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Synthetic, but how much risk transfer?

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Abstract

Banks use synthetic risk transfers (SRTs) to offload potential losses in their loan portfolios to non-bank investors while retaining the loans on their balance sheets. We investigate this trillion-euro market using transaction-level data from the euro area, the largest SRT market, and highlight three channels of potential risks to financial stability. First, we show that banks synthetically transfer loans that are capital-expensive relative to their riskiness. To establish causality, we exploit a regulation that causes a jump in the risk weights of loans without affecting their riskiness. As banks redeploy the freed capital, their loan portfolios become riskier relative to their capitalization. Second, after entering an SRT, banks reduce their monitoring efforts compared to other banks lending to the same firm. The reduction in monitoring is greater the larger the share of their firm exposure that banks synthetically transfer. Third, banks and non-bank investors are interconnected. Banks are more likely to sell SRTs to investors with whom they already have credit relationship.

Keywords: securitisation, capital regulation, bank monitoring, financial stability

JEL classification codes: G20, G21, G28

Non-technical Summary

Synthetic Risk Transfers (SRTs) are financial arrangements that allow banks to offload credit risk on parts of their loan portfolios to non-bank investors without actually selling the underlying loans. SRTs are becoming ever more popular: According to the International Monetary Fund, banks have synthetically transferred more than one trillion euros in assets to the non-bank financial sector between 2016 and 2024 globally (IMF, October 2024). For corporate loans alone, the outstanding amount of SRTs by euro area banks increased from 60 billion euros in 2018 to 300 billion euros at the end of 2024. While SRTs can provide regulatory capital relief and enhance financial resilience, this paper uncovers a number of potential risks to financial stability associated with how SRTs are used in practice.

Using proprietary, transaction-level data from the European Central Bank, we characterize the market and highlight three potential sources of risk to financial stability. First, we argue that banks strategically select loans for the SRT so that they become less capitalized relative to the economic riskiness of their loan portfolio. To achieve this, banks include loans in the SRT that require more capital relative to their economic riskiness than the loans they do not include in the SRT. To establish causality, we exploit a so-called SME supporting factor, which should incentivize lending to small and medium enterprises (SMEs). This factor biases risk weights in favor of smaller firms to which banks have little exposure, independent of loan characteristics.

Second, banks reduce their efforts to monitor the firms whose loans they synthetically transfer. To investigate this, we develop an innovative measure of monitoring. Monitoring allows banks' PD estimates to closely capture actual fluctuations in firm riskiness. We therefore measure monitoring as the frequency with which banks update their PD estimates. We validate this measure and show that after a loan is synthetically transferred, the bank reduces the PD update frequency by 15-30 percent compared to other banks lending to the same firm and other firms to which the bank lends.

Third, we provide micro-level evidence of the interconnectedness between banks and non-bank SRT investors. We show that relationships between banks and non-banks matter: Banks are around 60 percent more likely to sell SRTs to non-bank investors to whom they also grant credit during the sample period, compared to SRT investors with no such connection. In addition, the total loan liabilities of non-bank SRT investors tends to increase prior to the SRT investment, especially when the investment is collateralized and when it is large. Total leverage of investors, however, remains modest: they have an average bank debt to assets ratio of around 7%, likely limiting round-tripping risks.

"If you're unfamiliar with synthetic risk transfers, there's a chance you'll hear all about them when the next financial crisis hits."

Bloomberg's Editorial Board (2024)

1 Introduction

Synthetic risk transfer (SRT) is a financial instrument through which banks pool loans and sell tranches of the credit risk to non-bank investors while retaining the loans themselves on their balance sheets.[1] Thus, SRTs blend features of credit default swaps (CDS) and traditional securitizations. Like CDS, SRTs shift credit risk to an investor that is compensated with regular fee payments without transferring ownership of the underlying assets. Like traditional securitization, through which banks *do* transfer the ownership of the underlying assets in exchange for liquidity, SRTs consist of different risk tranches. The junior tranche of an SRT absorbs the first loan losses and is sold to non-banks such as investment or pension funds, while the senior tranche absorbs the subsequent loan losses and is typically retained by the bank.[2] By transferring credit risk, SRTs free regulatory capital.

The market for SRTs has grown rapidly. The International Monetary Fund estimates that banks have synthetically transferred more than €1 trillion in assets between 2016 and 2024 globally (IMF, 2024). The largest market is in Europe. For corporate loans alone, euro area banks had more than €300 billion of outstanding SRT amounts in 2024, a fivefold increase since 2018 (see Appendix Figure A.1). 35 banks, many of which are among the largest in the euro area, had more than 10% of their corporate loan portfolio synthetically transferred. The market in the US is smaller but growing fast, with an estimated growth rate of 400% in 2024 (Bank of America, 2024).

Despite their popularity, SRTs are entirely unexplored in academic research. We fill this gap

[1] SRT is also called synthetic securitization. In Europe, SRT also stands for significant risk transfer, which can include synthetic risk transfers and traditional securitizations. Here, we use the acronym to refer to the synthetic variant.

[2] Note three things. First, in Europe, government entities constitute another large investor type; Section 2.3.5 describes all types in detail. Second, there may be more than two tranches; Section 2.3.1 describes the transaction in detail. Third, the word "synthetic" in "SRT" indicates that the ownership of the underlying loans is not transferred. SRTs are different from synthetic collateralized debt obligations (CDOs), which were popular before the 2008 global financial crisis and allowed investors to insure securities they did not own.

using proprietary transaction-level data from the euro area. We characterize the market and highlight three potential sources of risk to financial stability. First, we show that banks select loans for the SRT strategically to reduce their effective capitalization. Second, banks reduce the monitoring of the firms whose loans they synthetically transfer. Third, we provide micro-level evidence of the interconnectedness between banks and non-bank SRT investors through the loan market.

Our analysis builds on the ECB's monthly credit registry AnaCredit, which registers all loans by euro area banks to firms to which the bank has an exposure of at least €25,000. Through AnaCredit, we know the SRT-issuing banks ("SRT banks"), the synthetically transferred loans ("SRT loans"), the corresponding loan pools (i.e., the transaction), and the non-bank SRT investors. Since AnaCredit includes loans to financial firms, we also know the interconnectedness of the banking sector with these SRT investors. AnaCredit is complemented by COREP, another ECB dataset that provides information on the SRT itself, such as its structure or collateralization.

Our sample runs from September 2018 until July 2024. It consists of 94 SRT banks and 351 SRTs, which contain 171,482 corporate loans with a notional value of €187 billion. The credit risk of these loans is transferred to 91 non-bank investors, of which we can identify 65 as the ultimate investors. Since corporate loans are by far the most common asset class underlying SRTs, our sample is representative of the total European SRT market.

In the first part of the paper, we demonstrate that banks use SRTs as a tool to reduce their effective capitalization. The capitalization of banks is determined by their capital amounts and by the risk weights assigned to their loans. Ideally, these risk weights are an accurate reflection of the (true) economic riskiness of the loan. In reality, some loans have low risk weights but are risky, and vice versa.[3] Since capital is privately costly for banks, they prefer loans with low risk weights relative to their economic riskiness.

This is reflected in the selection of SRT loans by banks. We causally show that they

[3]There are at least three reasons why the risk weight may not reflect the loan's economic riskiness. (i) The bank uses the Standardized Approach of capital regulation; i.e., the regulator assigns the same risk weight to all loans within broad categories, almost independently of their economic riskiness. (ii) The bank uses the Internal Ratings Based Approach (IRBA), under which it determines the risk weight itself, but underestimates the true riskiness of the loan (e.g., Acharya, Engle, and Pierret (2014), Begley, Purnanandam, and Zheng (2017), Plosser and Santos (2018), Behn, Haselmann, and Vig (2022)). (iii) The bank uses the IRBA, but the risk weights are subject to regulatory interventions.

synthetically transfer loans with high risk weights relative to their economic riskiness. As banks redeploy the freed capital, they become effectively less capitalized.

To illustrate this, consider the following example. A bank has two loans, A and B, each €100, and each with the same economic riskiness. Loan A is relatively capital-cheap with a risk weight of 40%, and loan B is relatively capital-expensive with a risk weight of 60%. Assume that the bank has €10 of Tier 1 capital, so its Tier 1 capital ratio is 10%, and its regulatory leverage ratio (i.e., the ratio of Tier 1 capital to unweighted assets) is 5%. If the bank synthetically transfers the capital-expensive loan B, it frees €6 of capital and only has to hold capital against loan A, which requires less of it for the same economic riskiness (and the same return).[4] The bank's capital ratio temporarily increases to 25%, and its regulatory leverage ratio remains unchanged because loan B stays on its balance sheet.

Since the bank freed the capital-expensive loan, it can now grant a €150 loan (compared to previously €100) with a risk weight of 40% to achieve its previous capital ratio of 10%.[5] The bank's regulatory leverage ratio drops to 3% (total assets are now €350), and, since it now holds €10 of capital against €250 of loans (compared to previously €200), it becomes effectively less capitalized. If instead the bank synthetically transfers the capital-cheap loan A, it receives less capital relief, its regulatory leverage ratio decreases less, and it does not become effectively less capitalized.[6]

To show the strategic loan selection causally, we need an exogenous change in the risk weights of loans that keeps their economic riskiness—as reflected in observed *and* unobserved loan characteristics—constant. We achieve this by exploiting a regulation called the "SME supporting factor," which is intended to incentivize lending to small and medium enterprises (SMEs).[7] Due to this factor, risk weights exhibit a jump as firms' revenues exceed €50 million, while plausibly keeping the economic riskiness of loans unaffected. Using this jump, we show that a 15pp higher risk weight (approximately equal to the size of the jump), relative to the economic riskiness, increases the likelihood of synthetically transferring a loan by up to 70%.

[4] In reality, banks do not receive 100% capital relief; see Appendix B. The argument does not depend on this simplification.

[5] The bank could also grant a loan with a higher risk weight but a smaller amount; or it could pay the freed capital in dividends to its shareholders. We do not observe this in the data.

[6] The argument laid out is a comparison of the bank's effective capitalization before and after an SRT. It is not a judgment of the *appropriateness* of the risk weights before and after an SRT.

[7] The SME supporting factor is a Basel III regulation that is implemented in the euro area via Article 153 and 501 of Regulation (EU) No 575/2013.

After the SRT, banks redeploy the freed capital. SRTs are associated with increased lending (which is not capital-expensive), decreased regulatory leverage ratios, but no change in the Tier 1 capital ratios. While an increase in lending may be desirable, the redeployment of capital together with the strategic loan choice implies that banks decrease their effective capitalization.[8]

In the second part of the paper, we find that banks reduce their monitoring efforts of the firms whose loans they synthetically transfer. Our monitoring measure assumes that firms continuously produce new information that affects their probability of default (PD). Banks try to map the resulting fluctuations in PDs into their own PD *estimates* of the firms, which we observe in AnaCredit. Since monitoring allows banks to be more attentive to these fluctuations, we use the frequency with which banks update their PD estimates as our monitoring measure. We validate this measure by showing that banks that update their PD estimates have better information about firms, which we proxy as being better at predicting actual default at the firm level and at the portfolio level.

We then show that after a loan is synthetically transferred, the bank reduces the PD update frequency by 12–25% on average compared to other banks lending to the same firm and compared to other firms to which the bank lends. This reduction depends on how much of its firm exposure the bank synthetically transfers: if it synthetically transfers its entire exposure, it reduces the PD update frequency on average by up to 70%.

In the third part of the paper, we study the interconnectedness of banks and non-bank SRT investors through the loan market.[9] We find that the ratio of bank loan liabilities to assets of non-bank SRT investors is only 4%. Banks and non-banks are nevertheless interconnected. Banks are 57–66% more likely to sell SRTs to non-bank investors to which they also grant credit during the sample period, compared to SRT investors with no such connection. In addition, the loan liabilities of non-bank SRT investors increase in the five months before the

[8]We estimate, under stylized assumptions, that through its strategic loan choice based on the SME supporting factor the median bank saved an additional 3% of capital in 2023. Since the real difference between the riskiness reflected in the risk weights and the economic riskiness of loans is probably larger, this estimate presents a lower bound.

[9]In contrast to the first two parts of the paper, this part suffers from a low number of observations, which increases the uncertainty of our estimates. In addition, we only observe loans granted by euro area banks. Investors in 14% of SRTs are based outside of the euro area, most of them in the US. Furthermore, the descriptive statistics of non-bank SRT investors' are sensitive to the level of consolidation we consider and whether we include investments of government entities. Our baseline regression results are at the unconsolidated investor level, even though investors are often part of a larger corporation. We run robustness regressions in which we exclude government investors.

SRT investment, especially when the investment is funded (i.e., collateralized) and when it is large.[10] If we attribute the entire increase in debt to the SRT, this result suggests that, on average, 26% of the funding for SRT investments comes from bank credit. These loans to SRT investors bind, on average, only €230,000 of capital but free around €5 million. The circular chain of credit exposures between the banking sector and SRT investors was labeled "round-tripping" by the popular press but has so far not been tested.[11]

Finally, there is a trade-off between achieving a more significant transfer of credit risk by selling a larger fraction of the SRT (a "thicker" junior tranche) and the return for non-bank investors. All else equal, thicker tranches imply lower expected returns because it is more likely that a small share of the loan portfolio defaults than a large share. But lower returns can be offset by higher investor leverage or riskier loans in the SRT. Indeed, we find that SRTs that transfer thicker tranches tend to have more leveraged investors and contain riskier loans.[12] This has implications for the surging US market in which, due to regulatory requirements, banks have to sell thicker junior tranches than their European counterparts to achieve comparable capital relief. Our findings suggest that US SRTs may attract more leveraged investors and have higher expected losses than European SRTs.

To the best of our knowledge, this paper is the first comprehensive study of SRTs. Our work contributes to three strands of literature: one on the loan selection in credit risk transfers, one on moral hazard in credit risk transfers, and an emerging one on the interconnectedness of banks and non-banks.

An influential stream of literature studies the implications of credit risk transfers, which separate the originator of an asset from the holder of the credit risk. This literature has focused on two channels that can affect financial stability: adverse selection and moral hazard. The selection of loans may be affected by adverse selection when the loan originator is better informed about the loan quality than the holder of the credit risk (e.g., DeMarzo (2005), Parlour

[10] SRT transactions can be funded or unfunded. In funded transactions, banks receive highly liquid collateral upfront, while in unfunded transactions, banks are reimbursed in case of defaults on the underlying loans. In Europe, transactions can be unfunded and still achieve capital relief if the investor is a government entity (see Section 2.3.1).

[11] See, for example, Financial Times (2024).

[12] The causality in the latter result also runs reversely: The riskier the underlying loans, the thicker must be the junior tranche for the bank to receive the same capital relief. In addition, banks have to prove the "significance" of the risk transfer to achieve capital relief, which is a function of the expected losses. Nevertheless, our result exemplifies the trade-off between a safer SRT structure for banks and riskier underlying SRT characteristics.

and Plantin (2008), Downing, Jaffee, and Wallace (2009), Keys et al. (2010), Piskorski, Seru, and Witkin (2015), Rajan, Seru, and Vig (2015), Griffin and Maturana (2016)). We propose another channel through which the selection of loans can affect financial stability. When the objective of transferring risks is to receive capital relief, banks select capital-expensive loans to reduce their effective capitalization.

We also contribute to the literature on credit risk transfers and moral hazard, which has found mixed results on whether banks reduce their monitoring efforts after a credit risk transfer (e.g., Benmelech, Dlugosz, and Ivashina (2012), Y. Wang and Xia (2014), or Albertazzi et al. (2025)). We show that when credit risk is transferred through SRTs, which, unlike CDS or traditional securitization, span all sectors, borrower sizes, and loan types, moral hazard is a concern. Our monitoring measure is the frequency with which banks update their PD estimates, similar to Cerqueiro, Ongena, and Roszbach (2016). Our contribution to measuring monitoring is that we extensively validate this measure by showing that updated PD estimates contain more information about the firm than PD estimates that are not updated.

On the link between banks' and non-banks' balance sheets, Allen and Carletti (2006) discuss under which circumstances risk transfers to non-banks lead to financial stability risks. Acharya, Schnabl, and Suarez (2013) find that before the 2008 global financial crisis, banks often explicitly guaranteed the loans they securitized. Securitization therefore did not achieve actual risk transfer, but was used as a tool to bypass capital regulation. Acharya, Cetorelli, and Tuckman (2024) show that banks and non-banks finance each other, and their abnormal equity returns are correlated. T. Wang, Krainer, and Vaghefi (2025) find that bank lending to non-banks increases after shocks to banks' capital positions. Using proprietary micro data, we show novel evidence at the loan and investment level of circular risk exposures between banks and non-bank SRT investors.

The paper is structured as follows. In Section 2, we introduce the data and show descriptive statistics of the SRT transactions, SRT market, SRT banks, SRT loans, and non-bank SRT investors. Section 3 presents the results in three parts. Section 3.1 shows the strategic selection of SRT loans. Section 3.2 shows that banks reduce their monitoring efforts after the SRT. Section 3.3 investigates the interconnectedness of banks and non-bank SRT investors, and the trade-off between the thickness of the tranche sold and investor return. Section 4 concludes.

2 Data and descriptive statistics

2.1 Data

SRTs can be a black box due to the private nature of the transaction. We illuminate this black box by employing the ECB's euro area-wide credit registry called AnaCredit. AnaCredit records all loans by euro area banks to firms to which banks have an exposure of at least €25,000, on a monthly basis. The data start in September 2018 and include many loan and firm characteristics, such as the loan type (e.g., term loans or credit lines), loan amount, interest rate, collateral, realized payment delay, realized default, and the bank's estimate of the firm's PD.

AnaCredit also includes comprehensive information on SRTs. Once a loan is synthetically transferred, it receives an SRT flag and the originating bank continues to report the loan monthly. The bank also reports an SRT issue identifier, the amount of risk transferred, and, in most cases, the name of the investor. The SRT issue identifier pins down the loan pool and the transaction to which each loan belongs. The amount of risk transferred reflects the amount of potential losses borne by the non-bank SRT investor. This is the size of the junior tranche in a two-tranche SRT. The loan-exposure of banks to the investor also comes from AnaCredit, which includes bank loans to financial firms.

In addition to their loan reporting, euro-area banking groups report SRT transaction details in a database called COREP. It includes variables such as the issuance and maturity date, the number of tranches, the structure and size of the tranches, the amount transferred by the originating bank, the collateral that the investor pledges (if any), the expected and unexpected loss estimates, and the expected loss given default (LGD).

In some cases, AnaCredit does not report the ultimate investor, but an SPV through which the credit risk is transferred (see Section 2.3.1). In these cases, we use the ECB's Securities Holdings Statistics by Sector (SHSS) database to identify the *investor types*, which we use in our descriptive statistics.

Balance sheet and P&L information of the SRT banks, the non-bank SRT investors, and the firms whose loans are synthetically transferred come from AnaCredit and Bureau van Dijk's (BvD) Bankfocus and Orbis. Nearly 100% of the banks and firms in AnaCredit can be matched to their counterparts in BvD.

2.2 Sample construction

We use two samples. For our main analysis of Section 3, it is important to know precisely at which time a loan is synthetically transferred, which transaction it is part of, and which investor takes on how much of the risk. We therefore clean our data extensively. This means, however, that SRT loans that have an SRT loan flag but that are otherwise misreported are removed (e.g., if the SRT issue identifier is misreported). This reduces our first sample compared to the total SRT amount in the euro area.

We select the sample based on the SRT loan flag and the SRT issue identifier in AnaCredit. In rare instances, the SRT issue identifier differs across SRT loans, despite having identical dates of receiving an SRT flag, the same SRT bank, and the same SRT investor. In these cases, we harmonize the SRT issue identifiers to represent a single SRT. We then exclude loan pools with fewer than 15 loans *and* amounts of risk transferred below €1 million. Additionally, loan pools with fewer than five loans or fewer than three debtors are excluded, regardless of the amount of risk transferred. After these adjustments, our sample comprises 171,482 synthetically transferred loans to non-financial corporations, with a total value of €187 billion across 351 SRT issues.

We identify investors based on their names in AnaCredit. But not all investors are the ultimate holders of the credit risk; some are intermediaries in a derivative contract. We classify investors as intermediaries if they are a bank or an SPV and as the ultimate investors otherwise. There are a total of 91 non-bank SRT investors during our sample period, of which we classify 65 as the ultimate investors. These 65 ultimate investors invest in 280 of the 351 SRT issues (80%) and hold 63% of the total SRT volume issued.

We use a second sample for the descriptive statistics on the market size and for analyzing SRTs at the bank level. Here, we aim to describe the SRT market as holistically as possible and are less concerned with the reporting accuracy of the transaction or the investors. We therefore choose all loans to euro area non-financial corporations by euro area banks with an SRT flag without further cleaning (e.g., we allow for the SRT issue identifier to be misreported).

In our bank-level analysis, we compare SRT banks with banks of comparable size that do not use SRTs ("non-SRT banks"). We require SRT banks to issue SRTs with combined amounts of at least €50 million in a given year or €12.5 million in a given quarter. Since SRT banks tend to be large, we choose non-SRT banks that are at least as large as the SRT bank at the 10th percentile of the bank-size distribution in a respective country. This results in 94 SRT banks that are compared to 1,130 non-SRT banks.[13]

Our SRT samples are representative of the European SRT market. The European Securities and Markets Authority (ESMA) provides a public and anonymized list of all SRTs whose structure meets certain criteria of simplicity, transparency, and standardization (STS).[14] According to this list, corporate loans are the underlying assets in 83% of SRTs, with consumer credit accounting for most of the remaining.[15] Since AnaCredit covers all corporate loans, we cover the vast majority of European SRTs.

2.3 Descriptive statistics

Our loan-level data allow for the first detailed characterization of SRTs beyond aggregate statistics. First, we explain how the SRT transaction works and how it is structured. Next, we present descriptive statistics of the European SRT market for corporate loans, such as market size and country distribution. We then compare SRT banks with non-SRT banks. After that, we show descriptive statistics for the loans that are synthetically transferred. Finally, we introduce the non-bank SRT investors.

2.3.1 SRT transaction

In an SRT transaction, the bank pools loans and sells the first losses to one or multiple non-bank investors.[16] How does the transaction work? How large are SRTs? How much of the risk is transferred? Are SRT investments collateralized? And how high is the coupon payment that banks pay investors? In this section, we provide answers to these questions using the ECB's

[13]In the regressions, we typically compare the SRT banks to only 344 non-SRT banks—those whose capital ratios in Bankfocus are not missing.

[14]SRTs that meet the STS criteria receive more capital relief than SRTs that do not meet the STS criteria; see Appendices A and B. Not all SRTs in AnaCredit meet the STS criteria.

[15]Find the list here (last accessed 11 September 2025).

[16]SRTs are therefore closely related to credit risk transfers that government-sponsored enterprises (GSEs) in the US use to share some of their mortgage exposure with private investors (see Finkelstein, Strzodka, and Vickery (2018) or Capponi, Van Nieuwerburgh, and Wu (2025)).

AnaCredit, COREP, and SHSS datasets.

Credit risk transfer in SRTs is typically achieved through financial guarantees or credit linked notes (CLNs); the latter are issued either by the bank directly or by an SPV. CLNs are securities similar to funded CDS in which the CLN issuer (the bank or the SPV in our case) promises to pay back the principal minus the amount of the defaulted loans. Although neither AnaCredit nor COREP specify the financial instrument of a transaction, we can conjecture which one is used based on whether we can identify the ultimate investors in AnaCredit. When the investor is neither an SPV nor a bank, the SRT is likely executed through a financial guarantee, while when the investor is an SPV or a bank, they likely act as intermediaries in a CLN. Accordingly, 80% of European SRTs are done through financial guarantees and 20% through CLNs.[17]

Banks use SRTs to free regulatory capital. In the US, banks received capital relief for SRTs in the late 1990s and early 2000s (Fed Board and Office of the Comptroller of the Currency, 1999). After a period of regulatory uncertainty, the Federal Reserve provided clarifying statements in September 2023 that were widely interpreted as again systematically granting capital relief for SRTs (Fed Board, 2023).

In Europe, SRTs are a longstanding instrument to free capital, but the amount of capital relief was increased in April 2021 (see Appendix A). Capital relief is regulated in Article 259 of Regulation (EU) 2017/2401 and based on a reduction in risk weights of SRT loans. The risk weights of the (sold-off) junior tranche are zero, and the risk weights of the (retained) senior tranche are based on the riskiness of the underlying loans, but substantially reduced, often to 10% or 15% (see Appendix B for details). Given the SRT stock of €300 billion in the third quarter of 2024 and with assumed average LGD figures between 20% and 40%, banks freed between €11 and €24 billion of Tier 1 capital.[18]

The SRT size and maturity vary significantly. The median and mean SRT amounts are €27 million and €725 million, respectively, but range from €2.4 million (10th percentile) to €2.9 billion (90th percentile). The median and mean SRT contain 63 and 484 loans, respectively, and

[17]This classification is consistent with public information from ESMA for SRTs that meet the STS criteria. According to their data, 85% of SRTs are transferred with guarantees and 15% with derivatives (link).

[18]We have all variables to calculate risk weights, except the LGD. In line with the averages in our data, we use the following inputs: SRT amounts of €300 billion (Q3 2024 stock), PD of 1.4%, maturity of 5.6 years, firm revenue of €45 million, bank-firm exposure of €7 million, two tranches, junior tranche thickness of 15%, granular and senior exposures.

the 10th and 90th percentiles are 10 and 1,196. SRTs executed through CLNs are, on average, larger than SRTs executed through financial guarantees. The average maturity of SRTs is 11 years and the median, the 10th, and the 90th percentiles are 9, 6, and 21 years. Larger SRTs tend to have longer maturities.

The amount of credit risk that is transferred is determined by the tranching of the SRT. The median SRT has two tranches, a junior tranche and a senior tranche.[19] The attachment point of the risk sold, that is, the point after which the non-bank investor takes on losses, is 0% for the median SRT and 3% for the SRT at the 90th percentile. The attachment point of the senior tranche is equal to the detachment point of the risk sold at 15% for the median SRT. Put differently, the thickness of the junior tranche of the median SRT is 15% and that of the senior tranche is 85% and is entirely kept by the originating bank. But there is considerable variation in the share of the risk sold. The SRT at the 10th percentile only sells off 7% of the credit risk, while 30% of SRTs sell the risk of the entire loan portfolio.

In line with the dominant structure having two tranches, most SRTs have one investor. This is true for all, except for two, of the SRT transactions that are executed through financial guarantees. For SRTs that are executed through CLNs, we lack information about the number of ultimate investors, but for some, we know the number of ultimate *investor types* through the SHSS database. These SRTs have, on average, three investor types. Unsurprising, given the predominantly bilateral nature, 98% of all SRTs (whether executed through financial guarantees or CLNs) are placed in private transactions and only 2% are placed publicly.

SRTs are typically funded (i.e., collateralized), but can be unfunded if the investor is a government entity.[20] Information on collateralization is typically missing in COREP. In the few cases it does exist, it reveals that 60% of deals are collateralized with cash, 25% with other collateral that has a zero percent risk weight, and 15% are unfunded.

The size of the coupon payments by banks to investors is another area of scarce information. We never observe them when the risk is transferred through financial guarantees. When it is transferred through CLNs, the SHSS database shows that coupon payments are between 7%

[19] This assumes a zero value whenever the value for the number of mezzanine tranches in COREP is missing. We consider this a reasonable assumption. Without that assumption, the median SRT has three tranches; that is, a junior, a mezzanine, and a senior tranche.

[20] SRTs are naturally funded if the SRT is executed through CLNs, since the bank deposits the proceeds of the securities it sells.

and 13%.

2.3.2 SRT market

In the US, there was an active SRT market around the turn of the century (Bell and Dawson, 2002) and again in recent years. While the current market is estimated to have less than $100 billion of synthetically transferred assets, Bank of America expects growth rates of around 400% in 2024 (Bank of America, 2024).

In Europe, the SRT market is much larger and still growing. According to AnaCredit, the outstanding amount of synthetically transferred corporate loans in the euro area has quintupled from around €60 billion at the end of 2018 to more than €300 billion in the third quarter of 2024 (Appendix Figure A.1).[21] It is thereby larger than traditional securitization for corporate loans in the euro area.

In June 2024, the SRT market in our sample was largest in Germany (€120 billion outstanding) and Italy (€75 billion), and considerably smaller in Spain (€25 billion) and France (€15 billion).(Appendix Figure A.2). SRT issuance is somewhat seasonal. 22% of SRTs are issued in the first quarter of the year, 27% in the second, 23% in the third, and 28% in the last quarter. A slightly lower issuance in the first quarter and higher issuance in the last quarter are consistent with banks being especially concerned with balance sheet cosmetics toward the end of the year.

2.3.3 SRT banks

The number of banks with outstanding SRTs increased strongly during our sample, from only 20 at the end of 2018 to more than 60 in 2024. In line with this increase, the market concentration, measured with the Herfindahl-Hirschman Index (HHI) of outstanding SRT amounts, decreased from around 0.17 in 2018 to around 0.07 in 2024 (see Appendix Figure A.3).[22] In 2018, 9 banks issued 90% of outstanding SRTs, and 2024, it was 19.

SRTs have become an important tool for euro area banks. In July 2024, 15 banks had more than 25% of their corporate loan portfolio synthetically transferred, and another 20 banks had

[21]These figures show the sum of all synthetically transferred loans without the data cleaning steps described in Section 2.2.

[22]The HHI is defined as the sum over the squared values of banks' market shares. Here, we only consider banks with outstanding SRT amounts of at least €50 million.

more than 10% transferred. The average share of synthetically transferred loans among SRT banks was 19%, and the median was 12%. Of the 35 banks that transferred at least 10% of their corporate loans, 5 banks had a balance sheet size of more than €500 billion, and 11 banks of more than €100 billion.

How do SRT banks differ from non-SRT banks? In Table 1, we take the sample averages of financial figures and other characteristics for each bank and compare them across both groups. The table shows that despite our size-based sample selection, SRT banks are larger than non-SRT banks, with a median balance sheet size of €373 billion for SRT banks compared to €24 billion for non-SRT banks.

The table also shows that the median Tier 1 capital ratio of SRT banks is 14.9% and thereby significantly lower than that of non-SRT banks at 18.2%. We confirm these statistics in Appendix Figure A.4, which shows a binned scatter plot with the share of yearly SRT amounts to the total corporate loan portfolio on the y-axis and the Tier 1 capital ratio on the x-axis. It reveals a strongly negative relationship, in line with SRT banks being less capitalized than non-SRT banks. In Appendix A, we show that this result holds in regressions with tight fixed effects, and that it is stronger after a regulatory change in April 2021 that increased capital relief for SRTs by reducing the risk weight floor on the senior tranche from 15% to 10%.

Table 1: SRT bank are larger and less capitalized than non-SRT banks

This table shows the characteristics of SRT banks compared to non-SRT banks. We require SRT banks to issue SRTs of at least €50 million in a given year. We select non-SRT banks to be at least as large as the 10th percentile of SRT banks in a given country. For each bank, we take averages of the respective variable across our sample. Financial information is at the unconsolidated bank level. Capital ratios, liquidity, and ROE are from BvD's Bankfocus, and the rest are from AnaCredit. In this table, values are winsorized below the 1st percentile and above the 99th percentile.

	SRT banks *94*					Selected non-SRT banks *1, 130*				
	Mean	SD	10^{th}	Median	90^{th}	Mean	SD	10^{th}	Median	90^{th}
Balance sheet size (mn.)	478,000	502,000	5,000	373,000	1,360,000	119,000	244,000	2,000	24,000	392,000
Tier 1 capital ratio	15.6	2.6	12.3	14.9	19.6	20.5	7.5	14.0	18.2	30.3
Liquid assets to deposits (%)	41.9	23.9	17.8	32.3	81.2	36.7	24.2	11.2	29.3	75.3
PD loan portfolio (%)	2.5	2.4	0.3	1.9	5.8	1.9	2.2	0.0	1.0	5.3
Loan payments are overdue (%)	2.2	3.1	0.0	1.0	6.4	1.8	3.0	0.0	0.5	5.6
Loans are delinquent (%)	1.5	2.5	0.0	0.4	5.1	1.1	2.1	0.0	0.1	3.4
ROE (%)	9.1	5.3	2.7	8.4	16.8	7.5	7.0	1.1	6.3	16.1

Table 1 also shows that the median SRT bank has a higher ratio of liquid assets to deposits than the median non-SRT bank (32.3% compared to 29.3%). This may explain why, for loans that could be traditionally securitized, such as loans for commercial real estate, banks choose SRTs over traditional securitization, through which they would get liquidity.

The corporate loan portfolio of SRT banks is slightly riskier than that of non-SRT banks. Portfolio riskiness is measured as the average PD that banks assign to firms they lend to, weighted by the loan amounts. If they do not assign a PD estimate to a firm, we take the weighted average PD of the industry in which the firm operates. PD estimates concern the PD of the firm (not the PD of the loan) within the next 12 months. The average portfolio PD is 1.9% for the median SRT bank and only 1.0% for the median non-SRT bank. This is also reflected in the share of loans whose payments are overdue and delinquent (more than 90 days overdue). The median SRT bank has 1.0% of its loan portfolio overdue and 0.4% delinquent, while these numbers are only 0.5% and 0.1% for non-SRT banks.

Finally, the median SRT bank has a higher return on equity (8.4%) than the median non-SRT bank (6.3%).

2.3.4 SRT loans

Which loans are synthetically transferred? Table 2 compares characteristics of SRT loans with those of non-SRT loans granted by SRT banks. In the table, we report non-SRT loans at the loan-year level. Once a loan is chosen for an SRT, it is reported once as an SRT loan. Values in this table are winsorized below the 1st percentile and above the 99th percentile.

The table shows that the median SRT loan amount is €150,000, compared to only €20,000 for the median non-SRT loan. The median revenues of the respective borrowers are, however, equal, at €4 million. The interest rate on the median SRT loan is significantly lower than that of the median non-SRT loan (0.024 compared to 0.039). The loan maturity of the median SRT loan is 5 years, compared to only 2 years for the median non-SRT loan. The median PD estimates of the firms are similar for both groups (0.009), but the average PD is much lower for borrowers with SRT loans (0.023 compared to 0.076). In line with that, the share of overdue and delinquent loan payments is lower for SRT loans (0.031 compared to 0.075 for overdue loans and 0.017 compared to 0.050 for delinquencies). Finally, only 40% of SRT loans carry a fixed rate, compared to 68% non-SRT loans.

Table 2: SRT loans are larger than non-SRT loans

This table compares loans that are not synthetically transferred (non-SRT loans) with loans that are synthetically transferred (SRT loans). SRT loans are based on our cleaned sample. All loans are granted by SRT banks. Observations of non-SRT loans are at the loan-year level. Once a loan is chosen for an SRT, is is reported once as an SRT loan. *Loan payments overdue* equals 1 if at any point during a year the loan payments are overdue; and 0 otherwise. Similarly, *Loan is delinquent* equals 1 if at any point during a year the loan payments are more than 90 days overdue. All variables are winsorized below the 1st percentile and above the 99th percentile. If a variable is binary, we only show the mean.

	Non-SRT loans *66,897,026*					SRT loans *171,482*				
	Mean	SD	10^{th}	Median	90^{th}	Mean	SD	10^{th}	Median	90^{th}
Loan amount	286,000	1,620,000	788	20,000	300,000	731,000	1,965,000	25,000	150,000	1,562,000
Borrower revenue (mn.)	377	1,540	0.2	4	446	86	671	0.2	4	76
Loan rate	0.044	0.033	0.009	0.039	0.081	0.030	0.020	0.010	0.024	0.059
Loan maturity (years)	4.1	5.2	0.2	2.0	10.0	5.7	4.1	2.0	5.0	10.0
Borrower PD	0.076	0.220	0.001	0.009	0.102	0.023	0.086	0.002	0.009	0.034
Loan payments overdue	0.075					0.031				
Loan is delinquent	0.050					0.017				
Fixed rate	0.68					0.40				

When in the life of a loan does it get synthetically transferred? The risk of the average loan is transferred after 2.3 years, while the median, 10th, and 90th percentile are 1.6 years, 0.3 years, and 5.2 years, respectively.

Next, we investigate the differences between SRT loans and non-SRT loans along the dimensions of loan type (Appendix Figure A.5), loan purpose (Appendix Figure A.6), and borrowers' economic sectors (Appendix Figure A.7). The key takeaway from Appendix Figure A.5 is that credit lines are a prominent loan type. This demonstrates the benefits of SRTs over traditional securitization for these loans: The owner of revolving credit needs a liquidity facility to allow for potential draw-downs. Traditional securitization transfers the ownership of a loan to an investor that may not have this liquidity facility. By using an SRT and retaining ownership of the loans, banks, which *have* a liquidity facility, can transfer the credit risk of revolving credit.

Appendix Figure A.6 shows that loans made as working capital are underrepresented among SRT loans compared to non-SRT loans, while loans for construction purposes are slightly overrepresented. Appendix Figure A.7 shows that SRT loans span all sectors that non-SRT loans span.

While the characteristics of all SRT loans vary widely, they are more homogeneous within SRTs. SRT fixed effects explain 48% of the variation in the natural logarithm of the loan amount, 26% of the variation in maturity, 47% of the variation in the loan rate, 39% of the variation in the natural logarithm of firms' revenues, 17% of the variation in their PD estimates, and 51% of the variation in the loan type (fixed rate vs. flexible rate).

2.3.5 Non-bank SRT investors

Who are the non-bank SRT investors? Appendix Figure A.8 shows the types of non-bank SRT investors by SRT amounts at inception across our sample.[23] The largest investor type is government entities, with €60 billion. Among that group, the majority of the investment is made by the European Investment Fund (EIF). The second largest investor type, with close to €60 billion, is SPVs whose ultimate investor types we cannot identify.

In third place are private investment funds, which invest in SRTs with amounts of more than €30 billion. This is likely an underestimate. Many investment funds probably invest in SRTs whose risk is transferred through SPVs, but whose investors or investor types we do not know. Indeed, of the SRTs whose risk is transferred through SPVs and whose investor types we *do* know (24 out of 71), 72% are held by investment funds. If we assume a similar fraction of investment funds behind SRTs whose investor types we do not know, investment funds would be the largest investor type at more than €70 billion.

Financial firms classified as "other financial corporations," pension funds, insurance companies, captive financial companies, financial auxiliaries, and banks each invest in SRTs that sum up to less than €20 billion. Investors in around 14% of SRT amounts are domiciled outside of the EU, and most of the non-EU investors are US-based.

Appendix Figure A.8 masks important time variation. Appendix Figure A.9 therefore presents the SRT holdings by investor type over time. It shows that government entities and SPVs, whose ultimate investor types we do not know but believe to be investment funds, were early investors and built up their exposure over time. After 2022, other types of investors also increased their SRT holdings, such as companies classified as other finance corporations, pension funds, insurance companies, and captive finance companies.

The increase in non-bank investor types is also reflected in the total number of investors. Appendix Figure A.10 shows that at the end of 2018, the number of investors was 20 if we exclude government entities and SPVs and 30 if we include them. Until 2024, these numbers

[23]SRT amounts in Appendix Figure A.8 and this section refer to the sum of synthetically transferred loans rather than the amount of risk transferred. In addition, note that we only consider investors that invest according to our cleaned sample.

increased to 30 and 45, respectively.[24] The concentration of SRT holdings, measured by the HHI, remained stable or slightly decreased during our sample period and is well below 0.4 during most of it.

Table 3: SRT investors receive bank credit but leverage remains modest

This table shows characteristics of non-bank SRT investors at the time of the SRT investment (or during the entire sample if specified). Values that include total assets (indicated by $*$) are unreliable at the group level, as suggested by one-fourth of bank debt-to-asset ratios being larger than 1. We nevertheless show our estimates here for completeness, but work at the unconsolidated level in the regressions. All observations with ratios above 1 are dropped. To account for irregular reporting in AnaCredit, we take the maximum debt value and number of banks in a three-month window around the SRT issue. If a variable is binary, we only show the mean.

	All SRT investments *282*						SRT investments excl. Government / EIF *142*					
	Mean	SD	10^{th}	Median	90^{th}	N	Mean	SD	10^{th}	Median	90^{th}	N
Group level												
Total assets (mn. euros)*	168,000	309,000	32	3,040	5,690	133	134,000	393,000	9	23	220,000	34
Bank loans outstanding (mn.)	6,130	30,200	0	386	5,090	282	5,500	45,100	0	0.1	56	142
Bank loans committed (mn.)	6,550	30,200	0	1,250	6,070	282	5,190	40,500	0	0.5	146	142
Bank debt outstanding to assets*	0.25	0.32	0	0.06	0.79	133	0.04	0.07	0	0.02	0.17	34
SRT investment (first losses) to assets*	0.03	0.04	0	0	0.07	105	0.04	0.07	0	0.01	0.07	28
Number of bank relationships	18.2	33.6	1	7	28	282	7.3	31.0	1	1	3	142
Number of bank relationships during sample	35.4	60.3	2	10	55	282	12.8	52.6	2	3	7	142
Investor receives credit from SRT-bank during sample	0.50					282	0.22					142
Unconsolidated level												
Total assets (mn. euros)	36,000	199,000	9	2,490	2,490	107	91,000	337,000	5	39	781,000	34
Bank loans outstanding (mn.)	505	1,690	0	0.6	381	282	21	135	0	0.1	8	142
Bank loans committed (mn.)	678	2,910	0	2	394	282	23	126	0	0.2	22	142
Loans & securities (mn.)	20,300	211,000	0	5	381	282	49	193	0	0.2	61	142
Liabilities to assets	0.08	0.12	0	0.05	0.15	102	0.04	0.10	0	0	0.12	30
SRT investment (first losses) to assets	0.06	0.11	0	0.02	0.13	103	0.10	0.15	0	0.05	0.36	29
Number of bank relationships	4.6	7.6	1	1	8	282	1.4	0.9	1	1	2	142
Number of bank relationships during sample	8.2	11.2	2	3	12	282	3.0	2.0	1	3	4	142
Investor receives credit from SRT-bank during sample	0.18					282	0.15					142

Table 3 shows descriptive statistics of these investors at the SRT investment level. The table is divided along two dimensions; the first dimension differentiates between all SRT investments and non-government investments, and the second dimension differentiates between the consolidated investor group and the unconsolidated investor. With regard to financial stability considerations, unconsolidated statistics are more meaningful if subsidiaries raise their own funds and if parent companies do not bail them out in case of default. In contrast, group-level statistics are more meaningful if we want to allow for the possibility of one subsidiary rais-

[24]This probably underestimates the true number of non-bank investors, since SPVs are typically held by more than one investor.

ing debt on behalf of another, or if parent companies bail out subsidiaries in case of default. Either way, our numbers for total assets at the group level are unreliable, as suggested by around one-fourth of bank debt-to-asset ratios being larger than 1. All values greater than 1 are dropped, and statistics including group-level asset values are reported in Table 3 only for completeness—most regressions are at the unconsolidated investor level. Another caveat of the data is that some variables are sparsely populated. Table 3 includes a column with the number of observations for each variable.[25]

The non-bank investor (unconsolidated) in the median SRT has total assets of €2,500 million or €37 million if we exclude government entities. It has a ratio of bank debt to assets of 0.07 (all SRTs) and 0 (excluding government entities), and the ratio of SRT investment (potential losses, not the entire SRT amount) to total assets is 0.02 (all SRTs) and 0.05 (excluding government entities).[26] The median non-bank SRT investor group has 7 (all SRTs) or 1 (excluding government entities) bank relationships at the time of the SRT investment and 10 (all SRTs) or three (excluding government entities) during our sample from September 2018 until July 2024. The share of SRTs whose investors receive credit from the bank from which they buy the SRT during our sample is 0.50 (all SRT investments) or 0.22 (excluding government entities).

3 Main analysis

In our main analysis, we highlight three potential risks to financial stability. The first potential risk is that the strategic selection of SRT loans leaves banks less capitalized after the SRT compared to before. The second potential risk is that banks reduce their monitoring efforts of the firms whose loans they transfer. The third potential risk stems from an interconnectedness of banks and non-bank SRT investors and the trade-off between the significance of risk transfer and investor return.

[25] Asset values are available for 17 companies that are classified as other financial corporations, three insurance companies, three investment funds, two financial auxiliaries, one captive finance company, and one pension fund.

[26] We only capture bank loans by euro area banks. 14% of SRT amounts are held by non-euro area investors that may finance themselves outside of the euro area.

3.1 Loan selection

Our descriptive analysis shows that SRT banks are less capitalized than non-SRT banks. This suggests that a main reason for banks to use SRTs is to receive capital relief. In this section, we show that this reason determines the selection of loans that are synthetically transferred: banks transfer loans that are capital-expensive relative to their economic riskiness. We establish causality by exploiting a discontinuity in capital risk weights that plausibly leaves loan characteristics unchanged. Following the SRT transaction, banks redeploy the freed capital. As a result, they are left with loan portfolios that require less capital relative to their economic riskiness, compared to the counterfactual in which banks choose SRT loans randomly.

The strategic loan selection also allows banks to increase the gap between their Tier 1 capital ratios and their regulatory leverage ratios more than under random loan selection. In Appendix Table F.1, we show that banks with a smaller gap between the two ratios are significantly more likely to use SRTs.

3.1.1 Banks select SRT loans to reduce their effective capitalization

Banks are required to hold capital against assets such as loans. The amount of required capital each loan ties up is governed by regulatory risk weights, which in turn determine banks' capital ratios. From a financial stability perspective, the riskiness of the loan that is reflected in these risk weights should be equal to its economic riskiness, as reflected in the characteristics of the loan. In reality, banks have loans that are capital-expensive (i.e., loans with high risk weights) but safe (i.e., loans with a low economic riskiness), and vice versa. Because capital is costly, they generally prefer loans with a lower risk weights relative to their economic riskiness; that is, they prefer to be *effectively* less capitalized.

There are multiple reasons why the risk weights of a loan are not an accurate reflection of its economic riskiness. For example, under the Standardized Approach of capital regulation, a single risk weight applies to all loans of the same loan category. For these loans, it would be coincidental if the risk weights reflected the economic riskiness. But 96.5% of synthetically transferred loans in our sample are granted by banks that use the Internal Ratings Based Approach (IRBA). Under the IRBA, banks use internal models to estimate loan risk and use the resulting estimates to calculate risk weights with regulatory formulas. The literature has shown that some IRBA banks drive a wedge between the risk weights and the economic riskiness by underreporting to the regulator the true riskiness of a loan (e.g., Plosser and Santos (2018), Begley, Purnanandam, and Zheng (2017), and Behn, Haselmann, and Vig (2022)). Yet another reason for a wedge comes from regulatory interventions, such as the newly introduced "output floor," which is a lower bound on risk weights under the IRBA vis-à-vis risk weights under the Standardized Approach.[27]

We hypothesize that banks use SRTs as a tool to reduce their effective capitalization. To do so, they synthetically transfer loans that have high risk weights relative to their economic riskiness. There are two reasons for this. First, banks receive greater capital relief if they synthetically transfer loans that carry higher risk weights. We demonstrate this in Appendix B, in which we introduce the risk weight formulas for SRT exposures to senior tranches that the banks retain. Second, the remaining loans that have not been synthetically transferred have lower risk weights relative to their economic riskiness.

Importantly, we do not conjecture that banks synthetically transfer loans with high risk weights *per se*. Although that SRT would receive more capital relief, if the risk weights of the loans are an accurate reflection of their economic riskiness, the SRT investor would presumably require a higher compensation in line with the higher economic riskiness.[28] In addition, choosing loans with high risk weights, but which accurately reflect their economic riskiness, would not change banks' effective ex-post capitalization. Indeed, in column (1) of Appendix Table F.2, we show that if we do not control for the economic riskiness of loans (other than loan size), the probability of synthetically transferring a loan is uncorrelated with its risk weight.

Banks instead want to transfer loans that have high risk weights *relative* to their economic riskiness. Only then do banks optimize capital relief and reduce their effective capitalization. Indeed, column (2) of Appendix Table F.2 shows that when we control for an array of loan and firm characteristics as proxies for the loan's economic riskiness, the correlation between the probability of synthetically transferring a loan and the risk weights becomes positive and significant.

[27]In the euro area, the output floor is progressively increased, such that the capital risk weights under the IRBA cannot be lower than 50% of the risk weights under the Standardized Approach in 2025 and 72.5% at finalization in 2032.

[28]We do not have the coupon payments for almost any SRT, so we cannot directly study the relationship between riskiness and investor compensation.

This result is, however, correlational. Testing whether banks actually select SRT loans based on their risk weights *relative* to their economic riskiness is difficult because the latter is unobserved. The ideal experiment would exogenously shift the risk weights of loans, while keeping observed *and* unobserved loan characteristics (i.e., the economic riskiness) constant. We approximate this experiment by exploiting a regulation called the "SME supporting factor," which is intended to incentivize banks to lend to small firms. Due to this regulation, loans to firms with annual revenues below €50 million receive lower risk weights. Below €50 million, risk weights increase in the firm's revenue; then they experience a discrete upward jump at the €50 million threshold. Risk weights also increase (at a diminishing rate) in the bank's total exposure to the firm. As a result, the jump at the €50 million revenue threshold is greater the smaller the bank's firm exposure, a fact that we exploit in our analysis.[29] Figure 1 plots an example, with the risk weights on the y-axis and firm revenue on the x-axis, for different bank-firm exposures.

We start by showing that the likelihood of synthetically transferring a loan increases in the firm's revenue and the bank's exposure to the firm. This is true for loans to firms with annual revenues below €50 million, but not for loans to firms with revenues between €50 million and €100 million. This makes sense: Below €50 million, the SME supporting factor applies, and the risk weights of loans increase in firms' revenues and banks' firm exposure. Above €50 million, the SME supporting factor does not apply, and the risk weights are independent of revenue or firm exposure. We control for the economic riskiness of loans with an array of control variables and fixed effects. Specifically, the specification we test is

$$SRT\ loan_{i,t} = \beta_1 Revenue_{i,t} + \beta_2 Log\ bank\ firm\ exposure_{i,t} + \theta X_{i,t} + \epsilon_{i,t}. \tag{2}$$

[29] The risk weights formula for exposures to firms with below-€50 million revenues is outlined in Articles 153 and 501 of Regulation (EU) No 575/2013. It looks as follows, where the arrows indicate the directional influence on the risk weights:

$$\begin{aligned} RW =& \mathcal{F}(PD \uparrow, M \uparrow, LGD \uparrow, \frac{\min\{\max\{5, S\}, 50\} - 5}{45} \uparrow) \\ &\times \frac{\min\{E; €2.5\} \cdot 0.7619 + \max\{E - €2.5; 0\} \cdot 0.85}{E}. \end{aligned} \tag{1}$$

The loan's maturity in years is captured by M, S stands for the firm's annual revenue in million euros, and E for the bank's total exposure to the firm, also in million euros. The formula for risk weights of loans to firms with annual revenues of more than €50 million contains only the first three arguments and is not multiplied by an additional term. The full formulas that applied at different times are in Appendix B.

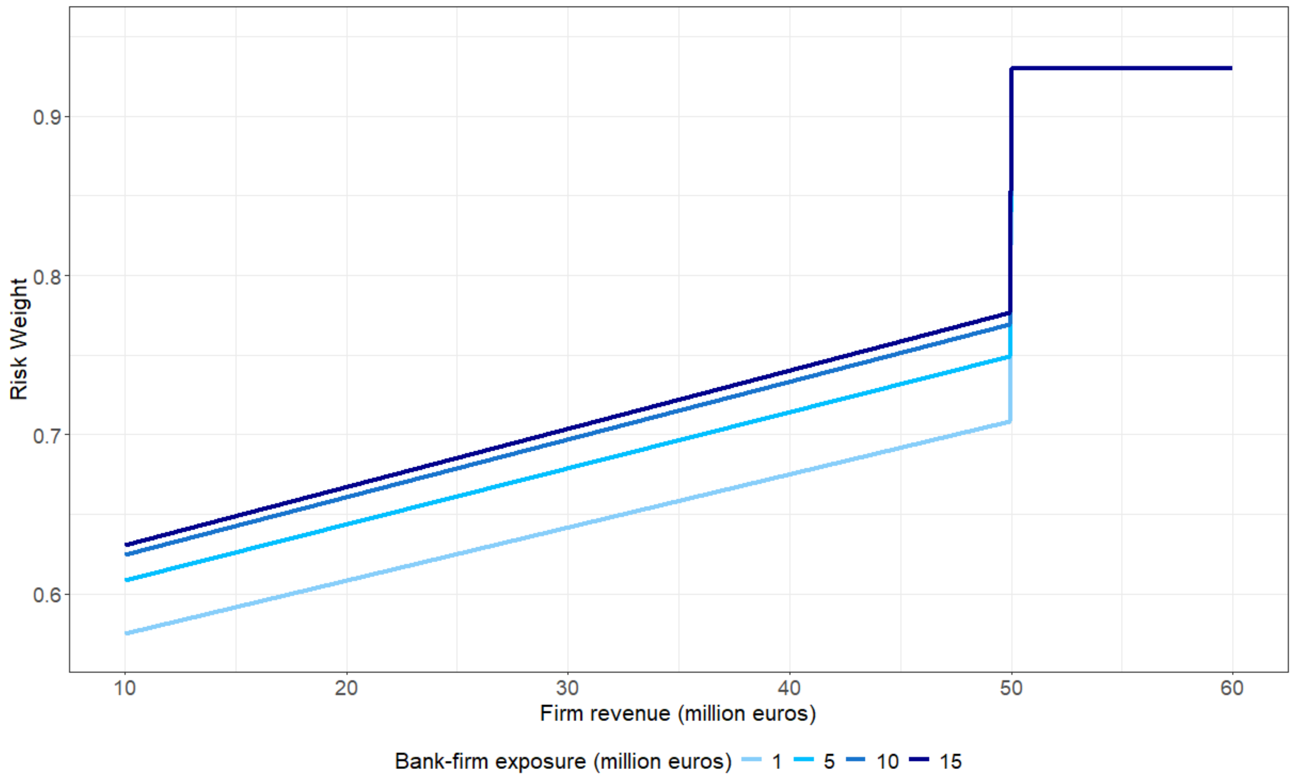

Figure 1: Risk weights exhibit a jump which decreases in the bank-firm exposure. This figure shows the risk weights on the y-axis as a function of firms' annual revenues in million euros on the x-axis and bank-firm exposures of €1, €5, €10, and €15 million. For firms with annual revenues above €50 million, the risk weight is not a function of the revenue or the bank's firm exposure. For the additional variables that enter the risk weight formula, we chose the following values: Firm PD is 0.5%, loan maturity is 5 years, and the LGD is 40%.

If a loan is newly synthetically transferred in a given year, $SRT\ loan_{i,t}$ equals 100; otherwise, it equals 0. We consider all loans of SRT banks, except those already synthetically transferred or those traditionally securitized. $Revenue_{i,t}$ features as is, and $bank\ firm\ exposure_{i,t}$ is log-linearized to approximate the functional form of the risk weight formula (1); both are in million euros. We estimate regression (2) on two subsamples, one with loans to firms with annual revenues below €50 million and another one with loans to firms with annual revenues between €50 and €100 million. To capture the economic riskiness of the loan, $X_{i,t}$ controls for the firms' probabilities of default, loan rates, and loan size bins interacted with the natural logarithm of the loan size. In addition, $X_{i,t}$ captures *bank* × *year* × *loan type* × *interest rate type* × *loan purpose* × *borrower industry* × *residual maturity* fixed effects.

Table 4 shows the results. Columns (1) and (2) feature the subsample of firms with annual revenues below €50 million, and columns (3) and (4) feature the €50 to €100 million subsample. In columns (1) and (3), we do not cluster standard errors, and in columns (2) and (4), we cluster them at the bank level.[30] Our results confirm that the likelihood of transferring loans is positively associated with the firm's annual revenue and the bank's firm exposures for firms with annual revenues below €50 million. For firms with annual revenues between €50 and €100 million, there is no such relationship. This is consistent with the notion that banks transfer loans with risk weights relative to their economic riskiness.

Next, we tighten the statistical identification by exploiting the discontinuity in the risk weights as firms' annual revenues increase above €50 million. At this threshold, risk weights exhibit a jump while the economic riskiness is plausibly unaffected. To show that this jump is accompanied by an increase in the probability of synthetically transferring a loan, we estimate

$$SRT\ loan_{i,t} = \beta Borrower\ revenue\ bins_{i,t} + \theta X_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $Borrower\ revenue\ bins_{i,t}$ are dummy variables that are 1 if a firm's annual revenue (in million euros) is within the following intervals, and 0 otherwise: [25,30), [30,35), [35,40), [40,45), [45,50), [50,55), [55,60), [60,65), [65,70).[31] The β coefficient of the [25,30) interval

[30] In the rest of this section, we use the wild cluster bootstrap at the bank-level (Roodman et al., 2019). Due to computational reasons that are caused by the size of the sample, this is not possible here.

[31] Banks may want to synthetically transfer loans to firms with annual revenues just below €50 million, in anticipation that their revenues increase above the €50 million threshold and become capital-expensive.

Table 4: SRT banks transfer capital-expensive loans

This table shows the results of a regression of whether a loan was synthetically transferred in a given year (= 100) or not (= 0) on firms' revenue and the natural logarithm of the bank's firm exposure. We control for the firms' PD, loan rate, and natural logarithm of the loan size × loan size bins. Our fixed effects are bank × year × loan type × interest rate type × loan purpose × borrower industry × residual maturity above 1 year.

	(1)	(2)	(3)	(4)
	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)
Revenue (million euros)	0.00661***	0.00661***	-0.000334	-0.000334
	(0.000134)	(0.00217)	(0.000264)	(0.000716)
Log bank firm exposure	0.0204***	0.0204**	-0.00223	-0.00223
	(0.000671)	(0.00975)	(0.00274)	(0.00503)
PD	-1.481***	-1.481*	-2.238***	-2.238*
	(0.0415)	(0.778)	(0.258)	(1.147)
Loan rate	-0.905***	-0.905	-0.249	-0.249
	(0.0554)	(1.395)	(0.284)	(0.926)
Mean	0.379	0.379	0.351	0.351
Estimation	OLS	OLS	OLS	OLS
Revenue (million)	[0,50]	[0,50]	[50,100]	[50,100]
Fixed effects	FE	FE	FE	FE
SE cluster	-	Bank	-	Bank
Controls	Loan size bins × log loan amount	Loan size bins × log loan amount	Loan size bins × log loan amount	Loan size bins × log loan amount
Adj. R-squared	0.221	0.221	0.406	0.406
N	29,531,049	29,531,049	1,919,159	1,919,159
Frequency	Yearly	Yearly	Yearly	Yearly

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

constitutes the base-coefficient against which the coefficients of the other intervals are compared. Because the discontinuity in the risk weights is greatest for low bank-firm exposures, we estimate regression (3) on a subsample of loans for which the bank has a low firm exposure. We choose a firm exposure below €15 million, since there is roughly the same number of loans above and below this exposure at the €50 million revenue threshold. To control for the economic riskiness of the loan, we feature the same fixed effects and controls as in regression (2). Standard errors are wild bootstrapped at the bank level.

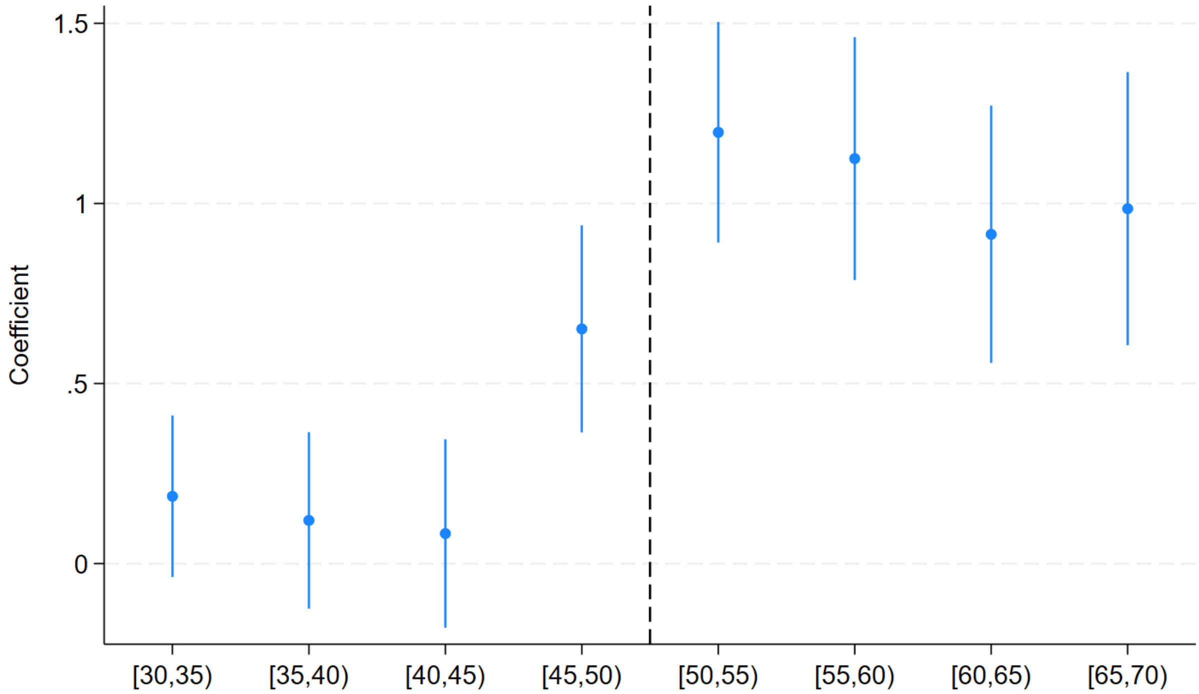

Figure 2: Jump in risk weights causes jump in transfer likelihood. This figure plots the β coefficients and their 95% confidence interval of the following regression: $SRT\ loan_{i,t} = \beta_1 Borrower\ revenue\ bins_{i,t} + \delta X_{i,t} + \epsilon_{i,t}$. $SRT\ loan_{i,t}$ is equal to 100 if a loan is synthetically transferred in a given year and 0 otherwise. The $[25, 30)$ bin serves as the benchmark. We limit our sample to bank-firm exposures below €15 million, for which the discontinuity at the €50 million revenue threshold is greatest. We control for the firm's PD, the loan rate, and loan-size bins interacted with the natural logarithm of the loan amount. In addition, we use the following fixed effects: Bank × year × loan type × interest rate type × loan purpose × borrower industry × residual maturity above 1 year. Standard errors are wild-bootstrapped at the bank level.

Figure 2 plots the β coefficients and the corresponding 95% confidence intervals. It shows that the probability of synthetically transferring a loan increases steeply at the €50 million threshold, in line with a jump in capital costs around that threshold. The likelihood of transferring a loan is 45% higher for loans that are granted to firms with annual revenues between €50

Indeed, most of the firms whose loans are synthetically transferred exhibit revenue growth. Our dummy variable approach can account for this possibility, while a regression discontinuity design cannot.

and €55 million, compared to those to firms with annual revenues between 40 and 45 million euros. If we zoom out, as we do in Appendix Figure A.11, we find that the coefficients linearly increase to the left of the €50 million threshold and discontinuously at the threshold, closely resembling the risk weights in Figure 1. In Appendix Figure A.12, we re-estimate regression (3) for the entire sample,[32] while Appendix Figure A.13 shows that other loan characteristics, all of which we control for, do not systematically vary at the €50 million threshold. The number of loans that are granted does not exhibit a discontinuity either (Appendix Figure A.14).

We now zoom in on the €50 million revenue threshold, where the risk weights exhibit a discontinuity. We also model explicitly the fact that the size of the discontinuity decreases in the bank's firm exposure. To do so, we estimate

$$\begin{aligned} \textit{SRT loan}_{i,t} =& \beta_1 \mathbb{1}(\textit{revenue} \geq \text{€}\textit{50 million})_{i,t} \\ &+ \beta_2 \mathbb{1}(\textit{revenue} \geq \text{€}\textit{50 million})_{i,t} \times \textit{Log bank firm exposure}_{i,t} + \theta X_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{4}$$

In line with a jump in capital costs around that threshold, we expect the β_1 coefficient to be positive. But in line with a smaller jump for greater bank-firm exposures, we expect the β_2 coefficient on the interaction term to be negative.[33] We use two different samples; one includes firms with annual revenues between €45 million and €55 million (€5 million on each side of the threshold), and the other includes firms with revenues between €40 million and €60 million (€10 million on each side of the threshold). We run placebo tests with thresholds of €40 million and €60 million, and again bin sizes of €5 million and €10 million on each side of the thresholds.

Table 5 shows the results. In columns (1)–(4), we use €5 million revenue bins, and in columns (5)–(8), we use €10 million revenue bins. Columns (1), (2), (5), and (6) use the €50 million revenue threshold, while columns (3) and (7) use the €40 million threshold, and columns (4) and (8) the €60 million threshold as placebo tests. In columns (1) and (5), we estimate regression (4) without the interaction term, while all other specifications additionally show the

[32] In line with a smaller discontinuity, the jump in the probability of synthetically transferring a loan becomes less pronounced for the entire sample.

[33] Consistent with most regressions in this paper, we use linear probability models. In non-linear models, the coefficient of two interacted variables does not capture the cross-partial derivative of the dependent variable with respect to the two interacted variables (Ai and Norton, 2003). It therefore does not have the desirable interpretation that we get from interaction terms in linear probability models.

Table 5: Transfer likelihood at the jump depends on the bank-firm exposure

This table shows the results of a regression of whether a loan was synthetically transferred in a given year (= 100) or not (= 0) on a dummy variable that is 1 if a firm's annual revenue is at least €50 (€40 or €60) million and 0 otherwise. In some specifications, the dummy variable is interacted with the natural logarithm of the firm exposure of banks. We control for the firm's PD, the loan rate, and loan-size bins interacted with the natural logarithm of the loan amounts. Our fixed effects are bank × year × loan type × interest rate type × loan purpose × borrower industry × residual maturity above 1 year. Standard errors are wild bootstrapped at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)	SRT loan (= 100)
Revenue > 50 mn=1	0.0351**	0.225**			0.0391***	0.258***		
	(0.0154)	(0.0992)			(0.0101)	(0.0634)		
Revenue > 50 mn=1 × Log bank firm exposure		-0.0114*				-0.0131***		
		(0.00589)				(0.00375)		
Revenue > 40 mn=1			-0.101				0.0269	
			(0.0842)				(0.0633)	
Revenue > 40 mn=1 × Log bank firm exposure			0.00605				-0.000116	
			(0.00514)				(0.00392)	
Revenue > 60 mn=1				0.0125				-0.135*
				(0.0928)				(0.0692)
Revenue > 60 mn=1 × Log bank firm exposure				-0.00102				0.00667*
				(0.00526)				(0.00401)
Log bank firm exposure		0.00582	-0.00307	-0.0103*		0.0102***	0.00149	-0.00655
		(0.00590)	(0.00507)	(0.00560)		(0.00382)	(0.00361)	(0.00413)
Mean	0.393	0.393	0.394	0.297	0.369	0.369	0.438	0.331
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Revenue bins	€5 million	€5 million	€5 million	€5 million	€10 million	€10 million	€10 million	€10 million
Fixed effects	FE	FE	FE	FE	FE	FE	FE	FE
SE cluster	WCR: Bank	WCR: Bank	WCR: Bank	WCR: Bank	WCR: Bank	WCR: Bank	WCR: Bank	WCR: Bank
Controls	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount	PD, loan rate, loan size bins × log loan amount
Adj. R-squared	0.481	0.481	0.431	0.493	0.427	0.427	0.400	0.451
N	594,714	594,714	769,729	514,814	1255,821	1,255,821	1,567,686	990,959
Frequency	Yearly	Yearly	Yearly	Yearly	Yearly	Yearly	Yearly	Yearly

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

coefficients of the interaction (β_2). In all specifications, we control for the same variables and fixed effects as in regression (2). Standard errors are wild bootstrapped at the level of the bank.

Columns (1) and (5) show that, on average, banks are 10% more likely to transfer loans to firms with revenues just above €50 million compared to firms with revenues just below €50 million. Columns (2) and (6) show that this effect is stronger the smaller the bank's firm exposure. For a hypothetical firm exposure of €1 million, an increase in the risk weights of 15% (roughly the size of the jump in risk weights), keeping constant the economic riskiness, causes an increase in the likelihood of transferring a loan of 57% (column (2)) or 70% (column (6)). Our placebo tests in columns (3), (4), (7), and (8) show that the likelihood of synthetically transferring a loan does not increase around revenue thresholds of €40 million or €60 million, independently of the bank's firm exposure.

In sum, we show in multiple specifications that banks tend to synthetically transfer capital-expensive loans. This opportunistic loan choice is particularly relevant for SRTs because they are issued with the primary objective of receiving capital relief. In addition, SRTs allow for the risk of any loan on banks' balance sheets to be transferred to the non-bank sector.

3.1.2 Banks redeploy the freed capital

If banks use SRTs to achieve higher capital ratios, SRTs would contribute to greater bank resilience, making banks' strategic loan selection secondary. The strategic loan selection leaves banks effectively less capitalized only if they redeploy the capital that the SRT releases. We show that this is the case. We first show that higher SRT issuance is not associated with higher Tier 1 capital ratios, despite releasing substantial capital. It is, however, associated with more lending in the current and next quarter. Accordingly, regulatory leverage ratios decrease in years with high SRT issuance. We then show that the new lending is not particularly capital-expensive by again exploiting the discontinuity in the SME supporting factor.

We start by showing that banks redeploy the capital that the SRT releases. To do so, we estimate

$$Y_{f,b,t} = \beta_1 SRT\text{-}intensity_{b,t} + \theta X_{f,b,t} + \gamma_f + \delta_b + \gamma_t + \epsilon_{f,b,t}. \tag{5}$$

$SRT\text{-}intensity_{b,t}$ is the ratio of SRT issuance in a given quarter or year to all corporate loans on the bank's balance sheet. The dependent variable $Y_{f,b,t}$ takes the values of loan growth, regulatory leverage ratio, and Tier 1 capital ratio, respectively. Loan growth is measured as the percentage change in lending and comes from AnaCredit.[34] Regulatory leverage ratios are approximated as the ratio of Tier 1 capital to total unweighted assets (in percent). These variables, as well as the Tier 1 capital ratios, come from Bankfocus. When measuring loan growth, we aggregate our monthly AnaCredit variables at the quarter level. When measuring changes in leverage and capital ratios, we aggregate them at the year level because Bankfocus variables are recorded at that frequency.

We investigate loan growth at the firm-bank level using *firm* × *quarter* and *bank* fixed effects. By comparing multiple banks that lend to the same firm (SRT banks and large non-SRT banks), we can control for the loan demand of the firm. Bank fixed effects additionally control for unobserved and time-invariant heterogeneity at the bank level. We also control for the capital ratios of the banks in the previous quarter.[35] In contrast, the analysis of the regulatory leverage ratio and the Tier 1 capital ratio is at the bank level. Here, we feature *bank* and *year* fixed effects. In all specifications, we control for bank size and cluster standard errors at the bank level.

Table 6 shows the results. In column (1), the dependent variable is loan growth, in column (2), it is the regulatory leverage ratio, and in column (3), it is the Tier 1 capital ratio, all measured in percent.

Column (1) shows that an increase in the SRT-intensity by 1 standard deviation (SD) or 1% (i.e., 1% of a loan portfolio gets synthetically transferred in a quarter) is associated with an increase in loan growth by 0.9% relative to the mean. An increase in the annual SRT-intensity by 1 SD (1.5% for the yearly data) is also associated with a decrease in the regulatory leverage ratio of a bank by 1% relative to the mean. This magnitude makes sense: An increase in the annual SRT-intensity by 1.5% is equal to an SRT amount of €525 million. This leads to a decrease in the leverage ratio by 1%, which—assuming no change in the Tier 1 capital

[34] We measure loan growth based on newly granted loans and maturing loans. Specifically, it is measured as $\frac{new\ loan\ amounts_t - maturing\ loan\ amounts_t}{loans\ outstanding_{t-1}}$. The alternative is to measure it as the ratio of outstanding loans in t and outstanding loans in $t-1$. This approach, however, is prone to reporting irregularities.

[35] Capital ratios are from Bankfocus and usually reported at a yearly frequency. Our results are robust to the exclusion of capital ratios.

Table 6: SRT banks redeploy the freed capital

This table displays the results of regressions of bank outcomes on the bank's SRT-intensity. SRT-intensity is measured as the ratio of newly synthetically transferred loans to all loans in a given period. Loan growth is measured as the ratio of the difference between new loan amounts and maturing loan amounts to the average loan amounts outstanding in the previous quarter (multiplied by 100 to depict it in percent). Regulatory leverage ratio is approximated as Tier 1 capital to total assets. Dependent variables are winsorized at the 5th and 95th percentiles. Standard errors are clustered at the bank level. Non-SRT banks are selected to be at least as large as the SRT bank at the 10th percentile in a given country. In addition, we control for bank size by interacting the logarithm of its balance sheet in the previous period with 10 bank size dummies in all specifications. Data are from AnaCredit and Bankfocus by BvD.

	(1) Loan growth (percent)	(2) Leverage ratio (percent)	(3) Tier 1 capita ratio (percent)
SRT intensity	0.336*	-5.204**	0.00641
	(0.188)	(2.152)	(0.0324)
Capital ratio	-0.321**		
	(0.145)		
Mean	0.357	7.665	0.202
Fixed effects	Firm × quarter, bank	Bank, year	Bank, year
Estimation	OLS	OLS	OLS
Frequency	Quarterly	Yearly	Yearly
Controls	Bank size	Size bins × bank size	Size bins × bank size
SE cluster	Bank	Bank	Bank
Adj. R-squared	0.406	0.804	0.925
N	36,508,494	1,960	2,131

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

amount—equals an increase in assets by €570 million. Column (3) shows that there is no significant relationship between the SRT-intensity and the Tier 1 capital ratio. Thus, Table 6 is consistent with banks redeploying the freed capital, in line with them having capital targets (see, e.g., Berger et al. (2008) or Gropp and Heider (2010)).

Banks may, however, free capital-expensive loans and redeploy the freed capital in capital-expensive loans. If that is the case, the effective capitalization of banks does not change. In Appendix C, we show evidence suggesting that this is not the case. If anything, new lending by SRT banks tends to be capital-cheap.

In sum, this section shows that through their strategic loan selection and subsequent redeployment of capital, banks become less capitalized relative to the riskiness of their loan portfolio. The economic significance of this loan selection is difficult to calculate because we do not know the true wedge between the riskiness of loans that is reflected in the risk weights and the economic riskiness of loans. We merely use the difference introduced by the SME supporting factor as an ideal setting to demonstrate that banks select SRT loans based on that wedge. Nevertheless, in Appendix D, we estimate the economic relevance of the loan selection induced by the SME supporting factor and consider it a lower bound. The analysis shows that the selection based on the SME supporting factor saved the median bank an additional 3% of capital.

3.2 Moral hazard

After banks select the SRT loans and transfer their credit risk, do they decrease their monitoring efforts? The consequences of separating the origination and servicing of a loan from the assumption of its credit risk for monitoring have been studied, but they depend on the underlying loan types and the monitoring measures (see, e.g., Benmelech, Dlugosz, and Ivashina (2012), Y. Wang and Xia (2014), or Albertazzi et al. (2025)). Moral hazard is arguably more prevalent for firms whose loans are synthetically transferred compared to firms whose loans are traditionally securitized or whose credit risk is transferred through CDS. The reason is that SRT loans are often nonstandardized and therefore more sensitive to monitoring, in contrast to credit that is traditionally securitized, such as mortgages or car loans. In addition, borrowers of SRT loans typically do not have public-equity shareholder supervision (unlike firms whose risk is transferred through CDS), making creditor engagement more relevant.

3.2.1 Monitoring measure

We start from the assumption that firms' actual PDs fluctuate over time as new information is produced.[36] The bank tries to map these fluctuations into its own PD estimates through regular updates. We further assume that banks that exert high monitoring efforts are more attentive to actual PD fluctuations and therefore incorporate new information into their own PD estimates by updating them more frequently. In contrast, banks that exert low monitoring efforts are less attentive and, therefore, have no new information to incorporate into their PD estimates and update them less frequently. We capture this assumption in two closely related monitoring measures. The first measure is a dummy variable equal to 1 if the bank updates its PD estimate in a given quarter and 0 otherwise, and the second measure is the within-quarter SD of the PD estimates.[37] We convert our data from monthly to quarterly, so banks can adjust their PD estimates at most twice per quarter.

We start by arguing that our monitoring measure plausibly captures actual bank monitoring. Banks that monitor more receive more information on the firm, including its health, than banks that monitor less. Banks that monitor more should therefore be better able to predict actual default than banks that monitor less. This ability should be reflected in our monitoring measure. Put differently, we have to show that banks that update their PD estimates more are better able to predict actual default than banks that update their PD estimates less. We perform two tests that confirm this; one demonstrates the ability to predict default at the firm level, and the other at the portfolio level. For both tests, we consider data on all firms that borrow from any euro area IRBA bank (i.e., whose PD estimates we have).[38]

In our first test, we show that a bank's average PD estimate is more positively associated with the actual default of an individual firm if it is updated than if it is not updated. To control for unobserved heterogeneity at the firm level and the bank level, we compare banks

[36]The asset pricing literature models probabilities of default through stochastic processes. E.g., in Merton (1974), the value of the firm, and through that its distance to default, is modeled with a Gauss-Wiener process.

[37]In addition to capturing the attentiveness of the bank to actual PD fluctuations, the SD of PD estimates captures an informational precision. Because actual default is a binary variable, we expect more extreme PD estimates, the better informed the bank is (through its monitoring activity). See, e.g., Fuster et al. (2022).

[38]Beyhaghi, Howes, and Weitzner (2024) confirm that updates in banks' internal assessments of firm risk reflect information production. Specifically, they find that updates in the expected loss estimates of banks (i.e. $PD * LGD$) predict future stock and bond returns, and analyst earnings surprises.

that lend to the same firm (to capture unobserved heterogeneity at the firm level) and the same bank that lends to different firms (to capture unobserved heterogeneity at the bank level). We estimate

$$Realized\ default_{f,t+4,b} = \beta Average\ PD_{f,t,b} \times Monitoring_{f,t,b} + \gamma_f + \omega_t + \delta_b + \epsilon_{f,t,b}. \quad (6)$$

$Realized\ default_{f,t+4,b}$ equals 100 if the firm does not default in the next three quarters, but defaults in the fourth quarter, and 0 if it does not default at all. We require the firm not to be in default in the next three quarters because we do not want to capture the mechanical effect of banks increasing their PD estimates after observing overdue payments by the firm, and thereby being able to predict actual default. Instead, we want to understand whether movements in PD estimates are informative about the longer-term prospects of the firm.[39] $Average\ PD_{f,t,b}$ is the average PD estimate of a firm by a bank in a given quarter. $Monitoring_{f,t,b}$ is equal to our two monitoring measures; that is, an indicator that captures whether the PD estimate is updated and the SD of the PD estimates. We interact $Average\ PD_{f,t,b}$ and $Monitoring_{f,t,b}$ to see whether the PD estimates are more strongly correlated with future default if they are updated.

Table 7 presents the results. In columns (1) and (2), we use the dummy variable that indicates whether the PD estimate was updated as our monitoring measure, and in columns (3) and (4), we use the quarterly SD of the PD estimates. Columns (1) and (3) use *firm*, *quarter*, and *bank* fixed effects, and columns (2) and (4) use more stringent *firm* × *quarter* and *bank* fixed effects. Standard errors are clustered at the bank level. The table shows that a bank's PD estimate is more positively associated with actual default 1 year ahead if it is updated.

Our second test is at the bank portfolio level. We estimate the percentage deviation of the realized default rate of a loan portfolio within 1 year from its expected default rate according to the PD estimates. We then test if that deviation is lower for banks that update the PD estimates of a higher share of their portfolio (our proxy for more monitoring) compared to banks that update the PD estimates of a lower portfolio share (our proxy for less monitoring). In other words, we test whether banks that update their PDs are better able to predict the actual default rate at the portfolio level.

[39] Our results are stronger if we require the firm not to be in default in the next two quarters instead of the next three quarters.

Table 7: Updated PD estimates better predict default at the firm level

This table shows the regression results of realized firm default on the banks' PD estimates and our monitoring measures. Our moral hazard measures capture whether the bank updates its PD estimate in a given quarter (*PD update*) and the quarterly SD of its PD estimates (*SD(PD)*). Our original data are monthly and include all euro area borrowers that receive a loan from an IRBA bank. Columns (1) and (3) feature firm, quarter, and bank fixed effects while columns (2) and (4) feature firm × quarter and bank fixed effects. Standard errors are clustered at the bank level.

	(1) Firm defaults (= 100)	(2) Firm defaults (= 100)	(3) Firm defaults (= 100)	(4) Firm defaults (= 100)
Average PD × PD update=1	0.656***	0.839***		
	(0.223)	(0.260)		
Average PD × SD(PD)			6.702	17.05***
			(4.614)	(5.723)
Average PD	1.728***	0.626***	1.978***	0.895***
	(0.311)	(0.106)	(0.364)	(0.163)
PD update=1	0.0252*	0.00153		
	(0.0130)	(0.0107)		
SD(PD)			4.789***	1.441**
			(0.667)	(0.638)
Mean	0.447	0.412	0.438	0.404
Estimation	OLS	OLS	OLS	OLS
Fixed effects	Firm, quarter, bank	Firm × quarter, bank	Firm, quarter, bank	Firm × quarter, bank
Adj. R-squared	0.156	0.653	0.158	0.655
N	71,585,011	24,065,545	70,259,711	23,685,075
Frequency	Quarterly	Quarterly	Quarterly	Quarterly

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To do so, we estimate

$$\begin{aligned} \textit{Deviation from expected PD (percent)}_{p,t_{1-4}} = &\beta \textit{Share of PD updates (percent)}_{p,t_0} \\ &+ \gamma_p + \omega_t + \epsilon_{p,t}. \end{aligned} \tag{7}$$

Deviation from expected PD (percent)$_{p,t_{1-4}}$ captures the relative deviation of the realized default rate of a portfolio from its expected default rate in percent. The realized default rate is the share of loan amounts in a portfolio that default within the next four quarters, while the expected default rate is the average PD estimate of the loans, weighted by the loan amounts (t_{1-4} stands for quarters one to four).[40] *Share of PD updates (percent)*$_{p,t_0}$ captures the share of loan amounts in a portfolio whose PD estimates are updated by the bank (t_0 stands for time 0). We use three definitions of bank portfolios. The first is the entire bank loan portfolio, the second is all loans to firms operating in the same industry, and the third is all loans to firms

[40] The calculation of the expected default rate as the weighted average of PD estimates requires linearity of expectation.

operating in the same industry that are of similar size.[41]

Table 8: Updated PD estimates better predict default at the bank portfolio level

This table shows that the higher the share of a loan portfolio whose PD estimates are updated by the bank, the better these PD estimates are at predicting realized default at the portfolio level. *Deviation from expected PD (percent)*$_{p,t_{1-4}}$ captures the deviation of the realized default rate of a portfolio from its expected default rate. The realized default rate is the share of loan amounts in a portfolio that default within the next four quarters, while the expected default rate is the average PD estimate of the loans, weighted by the loan amounts. This calculation of the expected default rate requires the assumption that firms' probabilities of default are independent and identically distributed. *Share of PD updates (percent)*$_{p,t_0}$ captures the share of loan amounts in a portfolio whose PD estimates are updated by the bank in a given quarter. We use three definitions of bank portfolios. The first is the entire bank loan portfolio (column (1)), the second is all loans to firms operating in the same industry (column (2)), and the third is all loans to firms operating in the same industry and of similar size (column (3)). Size classifications are according to the Annex to Commission Recommendation 2003/361/EC. We require loans not to be in default in the current quarter and, to limit the influence of PD estimates of individual firms, we additionally require portfolios to be at least €100 million large. Standard errors are clustered at the bank level.

	(1) Deviation from expectation (percent)	(2) Deviation from expectation (percent)	(3) Deviation from expectation (percent)
Share of PD updates (percent)	-0.0480**	-0.0289*	-0.0307*
	(0.0242)	(0.0156)	(0.0170)
Mean	74.19	79.66	84.66
Estimation	OLS	OLS	OLS
Fixed effects	Quarter	Quarter × industry	Quarter × industry × firm size
Portfolio	Bank	Bank-industry	Bank-industry-firm size
SE cluster	Bank	Bank	Bank
Adj. R-squared	0.0609	0.190	0.343
N	11,315	115,414	149,638
Frequency	Quarterly	Quarterly	Quarterly

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8 shows the results. In column (1), we use the entire bank loan portfolio and *quarter* fixed effects to compare banks' forecasting ability in the cross-section. In column (2), we use the loan portfolio at the industry level and *quarter* × *industry* fixed effects. In column (3), we use the loan portfolio at the industry-firm size level and *quarter* × *industry* × *firm size* fixed effects. Standard errors are clustered at the bank level. The table consistently shows that a higher share of the portfolio whose PD estimates are updated is associated with a lower deviation of the realized share of default from its expected share. Thus, the two analyses at the firm and the bank-portfolio level show that our monitoring measure captures information that banks have about firms.

While capturing information, one might be concerned that it also captures confounding

[41] Industry classification is according to the two-digit NACE codes. Size classifications are according to the Annex to Commission Recommendation 2003/361/EC. We require loans not to be in default in the current quarter and, to limit the influence of PD estimates of individual firms, we also require portfolios to be at least €100 million large.

effects. First, there might be unobserved effects at the firm, time, or bank level. We address this by comparing the monitoring of different banks that lend to the same firm in the same quarter and the same bank that lends to different firms (econometrically, we again use *firm* $\times$ *quarter* and *bank* fixed effects). This within-firm comparison also addresses the concern that a bank actively updates its PD estimates but confirms its previous level. The updating of PD estimates is benchmarked against another bank that does not synthetically transfer its loans and that captures (more) PD fluctuations.[42]

Second, loan officers of a bank might continue to monitor a firm, but because the loan is synthetically transferred, their colleagues in the risk management department do not bother to update the PD estimates. That is, new information is available but not used. This seems unlikely. Monitoring is costly for the bank, while updating the PD estimate is arguably almost costless. It would be odd to produce information at great cost without using it. Instead, it is more reasonable to believe that banks reduce the production of information through monitoring and continue to use the information available to them.

Finally, PD estimates have the dual role of predicting default and determining risk weights (Behn, Haselmann, and Vig, 2022). Since SRTs decrease the risk weights of loans, the bank might no longer have an incentive to use the PD estimates to "optimize" their risk weights. Thus, one might argue that banks stop updating their PD estimates after the SRT, not because they stop monitoring, but because they no longer need to optimize their risk weights. We think this is unlikely for two reasons. First, it is unclear why risk weight optimization requires frequent updates of the PD estimates. Second, if risk weight optimization does require frequent updates, we would expect PD updating banks to be worse at predicting actual default, not better, as we show above.

3.2.2 SRT and monitoring

Having validated our monitoring measure, we use it to investigate the change in monitoring after a loan is synthetically transferred. We show that after the risk transfer, the monitoring intensity decreases compared to other banks lending to the same firm. This decrease in monitoring intensity is more pronounced if the bank synthetically transfers a larger share of its total firm

[42]In any case, it is hard to believe that the firm produces new information, which the bank reviews but which is not informative about changes in the probability of default.

exposure. To show this, we estimate

$$\begin{aligned} Monitoring_{f,b,t} = & \beta_1 SRT\ loan_{f,b,t-1} * Post\ SRT_{f,t-1} \\ & + \beta_2 Post\ SRT_{f,t-1} * SRT\ to\ total\ exposure_{f,b,t-1} \\ & + \gamma_f + \delta_b + \omega_t + \epsilon_{f,b,t}. \end{aligned} \tag{8}$$

$Monitoring_{f,b,t}$ represents our two monitoring measures; a dummy variable equal to 1 if the PD is updated and 0 otherwise, and the SD of the PD estimates. $SRT\ loan_{f,b,t-1}$ is a dummy variable equal to 1 if a loan is synthetically transferred during its lifetime and 0 otherwise, and $Post\ SRT_{f,t-1}$ is 1 after the transfer and 0 before (the latter is at the firm level). The interaction of the two variables tests whether banks decrease their monitoring intensity after a loan is synthetically transferred. $SRT\ to\ total\ exposure_{f,b,t-1}$ measures the share of loans (by a bank to a firm) that is synthetically transferred. The interaction with $Post\ SRT_{f,t-1}$ tests whether the decrease in monitoring is more pronounced the greater that share; that is, the lower the effective firm exposure that the bank retains.

Columns (1)–(3) of Table 9 show the results for the dummy variable that indicates PD updates as our monitoring measure. Column (1) uses *firm*, *quarter*, and *bank* fixed effects, and columns (2) and (3) use more stringent *firm* × *quarter* and *bank* fixed effects. In columns (1) and (2), we estimate regression (8) without the second interaction term, while in column (3) we include the term. Standard errors are clustered at the bank level. Columns (1) and (2) show that upon synthetically transferring the loan, the likelihood of updating the PD estimate decreases by 12–13%. Column (3) shows that the degree of this effect varies significantly with the firm exposure that the bank retains: the probability of updating the PD estimate decreases by as much as 35% for banks that synthetically transfer their entire firm exposure.

In columns (4)–(6), we do the same as in columns (1)–(3), but for the quarterly SD of the PD estimates as the monitoring measure. The results confirm those in columns (1)–(3) but are stronger in economic magnitude. Columns (4) and (5) show that the SRT is associated with a decrease in the SD of the PD estimates by more than one quarter. For banks that synthetically transfer their entire firm exposure, the decrease is 70% (column (6)).

These results should be interpreted against the backdrop of SRTs broadening the spectrum

Table 9: SRT banks decrease monitoring intensity

This table shows the regression results of our moral hazard measures on the interaction of synthetically transferring a given loan (*SRT loan*) and the post-transfer period (*Post SRT*). In columns (3) and (6), we additionally interact *Post SRT* with the share of loans (of a firm) that a bank synthetically transfers. Our moral hazard measures capture the frequency with which banks change firms' PD estimates in a given quarter (our original data are monthly). *SD(PD)* measures the quarterly SD of PD estimates and *SD(PD)* > 0 indicates changes. Columns (1) and (4) feature firm, quarter, and bank fixed effects, while columns (2), (3), (5), and (6) feature firm × quarter and bank fixed effects. The interpretation is as follows: synthetically transferring a loan is associated with a 26% decline in the SD of PD estimates (column (5)). The decline is more pronounced the greater the share of loans that are synthetically transferred (columns (3) and (6)).

	(1) PD update	(2) PD update	(3) PD update	(4) SD(PD)	(5) SD(PD)	(6) SD(PD)
SRT loan=1 × Post SRT=1	-0.0428**	-0.0384*	-0.0338	-0.0323**	-0.0283*	-0.0267*
	(0.0200)	(0.0216)	(0.0224)	(0.0147)	(0.0146)	(0.0158)
Post SRT=1 × SRT to total exposure			-0.0773***			-0.0489***
			(0.0268)			(0.0147)
Average PD	0.00781	0.00154	0.00158	0.0571***	0.0488***	0.0489***
	(0.00475)	(0.00376)	(0.00379)	(0.0188)	(0.0117)	(0.0117)
Mean	0.333	0.314	0.315	0.116	0.108	0.108
Estimation	OLS	OLS	OLS	OLS	OLS	OLS
Fixed effects	Firm, quarter, bank	Firm × quarter, bank	Firm × quarter, bank	Firm, quarter, bank	Firm × quarter, bank	Firm × quarter, bank
SE cluster	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R-squared	0.341	0.305	0.304	0.193	0.196	0.196
N	4,218,191	3,459,442	3,405,618	4,135,533	3,381,511	3,328,335

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of loans whose risks can be moved to the non-bank financial sector. Due to their bespoke and private nature and because the ownership of the loan does not change, banks can transfer the risk of almost any loan on their balance sheet, including loans that require substantial monitoring.

3.3 Risk transfer

Another potential risk to financial stability may stem from a possible interconnectedness of banks with the non-bank SRT investors. We investigate this interconnectedness here. While most data used in the newly emerging literature on the bank-non-bank interconnectedness are at the industry level, ours are at the loan and investment level and at a monthly frequency. But we lose a lot of statistical power and move from millions of observations in the previous sections to dozens in this one. The validity of our results may need to be confirmed as new transactions are recorded.

In Section 3.3.1, we show two results on the interconnectedness. First, we find that banks are more likely to sell an SRT to a non-bank investor to which they also grant credit compared to an investor with no such connection. Second, we show that the outstanding amounts of bank loan liabilities of SRT investors increase in the months before the SRT investment. Under the assumption that the increase is directly used to finance the SRT, our results suggest that euro area banks finance 26% of the average SRT investment. The loans to SRT investors free around €5 million of capital, while binding only around €230,000.

In Section 3.3.2, we argue that investors in US SRTs may be more leveraged and SRTs themselves riskier. To achieve similar capital relief as in Europe, US SRTs need to have thicker junior tranches. All else equal, thicker junior tranches imply a greater transfer of credit risk, but also a lower return for the non-bank SRT investor. Investors in thicker junior tranches may therefore increase their returns by being more leveraged and investing in riskier SRTs. Indeed, we find that in Europe thicker junior tranches are associated with investments by non-banks with higher bank debt-to-asset ratios and have higher expected losses.[43] Our results—while correlational—illustrate a trade-off between the significance of a risk transfer (thicker tranches)

[43]Importantly, the relationship between the thickness of the junior tranche and the expected loss is at least in parts by regulatory design, see below.

and investor return (as affected by their leverage and the SRT's expected losses).

3.3.1 Bank-non-bank nexus

We use the fact that AnaCredit records not only bank loans to non-financial firms, but also to financial firms, such as the non-bank SRT investors. This gives us a sense of whether investors finance themselves with bank loans. While providing unique insights, we miss bank loans that are made outside the euro area to SRT investors that invest in euro area SRTs.

We start by showing a natural connection between the SRT issuing bank and the non-bank SRT investor. Banks are more likely to sell credit risk to potential investors with which they have a substantial credit relationship during our sample compared to potential investors with which they are unconnected. To show this, we estimate

$$\textit{SRT investment}_{b,t,j} = \beta_0 + \beta_1 \textit{Credit relationship}_{b,t,j} + \delta_b + \omega_t + \eta_j + \epsilon_{b,t,j}. \tag{9}$$

The dependent variable $\textit{SRT investment}_{b,t,j}$ is a dummy that equals 1 if a non-bank (with subscript j) invests in a given SRT and 0 otherwise. The explanatory variable $\textit{Credit relationship}_{b,t,j}$ is a dummy that equals 1 if the non-bank SRT investor receives credit of at least €1 million from the SRT bank during our sample and 0 otherwise. We consider as potential investors all non-banks that actually invest in an SRT in a given country and during the respective year.

Table 10 features linear probability regressions with different samples and different fixed effects. Columns (1)–(3) use all investments, and columns (4)–(6) restrict the sample to exclude government investments. Columns (1), (2), (4), and (5) consider credit relationships at the unconsolidated investor level, while columns (3) and (6) consider the entire investor group. In columns (1) and (4), we use year fixed effects, while the other columns use bank, investor, and year fixed effects. In the latter case, standard errors are clustered at the bank level.

The table shows that having a credit relationship is positively associated with an SRT investment. Column (5), in which we exclude government investments and record credit relationships at the unconsolidated level, shows that having a credit relationship is associated with a 57% higher investment probability. This number is 66% in column (6), which also

Table 10: Banks sell SRTs to connected investors

This table shows the results of a regression of *SRT investment* on *Credit rel.* and *Credit rel. (group)*. SRT investment takes the value 1 if a given non-bank invests in an SRT issue and 0 otherwise. *Credit rel.* and *Credit rel. (group)* take values 1 if a potential non-bank SRT investor or non-bank SRT investor group receives credit of at least €1 million from the SRT-issuing bank during our sample and 0 otherwise. Potential non-bank SRT investors are all firms that actually invest in an SRT in a given country and year. All data are from AnaCredit. All columns show linear probability regressions.

	(1) SRT transaction	(2) SRT transaction	(3) SRT transaction	(4) SRT transaction	(5) SRT transaction	(6) SRT transaction
Credit rel.	0.0409	0.176*		0.0853**	0.0743**	
	(0.0265)	(0.0886)		(0.0372)	(0.0291)	
Credit rel. (group)			0.229***			0.0855**
			(0.0700)			(0.0384)
Mean	0.171	0.165	0.165	0.135	0.130	0.130
Estimation	OLS	OLS	OLS	OLS	OLS	OLS
Fixed effects	Year	Bank, investor, year	Bank, investor, year	Year	Bank, investor, year	Bank, investor, year
Restriction				No Government/ EIF	No Government/ EIF	No Government/ EIF
SE cluster		Bank	Bank		Bank	Bank
Adj. R-squared	0.0242	0.153	0.163	0.0248	0.153	0.154
N	1,691	1,677	1,677	1,055	1,050	1,050

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

excludes government investment, but which treats investors at the group level. These results suggest a familiarity or natural interconnectedness between the SRT bank and the non-bank SRT investor.

Next, we investigate whether SRTs are partially financed with bank loans (from any bank, not just the SRT bank). This is difficult because AnaCredit, like any credit registry, does not record the *exact* purpose of a loan; that is, it does not state that a loan is used to finance an SRT. We therefore approximate the exact purpose by studying the debt dynamics of the SRT investor over time. Do their liabilities increase in the months before the SRT investment? This could suggest that SRTs are partially debt-financed.

Not all investments, however, are funded (see Section 2.3.1). For unfunded investments, we do not expect investors to get credit in the run-up to the SRT investment. In addition, we expect debt to matter more for larger investments. We capture these differences by investigating the debt dynamics for three subsamples. The first subsample includes all investments, the second includes only funded investments, and the third includes funded and large investments. Although AnaCredit does not provide information on collateralization,[44] it is safe to assume that investments by government entities are unfunded. We classify large investments as those whose junior tranche exceeds €50 million. Differences in results across these three subsamples would support the assumption that increases in the loan amounts before the SRT investment

[44] COREP has information on collateralization, but merging AnaCredit and COREP has proven difficult.

are indeed connected to the SRT investment itself.

We test the loan dynamics by estimating

$$\textit{Log debt amount outstanding}_{s,\tau,t} = \beta_0 + \beta_1 \textit{Months to SRT investment}_{s,\tau,t} + \delta_s + \omega_t + \epsilon_{s,\tau,t}. \tag{10}$$

The dependent variable *Log debt amount outstanding*$_{s,j,\tau}$ is the natural logarithm of the sum of loan amounts the investor owes to euro area banks in a given month. We consider loans from all banks, not just the SRT bank, but exclude loans made for real estate and construction purposes.

The explanatory variable *Months to SRT investment*$_{s,j,\tau}$ represents fixed effects that capture the months until an SRT investment (with subscript τ, which is different from the calendar time t). We approximate the date of the SRT investment with the most common date on which loans receive the SRT flag. We do not know when the investor transfers the money for the SRT, but take 6 months before the SRT as a baseline and count increases in the loan amount thereafter toward the SRT. The unit of observation is the investment s; that is, if an investor invests twice during our sample, it also appears twice in this regression. We control for SRT-investment fixed effects (δ_s) and calendar-time fixed effects (ω_t) to capture a time trend. Standard errors are clustered at the SRT investment level.

Figure 3 plots the β_1 coefficients and their 95% confidence intervals. We depict all investments in blue, funded investments in red, and funded and large investments in green (Appendix Table F.3 is the corresponding table, which includes 6 months of pre-trends). We find that for all investments, there is a small increase in the loan liabilities of investors in the 5 months before the SRT investment. In line with the fact that only funded SRTs require financing with bank loans, the increase is much more pronounced and strongly statistically significant for funded investments. The strongest uptake of debt is observed for funded and large investments. The coefficients become statistically insignificant a few months after the SRT investment, but their values suggests that debt levels remain elevated relative to 6 months before the investment. These results are consistent with the presumption that some of the financing for SRTs comes from banks.

How large is the debt increase compared to the SRT investment? For SRT investors that have

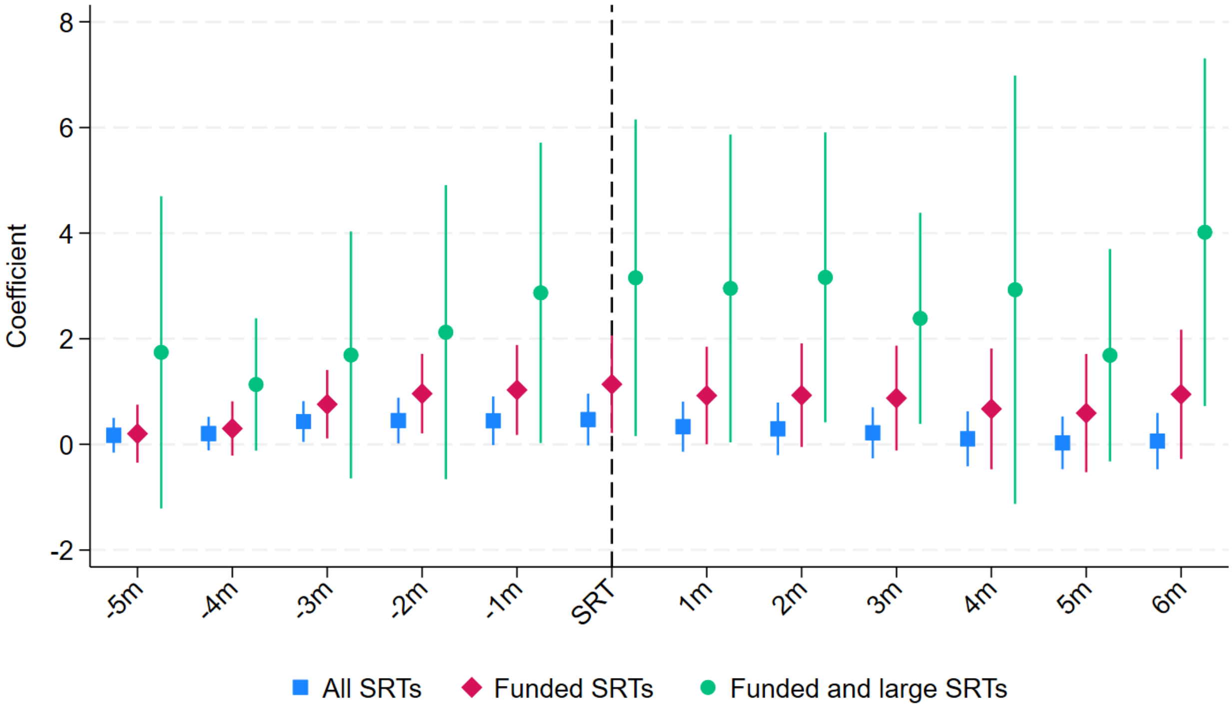

Figure 3: Bank loan amounts to investors increase around the SRT investment. This figure shows the months until SRT investment fixed effects as estimated in regression 10, with 6 months before the SRT investment as the baseline. The dependent variable is the natural logarithm of debt outstanding of non-bank SRT investors. "Funded SRTs" are approximated as all except government investments. "Funded and large SRTs" are additionally restricted to investments with a junior tranche that is larger than €50 million. We control for SRT investment and calendar time fixed effects. Standard errors are clustered at the SRT investment level.

to fund their investments, the average loan amount outstanding 6 months before the investment is €4.9 million. The red β coefficients in Figure 3 imply that the average loan amounts increase by €10 million in the months leading up to the SRT investment. The average SRT investment (i.e., the junior tranche) amounts to €39 million.[45] If we count the entire increase in the loan amount toward the SRT, this suggests that 26% of the average SRT investment are debt-financed.

What are the possible effects of the interconnectedness on financial stability? In the event of an adverse shock to the firms whose loans are synthetically transferred, the non-bank investor could default on its bank loans. But whether that is the case depends not on the share of the SRT that is financed through bank credit but on its overall leverage. Since debt is senior to equity, the adverse shock would have to be severe for banks to experience losses or investors would have to be very leveraged. Our descriptive statistics of Section 2.3.5 show that the ratio of bank loan liabilities to total assets of SRT investors is low—but also that the asset values are usually missing.

The partial debt financing does, however, imply that the system as a whole becomes less capitalized. Loans to SRT investors bind, on average, €230,000 but free around €5 million. The financing of the average SRT with debt therefore strips the banking sector as a whole of €4.77 million in capital.[46] But this stylized analysis does not account for the distribution of capital across banks.

3.3.2 Significance of risk transfer and investor return

There exists a trade-off between the significance of the credit risk transfer and the return of the investor. The significance of the credit risk transfer increases in the thickness of the junior tranche. The return of the investor, on the other hand, decreases in the thickness of the junior tranche—simply because it is more likely for a small share of the loan portfolio to default than a large share. This decrease can be undone by higher leverage of the investor or by higher expected losses of the SRT. We show that in the data both are positively correlated with the

[45] Numbers between AnaCredit (used here for consistency) and COREP (used in Section 2.3.1) differ slightly.

[46] The weighted average risk weight on loans to SRT investors is only 29 percent (assuming a LGD of 40%). The €10 million loan therefore costs banks around €230,000 in capital ($0.08 * 0.29 * €10,000,000$). How much capital does that loan free? With a junior tranche of €39 million, an assumed thickness of the junior tranche of 15%, we have an SRT amount of €260 million. The total capital saving for that SRT are around €20 million. The loan accounts for a quarter of that, so for €5 million.

thickness of the junior tranche. This result has implications for the growing US SRT market, on which banks need to sell a thicker tranche than their European counterparts to achieve similar capital relief, due to the Collins Amendment to the Dodd-Frank Act.

To test the implications of different sizes of the junior tranches, we estimate

$$Y_{s,b,j} = \beta_0 + \beta_1 * Thickness\ tranche\ sold_{s,b,j} + \theta X_{s,b,j} + \epsilon_{s,b,j}. \tag{11}$$

The dependent variable $Y_{s,b,j}$ takes on two values; the investors' loan liabilities over assets, as our proxy for leverage,[47] and the expected losses of the SRT. The latter is from the ECB's COREP dataset. We have two variables for the $Thickness\ tranche\ sold_{s,b,j}$, the first is calculated from AnaCredit as the ratio of the risk amount transferred and the total SRT amount, and the second is given in COREP. Since we find it difficult to match AnaCredit and COREP, we use both datasets separately.

Table 11: Thicker tranches are bought by more leveraged investors

This table shows the results of a regression of *Bank debt to assets* of the SRT investors on the *Thickness of tranche sold*. Bank debt comes from AnaCredit, and assets come from Orbis by BvD. Bank debt and assets are at the unconsolidated non-bank investor level, as our values for assets are currently more reliable at that level. The thickness of the tranche sold is calculated as the credit risk transferred over the sum of all loans in an SRT issue, both from AnaCredit. Control variables are the natural logarithm of the SRT amount and the average PD of the underlying loans. In column (5), we restrict the sample to investors with a positive bank debt-to-asset ratio.

	(1) Bank debt to assets	(2) Bank debt to assets	(3) Bank debt to assets	(4) Bank debt to assets	(5) Bank debt to assets
Thickness of tranche sold	0.0847**	0.0851***	0.0969***	0.127	0.108***
	(0.0407)	(0.0234)	(0.0290)	(0.0847)	(0.0353)
Mean	0.0634	0.0640	0.0643	0.0295	0.0790
Estimation	OLS	OLS	OLS	OLS	OLS
Fixed effects		Investor type, country	Investor type, country	Investor type, country	Investor type, country
Restriction				No Gvrnmt/ EIF	Bank debt to assets > 0
SE cluster	Bank	Bank	Bank	Bank	Bank
Controls			SRT size, PD	SRT size, PD	SRT size, PD
Adj. R-squared	0.0850	0.424	0.437	0.850	0.363
N	106	105	102	37	83

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We start by estimating regression (11) with investors' loan liabilities over assets as the dependent variable. For this specifications, data are entirely from AnaCredit. Column (1) of Table 11 uses no controls and no fixed effects, column (2) features investor type and country fixed effects, and column (3) additionally controls for the SRT size and the average PD of the underlying loans. Columns (4) and (5) are similar to column (3) but exclude govern-

[47]We again exclude loans that are made for construction and real estate purposes.

ment investments (column (4)) and investors with no debt from European banks (column (5)). Investor-type fixed effects are used to account for differences in risk-taking and expected yields.

Column (3) shows that a 28pp thicker junior tranche that is sold (1 SD) is associated with investors having 3pp higher values of loan liabilities over assets (or 30% of their SD). Column (4) without government investments shows a larger coefficient, but it loses significance due to the very lower number of observations.

Next, we estimate regression (11) with the expected loss as the dependent variable. In COREP, banks report the expected loss, and the detachment point of the risk sold reflects the thickness of the tranche. In column (1) of Table 12, we use no controls, while in column (2), we control for the natural logarithm of the SRT amount and bank and year fixed effects (not that COREP does not have investor data). In column (3), we limit our data to SRTs with a tranche thickness of at least 8.5%. All columns show a positive relationship between the thickness of the sold tranche and the expected losses.

Table 12: Thicker tranches have higher expected losses

This table shows the results of a regression of the expected loss of an SRT on the thickness of the SRT share sold. Data come from COREP and variables are reported at the SRT level.

	(1) Expected losses	(2) Expected losses	(3) Expected losses
Thickness of tranche sold	0.114***	0.119***	0.0918***
	(0.0297)	(0.0200)	(0.0276)
Log SRT amount		-0.00154	-0.00360
		(0.00266)	(0.00369)
Mean	0.0141	0.0151	0.0193
Estimation	OLS	OLS	OLS
Fixed effects		Bank, year	Bank, year
Restriction			Tranche sold > 8.5%
SE cluster	Bank	Bank	Bank
Adj. R-squared	0.405	0.761	0.419
N	103	92	67

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Importantly, for this result the causality may run reversely. The riskier the underlying loans are, the smaller the capital relief. Banks may counteract this and obtain more capital relief by creating a thicker junior tranche (see Appendix B). In addition, banks need to prove the *significance* of the risk transfer, which means that riskier SRTs must have thicker junior tranches. The strong correlation between the thickness of the junior tranche and expected loss may, nevertheless, reflect a conflict between the significance of the risk transferred and investors' search for yield, as reflected in the riskiness of the underlying assets.

At face value, our results suggest that investors in US SRTs, whose junior tranches are thicker than European SRTs, may be more leveraged and the underlying loans riskier.

4 Conclusion

This paper is the first to investigate the rapidly growing synthetic risk transfer market, on which banks sell the first losses on a loan portfolio while retaining the loans on their balance sheets. We use proprietary transaction-level data and discuss three potential risks to financial stability.

First, banks use SRTs to increase the economic riskiness of their portfolios, relative to the riskiness assigned by the capital ratio. This has implications for financial stability and the effectiveness of a new Basel regulation, called the "output floor," which is a lower bound on risk weights under the IRBA, relative to risk weights under the Standardized Approach. Our findings suggest that the impact of the output floor could be partially undone by banks with access to SRTs.

Second, we show within-firm and within-bank evidence that banks reduce their monitoring efforts of firms whose loans they synthetically transfer. Monitoring is arguably more important for SRT loans than for traditionally securitized loans or assets underlying CDS.

Third, we find that investors have low leverage (this finding is subject to data limitations). They are nevertheless connected to banks through the loan market. Banks are 57–66% more likely to sell SRTs to non-bank investors with which they have a credit relationship. Investors' debt levels increase prior to the SRT investment, consistent with on average 26% of the funding for the SRT coming from the banking sector.

The amount of capital relief that banks receive for SRTs should reflect these three channels.

In ongoing work, we are examining why banks use SRTs instead of issuing equity. Is the debt-value that SRT banks own overvalued relative to their equity? Or are banks simply over-exposed to SRT loans and non-bank investors better able to take on the credit risk of these loans?

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Appendices

A SRT banks are less capitalized

We reinforce our descriptive findings and show that SRT banks have lower capital ratios than non-SRT banks. This result is more pronounced after capital relief was increased in April 2021.

To show this, we estimate

$$\begin{aligned} SRT_{b,t} =& \beta_1 \textit{Tier 1 capital ratio}_{b,t-1} \\ & + \beta_2 \textit{Tier 1 capital ratio}_{b,t-1} * \textit{Post April 2021}_t + \beta_3 X_{b,t-1} + \epsilon_{b,t}. \end{aligned} \tag{A.1}$$

$SRT_{b,t}$ captures two variables; one is a dummy that indicates SRT issues of at least €50 million in a given year, and the other is the natural logarithm of the SRT amount. We start by estimating (A.1) without the interaction term. We then include the interaction term to show a differential effect of banks' Tier 1 capital ratios on SRT issuance after April 2021. *Post April 2021*$_t$ is a dummy variable equal to 1 for the years 2022–2024, and 0 before 2022.

Effective on 9 April 2021, the existing EU framework for simple, transparent, and standardized (STS) traditional securitizations was extended to SRTs.[48] Following that change, banks that structure their SRTs according to the STS criteria could benefit from a risk weight floor on the senior tranche (that the bank retains) of 10% instead of previously 15%. This had an effect on the type and the amount of SRT issuance. Appendix Figure A.15 shows that the share of SRTs that received capital relief under the STS label in a quarter increased strongly after the April 2021 regulatory change. Similarly, Appendix Figure A.16 shows that the amounts of new SRTs decreased to around €70 billion per quarter in the year leading up to the regulatory change and began to increase significantly thereafter to more than €130 billion in Q2 of 2024.[49]

[48]The STS framework requires the following SRT structure. "Simplicity": underlying assets meet eligibility criteria such as being part of the core business, being homogeneous, or not being re-securitized. "Transparency": disclosure of performance to investors, documentation requirements, etc. "Standardization": Requirements for the tranching structure, risk retention, the hedging of interest rate and currency risk, among others.

[49]The effect of the regulatory change on SRT issuance was also recognized in a "Joint Committee" report of the European supervisory authorities which writes that "[SRTs] have demonstrated significant growth in the last years, especially following the introduction of the STS framework for [SRTs] in 2021." (Joint Committee, 2025). The Joint Committee is a cooperation between the European Banking Authority (EBA), the European Insurance and Occupational Pension Authority (EIOPA), and the European Securities and markets Authority (ESMA).

Table A.1 shows the results of regression (A.1). Columns (1)–(4) do not feature the interaction term, while columns (5) and (6) do. Columns (1), (2), and (5) use the SRT dummy as the dependent variable, and columns (3), (4), and (6) use the SRT amount. In the estimation without the interaction term, we use OLS (columms (1) and (3)), a logistic regression (column (2)), and an exponential-mean regression (column (4)).[50] When we include the interaction term, we use OLS to maintain the interpretability of the coefficients. In columns (1)–(4), we use *country* × *year* fixed effects and wild-bootstrap standard errors at the country level. In columns (5) and (6), we use *bank* and *year* fixed effects and wild-bootstrap standard errors at the bank level. In all columns, we control for the size of banks (in addition to our size-based sample selection) by creating 10 bins of banks' balance sheets and interacting them with the natural logarithm of banks' balance sheets (similar to specifications in Sufi (2007)). In addition, we always control for banks' liquidity using the ratio of liquid assets to deposits.

Columns (1)–(4) show that lower Tier 1 capital ratios are strongly negatively associated with whether a bank issues an SRT and with the SRT amount. According to column (1), a 1 SD decrease in a bank's Tier 1 capital ratio (equal to 0.073) is associated with a 30% higher likelihood of issuing an SRT in a given year. Column (6) shows that lower Tier 1 capital ratios are more strongly negatively associated with SRT amounts after capital relief was increased in April 2021. This confirms our descriptive statistics and shows that bank capitalization is a key driver of using SRTs and capital relief a major motivation.

[50]SRT amounts contain many zeros and are therefore more closely mapped by an exponential distribution compared to a linear regression.

Table A.1: SRT banks have lower capital ratios than non-SRT banks

This table shows the results of regressions of an SRT dummy (columns (1), (2), (5) and the natural logarithm of the SRT amount plus one (columns (3), (4), (6)) on banks' Tier 1 capital ratios and its interaction with a post-2021 dummy. The data are aggregated at the year-level as our Tier 1 capital ratios are yearly from Bankfocus by BvD. That is, SRT amounts are summed up within years or quarters. The SRT dummy equals 1 if the yearly SRT amount is at least €50 million, and 0 otherwise. Fixed effects are at the country × year level. Standard errors are wild-bootstrapped at the country cluster. Our sample of non-SRT banks is selected to be at least as large as the 10th percentile of SRT banks in a given country. We additionally control for bank size by interacting the logarithm of its balance sheet with 10 bank size dummies in all specifications.

	(1) SRT	(2) SRT	(3) Log SRT amount	(4) Log SRT amount	(5) SRT	(6) Log SRT amount
Tier 1 capital ratio	-0.275***	-25.17***	-7.286***	-16.42***	-0.154	-1.238
	(0.0867)	(1.675)	(1.974)	(0.253)	(0.169)	(3.375)
Post 2021=1 × Tier 1 capital ratio					-0.190	-5.938**
					(0.122)	(2.445)
Liquid assets to deposits	0.0293	1.546***	0.146	0.738***	0.0672	0.431
	(0.0274)	(0.492)	(0.623)	(0.0743)	(0.0515)	(1.031)
Mean	0.0672	0.0928	1.710	1.928	0.0676	1.720
Estimation	OLS	Logit	OLS	Exponential mean	OLS	OLS
Fixed effects	Country × year	Country × year	Country × year	Country × year	Bank, year	Bank, year
SE cluster	WCR: Country	WCR: Country	WCR: Country	WCR: Country	WCR: Bank	WCR: Bank
Additional controls	Size bins × bank size	Size bins × bank size	Size bins × bank size	Size bins × bank size	Size bins × bank size	Size bins × bank size
Adj. R-squared	0.300		0.312		0.750	0.810
N	1,934	1,315	1,934	1,715	1,922	1,922
Frequency	Yearly	Yearly	Yearly	Yearly	Yearly	Yearly

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Risk weights in the euro area under the IRBA

B.1 Loan exposures

Since June 2020

According to Articles 153 and 501 of Regulation (EU) No 575/2013 of the European Parliament and of the Council, the risk weights are calculated as

$$RW = \left(LGD \cdot N \left(\frac{1}{\sqrt{1-R}} \cdot G(PD) + \sqrt{\frac{R}{1-R}} \cdot G(0.999) \right) - LGD \cdot PD \right) \cdot \frac{1 + (M-2.5) \cdot b}{1 - 1.5 \cdot b} \cdot 12.5 \cdot 1.06. \tag{B.2}$$

$N(x)$ and $G(Z)$ are the cumulative distribution function and the inverse cumulative distribution function of a standard normal random variable, respectively. PD stands for a firm's PD, and LGD stands for the loan's LGD. M is the loan maturity in years. In addition, the following definitions apply:

$$b = (0.11852 - 0.05478 \cdot ln(PD))^2 \tag{B.3}$$

$$R = 0.12 \cdot \frac{1 - e^{-50 \cdot PD}}{1 - e^{-50}} + 0.24 \cdot \left(1 - \frac{1 - e^{-50 \cdot PD}}{1 - e^{-50}}\right) - 0.04 \cdot \left(1 - \frac{\min\{\max\{5, S\}, 50\} - 5}{45}\right), \tag{B.4}$$

where S is the firm's annual revenue in million euros. If the risk exposure is to a financial institution, R is multiplied by 1.25.

For exposures to firms with annual revenues below €50 million, the risk weights are adjusted as follows:

$$RW\text{-}adjusted = RW \cdot \frac{\min\{E; €2.5\} \cdot 0.7619 + \max\{E - €2.5; 0\} \cdot 0.85}{E}, \tag{B.5}$$

where E is the total amount owed to a firm, in million euros.

Before June 2020

Before June 2020, the RW adjustment applied to all firms with revenues below €50 million and bank-firm exposures below €1.5 million as follows: $RW\text{-}adjusted = RW \cdot 0.7619$.

B.2 Securitization exposures

The risk weights for securitization exposures are specified in Article 259 of Regulation (EU) 2017/2401, which amends Regulation (EU) 575/2013. They are given by the following formula, but subject to a floor of 10% for securitizations that comply with the STS criteria and 15% for securitizations that do not.

$$RW = \begin{cases} 12.50 & \text{if } detach \leq K_{IRB} \\ 12.5 * K_{SSFA(K_{IRB})} & \text{if } attach \geq K_{IRB} \\ \frac{K_{IRB}-attach}{detach-attach} * 12.5 + \frac{detach-K_{IRB}}{detach-attach} * 12.5 * K_{SSFA(K_{IRB})} & \text{if } attach < K_{IRB} < detach, \end{cases} \tag{B.6}$$

where K_{IRB} is the ratio of the capital requirement of the underlying loans (including expected losses) and the securitized amount. *attach* and *detach* are the attachment point and the detachment point of the tranche, respectively. The attachment point is the share of loans that have to default above which the holder of the tranche (i.e., the bank if it retains the senior tranche) is liable. The detachment point is the share of loans that have to default above which the holder of the tranche is no longer liable (equal to 1 if the bank retains the senior tranche).

Furthermore,

$$K_{SSFA(K_{IRB})} = \frac{e^{a*u} - e^{a*l}}{a(u-l)}, \tag{B.7}$$

where $a = -\frac{1}{p*K_{IRB}}$, $u = detach - K_{IRB}$, and $l = \max(attach - K_{IRB}; 0)$. p in the definition of a takes the value of $\max(0.3; A + B * \frac{1}{N} + C * K_{IRB} + D * LGD + E * M_T)$ or $\max(0.3; 0.5 * (A + B * \frac{1}{N} + C * K_{IRB} + D * LGD + E * M_T))$ for STS securitizations, where N is the number of securitized loans, LGD is the weighted average LGD, and M_T is the maturity in years (bound by 1 and 5 years).[51] The parameters A–E are determined according to Table B.2.

With this formula, it is straightforward to show that the higher the risk weights of the

[51]The precise calculations of N, LGD and M_T follow defined formulas.

Table B.2: Parameter values

This table shows the values of parameters A–E that are used in the calculation of the risk weights of securitization exposures.

	A	B	C	D	E
Non-retail					
Senior, granular (N $\geq$ 25)	0	3.56	-1.85	0.55	0.07
Senior, non-granular (N $<$ 25)	0.11	2.61	-2.91	0.68	0.07
Non-senior, granular (N $\geq$ 25)	0.16	2.87	-1.03	0.21	0.07
Non-senior, non-granular (N $<$ 25)	0.22	2.35	-2.46	0.48	0.07
Retail					
Senior	0	0	-7.48	0.71	0.24
Non-senior	0	0	-5.78	0.55	0.27

underlying loans, the greater the capital savings. Consider a bank that retains the senior tranche of a non-retail STS securitization with $N = 20$ and an amount of €1 billion. Let the attachment and detachment points be 0.1 and 1, the LGD be 50%, the maturity be 4 years, the expected losses 1%, and the weighted average of the risk weights on the underlying loans be 0.50. This yields a securitization risk weight of 0.1 and capital savings of €32.8 million. In contrast, if the weighted average of the risk weights on the underlying loans is 0.60, the securitization risk weight would also be 0.1, and the bank would save €40.8 million in capital. The bank therefore saves 24% more capital by securitizing loans that have 10pp higher risk weights. This difference also exists for risk weights above the 10% floor.

C New lending by SRT banks is not capital-expensive

In this section, we test if the new lending by SRT banks is capital-expensive. But while it is fairly easy to show that total lending increases upon issuing SRTs, it is more difficult to know to which firms the new lending is directed. Put differently, we do not know which loans would not have been made had the bank not issued an SRT. We therefore simply investigate net credit expansions by SRT banks at the firm level and check if these expansions are capital-expensive. We take two approaches. First, we test whether credit expansions are positively associated with the risk weights of loans, while tightly controlling for their economic riskiness (based on the existing stock of loans). Second, we again exploit the €50 million annual revenue threshold, where risk weights exhibit a jump. If banks used SRTs to make particularly capital-expensive loans, we would expect credit expansions to firms that have annual revenues just above €50 million.

For our first test, we estimate

$$New\ lending_{f,b,t} = \beta Risk\ weight_{f,b,t} + \theta X_{f,b,t} + \epsilon_{f,b,t}. \tag{C.8}$$

$New\ lending_{f,b,t}$ captures two variables; one is a dummy variable equal to 1 if the bank expands credit to a firm in a given year and 0 otherwise, and the other is the logarithm of the net amount granted. The risk weight is based on existing loans the firm has with the bank (this gives us a risk weight for the firms whose credit is not expanded) and assumes a LGD of 40%.[52] $X_{f,b,t}$ features the firm's PD, its revenue, the logarithm of its outstanding loan amounts, its average loan rate, and the bank's firm exposure as controls for the loan's economic riskiness. Fixed effects are *bank* × *industry* × *year*. Standard errors are clustered at the bank level.

Table C.3 shows the results. Columns (1) and (2) use the credit expansion dummy as the dependent variable, and columns (3) and (4) use the amounts. Columns (2) and (4) use firm fixed effects in addition to the baseline fixed effects described above and used in columns (1) and (3). All columns show that *lower* risk weights are associated with net credit expansions by SRT banks.

This approach captures all net lending, but has the disadvantage that we cannot properly

[52] As the maturity of the loan, we take the average maturity of existing loans, weighted by their loan amounts.

Table C.3: Banks with a low gap between leverage and Tier 1 capital ratio use SRTs

This table shows the results of linear regressions. As dependent variables, columns (1) and (2) feature a dummy that is 1 if a bank expands its lending to a firm in a given year and 0 otherwise, and columns (3) and (4) feature the logarithm of the amount of net credit expanded. The risk weight is based on existing loans the firm has with the bank (this gives us a risk weight for the firms whose credit is not expanded) and assumes a LGD of 40%. It is also based on the average maturity of existing loans, weighted by their amounts. We use the firm's PD, its revenue, the logarithm of its outstanding loan amounts, its average loan rate, and the bank's firm exposure as controls for the loan's economic riskiness. Our sample only uses SRT banks.

	(1) Net new lending (dummy)	(2) Net new lending (dummy)	(3) Net new lending (log amount)	(4) Net new lending (log amount)
Risk weight	-0.123***	-0.129***	-2.430***	-2.645***
	(0.0200)	(0.0265)	(0.299)	(0.461)
Mean	0.292	0.293	3.931	3.964
Estimation	OLS	OLS	OLS	OLS
Fixed effects	Bank × industry × year	Bank × industry × year, firm	Bank × industry × year	Bank × industry × year, firm
SE cluster	Bank	Bank	Bank	Bank
Controls	✓	✓	✓	✓
Adj. R-squared	0.142	0.425	0.223	0.545
N	4,664,364	4,379,871	3,735,019	3,422,281
Frequency	Yearly	Yearly	Yearly	Yearly

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

control for the economic riskiness of a new loan. To control for it, we study net lending around a firm revenue threshold of €50 million, where risk weights exhibit a jump. To do this, we estimate

$$New\ lending_{f,b,t} = \beta Borrower\ revenue\ bins_{f,b,t} + \theta X_{f,b,t} + \epsilon_{f,b,t}. \tag{C.9}$$

$New\ lending_{f,b,t}$ is the dummy variable that captures net credit expansions. $Borrower\ revenue\ bins_{f,b,t}$ are dummy variables that are 1 if a firm's annual revenue (in million euros) is within the following intervals, and 0 otherwise: [25,30), [30,35), [35,40), [40,45), [45,50), [50,55), [55,60), [60,65), [65,70). The β coefficient of the [25,30) interval constitutes the base-coefficient against which the coefficients of the other intervals are compared. We estimate the regression for firm exposures below €15 million (net of new lending), for which the jump in the risk weight is largest. We use *bank* × *firm industry* × *year* fixed effects and wild bootstrap our standard errors at the bank level. Figure C.1 shows no increase in net lending around the €50 million threshold. Thus, SRT banks do not disproportionately increase their capital-expensive lending.

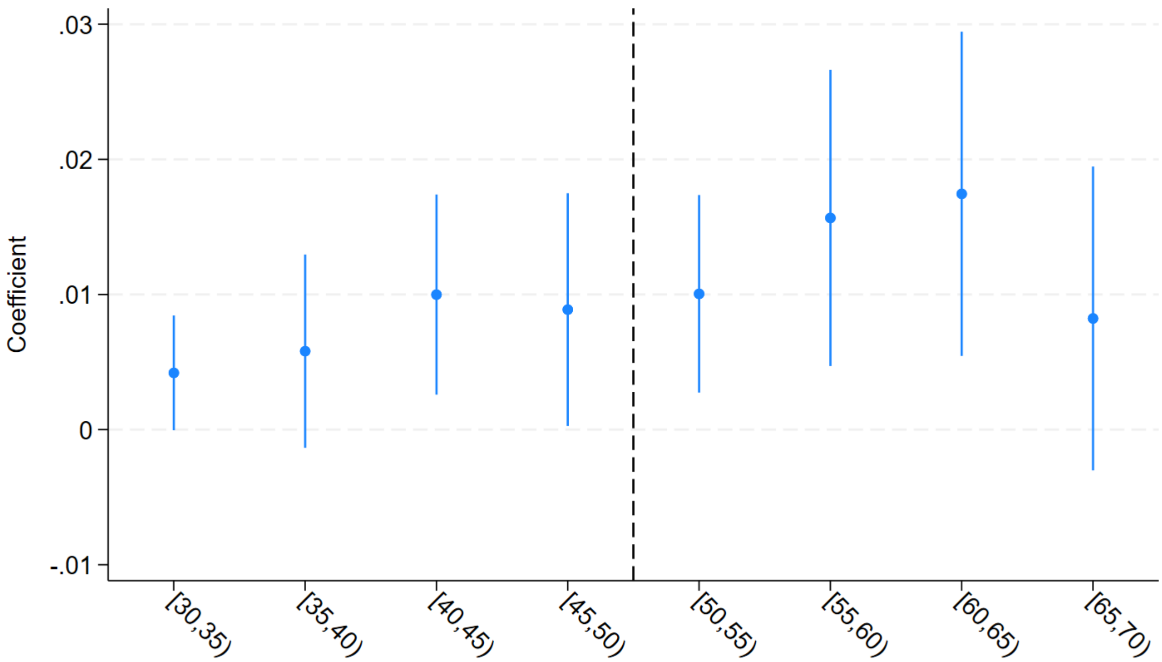

Figure C.1: SRT banks do not disproportionately increase capital-expensive lending. This figure plots the β coefficients and their 95% confidence interval of the following regression: $Net\ new\ lending_{f,b,t} = \beta_1 Borrower\ revenue\ bins_{f,b,t} + \epsilon_{f,b,t}$. *Net new lending* is a dummy variable equaling 1 if bank b expanded their credit to firm f and 0 otherwise. In line with Figure 2, we limit our sample to bank firm exposures below €15 million. The $[25, 30)$ bin serves as the benchmark. We use *bank* × *year* × *borrower industry*. Standard errors are wild-bootstrapped at the bank level.

D Economic relevance of the loan selection

In this section, we estimate the additional capital savings through the strategic SRT loan selection, based on the SME supporting factor. To do that, we estimate the change in the benefit from the SME supporting factor with and without SRTs. The benefit of the SME supporting factor is expressed as the difference between the capital required without and with the SME supporting factor. It is an estimate of the change in the difference between the riskiness of the portfolio reflected in the risk weights and an approximation of its economic riskiness.[53]

Let $\widehat{CAP}$ and $\widetilde{CAP}$ be the Tier 1 capital required without and with the SME supporting factor, respectively; that is, $\widehat{CAP}$ reflects the capital required under the economic riskiness of the loan portfolio and $\widetilde{CAP}$ under the riskiness reflected by the risk weights. To understand the relative capital improvement of banks through SRTs, we calculate

$$\begin{aligned}
\Delta\text{Cap. benefit}_{b,t} &= \text{Cap. benefit}_{b,t}^{with\ SRT} - \text{Cap. benefit}_{b,t}^{without\ SRT} \cdot \text{scaling factor}_{b,t} \\
&= \left(\widehat{CAP}_{b,t}^{with\ SRT} - \widetilde{CAP}_{b,t}^{with\ SRT}\right) \\
&\qquad - \left(\widehat{CAP}_{b,t}^{without\ SRT} - \widetilde{CAP}_{b,t}^{without\ SRT}\right) \cdot \frac{\widehat{CAP}_{b,t}^{with\ SRT}}{\widehat{CAP}_{b,t}^{without\ SRT}} \qquad \text{(D.10)} \\
&= \widetilde{CAP}_{b,t}^{without\ SRT} \cdot \frac{\widehat{CAP}_{b,t}^{with\ SRT}}{\widehat{CAP}_{b,t}^{without\ SRT}} - \widetilde{CAP}_{b,t}^{with\ SRT}.
\end{aligned}$$

$CAP_{b,t}^{with\ SRT}$ is the capital required under the assumption that all synthetically transferred loans have a risk weight of zero.[54] $CAP_{b,t}^{without\ SRT}$ calculates the capital as if no loans were synthetically transferred. The scaling factor $= \frac{\widehat{CAP}_{b,t}^{with\ SRT}}{\widehat{CAP}_{b,t}^{without\ SRT}}$ accounts for the mechanical change in the size of the capital benefit that is due to a smaller capital-relevant loan portfolio after the SRT. $\widehat{CAP}$ and $\widetilde{CAP}$ are calculated based on an assumed minimum capital requirement of 8% and the risk weights of each loan in a bank portfolio.[55] Risk weights are calculated according to the IRBA formula in Appendix B. All variables in the formula are given in AnaCredit except for the LGD, which we assume to be 0.4 for all loans.

[53]The true economic riskiness remains unknown. Here, we approximate it through the risk weights without the SME supporting factor.

[54]In practice, the risk weights of synthetically transferred loans are small but positive.

[55]Here, we make use of the previous result, which shows that banks redeploy freed capital.

We argue that the additional capital benefit is at least partially due to loan selection. But it might be that banks synthetically transfer loans of large firms (i.e., capital-expensive loans) because investors demand SRTs with large loans. By removing loans with a small wedge between the riskiness reflected in risk weights and the economic riskiness, the bank becomes less capitalized relative to the economic riskiness of its loan portfolio. But the effect would be entirely due to demand factors. Instead, we study the effect of the loan choice within granular fixed effects, namely bank $\times$ year $\times$ loan type $\times$ interest rate type $\times$ loan purpose $\times$ borrower industry $\times$ residual maturity above 1 year. Within these fixed effects, the effect is more likely to be influenced by supply.

Under the stylized assumptions laid out above, we find that in 2023, synthetically transferring capital-expensive loans led to an additional capital savings of 2.2% for the mean SRT bank and 3.0% for the median SRT bank.

E Figures

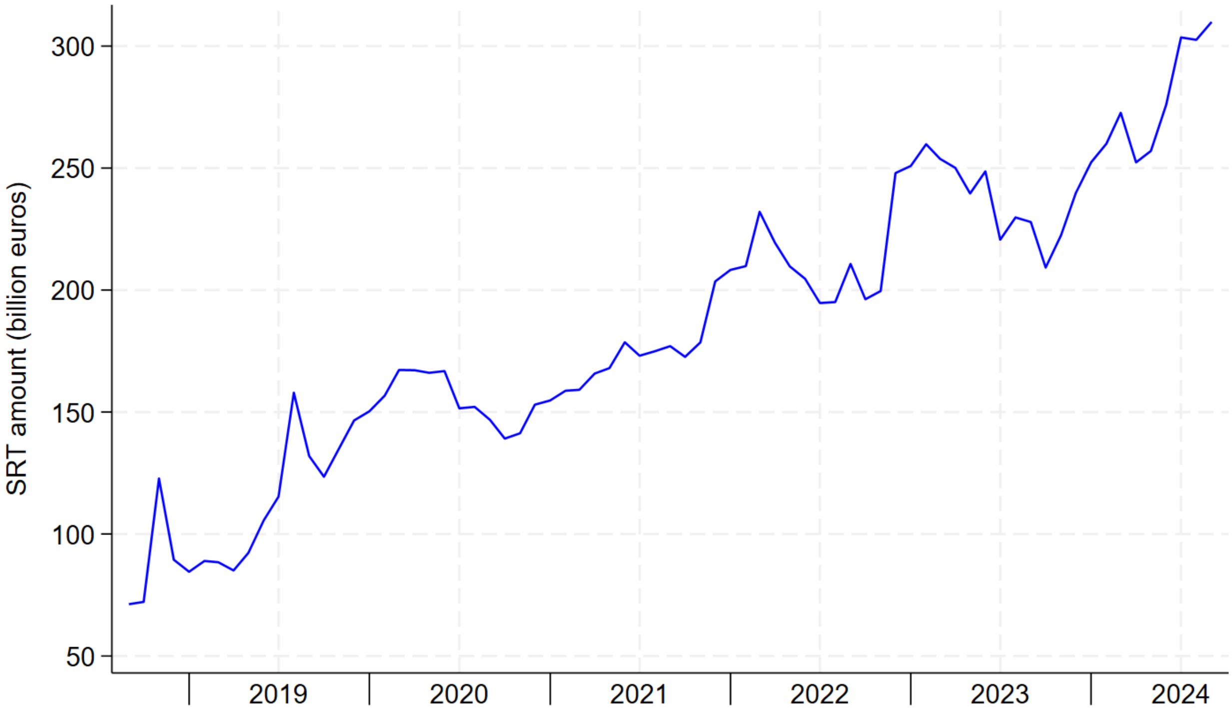

Figure A.1: Stock of synthetically transferred corporate loans in the euro area over time. This figure shows the stock of SRT amounts in billion euros over time, for which the underlying loans go to non-financial corporations. The original data are at the loan level and from the ECB's credit registry AnaCredit. SRT loans are selected based on the SRT flag in AnaCredit.

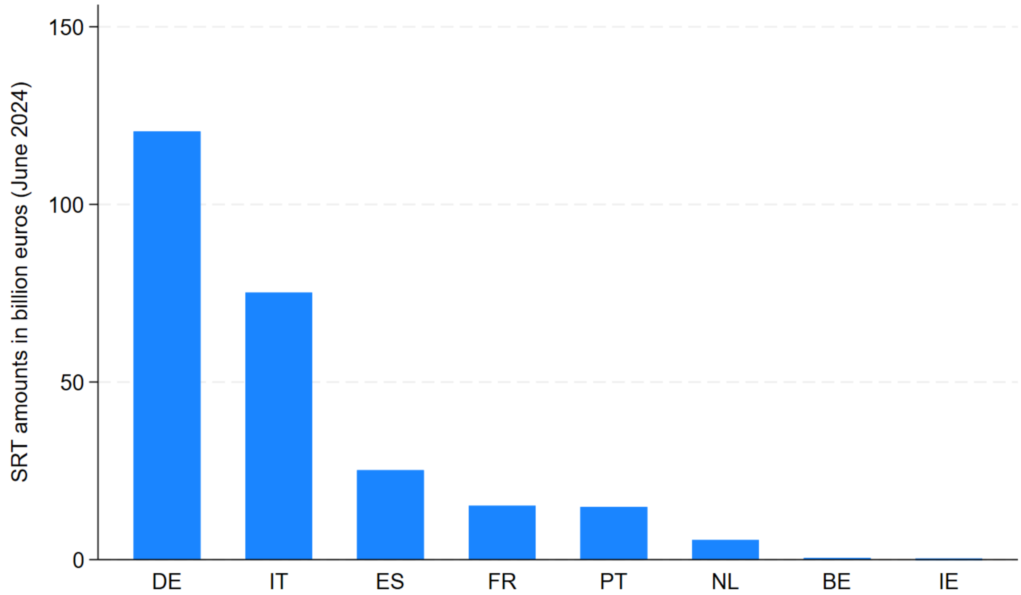

Figure A.2: Market size by country. This figure shows the SRT amounts in billion euros by country in June 2024. Data include all synthetically transferred corporate loans in our sample. SRT loans are selected based on the SRT flag in AnaCredit.

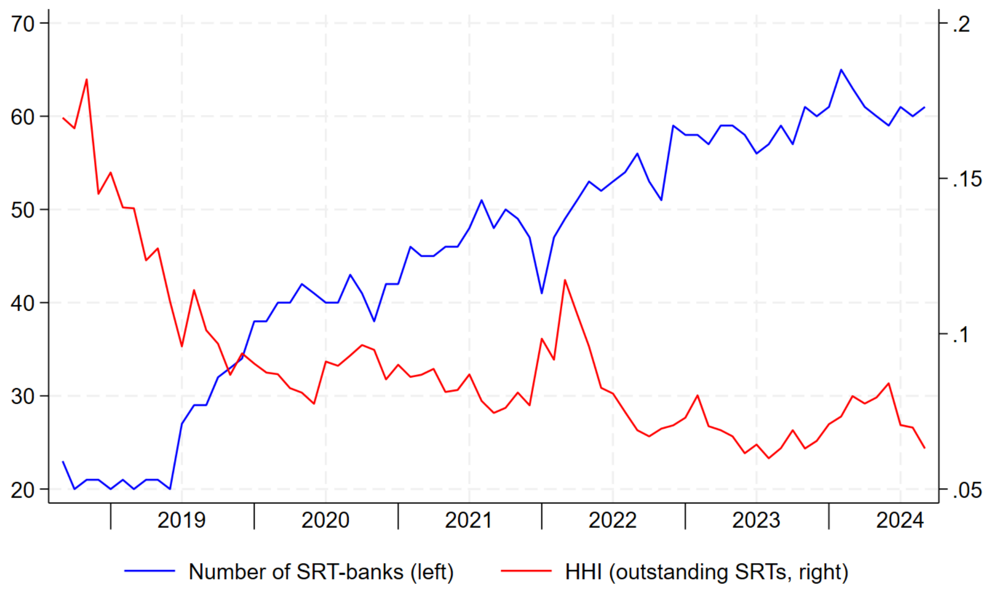

Figure A.3: SRT banks over time. This figure shows the number of SRT-issuing banks in blue on the left y-axis, and the concentration of SRT amounts in red on the right y-axis. Concentration is measured with the Herfindahl-Hirschman Index (HHI). For this figure, SRT banks are selected according to their total outstanding SRT amounts exceeding €50 million.

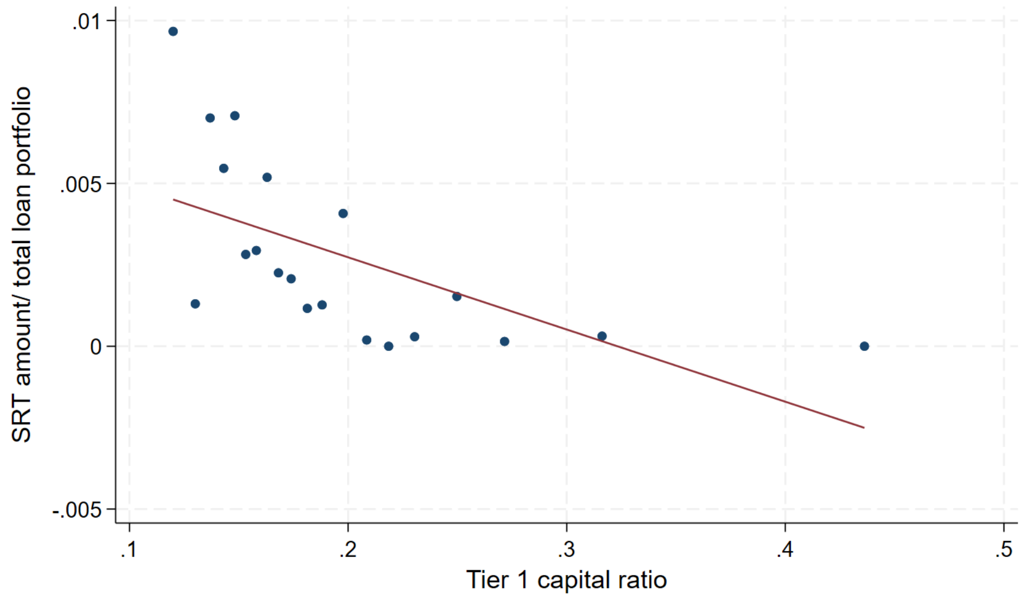

Figure A.4: SRT amounts/loan portfolio and Tier 1 capital ratios. This figure shows a binned scatter plot. On the y-axis, we plot the ratio of the sum of newly synthetically transferred loans in a given year by a given bank to the bank's total corporate loan portfolio. On the x-axis, we plot the bank's Tier 1 capital ratio. The data for this graph are therefore at the bank-year level. SRT banks are selected to issue SRTs of at least €50 million in a given year. Non-SRT banks are selected to be at least as large as the 10th percentile of SRT banks in a given country.

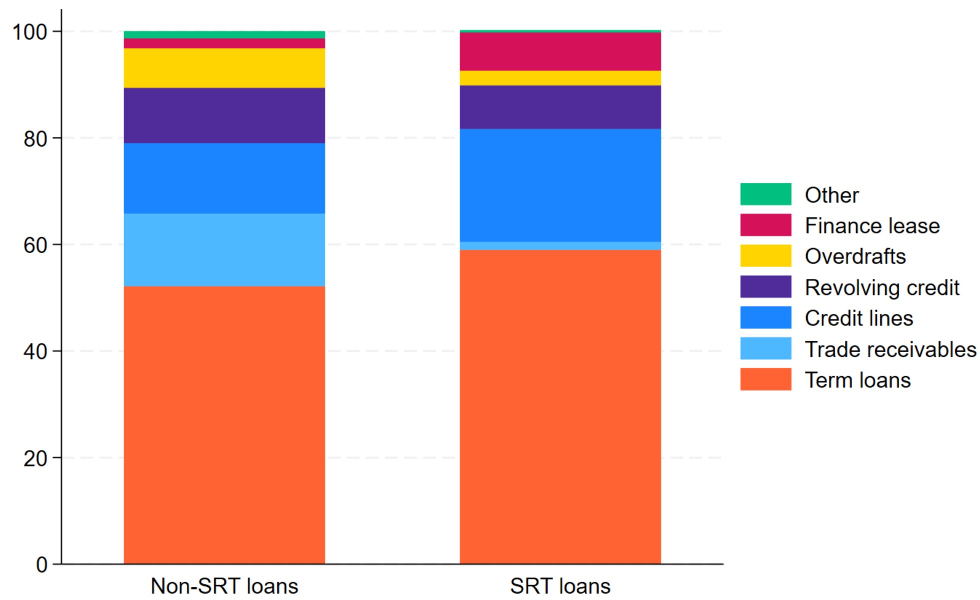

Figure A.5: SRT loans can be credit lines. This figure compares the loan types of SRT loans (right) with those of non-SRT loans (left) granted by SRT banks. The proportions are based on the loan amounts committed. Observations of non-SRT loans are at the loan-year level. Once a loan is synthetically transferred, it is counted once as an SRT loan. Loan amounts are winsorized below the 1st percentile and above the 99th percentile.

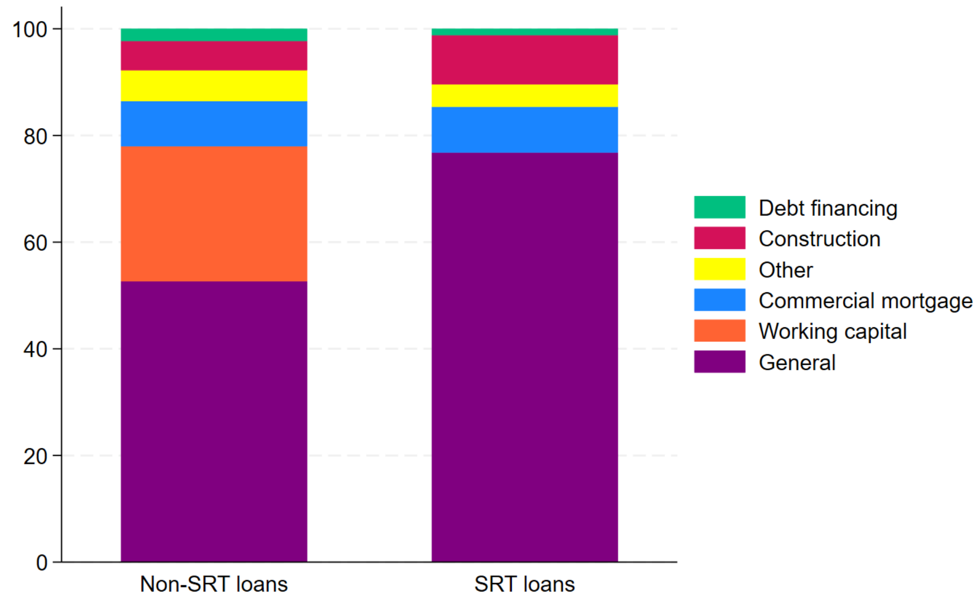

Figure A.6: SRT loans often fund working capital. This figure compares the loan purposes of SRT loans (right) with those of non-SRT loans (left) granted by SRT banks. The proportions are based on the loan amounts committed. Observations of non-SRT loans are at the loan-year level. Once a loan is synthetically transferred, it is counted once as an SRT loan. Loan amounts are winsorized below the 1st percentile and above the 99th percentile.

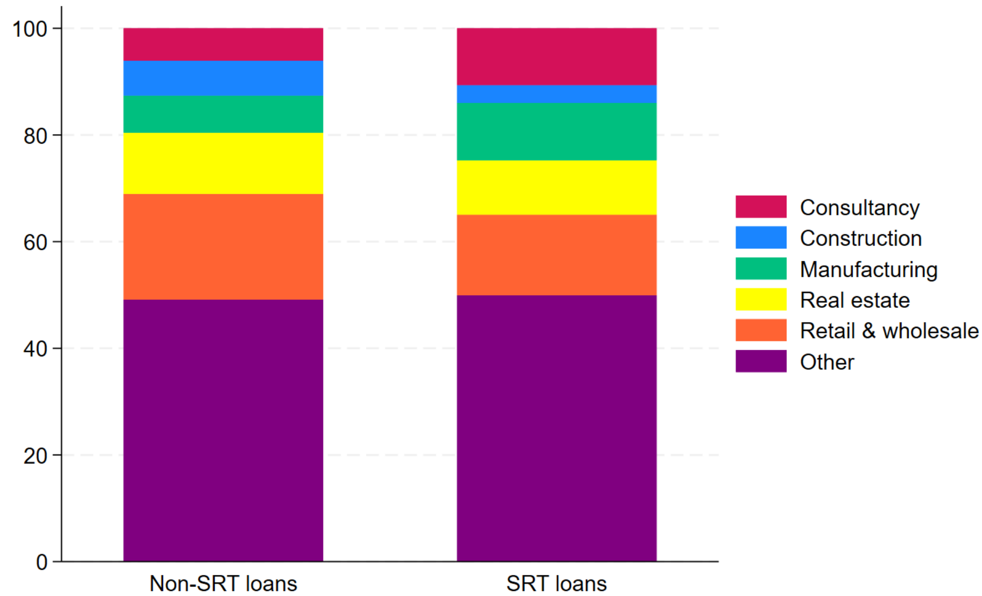

Figure A.7: SRT loans by borrower industry. This figure compares the economic sectors of borrowers whose loans are synthetically transferred (right) and those whose loans are not synthetically transferred (left). The proportions are based on the loan amounts committed. Economic sectors are defined according to firms' two-digit NACE codes. Observations of non-SRT loans are at the loan-year level. Once a loan is synthetically transferred, it is counted once as an SRT loan. Loan amounts are winsorized below the 1st percentile and above the 99th percentile.

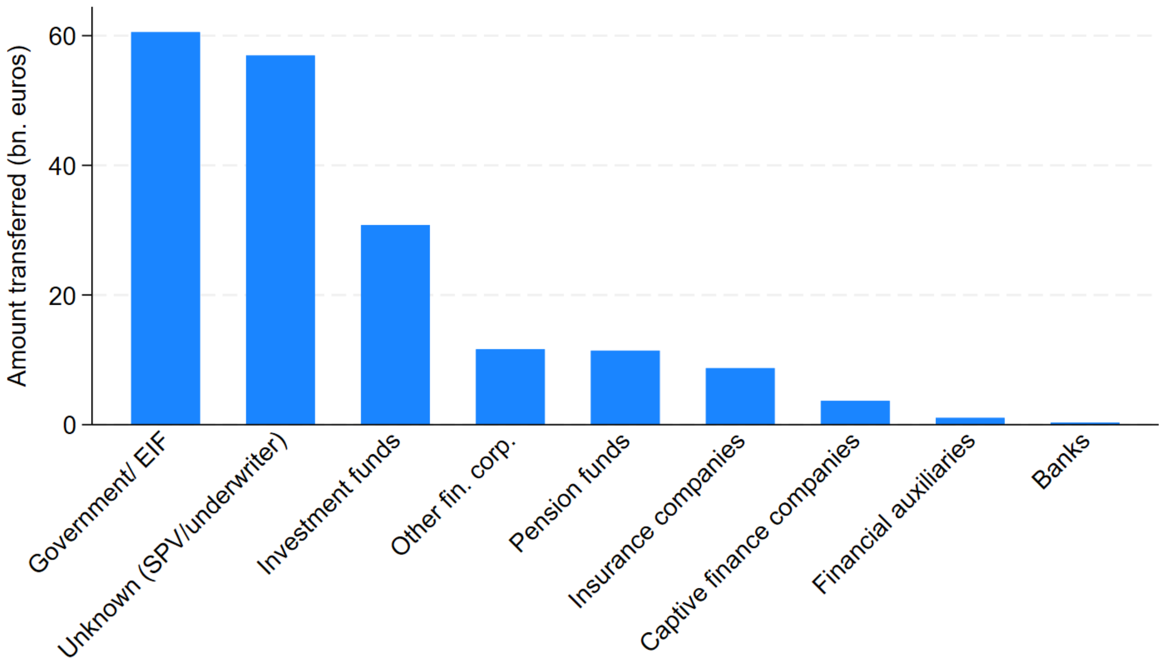

Figure A.8: Total SRT amounts by investor type. This figure shows the SRT amounts and their corresponding investor types. It does not sum up the actual amount invested (i.e., the amount of the junior tranche), but it sums up *all SRT loans* by investor type. We consider the entire sample period but count each SRT loan only once. In case of more than one investor per SRT, we divide the SRT amount by the number of investors. EIF stands for European Investment Fund.

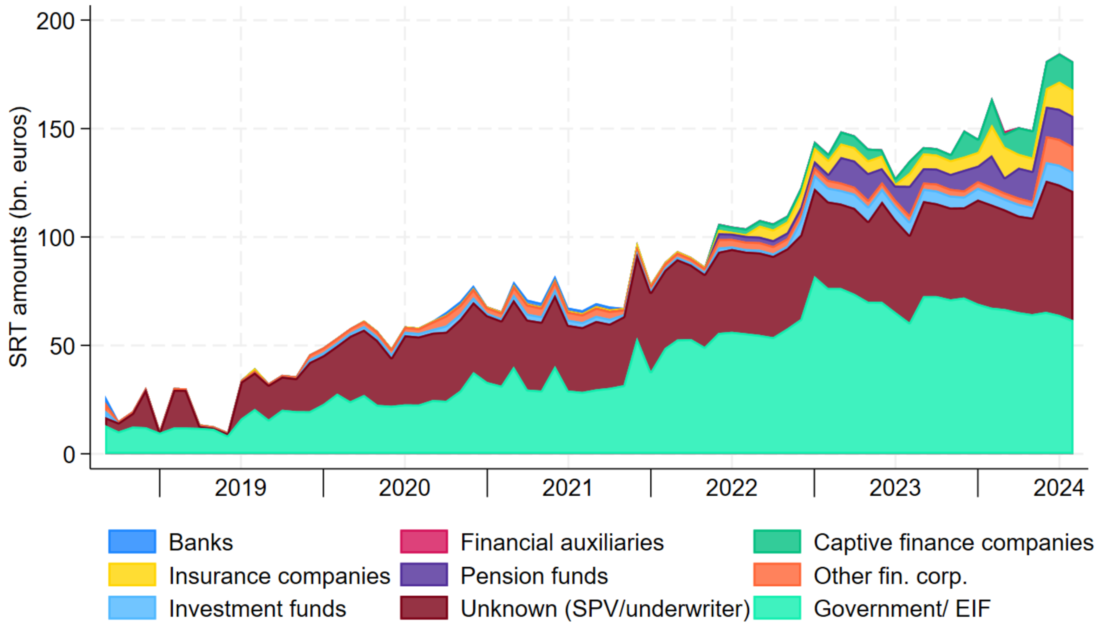

Figure A.9: SRT holdings by investor type over time. This figure shows the SRT amounts and their corresponding investor types over time. We only consider SRT investors that invest according to our cleaned sample. In case of more than one investor per SRT, we divide the SRT amount by the number of investors. EIF stands for European Investment Fund.

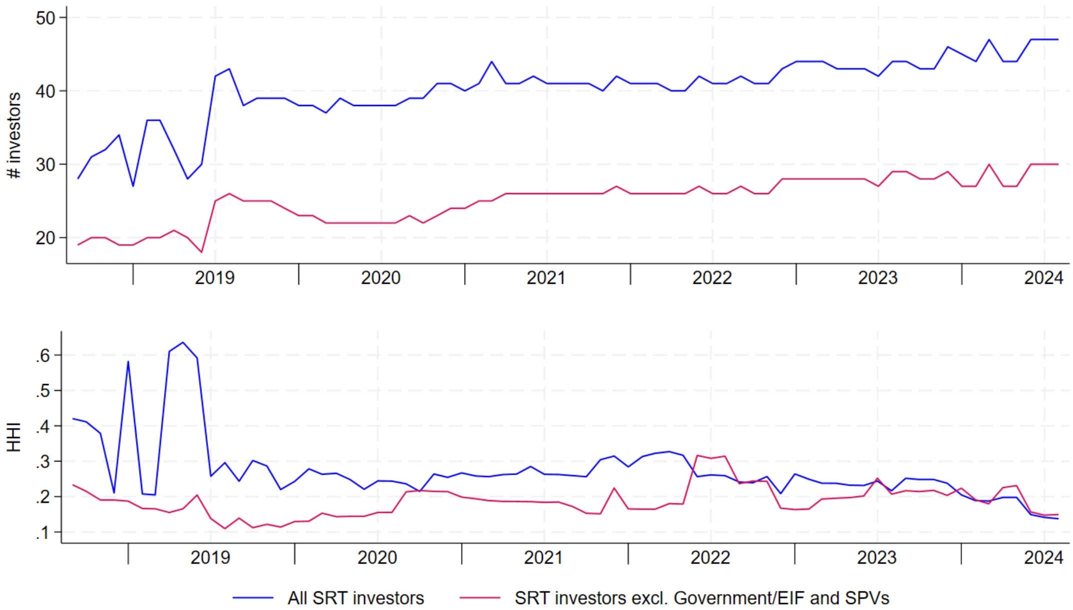

Figure A.10: Number and concentration of SRT investors over time. This figure shows the number of non-bank investors who hold SRTs of non-financial corporations over time (top) and the concentration of SRT holdings as measured by the Hirschman-Herfindahl-Index (HHI) (bottom). We show all investors, including governments/ EIF and SPVs, in blue and exclude them for the red line. The blue line probably underestimates the true number of investors as it assumes a single ultimate investor per SPV.

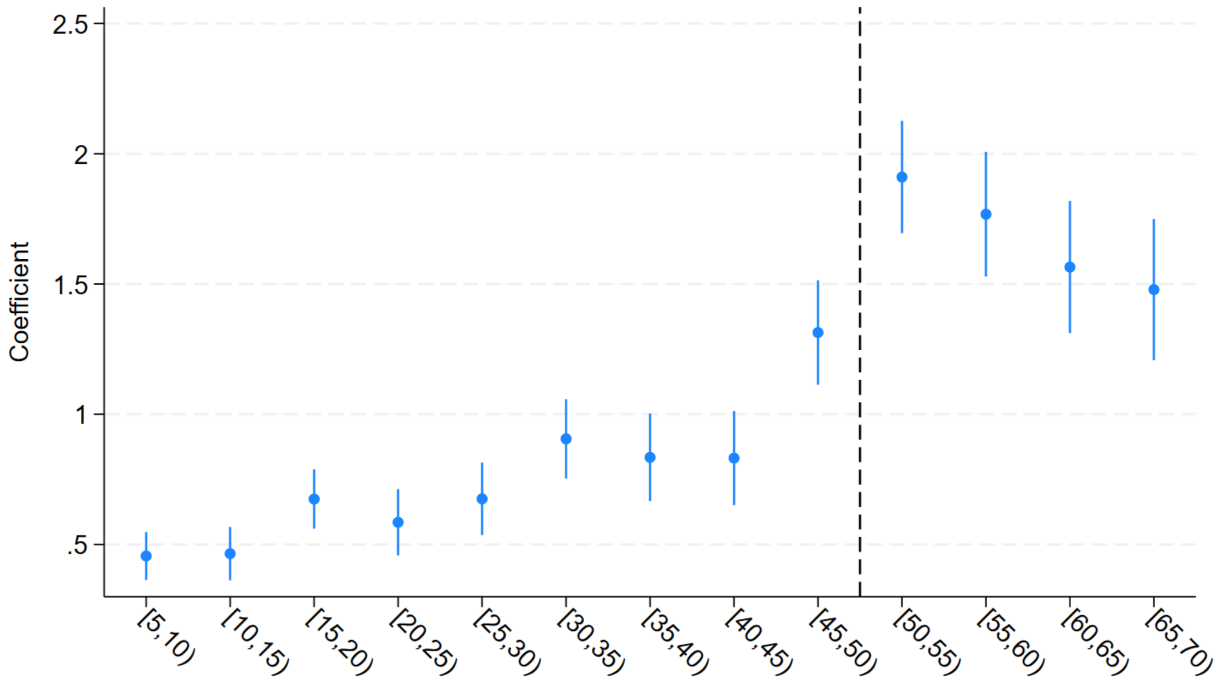

Figure A.11: Zooming out: Jump in risk weights causes jump in transfer likelihood. This figure plots the β coefficients and their 95% confidence interval of the following regression: $SRT\ loan_{i,t} = \beta_1 Borrower\ revenue\ bins_{i,t} + \delta X_{i,t} + \epsilon_{i,t}$. $SRT\ loan_{i,t}$ is equal to 100 if a loan is synthetically transferred in a given year and 0 otherwise. The $[0, 5)$ bin serves as the benchmark. We limit our sample to bank-firm exposures below €15 million, for which the discontinuity at the €50 million revenue threshold is greatest. We control for the firm's PD, the loan rate, and loan-size bins interacted with the natural logarithm of the loan amount. In addition, we use the following fixed effects: Bank $\times$ year $\times$ loan type $\times$ interest rate type $\times$ loan purpose $\times$ borrower industry $\times$ residual maturity above 1 year. Standard errors are wild-bootstrapped at the bank level.

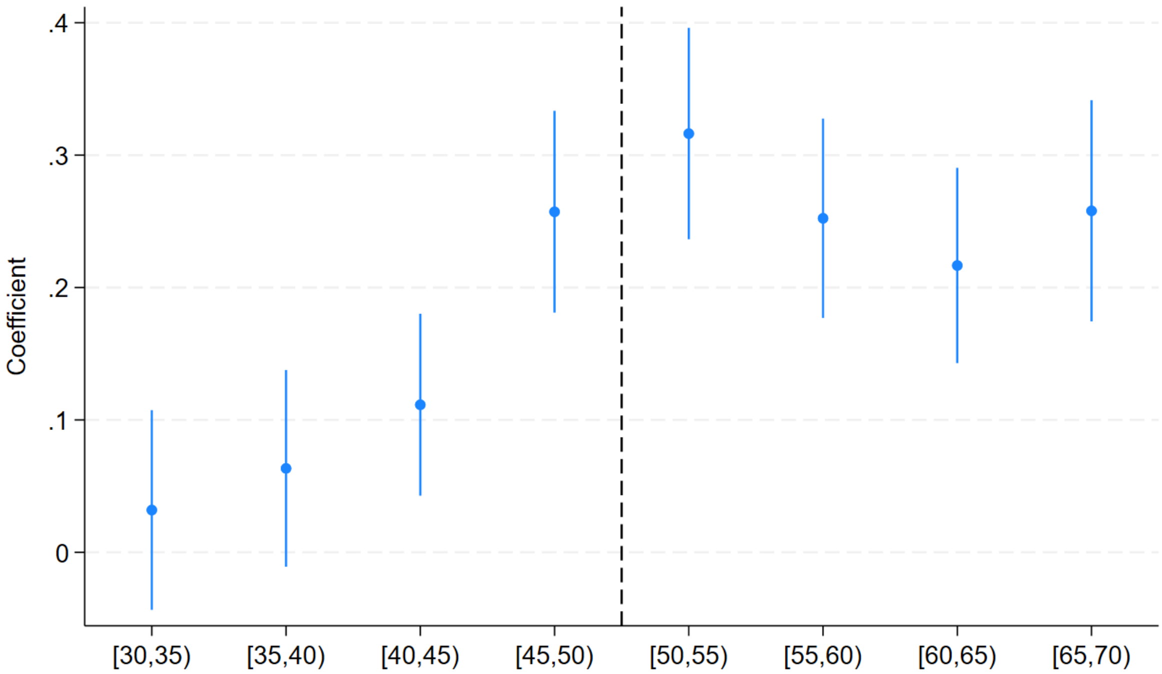

Figure A.12: All loans: jump in risk weights causes jump in transfer likelihood. This figure plots the β coefficients and their 95% confidence interval of the following regression: $SRT\ loan_{i,t} = \beta_1 Borrower\ revenue\ bins_{i,t} + \delta X_{i,t} + \epsilon_{i,t}$. $SRT\ loan_{i,t}$ is equal to 100 if a loan is synthetically transferred in a given year and 0 otherwise. The $[25, 30)$ bin serves as the benchmark. We control for the firm's PD, the loan rate, and loan-size bins interacted with the natural logarithm of the loan amount. In addition, we use the following fixed effects: Bank $\times$ year $\times$ loan type $\times$ interest rate type $\times$ loan purpose $\times$ borrower industry $\times$ residual maturity above 1 year. Standard errors are wild-bootstrapped at the bank level.

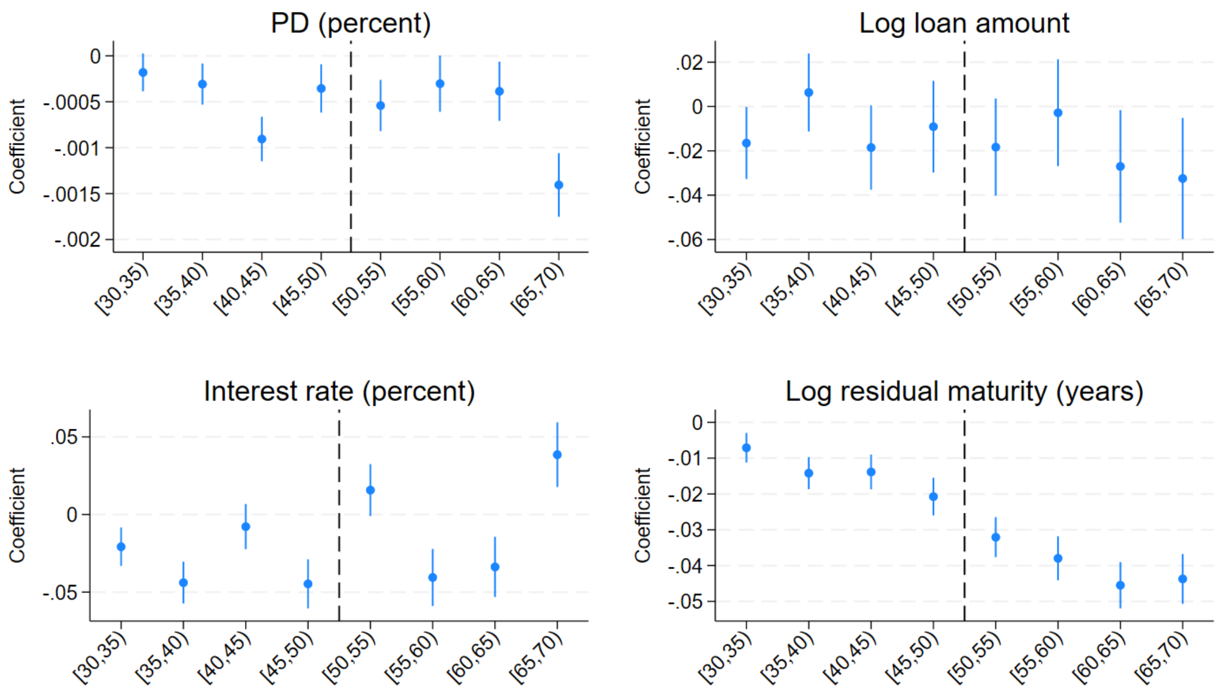

Figure A.13: Loan characteristics are not affected by the 50 million revenue threshold. This figure shows that covariates are smooth around the threshold of €50 million in annual firm revenue. It plots the β coefficients and their 95% confidence interval of the following regression: $Y_{i,t} = \beta_1 Borrower\ revenue\ bins_{i,t} + \delta X_{i,t} + \epsilon_{i,t}$. $Y_{i,t}$ is equal to the firm's PD, the natural logarithm of the loan amount, the interest rate, and the natural logarithm of the residual maturity in years. Our sample includes all loans for which the bank has a firm exposure of below €15 million. The $[25, 30)$ bin serves as the benchmark. We control for the variables that are not featured as the dependent variables. In addition, we use the following fixed effects: Bank $\times$ year $\times$ loan type $\times$ interest rate type $\times$ loan purpose $\times$ borrower industry $\times$ residual maturity above 1 year. Standard errors are wild-bootstrapped at the bank level.

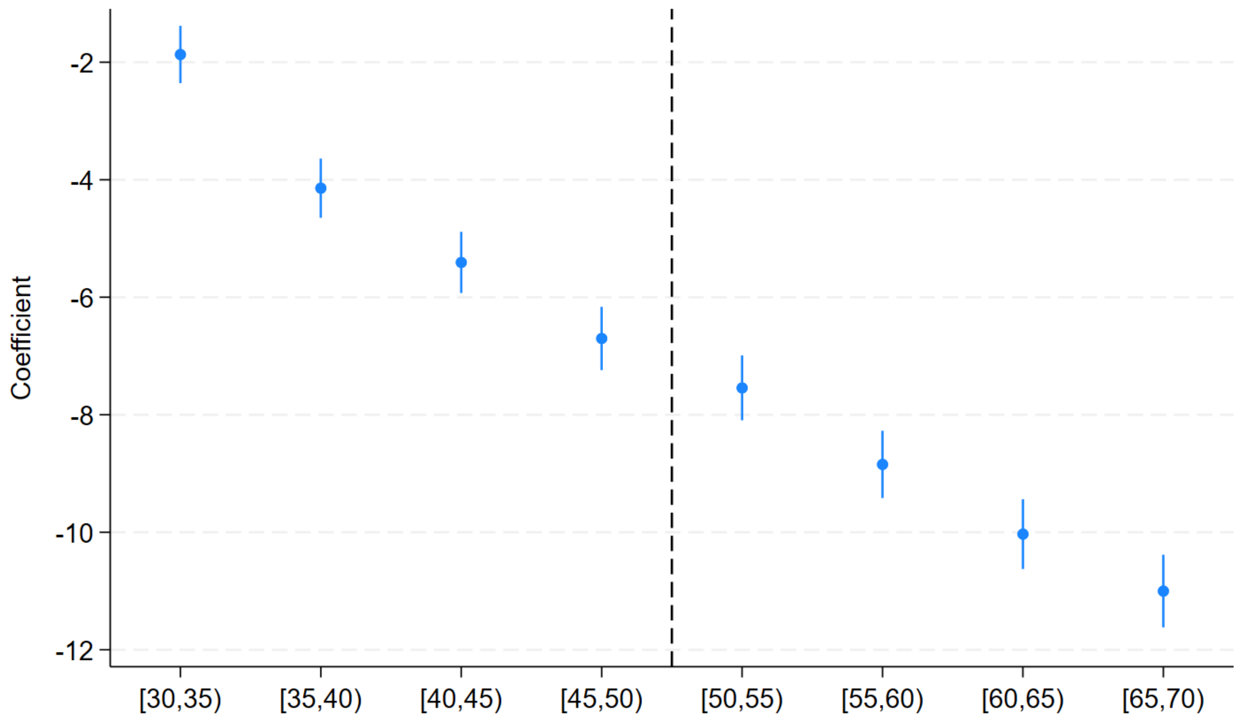

Figure A.14: The number of loans is unaffected by the 50 million revenue threshold. This figure shows that the number of loans decreases in firms' revenues (in line with more firms being small than large) but exhibits no discontinuity at the €50 million threshold. It plots the β coefficients and their 95% confidence interval of the following regression: $Number\ of\ loans_q = \beta_1 Borrower\ revenue\ bins_q + \epsilon_q$. The number of loans is measured at the level of the *fixed effects* $\times$ *revenue bin* (q in the regression). The fixed effects are bank $\times$ year $\times$ loan type $\times$ interest rate type $\times$ loan purpose $\times$ borrower industry $\times$ residual maturity above 1 year. That means that the data are collapsed at the *fixed effect* $\times$ *revenue bin* level, resulting in one observation per fixed effect and regression bin. Our sample includes all loans for which the bank has a firm exposure of below €15 million. The $[25, 30)$ bin serves as the benchmark. Standard errors are wild-bootstrapped at the bank level.

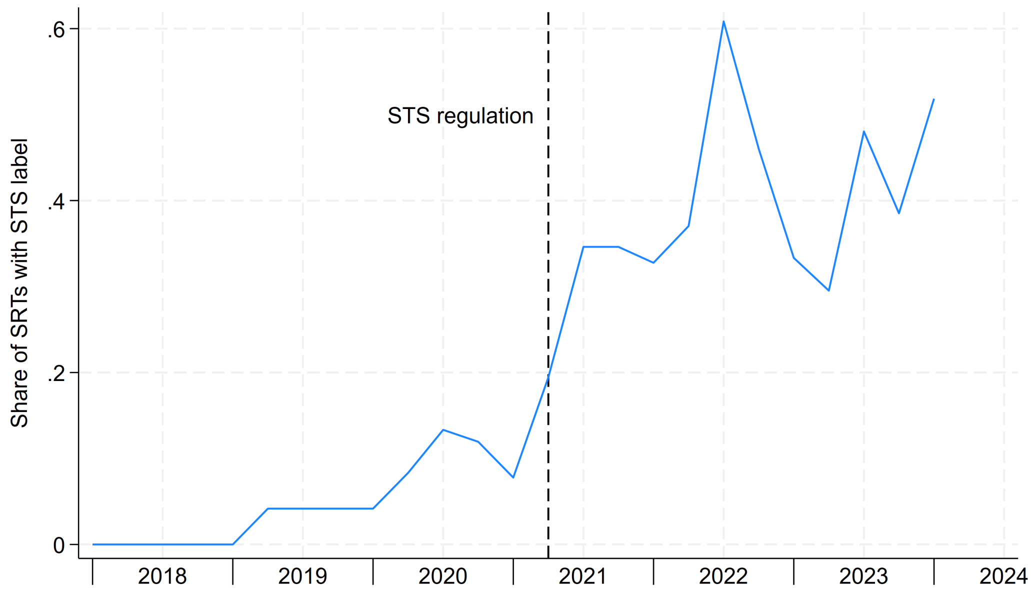

Figure A.15: Increase in SRTs with STS label around regulatory change. This figure shows the three-month moving average of the fraction of SRTs for which the banks receive capital relief under the STS label in a given quarter. The vertical line depicts the April 2021 regulatory change after which SRTs could get facilitated capital relief under the STS label. Data are from the ECB's COREP dataset.

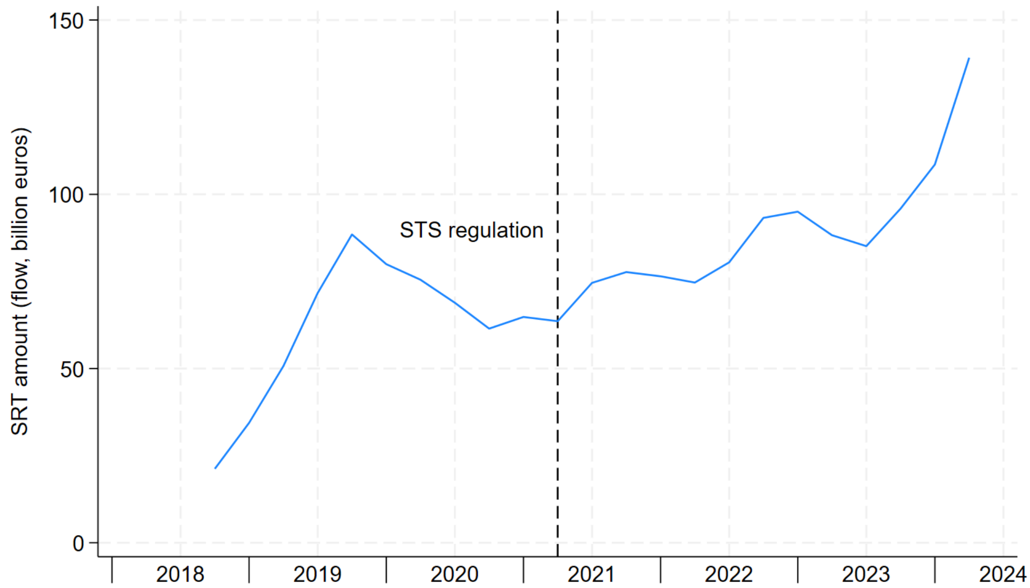

Figure A.16: Quarterly SRT issuance. This figure depicts a three-month moving average of the SRT amounts over time. Data are from the ECB's AnaCredit dataset.

F Tables

Table F.1: Banks with a low gap between leverage and Tier 1 capital ratio use SRTs

This table shows the results of linear regressions of an SRT dummy (columns (1) and (2)) and the natural logarithm of the SRT amount (columns (3) and (4)) on the gap between the banks' regulatory leverage ratio and its Tier 1 capital ratio (measured as fraction). The data are aggregated at the year-level as our Tier 1 capital ratios are yearly from Bankfocus by BvD. The SRT dummy equals 1 if the yearly SRT amount is at least €50 million, and 0 otherwise. Fixed effects are at the country and year level or the country × year level. Standard errors are clustered at the bank level. Our sample of non-SRT banks is selected to be at least as large as the 10th percentile of SRT banks in a given country. We additionally control for bank size by interacting the logarithm of its balance sheet with 10 bank size dummies in all specifications.

	(1) SRT	(2) SRT	(3) Log SRT amount	(4) Log SRT amount
Gap b/w leverage and Tier 1 ratio	-0.0190**	-0.0183**	-0.549***	-0.535***
	(0.00825)	(0.00831)	(0.189)	(0.190)
Mean	0.0742	0.0710	1.889	1.821
Estimation	OLS	OLS	OLS	OLS
Fixed effects	Bank, year	Bank × year	Bank, year	Bank × year
SE cluster	Bank	Bank	Bank	Bank
R-squared	0.279	0.279	0.304	0.305
N	1,617	1,606	1,617	1,606
Frequency	Yearly	Yearly	Yearly	Yearly

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table F.2: Loan risk transfer is positively correlated with risk weights

This table shows the results of the following regression: $SRT\ loan_{i,t} = \beta_1 Risk\ Weight_{i,t} + \delta X_{i,t} + \epsilon_{i,t}$. $SRT\ loan_{i,t}$ is equal to 100 if a loan is synthetically transferred in a given year and 0 otherwise. Risk weights are calculated according to the formulas presented in Appendix B, including the discount through the SME supporting factor. Since we do not have data on the LGD we assume the value 40% for all loans. We use the following fixed effects (FE): Bank × year × loan type × interest rate type × loan purpose × borrower industry × residual maturity above 1 year. Standard errors are clustered at the bank level.

	(1) SRT loan (= 100)	(2) SRT loan (= 100)
Risk weight	0.205	0.505**
	(0.136)	(0.225)
PD		-5.563***
		(1.998)
Loan rate		-0.454
		(1.575)
Log residual maturity (years)		-0.152***
		(0.0381)
Log bank firm exposure		0.0182
		(0.0115)
Log revenue (million euros)		0.0410**
		(0.0179)
Mean	0.389	0.427
Estimation	OLS	OLS
Fixed effects		FE
SE cluster	Bank	Bank
Controls	Loan size bins × log loan amount	Loan size bins × log loan amount
Adj. R-squared	0.00291	0.230
N	35,429,572	30,268,010
Frequency	Yearly	Yearly

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table F.3: Debt amounts increase prior to the SRT investment

This table shows the months until SRT investment fixed effects as estimated in regression the following regression: $Log\ debt\ amount\ outstanding_{s,\tau,t} = \beta_0 + \beta_1 Months\ to\ SRT\ investment_{s,\tau,t} + \delta_s + \omega_t + \epsilon_{s,\tau,t}$. 6 months before the SRT investment serves as the baseline. The dependent variable is the natural logarithm of debt outstanding of non-bank SRT investors. "Funded SRTs" are approximated as all except governmental and EIF investments. "Funded and large SRTs" are additionally restricted to investments with a junior tranche that is larger than €50 million. We control for SRT investment and calendar time fixed effects. Standard errors are clustered at the SRT investment level. The coefficients are plotted in Figure 3.

	(1)	(2)	(3)
	Log amount outstanding	Log amount outstanding	Log amount outstanding
-12 months	0.106	0.0619	-0.250
	(0.259)	(0.496)	(1.554)
-11 months	-0.0270	0.00279	-0.515
	(0.228)	(0.446)	(1.470)
-10 months	-0.118	-0.185	0.833
	(0.226)	(0.424)	(1.902)
-9 months	0.0639	0.177	-0.0373
	(0.171)	(0.307)	(1.334)
-8 months	0.202	0.0994	1.238
	(0.167)	(0.271)	(1.017)
-7 months	0.271	0.498*	1.814
	(0.166)	(0.286)	(1.107)
-6 months (baseline)	0	0	0
	(.)	(.)	(.)
-5 months	0.172	0.203	1.743
	(0.167)	(0.278)	(1.395)
-4 months	0.203	0.301	1.135*
	(0.162)	(0.260)	(0.591)
-3 months	0.432**	0.759**	1.693
	(0.196)	(0.328)	(1.103)
-2 months	0.451**	0.960**	2.124
	(0.220)	(0.381)	(1.313)
-1 month	0.446*	1.030**	2.870**
	(0.234)	(0.431)	(1.341)
SRT investment	0.470*	1.139**	3.155**
	(0.249)	(0.467)	(1.413)
1 month	0.336	0.925**	2.953**
	(0.241)	(0.467)	(1.375)
2 months	0.293	0.931*	3.162**
	(0.253)	(0.496)	(1.295)
3 months	0.219	0.876*	2.386**
	(0.245)	(0.502)	(0.943)
4 months	0.105	0.672	2.928
	(0.265)	(0.579)	(1.913)
5 months	0.0287	0.592	1.688*
	(0.254)	(0.566)	(0.949)
6 months	0.0616	0.948	4.017**
	(0.271)	(0.619)	(1.553)
Sample	All SRTs	Funded SRTs	Funded and large SRTs
Estimation	OLS	OLS	OLS
Fixed effects	SRT, calendar month	SRT, calendar month	SRT, calendar month
SE cluster	SRT	SRT	SRT
Adj. R-squared	0.837	0.633	0.552
N	20,880	10,224	1,368

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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