structure and cost of funding. Our findings indicate that following the enactment of the LBR, Dutch banks alter their funding structure by increasing capital and deposits. We also find that profitability declines despite reduced funding costs. A decline in interest revenue at Dutch banks drives this observed decline in profitability. Nevertheless, the impact of the LBR on profitability is short-lived and disappears four years following the introduction of the LBR.

Our baseline results are insensitive to: variations in matching procedures; countries used to match treated and control banks; covariates used in the propensity score matching; and the number of matched banks in the sample to conduct the empirical analysis. A placebo test, which assumes falsely that the LBR is introduced in an earlier time period, confirms the internal validity of our findings. If banks anticipate the introduction of the LBR, we expect a change in bank risk during this earlier period. The results of this placebo test do not show any evidence of anticipation effects. in order to test for regression-to-the-mean (RTM) bias due to matching, we also re-estimate our baseline model using an unmatched sample. The results suggest that our matching approach does not suffer from RTM bias.

Our study contributes to the recent literature on how liquidity regulations affect bank behavior. Salient literature focuses on bank contributions to real economic activity (De Nicolo et al., 2014; Covas and Driscoll, 2014; Duijm and Wierts, 2016; Banerjee and Mio, 2018; Reinhardt et al., 2020; Ananou et al., 2021). In general, this literature identifies several ways that banks comply with liquidity requirements, which ultimately affects their risk. For example, Duijm and Wierts (2016) and Banerjee and Mio (2018) show that the introduction of liquidity regulation requires banks to adjust their balance sheets by increasing high-quality liquid assets and reducing reliance on short-term wholesale funding. In the case of the Netherlands, the setting of the present study, prior evidence indicates that introducing the

LBR led affected banks to change the volume and composition of lending. Bonner and Eijffinger (2016) show that an increase in the rates of longer-term interbank loans is associated with the LBR. More recently, Ananou et al. (2021) document that the enactment of the LBR led to: an increase in the overall volume of lending; a reorientation toward corporate lending; and an increase in deposit and equity funding. None of these aforementioned studies investigate the impact of liquidity regulation on individual bank default risk and systemic risk. 4 With regard to the impact of liquidity regulation on bank risktaking the evidence is limited. Bosshardt et al. (2021) introduce a theoretical model to assess how much risk banks take in order to comply with liquidity requirements (similar to the LCR). The model shows that in reaction to more onerous liquidity requirements, banks with a significant proportion of stable liabilities select riskier long-term investments to maintain profitability. These predictions are supported by data showing that large US LCR-complying banks originate riskier syndicated and mortgage loans when they have more stable funding. Using a large dataset of European banks Chiaramonte and Casu (2017) find that the LCR is unrelated to default risk. Complementing this literature, the present study identifies the causal impact of liquidity requirements on banks' risk and pricing of assets and liabilities.

The remainder of the paper is organized as follows. Section 2 describes the dataset and methodology. In section 3, we present the results of our empirical analysis. Section 4 provides additional evidence to support our main results. Sensitivity checks are reported in section 5. Section 6 concludes.

#### 2. Research design

### 2.1 Data and sample

Our sample period spans 1998-2008 and straddles the introduction of the LBR in 2003.<sup>5</sup> We use a sample of commercial banks from 12 European countries (Austria, Belgium, Finland,

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<sup>&</sup>lt;sup>4</sup> Prior evidence suggests there are a myriad of other factors affecting bank risk-taking including: macroeconomic conditions (Albertazzi and Gambacorta, 2009); competition (Beck et al., 2013; Liu et al., 2013; Goetz, 2018); ownership (Iannotta et al., 2007; Barry et al., 2011); size (De Haan and Poghosyand, 2012); funding structure (Demirguc-Kunt and Huizinga, 2010; Vazquez and Federico, 2015; Khan et al., 2017); capital (Berger, 1995; Giordana and Schumacher, 2017); diversification (Demsetz and Strahan, 1997; DeYoung and Roland, 2001; Lepetit et al., 2008); corporate governance (Berger et al., 2016; Anginer et al., 2018); loan growth (Foos et al., 2010); business models (Altunbas et al., 2011; Kohler, 2015); and supervisory oversight (Kandrac and Schlusche, 2021; Chronopoulos et al., 2023).

<sup>&</sup>lt;sup>5</sup> The main analysis is carried out on the period 2000-2006. The longer sample period enables us to investigate the long-term impacts of the LBR on various bank outcome variables (in section 4 of the paper).

France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain) forming the Eurozone in 2003. We collect accounting data from the BankScope database compiled by Bureau van Dijk. All the banks in our sample report annual financial statements with the fiscal year ending December 31. For each bank, we use unconsolidated data if available. Otherwise, we use consolidated statements. We use commercial banks with at least three consecutive years of observations for net income, total equity, and total assets. This allows us to compute the rolling-window standard deviations, which form a crucial component in the construction of our risk indicators. To minimize the impact of outliers on our results, we eliminate extreme observations (5% lowest and highest values) for each variable of interest. In order to reduce the impact of mergers and acquisitions that occur during the sample period, we also discard all bank-year observations where growth in total assets exceeds 25%. Our final sample (prior to matching) comprises 400 commercial banks, including 16 Dutch banks.

We also construct a subsample dataset of listed banks. In order to do so, we retrieve daily market data from the Bloomberg database. The subsample is restricted to banks with continuously daily traded stocks between January 1st 1998 and December 31st 2008. We obtain (before matching) a final subsample of 117 listed banks. Columns (1) and (3) of Table 1 present information on the geographic distribution of the initial sample of banks.

#### [Insert Table 1 here]

#### 2.2 Methodology

The research design employed in this study allows us to identify the causal impact of liquidity regulation on bank risk. To that end, we rely on the introduction of the LBR in the Netherlands in 2003. This provides exogenous variation in the liquid assets Dutch banks hold. The LBR was announced in January 2003, and Dutch banks had until July 2003 to comply with the requirements (de Haan and den End, 2013). This minimizes the possibility of anticipatory effects and subsequent changes in bank behavior prior to implementation. Given that the LBR was unique to the Netherlands, bank regulators based in other Eurozone

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<sup>&</sup>lt;sup>6</sup> The LBR is conceptually similar to the Basel III LCR, which requires banks to hold a minimum level of liquid assets to meet a stress scenario of outflows. The main difference is in the weighting scheme and the range of items in the stock of liquid assets, which is more extensive for the LBR.

countries did not consider this type of rule until the global financial crisis of 2007-2009, following which the liquidity coverage ratio was introduced (Bonner and Hilbers, 2015). Unfortunately, other regulatory events at national or international level when the LBR was announced and implemented (such as the publication of the preliminary draft of the Basel II requirements) during this period, and thus confound any subsequent analysis of the impacts of the LCR on banks. In the present setting, however, the introduction of the LBR represented an exogenous change to the regulatory environment facing Dutch banks.

The LBR stipulates that banks should hold high-quality liquid assets greater than or equal to net cash outflows over a 30-day stress period. The LBR is defined as:

where *AL* denotes actual liquidity, which comprises the weighted sum of the stock of liquid assets and cash inflow scheduled within the next 30 days, such as securities, interbank assets payable on demand, and debts immediately due or payable by public authorities and professional money-market participants. *RL* denotes required liquidity, which is the weighted sum of the stock of liquid liabilities and cash outflow scheduled within the next 30 days, such as any bank debt immediately callable (e.g., deposits without a fixed maturity). In order to comply with the regulation, a bank's LBR should be at least equal to one. Each item in *AL* and *RL* carries an associated weight to reflect the degree of illiquidity and account for market and funding liquidity risks. The regulator determines these weights (DNB, 2011). For example, asset-backed securities carry a lower weight than high-quality bonds. Wholesale deposits carry a higher weight than retail deposits.

Our analysis is based on a propensity score matched sample combined with a difference-in-differences estimation, which compares the change in risk of Dutch banks between the pre-LBR and post-LBR period, with the change in risk of a similar group of European banks for which the LBR does not apply. The baseline model is as follows:

$$Y_{i,t} = \beta_1(Affected_i \times PostEvent_t) + \delta X_{i,t-1} + \alpha_i + \lambda_t + \varepsilon_{i,t}$$
 (1)

where i indexes bank and t indexes time.  $Y_{i,t}$  denotes various bank risk measures, whether derived from accounting or market data, or pertaining to systemic risk.  $Affected_i$  is a dummy variable equal to one for banks subject to the LBR (Dutch banks), and zero otherwise.

*PostEvent*<sub>t</sub> is a dummy variable for the treatment period, equal to one for the years 2003 to 2006, and zero for the years 2000 to 2002. The  $X_{i,t-1}$  variable represents a vector of bank-level and country-level control variables that prior literature considers important determinants of bank risk. To avoid simultaneity, we lag each of our control variables by one period. The model also includes bank-specific fixed effects,  $\alpha_i$ , to control for unobserved bank heterogeneity, as well as time dummies  $\lambda_t$  to capture time effects common to all banks.

## 2.3 Measures of bank risk-taking, default risk and systemic risk

To measure individual bank risk, we use the standard deviation of the return on assets (*SD(ROA)*), which we compute on a three year rolling-window. The Z-Score is a proxy for bank default risk. We follow established practice and construct a variable, ZSCORE:

$$ZSCORE = \frac{MROA + EQUITY}{SDROA}$$
 (2)

where *MROA* is the three-year rolling window average return on assets, defined as the ratio of net income to total assets, and *CAPITAL* is the ratio of total equity to total assets (Boyd and Graham, 1986; Berger et al., 2004; Laeven and Levine, 2009; Anginer et al., 2021; Beck et al., 2013; Fang et al., 2014 Allen and Gale, 2004; Ashraf, 2017).

We follow Goyeau and Tarazi (1992) and Lepetit et al. (2008) and decompose *ZSCORE* into its constituent components, *Z1* and *Z2*. *Z1* measures asset risk, and *Z2* is a measure of leverage risk. These two measures allow us to capture whether a change in asset and/or leverage risk drives a change in *ZSCORE*. For robustness, we also consider *SD(ROA)*, using four- and five-year rolling windows. We then compute *ZSCORE* with these alternative definitions of *SD(ROA)*.

Given that accounting-based variables may not accurately capture sudden changes in bank risk, we complement these measures with market-based indicators for the listed banks in our sample. Risk is the standard deviation of bank daily stock returns within a calendar year (SD(R)). To assess default risk, we calculate a market-based Z-Score (*MZscore*) as:

$$MZscore = (1+\overline{R})/SD(R)$$
 (3)

where  $\overline{R}$  is the average of bank daily stock returns in a calendar year. We also consider systematic risk (*BETA*) and bank-specific risk (*IVOL*). We obtain *BETA* and *IVOL* by estimating

<sup>&</sup>lt;sup>7</sup> Bank daily stock return  $(R_{i,t})$  is the logarithm of the ratio of two adjacent daily stock prices (i.e.,  $In(Price_t/Price_{t-1})$ ).

the market model for each year:

$$R_{i,t} = a_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{4}$$

where  $R_{i,t}$  is bank i's daily stock return, and  $R_{m,t}$  is the daily return of a market portfolio m. We use the Euro Stoxx Bank Index rate as a proxy for the market portfolio. *BETA* takes the value of the estimated coefficient  $\beta_i$  and *IVOL* is the standard deviation of the residuals from estimating equation (4). For robustness and to ensure that seasonality does not drive our results, we also compute SD(R), MZscore, BETA, and IVOL using daily bank stock returns over the last three months of each year from 2000 to 2006 (Keloharju et al., 2016).

We also consider the marginal expected shortfall ( $MES_{i,t}$ ) as a measure that captures the marginal contribution of bank i to systemic risk. Essentially,  $MES_{i,t}$  reflects the change in the overall risk of the financial system due to a change in the capitalization of bank i. In simpler terms, this measure captures how the stock returns of individual banking institutions react during periods characterized by low market returns. Since the calculation of this measure requires market-based data, we are limited to listed banks. We calculate  $MES_{i,t}$  by first determining the average daily bank returns on the 5% worst days in the stock market during a quarter. That is, when the daily returns of the stock market fall below (or are equal to) their 5th percentile. We then multiply this average by minus one(Acharya et al., 2017). Returns on the Euro Stoxx Banks Index are used as a proxy for the stock market.<sup>8</sup> The systemic risk measure is calculated using quarterly data, which is subsequently aggregated to annual frequency.<sup>9</sup>

#### 2.4 Individual bank control variables

All regressions include a set of control variables expected to affect bank risk. The natural logarithm of total assets (*SIZE*) and the ratio of equity to total assets (*CAPITAL*) account for bank size and capitalization. Larger banks have a greater ability to diversify activities in order to reduce risk (Demsetz and Strahan, 1997). However, because of too-big-to-fail incentives, these banks may assume additional risk (Galloway et al., 1997). We expect bank capitalization to have a negative impact on default risk. However, the impact of capital on

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<sup>&</sup>lt;sup>8</sup> The results are robust to the use of returns on the Euro Stoxx 50 Index as an alternative proxy for the stock market. We report results based on MES computed using the Euro Stoxx Banks Index to focus on the European banking sector.

<sup>&</sup>lt;sup>9</sup> Annual frequency MES values are obtained by taking the maximum of quarterly MES values within a given year. The results are robust to the use of median quarterly MES values as the annual MES for each bank.

risk-taking is unclear. Banks with higher capital ratios (on a market-value basis) are safer and take less risk in order to preserve charter values (Keeley, 1990). However, more stringent capital regulation can encourage banks to take on more risk in order to sustain expected returns to shareholders (Koehn and Santomero, 1980; Kim and Santomero, 1988).

Bank funding is the ratio of deposits to total assets (*DEPOSITS*). We expect banks with a higher deposits-to-assets ratio to be riskier. Prior evidence suggests that when deposits are insured, depositors lack the incentive to monitor activities, thus encouraging banks to take excessive risk (Demirguc-Kunt and Detragiache, 2002; Demirguc-Kunt and Kane, 2002; Barth et al., 2004). We also include the ratio of net loans to total assets (*LOANS/ASSETS*). We expect a negative relationship between the loan-to-total-assets ratio and risk given that loans are normally more stable than nontraditional financial intermediation activities (lannotta et al., 2007).

To control for differences in bank business models, we include the ratio of net non-interest income to net operating income (*NNI*). A greater reliance on non-interest income is associated with higher risk, given that the income from non-interest activities is more volatile and can negatively affect bank stability (Stiroh, 2004; Lepetit et al., 2008, Demirgüc-Kunt and Huizinga, 2010; Altunbas et al. 2011).

To account for operational efficiency, we include the operating expense to operating income ratio (*COST/INCOME*). Under the so-called bad management hypothesis, banks operating at low levels of efficiency have higher costs due to inadequate credit monitoring and inefficient control of operating expenses, which is reflected in lower cost efficiency (Berger and DeYoung, 1997). Declines in cost and revenue efficiency temporally precede increases in risk due to credit, operational, market, and reputational problems. Empirical evidence corroborates this (Shehzad et al., 2010; Barry et al., 2011; Saramiento and Galan, 2017).

A list of all the variables in the empirical analysis is in Table 2. Table 3 presents a correlation matrix of all variables. The pairwise correlations suggest that the independent variables in equation (1) are not highly correlated. Consequently, multicollinearity is not a concern.

[Insert Table 2 here]

[Insert Table 3 here]

#### 2.5 Matching estimation, matched sample and parallel trend assumption

A potential issue when comparing Dutch banks to other Eurozone banks is that they might differ along a number of financial characteristics. These differences in characteristics may suggest that, even in the absence of the LBR, Dutch banks could display different trends in risk relative to Eurozone counterparts after 2003. In order to alleviate concerns regarding potential bias in the coefficient of  $\beta_1$  in equation (1) stemming from such differences in observable characteristics, we use a propensity score matching procedure. This approach allows us to construct a control group of European banks that ensures a balance in observable characteristics between treated and control banks (Roberts and Whited, 2013; Schepens, 2016).

Following Daw and Hartfield (2018), we compute propensity scores using the 2002 levels for: the ratio of total deposits to total assets; the ratio of total equity to total assets; the ratio of liquid assets to total assets; return on assets; real GDP growth; inflation; total assets; lagged *ZSCORE* (*MZscore*); and the average growth rate in *ZSCORE* (*MZscore*) over the pre-treatment period. <sup>10</sup> We select banks of similar size, portfolio composition, capital structure, income, and which operate under similar economic conditions in the pre-treatment period. We use the estimated propensity scores to match each Dutch bank with its three nearest neighbors for the full sample, and five nearest neighbors for the subsample of listed banks. <sup>11</sup> The propensity score matching is executed with replacement. This means that each non-Dutch bank can serve as a control for multiple Dutch banks. This improves the accuracy of the matching procedure (Smith and Todd, 2005).

The matching procedure yields a control group that comprises 42 banks from other Eurozone countries for the broad sample of banks. For the subsample of listed banks, we end up with a control group that comprises 13 banks drawn from other Eurozone countries. Columns (2) and (4) of Table 2 present the distribution of banks in the control group by country. Summary statistics of the full and matched samples are presented in Table 4. Table 4 provides summary statistics for the main variables of interest for the three years prior to the

 $^{10}$  We consider trends in *ZSCORE* (*MZscore*) because all the risk measures are highly correlated, as shown in Table 3. Consequently, we are confident that the other measures of risk in our analysis follow a similar trend. For robustness (section 5), we use trends in SD(ROA), SD(R) and MES to run our matching process. Our findings

remain the same when using these measures.

<sup>&</sup>lt;sup>11</sup> We use five neighbors for the listed banks to gain sufficient observations necessary to compute statistical tests.

introduction of the LBR (panel A), the three years after the introduction (panel C), as well as pre-trends of the risk measures (panel B). The table also reports the results of mean differences tests between Dutch and the broader sample of Eurozone banks from which we select the control group of banks.

The summary statistics show that the difference in means between Dutch banks and the matched group of banks is not statistically significant at the 5% level for all bank characteristics. Moreover, the trends in bank-risk measures are similar between treated and control group banks after the matching in the pre-treatment period. This provides some assurance that the parallel trend assumption (which is key to our identification strategy) is not violated. To further ensure that this assumption holds in our matched sample, we inspect graphically the evolution of the bank risk measures in our analysis from 2000 to 2006 as depicted in Figure 1. The trends in all outcome variables follow similar paths in the pre-treatment period, supporting the notion that the parallel-trends assumption is valid in our setting. However, from 2003 we observe diverging trends for the affected and control banks. This suggests that introducing the LBR affects the financial stability of the Dutch banking system at both bank and system levels.

[Insert Table 4 here]

[Insert Figure 1 here]

We further test for the parallel-trend assumption by performing a placebo test. We assume that the LBR was introduced in 2001 rather than in 2003. We then re-run the matching process. The results are tabulated in row (1) of Table 10 and suggest that the parallel-trend assumption is not violated. Thus, our identification strategy is valid.

#### 3. Results

Baseline results

In this section, we discuss the results of our empirical analysis. Table 5 presents the results of estimating equation (1). We follow established practice when analyzing bank-risk measures (such as the Z-Score or the standard deviation of returns) and apply a log transformation to

all outcome variables (with the exception of MES).<sup>12</sup> The estimated models include bank-specific control variables to capture potential shocks to one of the time-varying determinants of bank risk. We also include year fixed effects to capture effects common to all banks and bank fixed effects in order to account for any unobservable time-invariant bank characteristics.

#### [Insert Table 5 here]

The coefficient of interest  $\beta_1$ , is negative and significant for SD(ROA), SD(R) and positive and significant for ZSCORE, Z2, and MZscore. This suggests that relative to counterparts not subject to the LBR, the risk of Dutch banks declines following the introduction of the LBR. For example, the standard deviation of the return on assets of the average Dutch bank declines by 45% relative to the average bank not subject to the LBR. The ZSCORE increases by 51% for the average Dutch bank relative to the average non-Dutch bank not subject to the LBR. These changes in risk occur via a reduction in leverage. Specifically, we observe a positive impact of the introduction of the LBR on Z2. The impact on Z1 is not significant. Our results also suggest that, on average, the specific risk of Dutch banks decreases relative to counterparts not subject to the provisions of the LBR. This is in line with the view that the introduction of liquidity requirements leads to a decline in both bank risk and the probability of depositor runs (Diamond and Kashyap, 2016; Hoerova et al., 2018).

Liquidity regulation primarily targets the liquidity risk of individual banks (Basel Committee on Banking Supervision, 2013). However, its repercussions may extend to systemic levels. Systemic risk is not solely shaped by individual bank risk-taking, but also by the interconnectedness of banks, which can amplify minor shocks into significant systemwide losses. Our findings thus far provide evidence supporting the effectiveness of LCR-like regulation in reducing individual bank risk. However, it is important to recognize that a reduction in individual bank risk does not necessarily translate into a corresponding decrease in overall systemic risk. Column 9 of Table 5 presents the estimates of the impact of the LBR on systemic risk. The coefficient on  $Affected \times PostEvent$  is negative and statistically significant. This suggests that liquidity regulation is indeed associated with a decreased

<sup>&</sup>lt;sup>12</sup> Lepetit and Strobel (2015) indicate that log-transformed Z-scores may be more appropriate in applied work due to the skewness of Z-scores in levels. They add that the log of the Z-score can be negatively proportional to the log odds of insolvency, giving it a sound probabilistic foundation. For comparability, we harmonize all the variables by applying a log transformation.

contribution to systemic risk. Thus underscoring the importance of such regulations in promoting financial stability at both individual and system levels.

Turning to our control variables, for brevity we focus our discussion on the model specification using the ZSCORE as an outcome variable (column 1 in Table 5). SIZE enters the regression with a positive coefficient, and is statistically significant at the 1% level. This indicates that a 1% increase in SIZE is associated with a 0.7% increase in ZSCORE. This is line with the view that larger banks have greater ability to diversify activities and reduce risk (Demsetz and Strahan, 1997). As expected, we also find that better-capitalized banks (CAPITAL) are associated with lower default risk. When the outcome variable is SD(ROA) (column 4), better-capitalized banks assume higher asset risk. This is consistent with the view that more capital allows banks to fund riskier projects without damaging solvency. DEPOSITS and COST/INCOME enter the regression with positive, but insignificant coefficients, and LOAN and NNI enter the regression with a negative, but insignificant coefficients. These variables are also insignificant in model specifications using different outcome variables. Finally, GDPgr enters the regression with a negative, but marginally significant coefficient, while the coefficient on INFLATION is negative and statistically insignificant. GDPgr is only significant in column 4, where the outcome variable is SD(ROA). Our results show that banks tend to increase the risk of asset portfolios during periods of buoyant economic conditions. This is consistent with prior evidence (Bohachova, 2008; Altunbas et al., 2010; Maddaloni and Peydro, 2010; Haq and Heaney, 2012).

We also investigate whether the impact on risk of the introduction of the LBR is similar across all Dutch banks. Given the heterogeneity in balance sheet structures and liquid asset holdings of Dutch banks prior to the introduction of the LBR, one might expect that banks with higher liquidity would invest in relatively riskier assets than their less liquid counterparts (Hoerova et al., 2018). Conversely, a decrease in risk for banks already compliant with the new rule would suggest that the LBR imposes additional costs only on these banks. Given the nature of the data (which lacks granularity regarding the maturities of liabilities/assets) and frequency (as the LBR relies on higher frequency data), we follow Brunella et al (2018), de Bandt et al (2021), and Raz et al (2022) in using the ratio of liquid assets to total assets, and the ratio of liquid assets to total deposits and short-term funding as proxies of the extent to

which banks are actually affected by the LBR (more or less binding constraint).<sup>13</sup> Figure 2 depicts the evolution of both the ratio of liquid assets to total assets, and the ratio of liquid assets to deposits and short-term funding for banks in the treatment and control groups. The trend suggests that this ratio increases around the introduction of the LBR. This lends support to the suitability of the ratio as a proxy of the LBR. We use the median value (and the third quartile) of this measure of bank liquidity as of 2002 to classify Dutch banks into compliant and non-compliant with the LBR the year prior to the introduction of the rule. Figure 3 confirms the differential increase in liquidity between ex-ante compliant and non-compliant Dutch banks around the introduction of the LBR. We then use the matching procedure described in section 2.5 to construct a control group for each subsample comprising banks from other European countries.

Insert Figure 2

**Insert Figure 3** 

[Insert Table 6 here]

The results, using different subsamples to distinguish banks that were more affected by the introduction of the rule from those less affected are presented in Table 6. Panel A presents results based on the ratio of liquid assets to total assets as a measure of liquidity. The coefficient of the interaction term (*Affected<sub>i</sub> x PostEvent<sub>t</sub>*) is positively and statistically significant for the subsample of Dutch banks with relatively low liquidity prior to the introduction of the LBR. However, the coefficient associated with the interaction term is not significant for the subsample of relatively highly liquid Dutch banks. The results remain identical when we further split the sample using the third-quartile values of liquidity in 2002.<sup>14</sup> The findings remain consistent when considering the ratio of liquid assets to total deposits and short-term funding as an alternative measure of liquidity (results are presented in Panel B of Table 6). These findings indicate that only banks with relatively low liquidity in 2002 are affected by the LBR. These are banks for which the LBR is most likely binding. Consequently, the LBR is efficient in achieving the regulatory objective of reducing bank risk-taking, while also improving liquidity.

<sup>&</sup>lt;sup>13</sup> Given the limited number of listed Dutch bank, we rely exclusively on the broad sample for this analysis.

<sup>&</sup>lt;sup>14</sup>We repeat the analysis including the subsample of relatively highly liquid Dutch banks in the control group (prior to matching). The results hold.

Overall, our results indicate that the introduction of the LBR reduces both the risk-taking and default risk of those banks for which the rule is most likely to be binding for. However, an important issue is whether such an impact is transitory or persistent. Indeed, in order to comply with the LBR, banks are often required to make quick adjustments to balance sheets by increasing liquid assets or reducing nonstable funding in liabilities. However, once adjusted to the new requirements, banks can react by increasing the risk of non-liquid assets in order to maintain profitability.

### Impulse response function

We investigate the dynamic impact of the LBR on bank risk (Jorda, 2005; Favara and Imbs, 2015). Specifically, we utilize the impulse response function for our outcome variables over different time horizons. The impulse response function corresponds to a sequence of estimates  $\beta_1^j$  from the estimations of:

$$Y_{i,t+j} = \beta_1^j(Affected_i \times PostEvent_t) + \delta X_{i,t+j-1} + \alpha_i + \lambda_t + \varepsilon_{i,t}$$
 (5)

where each  $\beta_1^j$  captures the effect of the introduction of the LBR at horizon j, with j=1,...,5. Figure 4 plots the impulse-response functions. The impulse response functions for both the *ZSCORE* and SD(R) indicate a significant impact that diminishes over time, persisting until the fifth year following the introduction of the LBR. This suggests that the introduction of the LBR has both an immediate and medium-term effect on bank risk. However, for MES, the impact is more transient, with significant effects observed only in the first three years. This shorter period may reflect market participants updating perceptions regarding tail risk. That is, the initial reaction to increased liquidity requirements may lead to a reduction in perceived risk. However, as markets adjust and participants update beliefs based on new information, the perceived impact of liquidity regulation diminishes.

[Insert Figure 4 here]

## 4. Impact of the LBR on profitability, income, cost, and structure of funding

In this section, we examine the impact of the LBR on profitability and the structure and cost of bank funding. Hoerova et al. (2018) argue that liquidity-constrained banks face a trade-off between risk and profitability. A decrease in bank risk should accompany a decline in

profitability given that the return on liquid assets is likely to be lower than the return on illiquid assets. The authors argue that funding costs matter for profitability and risk, particularly when banks are subject to liquidity regulation. When the return on liquid assets is lower than the cost of funding, banks may have incentives to invest in riskier assets in order to offset the negative impact on profitability. Banks can also adjust to any decline in income (driven by the constraint of holding larger shares of liquid assets) by increasing lending rates, albeit the viability of such a strategy depends on prevailing loan market competition. Giordana et al. (2017) contend that the impact of an increase in liquid assets on profitability is crucially dependent upon the structure of bank liabilities. Our results indicate that following the implementation of the LBR, Dutch banks become less vulnerable to default. A priori, we also expect to observe a negative or insignificant impact on profitability after the introduction of the LBR, but a significant effect on the structure and cost of funding. To investigate these issues, we consider a difference-in-differences model as follows:

$$Y_{i,t} = \beta_1(Affected_i \times PostEvent_t) + \alpha_i + \lambda_t + \varepsilon_{i,t}$$
 (6)

where  $Y_{l,t}$  denotes the outcome variable(s) of interest (profitability, cost of funding, or funding structure); i indexes bank, and t indexes time.  $Affected_i$  is a dummy variable equal to one for banks affected by the LBR (Dutch banks) and zero otherwise.  $PostEvent_t$  is a dummy variable for the treatment period and takes the value of one for the years 2003-2006, and zero for years 2000-2002.  $\beta_1$  is the coefficient of interest, which represents the impact of the LBR on the outcome variable in question. The model also includes bank-specific fixed effects,  $\alpha_i$ , to control for unobserved bank heterogeneity, as well as year dummies  $\lambda_t$  to capture time effects common to all banks. In the remainder of this section, we consider the impact of LBR on bank profitability, interest and non-interest income (section 4.1), cost of funding, loan pricing (section 4.2), and funding structure (section 4.3).

#### 4.1 Bank profitability, interest, and non-interest income

To assess the impact of the introduction of the LBR on bank profitability, interest income, and non-interest income, we estimate equation (6) using return on assets (*ROA*), the ratio of total interest income to total assets (*INTINC*), and the ratio of non-interest income to total assets (*NII*) as outcome variables. We further investigate the structure of bank revenue by analyzing the impact of the introduction of the LBR on the components of non-interest income. Specifically, we replace the outcome variable in equation (6) with the ratio of net

gain/loss from trading activities to total non-interest income (*TRADEGAIN*), the ratio of net fees and commissions to total non-interest income (*FEEINCOME*), and the ratio of other non-interest income to total non-interest income (*OTHERINCOME*). The results of these estimations are in Table 7.

#### [Insert Table 7 here]

As expected, the LBR has a negative and significant impact on bank profitability. A reduction in interest income drives this. However, the effect is not permanent. Figure 5 shows the impulse response function of *ROA* following the introduction of the LBR. We obtain this by estimating equation (5) using *ROA* as the dependent variable. The evolution of the impulse-response function shows that the impact on *ROA* becomes insignificant four years following the introduction of the LBR. A closer inspection of the evolution of non-interest income (in Table 8) reveals a heterogeneous impact of the LBR. Specifically, following the introduction of the LBR, the income from trading activities declines, other non-interest income increases, and income from fees and commissions remains unchanged. This suggests that following the introduction of the LBR, Dutch banks shift from trading to other non-interest-generating activities.

#### [Insert Figure 5 here]

Overall, the results suggest that the introduction of the LBR reduces profitability by encouraging banks to hold a larger share of less profitable liquid assets. An alternative explanation could be that, faced with higher funding costs, banks shift toward riskier assets. If depositors and other types of debt holders discipline banks effectively, then the required rate of return on bank liabilities increases. Banks could also adjust to the new regulatory environment by increasing the interest rate charged on illiquid assets. This could have a detrimental impact and lead to credit rationing by crowding out safe borrowers (Stiglitz and Weiss, 1981). We investigate this issue in section 4.2.

## 4.2 Cost of funding and loan pricing

To investigate the impact of the LBR on bank funding costs and loan pricing, we consider the net interest margin (*NIM*) as an outcome variable and re-estimate equation (6). NIM is the difference between the implicit interest rate on assets (*CHGDINT*), measured by the ratio of total interest income to total earning assets, and the implicit rate on liabilities (*INTEXP*), measured by the ratio of total interest expenses to total liabilities. The results are presented

in Table 8. We find that the coefficient of  $Affected_i \times PostEvent_t$  enters the regression with a negative and statistically significant coefficient at the 5% level. The magnitude of the coefficient suggests that net interest margins (NIM) at Dutch banks decline by 40 basis points on average following the enactment of the LBR. Further analysis suggests that both the implicit interest rate banks charge on their assets (INT), and what they pay on liabilities (INTEXP) decreases following the introduction of the LBR. However, CHGDINT declines by more than INTEXP, thus narrowing the NIM for Dutch banks.

Overall, it appears that relative to unaffected counterparts, Dutch banks do not attempt to offset any decline in profitability by increasing margins. Moreover, Dutch banks benefit from better financing conditions, which allows them to increase the share of deposits and capital on the liability side of the balance sheet and offset increases in insolvency risk stemming from a decline in profitability (Hartlage 2012).

[Insert Table 8 here]

## 4.3 Funding structure

To assess the impact of the LBR on bank funding structure, we use *CAPITAL* and *DEPOSITS* as outcome variables and re-estimate Equation (6). The results of the estimation are in Table 9.

[Insert Table 9 here]

The results indicate that Dutch banks experience an inflow of deposits and an increase in equity following the enactment of the LBR. A potential explanation is that Dutch banks increase equity to offset the increased insolvency risk arising from a decline in profitability. Prior evidence suggests that when bank profits decline as a result of an increase in liquid assets, insolvency risk also increases (Eisenbach et al., 2014; Konig, 2015). Therefore, by increasing capital, banks can offset any negative impact on risk.

#### 5. Robustness and sensitivity analysis

In this section, we examine the robustness of our main results to a myriad of additional tests.

#### RTM bias

Daw and Hatfield (2018) argue that matching in difference-in-differences analyses can introduce regression-to-mean (*RTM*) bias. RTM bias is a statistical phenomenon that can make a natural variation in repeated data appear like real change. Although the introduction of covariates (as performed in our analysis) helps mitigate this bias, Chabé-Ferret (2017)

suggest testing the potential impact of the shock on the unmatched sample. Consequently, in order to alleviate concerns regarding whether the matching procedure is forcing the parallel trend upon the sample, we re-estimate equation (1) on the unmatched sample of banks over 2000-2006. The results in row (2) of Table 10 suggest that the introduction of the LBR had a significant effect on Dutch bank risk-taking behavior relative to non-Dutch counterparts. These results confirm that the matching conducted using trends in the outcome variables and covariates does not generate a regression-to-the-mean bias.

#### Measures of bank risk

In order to ensure that the use of overlapping periods (rolling windows) does not affect our results, we compute our accounting-based risk variables based on four-year and five-year rolling windows instead of three-year rolling windows. For the subsample of listed banks, we consider the last three months of the year to compute the market-based risk indicators. We re-estimate equation (1) using these measures. The results are in rows (4), (5), and (6) of Table 10. The results remain qualitatively similar to those in Table 5.

### Matching procedures

We also assess whether variations in our matching procedure affect our results. First, we run the matching process using trends in SD(ROA) and SD(R) rather than ZSCORE and MZscore.<sup>15</sup> The results of the estimation of equation (1) using this alternative matching are in row (7) of Table 10. Our results continue to hold, and the magnitude of the coefficients are in line with our baseline results. We also vary the number of matched banks from three nearest neighbors to the nearest neighbor only, and then to the five nearest neighbors. Again, we obtain similar results (see rows 8 and 9).

#### The number of countries in the control group

Finally, we restrict the number of countries from which we select banks in the control group. We use Belgium and Luxembourg for the control group, given that along with the

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<sup>&</sup>lt;sup>15</sup> We also consider the trends in MES for the matching procedure for the subsample of listed banks. The results continue to hold, without any significant changes to the magnitude of the estimated coefficients.

Netherlands these countries are part of the historical Benelux economic union. An analysis based on these three countries is likely to address any omitted-variable bias. However, given the specific nature of the banking system in Luxembourg (which specializes in wealth management and is dominated by foreign banks), we conduct a further robustness check using Belgian banks only to form our control group. The results remain qualitatively unchanged (see rows 10 and 11 of Table 10).

#### Parallel trend and placebo test

Finally, we test for the parallel-trend assumption by performing a placebo test. In order to investigate the effect of a placebo treatment, we assume falsely that the LBR was introduced in 2001 rather than in 2003. We then re-run the matching using the growth rate of *ZSCORE* and *MZscore*, mirroring the approach employed in our baseline analysis. The results, which are presented in row (1) of Table 10 suggest that the parallel-trend assumption is not violated, and thus our identification strategy is valid.

[Insert Table 10 here]

#### 6. Conclusion

Bank liquidity mismatches and shortages have been discussed extensively since the global financial crisis. In order to reduce the potential risks of bank illiquidity and future spillovers to the real economy, the Basel Committee on Banking Supervision (BCBS) revised the regulatory framework to strengthen the global financial system (BCBS, 2011). In order to increase banks' resilience to liquidity shocks, the post global financial crisis regulatory framework (Basel III) introduced two types of liquidity requirements. The first measure is the liquidity coverage ratio (*LCR*), which requires financial institutions to hold enough liquid assets to withstand a 30-day stress period. The second measure, the net stable funding ratio (*NSFR*), aims to improve banks' longer-term, structural funding. Despite recent regulatory developments and the obvious importance of liquidity for individual banks, the financial system, and the real economy, there is a paucity of evidence regarding the impacts of liquidity regulation on bank risk.

In this study, we address this evidence gap via an in-depth investigation of how liquidity regulation affects bank risk at both the individual and system level. We use the liquidity

balance rule (similar to the Basel III LCR ratio) introduced in the Netherlands in 2003. This rule requires Dutch banks to hold high-quality liquid assets greater than or equal to net cash outflows over a 30-day stress period. We conduct an extensive empirical analysis at the bank level, where we compare the risk of Dutch banks between the pre-LBR and post-LBR period with the same difference in the stand-alone risk and systemic risk of a control group of banks from other Eurozone countries not subject to the provision of the LBR. Our results show that following the introduction of the LBR, Dutch banks became less risky, both at the individual and system level, albeit at the expense of profitability. This is particularly pronounced for banks with relatively low levels of liquidity prior to the introduction of the LBR. Reduced funding costs allow Dutch banks to change funding structure by increasing capital and improving solvency, which improves their stability relative to an average Eurozone bank not subject to the LBR. With regard to profitability, Dutch banks experience a reduction in the income from interest-bearing activities as opposed to non-interest income, relative to unaffected banks. Moreover, the income from trading activities declines, other non-interest income increases, and income from fees and commissions remains unchanged.

Overall, the findings of this study suggest that liquidity regulation reduces individual bank and systemic risk. Our findings do not support the view that liquidity requirements are counterproductive by encouraging banks to take on more risk. However, given that the introduction of the LBR leads to a decline in bank profitability, stability remains a concern. Going forward and based on insights from this study, there is a need for further research to better understand how more recent liquidity regulations, such as the LCR affects bank risk and performance.

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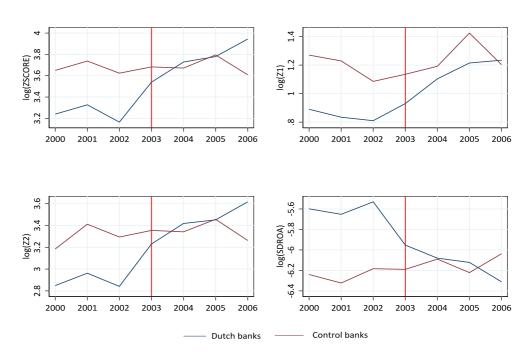
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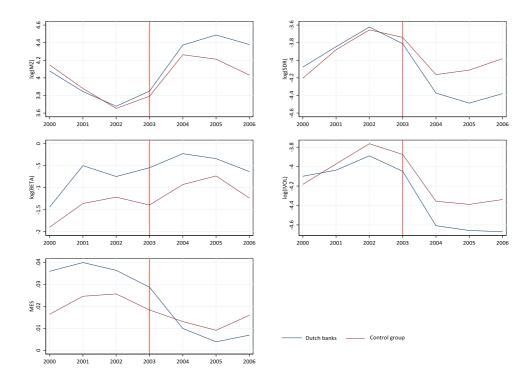
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Figure 1. Evolution of outcomes variable for Dutch banks and control banks

Panel A. Broad sample of banks



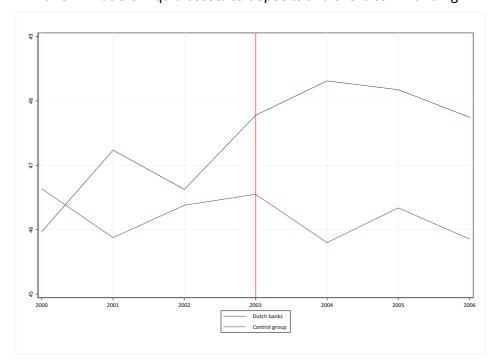
Panel B. Subsample of listed banks.



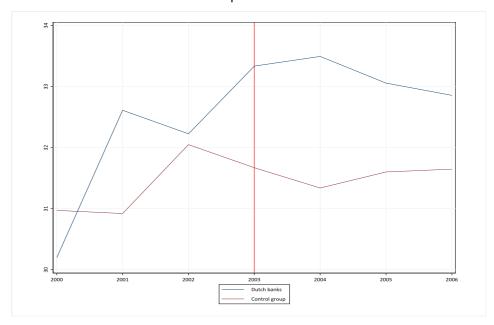
Note: This figure plots the evolution of the outcome variables for both treated and control banks over the period 2000-2006. The dashed vertical line in each graph marks 2003, the year LBR took effect. Panel A depicts the mean of the logarithm of *ZSCORE*, *Z1*, *Z2*, and *SD(ROA)* for the broad sample of banks. Panel B depicts the mean of MZscore, SD(R), *BETA*, *IVOL*, and MES for the subsample of listed banks. The control group includes all the banks selected via the nearest neighbor matching.

Figure 2. Evolution of the liquidity ratios for Dutch banks and the control group

Panel A: Ratio of liquid assets to deposits and short-term funding

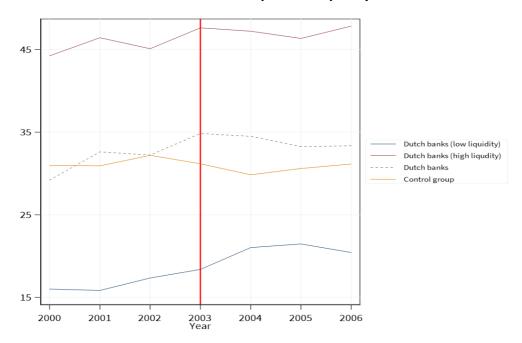


Panel B: Ratio of liquid assets to total assets



Note: Panel A (Panel B) of this figure plots the average of the ratio of liquid assets to deposits and short-term funding (the average of the ratio of liquid assets to total assets) for Dutch banks and of the control group.

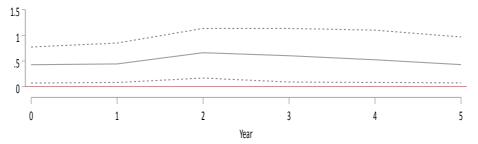
Figure 3. Evolution of the ratio of liquid assets to total assets for Dutch banks with high and low levels of pre-LBR liquidity



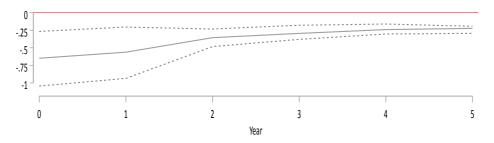
Note: This figure plots the average of the ratio of liquid assets to total assets for Dutch banks depending on their liquidity level and of the control group.

Figure 4. Impulse-response functions for bank risk and systemic risk

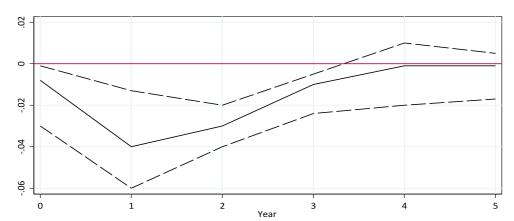
Panel A: Broad sample of banks, using ZSCORE



Panel B: Subsample of listed banks, using return volatility (SD(R))

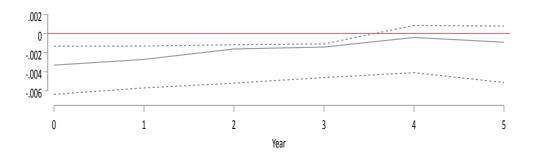


Panel C: Subsample of listed banks, using MES.



Note: This figure plots the impulse response of bank risk (*ZSCORE* and SD(R)) and bank systemic risk contribution (MES) to the introduction of the LBR using the method in Jorda (2005). Doted lines are the 95% confidence bands.

Figure 5. Impulse response function for bank profitability



Note: This figure plots the impulse response (*IRF*) of bank profitability to the introduction of the LBR using the method in Jorda (2005). Doted lines are the 95% confidence bands.

Table 1. Distribution of commercial banks in the sample by country

by country						
		Broad		sample		
	sam	ple of banks	of listed banks			
Country	Full	Matched	Full	Matched		
•	sample	sample	sample	sample		
	(1)	(2)	(3)	(4)		
Austria	38	5	8	0		
Belgium	20	3	4	1		
Finland	3	0	4	1		
France	90	9	26	3		
Germany	86	9	23	4		
Greece	11	0	1	0		
Ireland	5	1	0	0		
Italy	20	1	10	1		
Luxembourg	60	8	14	0		
Netherlands	16	16	4	4		
Portugal	11	3	7	1		
Spain	40	3	16	2		

Note: This table indicates for each country the number of commercial banks in the full sample.

**Table 2. Variable definitions** 

Variable	Description	Source	Expected sign
Dependent vario	ables		
BETA	Systematic risk computed by regressing bank daily stock return on a benchmark market excess return within a calendar year. <i>BETA</i> is the coefficient associated with the market excess return.	Author computed	
INTINC	Ratio of interest income to total assets (%).	Author computed	
CHGDINT	Ratio of total interest income to total earning assets (%).	Author computed	
IVOL	Bank-specific risk, computed as the annualized standard deviation of the residuals of the regression of bank daily returns on a benchmark market excess return.	Author computed	
INTEXP	Ratio of total interest expenses to total liabilities (%).	Author computed	
MZscore	Market based Z-Score, defined as $(100+\bar{R})/$ SD(R) where $\bar{R}$ and SD(R) are expressed as a percentage.	Author computed	
NII	Ratio of non-interest income to total assets (%).	Author computed	
NIM	Net interest margin, defined as the difference between <i>INT</i> and <i>COST</i> .	Author computed	
ROA	Return on assets, defined as the ratio of net income to total assets (%).	Bankscope	
SD(R)	Market-based bank risk, defined as the geometric standard deviation of daily stock returns within a calendar year (%).	Author computed from Bloomberg	
SD(ROA)	Three-year rolling window standard deviation of ROA (%).	Author computed	
ZSCORE	Bank default risk. <i>ZSCORE</i> = (MROA + CAPITAL)/SD(ROA), where CAPITAL is the ratio of total equity to total assets and MROA is the three-year rolling window average of ROA.	Author computed	
Z1	First component of ZSCORE. Z1 = MROA/SD(ROA).	Author computed	
Z2	Second component of ZSCORE. Z2 = CAPITAL/SD(ROA).	Author computed	
MES	Marginal expected shortfall as defined by Acharya et al (2017)	Author computed	
Control variable	s		
COST/INCOME	Ratio of operating expense to total operating income (%).	Bankscope	-
DEPOSITS	Ratio of customer deposits to total assets (%).	Bankscope	+
CAPITAL	Ratio of total equity to total assets (%).	Bankscope	+/-
GDPgr	Year-to-year growth rate of real GDP.	Eurostat	+
INFLATION	Year-to-year growth rate of harmonized price index.	Eurostat	-
LOANS/ASSETS	Ratio of net loans to total assets (%).	Bankscope	+/-
NNI	Ratio of net non-interest income to net operating income (%).	Bankscope	-
SIZE	Natural logarithm of total assets.	Bankscope	+/-
LLR	Loan loss reserves (%).	Bankscope	-

Note: This table presents definitions for all variables throughout the paper. The first column shows the name of the variable, the second describes the corresponding definition, and the third column gives the source.

**Table 3. Correlation matrix** 

Panel A. Broad	sample (	of banks										
	1	2	3	4	5	6	7	8	9	10	11	12
1. SD(ROA)	1.00											
2. ZSCORE	-0.37	1.00										
3. Z1	-0.40	0.73	1.00									
4. Z2	-0.36	0.97	0.70	1.00								
5. NII	0.12	-0.17	-0.06	-0.17	1.00							
6. COST/INCOME	0.14	-0.11	-0.28	-0.10	0.17	1.00						
7. DEPOSITS	-0.03	-0.02	0.07	-0.02	0.08	0.20	1.00					
8. CAPITAL	0.31	0.18	-0.05	0.19	-0.03	-0.14	-0.16	1.00				
9. SIZE	-0.23	-0.06	0.12	-0.07	-0.04	-0.11	-0.26	-0.42	1.00			
10. LOANS/ASSETS	-0.13	0.07	0.14	0.06	-0.35	0.06	0.18	-0.15	-0.02	1.00		
11. LLR	0.13	-0.11	-0.02	-0.11	-0.04	0.18	0.17	-0.07	-0.15	0.28	1.00	-
Panel B. Subsan	nple of I	isted baı	nks									
1. SD(R)	1.00											
2. MZscore	-0.35	1.00										
3. BETA	0.44	-0.18	1.00									
4. IVOL	0.99	-0.34	0.06	1.00								
5. NII	-0.01	0.02	0.08	-0.03	1.00							
6. COST/INCOME	0.22	-0.10	0.18	0.21	0.11	1.00						
7. DEPOSITS	0.13	-0.03	-0.14	0.16	0.09	0.11	1.00					
8. CAPITAL	-0.11	0.09	-0.14	-0.08	-0.12	-0.19	-0.23	1.00				
9. SIZE	-0.01	-0.17	0.64	-0.12	-0.01	0.21	-0.27	-0.07	1.00			
10. LOANS/ASSETS	-0.04	0.10	-0.02	-0.03	-0.06	0.00	0.20	0.17	-0.20	1.00		
11. LLR	-0.02	0.05	-0.22	0.03	-0.09	-0.12	-0.04	0.15	-0.34	0.43	1.00	
12.MES	0.31	-0.23	0.77	0.23	0.03	0.22	-0.03	-0.14	0.51	-0.02	-0.09	1.00

Notes: This table reports the correlation matrix for the outcome variables and control variables used in our analysis.

**Table 4. Summary statistics** 

	Dutch banks		Full control group			Matched control group			
•	Mean	Std. Dev.	Mean	Std. Dev.	Diff	Mean	Std. Dev.	Diff	
Panel A: Pre-LBR	period (2000-	-2003)							
SD(R)	1.970	1.105	1.841	1.546	0.129	2.182	0.861	-0.211	
MZscore	50.219	4.621	91.679	6.554	-41.460***	54.091	4.195	-3.872	
BETA	0.562	0.596	0.196	0.335	0.365**	0.443	0.458	0.119	
IVOL	1.600	0.738	1.757	1.516	-0.157	1.983	1.917	-0.383	
MES	0.035	0.007	0.012	0.001	-0.023**	0.021	0.003	-0.014*	
ROA	1.111	1.592	0.600	1.217	0.512**	0.842	1.501	0.271	
SD(ROA)	0.610	0.727	0.377	0.574	0.233**	0.453	0.674	0.156	
ZSCORE	49.796	9.349	76.265	13.543	-26.469***	66.887	6.458	-19.443*	
Z1	3.804	4.293	5.054	5.795	-1.249*	4.985	5.761	-1.182	
<b>Z</b> 2	46.105	8.854	71.126	2.541	-25.022***	64.180	6.791	-18.075*	
NNI	27.782	16.799	37.649	23.420	-9.866***	24.744	24.109	2.600	
COST/INCOME	53.401	18.444	62.532	22.166	-9.131***	51.726	24.152	1.680	
DEPOSITS	48.647	28.726	51.370	24.879	-2.727	45.685	20.208	2.962	
CAPITAL	11.415	11.435	9.733	12.955	1.681	10.280	9.644	1.135	
SIZE	8.115	1.776	7.403	1.991	0.711***	7.869	2.242	0.245	
LOANS/ASSETS	46.579	24.552	46.602	27.689	-0.592	48.729	27.041	-2.718	
LLR	0.631	0.489	1.999	2.302	-1.363***	0.863	2.061	-0.232	
GDPgr	1.350	0.656	2.009	1.894	-0.659***	2.009	1.894	-0.659**	
INFLATION	0.329	0.172	0.599	0.617	-0.269***	0.599	0.617	-0.269**	
Panel B: Pre-trend				0.017	0.203	0.555	0.017		
	4.420	13.896	9.310	14.929	-4.890**	3.386	15.1910	0.034	
SD(R)	-6.496	8.536	22.042	4.892	-28.539**	-6.155	6.184	0.058	
MZscore BETA	9.415	6.812	14.818	0.689	-4.613*	8.485	5.214	0.951	
VOL	-5.365	11.077	8.224	4.946	-13.587***	-3.737	15.258	1.628	
MES	-61.403	3.244	-49.698	9.146	-11.705*	-56.388	3.539	-5.015	
SD(ROA)	1.131	12.487	1.453	1.867	-0.231***	1.079	2.294	0.052	
ZSCORE	29.057	12.036	53.466	7.72	-24.409***	26.883	12.831	2.174	
Z3CORE Z1	-31.297	4.161	-24.241	5.639	17.11*	-27.347	8.740	3.819	
Z1 Z2	31.293	12.113	54.386	7.759	-23.092**	34.332	5.791	3.038	
Panel C: Post-LBR		12.113	34.300	7.733	25.052	34.332	3.731		
	-	0.500	1 200	1 020	-0.286	1 070	2 025	-0.157*	
SD(R)	0.923	0.588	1.209	1.830		1.079	2.825	10.611**	
MZscore	83.851	5.282	129.318	12.775	-45.467***	74.275	6.883	0.007	
BETA	0.534	0.566	0.231	0.389	0.303*	0.542	0.417		
IVOL	0.754	0.155	1.161	0.106	-0.407**	0.971	0.438	-0.216 0.006*	
MES	0.007	0.002	0.006	0.001	-0.001	0.012	0.001		
ROA	0.857	1.625	0.742	1.211	0.146	1.034	0.701	-0.178*	
SD(ROA)	0.407	0.549	0.362	0.581	0.0004	0.517	0.768	0.111	
ZSCORE	67.871	8.932	79.054	2.680	-11.182	71.488	7.076	-3.292	
21	4.486	3.414	5.342	5.661	-0.856	5.180	5.615	-0.694	
<u>7</u> 2	63.295	8.513	73.405	2.547	-10.110	66.233	6.696	-2.784**	
NNI	26.904	18.875	39.828	23.494	-12.925***	39.207	25/841	-8.894*	
COST/INCOME	52.348	16.445	59.879	21.944	-7.530***	57.743	24.205	-5.394**	
DEPOSITS	52.468	28.410	52.448	25.142	0.020	45.584	20.917	6.883**	
CAPITAL	11.940	10.432	9.662	12.874	1.431	9.682	12.363	1.358	
SIZE	8.425	1.849	7.653	2.020	0.772***	7.571	2.391	0.854**	
LOANS/ASSETS	47.993	26.154	48.026	28.738	-0.908	50.421	28.271	-3.203	
LLR	1.481	2.259	2.099	2.160	-0.617	1.261	1.286	0.221	

GDPgr	1.521	0.555	1.996	1.894	-0.474***	1.996	1.894	-0.474***
INFLATION	0.566	0.852	0.598	0.606	-0.032	0.598	0.606	-0.032

Note: This table reports summary statistics of the outcome variables and the control variables for Dutch banks and non-Dutch banks in the pre-treatment (panel A) and post-treatment (panel B) periods. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively, for the difference in means test (*t*-test) between Dutch and Eurozone banks.

Table 5. Impact of LBR on bank risk

	F	Panel A : Broad	sample of ban	ks	Panel B : Subsample of listed banks				
Variables	ZSCORE	Z1	Z2	SD(ROA)	SD(R)	BETA	IVOL	MZscore	MES
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Affected x PostEvent	0.434***	0.380	0.430***	-0.579**	-0.329**	-0.881	-0.301**	0.329**	-0.034***
	(0.190)	(0.641)	(0.189)	(0.196)	(0.115)	(0.934)	(0.107)	(0.133)	(0.005)
DEPOSITS	0.001	0.031**	-0.001	0.007	-0.002	-0.012	-0.023	0.021**	-0.001
	(0.005)	(0.013)	(0.005)	(0.007)	(800.0)	(0.021)	(0.076)	(0.008)	(0.001)
CAPITAL	0.041**	-0.025**		0.017**	-0.019**	-0.004	-0.024**	0.019**	-0.000
	(0.009)	(0.011)		(0.009)	(0.009)	(0.031)	(800.0)	(0.009)	(0.000)
SIZE	0.661***	0.316***	0.651***	-0.116***	-0.151**	0.021	-0.149***	0.151**	-0.007***
	(0.105)	(0.087)	(0.106)	(0.104)	(0.056)	(0.024)	(0.062)	(0.067)	(0.002)
LOANS/ASSETS	-0.005	-0.015**	-0.005	0.005	0.082	0.003**	0.083	-0.083	0.041** (0.011)
	(0.006)	(0.099)	(0.006)	(0.006)	(0.311)	(0.001)	(0.283)	(0.312)	
NNI	-0.004	-0.001	0.004	-0.0001	0.001	-0.000	0.000	-0.001	0.002 (0.001)
	(0.005)	(0.006)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	
COST/INCOME	0.005	-0.035***	0.004	0.003	0.004	0.001**	0.003	-0.004	0.001
	(0.005)	(0.008)	(0.004)	(0.004)	(0.006)	(0.000)	(0.006)	(0.007)	(0.001)
LLR	-0.013**	-0.029**	-0.013**	-0.020	-0.151**	-0.328*	-0.150**	0.151**	-0.007**
	(0.007)	(0.094)	(0.007)	(0.228)	(0.067)	(0.201)	(0.052)	(0.057)	(0.002)
GDPgr	-0.043*	0.059*	-0.045	0.022**	-0.054**	-0.008	-0.052*	0.053**	0.069**
	(0.027)	(0.036)	(0.053)	(0.004)	(0.019)	(0.071)	(0.043)	(0.020)	(0.008)
INFLATION	-0.055	0.012***	-0.052	-0.108	0.062	-0.033**	0.078**	-0.062	-0.031
	(0.074)	(0.000)	(0.074)	(0.101)	(0.072)	(0.011)	(0.034)	(0.039)	(0.109)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	294	294	294	294	86	86	86	86	86
R-squared	0.974	0.826	0.973	0.904	0.978	0.903	0.982	0.978	0.944

Note: The table analyzes the impact of the introduction of the liquidity balance rule in the Netherlands on bank risk in a difference-in-differences setup. The sample consists of banks from the Netherlands and the matched non-Dutch banks over the 2000-2006 period. In panel A, we perform all the regressions on a sample of 58 commercial banks. In Panel B, we perform all regressions on a sample of 18 listed banks. ZSCORE is a measure of bank default risk, Z1 is a measure of bank asset risk, and Z2 is a measure of bank leverage risk. SD(R) is the standard deviation of daily stock returns within a calendar year. BETA is a measure of systematic risk, and IVOL is a measure of idiosyncratic risk. MZscore is a market-based Z-score defined as (100+RETURN)/ SD(R). MES is the marginal expected shortfall, measured as proposed by Acharya et al. (2017). All the dependent variables are log transformed. AFFECTED equals 1 when the bank is a Dutch bank and 0 otherwise. POSTEVENT equals 1 for the years 2003 to 2006 and 0 otherwise. We estimate the model using OLS. For the control variables, SIZE is the natural logarithm of total assets, CAPITAL is the ratio of total equity to total assets, and DEPOSITS is the ratio of total customer deposits to total assets. LOANS/ASSETS is the ratio of net loans to total assets. COST/INCOME is the ratio of operating expense to total operating income. LLR is the ratio of loan loss reserves to total assets, GDPgr is the real GDP growth, and INFLATION is the inflation rate. The effect of LBR is captured by the coefficient on the interaction term Affected × Post Event. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Liquidity regulation and bank risk: Disaggregation by banks' liquidity level pre-LBR

		ZSCORE	Z1	Z2	SD(ROA)
(1)	Full sample	0.434***	0.380	0.430***	-0.579**
		(0.190)	(0.641)	(0.189)	(0.196)
Pane	el A: Restricting sample based or	n liquid assets to total assets	ratio		
(2)	Below the median	0.351***	0.331	0.345**	-0.516***
		(0.098)	(0.396)	(0.127)	(0.224)
(3)	Above the median	0.048*	-0.533	0.036*	-0.008**
		(0.029)	(0.696)	(0.017)	(0.007)
(4)	Below 3 <sup>rd</sup> quartile	0.419***	0.370	0.415***	-0.627**
		(0.119)	(0.383)	(0.129)	(0.209)
(5)	Above 3 <sup>rd</sup> quartile	-0.251	-0.534	-0.265	0.074
		(0.417)	(0.890)	(0.526)	(0.106)
Pane	el B: Restricting sample based or	n liquid assets to total deposi	ts and short-term fu	nding	
(6)	Below the median	0.375***	0.263	0.367**	-0.571**
		(0.153)	(0.267)	(0.148)	(0.251)
(7)	Above the median	0.482	-0.155	0.494	-0.453
		(0.434)	(0.475)	(0.459)	(0.498)
(8)	Below 3 <sup>rd</sup> quartile	0.345***	0.364	0.344***	-0.541**
		(0.130)	(0.399)	(0.226)	(0.239)
(9)	Above 3 <sup>rd</sup> quartile	0.117	-0.323	0.157	-0.335
		(0.536)	(0.628)	(0.547)	(0.537)

Note: The table analyzes the impact of the introduction of the liquidity balance rule in the Netherlands on bank risk in a difference-in-differences setup. Each row reports the estimates on a subsample consisting of banks from the Netherlands with a given level of liquidity and the matched non-Dutch banks over the 2000-2006 period. For brevity, we only report the estimated coefficients of the variable of interest *Affected* × *Post Event. ZSCORE* is a measure of bank default risk, *Z1* is a measure of bank asset risk, and *Z2* is a measure of bank leverage risk. SD(R) is the standard deviation of daily stock returns within a calendar year. All the dependent variables are log transformed. Row 1 reports the estimate on the full sample. Row 2 (6) presents the estimates when the treated group consists of Dutch banks with a ratio of liquid assets to total assets (ratio of liquid assets and short-term funding) below the median, and row 3 (7) reports the opposite. Rows 4 (8) and 5 (9) report respectively the estimates when the subsample consists of banks with a level of liquid assets to total assets (ratio of liquid assets to total deposits and short-term funding) below and above the 3rd quartile. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Impact of LBR on bank profitability and income

Variables	ROA	ROA INTINC		TRADEGAIN	FEEINCOME	OTHERINCOME
- Variables	(1)	(2)	(3)	(4)	(5)	(6)
Affected x PostEvent	-0.004**	-0.019**	-0.006	-0.123**	0.823	0.076**
	(0.002)	(0.007)	(0.009)	(0.047)	(1.824)	(0.028)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	406	258	258	95	95	95
R-squared	0.769	0.908	0.744	0.515	0.942	0.896

Note: The table analyzes how the introduction of the liquidity balance rule in the Netherlands affects bank profit, equity, and deposits in a difference-in-differences setup. The sample consists of banks from the Netherlands and the matched non-Dutch banks over the 2000-2006 period. *ROA* is a measure of bank's profitability, *INTINC* is the ratio of interest income to total assets, *NII* is the ratio of non-interest income to total assets, *TRADEGAIN* is the ratio of net gain/loss from trading activities to total non-interest income, *FEEINCOME* is the ratio of net fees and commissions to total non-interest income, and *OTHERINCOME* is the ratio of other non-interest income to total non-interest income. *AFFECTED* is a dummy is equal to 1 when the bank is a Dutch bank and 0 otherwise. *POSTEVENT* is a dummy equal to 1 for the years 2003 to 2006 and 0 otherwise. We estimate the model using OLS. The effect of LBR is captured by the coefficient on the

Table 8. Impact of LBR on bank interest margin, interest charged, and funding cost

Variables	NIM	CHGDINT	INTEXP
Variables	(1)	(2)	(3)
Affected x PostEvent	-0.004**	-0.021**	-0.016**
	(0.002)	(0.009)	(0.006)
Year fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Observations	261	261	261
R-squared	0.848	0.913	0.819

Note: The table analyzes how the introduction of the liquidity balance rule in the Netherlands affects bank profit, equity, and deposits in a difference-in-differences setup. The sample consists of banks from the Netherlands and the matched non-Dutch banks over the 2000-2006 period. *COST* is the ratio of total interest expenses to total liabilities, *INT* is the ratio of total interest income to total earning assets, and *NIM* is the difference between *CHGDINT* and *INTEXP* (*NIM* = *CHGDINT-INTEXP*). *AFFECTED* equals 1 when the bank is a Dutch bank and 0 otherwise. *POSTEVENT* equals 1 for the years 2003 to 2006 and 0 otherwise. We estimate the model using OLS. The effect of LBR is captured by the coefficient on the interaction term *Affected* × *PostEvent*. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Impact of LBR on bank funding structure

Variables	DEPOSITS	CAPITAL		
- Variables	(5)	(6)		
Affected x PostEvent	0.009**	0.019**		
	(0.004)	(0.007)		
Year fixed effects	Yes	Yes		
Bank fixed effects	Yes	Yes		
Observations	364	406		
R-squared	0.963	0.927		

Note: The table analyzes how the introduction of the liquidity balance rule in the Netherlands affects bank profit, equity, and deposits in a difference-in-differences setup. The sample consists of banks from the Netherlands and the matched non-Dutch banks over the 2000-2006 period. *DEPOSITS* is the ratio of total customer deposits to total assets and *CAPITAL* is the ratio of total equity to total assets. *AFFECTED* equals 1 when the bank is a Dutch bank and 0 otherwise. *POSTEVENT* equals 1 for the years 2003 to 2006 and 0 otherwise. We estimate the model using OLS. The effect of LBR is captured by the coefficient on the interaction term *Affected* × *PostEvent*. \*, \*\*\* indicate significance at the 10%, 5%, and 1% levels,

respectively.

Table 10. Robustness analysis and sensitivity tests

		F	Panel A. Broad sample of banks				l B. Subsamp	le of listed ba	nks	
		ZSCORE	Z1	<b>Z2</b>	SD(ROA)	SD(R)	BETA	IVOL	MZscore	MES
(1)	Placebo test	0.193	0.647	0.176	-0.539	-0.157	-0.021	-0.190	0.162	-0.016
		(0.264)	(0.766)	(0.264)	(0.751)	(0.175)	(0.024)	(0.213)	(0.182)	(0.07)
(2)	Broad sample	0.181**	0.029	0.174**	-0.617*	-0.234**	-0.342*	-0.225**	0.436**	-0.023**
		(0.091)	(0.052)	(0.107)	(0.352)	(0.112)	(0.253)	(0.109)	(0.146)	(0.146)
(3)	Without controls	0.3291**	0.369	0.309**	-0.416**	-0.361**	-0.661	-0.321**	0.362**	-0.019**
		(0.121)	(0.373)	(0.116)	(0.156)	(0.068)	(0.731)	(0.073)	(0.068)	(0.006)
(4)	4-year rolling window	0.362***	0.442	0.335***	-0.556**					
		(0.105)	(0.572)	(0.104)	(0.209)					
(5)	5-year rolling window	0.345**	0.337	0.339**	-0.498**					
		(0.130)	(0.502)	(0.135)	(0.187)					
(6)	Last 3 months					-0.263**	-0.934	-0.255**	0.319**	
						(0.129)	(1.394)	(0.112)	(0.124)	
(7)	Alternative matching	0.305**	0.571	0.296**	-0.356**	-0.262**	-0.522	-0.244**	0.262**	-0.032**
		(0.116)	(0.738)	(0.119)	(0.133)	(0.094)	(0.771)	(0.091)	(0.098)	(0.018)
(8)	1 neighbor	0.451***	0.618	0.413***	-0.832*					
		(0.115)	(0.824)	(0.113)	(0.498)					
(9)	5 neighbors	0.484**	0.462	0.472**	-0.547**					
		(0.181)	(0.689)	(0.173)	(0.204)					
(10)	Benelux only	0.305**	0.562	0.296**	-0.356**					
		(0.113)	(0.837)	(0.119)	(0.133)					
(11)	Belgium only	0.532**	0.320	0.476**	-0.687***					
		(0.201)	(0.468)	(0.179)	(0.157)					

Note: The table presents the sensitivity of the baseline model to variations in the definition of the outcome variable, the sample size, and matching procedure, as well as false timing of the introduction of the LBR. For brevity, we only report the estimated coefficients of the variable of interest, *Affected* × *Post Event*. The bank- and country-level controls, as well as fixed effects, are identical to those in table 6. Row (1) conducts a placebo test by falsely assuming the LBR was implemented in 2001 rather than 2003. Row (2) considers the unmatched sample of banks, and row (3) excludes control variables from the estimated model. In rows (4) and (5), we measure *ZSCORE*, *Z1*, *Z2*, and *SD(ROA)* using a four-year rolling and five-year rolling window. Row (6) uses the last three months of the year to compute SD(R), BETA, *IVOL*, and *MZscore*. Row (7) use alternative variables for the matching procedure. Instead of the growth rate in ZSCORE and MZscore, we use the growth rates of SD(ROA) and SD(R). Rows (8) and (9) match each Dutch bank with one and five unaffected banks, respectively. Rows (10) and (11) restrict the number of countries from which banks in the control group are selected to Benelux (i.e., Belgium and Luxembourg) and Belgium, respectively. \*, \*\*\*, \*\*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively.