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## Abstract

This paper explores the impact of bank transparency on market efficiency by comparing banks that disclose supervisory capital requirements to those that remain opaque. Due to the informational content of supervisory capital requirements for the market this opacity might hinder market efficiency. The paper estimates an average 11.5% reduction in funding costs for transparent versus opaque banks. However, there is some heterogeneity in those effects. Transparency helps the market to sort across safer and riskier banks. Conditional on disclosure, the safest quartile of banks, those with a CET1 P2R lower than 1.5% of risk-weighted assets, benefits in average from 31.1% lower funding costs. The paper concludes that supervisory transparency is beneficial, supporting the view that supervisory transparency enhances market discipline by allowing markets to better evaluate and price the risk associated with each bank.

JEL Classification: D5, E5, E58, G18, G21

Keywords: Bank transparency, market efficiency, market discipline, supervisory effectiveness

## Non-technical summary

This study explores the economic implications of increased transparency in banking supervision, particularly focusing on the disclosure of Pillar 2 capital requirements (P2R) in the Banking Union, where P2R refers to additional capital requirements imposed on banks to address risks not fully covered by standard regulatory thresholds (Pillar 1). Since January 2021, the P2Rs of Significant Institutions (SIs) in the Banking Union are being publicly disclosed, following initiatives by the Single Supervisory Mechanism (SSM) to enhance supervisory transparency.

In theory, transparency in supervisory assessments can improve market efficiency by reducing information asymmetry. When P2R information is disclosed, market participants can better evaluate a bank's financial health, allowing safer banks to benefit from lower funding costs and encouraging riskier banks to adopt sounder practices. Similarly, in absence of full disclosure, non-transparent banks could enjoy lower funding costs despite higher risk levels. These inefficiencies are a clear indication of market failure.

The study uses detailed data on banks' P2R disclosure practices to test whether transparency allows to clear the fog on the supervisory assessment, and sorts, as a consequence, funding costs for safer and sounder banks versus riskier ones, promoting therefore market discipline. In our econometric identification framework we compare transparent and non-transparent banks, controlling for potential self-selection bias (e.g., better-performing banks being more likely to disclose voluntarily).

The findings reveal that disclosure of P2R helps indeed to sort good versus bad banks, and promotes lower funding costs for transparent banks. On average, banks disclosing their P2R experience an 11.5% reduction in funding costs compared to opaque banks, with the safest banks benefiting most (up to 31.1% reduction).

A consequence of this result is that market efficiency and discipline are enhanced. Transparency helps markets price funding more accurately, aligning costs with actual risk profiles and encouraging riskier banks to improve governance and risk management. By eliminating market failures where riskier banks enjoy lower costs.

The findings underscore the importance of supervisory transparency in fostering market efficiency and discipline. By enabling an improvement in market risk differentiation and lowering information collection costs for investors, transparency not only benefits banks with sounder practices but also strengthens market confidence and supervisory accountability.

# 1 Introduction

In recent years, there has been a general trend toward increased transparency of banking supervisors. In the European Union for instance, according to the European Capital Requirements Regulation 2 (CRR2), since June 2021, all banks are mandated to disclose their Pillar 2 Requirements (hereafter, P2R). The P2R establishes the minimum capital threshold that European banks must maintain to be assessed as solvent by supervisory and regulatory authorities in the European Union. Non-compliance with this requirement may result in supervisory actions, including sanctions and assessments of failure.<sup>1</sup> In anticipation of this regulatory change, in January 2020 the euro area Single Supervisory Mechanism (SSM henceforth) published, for the first time, bank-specific data on P2Rs following a supervisory transparency initiative and its annual assessments within the Supervisory Review and Evaluation Process (SREP).

In this study we analyse the economic implications of additional transparency in the disclosure of capital requirements for market efficiency. In theory, disclosure of supervisory requirements can improve *market efficiency* by reducing asymmetric information and promoting the allocation of resources to the most productive uses. This is because disclosing information about supervisors' assessment allows market participants to distinguish banks "in good shape" from banks "in bad shape", and to reward the former according to their performance and risks, exercising ultimately discipline on banks and cushioning their risk-taking incentives.

As shown in Figure 1, descriptive evidence points-out to a market failure manifesting itself in distorted pricing mechanisms. In fact, opaque banks that do not disclose their P2R, show a negative relationship between their safety and soundness proxy and the cost of funding. In other terms, in the case of imperfect information it can happen that riskier but opaque banks are rewarded by the market with lower cost of funding, they expend less resources on interest when P2R is not disclosed. This is not the case for transparent banks, which have a clear positive relationship between cost of funding and their P2R safety and soundness supervisory assessment. This market failure can be reconciled to inefficiencies arising from the asymmetric information problem which in turn fosters adverse selection when investors, or creditors, cannot fully assess the risk or quality of a bank's assets or operations due to insufficient

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<sup>1</sup>The P2R is a bank-specific capital requirement which applies in addition to the Pillar 1 capital requirement where this underestimates or does not cover business model and profitability risks, internal governance and risk management issues, capital risk, liquidity and funding risks. In the euroarea, a bank's P2R is determined as part of the Supervisory Review and Evaluation Process by the European Single Supervisory Mechanism (SSM), and it does not encompass the risk of excessive leverage, which is covered by the leverage ratio Pillar 2 requirement.

transparency. Our study tests empirically whether this market distortion is associated with the lack of disclosure of supervisory capital requirements.

To find an answer to our research question, we compare empirically transparent versus non-transparent banks and estimate the benefit of Pillar 2 disclosure. Our empirical design mimics a difference-in-differences approach, comparing "treated" and "control" banks under the common trend assumption, i.e., both groups would have followed similar trends absent the treatment. Although this assumption is not directly testable, we incorporate bank-specific trends into the model as a robustness check following Wolfers (2006) and Angrist and Pischke (2008), including trends tied to the policy variable is a standard robustness test in difference-in-differences frameworks.

We leverage on a detailed data collection of banks' P2R disclosure practices to estimate whether more transparent banks benefit from a funding cost premium, and whether disclosure helps guiding markets toward improved market efficiency by reducing uncertainty on the supervisory assessment of banks. Since banks choose to disclose their P2R they could generate a bias to our estimates driven by self-selection into treatment as, more profitable or better capitalised banks, that have a better assessment from the supervisor, could have a greater incentive to disclose their capital requirements. We run a series of tests to exclude this possibility.

The literature has provided limited evidence on the market efficiency and adverse selection mechanism so far, and has focused more on other aspects related to disclosure of supervisory information, more specifically, the role of supervisory transparency in fostering market *discipline* by reducing risk-taking incentives has been the extensively explored. An exception is Elahie (2013, 2016) investigates the impact of the 2011 EU stress test disclosure on the ability to separate stronger from weaker banks as measured by bond bid-ask spreads. On the other side, Jordan et al. (1999) provide empirical evidence about the beneficial effect of transparency on market discipline. Huizinga (2018) concludes that, based on the 2017 SREP information that was available to the public, it was empirically not possible to evaluate the efficacy of that disclosure with respect to improving market discipline. A similar point is also raised by Resti (2018). He shows that the public disclosure of SREP results can strengthen market discipline, but at the cost of potentially triggering unintended consequences such as deposit outflows.<sup>2</sup>

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<sup>2</sup>Resti (2018) acknowledges that the SREP decisions (e.g. hard requirements such as Pillar 2 add-ons) meet the definition of inside information provided in the Market Abuse Regulation for listed financial instruments, and must therefore be disclosed despite possible negative impacts.

A few papers in the academic literature have questioned the beneficial role of information disclosure on bank risk-sharing by highlighting the importance that some opacity plays for banks' ability to enter in risk-sharing agreements, Hirshleifer (1971), Allen and Gale, (2000). It has been also shown that the provision of supervisory information also increases *cost-efficiencies for market participants* by reducing expensive information collection (see e.g. Diamond and Verrecchia, 1991 or Baiman and Verrecchia, 1996).

The accounting research literature also highlights the benefits associated with enhanced information disclosure on *market discipline*. A number of contributions show that the quality of banks' financial reporting is crucial for the efficacy of market discipline (Bischof and Daske, 2013; Bischof et al 2021, 2023). Furthermore, this literature also highlights how enhanced transparency fosters non-market mechanisms (e.g. self-disciplinary measures) that limit banks' debt and risk overhangs (Acharya and Ryan, 2016).

There is a rich academic literature that explores the effects of firms' disclosure of accounting information. Those papers explicitly distinguish between mandatory and voluntary disclosure, and in this respect are very close in spirit to our study. They build on the seminal paper by Myers and Majluf (1984) on asset prices and funding costs under asymmetric information, these models examine drivers and effectiveness of disclosure choices (see e.g. the survey by Beyer et al., 2010). Closer to our application, Leuz and Verrecchia (2000) study German firms that have switched to a more transparent reporting regime (IAS or U.S. GAAP) concluding that those firms exhibit lower percentage bid-ask spreads than firms using German GAAP without significant effects on volatility.

As a direct consequence of the empirical findings, this paper will inform whether the SSM transparency initiative is improving market efficiency by steering markets to grant better funding terms to safer and sounder banks.<sup>3</sup> Figure 2 shows the evolution of P2R banks' disclosure practices from 2017. Until January 2020, only 69% of the 120 Significant Institutions (SIs) supervised by the SSM published their P2R, either due to obligation under the provisions of the EU Market Abuse Regulation (MAR) or on a voluntary basis. Due to the SSM transparency

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<sup>3</sup>It is important to note that, in addition to market efficiency, transparency allows market participants and the public to hold the supervisor accountable. Since transparency about the outcomes of supervisory assessments helps market participants to better assess supervisory actions ex-post, transparency can reinforce (or dampen) the legitimacy of the supervisor. In addition to banks, disclosure thus enhances the ability to also evaluate the supervisor, to anticipate its "reaction function", and to identify time-inconsistent behaviour. This interaction can promote credibility and can improve market confidence, and is likely to reduce the risks of regulatory capture.



initiative, in 2020 the number of publicly available P2Rs has increased significantly and, at that time, only a small number of banks has not yet disclosed the P2R but for operational reasons.<sup>4</sup> As of January 2024, all banks supervised centrally by the SSM disclose their P2R.<sup>5</sup>

Moreover, we describe and show how the lack of transparency surrounding P2R disclosures tends to confer an undue advantage to banks assessed by supervisors as having higher risk levels. This suggests that less transparent banks with elevated P2R values may benefit from lower funding costs due to the incomplete information created by opacity. This is a clear case of market failure that can be addressed through regulatory or supervisory intervention and improve the overall allocation of resources.

When P2R is interacted with the transparency indicator, this market inefficiency is canceled-out, resulting in improved funding allocation as transparency mitigates the issue of asymmetric information. For transparent banks, the market more accurately incorporates P2R information into funding costs, indicating that transparency enhances the alignment between funding costs and actual risk profiles.

We estimate that, on average, banks that disclose their supervisory capital requirements (transparent banks) experience an 11.5% reduction in funding costs compared to their opaque counterparts. This suggests that transparency provides a tangible financial benefit by lowering the perceived risk among investors and creditors. However, the effect of transparency is not uniform across all banks, indicating significant heterogeneity in its impact. Transparency enables the market to more effectively differentiate between safer and riskier banks. For instance, among banks that disclose their capital requirements, those in the safest quartile—characterized by a Common Equity Tier 1 (CET1) Pillar 2 Requirement (P2R) of less than 1.5% of risk-weighted assets—experience the most pronounced advantage, enjoying a 31.1% reduction in funding costs on average. These estimates reflect the net effect of transparency, isolating its influence after adjusting for other influencing factors such as business model, country risk, or financial situation.

These findings highlight the role of transparency in enhancing market efficiency by reducing the adverse selection problem, as it allows safer banks to benefit from lower borrowing costs while encouraging riskier banks to improve their practices to remain competitive fostering

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<sup>4</sup>Note that 8 SIs were not yet disclosing the bank-specific P2R in January 2020 for one of the following reasons: i) designated as significant institution late 2019/beginning of 2020, therefore no 2019 SREP decision has been made, or ii) 2019 SREP decision was signed later during 2020.

<sup>5</sup>See ECB [publication](#) of 2024 P2Rs

market discipline.

In the remainder of the paper Section 2 reviews main stylised facts and presents descriptive statistics, identification issues are presented in Section 3, while the empirical design and results are described in Section 4. Section 5 concludes.

## 2 Descriptive statistics

This section reviews the main stylised facts on the disclosure of P2R for the SIs supervised by the SSM. Simple regression analysis is used to facilitate the discussion and describe the role of country and bank characteristics in determining the decision to publish the P2R.

The analysis leverages upon a hand collected database on banks' disclosure practices on regulatory requirements for the period 2017-2020. For the rest of the paper, we distinguish "transparent" banks as those that disclose the P2R publicly, from "non-transparent" banks as those that do not publish their P2R, either due to obligations under the EU Market Abuse Regulation (MAR) or through voluntary disclosure. We also describe how transparent banks are distributed across Euro Area (EA) countries, and the banking business models.

Furthermore, bank-level balance sheet data, as well as Pillar 2 capital requirements together with data on bank characteristics, are collected from ECB Supervisory Statistics, the European Common Reporting Standard (COREP) and the Financial Reporting (FINREP) templates. These data are available from 2014Q1 until 2020Q1. We limit our data collection to the first quarter of 2020, i.e. prior the Covid-19 pandemic, to limit the influence of this large exogenous shock to our results.

### 2.1 Cost of funding and transparency

The aim of this paper is to assess whether the lack of transparency in disclosing supervisory requirements can distort the functioning of an efficient allocation of resources. Since supervisors possess a superior set of information – due to access to confidential information on banks, intrusive on-site inspections, and very granular financial information among others – P2Rs should be a preferable measure for the assessment of the safety and soundness of a bank in contrast to market data such as credit ratings which might have additional informational noise.



As such, transparent banks that put markets to work efficiently by disclosing the supervisory P2R can have clear benefits in terms of aligned pricing mechanisms. In the case of transparent banks, it is expected that market prices and banks' funding costs have a more accurate representation of banks' fundamentals: safer and sounder banks receive more funds at lower costs, while riskier ones become subject to tighter and more expensive funding conditions. In the case of opaque banks this relationship is expected to be less clear.

Simple descriptive evidence can confirm this market failure. Figure 1 plots the relationship between the cost of funding and the P2R for transparent and non-transparent banks. For non-transparent banks there is a significant disconnect between pricing and riskiness of a bank as assessed by supervisory P2Rs. Bad banks that do not disclose their P2R requirement manage to have lower cost of funds, suggesting an inefficient allocation of resources by the market. In this simple descriptive framework, however conditional on interacted country-time fixed effects cleaning the aggregate time variation induced by general country-level risk demand and supply effects, the slope difference between the transparent and non-transparent banks' coefficients is 0.222 and statistically significant at standard confidence levels with a p-val equal to 0.042. Due to the inherent opacity of non-transparent banks, markets have imperfect information, as a result are more likely to misallocate resources to worst performing banks at better financial terms.

In the remainder of the paper, we shed more light on this descriptive relationship by adopting a more rigorous econometric approach to this question. Before delving into the econometrics, and to set the ground for the robustness of our estimates we perform a series of tests to inspect the issue of self-selection into voluntary disclosure and the balance of our treated and control groups across a wide range of bank characteristics.

## **2.2 Time-invariant heterogeneity in transparency**

In this section we briefly show how transparent and non-transparent banks differ across a series of time invariant variables such as country of incorporation or the business model. This is important to show the need of controlling for those time invariant characteristics using bank fixed effects in our research design, discussed in Section 4, to avoid that these drive our results. If we were to omit those time invariant characteristics we would bias our estimates and would

not be confident to associate transparency with the cost of funding.

### 2.2.1 Cross-country heterogeneity

Transparency practices across countries and continents are very heterogeneous. A key driver of these differences is that supervisors are constrained by confidentiality rules enshrined within the national legal frameworks and that regulate in each jurisdiction the degree of confidentiality for protection of privacy. Different international practices suggest that there exist a trade-off between protection of individual confidentiality rights on the one hand, and public sector accountability through transparency on the other hand.

In some European jurisdictions, supervisory authorities have an obligation for secrecy, see Gandrud and Hallerberg (2015, 2018). One of the consequences of this obligation is that in average Banking Union (BU)<sup>6</sup> supervisors tend to publish less than what is publicly available in other Western jurisdictions. For instance, there exists a significant difference between the BU and the United States in the level of disclosure of bank-level data and other supervisory disclosures.<sup>7</sup>

Figure 3 shows the average fraction of SIs disclosing P2R for each SSM jurisdiction. As shown, some jurisdiction have a higher number of banks disclosing their solvency requirements with respect to others. The diversity of disclosure of P2R within Europe is in line with the evidence in Gandrud and Hallerberg (2015, 2018). This heterogeneity is a consequence of not yet harmonised disclosure practices until June 2021, since then all EU banks are required to publish their P2R according to the Capital Requirement Regulation 2 (CRR2).

Cross-country heterogeneity is important not only for disclosing requirements, but can also be seen if we look at our dependent variable of interest: cost of funding, which is defined as annualised interest rate expenses over total liabilities. Figure 4 illustrates this variation. Dutch banks show the highest average cost of funding (2.33%) in our sample, with Slovak banks

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<sup>6</sup>The banking union in the European Union aims to ensure that the banking sector in the euro area and the wider EU is stable, safe and reliable, thus contributing to financial stability by implementing Basel III reforms. It is composed by three main pillars: the Single Supervisory Mechanism (SSM), the Single Resolution Mechanism (SRM), the, still to be ratified, European Deposit Insurance Scheme (EDIS). For more information see [EU Council page on Banking Union](#)

<sup>7</sup>For instance, the SSM does not release individual bank financial accounts (i.e. COREP/FINREP reporting data) because this information is regarded as confidential and commercially sensitive. By contrast, in the U.S., all banks subject to a federal deposit insurance system file a [Consolidated Report of Condition and Income](#) which is then made available by the Federal Financial Institutions Council (FFIEC) on its web page.

presenting the lowest ratio (0.27%). Therefore, for what concerns our dependent variable there is an even more significant variability across euro area countries.

A first glimpse on the relationship between disclosure and cost of funding is provided in Figure 6 which further refines the visual inspection by distinguishing between transparent and non-transparent banks. In some countries non-transparent banks have higher average costs of funding (France, Luxembourg, Cyprus etc.) while in others transparent banks incur higher funding costs (Belgium, Germany, Malta, Spain.). Note that in the Netherlands - where all banks disclose their P2R - there is no variation within a country across treated and control group. In other terms, when we include country fixed effects in our regressions the identification would not arise from Dutch banks.

The inclusion of country fixed effects in regression analyses is crucial for one more reason in our identification strategy: in light of the observed variation in the P2R across countries. Country-specific factors, such as aggregate demand and supply effects, country sovereign risk, banking sector competition and related market structures, institutional settings, housing market regulations, and to some extent investors and depositors cultural preferences, significantly influence the common factor within a country in the determination of the P2R and may confound estimates if not properly accounted for. Figure 5 illustrates the variation of the P2R across the euro area countries.

Overall, this discussion is functional to highlight the importance of including country fixed effects in our regression. By incorporating country fixed effects, the model effectively controls for unobservable, time-invariant heterogeneity across countries, thereby isolating the impact of the variables of interest on the outcome. This adjustment enhances the identification of estimates by reducing bias and ensuring that within-bank variation drives the results. As the country fixed effects absorb cross-country disparities that might otherwise obscure the true relationships under investigation, they allow for more accurate inference and better comparability of results.

### **2.2.2 Heterogeneity across the business model**

Less time-variant bank characteristics such as their business model can be significant drivers of the decision to be transparent. This can be seen more clearly in Figure 7 which sorts banks' business models from the less transparent to the more transparent.

In addition to cross-country heterogeneity, there is a considerable heterogeneity in disclosure

practices across the business model of banks. Some business models, such as the custodian banks, show a very low proportion of P2R disclosure with only 25% of banks disclosing their capital requirements over the period 2017-2020. Other specialised banks, such as asset managers and consumer credit lenders have less than half of their constituent banks disclosing the P2R. Global systemically important banks (G-SIB), and publicly oriented banks such as development and promotional lenders, show a greater inclination to publish their capital requirements.

A similar variation can be seen also in the cost of funding, across business models as shown in Figure 8, and across transparent and non-transparent banks within a certain business model, see Figure 9. This heterogeneity highlights the importance of including bank fixed effects (i.e.,  $\alpha_i$  in Equation 1) in our regression analysis on the impact of transparency on the cost of funding. In other words, omitting the bank fixed effects from the empirical analysis would confound our findings.

Despite this a significant source of endogeneity in our estimates can still come from self-selection. For instance, good banks can have an incentive to disclose their requirement independently of the business model. We will discuss these aspects in more detail in the context of self-selection into treatment in the next Section 3.1, and present subsequently tests on the balance of banks' characteristic across treated and control groups in Section 3.2.

## 3 Identification issues

### 3.1 Self-selection into disclosure?

In this section we look at the possibility that banks self-select into disclosure since, independently from the MAR and the provisions of mandatory disclosure for listed banks therein contained, some banks might opt for disclosing P2R out of economic interest. Ex-ante, we might be inclined to think that P2R disclosure practices are directly proportional to the P2R level: a good bank (i.e., with therefore a lower P2R) might have higher incentives to signal to the markets its good quality.

We first look into this issue descriptively. Figure 10 shows that there is no clear relationship between average disclosure practices within a business model and the P2R level. This is in

principle a reassuring sign for our identification strategy. This descriptive evidence suggests that there is no clear correlation between the share of transparent banks across the business model and the supervisory assessment. This, if confirmed, would be crucial for the robustness of our empirical findings on banks' transparency and market efficiency.

This descriptive evidence notwithstanding, problems may lie at the tails of the distribution. For instance we can expect that very good banks, the stars, would have an incentive in disclosing their requirement to signal their soundness to the markets, to inform market participants that the bank has been assessed much safer and sounder by the supervisor with respect to less safer and less sounder peers. On the other side, some very weak banks may be reluctant in voluntarily disclosing their P2R since disclosure might affect their competitiveness. If this is the case, the self-selection into treatment by tail banks would create an estimation bias.

To see this, Figure 12 presents the distribution of P2R for the group of transparent and non-transparent banks. It is expected that transparent banks have a lower P2R mean and a distribution shifted to the left with respect to non-transparent banks, signaling thus to the markets a better SREP assessment. This conjecture is however not confirmed as, the distributions of P2R across the two groups overlap almost perfectly, thereby suggesting that the choice of disclosing the P2R is *not* driven by the SREP assessment, and the resulting level of P2R. A formal Kolmogorov-Smirnov test for the equality of distributions between transparent and non-transparent banks has a p-value of 0.218 for smaller values in the transparent group, a p-value of 0.429 for larger values in the same group, and a combined distribution test p-value of 0.431 failing thus in all three instances to reject the null of equal distributions across the two samples of banks.

We conclude from this evidence that banks are unlikely to self-select and disclose P2R if they have obtained good grades by the supervisor, rather, this evidence points out to the possibility that other determinants lie behind disclosure of P2R. For instance, in the European Union publicly listed banks must disclose their P2R due to the fact that the SREP assessment constitutes inside information within the provisions of the MAR, we can interpret this evidence as confirmation of the dominance of regulatory constraints versus economic and financial considerations in the "choice" of disclosure of supervisory requirements.

In the next Section 3.2 we expand this endogeneity analysis within a regression framework to investigate whether these simple descriptive evidence is supported in a more robust econometric

set-up.

### 3.2 Balance of treatment and control groups

A comparative across groups research design is more robust if it has a balanced set of bank characteristics across the treated (i.e. transparent banks) and the control (i.e. non-transparent banks) groups. To verify the groups' balance we use a simple t-test for the difference of the means of a set of banks' characteristics between transparent and non-transparent banks. The t-test framework can be formally written as follows:

$$Y_{ict} = \beta \text{Transparent}_{it} + \alpha_i + [\gamma_t] + [\delta_{ct}] + \epsilon_{ict} \quad (1)$$

where  $Y_{ict}$  represent the outcome variable of interest,  $\text{Transparent}_{it}$  is a dummy variable for transparent (=1) banks that publish the P2R, subscripts  $i$ ,  $c$  and  $t$  represent respectively individual banks, countries and time (i.e. quarters), and  $\epsilon_{ict}$  is an error term.

The coefficient  $\beta$  is the main coefficient of interest for this analysis, it represents the mean difference between transparent and non-transparent banks with respect to the dependent variable  $Y_{ict}$ , and after controlling for the fixed effects. The fixed effects that we include are the same as in the baseline regression in Section 4, namely:  $\alpha_i$  is the bank fixed effect representing time-invariant bank characteristics;  $\gamma_t$  represents the quarter within the financial cycle, i.e. this is a time-variant controlling for seasonal effects and common shocks across time which affect all banks in the sample;  $\delta_{ct}$  is the product of the quarter and country fixed effects capturing time variant country characteristics such as macroeconomic shocks affecting a specific country at a point in time.

Table 1 presents the first evidence from Equation 1 for the P2R and the Pillar 2 Guidance (P2G)<sup>8</sup> balance between transparent and non-transparent banks. Each cell of the table represents a separate regression, as specified in Equation 1, testing the mean difference of P2R and P2G across a battery of fixed effects. In columns we show the set fixed effects applied in each separate regression: respectively, Column (1) shows the bank fixed effect, Column (2) the bank and quarter fixed effects in additive form, and Column (3) adds the bank fixed effect to the

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<sup>8</sup>The Pillar 2 guidance is a bank-specific recommendation that indicates the level of capital the ECB *expects* banks to maintain in addition to their binding P2R capital requirements to ensure they can absorb *potential* losses resulting from adverse scenarios in stress tests.

interaction country-quarter fixed effects.

The basic insight from Figure 12 on self-selection into treatment tend to be corroborated also from this simple t-test of means. The differences in the means of the P2R between transparent and non-transparent banks are marginal, and are not robust to the inclusion of time fixed effects. The coefficient on P2R tends to be positive suggesting that transparent banks have a higher P2R, i.e. the riskier banks tend to disclose more. There is a marginal significance at 10% confidence level when we use bank fixed effect in Column (1), however this significant mean difference is not robust across specifications. This suggests that the differences in capital requirements arise from idiosyncratic shocks not related to the tendency of being a transparent bank.

Similarly, in Figure 13 we plot total assets for transparent and non-transparent banks (left panel) and next to it the residualised total assets partialled-out by bank fixed effects. While on the unconditional left hand side chart there is a mean divergence between transparent and non-transparent banks, it however vanishes once we control for bank fixed effect, this is confirmed also by the regression output in Table A-VI of Appendix A.

To show the importance of including bank fixed effects to the set of control variables which we use in the empirical framework, Table 2 presents the simple t-test of mean difference of control variables. This is not conditional on other control variables and on bank or country and time fixed effects. Importantly, the unconditional difference between the cost of funding for transparent and non-transparent banks is not statistically significant, suggesting those two groups could be comparable unconditionally on this metric. However, as can be seen without conditioning the mean differences can be statistically significant between treated (i.e. transparent) and control banks. However, for the same set of control variables, once we condition for bank fixed effects mean differences are not statistically significant as show in Table 3.

We extend this conditional balance of the mean analysis to a much wider set of time-variant bank characteristics in Appendix A covering solvency, profitability, liquidity, SREP scores, risk-taking and profitability, asset quality, and balance sheet structure. The results are in line with the evidence on supervisory requirement and do not show any systematic relationship between transparent and non-transparent banks along those bank characteristics.

Overall, these results alleviate concerns on self-selection into treatment by less riskier banks and clarify potential concerns on the unbalance between treatment and control groups.



## 4 Empirical design and results

This section outlines our empirical strategy, focusing on the categorization of banks based on their disclosure practices. Specifically, we classify banks into two groups: those that disclose their P2R and those that not. This classification allows us to examine the relationship between disclosure and the bank cost of funding to learn whether more transparent banks can improve market efficiency and reduce asymmetric information inefficiencies linked with adverse selection. To rigorously evaluate these effects, we define our baseline specification, which can be formally expressed as follows:

$$CoF_{ict} = \alpha_i + \beta \text{Transparent}_{it} \times [\text{P2R}_{it}] + \delta_{ct} + \mathbf{x}_{it}\Gamma + \mathbf{z}_{it}\Psi + [\rho \cdot t] + \epsilon_{ict} \quad (2)$$

where  $CoF_{ict}$  is the trailing annualised cost of funding for each bank defined as annualised quarterly interest expenses divided by total liabilities;  $\alpha_i$  is the bank-level fixed effect. The inclusion of bank fixed effects is crucial in panel data models as it allows for the control of unobserved heterogeneity across banks that may influence the dependent variable. This is particularly important because the *variation* of the bank-specific transparency dummy variable is explained in the cross-sectional dimension by the bank fixed effects. By accounting for these time invariant fixed effects, the model isolates the within-bank variation over time, ensuring that the analysis identifies more accurately, reducing potential bias in estimates, the effects of transparency as determined by the residual variation across banks and time.

It follows that  $\beta$  is our coefficient of interest measuring the relationship between the bank disclosure of the P2R and the cost of funding. In each specification we include country-quarter fixed effects  $\delta_{ct}$  to account for country level variation over time. We then add two main sets of control variables: the first being represented by the vector  $\mathbf{x}_{it}$  in Equation 2 is a set of bank balance sheet control variables (i.e.,  $\ln(\text{Tot. Assets})$ , Deposit ratio,<sup>9</sup> NPL ratio and the annualised trailing Net Interest Margin); the second set of controls are the regulatory ratios represented by the vector  $\mathbf{z}_{it}$  containing the Leverage Ratio, the LCR and the risk-weighted CET1 ratio. It is important to highlight that the inclusions of regulatory ratios as control variables is

In all specifications we keep the sample size equal across specifications to avoid that sample

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<sup>9</sup>The Deposit Ratio is the ratio of total overnight deposits, i.e., the sum of NFC, government, households, other financial institutions and credit institutions overnight deposits, over total assets

composition affect our inference. We augment the baseline specification by interacting the P2R.

Since our empirical design is akin to a difference-in-difference exploration method, where we compare "treated" and "control" groups of banks, the underlying identification assumptions for unbiased estimates is the common trend assumption. In other words both groups would have had similar trends in absence of treatment. While the common trend assumption is not directly testable, we can augment the specification with bank specific trends to see if those might have had an influence on the results. Therefore, a version of Equation 2 is augmented with the bank specific trends  $\rho \cdot t$  for a robustness test of the common trends assumption. As mentioned in Wolfers (2006) and Angrist and Pischke (2008), the inclusion of trends at the level of the policy variable should be a standard robustness test for difference-in-difference specifications.

Finally, in all our specifications we employ two-way clustered standard errors, at the choice/policy variable at bank-level and also at the time period variable *quarter*. Standard errors are also robust for heteroschedasticity and serial correlation.

## 4.1 Results

### 4.1.1 Baseline: transparency and cost of funding

Table 4 presents the results of the baseline model, examining the relationship between transparency and the cost of funding. In Column (1), we display the conditional correlation between the dummy variable *Transparent* and the dependent variable *Cost of Funding*, after controlling for the bank-level time-invariant component and the interaction of aggregated demand and supply effects by using the country-quarter fixed effects. This adjustment, explained in more detail in Section 2.2.2, is applied to account for the unique, fixed characteristics of each bank over time and aggregate variation such as country risk which may affect valuation of yields on sovereign bonds and hence trickle down to funding costs for banks in that specific country. The analysis includes data from 118 banks.

The coefficient estimate in Column (1) suggests a negative association between transparency and cost of funding: on average, transparency brings 0.29 percentage points less interest expenses compared to non-transparent competitors. This reduction represents a 22.2% ( $= 0.29 / 1.308$ ) savings in the cost of funding for transparent banks, as compared to their non-transparent

counterpart, see Table 2 for further reference on unconditional mean differences in the sample.

In Columns (2) through (5) of Table 4, we progressively introduce additional balance sheet and regulatory control variables to the model. As anticipated, the transparency benefit diminishes with the inclusion of these controls, as they are correlated with the cost of funding. In the preferred model presented in Column (5), which includes the set of control variables, the estimated benefit from disclosing P2R decreases by half, to 0.15 percentage points, equating to an 11.5% ( $= 0.15 / 1.308$ ) reduction in the cost of funding for transparent banks relative to non-transparent banks. This adjustment reflects the net effect of transparency after accounting for correlated factors.

#### 4.1.2 Transparency and market efficiency

Table 5 shows the results for the interaction of the transparency variable with the P2R. The first row of Table 5 indicates a negative relationship between P2R and the cost of funding. This is counterintuitive since we would expect higher costs of funding for less safer and sounder banks. In other words, the opacity surrounding P2R disclosures is associated with an undue benefit for banks that are evaluated by the supervisor as having higher risks. This indicates that less transparent banks with higher P2R may experience cost advantages due to incomplete information that opacity creates.

However, when we interact the P2R with the dummy for transparent banks this market inefficiency is canceled-out. The estimated interaction effect between transparency and P2R reveals the improved market efficiency arising due to the elimination of the asymmetric information problem. For transparent banks, the market incorporates more accurately P2R information into the cost of funding, suggesting that transparency helps aligning funding costs with underlying risk factors.

It could be inferred from this analysis that *supervisory* transparency is generally beneficial, and allows the market to discriminate between safer banks from those that are less sound. This finding supports the idea that *supervisory* transparency enhances also market discipline by allowing investors to better evaluate and price the risk associated with each bank. These findings underscore the role of supervisory transparency in promoting efficient market outcomes, particularly for banks that are open about their supervisory assessments.

In terms of magnitudes, it is important to notice that the *average* marginal effect of trans-

parency increases once we control for the P2R. In Column (5) of Table 5, the marginal effect estimated at the mean value of P2R is -0.19 percentage points and therefore higher than the comparable estimate in Column (5) of Table 4.

To shed more light on this relationship, we plot the marginal effect of the interacted regression to show the evolution of the relationship between transparency and cost of funding across the P2R. Figure 14 plots the marginal effect of transparency on cost of funds through the range of values of the P2R, conditional on a bank being transparent. From this, it is clearer how the benefits of disclosing capital requirements manifest for the safer and transparent banks, i.e., those with a P2R below 2.407% of risk-weighted assets. At the same time, due to this additional information, the market is able to penalize worse banks, and indeed funding costs increase for riskier banks, i.e., those with a P2R above 4.069% of risk-weighted assets.

Note that there is an indeterminate zone where it is not clear whether we can reject the null hypothesis of no-effect. Importantly, for the safest quartile of banks, those with a P2R lower than 1.5% of risk-weighted assets, the average benefit of disclosing their own P2R translates in a 54.06% lower interest expenses than those of opaque counterparts.

### 4.1.3 Robustness for business models

The inclusion of bank business models such as custodians and consumer credit lenders in the analysis could significantly impact our results due to the distinct characteristics of these institutions. Figure 7 shows that banks with those business models are the more opaque ones, first because they are not subject to the MAR and have more discretion in their disclosure policy which could bias our results due to self-selection, second because typically maintain high levels of capitalization as part of their risk management strategies and therefore are under a lower scrutiny from the markets.

We run the model without those banks and present the results in Tables 6 and 7. The results are unchanged and remarkably stable despite the marginal loss of information. The estimated magnitudes are very close and not statistically different from the ones of Table 5.

To ensure robustness and mitigate the potential influence of outliers associated with specific business models, we rerun the model excluding custodian banks and consumer credit lenders, and the results are presented in Tables 6 and 7. The findings demonstrate remarkable stability, even with the marginal loss of information caused by the exclusion of these specialized insti-

tutions. The estimated magnitudes remain highly consistent with those reported in Table 5, showing only negligible differences. Importantly, the differences in the estimates are neither economically nor statistically significant, underscoring the resilience of our results. This stability affirms that the observed effects are not driven by the unique characteristics or disclosure practices of custodian banks and consumer credit lenders, which often exhibit distinct behaviors due to their high capitalization levels and lower incentives to disclose P2R. Consequently, our conclusions remain robust and unaltered.

Similarly, we perform the same test by focusing on other most capitalised business models. In our sample three business model have most of the buffer capital on top of the Maximum Distributable Amount (MDA) threshold: custodians, the development/promotional lenders, and the small market lenders.<sup>10</sup> Table 11 shows the capital buffer above the MDA for each business model.

This robust capitalization not only serves to buffer against financial shocks but also alters their regulatory disclosure incentives, particularly regarding P2R. Highly capitalized institutions may perceive reduced incentives to disclose P2R, as their capital buffers exceed regulatory thresholds by much and the market is generally aware of this situation, diminishing the need to signal financial resilience to stakeholders. Furthermore, their business models are less sensitive to market perceptions of creditworthiness compared to traditional commercial or investment banks, potentially leading to different patterns of regulatory compliance and transparency. Consequently, including these types of banks in the dataset might bias the analysis.

Table 8 presents the results by eliminating development/promotional lenders from the sample, while Table 9 eliminates further the small market lenders. The results are consistent with our previous findings, and the key inferences remain unchanged. This stability is reassuring, as it suggests that the potential bias arising from self-selection by more capitalised banks does not materially affect our conclusions.

Overall, we reaffirm that the disclosure of P2R plays an effective role in reducing asymmetric information and enhancing market efficiency, highlighting its importance as a regulatory tool in promoting transparency and fostering well-functioning financial markets.

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<sup>10</sup>The MDA is the minimum capital requirement in the European union for banks below which distribution restrictions can be imposed.

#### 4.1.4 Robustness for parallel trends

In this section, we present a robustness test to verify the parallel trends assumption, which underpins the validity of our estimates. This assumption is critical, as it posits that, in the absence of the treatment, both transparent and non-transparent banks would have followed similar pre-treatment trends. If these groups were already on diverging paths prior to the disclosure of P2R, any observed post-treatment differences could reflect pre-existing trend disparities rather than the causal impact of transparency itself. Such a divergence would risk inflating our estimates, attributing a larger-than-warranted effect to the decision to disclose the P2R. Consequently, our robustness test aims to isolate and control for any potential deviations in pre-treatment trajectories between these groups, thereby enhancing the reliability of our findings and mitigating the risk of overestimating the effect of P2R disclosure. If our results are not robust to the inclusion of bank specific time trends, then it is likely that those are explaining the divergence between "treated" and "control" banks. Further the inclusion of bank trends can help in pinning down a more precise magnitude estimate.

We present the results of this test in Table 10. While the main message of the previous findings is not altered, it is important to highlight the reduction of point estimates. Transparent banks still show a significant but, as expected, reduced positive effect. Evaluated at the mean P2R, the benefit of transparency is now reduced to 0.08 percentage points, in other words is halved. This represents a reduction for transparent banks of 6.1% ( $= 0.08 / 1.308$ ) with respect to the average of non-transparent banks, see Table 2 for the unconditional means. At the same time, for the safest quartile of banks, those with a CET1 P2R lower than 1.5% of risk-weighted assets, the average benefit of disclosing their own P2R is reduced now to 31.06% lower cost of funding than those of opaque banks.

These updated estimates suggest that the diverging trend component of the two cost of funds series across the two groups was explaining almost half of the magnitude of Table 4 and should be, as a rule, included in the model. Finally it is worth emphasizing the higher explanatory power as computed by the  $R^2$  statistics of the model with bank trends. In Column (5) of Table 10 the  $R^2$  is 0.887 and 54.5% higher than the same statistics from Table 5, suggesting that trend divergence has also significant power in terms of the proportion of variance in the dependent variable that can explain.

### 4.1.5 Dynamic regressions

The cost of funds as measured by total interest expenses over total liabilities is a structural ratio with little variation over time within a bank. In panel data, the dependent variable often exhibits serial correlation within the bank. Ignoring this can lead to model misspecification. By including a lagged dependent variable, we account for autocorrelation in the dependent variable, leading to more accurate parameter estimates of interests on transparency and improving the model's fit.

While dynamic panel data models are well-suited for studying dynamic relationships, they come with significant econometric challenges, as outlined by Kiviet (1995). The primary issue is that the lagged dependent variable is by construction correlated with the error term, introducing endogeneity and biasing point estimates. Formally:

$$CoF_{ict} = \alpha_i + \rho CoF_{ict-1} + \beta Transparent_{it} \times [P2R_{it}] + \delta_{ct} + \mathbf{x}_{it}\Gamma + \mathbf{z}_{it}\Psi + [\rho \cdot t] + \epsilon_{ict} \quad (3)$$

where  $CoF_{ict-1}$  is the lagged dependent variable term, and this introduces error term correlation by construction, i.e.,  $Cov(\epsilon_{ict}, \epsilon_{ict-1}) \neq 0$ .

To address this problem, the econometric literature has proposed various estimators. The traditional approach relies on first-difference instrumental variable estimators, as developed by Anderson and Hsiao (1981), and the more advanced first-difference generalized method of moments (GMM) estimator introduced by Arellano and Bond (1991).

However, these estimators were designed for micro panels characterized by a small time dimension and a large number of cross-sectional units, i.e.  $N \rightarrow \infty$ . In contrast, the panel data structure in this study has a bank-level mesoeconomic focus, featuring a relatively small number of cross-sections. This structure introduces additional challenges in selecting an appropriate estimator.

To address this, the approach in this paper follows the recommendations of Judson and Owen (1999) for estimating dynamic macro panels with fewer cross-sectional units than typical micro panels. The preferred specification here is estimated using the least square dummy variable (LSDV) estimator. The LSDV estimator exhibits a relatively small bias in estimating the coefficient of the lagged dependent variable under such conditions, and the bias for the



remaining explanatory variables, which are our main interest, is fairly negligible.

Results are presented in Table 11. It is noticeable the behaviour of the lagged dependent variable term with a very high autocorrelation coefficient in the range of 0.917-0.946 depending on the specification. However, the lagged coefficient becomes significantly smaller in Column (5) when we control for bank specific trends highlighting once more the importance of conditioning for the trend behaviour within banks.

More interesting is the result on transparency and the P2R. As already shown in Table 5, the opaque banks with a high P2R show a negative coefficient which is now robust to the inclusion of the lagged dependent variable. Note that the estimated negative coefficient on the P2R is however halved since now it is explaining the *change*, i.e. the *new* information at time  $t$  after we conditioned for the lagged cost of funding at time  $t - 1$ , in the cost of funding and not the *level*.

Similarly, the effects on the transparency dummy are negative as in Table 5, however now they are weakly significant and much smaller. The fact of a weaker significance is not concerning because the variation of the transparency dummy variable, which is at bank-level by construction, is very low across banks, and even more within bank. This variation of the transparency dummy is predominantly absorbed by the inclusion of bank fixed effects in our baseline, if anything this weak significance highlights the importance on the findings in the previous section.

The effects show an average coefficient of 0.13 percentage points reduction in the cost of funding for transparent banks relative to non-transparent banks in Column (5) of Table 11. We can compute the marginal effects at different P2R levels. For instance, assuming that the coefficient on the transparency dummy is statistically significant, at mean value of the P2R which is 2.091 in the regression sample, the estimated marginal effect is not statistically different from zero. Whereas it becomes relevant only for the best banks. For the best quartile of banks, those with a P2R lower than 1.5% of risk-weighted assets, the marginal effect reduces to  $1.5\% = -0.133 \cdot (1.5 \cdot 0.075)$ .

But an important caveat has to be mentioned. While these estimates are significantly lower they capture the effect on the remainder of the cost of funding ratio after controlling for its lagged value. When we scale it by the average of the change of the cost of funding in the control group we obtain that this 1.5% corresponds to an average reduction of the change in cost of

funding with respect to the control group by 39.5% ( $= 0.015 / 0.038$ ), where 0.038 is the mean value of the change in the cost of funding ration in the control group within the estimation sample.

Finally it is worth emphasizing once more how the inclusion of a lagged dependent variable term improves further the fit of the model as described by the R-squared statistics. In Column (4) of Table 11 the R-squared is 0.984 which is a significant improvement in explaining the variation of the dependent variable when compared with the Column (5) of Table 5 where the R-squared statistics is 0.574. Similarly, the goodness of fit improves in Column (5) of Table 11 in comparison to the counterpart with bank trends.

## 5 Conclusions

When market prices have greater signaling power, safer and sounder banks benefit by receiving more funds at reduced costs, while riskier banks face more constrained and expensive funding conditions. This dynamic provides an incentive for banks to avoid excessive risk-taking, as they seek to maintain investor confidence and minimize funding costs (see, e.g., Calomiris and Kahn, 1991). In turn, this alignment promotes financial stability. However, these conclusions rest on the assumption of complete and accurate information availability. In scenarios where opacity prevails, or when information is incomplete, markets may struggle to distinguish safer banks from riskier ones.

Increasing transparency, particularly regarding supervisory assessments of banks, could be essential to foster both market discipline and efficiency. Supervisors, with access to a more comprehensive set of information, set individualized capital requirements that hold significant informational value for market participants. Without access to these insights, market participants cannot fully assess the risk profiles of individual banks, leading to potential mispricing and misallocation of resources. This paper addresses this market failure by comparing banks in the euro area that disclose their capital requirements (P2R) to those that remain opaque, exploring the impact of transparency on market discipline.

Our empirical findings suggest that opacity around P2R disclosures indeed confers a disproportionate advantage to banks that supervisors assess as higher-risk. Specifically, non transparent banks with elevated risk values seem to enjoy lower funding costs, benefiting from the

incomplete information that opacity fosters. This constitutes an instance of market failure, as resources may be misallocated to riskier banks simply due to a lack of information. However, when transparency is introduced by interacting P2R with a transparency indicator, this market inefficiency disappears, yielding an alignment between funding costs and banks' actual risk profiles. In transparent settings, market discipline is enhanced as funding costs more accurately reflect underlying risk, thereby underscoring the efficiency gains of transparency.

In conclusion, a commitment to higher levels of supervisory transparency, exemplified by the SSM policy introduced in January 2020 to disclose Pillar 2 capital requirements for all significant institutions in the eurozone, reduces the potential for information asymmetries. This move not only improves market efficiency but also strengthens market discipline, creating a more stable financial environment overall. Transparent disclosure of supervisory assessments thus emerges as a key mechanism to support a more efficient and disciplined market structure, ultimately contributing to financial stability.

## References

1. Acharya, V. V., and Ryan, S. G. (2016). Banks' financial reporting and financial system stability. *Journal of Accounting Research*, 54(2), 277-340.
2. Allen, F., and D. Gale (2000). Financial contagion. *Journal of Political Economy*. 108(1), 1-33.
3. Anderson TW, Hsiao C (1981) Estimation of dynamic models with error components. *J Am Stat Assoc* 76:589–606
4. Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev Econ Stud* 58:277–297
5. Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press
6. Baiman, S., and R. Verrecchia (1996). The Relation Among Capital Markets, Financial Disclosure, Production Efficiency, and Insider Trading. *Journal of Accounting Research*, 34(1), 1-22.
7. Beyer, A., Cohen, D. A., Lys, T. Z., and Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of accounting and economics*, 50(2-3), 296-343.
8. Bischof, J., and Daske, H. (2013). Mandatory disclosure, voluntary disclosure, and stock market liquidity: Evidence from the EU bank stress tests. *Journal of Accounting Research*, 51(5), 997-1029.
9. Bischof, J., Laux, C., and Leuz, C. (2021). Accounting for financial stability: Bank disclosure and loss recognition in the financial crisis. *Journal of Financial Economics*, 141(3), 1188-1217.
10. Bischof, J., Foos, D., and Riepe, J. (2023). Does greater transparency discipline the loan loss provisioning of privately held banks?. *European Accounting Review*, 1-31.
11. Calomiris, C.W, and C.M., Kahn (1991). The role of demandable debt in structuring optimal debt arrangements. *American Economic Review*, 81, 497-513.

12. Diamond, D.W., and R. Verrecchia (1991). Disclosure, liquidity and the cost of capital. *Journal of Finance*, 46(4), 1325-1359.
13. Ellahie, A. (2013). Capital market consequences of EU bank stress tests. Working Paper Available at SSRN 2157715.
14. Ellahie, A. (2016). Information content of mandated bank stress test disclosures. Available at SSRN 2685919.
15. Gandrud, C., and Hallerberg, M. (2015). Does banking union worsen the EU's democratic deficit? The need for greater supervisory data transparency. *JCMS: Journal of Common Market Studies*, 53(4), 769-785.
16. Gandrud, C., and Hallerberg, M. (2018). Explaining variation and change in supervisory confidentiality in the European Union. *West European Politics*, 41(4), 1025-1048.
17. Hirshleifer, J. (1971). Suppression of inventions. *Journal of Political Economy*, 79(2), 382-383.
18. Huizinga, H. (2018). Review of the 2017 SREP results. Banking Union Scrutiny. European Parliament
19. Jordan, J. S., Peek, J., and Rosengren, E. S. (1999). The impact of greater bank disclosure amidst a banking crisis. (Vol. 2). Federal Reserve Bank of Boston.
20. Judson RA, Owen AL (1999) Estimating dynamic panel data models: a guide for macroeconomists. *Econ Lett* 65:9–15
21. Kiviet JF (1995) On bias, inconsistency, and efficiency of various estimators in dynamic panel data models". *J Econ* 68:53–78
22. Leuz, C., and Verrecchia, R. E. (2000). The economic consequences of increased disclosure. *Journal of accounting research*, 91-124.
23. Myers, S. C. and Majluf, N. S. (1984). Corporate Financing and Investment Decisions When Firms have Information that Investors do not have.
24. Resti, A. C. (2018). Review of the 2017 SREP results. Banking Union Scrutiny. European Parliament

25. Wolfers, J. (2006). Did unilateral divorce laws raise divorce rates? a reconciliation and new results. *The American Economic Review*, 96(5):1802–1820

Figure 1: Transparency, Cost of funding and Pillar 2 Requirements

Note: the figure scatter plots the relationship between the cost of funding and the P2R computed across 2017Q1-2020Q1. Cost of funding and P2R are residualised on country-time fixed effects, N=1294, observation are divided in 20 bins, 10 for each group. Cost of funding is defined as interest expenses divided by total liabilities.

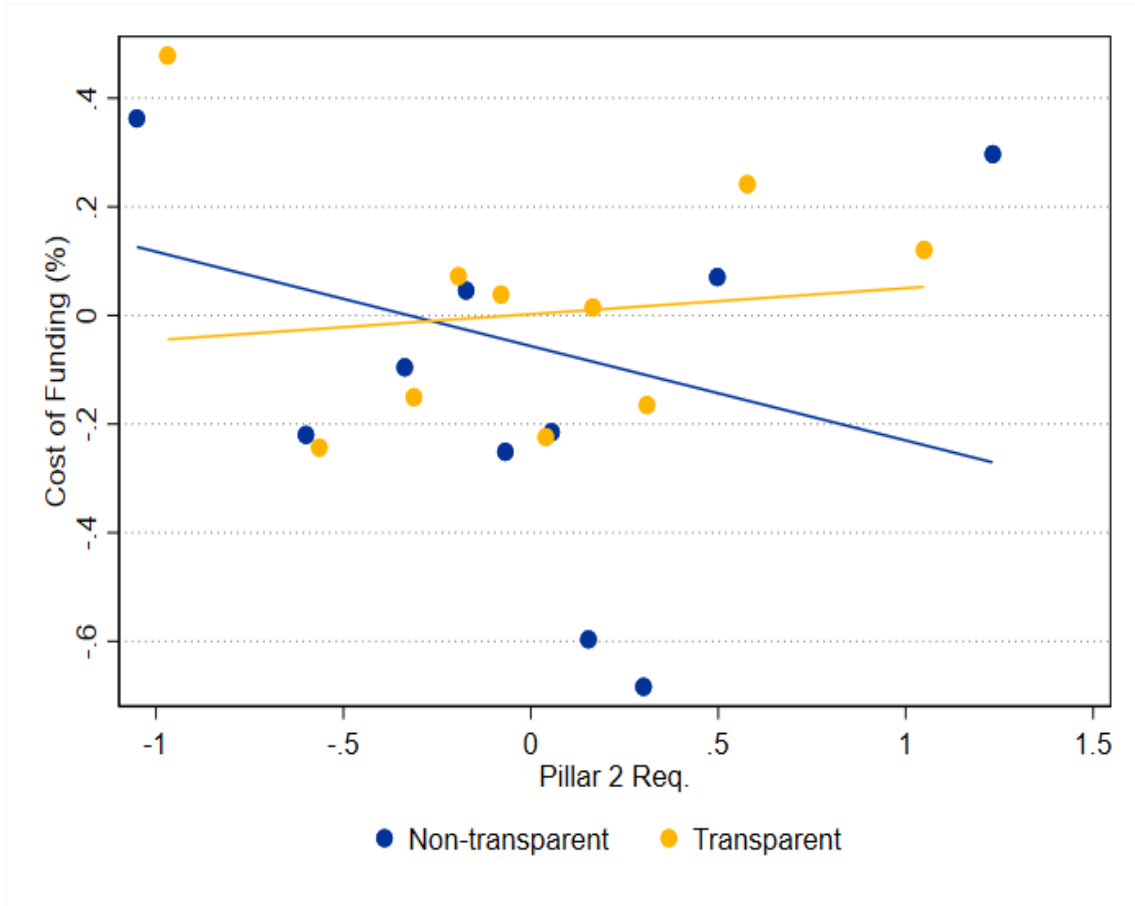




Figure 2: Evolution of P2R Disclosure practices across the SSM

Note: the figure shows the number of SSM banks disclosing their P2R within their annual financial accounts. Non-transparent indicates banks that do not disclose the P2R. The total number of banks understates the total number of SIs prior to 2019 due to missing information on disclosure practices.

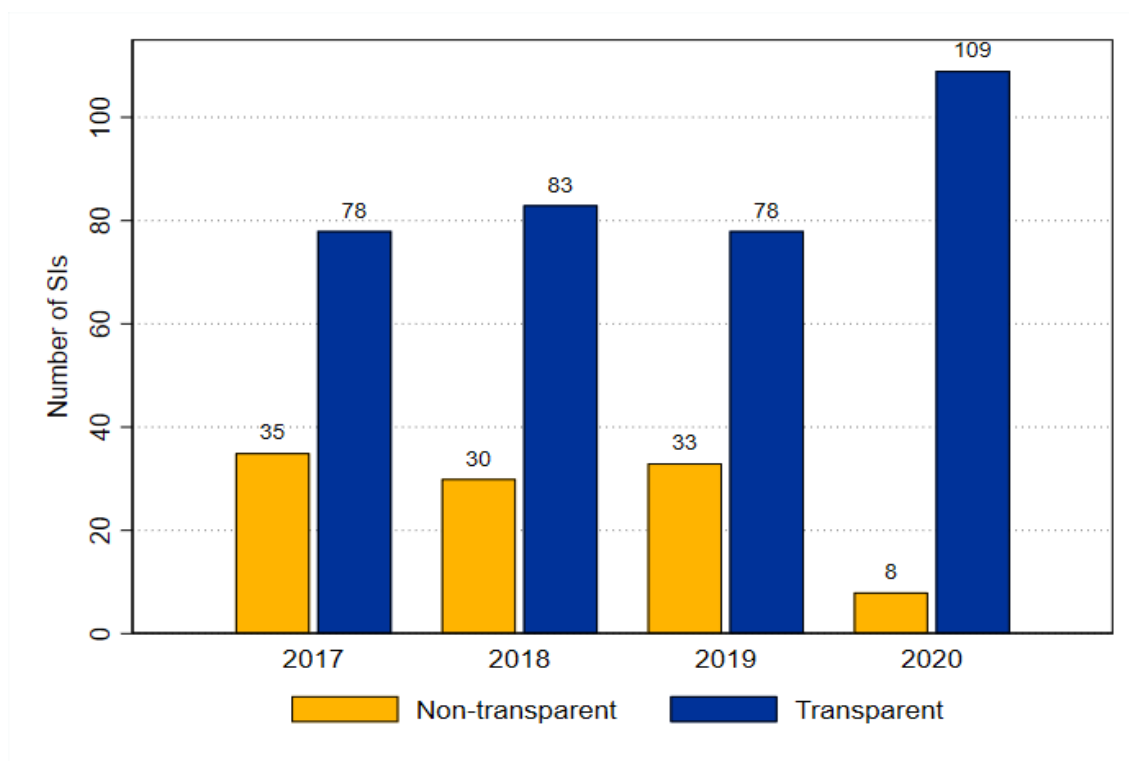


Figure 3: Disclosure by Banks' Country

Note: the figure shows the fraction of banks that disclose their P2R in each country across the 2017Q1-2020Q4 period. Transparent banks are defined with a binary variable equal to one if they disclose their P2R.

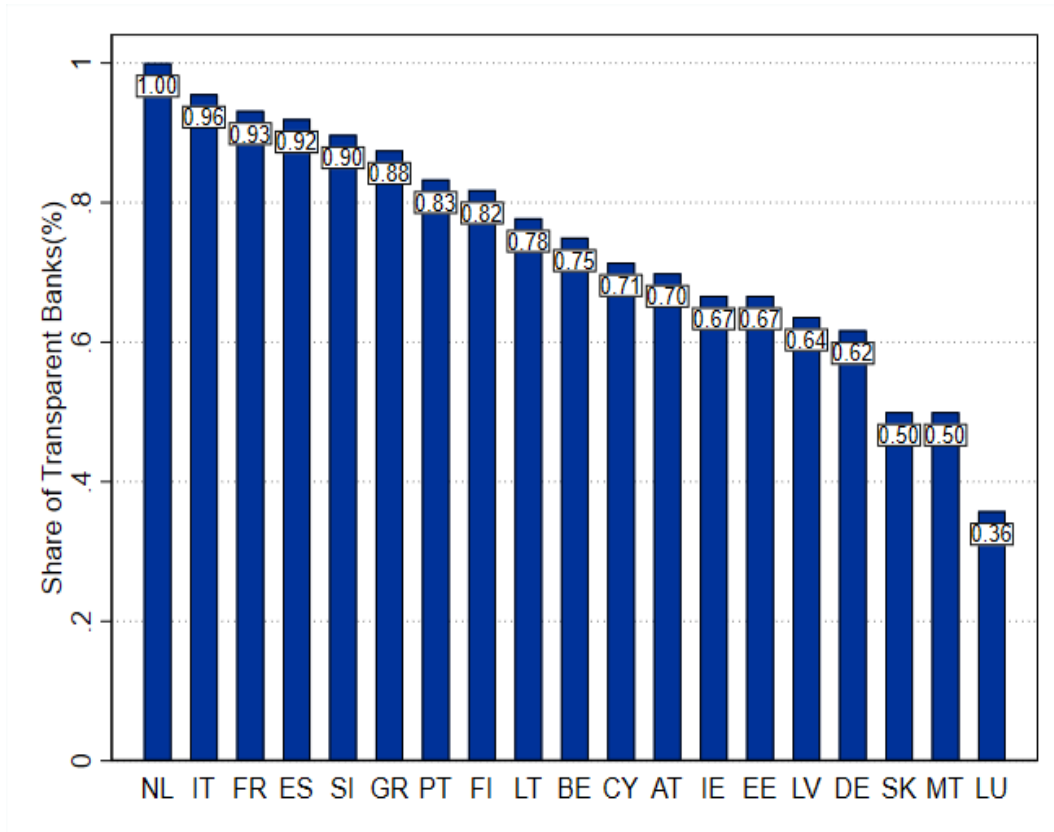


Figure 4: Cost of Funding by Banks' Country

Note: the figure shows the average cost of funding for transparent and non-transparent banks within a country for the period 2017Q1-2020Q1. Cost of funding is defined as interest expenses divided by total liabilities. Transparent banks are defined with a binary variable equal to one if they disclose their P2R.

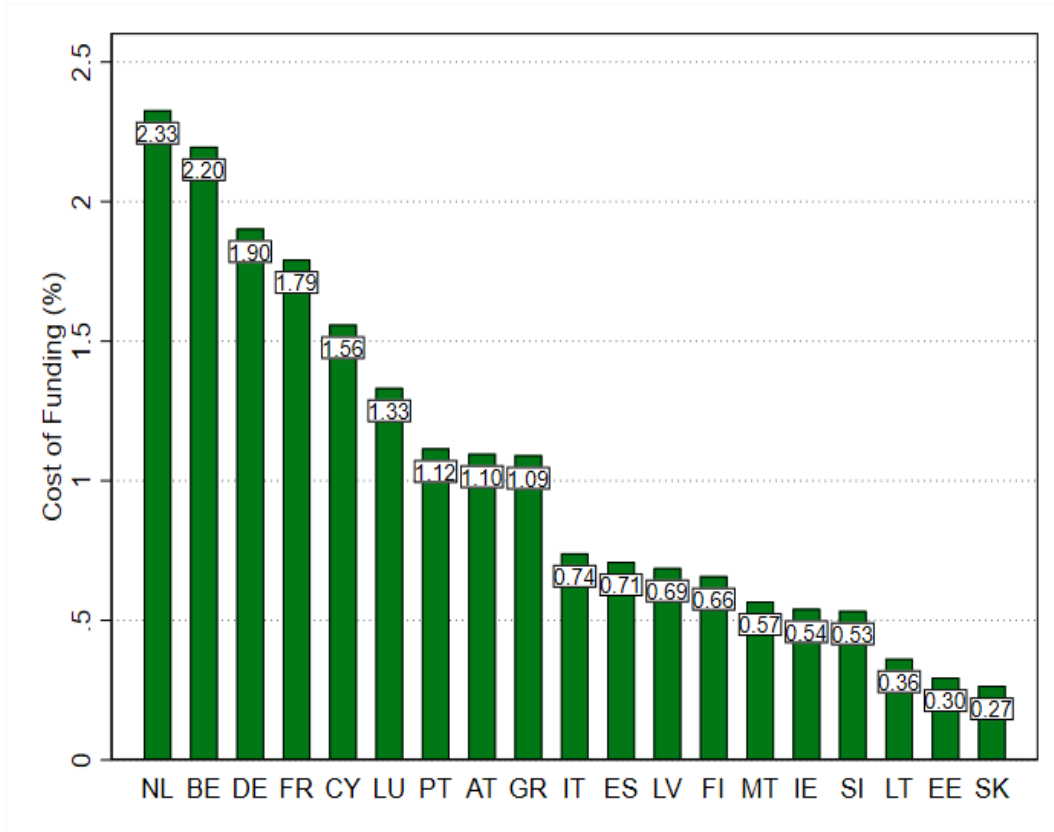


Figure 5: P2R variation across euro area countries

Note: the figure shows the average Pillar 2 Requirement expressed as a percentage of Risk Weighted Assets (RWA) across euro area countries for the period 2017Q1-2020Q1.

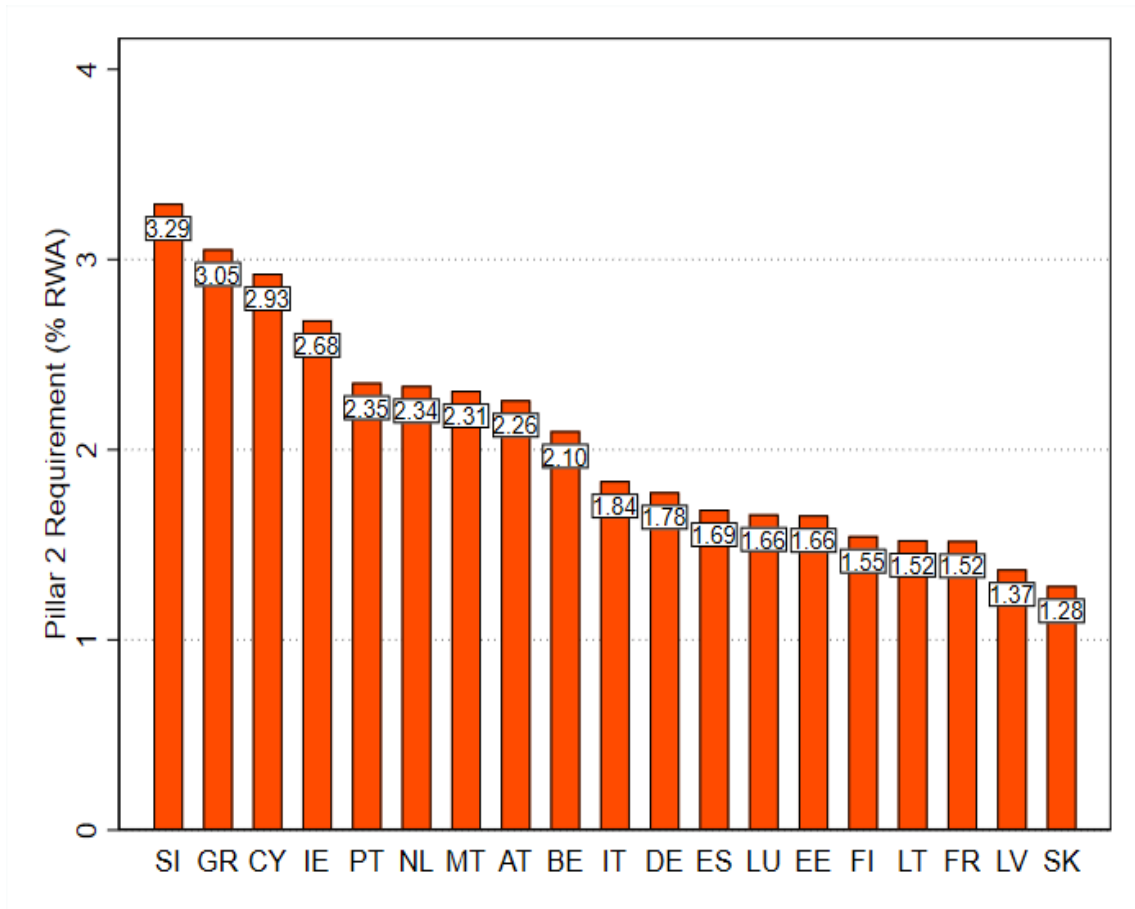


Figure 6: Disclosure of P2R and Cost of Funding by Banks' Country

Note: the figure shows the average cost of funding per country . across the 2017Q1-2020Q4 period. Cost of funding is defined as interest expenses divided by total liabilities. Disclosure is a dummy 1/0 on whether a SI has disclosed their P2R.

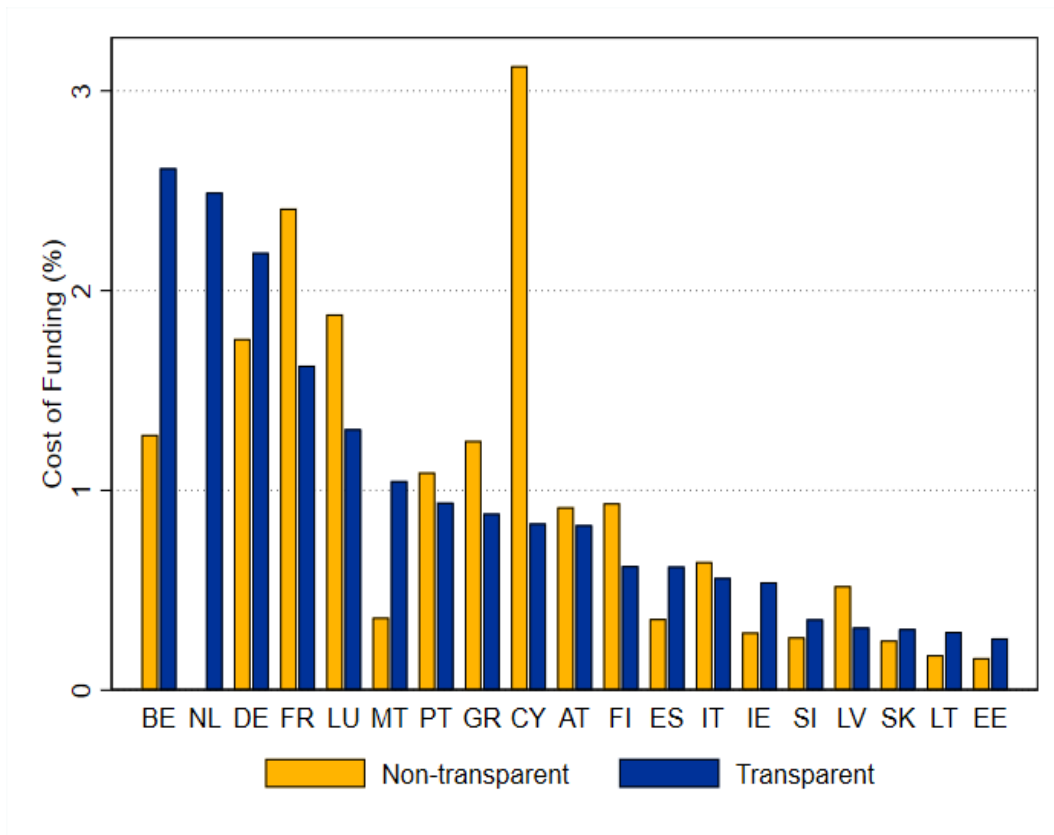


Figure 7: Disclosure of P2R by business Model

Note: the figure plots the fraction of SSM banks disclosing their P2R by business model. The fraction is shown in the white box and represents an average of transparent banks over the 2017Q1-2020Q4 period. Note that G-SIBs have only transparent banks since all of them disclose their P2R.

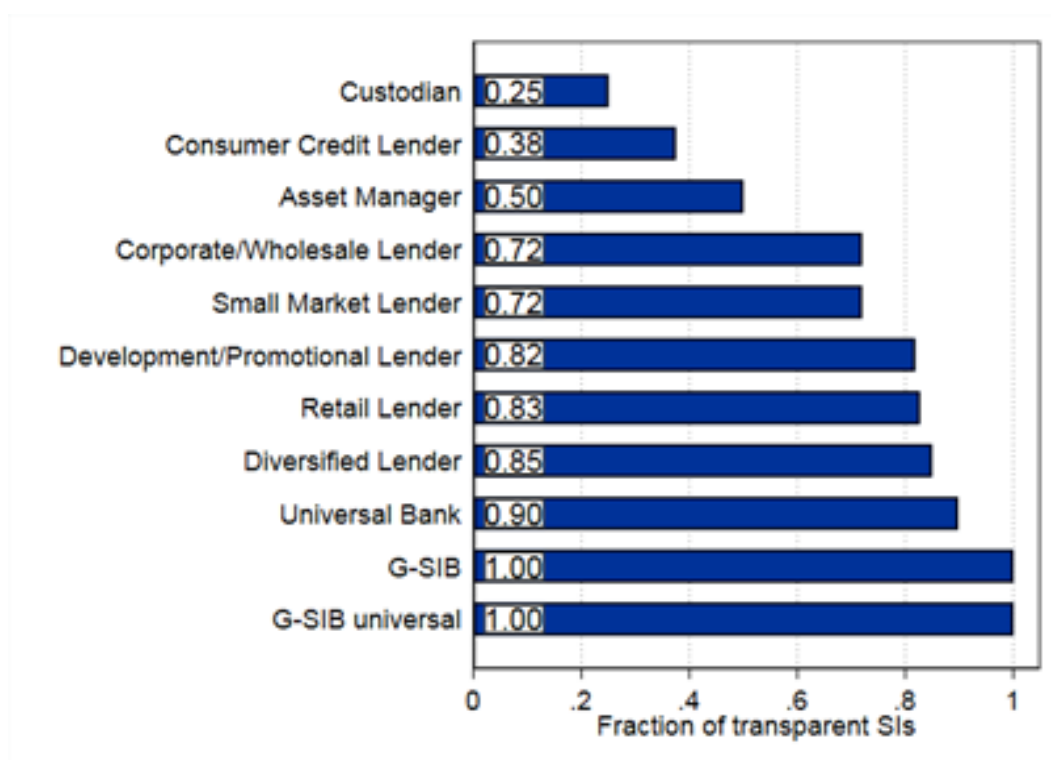


Figure 8: Cost of Funding by Business Model

Note: the figure plots the average cost of funding across business models for the period 2014Q4-2020Q1. The fraction is shown in the white box. Note that G-SIBs have only transparent banks since all of them disclose their P2R. Cost of funding is defined as interest expenses divided by total liabilities.

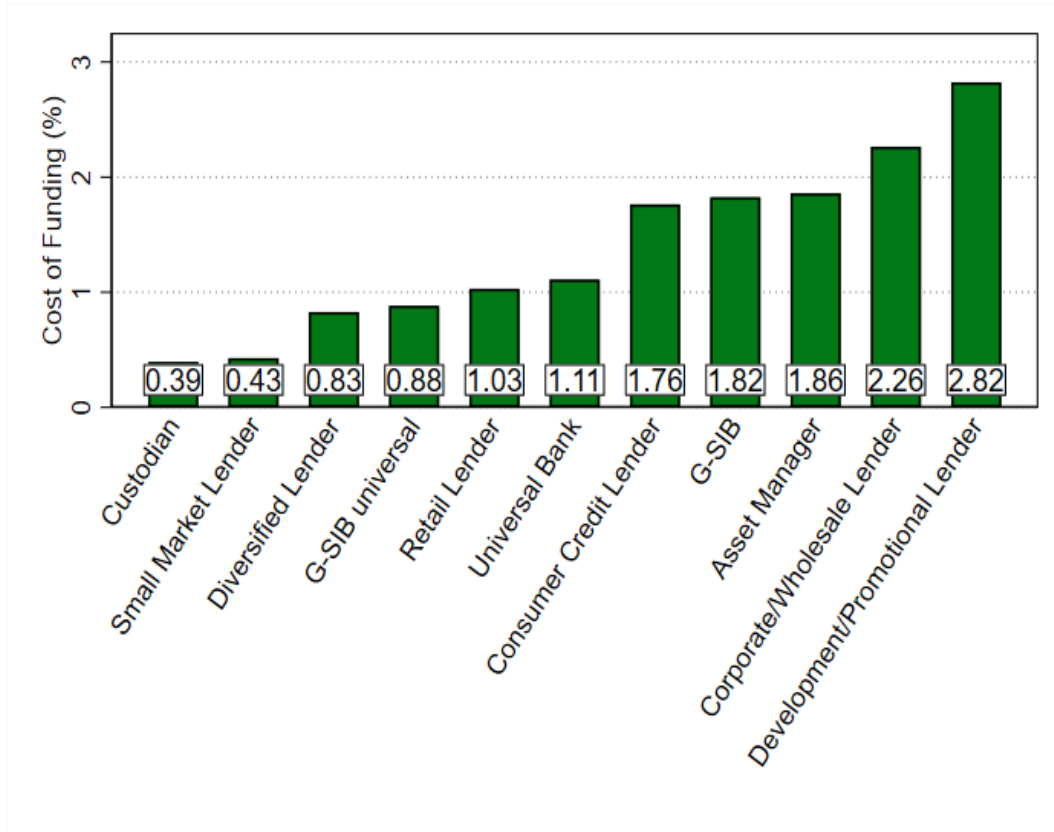




Figure 9: Disclosure and Cost of Funding by Business Model

Note: the figure plots the average cost of funding for transparent and non-transparent banks within a business model for the period 2017Q1-2020Q1. Cost of funding is defined as interest expenses divided by total liabilities.

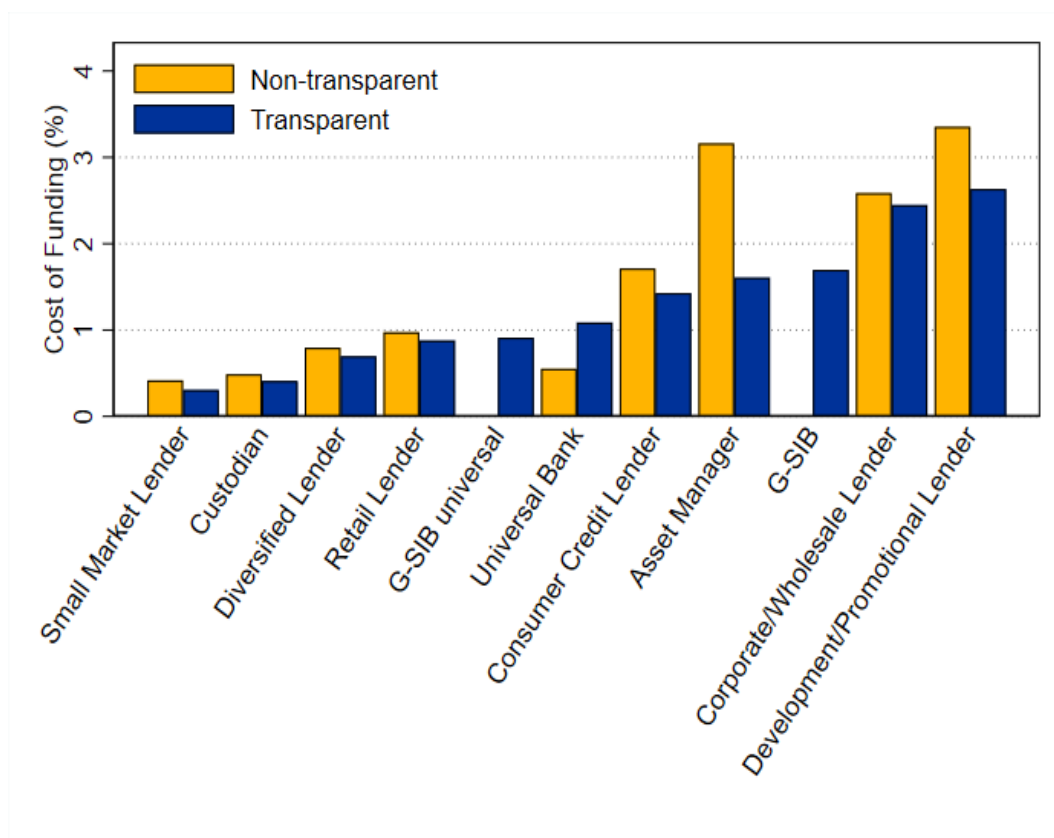


Figure 10: P2R and Transparency by Business Model

Note: the figure shows the average P2R for transparent and non-transparent banks subdivided by business model. It also shows (blue bars) the share of transparent banks across business models, for this share 1 corresponds to 100% of banks within the business model classification. The average is computed across the 2017Q1-2020Q4 period. Note that G-SIBs have only transparent banks since all of them disclose their P2R.

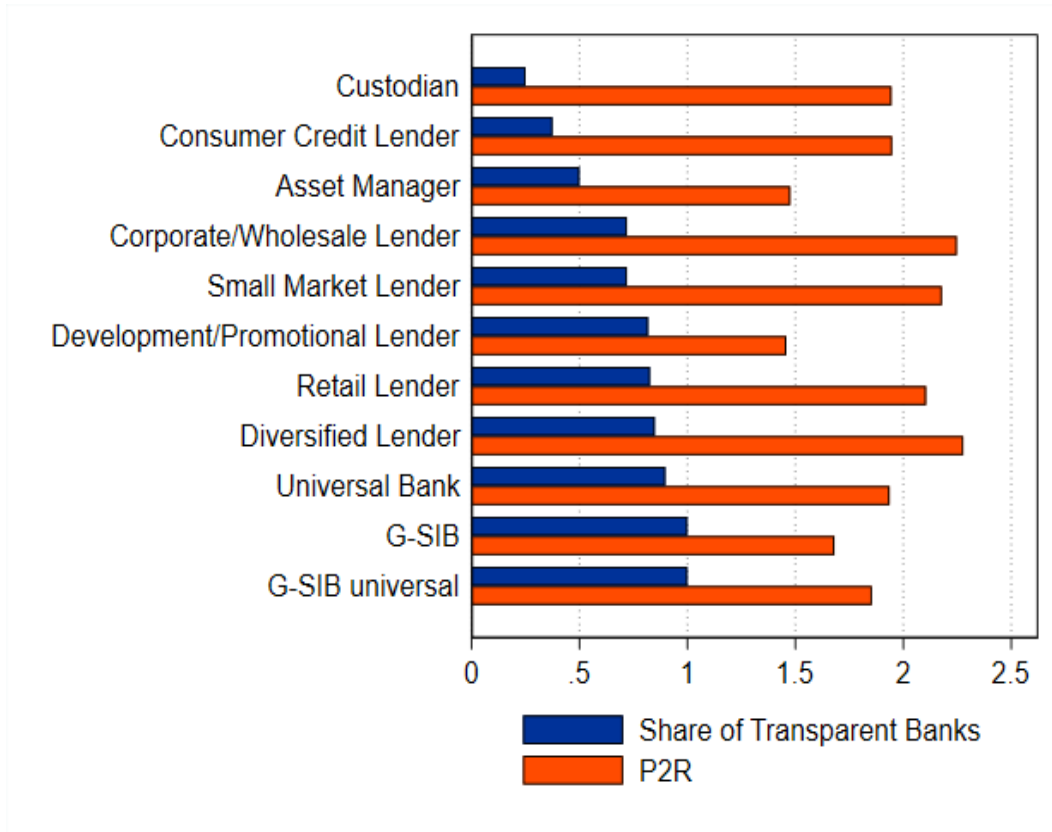


Figure 11: CET1 buffer by Business Model

Note: the figure plots the average CET1 buffer from the MDA across business models for the period 2014Q4-2020Q1. The fraction is shown in the white box.

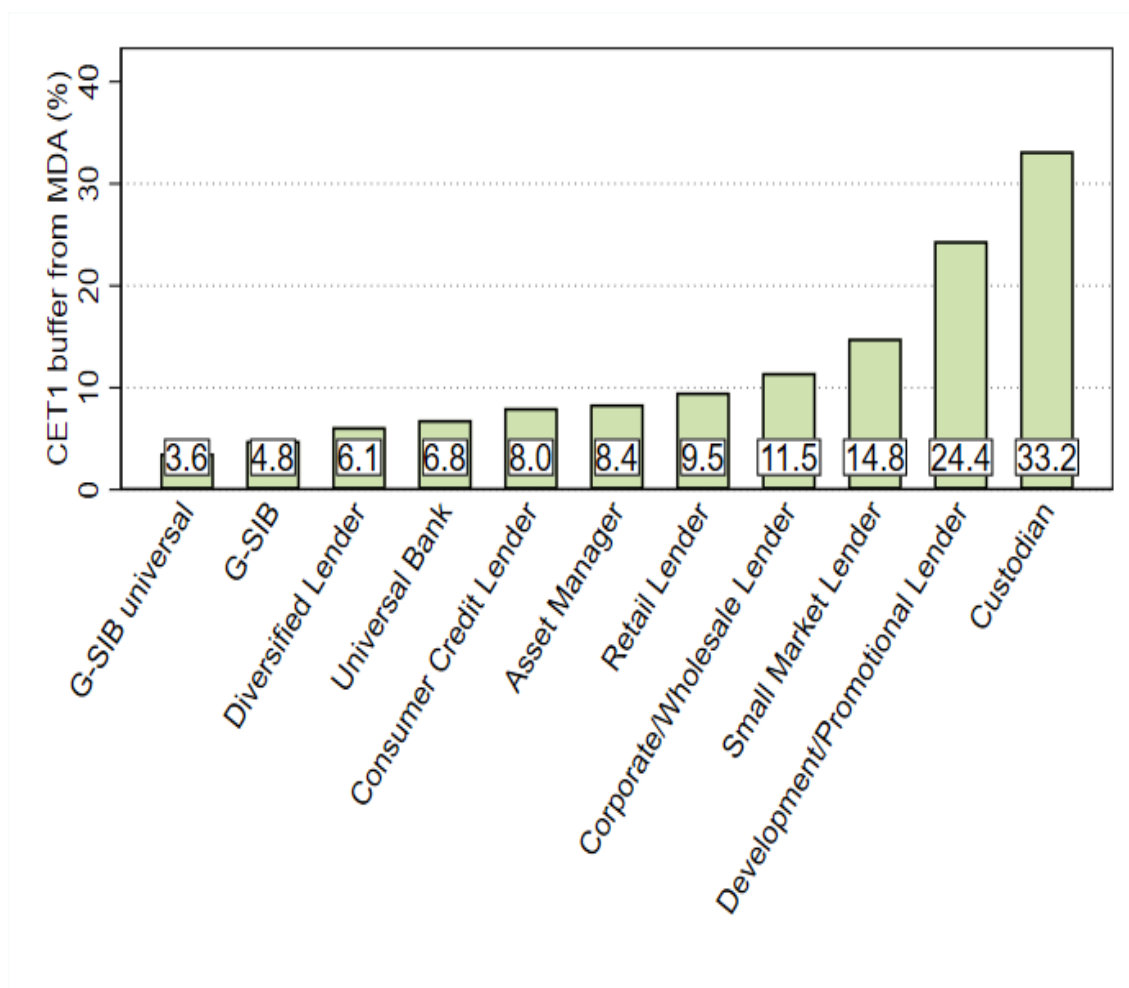


Figure 12: Distribution of Pillar 2 Requirements and Transparency

Note: the figure plots the (Epanechnikov) kernel density of the P2R for transparent and non-transparent SIs within the SSM. The kernel is computed across 2017-2020. The left y-axis shows the probability density function while the right y-axis depicts the number of observations. Banks are divided in 50 bins (dots) for the aggregate of transparent and non-transparent banks.

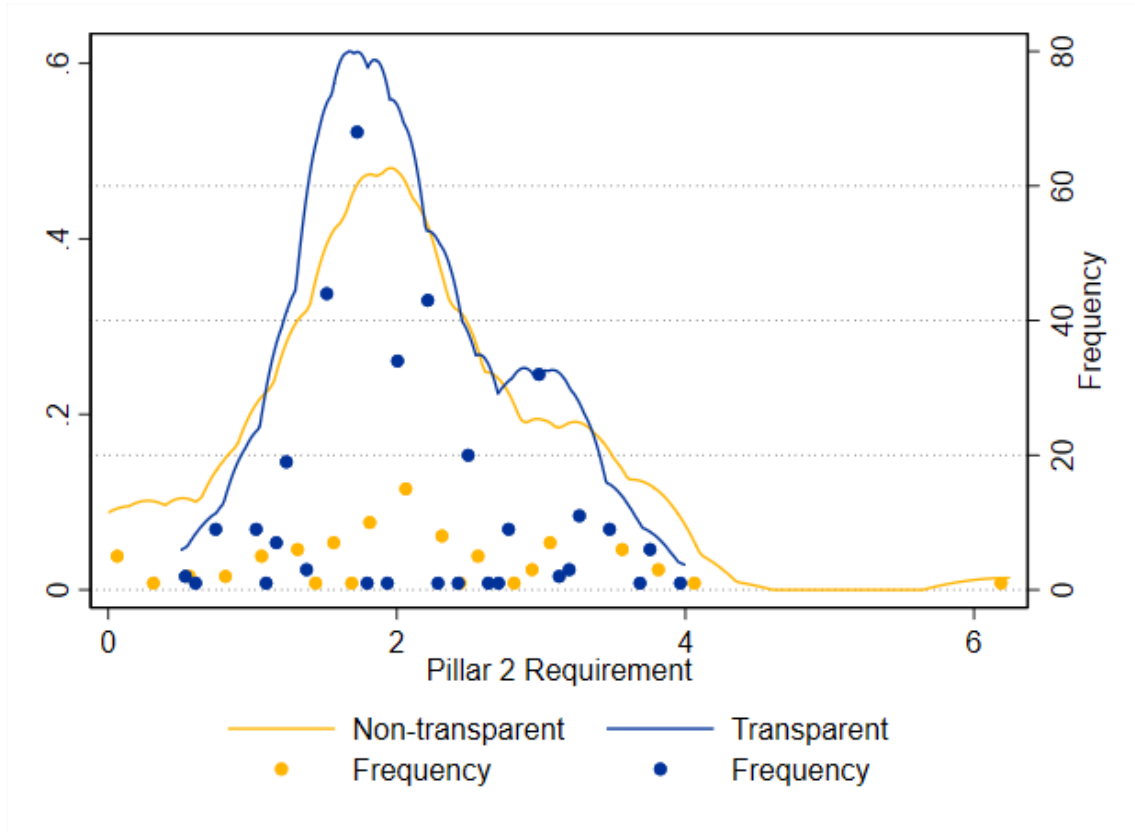


Figure 13: Distribution of Total Assets and Transparency

Note: the graph shows the (Epanechnikov) kernel density. The first panel plots the kernel density of the natural logarithm of total assets for transparent and non-transparent SIs. The second panel plots the kernel density of the residualised logarithm of total assets on bank fixed effects. The kernel is computed for the period 2017Q1-2020Q4. The left y-axis shows the probability density function (%) while the right y-axis depicts the number of SIs. Banks are divided in 50 bins (dots) each for transparent and non-transparent banks.

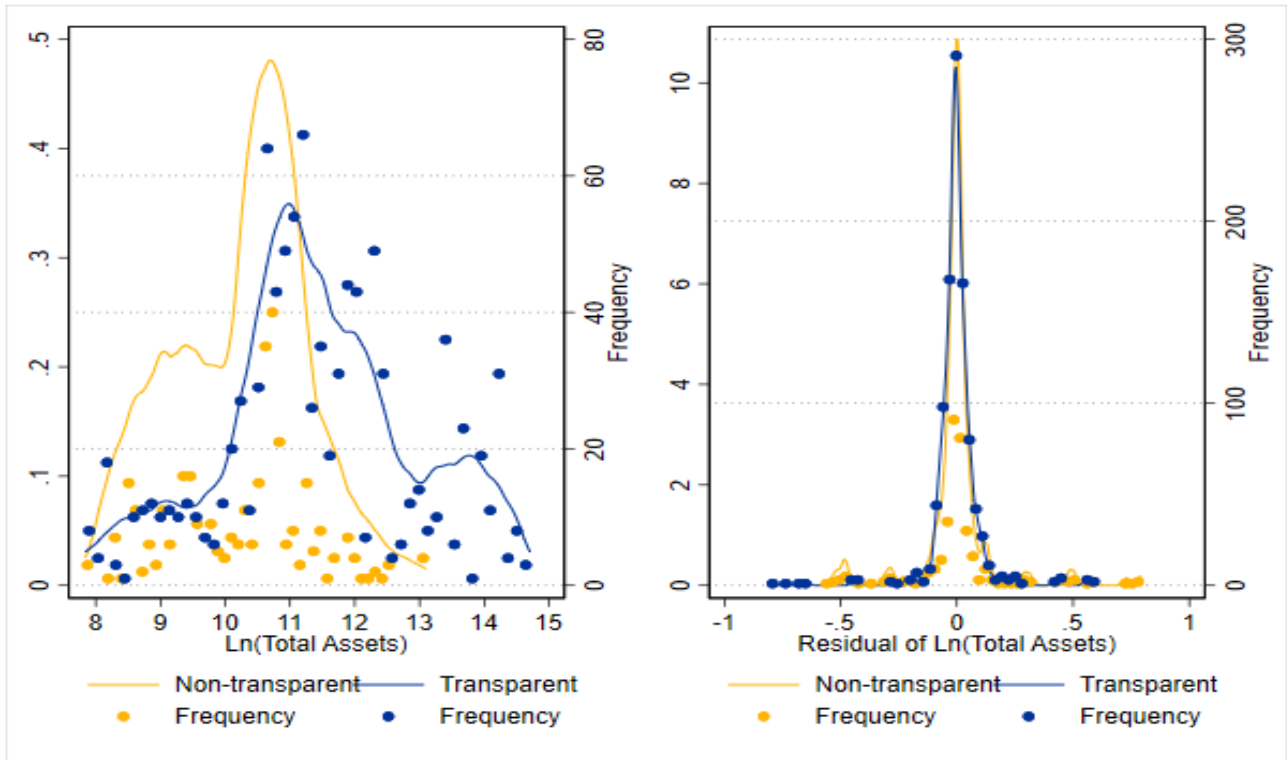


Figure 14: Marginal Effect of transparency on cost of funds across P2R

Note: the graph shows the average marginal effect for transparent banks across the spectrum of P2R values. Outer dotted lines represent confidence intervals at 5% level. The vertical dashed lines are represent the P2R region between 2.407 and 4.069 which signals the no-effect zone, i.e. for those levels of P2R the average marginal effect of transparency on cost of funding fails to be distinguished statistically from zero at the 5% confidence level.

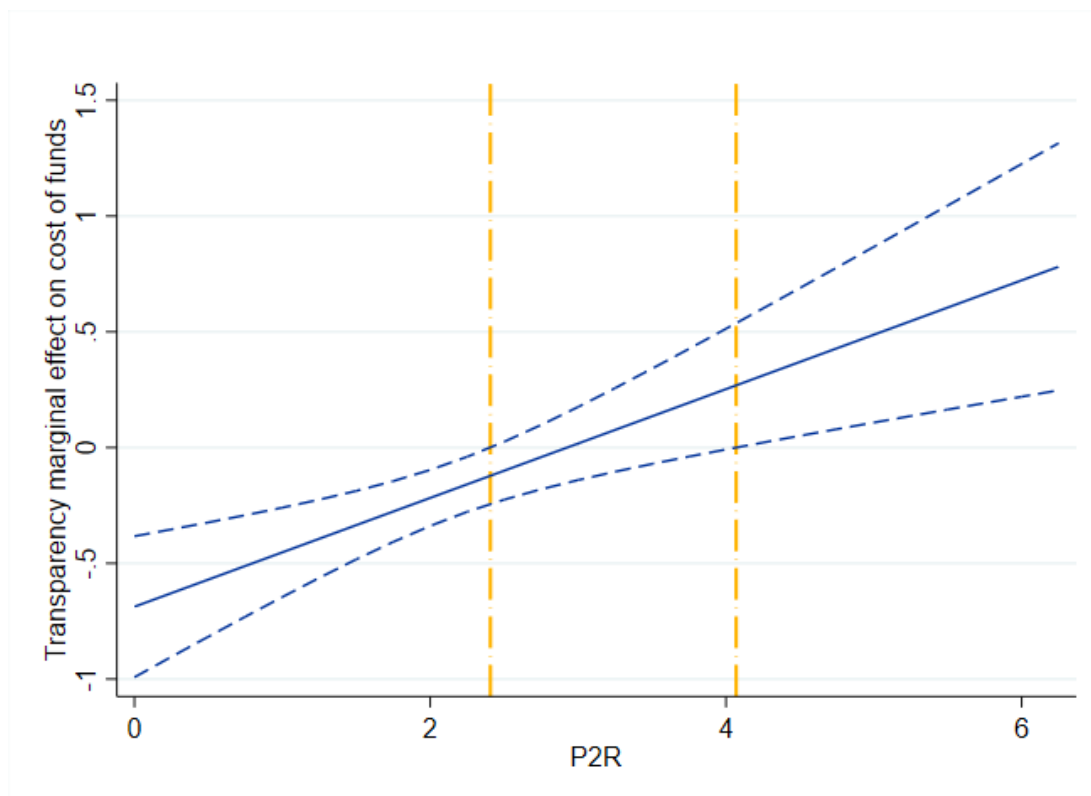


Table 1: Transparency and Supervisory Requirements

	(1)	(2)	(3)
<i>Dependent variables:</i>			
P2R	0.088* (0.052)	0.048 (0.056)	0.053 (0.055)
P2G	-0.165* (0.095)	0.003 (0.092)	-0.123 (0.117)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,710	1,710	1,710
N. of banks	123	123	123

*Note:* Each cell represents a separate regression of the Transparency indicator (1/0) on the dependent variable. Stars indicate statistical significance at  $***p < 0.01$ ,  $**p < 0.05$ ,  $*p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table 2: Unconditional t-test mean difference control variables

	Transparent Banks	Non-transparent Banks	
	mean (St.dev.)	mean (St.dev.)	mean diff. (St.err.)
<i>Dependent variable:</i>			
Cost of Funds	1.223 (1.308)	1.308 (1.810)	0.085 (0.805)
<i>Control variables:</i>			
ln(Tot. Assets)	11.407	10.256	-1.152*** (-15.426)
Deposits ratio	36.700	47.861	11.160*** (7.525)
NPL ratio	4.325	3.451	-0.875* (-2.096)
Net Int. Margin	1.274	1.224	-0.050 (-1.077)
Leverage Ratio	6.945	8.064	1.119*** (5.164)
LCR	157.134	247.659	90.525 (0.618)
CET1 ratio	17.863	20.756	2.893*** (4.396)
Observations	990	341	1331
N. of banks	123	123	123

*Note:* Stars indicate statistical significance in unconditional mean differences at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The table shows the t-test of the differences of the means between transparent and non-transparent banks unconditional to control variables and fixed effects.



Table 3: Conditional t-test mean difference control variables

	(1)	(2)	(3)
<i>Variables:</i>			
ln(Tot. Assets)	0.018 (0.017)	0.005 (0.017)	0.011 (0.027)
Deposits ratio	0.428 (0.645)	-0.648 (0.519)	-0.809 (0.568)
NPL ratio	-0.525 (0.558)	-0.102 (0.515)	-0.065 (0.388)
Net Int. Margin	0.015 (0.029)	0.038 (0.031)	0.046 (0.034)
Leverage Ratio	0.128 (0.122)	0.180 (0.119)	0.057 (0.113)
LCR	-123.051 (120.631)	-268.340 (261.815)	-223.575 (224.303)
CET1 ratio	0.004 (0.335)	-0.038 (0.358)	-0.286 (0.567)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,710	1,710	1,710
N. of banks	123	123	123

*Note:* Each cell represents a separate regression of the Transparency indicator (1/0) on the dependent variable. Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table 4: Baseline regression: Transparency and cost of funds

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
Transparent Banks	-0.290*** (0.093)	-0.180** (0.076)	-0.186** (0.075)	-0.199*** (0.075)	-0.151** (0.068)
ln(Tot.Assets)		-2.009*** (0.346)	-2.032*** (0.348)	-2.026*** (0.341)	-2.291*** (0.348)
Deposits ratio		0.049*** (0.012)	0.048*** (0.011)	0.046*** (0.011)	0.052*** (0.011)
NPL ratio			0.034** (0.015)	0.022 (0.014)	0.045*** (0.013)
Net Int. Margin				0.394*** (0.086)	0.463*** (0.094)
Leverage Ratio					-0.247*** (0.047)
LCR					0.033* (0.018)
CET1 ratio					0.072*** (0.012)
Observations	1,190	1,190	1,190	1,190	1,190
R-squared	0.385	0.540	0.543	0.560	0.602
Number of banks	118	118	118	118	118
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation.

Table 5: Transparency, cost of funds and P2R

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
P2R	-0.148 (0.096)	-0.183** (0.083)	-0.203** (0.085)	-0.193** (0.082)	-0.202*** (0.078)
Transparent Banks	-1.022*** (0.371)	-0.787*** (0.274)	-0.808*** (0.275)	-0.817*** (0.272)	-0.688*** (0.252)
Transparent Banks $\times$ P2R	0.332** (0.136)	0.264** (0.106)	0.275** (0.107)	0.273*** (0.105)	0.235** (0.099)
ln(Tot.Assets)		-1.628*** (0.316)	-1.642*** (0.318)	-1.645*** (0.310)	-1.878*** (0.329)
Deposits ratio		0.043*** (0.011)	0.041*** (0.011)	0.040*** (0.011)	0.045*** (0.011)
NPL ratio			0.036** (0.016)	0.023 (0.014)	0.051*** (0.015)
Net Int. margin				0.359*** (0.064)	0.413*** (0.066)
Leverage ratio					-0.203*** (0.044)
LCR					0.025 (0.017)
CET1 ratio					0.058*** (0.010)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,171	1,171	1,171	1,171	1,171
R-squared	0.373	0.513	0.517	0.537	0.574
Number of banks	115	115	115	115	115

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation.

Table 6: Robustness without custodians

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
P2R	-0.156*	-0.191**	-0.211**	-0.201**	-0.212***
	(0.095)	(0.083)	(0.086)	(0.083)	(0.079)
Transparent	-1.046***	-0.811***	-0.830***	-0.841***	-0.702***
	(0.370)	(0.275)	(0.277)	(0.274)	(0.253)
Transparent Banks $\times$ P2R	0.339**	0.270**	0.280***	0.279***	0.237**
	(0.135)	(0.106)	(0.107)	(0.105)	(0.099)
Ln(Total assets)		-1.626***	-1.639***	-1.640***	-1.890***
		(0.314)	(0.315)	(0.308)	(0.325)
Deposits ratio		0.043***	0.042***	0.041***	0.046***
		(0.011)	(0.011)	(0.011)	(0.011)
NPL ratio			0.034**	0.022	0.052***
			(0.016)	(0.014)	(0.015)
Net Int. margin				0.357***	0.413***
				(0.064)	(0.066)
Leverage ratio					-0.220***
					(0.045)
LCR					0.022
					(0.017)
CET1 ratio					0.067***
					(0.010)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,151	1,151	1,151	1,151	1,151
R-squared	0.380	0.521	0.524	0.544	0.586
Number of banks	111	111	111	111	111

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation. The table excludes 4 banks with the custodians business model from the sample.

Table 7: Robustness without custodians, consumer lenders and asset managers

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
P2R	-0.159 (0.097)	-0.193** (0.085)	-0.212** (0.087)	-0.202** (0.084)	-0.212*** (0.080)
Transparent	-1.073*** (0.388)	-0.804*** (0.285)	-0.823*** (0.286)	-0.827*** (0.283)	-0.673*** (0.260)
Transparent Banks $\times$ P2R	0.345** (0.139)	0.269** (0.108)	0.279** (0.109)	0.277*** (0.107)	0.230** (0.100)
Ln(Total assets)		-1.653*** (0.320)	-1.667*** (0.321)	-1.668*** (0.314)	-1.930*** (0.329)
Deposits ratio		0.045*** (0.011)	0.043*** (0.011)	0.042*** (0.011)	0.048*** (0.011)
NPL ratio			0.035** (0.016)	0.022 (0.015)	0.053*** (0.015)
Net Int. margin				0.354*** (0.065)	0.410*** (0.067)
Leverage ratio					-0.223*** (0.046)
LCR					0.025 (0.017)
CET1 ratio					0.069*** (0.010)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,128	1,128	1,128	1,128	1,128
R-squared	0.381	0.524	0.528	0.547	0.591
Number of banks	108	108	108	108	108

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation. The table excludes 3 banks with the custodians business model, and 4 banks with consumer lending or asset manager model from the sample.

Table 8: Robustness without development/promotional lenders

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
P2R	-0.145 (0.096)	-0.181** (0.083)	-0.201** (0.086)	-0.190** (0.082)	-0.206*** (0.078)
Transparent Banks	-0.961** (0.390)	-0.701** (0.285)	-0.722** (0.286)	-0.729** (0.283)	-0.644** (0.259)
Transparent Banks × P2R	0.317** (0.141)	0.241** (0.108)	0.252** (0.109)	0.248** (0.107)	0.225** (0.100)
Ln(Total assets)		-1.626*** (0.320)	-1.640*** (0.322)	-1.644*** (0.314)	-1.894*** (0.336)
Deposits ratio		0.043*** (0.011)	0.042*** (0.011)	0.041*** (0.011)	0.046*** (0.011)
NPL ratio			0.035** (0.016)	0.022 (0.014)	0.050*** (0.015)
Net Int. margin				0.371*** (0.064)	0.429*** (0.069)
Leverage ratio					-0.210*** (0.050)
LCR					0.042** (0.019)
CET1 ratio					0.053*** (0.014)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,119	1,119	1,119	1,119	1,119
R-squared	0.371	0.515	0.518	0.540	0.573
Number of banks	109	109	109	109	109

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation. The table excludes 9 banks with the development or promotional business model.

Table 9: Robustness without development/promotional and small market lenders

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
P2R	-0.249** (0.117)	-0.255** (0.102)	-0.263** (0.102)	-0.250*** (0.097)	-0.243*** (0.088)
Transparent	-1.504*** (0.469)	-1.210*** (0.351)	-1.212*** (0.351)	-1.232*** (0.343)	-1.131*** (0.316)
Transparent Banks × P2R	0.510*** (0.171)	0.411*** (0.132)	0.413*** (0.132)	0.410*** (0.127)	0.379*** (0.120)
Ln(Total assets)		-1.539*** (0.277)	-1.545*** (0.278)	-1.565*** (0.268)	-1.776*** (0.279)
Deposits ratio		0.039*** (0.009)	0.038*** (0.009)	0.036*** (0.009)	0.043*** (0.009)
NPL ratio			0.015 (0.015)	-0.001 (0.014)	0.026** (0.012)
Net Int. margin				0.417*** (0.051)	0.456*** (0.060)
Leverage ratio					-0.193*** (0.043)
LCR					0.035** (0.017)
CET1 ratio					0.048*** (0.014)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,022	1,022	1,022	1,022	1,022
R-squared	0.478	0.588	0.589	0.615	0.640
Number of id	101	101	101	101	101

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation. The table excludes 9 banks with the development or promotional business model, and 8 banks with a small market lender business model.

Table 10: Robustness for parallel trends

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
P2R	-0.217** (0.102)	-0.213** (0.087)	-0.220** (0.089)	-0.212*** (0.071)	-0.219*** (0.070)
Transparent Banks	-0.543** (0.261)	-0.448* (0.233)	-0.436* (0.229)	-0.376* (0.192)	-0.408** (0.193)
Transparent Banks $\times$ P2R	0.191* (0.112)	0.176* (0.098)	0.170* (0.096)	0.140* (0.081)	0.155* (0.081)
ln(Tot.Assets)		-0.889** (0.392)	-0.904** (0.389)	-0.631* (0.343)	-0.739** (0.344)
Deposits ratio		0.036*** (0.010)	0.035*** (0.010)	0.034*** (0.009)	0.034*** (0.009)
NPL ratio			0.023 (0.023)	0.019 (0.018)	0.025 (0.016)
Net Int. Margin				0.489*** (0.071)	0.498*** (0.076)
Leverage Ratio					-0.092*** (0.030)
LCR					-0.029** (0.013)
CET1 ratio					0.027** (0.012)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank-level trends	Yes	Yes	Yes	Yes	Yes
Observations	1,171	1,171	1,171	1,171	1,171
R-squared	0.827	0.854	0.855	0.884	0.887
Number of banks	115	115	115	115	115

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation. The regression includes individual bank trends as specified by the term  $\rho \cdot t$  in Equation 2.



Table 11: Dynamic regression

	Cost of Funds				
	(1)	(2)	(3)	(4)	(5)
Cost of Funds <sub>t-1</sub>	0.942*** (0.018)	0.946*** (0.018)	0.939*** (0.018)	0.917*** (0.018)	0.603*** (0.021)
P2R	-0.062** (0.027)	-0.054** (0.027)	-0.051* (0.027)	-0.060** (0.026)	-0.092*** (0.027)
Transparent Banks	-0.136* (0.081)	-0.126 (0.081)	-0.134* (0.080)	-0.111 (0.080)	-0.133 (0.088)
Transparent Banks × P2R	0.073** (0.034)	0.069** (0.034)	0.068** (0.034)	0.062* (0.033)	0.075** (0.037)
Ln(Total assets)	-0.448*** (0.057)	-0.468*** (0.066)	-0.481*** (0.066)	-0.612*** (0.069)	-0.772*** (0.101)
Deposits ratio	0.016*** (0.002)	0.017*** (0.002)	0.017*** (0.002)	0.019*** (0.002)	0.025*** (0.002)
NPL ratio		-0.011* (0.006)	-0.016** (0.007)	-0.008 (0.007)	0.015 (0.012)
Net Int. Margin			0.153*** (0.037)	0.214*** (0.039)	0.355*** (0.037)
Leverage Ratio				-0.079*** (0.013)	-0.059*** (0.016)
LCR				0.026** (0.012)	0.004 (0.012)
CET1 ratio				0.015*** (0.005)	0.017** (0.007)
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank-level trends	No	No	No	No	Yes
Observations	1,093	1,093	1,093	1,093	1,093
R-squared	0.982	0.982	0.983	0.984	0.992
Number of banks	107	107	107	107	107

*Note:* Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are two-way clustered at bank-level and quarter, robust for heteroschedasticity and serial correlation. Estimates are obtained with the LSDV estimator. Column (5) includes individual bank trends as specified by the term  $\rho \cdot t$  in Equation 2.

# Appendix

## Bank Transparency and Market Efficiency

## A Bank characteristics' balance: treated vs. control

Table A-I: Transparency and Solvency

	(1)	(2)	(3)
<i>Dependent variables:</i>			
CET1 Capital ratio	0.004 (0.335)	-0.038 (0.358)	-0.286 (0.567)
CET1 MDA Distance	-0.521 (0.473)	-0.394 (0.484)	-0.694 (0.641)
Leverage Ratio	0.110 (0.118)	0.150 (0.115)	0.039 (0.110)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,328	1,328	1,328
N. of banks	128	128	128

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. MDA stands for Maximum Distributable Amount, it is the minimum capital requirement in the European union for banks below which distribution restrictions can be imposed. Stars indicate statistical significance at  $***p < 0.01$ ,  $**p < 0.05$ ,  $*p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table A-II: Transparency and Liquidity

	(1)	(2)	(3)
<i>Dependent variables:</i>			
Cash at ECB/Tot. Assets	-0.378 (0.468)	-0.740 (0.508)	-0.570 (0.482)
CBC/Tot. Assets	-1.160 (0.755)	-1.133 (0.892)	-0.450 (0.763)
Liquidity Buffer/Tot. Assets	-0.339 (0.435)	-0.737 (0.467)	-0.348 (0.484)
Retail Deposits/Tot. Assets	0.395 (0.510)	-0.252 (0.520)	-0.476 (0.579)
Unsecured Deposits/Tot. Assets	1.902 (1.290)	0.704 (1.139)	0.359 (1.379)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,301	1,301	1,301
N. of banks	128	128	128

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. CBC stands for Counterbalancing Capacity from the definition in the Liquidity Coverage Ratio templates from the EU Common Reporting Standards (COREP). Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table A-III: Transparency and SREP Scores

	(1)	(2)	(3)
<i>Dependent variables:</i>			
Overall SREP Score	0.007 (0.047)	-0.004 (0.046)	0.015 (0.052)
SREP Element 1 - Business Model	0.066 (0.066)	0.096 (0.070)	0.070 (0.069)
SREP Element 2 - Internal Governance and Risk Management	0.139* (0.076)	0.082 (0.077)	0.033 (0.075)
SREP Element 3: Credit and Counterparty Risk	0.007 (0.058)	0.059 (0.060)	0.089 (0.070)
SREP Element 3: Market Risk	0.062 (0.065)	0.100 (0.068)	0.106 (0.075)
SREP Element 3: IRRBB	0.076 (0.069)	0.018 (0.071)	0.016 (0.092)
SREP Element 3: Operational Risk	0.061 (0.070)	-0.002 (0.074)	0.059 (0.085)
Element 3 - Capital Adequacy	0.024 (0.062)	0.008 (0.067)	0.030 (0.068)
Element 4 - Block 1: Liquidity Risk	0.044 (0.052)	0.024 (0.055)	0.040 (0.067)
Element 4 - Liquidity Adequacy	-0.091 (0.099)	-0.193* (0.112)	-0.210 (0.164)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,768	1,768	1,768
N. of banks	125	125	125

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. SREP stands for [Supervisory Review and Evaluation Process](#). Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table A-IV: Transparency and Profitability

	(1)	(2)	(3)
<i>Dependent variables:</i>			
RoE	-2.096 (1.271)	-1.961 (1.391)	-2.022 (1.994)
Core Revenues/Tot. Assets	0.020 (0.035)	0.042 (0.036)	0.036 (0.042)
Cost to Income Ratio	0.355 (3.967)	-0.648 (4.261)	-0.688 (4.407)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1328	1328	1328
N. of banks	128	128	128

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table A-V: Transparency and Asset Quality

	(1)	(2)	(3)
<i>Dependent variables:</i>			
NPL gross: NPL/Tot. Loans	-0.696 (0.825)	-0.034 (0.748)	0.096 (0.564)
Cost of Risk: LLP/Tot. Loans	-0.520 (0.664)	-0.146 (0.657)	-0.350 (0.550)
NPLs coverage: Acc. Impairments/NPL	-0.381 (1.002)	-0.575 (1.056)	-0.082 (1.234)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1263	1263	1263
N. of banks	124	124	124

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. NPL stands for Non-performing Loans, LLP stands for Loan Loss Provisions. Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table A-VI: Transparency and Balance Sheet Structure: Assets and Liabilities

	(1)	(2)	(3)
<i>Dependent variables:</i>			
Ln(Tot. Assets)	0.018 (0.017)	0.005 (0.017)	0.011 (0.027)
Gross Loans/Tot. Assets	0.076 (0.598)	0.035 (0.647)	-0.709 (0.606)
Total deposits/Tot. Assets	0.235 (0.364)	0.070 (0.377)	-0.186 (0.483)
Total Debt Securities/Tot. Assets	0.111 (0.259)	0.306 (0.292)	0.318 (0.342)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,710	1,710	1,710
N. of banks	128	128	128

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.



Table A-VII: Transparency and Lending by Counterparty

	(1)	(2)	(3)
<i>Dependent variables:</i>			
NFC Gross Loans/Tot. Assets	-0.227 (0.659)	-0.083 (0.635)	0.069 (0.671)
HH Gross Loans/Tot. Assets	0.485 (0.423)	0.633 (0.451)	0.340 (0.369)
Credit Institutions Gross Loans/Tot. Assets	0.727* (0.408)	0.691 (0.427)	0.100 (0.508)
OFC Gross Loans/Tot. Assets	-0.556 (0.549)	-0.547 (0.473)	-0.810 (0.503)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,299	1,299	1,299
N. of banks	127	127	127

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. NFC stands for Non-financial corporations, HH stands for households, and OFC stands for other financial corporations. Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

Table A-VIII: Transparency and Deposits by Counterparty

	(1)	(2)	(3)
<i>Dependent variables:</i>			
NFC Deposits / Total Assets	-0.333 (0.310)	-0.448 (0.324)	-0.683* (0.346)
HH Deposits / Total Assets	0.159 (0.419)	-0.201 (0.420)	-0.359 (0.497)
Credit Institutions Deposits / Total Assets	0.559 (0.533)	0.879 (0.541)	0.624 (0.479)
OFC Deposits / Total Assets	-0.046 (0.264)	-0.026 (0.305)	0.061 (0.473)
Bank FE	Yes	Yes	Yes
Quarter FE	-	Yes	-
Country-quarter FE	-	-	Yes
Observations	1,710	1,710	1,710
N. of banks	128	128	128

*Note:* Each cell represents a separate regression of the Transparency indicator on the dependent variable. NFC stands for Non-financial corporations, HH stands for households, and OFC stands for other financial corporations. Stars indicate statistical significance at \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The sample period runs from 2017Q1 to 2020Q4. Standard errors are clustered at bank-level and are robust for heteroschedasticity and serial correlation.

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The views expressed in this paper are those of the authors and do not necessarily reflect the official positions of the ECB or the SSM. All errors are our responsibility. The dataset used in this paper contains confidential statistical information. Its use for the purpose of the analysis described in the text has been approved by the relevant ECB decision making bodies. All the necessary measures have been taken during the preparation of the analysis to ensure the physical and logical protection of the information.

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