Drivers of Convenience Yields

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Abstract

Investors value financial assets not only for their cash flows, but also for the additional services they provide, like liquidity and regulatory benefits. These services give rise to a convenience yield—a yield spread between assets with similar cash flows. However, convenience yields are residual measures that reveal little about the underlying drivers of this price gap. Using comprehensive bond characteristics and portfolio holdings data for corporate and sovereign bonds in the eurozone, we estimate premia for three key services—liquidity, regulatory capital efficiency, and collateral value—and decompose EU AAA sovereign bond convenience yields into these components. Our findings show that over the past decade, convenience yields have been primarily driven by demand for collateral. Policy-induced shocks to these services significantly impact asset prices and portfolio allocations. These results highlight the importance of asset-specific service flows and policy decisions in determining bond valuation.

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1. Introduction

Bond prices are a key determinant of governments' and corporations' cost of capital. The modern asset pricing literature recognizes that investors value financial assets not only for their promised cash flows, but also for the additional services they provide, such as liquidity, collateral pledgeability, or the ability to satisfy regulatory requirements. A common way in the literature to estimate the value of these services is to calculate "convenience yields," i.e., the yield differential between assets that generate comparable cash flows, but different service flows. Although convenience yields explain a significant share of the time series and cross-sectional variation of sovereign and corporate bond valuations, they are typically measured as a residual term.[1] Thus, "convenience yield", albeit key to understanding the cost of capital for government and firm financing, is usually an umbrella term that is silent on the precise services investors value.[2]

We exploit comprehensive bond characteristics and sectoral portfolio holdings data to estimate convenience premia for three key bond services: liquidity, regulatory capital compliance, and collateral value. This approach enables us to decompose the convenience yields of European AAA sovereign debt and quantify each service's contribution. Our identification strategy relies on analyzing the return spread of a long-short portfolio that buys safe Treasuries and shorts a CDS-hedged bond with identical duration. Since the CDS-hedged bond should replicate the Treasury's cash flows, the yield spread between these instruments—the so-called CDS-bond basis—should theoretically equal zero. In practice, however, the CDS-bond basis is systematically negative and exhibits significant cross-sectional variation across our sample of sovereign and corporate euro-denominated bonds.[3] This persistent deviation

[1] See, e.g., Krishnamurthy and Vissing-Jorgensen [2012] and Mota [2023].

[2] A substantial body of literature documents the influence of liquidity premia on corporate bond valuation (e.g., Longstaff et al. [2005], Bao et al. [2011]). Others document the impact of collateral eligibility influencing corporate bond valuation (Chen et al. [2023]). The term "convenience yield" in this paper denotes the value of *all* services that contribute to corporate bond valuation beyond cash flows, including liquidity and pledgeability.

[3] Research about the U.S. market (Bai and Collin-Dufresne [2019], Mota [2023]) has shown that the CDS-

from theoretical parity allows us to estimate the premia investors attach to non-cash-flow services. Moreover, ISIN-level portfolio holdings data reveal substantial heterogeneity in bond ownership patterns, demonstrating that different investor types systematically value distinct services and accept correspondingly lower yields. We exploit this cross-sectional variation in investor holdings to identify and quantify the sector-specific demand for each service.

Our main finding is that, over the past decade, AAA-rated sovereign convenience yields in the euro area have been primarily driven by risk-based regulatory capital requirements, which force insurance companies to hold low-risk-weight and high-duration assets. Consistent with this finding, portfolios mimicking insurance corporations and pension funds (ICPF) have consistently underperformed the market portfolio, as a sign that this investor group is willing to forgo yields as compensation for the regulatory services. To validate our identification of these services, we conduct a series of event studies around policy-driven shocks affecting each service.

Our paper is organized into three parts. First, we build on Fama and French [2007] and Pástor et al. [2021] and present a model in which investors value not only cash flows but also service flows in financial assets. The preferences for service flows are heterogeneous among investors. The model generates a multifactor representation of bond returns, where factors account not only for traditional risk sources, but also for service flows. As a result, the finance textbook version of the law of one price, which focuses solely on cash flows, does not apply—two assets generating identical cash flows can trade at different prices when they provide distinct service flows. We define convenience yields as the equilibrium expected return differential between two scenarios: a benchmark case where investors value only cash flows, and an environment where investors also value service flows. A key insight from the model is that investors tilt their portfolios towards assets that provide the services they value most. Thus, variation in portfolio convenience yields across investors stems solely

bond basis is, on average, negative and increases in credit quality. As we show below, the same pattern emerges for the euro area.

from differences in the value they assign to each service. In equilibrium, convenience yields represent the equilibrium premium investors are willing to forgo to hold assets that provide services they value.

Second, we leverage our model's insights to empirically quantify how various services and investor groups contribute to convenience yields. We collect data measuring three key services: liquidity, collateral value, and risk-based capital value (RBC). We measure liquidity through bid-ask spreads, collateral value through ECB collateral framework haircuts, and RBC value via Solvency II insurance regulation's "spread risk" parameter. For our empirical analysis, we map service flow values (convenience yields) to the CDS-bond basis. Through the lens of our model, since the synthetic risk-free bond replicates cash flows but not service flows, the CDS-bond basis captures the relative convenience yield between corporate bonds and safe Treasuries.

There is substantial cross-sectional variation in the CDS-bond basis. We exploit this variation by running cross-sectional regressions at each point in time, following the approach of Fama and MacBeth [1973], to estimate the premium associated with each service. Our main findings indicate that over the past decade, the convenience yield of AAA-rated sovereign bonds in the euro area has been primarily driven by collateral value. More specifically, the premium for assets with high collateral value accounts accounts for 60–90% of the average convenience yield throughout most of our sample period.

In the third part of the paper, we study policy shocks to the services whose contributions we estimated in the previous part. This serves two purposes: (a) it validates our choice of services for the decomposition of convenience yield, and (b) it illustrates how regulation and monetary policy (conventional or unconventional) are transmitted to asset prices through the convenience yield component.

First, we focus on collateral value, which mainly impacts the banking sector. Motivated by the fact that banks are the only entities that can directly borrow from the ECB against high-quality collateral, we study the impact of haircuts (and hence collateral value) on convenience yield. We show that after a change in the ECB's collateral framework that reduced

the collateral value of a large class of bank bonds after 2018, the average CDS-bond basis of these bonds fell significantly relative to that of otherwise similar bank bonds. In response to that shock, banks tilted their corporate bond portfolio toward securities with low haircuts (and thus high collateral value), which emphasizes banks' particular preference for bonds with high collateral value.

Second, we study how bond-level capital charges for European insurance companies affect convenience yield. We do so by analyzing how the CDS-bond basis and insurers' portfolios behave depending on the level of long-term interest rates. This is informative because ICPF traditionally have large negative duration mismatches that compress their net assets and funding ratios whenever long-term interest rates are low. We show that in a low-rate environment, bonds with low Solvency II capital requirements exhibit higher convenience yields, and ICPF rebalance towards these high-regulatory value bonds. We interpret these results as evidence that regulatory constraints on the balance sheets of ICPF are key drivers of the convenience yield, particularly by increasing the valuation of bonds with high regulatory value.

Third and finally, we study the impact of ECB's corporate bond quantitative easing (QE) programs. We focus on two specific programs through which the ECB directly purchased corporate bonds: (1) the Corporate Sector Purchase Program (CSPP), announced in March 2016, which initiated large-scale acquisitions of investment-grade, non-bank corporate bonds from the euro area; and (2) the Pandemic Emergency Purchase Program (PEPP), announced in March 2020. Consistent with the existing literature, we find that both programs generated a significant relative decrease in the credit spreads of eligible versus ineligible bonds on average, even when comparing bonds with similar default and duration characteristics.[4] For our sample, the CSPP announcement effect amounts to 22.3 basis points, equivalent to 25% of the average credit spread. The price effect attributed to PEPP is considerably smaller at 5.0 basis points.

[4]See, e.g., Arce et al. [2017], Abidi and Miquel-Flores [2018], Todorov [2020], Grosse-Rueschkamp et al. [2019], and De Santis and Zaghini [2021].

A key innovation of our analysis is to decompose these effects into two distinct components: a credit risk component, measured by the credit default swap (CDS), and a convenience yield component, measured by the CDS-bond basis. We show that QE announcements cause the spread between the CDS-bond basis of eligible and ineligible bonds to increase by 15.7 basis points for CSPP and by 9.3 basis points for PEPP. Notably, more than 70% of the observed QE effect can be attributed to the convenience yield component. This finding provides compelling empirical evidence that corporate QE affects not only eligible bonds' default risk, but also their service flows.

This result is at odds with traditional models that justify QE's price impact through preferred habitat investors (Vayanos and Vila [2021]), which would predict that all price impact should operate through the price of risk rather than convenience yield. Instead, our results support the hypothesis that QE eligibility fundamentally alters asset characteristics by increasing the liquidity of eligible corporate bonds.[5]

To reinforce this interpretation, we demonstrate that corporate QE triggered substantial rebalancing across investor types. In particular, we show that mutual funds *increased* their holdings of eligible bonds relative to ineligible ones after controlling for other characteristics driving bond demand. This pattern is counterintuitive, as eligible bonds became relatively more expensive than ineligible bonds; under standard assumptions, this increased demand would imply an upward-sloping demand curve for corporate bonds. Given that mutual funds face redemption shocks (see Ma et al. [2022] for recent evidence), they particularly value liquidity services—specifically, the ability to sell bonds with minimal fire sale discounts, especially during periods of distress and high redemption volumes. We therefore conclude that QE enhanced the relative liquidity of eligible bonds.

Our work offers important insights into corporate bond pricing and how it is shaped by policy decisions. Demand-based asset pricing uses characteristics known to predict returns

[5]This interpretation aligns with Haddad et al. [2024], who argue that QE "constitutes a dynamic state-contingent plan instead of a succession of independent interventions." This state-contingency introduces an insurance channel and provides an "exit option" to which mutual funds are particularly responsive.

to estimate investors' heterogeneous demand curves and their impact on asset prices [Koijen and Yogo, 2019; Bretscher et al., 2023]. However, our paper shows that characteristics driving risk and returns alone are not sufficient to fully explain demand for assets. Preferences for specific service flows might be one of the reasons why investors' demand for bonds appears so inelastic to price variation. Furthermore, our empirical tests show that asset-specific service flows vary over time, particularly in response to regulatory and monetary policy changes. Therefore, models that assume time-invariant demand for assets such as Treasuries, due to their non-pecuniary benefits, will overstate the impact of supply channels on convenience yields. Fundamentally, such models will miscalculate the ability of governments and firms to issue bonds without affecting prices. This demand elasticity is key to understanding governments' fiscal space [Mian et al., 2022].

In addition, the direct impact of regulation and monetary policy on asset characteristics, such as liquidity or collateral value, highlights an important consideration for policymakers regarding the effects of policies on asset prices and capital allocation. In a world with high indebtedness, particularly among government of developed countries, actions that force regulated institutions to hold certain assets have a large impact on asset prices and wealth allocation. A large literature on "financial repression" has studied the important role of banks holding sovereign debt (some recent references are Chari et al. [2020], Jeanne [2025], Payne and Szoke [2025]). Our work shows that the focus should not only be on banks, but on long-term investors like insurance companies and pension funds that are incentivized to hold certain assets due to the regulatory framework and duration exposure.

2. Related Literature

This paper connects several important strands of literature. First, we build on the growing research on safe assets and convenience yields, which highlights the large impact of convenience yields for bond valuation, and therefore cost of capital of countries and firms. Following the work of Krishnamurthy and Vissing-Jorgensen [2012] and Mota [2023], we explore the fact that corporate bonds are imperfect substitutes for traditional safe assets

like Treasuries, commanding their own convenience yields. Key to our analyses is that both asset classes carry service flows on their own, suggesting common factors linking convenience yields across different fixed income assets.

Several papers explore the nature of convenience yields. For example, Acharya and Laaritis [2023] explore the dynamics of Treasury convenience yields by exploring their relationship with hedging demand. They document the time-varying nature of convenience yields and their connection to broader market conditions. Our work extends this research by exploiting the substantial cross-sectional variation in the CDS-bond basis to identify the specific drivers of convenience yields. We provide novel evidence that convenience yields cannot be explained by a single factor but rather require a multi-factor framework incorporating services such as liquidity, duration, regulatory capital requirements, and collateral value.

Second, our paper advances the literature on clientele or preferred habitat effects on asset prices (Amihud and Mendelson [1986], Vayanos and Vila [2021]). For example, Amihud and Mendelson [1986] propose a model in which investors differ in their trading horizons, leading to an equilibrium where liquid assets are held by frequent traders and illiquid assets by investors with longer holding periods. Chen et al. [2020] empirically test this theory in the corporate bond market, showing that the non-default component correlates with insurance companies' illiquidity preferences. We extend this framework by recognizing that investors value not only liquidity but also other services such as pledgeability (Chen et al. [2023]) and regulatory capital advantages (Becker and Ivashina [2015], Koijen and Yogo [2022a], Sen [2023]). Our model incorporates demand for these various services in reduced form, acknowledging their endogenous and time-varying nature. This approach contributes to the emerging literature on investor-specific demand shocks and their impact on asset price fluctuations (Koijen and Yogo [2019] and Gabaix and Koijen [2020]). Our key innovation is mapping investor holdings to the value of different bond services, demonstrating how preferences for these services drive portfolio decisions and bond valuation.

Third, we contribute to the extensive literature on corporate bond pricing. Numerous studies establish that default risk alone cannot explain corporate bond valuations (Elton

et al. [2001] and Huang and Huang [2012]) and that liquidity significantly affects prices (see Amihud et al. [2006] and Vayanos and Wang [2013] for surveys). Liquidity, though, may have multiple meanings. For example, Dick-Nielsen and Rossi [2018] show that funding liquidity and market liquidity interact to affect corporate bond prices, with dealers reducing inventory and market-making activities when funding constraints tighten. Bai and Collin-Dufresne [2019] explore determinants of cross-sectional variation in the US corporate CDS-bond basis and find that multiple measures of arbitrage limits, including collateral value and trading liquidity, affect the basis. Furthermore, Pelizzon et al. [2024] document an "eligibility premium" in European corporate bonds when they become eligible as collateral in ECB repo operations. Similarly, Chen et al. [2023] show that Chinese investment-grade corporate bonds experience significant yield increases when they become ineligible for repo collateral. We build on the idea that corporate bond valuation is influenced by various factors beyond cash flows and apply traditional asset pricing techniques to the cross-section of sovereign and corporate bonds to attribute premiums to different services driving yields spreads. Furthermore, we demonstrate that variation in holdings plays a significant role in explaining the cross-sectional returns of corporate bonds.

Fourth, our research expands the growing literature on the impact of unconventional monetary policy on asset prices (Andrade et al. [2016], Koijen et al. [2016], Krishnamurthy and Vissing-Jorgensen [2012], Krishnamurthy et al. [2018]). Our analysis of corporate QE programs is closely related to Todorov [2020] who finds that the CSPP had a negative impact on bond yields, with a magnitude comparable to what we find when we examine the CSPP. Breckenfelder and Hoerova [2023] show that during the Covid-19 outbreak, when corporate bond markets were in severe distress, funds holding a higher proportion of assets eligible for purchase in their portfolios before the crisis experienced improved performance and smaller outflows after the announcement of the European Central Bank's large-scale asset purchase program. This aligns with the strategy of mutual funds to strategically maintain eligible bonds, even when they appear relatively expensive compared to other bonds with similar credit and duration risks. Our paper connects these results by showing that corporate QE persistently affected the convenience yield of eligible bonds, which is likely due to the

increased perceived liquidity of eligible bonds. Eligibility effectively serves as a safeguard against fire sale discounts, acting as insurance for funds.

By showing that interest rates, corporate QE, and collateral policy cause significant variation in convenience yields, this paper presents new perspectives on the mechanism through which monetary policy can affect asset prices, which opens the door for policies that target service flows; we explore this channel in detail in our accompanying paper **?**. For example, in line with what Haddad et al. [2024] find for sovereign bonds, if a central bank commits to purchasing corporate bonds in times of distress, it can influence the fire sale price of these assets, thereby altering their price ex-ante, even if default expectations remain unchanged. The ability to sell in times of distress is a service flow that liquidity-sensitive investors value, so a commitment by a central bank can change the liquidity service associated with each asset.[6]

Arguably, collateral policy can also be seen as a form of (unconventional) monetary policy. We are not the first to study the effect of ECB collateral eligibility on the corporate bond market. In particular, Pelizzon et al. [2024] show that when bonds become eligible to be pledged in the "primary" collateral market (i.e., in open market operations with the ECB), their use in the "secondary" money market (so-called securities lending) also increases. In addition, yields decline relative to the control group of ineligible bonds. These findings relate to our paper in two important ways: First, the documented "eligibility premium" in bond prices is consistent with our interpretation of collateral value as a service that gives rise to convenience yield. We go beyond Pelizzon et al. [2024] in showing that ECB collateral eligibility significantly affects not just yields, but the CDS-bond basis. Second, the fact that ECB-induced changes to collateral eligibility spill over to secondary markets suggests that ECB collateral haircuts are a useful proxy for overall collateral value, even though central bank open market operations are exclusively available to banks.[7]

[6]Notice that what we call liquidity services has long been studied in the literature as liquidity premium or risk, see for example Acharya and Pedersen [2005]. The advantage of our framework is the ability to combine other possible services under the same framework.

[7]Pelizzon et al. [2024] use bond-level data from IHS Markit on the fees banks pay in the securities lending

Our work also shares insights with the recent literature on how regulatory and business-model-related constraints affect portfolio decisions for insurance companies and pension funds (ICPF) (see, e.g., Koijen and Yogo [2015], Koijen and Yogo [2022b]), and how these in turn affect asset prices (Kubitza [2025]). For instance, both Alfaro et al. [2024] and Jansen et al. [2023] study the effects of ICPF hedging interest rate risk, such as through the use of interest rate swaps. Specifically, due to their negative duration gap, ICPF have an incentive to hedge against falling interest rates to maintain solvency. As it is intuitive that these institutions value regulatory compliance in financial assets, this hedging strategy in turn exposes these institutions to significant risk of margin calls in the event of rising rates. We view this finding as one reason why long-term investors like insurance companies might also value liquidity, especially when interest rates rise. Our paper contributes to this literature by showing how these constraints have a large and direct impact on the government cost of funding, as regulatory capital alone accounts for up to 90% of the AAA-sovereign convenience yield.

3. Model

In this section, we develop an asset pricing model in which investors value financial assets not only for their cash flows, but also for a vector of service attributes they provide. Our model is similar to Pástor et al. [2021], which focuses on a single non-pecuniary benefit (greenness). We generalize their approach to accommodate multiple service dimensions simultaneously. Our goal is to describe convenience yields and their connections to portfolio allocations.

Consider a market with N assets indexed by $n \in \{1, 2, \ldots, N\}$ and a continuum of heterogeneous investors indexed by i, each with distinct preferences over the various service

market to borrow specific ECB-eligible bonds. Unfortunately, we do not have access to these data, but it would be an interesting exercise to use them as market-based proxies for bonds' collateral value.

attributes. Let $\boldsymbol{r}_t$ be the $(N \times 1)$ vector of returns in excess of the risk-free rate, $r_t(f)$.

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{\epsilon}_t \tag{1}$$

where $\boldsymbol{\mu}_t$ contains the expected equilibrium excess returns and $\boldsymbol{\epsilon}_t \sim N(0, \Sigma_t)$.

Investors have indirect utility over augmented wealth, which is the sum of dollar wealth and the service flows associated with holding an asset. The dollar wealth of each agent at time t is w_{it}, and $\boldsymbol{x}_{it}$ is a $(N \times 1)$ vector which denotes the fraction of wealth invested in each asset n. Each period, agents maximize

$$\begin{aligned} \max_{\boldsymbol{x}_{it}} \quad & \mathbb{E}_t\left[\tilde{w}_{it+1}\right] - \frac{\gamma_{it}}{2} Var_t\left[\tilde{w}_{it+1}\right] \\ s.t. \quad & \tilde{w}_{it+1} = w_{it+1} + w_{it}\boldsymbol{x}_{it}^{\top}\boldsymbol{s}_{it} \\ & w_{it+1} = w_{it}\left(1 + r(f)_{t+1} + \boldsymbol{x}_{it}^{\top}\boldsymbol{r}_{t+1}\right) \end{aligned} \tag{2}$$

where $\boldsymbol{s}_{it}$ is a vector $(N \times 1)$ denoting the service flows investors receive from holding assets (per dollar of a bond's face value), over and above the cash flows. We chose to measure services in "wealth-units" for simplicity.[8]

The service flows have an asset-specific and an agent-specific component

$$\boldsymbol{s}_{it} = Z_t \boldsymbol{\lambda}_{it} \tag{3}$$

where Z_t is a matrix $(N \times K)$ of assets characteristics that determine the quantity of service k in asset n and $\boldsymbol{\lambda}_{it}$ is a $(K \times 1)$ vector that represents how much investor i values each characteristic k.

We can solve for agents' optimal portfolio allocation as well as for equilibrium expected returns.[9] Due to their infinitesimal size, agents take asset prices (and thus the return distribution) as given when choosing their optimal portfolios at time t. We define $a_{it} = w_{it}\gamma_{it}$.

[8]We model the demand for services in a reduced-form framework, which, in many applications, is isomorphic to modeling mean-variance agents subject to regulatory or collateral constraints (e.g. Frazzini and Pedersen [2014]). The key advantage of our approach is its ability to incorporate multiple frictions within a unified framework.

[9]For all intermediate steps, see Appendix A.

From the first-order condition with respect to $\boldsymbol{x}_{it}$, we have that the optimal portfolio allocation is

$$\boldsymbol{x}_{it} = \frac{1}{a_{it}} \Sigma_t^{-1} \left(\boldsymbol{\mu}_t + Z_t \boldsymbol{\lambda}_{it} \right), \tag{4}$$

We can then write a linear demand curve for each asset n by assuming that returns follow an M-factor structure $\boldsymbol{r}_{t+1} = \boldsymbol{\delta}_t^\top \boldsymbol{f}_{t+1} + \boldsymbol{\varepsilon}_{t+1}$, with i.i.d. errors with volatility $\boldsymbol{\sigma}_t$. In this specification, the factors $\boldsymbol{f}_{t+1}$ explain the full covariance structure of returns, not only the expected returns. Using the Woodbury matrix identity, we can write the optimal portfolio weight for each agent i and asset n as:

$$x_{it}(n) = x_{mt}(n) + \frac{1}{a_{it}\sigma_t(n)^2} \left[Z_t(n)(\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t) - \boldsymbol{\delta}_t(n)^\top \boldsymbol{\kappa}_{it} \right] \tag{5}$$

where $x_{mt}(n)$ is the portfolio weight of asset n in the market portfolio and the last term is equal to $\boldsymbol{\kappa}_{it} = \left(\Sigma_f^{-1} + \boldsymbol{\delta}_t \Sigma_u^{-1} \boldsymbol{\delta}_t^\top \right)^{-1} \boldsymbol{\delta}_t \Sigma_u^{-1} Z_t (\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t)$.

Equation (5) reveals two important insights about portfolio choice. First, compared to a benchmark model without service flows, investors diverge from the standard tangency portfolio and overweight assets that provide services Z_t. This represents a deviation from the two-fund separation theorem, which predicts that investors would always choose the same risky asset portfolio, with differences in risk aversion determining only how much they invest in risk-free assets versus the risky portfolio. Private valuations for services cause investors to tilt their portfolios away from the market portfolio, and the magnitude of this portfolio tilt increases with investors' preferences for the respective services, $\boldsymbol{\lambda}_{it}$. This is a key feature to explain the portfolio heterogeneity we observe empirically.

Second, and more subtly, the valuation of service flows fundamentally alters how investors respond to traditional risk factors. The last term in equation (5) shows that an investor's exposure to systematic risk factors $\boldsymbol{\delta}(n)$ is modified by $\boldsymbol{\kappa}_{it}$, which itself depends on their service valuations λ_{it}. This creates a feedback effect where preferences for non-pecuniary benefits change investors' appetite for asset risk, leading investors with different service valuations to have systematically different sensitivities to the same underlying risk factors.

We can now use market clearing to compute expected returns. For simplicity, assume

$a_{it} = a_t$ for all agents, and let $\tilde{w}_{it} := w_{it}/w_t$, where w_t is total wealth in the economy. Because the risk-free asset is in zero net supply, market clearing implies that the weights of the market portfolio $\boldsymbol{x}_{mt}$ are

$$\begin{aligned} \boldsymbol{x}_{mt} &= \int_i \tilde{w}_{it} \boldsymbol{x}_{it} di \\ &= \frac{1}{a_t} \Sigma_t^{-1} \left(\boldsymbol{\mu}_t + Z_t \bar{\boldsymbol{\lambda}}_t \right) \end{aligned} \tag{6}$$

where $\bar{\boldsymbol{\lambda}}_t = \int_i \tilde{w}_{it} \boldsymbol{\lambda}_{it} di$ denotes the wealth-weighted service value across individuals.

Before we solve for the equilibrium expected returns, it is useful to normalize service flows of the market portfolio to zero, i.e.,

$$\boldsymbol{x}_{mt}^\top Z_t = \mathbf{0} \tag{7}$$

It follows that the expected excess returns are given by:

$$\boldsymbol{\mu}_t = \boldsymbol{\beta}_t \mu_{mt} - Z_t \bar{\boldsymbol{\lambda}}_t \tag{8}$$

where $\beta_t(n)$ is the covariance of asset n with the market portfolio divided by the variance of the market portfolio, σ_{mt}^2.

Equation 8 shows that the CAPM does not hold. In equilibrium, two assets with the same risk exposure $\beta_t(n)$ can have different returns because they have different service flows Z. In fact, we define the convenience value of asset n to be

$$cy_t(n) = Z_t(n) \bar{\boldsymbol{\lambda}}_t \tag{9}$$

which represents the returns that investors are willing to forgo because of the extra benefits the asset provides, measured by $Z_t(n)$.

Based on the model, we derive three testable predictions (formal derivations are provided in the appendix):

Prediction 1: *The cross-sectional variation of convenience yields is driven by the variation in bond-specific service flows, Z_t.* In our model, convenience yield—defined as the

gap between frictionless pricing and pricing that incorporates investors' valuation of service flows—is fully explained by the characteristics driving the service flow Z_t and the equilibrium premium on each of these characteristics, $\bar{\lambda}_t$, as shown in equation (9). There is a large literature exploring the characteristics that drive expected returns and their relationship to exposure to systematic risk factors [Fama and French, 1993; Daniel and Titman, 1997; Daniel et al., 2020]. In our setting, not only characteristics related to cash flows, but also characteristics related to service flows explain returns. Thus, omitting characteristics related to service flows would lead to misspecified asset pricing models. The private valuation of these specific services causes bonds to have different prices, even when bonds have identical expected cash flows.

Prediction 2: *Everything else constant, an increase in service flow k of asset n causes the convenience yield of asset n to increase. Furthermore, agents with high demand for service k rebalance their portfolios more strongly toward this asset than investors with lower demand for service k.* When investors value service k, this service is priced accordingly in the cross-section of bond returns. Increasing an asset's service content decreases its expected return, as investors who value this service are willing to forgo returns in exchange for the additional benefits. This suggests that an increase in the services associated with an asset will have a direct effect on its convenience yield, even if there is no observed shift in the portfolio allocations. Furthermore, investors' rebalancing behavior depends on their preference for the increased service flow.

Prediction 3: *Everything else constant, when investor i's preference for service k increases, the convenience yield rises more for assets with higher Z_t^k than for those with lower Z_t^k.* Variation in investor preferences create variation in both portfolio allocations and expected returns. When investors develop stronger preferences for a particular service (higher $\lambda_{it}(k)$), they shift their portfolios toward assets that provide more of that service, creating a direct link between preference heterogeneity and portfolio heterogeneity across investors.

In the next sections, we test these hypotheses using a detailed dataset on corporate and sovereign bond characteristics, returns, and portfolio holdings for the euro area from 2010

to 2025.

4. Data

Our objective is to use variation in convenience yields across assets and investors' portfolios to infer the nature of service flows in financial assets that investors value over and above cash flows. Our exercise requires a rich cross-section of assets with equal cash flows but different expected returns, combined with rich variation in holdings. Because of the richness of the data maintained by the ECB, the euro area is an ideal laboratory for our study. We construct a panel of euro area sovereign and corporate bonds that includes information on yields, CDS spreads, ratings, and detailed investor holdings. The main data come from harmonized datasets maintained by the European Central Bank and the Eurosystem.

4.1. Bond Price Data

The first dataset comes from the Centralised Securities Database (CSDB), which is maintained by the Eurosystem and consists of monthly security-by-security information on instruments, issuers, and prices for debt securities traded in the euro area. For the purpose of our analysis, we restrict our sample to senior unsecured bonds with fixed or zero coupon that are issued by euro area entities (corporate or sovereign), euro-denominated, and that have a residual maturity of at least one year.

For each outstanding bond, we observe its issuer, issuance size, maturity date, price and yield information, and other bond characteristics. Secondary market prices are recorded in a monthly panel. We add information on long-term credit ratings from the four main rating agencies (Standard and Poor's, Fitch, Moody's, DBRS). If applicable, we use the best available rating of the instrument; otherwise, we use the best issuer rating across agencies. Moreover, we add bond-level information on monthly turnover and average bid-ask spreads from the TraX dataset, provided by MarketAxess. CSDB does not provide some important metrics, like duration. We collect the coupon schedule of each bond and calculate the

modified duration for each bond in our sample.[10]

We complement the CSDB pricing data with iBoxx EUR index data for both investment-grade and high-yield bonds. iBoxx provides daily prices, returns, and bond metrics, which are valuable for certain aspects of our analysis. Higher-frequency data is particularly useful for estimating correlations and volatility, both of which are crucial for some of our analyses. However, a limitation of the iBoxx data is that it only includes bonds within the index universe, which tend to be larger and more liquid. We apply similar filters as for the CSDB sample, i.e., we restrict our sample to senior unsecured corporate bonds with fixed or zero coupon that are issued by euro area entities, euro-denominated, and that have a residual maturity of at least one year.

For risk-free rates, we use the ECB benchmark interest rate provided under the euro area yield curves estimation.[11] These are estimated daily using AAA-rated euro area central government bonds. Figure B.11 in the appendix presents the time series of the implied benchmark interest rate for different maturities. We merge the benchmark interest rate with the CSDB data based on the month-year and on the bond's duration to compute the credit spread for each bond. We thus obtain credit spreads for a sample of 29,024 bonds (26,910 of which are corporate) by 2,306 distinct issuers.

To create bonds with virtually the same cash flows, we need to hedge the default risk. We use credit default swaps (CDS) to do so. We merge the CSDB and iBoxx data with single-name CDS data from Markit Inc. The merge is done using the Markit reference obligation mapping, LEI codes, name string matching, and manual searches. The prices are quoted in basis points per annum for a notional value of $10 million and are based on the standard ISDA contract for physical settlement. The original dataset provides daily market CDS prices in various types of restructuring documentation clauses. Following a conventional rule, we choose the CDS price under documentation clause type as "modified restructuring" (MR),

[10]For a subset of bonds, we obtain duration estimates from the iBoxx index provider. We validate our calculations by achieving a 99% correlation between our estimated durations and those provided by iBoxx.

[11]These benchmark rates are published by the ECB on this website.

the standard clause type in Europe. The original data set provides a term structure of CDS spreads incorporating maturities of different years.[12] We use a linear interpolation to find the duration-matched CDS spread for each bond. We only consider CDS spreads with an average quote rating above BBB. The CDS average rating reflects a Markit measure of how reliable a reported CDS spread is.[13] To match the seniority and guarantee characteristics of the underlying bonds, we only consider senior and unsecured CDS.

The combined dataset allows us to calculate the *CDS-bond basis* as the difference between a bond's CDS spread and its credit spread. We discard all observations below the 1st and above the 99th percentile in terms of the CDS-bond basis. Our final sample consists of 16,762 distinct bonds (issue by 479 distinct entities) and 648,305 bond-month observations between January 2010 and February 2025. In terms of outstanding amounts, this CDS-matched sample covers more than 80% of the initial CDSB sample. Summary statistics regarding all variables used in our analysis can be found in Table 1.

[Table 1 about here.]

Figure 1 shows the average credit spread and the CDS spread for different rating categories in the period from January 2010 to February 2025. Note that this is a period of significant fluctuations in corporate spreads across all ratings, with a significant spike in March 2020 that was caused by the Covid-19 outbreak. As expected, the credit spread and the CDS spread are higher for lower rated categories with a significant difference between high-yield (HY) and investment-grade (IG) bonds.

[Figure 1 about here.]

In a similar manner, Figure 2 presents the average CDS-bond basis, calculated as the difference between a bond's CDS spread and its credit spread, across different rating categories.

[12]Specifically, the maturities included in the data set are of 1, 2, 3, 4, 5, 7, 10, 15, 20 and 30 years.

[13]This filter mitigates the concern that the CDS market is most liquid for contracts with 5 years maturity.

Throughout the entire period, the average CDS-bond basis remains significantly negative for all rating categories, indicating that investors are willing to forgo yields to hold AAA sovereign bonds rather than other bonds, even after adjusting for credit risk through CDS hedging. Moreover, the CDS-bond basis exhibits a monotonic relationship with ratings, suggesting a consistent preference for higher-rated bonds, even after controlling for credit risk.

[Figure 2 about here.]

In the absence of frictions, the CDS-bond basis should be zero. The prevalence of negative CDS-bond bases in the market is a well-known empirical regularity in the corporate bond literature (e.g., Longstaff et al. [2005], Oehmke and Zawadowski [2017], and Bai and Collin-Dufresne [2019]). The persistent cross-sectional variation across bonds captures the premium attached to the services associated with the ownership of high-quality bonds, such as collateral value and regulatory relief. All these interpretations are consistent with the model in Section 3. However, it may also capture frictions in the CDS market, which might not be a perfect hedge against default risk. We refer the reader to Mota [2023] for a longer discussion on why frictions in the CDS market are unlikely to affect the cross-sectional variation of the CDS-bond basis.

4.2. Holdings Data

An important part of our analysis focuses on investor heterogeneity with respect to preferences for services associated with different bonds. To analyze this investor heterogeneity, we use data from the Securities Holdings Statistics by Sector (SHSS), which are collected by the Eurosystem. The SHSS dataset provides information at the security level on the amount held by euro area investors. The data is aggregated at the selected investor type level. For our analysis, we group the investor types into the following categories: Banks (defined as deposit-taking corporations), insurance companies and pension funds (ICPF), mutual funds (MF), central banks, and others (which include non-financial corporations, households, general government, and other financial institutions such as hedge funds). The rest of the world

(RoW) is estimated as the residual amount, i.e., the difference between the total amount outstanding and the amount held by the above-mentioned sectors. The frequency of these data is quarterly. As a final step, we match the price dataset at the ISIN-quarter level with the data on investor holdings.

The holdings data shows large heterogeneity in corporate bond portfolio holdings across investors. Figure 3 presents the investor composition for euro area corporate bonds during the period 2011–2024.

[Figure 3 about here.]

In aggregate, the largest investors are insurance companies and pension funds, mutual funds, and banks. Direct holdings of the ECB have been growing significantly after the initiation of its corporate sector purchase programs. At the end of June 2024, the ECB held approximately 13.1% of the total outstanding EA corporate bond market, banks 13.9%, mutual funds 21.1%, ICPF 22.0%, other sectors 7.0%, and the rest of the world 22.8%.

The investor composition differs significantly in the cross-section, as also documented by Darmouni and Papoutsi [2023].[14] Figure 4 presents the investor composition of EA corporate bonds by rating and maturity at the end of 2021.

[Figure 4 about here.]

It is evident that the investor base differs significantly based on these two characteristics of the bonds. Insurance companies and pension funds hold a large share of investment grade bonds (both in the AAA-A and in the BBB segment), and their holding share increases with maturity, reaching almost 40% of the amount outstanding for AAA-A bonds with remaining maturity above 10 years. Mutual funds, on the contrary, hold a significantly larger share for BBB and HY bonds across all maturity categories. The ECB holds bonds

[14]Darmouni and Papoutsi [2023] focus on bonds issued by EA non-financial corporations, while we also include bonds issued by financial corporations.

only in the investment grade category, and the relative share is higher for BBB bonds with long maturities (5 years and above). The documented segmentation in the corporate bond market demonstrates that investors value specific bond characteristics differently, and for that reason, we expect this heterogeneity in preferences to have implications for bond prices.

4.3. Service flows

Finally, we need proxies for the service flows that drive convenience yields. We identify three measurable services:

1. **Liquidity**: The ability to liquidate bonds at low or no discount—especially in times of funding stress—is valuable, particularly for investors exposed to redemption risk, such as mutual funds. We measure liquidity by $1 - \textit{bid-ask spread}$, where bid-ask spreads are measured as $\frac{ask-bid}{bid}$.[15]

2. **Collateral value**: Banks can use corporate bonds as collateral to obtain funding from the ECB. The central bank publishes daily lists of the ISINs of securities that it considers eligible collateral—the so-called "eligible assets database" (EADB). Among other things, these lists contain the respective haircut applied to the market value of a given bond. For example, if a bond carries a 5% haircut and a bank pledges 10 million euros of that bond, it can only obtain 9.5 million euros of cash in return.[16] We measure the collateral value of bond n at time t as $1 - haircut_t(n) \in [0, 1]$. Our assumption is that ECB haircuts are good proxies for haircuts in private markets, such as repo facilities.

3. **Risk-based capital (RBC) value:** Regulatory frameworks such as Basel III for

[15]We also estimated the value of liquidity using turnover. Our analysis of the cross-section of the CDS-bond basis reveals no premium for high-turnover bonds, and the turnover premium remains largely negligible over time. Thus, we conclude that turnover is not a reliable measure of corporate bond liquidity that is valuable to investors in the euro area.

[16]These haircuts are a function of the bond's issuer sector, residual maturity, credit rating, and coupon structure. For more details, see https://www.ecb.europa.eu/mopo/coll/standards/html/index.en.html.

banks or Solvency II for insurance companies require minimum capital in proportion to asset values. Using the regulatory formula for "spread risk" in Solvency II, we measure RBC as $1 - stress_t(n) \in [0, 1]$, where $stress_t(n)$ is increasing in both the duration and credit risk of bond n. While this exact measure is derived from insurance regulation, the regulatory capital value for banks (e.g., Basel III risk weights) is qualitatively similar.[17]

5. Decomposing Convenience Yields

Our objective is to use bond characteristics and portfolio holdings data to quantify the market value of each service k, their relative importance in explaining the convenience yield of safe sovereign bonds, and the value each investor i assigns to service flows. As such, this section can be seen as a direct empirical test of our model-implied *Prediction 1.*

We begin by linking the CDS-bond basis to three specific service flows: liquidity, collateral, and risk-based regulatory capital relief (RBC). The reader should view this exercise as a projection of the CDS-bond basis onto these three services. If there are services not included in our analysis that also drive convenience yield, our results could be affected in two ways: there would be a large portion of convenience yield unexplained by our chosen services, or if omitted services are correlated with any of our included services, omitted variable bias would arise, with the correlation determining the sign of the bias. One can always extend our framework to include additional services. We believe that this three-service specification strikes the optimal balance between comprehensiveness and tractability: it captures the economically significant drivers of convenience yield for which we have good measures, and this specification delivers strong empirical performance, explaining up to 90% of the level of sovereign convenience yield.

To see how our model-implied measure of convenience yield maps to the empirically

[17]The exact formula for the stress calculation is reported in the Appendix D. For more details on how we measure collateral and regulatory capital value, see sections 7.1 and 7.2 below.

measured CDS-bond basis — defined as the difference between the yields of a risk-free Treasury bond and the duration-matched risky bond whose default risk is fully hedged using a maturity-matched CDS — consider the following: In this framework, the CDS-bond basis represents the one-year expected return of a portfolio that keeps a long position in the sovereign risk-free bond and a short position in the hedged risky bond, holding both positions to maturity. Under the assumptions that (1) the CDS fully hedges the bond's credit risk, (2) AAA-rated Treasury bonds are default-free, and (3) holding CDS contracts provides no additional services, we can express the CDS-bond basis of bond n as follows, based on equation (8):

$$b_t(n) = y_{T,t} - (y_{i,t} - CDS_{i,t}) = [\boldsymbol{Z}_t(n) - \boldsymbol{Z}_t(T)] \times \bar{\boldsymbol{\lambda}}_t \tag{10}$$

The CDS-bond basis thus directly maps to a bond's convenience yield relative to that of safe treasuries. Once we make specific assumptions about the number and type of service flows in the matrix $\boldsymbol{Z}_t$, we can estimate the average service value $\bar{\lambda}_t(k)$ for each of the K services using cross-sectional regressions of the basis on the spread in services between bond n and the matched treasury T.

To estimate equation (10), we construct service spreads by measuring the difference in each service provision between bond n and its duration-matched Treasury T. We directly observe collateral values and regulatory capital requirements for both corporate bonds and Treasuries across all maturities. For liquidity, we measure bid-ask spreads for both bond types, using linear interpolation between the closest-duration Treasuries when an exact duration match is unavailable.

To ensure comparability across services and time periods, we standardize each service measure by subtracting its cross-sectional mean and dividing by its standard deviation before calculating spreads. This normalization allows our estimated coefficients λ_k to be interpreted as the basis points earned by a zero-investment portfolio with one standard deviation of exposure to service k and zero exposure to all other services.[18] The caveat of this approach

[18]To see this, let Z_{st} be the service spread. Notice that the OLS coefficient implies that $\hat{\boldsymbol{\lambda}}_t =$

is that it does not capture changes in aggregate service supply, focusing instead on the relative value of different service types.

To reduce idiosyncratic noise, we aggregate individual bonds into portfolios of granular bond categories rather than using bond-level data.[19] In the rest of this section, the index n thus refers to bond categories rather than individual bonds.

We assume that measurement error and idiosyncratic shocks affect the observed CDS-bond basis. Therefore, we map equation 10 to the following cross-sectional regression for each month t:

$$b_t(n) = \lambda_{lt} Liquidity_t^s(n) + \lambda_{ct} Collateral_t^s(n) + \lambda_{rt} RBC_t^s(n) + \varepsilon_t(n) \tag{11}$$

where $b_t(n)$ is the CDS-bond basis of each portfolio n, the superscript s stands for the spread in service between each portfolio n and the duration-matched AAA Treasury, and the services are defined as above. We then aggregate $\boldsymbol{\lambda}_t$ into quarterly averages to match the frequency of our holdings data in the subsequent exercise. We interpret the estimated $\boldsymbol{\lambda}_t$ as a measure of the value of the three services described above—specifically, the yield investors are willing to forgo to hold a portfolio that, all else constant, is one standard deviation higher for a given service.

The estimated convenience yield of the AAA treasury portfolio is then

$$cy(T) = \sum_k \hat{\lambda}_{kt} \times \bar{z}(T)_{kt} \tag{12}$$

where $\bar{z}(T)_{kt}$ is the face-value weighted average of service k of all AAA Treasury bonds outstanding.

$(Z_{st}^\top Z_{st})^{-1} Z_{st}^\top \boldsymbol{b}_t$. Define $W_t^\top = (Z_{st}^\top Z_{st})^{-1} Z_{st}^\top$, the $K \times N$ matrix of portfolio weights. The service flows of these portfolios are $W_t^\top Z_{st} = I$, where I is the identity matrix.

[19] A category is defined as a combination of credit rating (*AAA*, *AA*, *A*, *BBB+*, *BBB*, *BBB-*, *BB*, *B and below*), residual maturity (*1-3y*, *3-5y*, *5-7y*, *7-10y*, *10-30y*), issuer country, 1-digit NACE industry, sovereign dummy, and eligibility dummy that is equal to one the bond is eligible for ECB asset purchase under the PSPP, CSPP or PEPP.

Table 2 presents the average service values for the full sample. Column (5) demonstrates that premiums for all services are positive on average.

[Table 2 about here.]

The premium for each service is not constant over time. In Figure 5, we report the time series of each λ_k estimate with 5% confidence intervals.

[Figure 5 about here.]

We plot the AAA Treasury convenience yield decomposition resulting from our estimates in Figure 6. Figure 6b shows the contribution of each service to the explained part of convenience yields. Figure 6a plots the same quantities in levels and the negative of the CDS-bond basis.

[Figure 6 about here.]

For most of our sample period, the explained convenience yield is mainly driven by collateral value. This regulatory capital value explains, on average, 60% of the convenience yields in our sample.

6. Investor Specific Valuation of Service Flows and Expected Returns

Our model predicts that investors with higher demand for service flows will accept lower returns, i.e., negative alphas compared to the market benchmark. On the other hand, we expect that sectors with lower demand for service flows earn higher returns and positive alphas. By examining portfolio performance, we can infer the sectors that value service flows the most.

Our empirical strategy is to construct portfolios that have high exposure to each investor type's portfolio, and still have neutral exposure to traditional sources of risk, as represented by $\boldsymbol{\delta}$ in our model. Recognizing that credit and duration risk are the main drivers of returns of bonds, we first sort bonds into rating and maturity buckets, then bonds in each bucket are sorted according to the share of the amount outstanding held by each investor class (we call this "triple sorting"). The top 30% are classified as "high", while those in the bottom 30% are classified as "low". We calculate portfolio returns as the value-weighted average return in each bucket. We then construct a long-short portfolio for each investor type that buys with equal weights all the high holdings share portfolios and sell low holdings share portfolios. Portfolios are rebalanced quarterly, returns are weekly, and excess returns use the weekly EURIBOR rate as the risk-free rate.

To align the portfolios with the corresponding returns, we use information available at time t to categorize assets into portfolios for the same period. For example, holdings data from the last day of Q1-2022 are used to create portfolios from the first week of January 2022, to the last week of Q1-2022. In addition, we have explored using lagged categories, where holdings data from one quarter are used to create portfolios for the subsequent quarter. However, since the holdings profile tends to remain relatively stable over time, our findings remain consistent, with only minor quantitative differences.

Figure 7 shows the portfolio returns of the triple-sorted portfolios for all investor classes, plus the market portfolio. As one can see, even though they are ratings and duration neutral, these portfolios have very different returns. The ICPF-based portfolio exhibits the lowest realized return in the sample, followed by the bank-based one. The RoW-portfolio is the one with the largest realized returns, whereas the mutual fund-based portfolio shows relatively flat realized returns.

[Figure 7 about here.]

We can now formally test whether portfolio holdings help to price the cross-section of bond returns. To do so, we run the following time series regression for each triple-sorted

long-short portfolio i:

$$r_{it} = \alpha_i + \beta_{it} r_{m,t} + \beta_{it} r_{term,t} \varepsilon_{it} \tag{13}$$

where α_i is of particular interest as it provides insights about $Z_t \bar{\boldsymbol{\lambda}}_t$ per equation (8), $r_{m,t}$ is the market factor (CAPM) which is the value-weighted portfolio of all assets in excess of the risk-free rate, and $r_{term,t}$ is a term factor, which is the 10-year minus 1-year AAA Treasury returns.

We note that data from the Covid-19 period should be treated with caution for two main reasons. First, there is an increase in correlation across various asset classes during the crisis period, which could potentially obscure the normal relationships we aim to investigate. Second, there is likely to be a shift in the premia for bond services during periods of uncertainty, which may affect our results. Specifically, we observed a tendency for the alphas of banks and pension funds to become less negative and those of mutual funds and the rest of the world to become less positive during the Covid-19 period. However, it is important to note that these changes in alphas were not statistically significant, and the number of observations during this period was very limited (8 weeks). Therefore, conclusions from this period should be viewed carefully.

Table 3 consolidates these findings.

[Table 3 about here.]

Portfolios tilted towards insurance and pension fund holdings show significantly negative weekly alphas of -0.020%, which annualizes to -1.03%. Bank alphas, while not statistically significant, lean negatively as well, but at a reduced magnitude. Mutual funds and ECB holdings do not show significant alpha, contrasting with the significantly positive alpha for the rest of the world holdings, at 0.021% weekly or 1.10% annually. These outcomes are consistent with the asset pricing model's prediction that heterogeneous preferences for service flows are a critical driver of bond return differentials. Furthermore, we interpret the statistically significant negative *alphas* in the ICPF portfolio as evidence that they are the sector that values service flows the most.

7. Policy-Driven Changes to Service Flows

So far, we have analyzed and estimated the drivers of convenience yield in the cross-section of European bonds. To do so, we had to make explicit assumptions about the services that investors value. However, without exogenous variation in services or preferences, we cannot gauge the causal impact of services on prices or portfolio allocation. In the remainder of this paper, we use policy shocks that provide exogenous variation in services or preferences to validate our choice of services. We study three types of policy shocks, each targeting a different service. Our objective is twofold: first, to provide evidence that the services we measure indeed map to the economic forces we have postulated; second, to show causal evidence that policy decisions affect both convenience yields and portfolio allocation. In this way, the empirical results that follow allow us to test the predictions developed in Section 3.

7.1. Collateral Value for the Banking Sector

First, we turn our attention to banks and the fact that they are the only institutions that can borrow directly from the ECB by pledging high-quality bonds (incl. corporate bonds) as collateral. Therefore, ECB collateral eligibility is a service that banks are particularly likely to value. To substantiate this claim, Figure 8 plots the average collateral value of each institutional investor's corporate bond portfolio. In line with our hypothesis above, banks clearly emerge as the sector that holds corporate bonds of the highest collateral value (i.e., the lowest haircuts). After a strong drop in December 2018, euro area banks replenished their collateral pools by buying disproportionately more collateral-eligible bonds.

[Figure 8 about here.]

The striking drop in the average collateral value of banks' corporate bond holdings in December 2018 was caused by the loss of eligibility of a large set of German bank bonds, providing us with a useful policy experiment that can help understand the drivers of convenience yield in corporate bonds. More precisely, in December 2017, the ECB announced

that (statutorily) *subordinated* unsecured bank bonds (sUBB) issued before April 16, 2018 would cease to be eligible for ECB collateral after December 31, 2018. Due to differences in the national implementation of EU directives across Member States, this shock only affected sUBBs issued by German banks.[20]

This change in collateral eligibility offers a clean shock for studying the value of pledgeability and how it maps to the CDS-bond basis. The most useful aspect of this experiment is that the loss of eligibility happens orthogonally to other bond characteristics such as credit risk and residual maturity. Using the publicly available EADB data, we can identify the set of German sUBBs and interpret the outright loss of their collateral value as a reduction in the service flows that these bonds provide. To test this hypothesis formally, we compare the average CDS-bond basis of eligible German sUBBs issued before April 2018 (the "treatment group") with that of a control group (consisting of eligible bank bonds from other EA countries), before and after the loss of eligibility at the end of 2018. Specifically, we estimate the DiD equation

$$b_t(n) = \beta \, German(n) \times Post_t + \delta_t + \gamma_n + \theta_{r\times m} + \varepsilon_t(n), \tag{14}$$

where $b_t(n)$ denotes the CDS-bond basis of bond n in month t, $German(n)$ is a dummy variable identifying bonds issued by German banks, and $Post_t$ is a dummy variable equal to one for all months after (and including) December 2018, and zero otherwise. δ_t, γ_n, and $\theta_{r\times m}$ are placeholders for time, bond, and rating $\times$ residual maturity fixed effects, respectively.[21] Since bank bonds often exhibit small lot sizes, we weight observations by outstanding amounts to reduce the impact of small issuances. We estimate equation (14) within one year around the loss of eligibility in December 2018 and present the results in

[20] See Appendix I for a more detailed account of the collateral framework amendment regarding sUBBs, including a timeline of events.

[21] Specifically, we construct twelve rating-maturity buckets where each bucket is a combination of one of three rating categories (AAA–A, BBB, or high-yield) with one of four residual maturity categories (1-3y, 3-5y, 5-10y, 10-30y). The corresponding fixed effects control for duration and credit risk. In a benchmark model with no demand for service flows, these would be the two main sources of risk driving investors' portfolio allocation and prices.

Table 4.

[Table 4 about here.]

In line with our hypothesis that collateral eligibility is a major driver of convenience yield, the loss of eligibility of German sUBB leads to a statistically significant drop in the CDS-bond basis of 4–7 basis points relative to bank bonds from other countries. The baseline estimate is robust to using variation within rating × maturity buckets and even within ISINs for identification. Given an average pre-shock CDS-bond basis of -40 basis points, even our smallest estimate corresponds to an economically meaningful 10% reduction in convenience yield. Importantly, Figure 9 confirms that, before the loss of eligibility, the average CDS-bond basis of both treatment and control group followed parallel trends, strenghthening our identifying assumption.

[Figure 9 about here.]

To complement our analysis of the impact of ECB collateral eligibility on bond prices, we now look at the quantity response, i.e., the portfolio rebalancing behavior of European banks. As Figure 10 illustrates, banks started decreasing their aggregate holdings of German sUBB relative to other eligible senior bank bonds immediately after the ECB announced in December 2017 that German bonds would lose eligibility one year later. More precisely, between the start of 2017 and the actual loss of eligibility at the end of 2018, banks' holdings of German sUBB (as a share of their total outstanding amount) fell by almost 5% whereas holdings of other eligible bank bonds rose by 5%.

[Figure 10 about here.]

For a formal test, we again employ a DiD design and estimate the following equation, where we only focus on collateral-eligible senior bank bonds issued before April 2018 to keep the treatment and control group as similar as possible:

$$\frac{B_{it}(n)}{\sum_n B_{it}(n)} = \beta_i German(n) \times Post_t + \gamma_i German(n) + \alpha_c + \alpha_r \times \alpha_m + \alpha_t + \varepsilon_{it}(n) \quad (15)$$

To ensure a tight correspondence between the empirical specification and the theoretical model predictions in equation (4), $B_{it}(n)$ denotes the market value of investor i's holdings of bond n in quarter t, so the left-hand side expression can be interpreted as the weight of bond n in investor i's portfolio of bank bonds. As in the previous equation, $German(n)$ is a dummy variable identifying bonds issued by German banks, and $Post_t$ is a dummy variable equal to one for all quarters after (and including) December 2017, and zero otherwise. α_c, α_t, and $\alpha_{r\times m}$ denote investor country, time, and rating $\times$ residual maturity fixed effects, respectively. Controlling for unobservable time-invariant investor country characteristics via α_c is particularly important here, since the loss of eligibility is country-specific and it is well known that investors' portfolios exhibit "home bias". We estimate equation (15) separately for each investor sector within one year around the ECB announcement in December 2017.

[Table 5 about here.]

The results are summarized in Table 5. The statistically significant estimate of interest in column (1) implies that European banks reduced the share of German bank bonds in their bank bond portfolios by 4.5 basis points on average in response to the announced loss of collateral eligibility. Since the average portfolio share at the bond level in the estimation sample amounts to 0.3%, the estimate corresponds to a significant reduction 15% for the average bond. Crucially, we do not find the same rebalancing response for the other investor sectors (which arguably do not value ECB collateral eligibility).

Taken together, these results confirm Prediction 2 above and suggest that the "service flow" of collateral eligibility is a major component of convenience yields in euro area corporate bonds.

7.2. Regulatory Capital Requirements in the Insurance Sector

We now turn our attention to the insurance sector, which is well known to be subject to minimum capital requirements under the regulatory Solvency II regime. Specifically, their investment portfolios are governed by risk weights that determine how each security

contributes to the insurer's Solvency Capital Requirement (SCR). Consequently, insurers prefer to hold assets that are favorable in terms of regulatory capital. Insurers facing these constraints may be willing to forgo yields to hold such assets, resulting in portfolios with high convenience yields due to capital constraints.

Mapping the service flows of corporate bonds to their regulatory capital value for insurance companies is challenging, as we did not observe any regulatory shocks during our study period that would enable us to clearly identify this channel. However, we can exploit the fact that both life insurance companies and pension funds are exposed to significant duration mismatches between their assets and liabilities (see, e.g., Domanski et al. [2015] or Koijen and Yogo [2022b]). This means that when interest rates decline, the value of liabilities typically increases more than the value of assets, which pushes insurers closer towards their Solvency Capital Requirement. Therefore, low long-term interest rates might increase insurers' appetite for bonds with high regulatory capital value and compel them to rebalance their portfolios to meet regulatory capital requirements.[22] We use this argument to conduct a test of Prediction 3 from Section 3.

The basic SCR, as defined in Art. 87 of Delegated Regulation (EU) 2015/35, can be obtained as a function of the capital charges arising from each of the following "risk modules" and their correlations: (a) *Underwriting risk*, which refers to the risks that are inherently associated with the insurance business, e.g., the risk of claim settlements, natural disasters, or longevity/mortality risk in the case of life insurers; (b) *Market risk* that arises from fluctuations in the market value of insurers' assets and liabilities; and (c) *Counterparty risk*. Each of these modules is further divided into sub-modules, and for the purpose of our analysis, we focus on the so-called *spread risk* sub-modules.

To be precise, *spread risk* is defined in Art. 176 of the above regulation, which specifies a bond-specific *stress* function that takes values between 0 and 1 and decreases with the

[22] Although pension funds in the EU are not subject to a harmonized regulatory framework like Solvency II, their negative duration gap (and hence the risk of underfunding when interest rates are low) suggests that they are subject to qualitatively similar constraints.

bond's credit quality and increases with modified duration. We omit the exact formula here, but crucially, bonds with low credit ratings and longer durations carry a higher *stress* value and are thus associated with a higher capital requirement per unit of market value held. Therefore, we can use $RBC_t(n) = 1 - stress_t(n)$ as a measure of the regulatory capital value of bond n at time t.

We then examine whether long-term interest rates influence the convenience yield of corporate bonds with high regulatory value differently than those with lower regulatory value. Specifically, we estimate the following model:

$$b_t(n) = \beta \times RBC_t(n) \times r_t + \alpha_n + \alpha_r \times \alpha_m + \alpha_t + u_t(n) \tag{16}$$

In this equation, $b_t(n)$ represents the CDS-bond basis of bond n and $RBC_t(n)$ is the value of bond n's risk-based capital relief at time t as defined above. The variable r_t denotes the long-term nominal interest rate, measured by the 10-year Euro area government yield. We also include time, bond, and rating-by-time-to-maturity fixed effects. Our hypothesis is that β will be negative, i.e., in times of low interest rates, bonds with high regulatory value should exhibit a higher convenience yield.

The results reported in Table 6 confirm our prior, based on Prediction 3 above. Specifically, column (4) shows that a 1-percentage-point drop in interest rates is associated with a CDS-bond basis that is approximately 5 basis points higher for bonds with above-median regulatory value compared to those with below-median regulatory value. This result persists even if we replace the rating-by-maturity fixed effects by more stringent bond fixed effects (see columns (2) and (5)).

[Table 6 about here.]

However, it is important to note that this observation may stem from correlations between interest rates and the demand for other services, such as liquidity or collateral, rather than being directly related to regulatory capital. High-regulatory value assets often simultaneously exhibit greater liquidity and lower haircuts, which complicates this relationship. Therefore,

to strengthen our identification of the effects of regulatory capital, we next analyze portfolio rebalancing behavior. Specifically, for each investor sector i in country c we estimate

$$x^i_{ct}(n) = \beta^i_r \times RBC_t(n) \times r_t + \alpha_n + \alpha_c \times \alpha_t + u_{ict}(n), \tag{17}$$

where $x^i_{ct}(n)$ is the portfolio weight of investor type i' at country c, of bond n in quarter t. The regression includes investor country-by-time fixed effects to account for time-varying outside assets. Our hypothesis is that β^i_r is negative for ICPF, as they rebalance toward high-RBC bonds when interest rates are low to mitigate their negative duration gap.

[Table 7 about here.]

Strikingly, as columns (1) and (3) of Table 7 show, our estimate is negative *only* for banks and ICPF, and positive for all other sectors. One possible interpretation is that during times of low long-term interest rates, most investors reach for yield (e.g., by investing in assets of lower credit quality) whereas the widening negative duration gap forces ICPF to shift to high-RBC bonds to satisfy their minimum capital requirements. Similarly, banks (whose regulatory minimum capital requirements follow the same logic) appear to focus their yield-chasing behavior on high-RBC bonds.

7.3. Corporate QE as a Shock to Bond Liquidity

Finally, we study the effect of corporate QE announcements on corporate bond prices and convenience yields. We show evidence that bonds eligible for the ECB purchases experienced an increase in their perceived liquidity service, a service especially valued by mutual funds.

We study the two programs under which the ECB engaged in large-scale corporate bond purchases: (1) the Corporate Sector Purchase Program (CSPP), announced in March 2016 and launched in June 2016, which introduced large-scale net purchases of investment-grade non-bank corporate bonds in the euro area; and (2) the Pandemic Emergency Purchase Program (PEPP), announced in March 2020, a temporary asset purchase program of private and public sector securities that was initiated in response to the coronavirus outbreak. In

total, the ECB accumulated more than €400 billion by 2023, or approx. 15% of the total European corporate bond market.

Various criteria determined the eligibility of the bonds to be purchased under the CSPP and the PEPP. Specifically, the CSPP was limited to investment-grade non-bank corporate bonds issued in the euro area. Only bonds with a remaining maturity of between 6 months and 31 years and with a yield to maturity (YTM) above the ECB's deposit facility rate were CSPP-eligible. In contrast, the PEPP extended eligibility to a wider range of assets that had previously been eligible for other ECB asset purchases, e.g., sovereign bonds under the Public Sector Purchase Program (PSPP). In addition, the eligibility of non-financial commercial papers under the CSPP was expanded to include securities with a remaining maturity of at least 28 days.[23] Moreover, the above-mentioned minimum-YTM requirement had been lifted in 2019.

Table 8 presents the summary statistics for eligible and ineligible bonds to be purchased under the CSPP and the PEPP.

[Table 8 about here.]

Panel (a) refers to the six-month period ahead of the CSPP announcement, and panel (b) refers to the six-month period ahead of the PEPP. In both periods, eligible bonds are significantly larger in size. Interestingly, the average credit spread of eligible bonds was initially higher than that of ineligible bonds because the latter included bonds issued by banks, among which there are many AAA-rated issuers, partly thanks to implicit (or even explicit) government guarantees.

The exogenous nature of the CSPP and the PEPP announcements allows us to employ a difference-in-differences (DiD) identification strategy to study the impact of the two programs on bond yields and their decomposition into credit spreads, CDS spreads, and the CDS-bond

[23] We do not include commercial paper in our analysis as we would not be able to accurately match the CDS based on maturity. Our analysis also excludes bonds with less than one year remaining maturity.

basis for eligible versus ineligible bonds.

Our main specification is:

$$y_t(n) = \theta \, Treat_t(n) \times Post_t + \alpha_r \times \alpha_m + \alpha_t + u_t(n) \tag{18}$$

For each bond n and month t the dependent variables $y_t(n)$ are: corporate bond yields, credit spreads, CDS-spread, or the CDS-bond basis. $Treat_t(n)$ is a dummy equal to 1 if the bond is eligible to be purchased under the CSPP or the PEPP,[24] and $Post_t$ is a dummy equal to 0 for the period preceding the announcement date of the respective purchase program, and 1 after it. We include month and rating $\times$ maturity fixed effects, just as in the previous subsection.

The identifying assumption is that, in the absence of the ECB purchases, corporate bond yields, credit spreads, CDS spreads, and CDS-bond basis of the treatment group and the control group would have maintained parallel trends. Regardless of the parallel trend assumption, one could still worry that eligible and ineligible bonds are fundamentally different, and that ECB decisions could potentially be concurrent with other news that affect the two groups differently. For example, the announcement of ECB purchase programs is usually a response to the deterioration of an economic scenario. Since eligible bonds are, in general, of higher credit quality than non-eligible bonds, they might be less exposed to macroeconomic risks. Therefore, the ex-post credit spread gap between the groups might just be the consequence of a higher risk premium. We believe that the CDS-bond basis analyses are not

[24]The eligibility criteria for the CSPP can be summarized in the following: a) to be rated by accepted external credit assessment institutions and third-party rating tools and to have a minimum rating of BBB-; b) to have initial maturity of 367 days or more and the minimum remaining maturity to be six months and the maximum remaining maturity 30 years and 364 days; c) to be euro-denominated; d) to be issued in the euro area; e) the issuer to be established in the euro area and the place of settlement to be in the euro area; and f) to have either a fixed and unconditional principal amount or an unconditional principal amount that is linked, on a flat basis, to only one euro area inflation index at a single point in time, containing no other complex structures. Further criteria are included with respect to acceptable markets and coupon payments, but they do not apply for our analysis as the sample used in the analysis is already restricted.

subject to this critique. Any variation in the risk premium that affects default should be reflected in the CDS-spreads, since the payoff of the CDS is directly linked to the default probability. Furthermore, our empirical methodology mitigates concerns about the mismeasurement of the default component of credit spreads. Any friction that could affect CDS spreads and is not related to default risk, such as counterparty risk, would have to affect treatment and control group differently in order to affect our results. This is not likely to be the case.

We estimate the baseline equation (18) separately for the two ECB programs — CSPP and PEPP. We define six months before the announcement date as the pre-period and six months after as the post-period. We differ from other studies (most importantly, Todorov [2020]) and include a longer window around the event. Our longer window is crucial to connect these results to the portfolio rebalancing exercise that follows. Holdings are unlikely to change significantly in very short windows, especially when considering long-term investors such as insurance companies and pension funds. Therefore, our exercise is only valid because we observe a persistent price impact from the CSPP and PEPP announcements.

In panel (a) of Table 9, we examine the impact of the CSPP in March 2016. We find that the CSPP decreased the credit spread of eligible bonds with respect to ineligible bonds by 22.3 basis points, consistent with our Prediction 2. In columns (3) and (4), it is shown that the decrease in credit spreads is explained mainly by the non-default component of the spread, the CDS-bond basis, and less by the default component, the CDS spread.[25]

[Table 9 about here.]

Our last step is to understand *why* ECB eligibility caused an increase in the convenience yield of eligible bonds. To unveil the mechanism through which the corporate QE programs of the ECB affect corporate bond prices, we need to look at the response of different investors around the programs. For that reason, we estimate the effect of the ECB corporate QE programs on portfolio rebalancing, using micro-level holdings data. Holdings information at

[25] We test the parallel trend assumption in the Appendix.

the ISIN-level allows us to analyze the heterogeneous investor composition and infer how different investors value the QE-eligibility feature. To do so, we estimate the effect of the announcement of the ECB corporate QE programs on portfolio holdings for different investor groups.

Explicitly, we use a DiD specification where the dependent variable is the portfolio share $x_{it}^{c}(n)$ for each investor type i, in country c, in asset n, and quarter t.

$$x_{it}^{c}(n) = \psi_i Treat(n) \times Post_t + \alpha_r \times \alpha_m + \alpha_c \times \alpha_t + \varepsilon_{i,t}(n) \tag{19}$$

where the time-varying outside option of investors in country c is captured by $\alpha_c \times \alpha_t$. Maturity $\times$ rating fixed effects are meant to capture duration and credit risk. Holder country $\times$ quarter fixed effects are meant to capture investor-specific demand (which is likely to be country-specific) and time-varying outside options.

The results are reported in Table 10. They show that the CSPP announcement caused an increase in holdings for eligible bonds only for mutual funds, while all other investor sectors decreased their holdings of eligible bonds relative to ineligible. The results are similar also around the PEPP announcement when mutual funds appear to increase holdings of eligible bonds relative to ineligible bonds in contrast to the behavior of the other investor groups. These results align with the strategy of mutual funds to strategically maintain eligible bonds, even when they appear relatively expensive compared to other bonds with similar credit and duration risks.

[Table 10 about here.]

These results are striking, as we observe that mutual funds buy more eligible bonds as they become more expensive, even though the mutual fund sector is believed to be very price elastic (Koijen et al. [2021]). We explain this pattern by arguing that QE announcements affect prices not only through supply changes, but also by altering the characteristics of eligible bonds. In particular, because mutual funds place particular value on liquidity, and they are the ones who rebalance most strongly toward eligible bonds, we view this as evidence

that QE fundamentally changes the liquidity services of eligible bonds. The liquidity concept here is broader than the bid-ask spreads we measured in the previous section. It encompasses the expectation that the ECB will step in to purchase these bonds, especially in times of distress.

8. Conclusion

The bond market serves as a crucial financing source for corporations and governments. This paper demonstrates that investors value bonds not only for their cash flows but also for the additional services they provide. Using comprehensive data on euro area corporate and sovereign bonds, we decompose convenience yields into three measurable service flows—liquidity, collateral value, and regulatory capital relief—and show how heterogeneous investor preferences for these services drive cross-sectional return patterns and portfolio allocations.

Our findings reveal that collateral value is the dominant driver of convenience yields in the euro area bond market. Over most of our sample period, collateral value explains 60–90% of AAA sovereign convenience yields, reflecting the significant influence of financial institutions with bidding leverage constraints in driving convenience yields.

The policy implications are far-reaching. We provide compelling evidence that monetary and regulatory policies transmit to asset prices through service flows. The ECB's corporate QE programs illustrate this vividly: more than 70% of the observed price impact operates through convenience yields rather than credit risk reduction, fundamentally altering the liquidity characteristics of eligible bonds. Similarly, when the ECB modified its collateral framework in 2018, we observe immediate effects on both bond prices and portfolio allocations as banks rebalanced toward securities with higher collateral value.

These results suggest three key implications for policymakers. First, regulatory design should consider the unintended consequences of capital requirements on asset pricing and market stability. Second, central banks possess powerful tools to influence specific market segments through service flows, opening new avenues for precision monetary policy. Third,

our findings extend the financial repression literature by showing that the focus should not be solely on banks holding sovereign debt, but on long-term investors like insurance companies and pension funds who are directly compelled by regulatory frameworks to hold certain assets. This regulatory-induced demand has large cross-sectional effects on bond prices, fundamentally affecting the cost of capital for governments and corporations.

From a methodological perspective, our work demonstrates the importance of incorporating service flows into asset pricing models. Traditional approaches that focus solely on risk-return trade-offs may systematically misprice assets and misunderstand return predictability. Our framework provides a foundation for analyzing other asset classes where investors value characteristics beyond cash flows.

In conclusion, service flows are fundamental drivers of asset prices with significant implications for monetary policy transmission, financial stability, and market efficiency. By providing a framework for measuring the value of these service flows, we open new avenues for understanding how financial markets function and how policy interventions can achieve more targeted outcomes.

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Figures

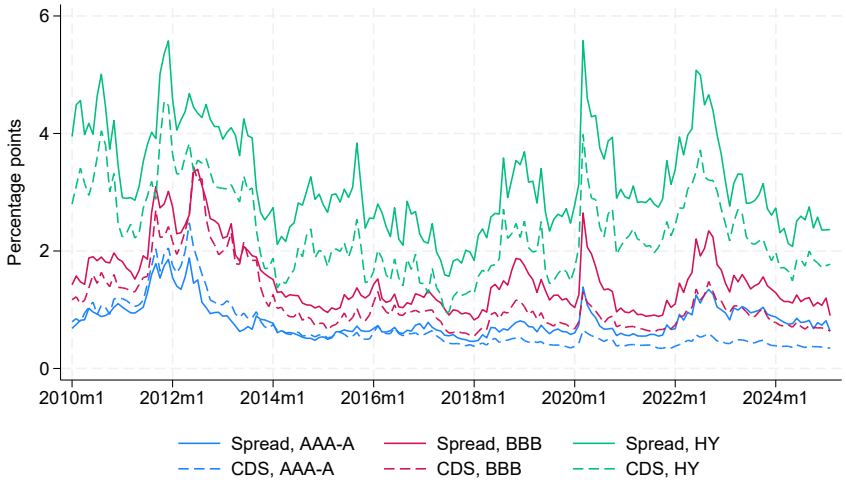


Figure 1: Average credit and CDS spread for euro area corporate bonds by rating. This plot presents average credit and CDS spreads (weighted by outstanding amounts) for each rating category. $AAA - A$ includes all bonds with a rating of at least A-; BBB includes bonds with ratings between $BBB+$ and BBB-; and HY includes all rated bonds with a rating of $BB+$ or below. For this plot, we excluded bonds of three Italian banks (Banco Popolare, Banca Monte dei Paschi di Siena, and UBI Banca) that exhibited excessively volatile CDS spreads in 2012–2013, possibly related to the ECB's OMT announcement.

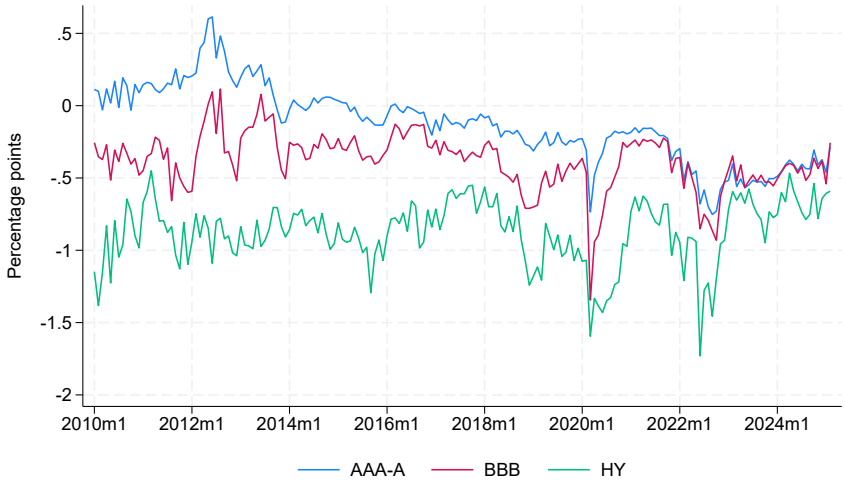


Figure 2: Average CDS-bond basis for Euro area corporate bonds by rating. This plot presents the average CDS-bond basis (weighted by outstanding amounts) for each rating category. $AAA - A$ includes all bonds with a rating of at least A-; BBB includes bonds with ratings between $BBB+$ and BBB-; and HY includes all rated bonds with a rating of $BB+$ or below. For this plot, we excluded bonds of three Italian banks (Banco Popolare, Banca Monte dei Paschi di Siena, and UBI Banca) that exhibited excessively volatile CDS spreads in 2012–2013, possibly related to the ECB's OMT announcement.

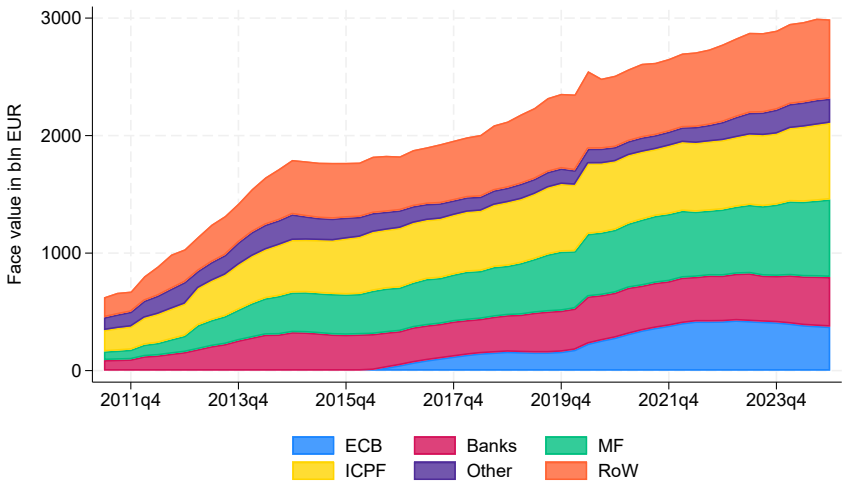


Figure 3: Sectoral holdings of euro area corporate bonds This plot presents the total outstanding face value (in bln EUR) of euro area corporate bonds over time, split by investor sectors. *Other* includes non-financial corporations, households, and government agencies, and *RoW* (rest of the world) is calculated as a residual to match total outstanding amounts.

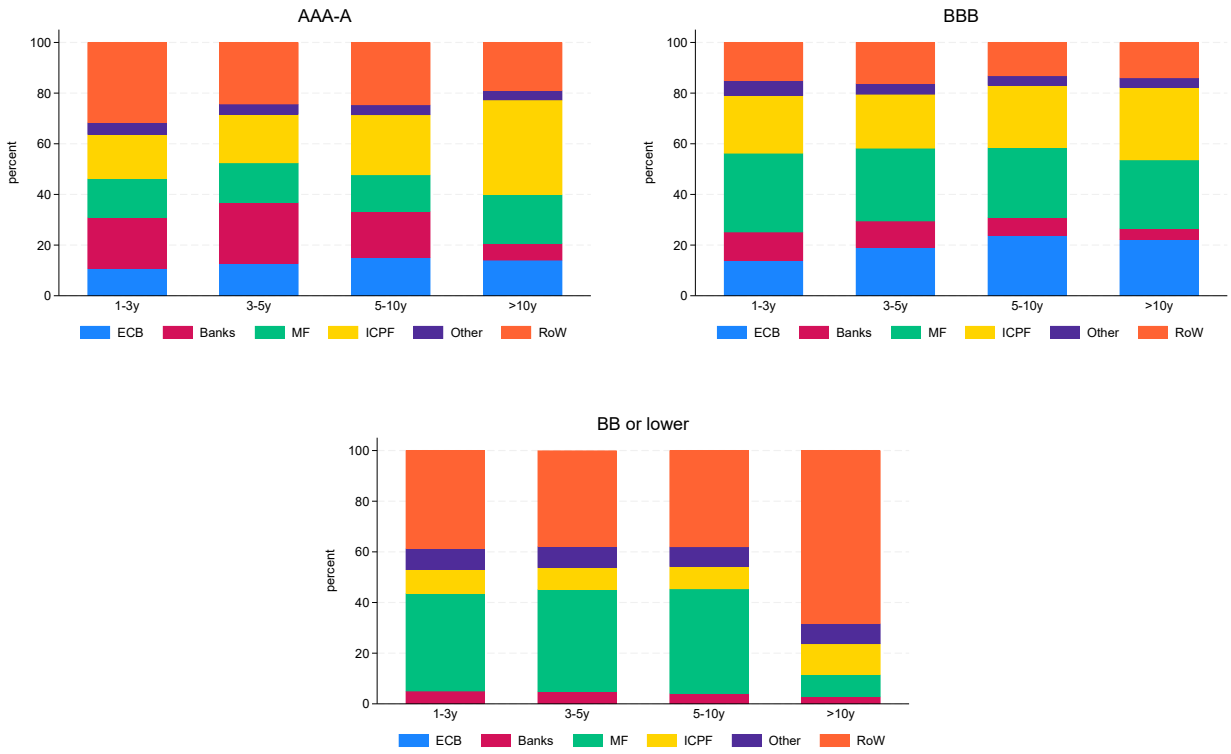
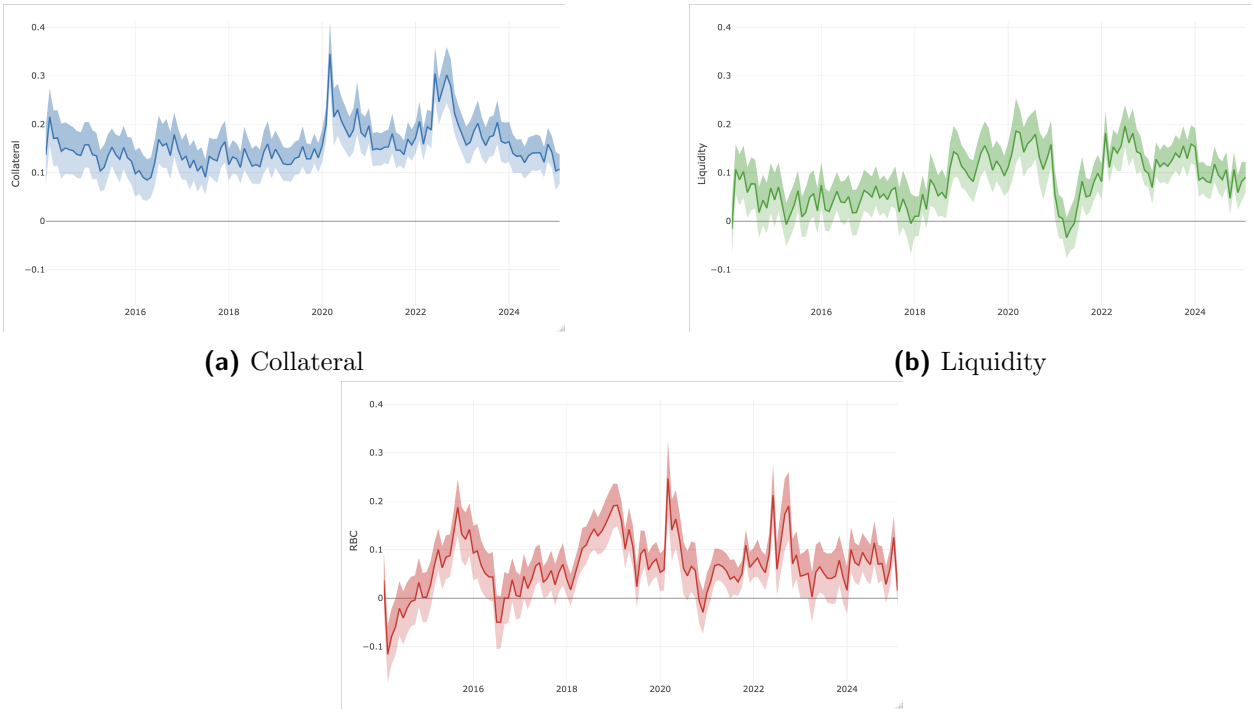


Figure 4: Investor composition of corporate bonds by rating and maturity. This plot illustrates the sectoral holder composition of euro-denominated, EA-issued corporate bonds in 2021Q4, for different residual maturity brackets (x-axis) and rating categories. $AAA - A$ includes all bonds with a rating of at least A-; BBB includes bonds with ratings between $BBB+$ and BBB-; and HY includes all rated bonds with a rating of $BB+$ or below.

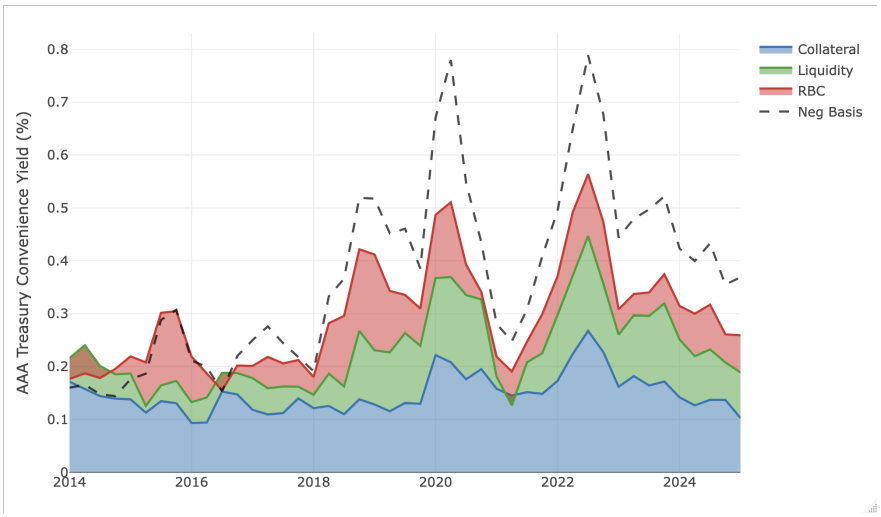


(a) Collateral

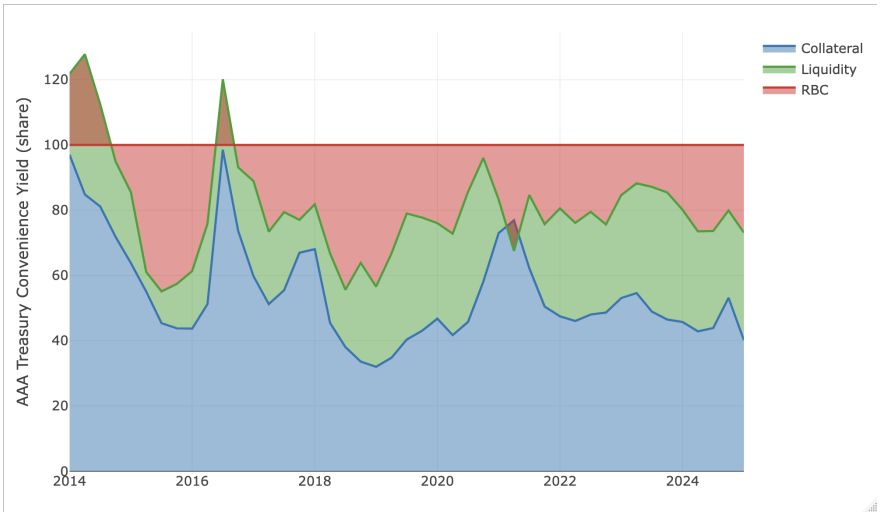
(b) Liquidity

(c) RBC

Figure 5: Service value estimates This plot shows the monthly service value estimated from equation 11 with 5% confidence interval.



(a) Contribution of services to Treasury convenient yields.



(b) Relative contribution of services to Treasury convenient yields.

Figure 6: Contributions of service flows to AAA sovereign bonds convenience yield. Panel (a) shows the contribution of each service, which is the value estimated in (11) times the average service, $Z(T)$, of all AAA sovereign bonds outstanding. Panel (b) shows the relative contribution of each service.

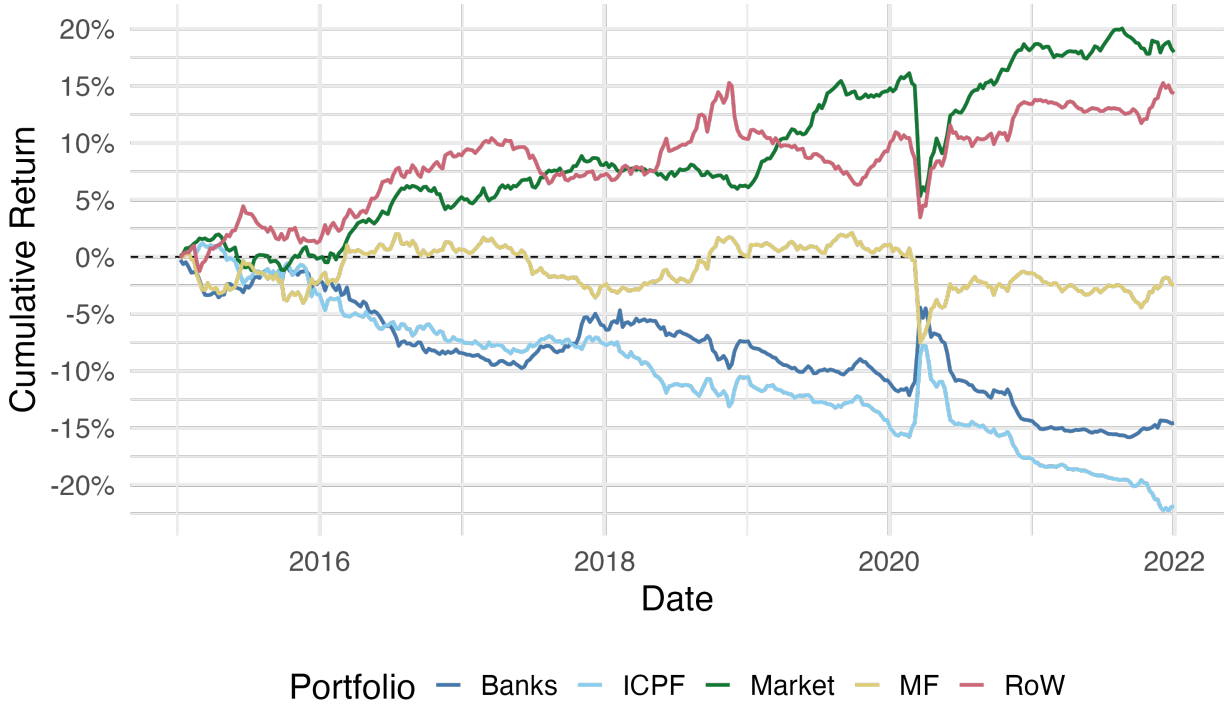


Figure 7: Cumulative Returns of Market-Neutral Long-Short Triple-Sorted Portfolios. This graph depicts the cumulative excess returns of market-neutral long-short portfolios, which are constructed by first categorizing bonds into maturity and rating groups and then sorting by the proportion held by each investor class. The triple-sorted portfolios take long positions in the top 30% and short positions in the bottom 30% of these classifications. Portfolios are scaled to match the market factor's standard deviation, are balanced quarterly with weekly returns and cumulated with the inclusion of Euribor as the risk-free rate to account for the return generated by the long-short strategy.

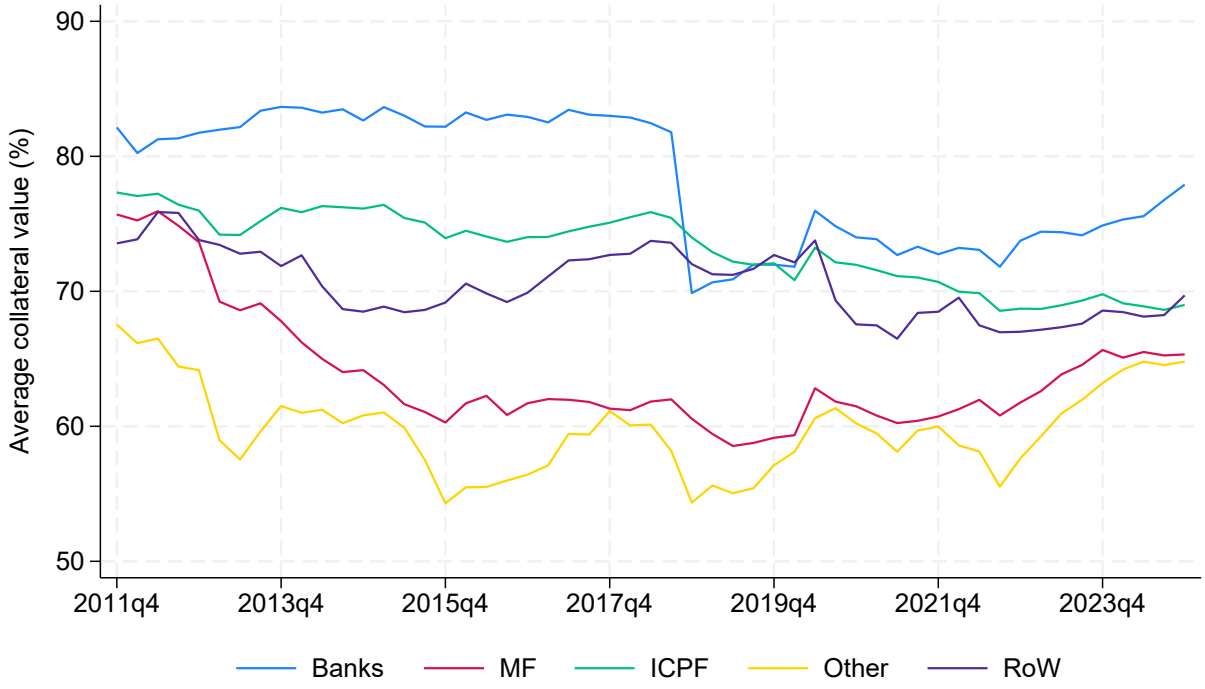


Figure 8: Average Collateral Value of Corporate Bond Portfolios by Investor Sector. The series above show the average collateral value (i.e., 100 minus the ECB collateral haircut in percentage points) of corporate bonds in each sector's portfolio at a quarterly basis. To calculate sector-level averages, bond-level haircuts are weighted by the face value of sectoral holdings. At the end of December 2018, a large set of German bank bonds became ineligible (details in Appendix I), so their collateral value effectively dropped to zero, which explains the drop in banks portfolios' average collateral value.

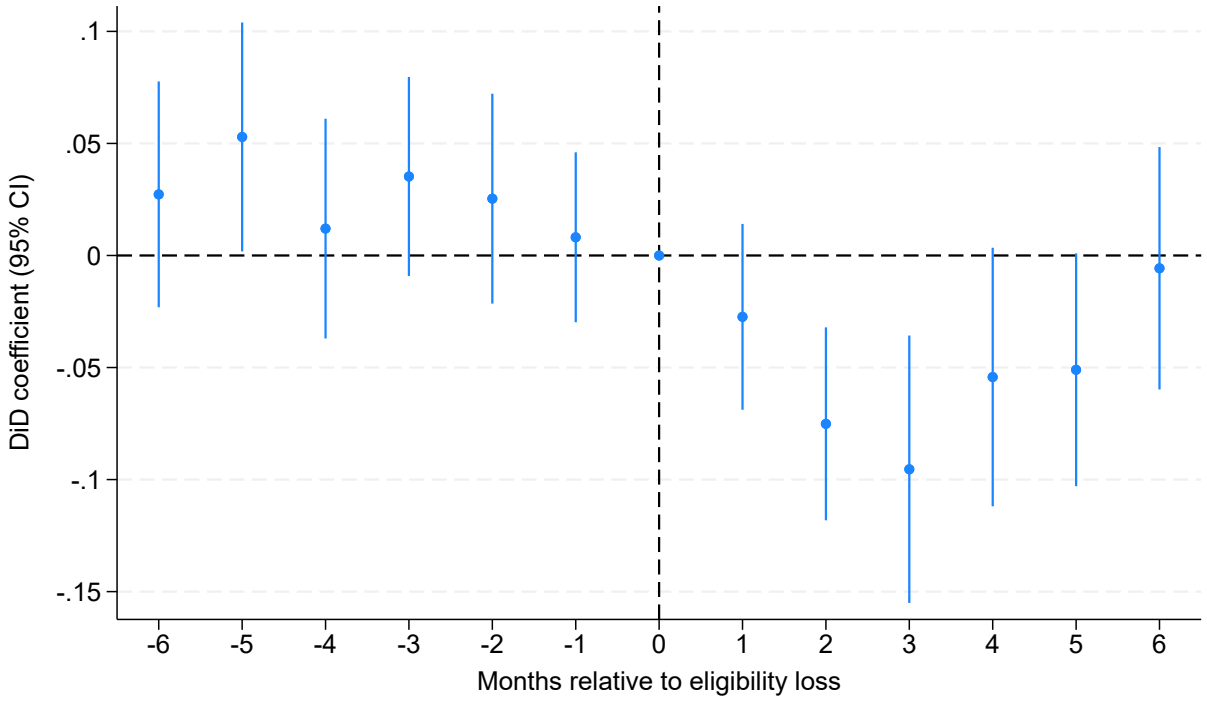


Figure 9: DiD coefficients around the loss of collateral eligibility. This plot displays the estimated coefficients of equation (14) where, instead of the $Post_t$ dummy, the treatment variable has been interacted with monthly dummy variables to trace the dynamic impact of the policy over time. The vertical line marks the loss of eligibility on December 31, 2018.

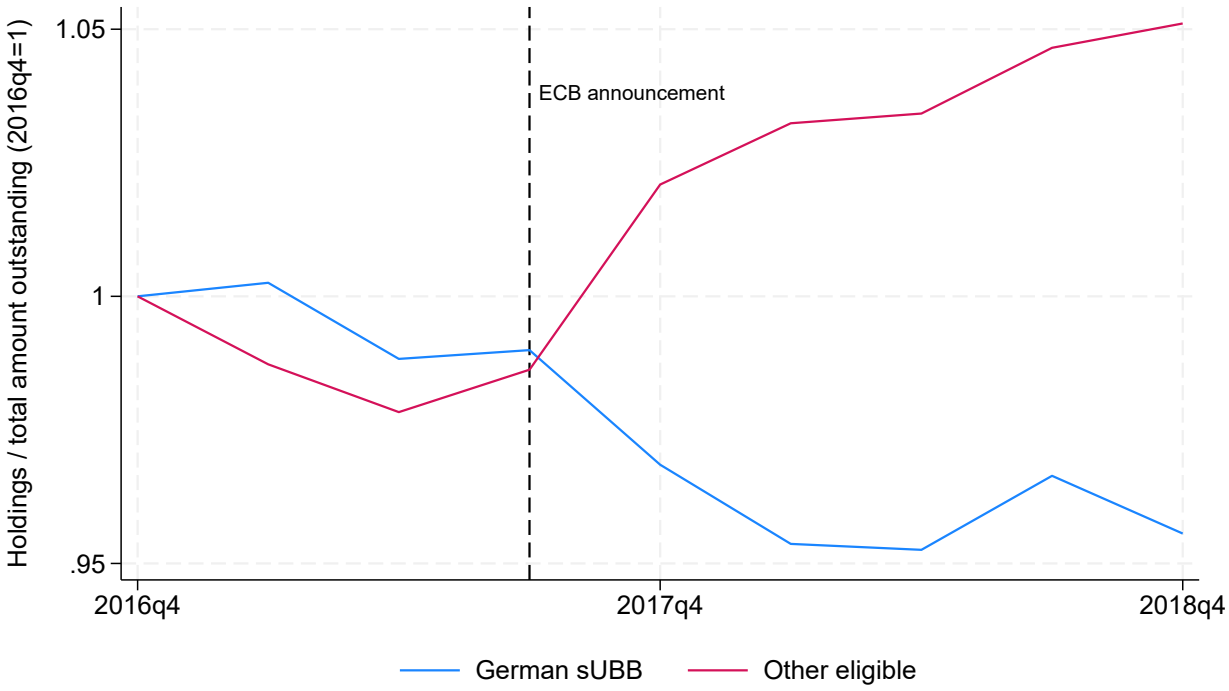


Figure 10: Banks' holdings of bank bonds around loss of collateral eligibility. This plot displays the nominal value of banks' total holdings of German sUBB (blue) and those of other collateral-eligible bank bonds (pink), each divided by their total amount outstanding and normalized to their respective 2016q4 holdings. In December 2017, German sUBB were announced to lose ECB collateral eligibility one year later, at the end of 2018.

Tables

Table 1: Summary Statistics. This table contains descriptive statistics about key variables used during our analysis. *Modified duration* measures the percentage bond price change in response to a change in yields. Due to the presence of non-zero coupon bonds, modified duration is weakly smaller than *residual maturity*. *Credit spreads* are the difference between a bond's yield to maturity and the duration-matched AAA sovereign bond yield. The *CDS-bond basis* is the difference between a bond's CDS spread and credit spread. *Collateral value* is calculated as $1-haircut$, *regulatory capital value* as $1 - stress$, where the stress parameter is an increasing function of duration and credit risk, defined in Art. 176 of Delegated Regulation (EU) 2015/35. *Bid-ask spreads* are calculated as $\frac{ask-bid}{bid} \times 100$.

(a) Corporate bonds

	Mean	SD	p10	Median	p90	N
Amount outstanding (bln EUR)	0.33	0.63	0.01	0.05	1.00	528,797
Residual maturity (years)	6.07	5.14	1.69	4.70	11.58	528,797
Modified duration (%)	5.39	4.03	1.64	4.39	10.01	528,797
Yield to maturity (%)	1.80	1.57	0.06	1.33	4.04	528,797
Credit spread (%)	1.16	0.81	0.43	0.99	2.05	528,797
CDS-bond basis (%)	-0.29	0.73	-1.06	-0.34	0.44	528,797
Collateral value	0.61	0.40	0.00	0.86	0.94	526,647
Regulatory capital value	0.93	0.05	0.87	0.94	0.98	528,797
Bid-ask spread (%)	0.51	0.49	0.15	0.40	0.97	166,146

(b) Sovereign bonds

	Mean	SD	p10	Median	p90	N
Amount outstanding (bln EUR)	7.31	9.90	0.03	1.45	22.15	119,458
Residual maturity (years)	11.62	9.95	2.29	8.24	26.16	119,508
Modified duration (%)	10.00	8.11	2.22	7.47	21.40	119,508
Yield to maturity (%)	1.70	1.66	-0.26	1.41	3.86	119,508
Credit spread (%)	0.84	0.97	0.02	0.59	1.92	119,508
CDS-bond basis (%)	-0.22	0.57	-0.87	-0.17	0.28	119,508
Collateral value	0.91	0.21	0.90	0.95	0.99	118,893
Regulatory capital value	1.00	0.00	1.00	1.00	1.00	119,508
Bid-ask spread (%)	0.23	0.40	0.02	0.09	0.61	77,916

Table 2: Average value of services. This table shows the results of the Fama-Macbeth regression of the CDS-bond basis on the proxy of four service flows in consideration.

	Dependent variable:				
	basis				
RBCvalue	0.086***				0.087***
	(0.002)				(0.003)
Duration		0.086***			0.203***
		(0.002)			(0.003)
Collateral			0.112***		0.031***
			(0.002)		(0.002)
Liquidity				0.073***	0.117***
				(0.002)	(0.003)
Observations	31,296	31,296	31,296	31,296	31,296
R^2	0.061	0.051	0.147	0.042	0.291
Adjusted R^2	0.057	0.047	0.143	0.038	0.288
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression Analysis of Triple-Sorted Portfolios. This table presents the coefficients obtained from a CAPM regression for portfolios sorted based on holdings, maturity, and credit ratings across different investor classes. Panel A excludes the eight-week Covid-19 disruption period in March and April 2020, while Panel B incorporates these weeks with an additional dummy variable to account for the pandemic's impact. The term *Combination* refers to an equally weighted portfolio of the Banks, Insurance Companies, Pension Funds (ICPF), and Mutual Funds (MF) portfolios.

	Panel A: Excluding Covid period				
	Banks	ICPF	MF	RoW	Combination (Banks+ICPF+MF)
	(1)	(2)	(3)	(4)	(5)
α	−0.011	−0.020***	0.004	0.021**	−0.009**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.004)
β_m	−0.076***	−0.075***	0.104***	0.071**	−0.016
	(0.027)	(0.027)	(0.026)	(0.030)	(0.013)
β_{term}	0.019	0.035***	−0.028**	−0.042***	0.009
	(0.013)	(0.013)	(0.012)	(0.014)	(0.006)
Observations	356	356	356	356	356
R^2	0.022	0.027	0.045	0.026	0.007
Adjusted R^2	0.016	0.022	0.039	0.020	0.001

	Panel B: All periods with Covid dummy				
α	−0.009	−0.020***	0.005	0.023***	−0.008**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.004)
$\beta_{m,\text{No Covid}}$	−0.077***	−0.076***	0.104***	0.069**	−0.016
	(0.027)	(0.027)	(0.026)	(0.030)	(0.013)
$\beta_{term,\text{No Covid}}$	0.019	0.035***	−0.027**	−0.042***	0.009
	(0.013)	(0.013)	(0.012)	(0.014)	(0.006)
$\beta_{m,\text{Covid}}$	−0.326***	−0.395***	0.304***	0.260***	−0.139***
	(0.034)	(0.034)	(0.032)	(0.037)	(0.016)
$\beta_{term,\text{Covid}}$	0.002	0.222***	−0.026	−0.080	0.066**
	(0.065)	(0.065)	(0.061)	(0.071)	(0.031)
Observations	364	364	364	364	364
R^2	0.406	0.389	0.394	0.228	0.261
Adjusted R^2	0.399	0.382	0.387	0.219	0.253

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: The effect of ECB collateral eligibility on convenience yield. This table displays the results of estimating equation (14), where each bond-month observation is weighted by its outstanding amount. The sample consists of senior unsecured bank bonds issued before April 2018 by euro area banks (which were eligible to be pledged as collateral with the ECB). The binary treatment variable *German* identifies German bank bonds that became ineligible for use as ECB collateral after December 2018. The indicator variable *Post* is equal to one for all observations after that event, and zero before. The sample period is June 2018 – June 2019, at monthly frequency. Standard errors are clustered at the bond-level.

	Dependent variable: CDS-bond basis			
	(1)	(2)	(3)	(4)
German=1 × Post=1	-0.0374*	-0.0412*	-0.0444**	-0.0708***
	(0.0227)	(0.0219)	(0.0226)	(0.0140)
German=1	0.0180	0.0213	0.0361	
	(0.0419)	(0.0414)	(0.0350)	
Post=1	-0.0589***			
	(0.0165)			
Time FE		✓	✓	✓
ISIN FE				✓
Rating x Maturity FE			✓	
R^2	0.01	0.03	0.16	0.85
Observations	16,840	16,840	16,840	16,793

Standard errors in parentheses

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

Table 5: The effect of ECB collateral eligibility on sectoral corporate bond holdings. This table displays the results of estimating equation (15) separately for five holdings sectors: Banks, mutual funds, insurance companies & pension funds, others (incl. households and non-financial corporations), and rest of the world (i.e., non-euro area holdings estimated as the residual). The sample consists of senior unsecured bank bonds issued before April 2018 by euro area banks (which were eligible to be pledged as collateral with the ECB). The binary treatment variable *German* identifies German bank bonds that became ineligible for use as ECB collateral after December 2018. The indicator variable *Post* is equal to one for all observations after the announcement in December 2017, and zero before. The sample period is June 2017 – June 2018, at quarterly frequency. The dependent variable has been rescaled to be measured in basis points. Standard errors are clustered at the bond-level.

	Dependent variable: Portfolio share				
	(1) Banks	(2) MF	(3) ICPF	(4) Other	(5) RoW
Post=1 × German=1	-4.533***	-0.686	-3.026	-0.661	-1.284
	(1.090)	(2.122)	(1.912)	(1.043)	(0.827)
German=1	-6.168***	-12.43***	-16.92***	-9.515***	-14.30***
	(1.200)	(2.765)	(2.089)	(1.197)	(1.497)
Time FE	✓	✓	✓	✓	✓
Holder country FE	✓	✓	✓	✓	✓
Rating x Maturity FE	✓	✓	✓	✓	✓
R^2	0.40	0.21	0.19	0.17	0.10
Observations	26,864	21,351	24,226	27,677	10,886

Standard errors in parentheses

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

Table 6: CDS-bond basis and regulatory value. This table displays the results of estimating equation (16) with either rating-by-maturity fixed effects or bond fixed effects. $HighRBC$ is a binary variable that indicates whether a bond's regulatory value (defined as $1 - stress$) exceeds the sample median. $10yRate$ is the ten-year sovereign debt interest rate obtained from the ECB yield curve estimation.

	Dependent variable: CDS-bond basis					
	(1)	(2)	(3)	(4)	(5)	(6)
RBC Value × 10yRate	-0.580***	-0.506***	-1.016***			
	(0.0148)	(0.0122)	(0.0185)			
High RBC=1 × 10yRate				-0.0536***	-0.0158***	-0.0719***
				(0.00144)	(0.00122)	(0.00173)
RBC Value	0.268***	-0.780***	0.588***			
	(0.0232)	(0.0336)	(0.0250)			
High RBC=1				0.0640***	-0.0842***	0.0822***
				(0.00250)	(0.00238)	(0.00265)
Time FE	✓	✓		✓	✓	
ISIN FE		✓			✓	
Rating x Maturity FE	✓			✓		
Rating x Maturity x Time FE			✓			✓
R^2	0.27	0.68	0.31	0.27	0.68	0.31
Observations	578,941	578,164	578,895	578,941	578,164	578,895

Standard errors in parentheses

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

Table 7: Sectoral holdings and regulatory value. This table displays the results of estimating equation (17) separately for five investor sectors: Banks, mutual funds, insurance companies & pension funds, others (incl. households and non-financial corporations), and the rest of the world (i.e., non-euro area holdings imputed as the residual). $HighRBC$ is a binary variable that indicates whether a bond's regulatory value (defined as $1 - stress$) exceeds the sample median. $10yRate$ is the ten-year sovereign debt interest rate obtained from the ECB yield curve estimation. The dependent variable has been rescaled to be measured in basis points.

	Dependent variable: Portfolio share				
	(1) Banks	(2) MF	(3) ICPF	(4) Other	(5) RoW
RBC Value × 10yRate	-1.247***	0.0713	-0.539***	0.264	0.777***
	(0.294)	(0.163)	(0.174)	(0.175)	(0.139)
RBC Value	1.753**	9.635***	0.0853	3.412***	9.805***
	(0.803)	(0.445)	(0.504)	(0.493)	(0.376)
Rating x Maturity x Time FE	✓	✓	✓	✓	✓
ISIN FE	✓	✓	✓	✓	✓
Holder country x Time FE	✓	✓	✓	✓	✓
R^2	0.44	0.46	0.37	0.27	0.90
Observations	553,972	922,690	1,009,399	787,139	180,277

Standard errors in parentheses

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

Table 8: Summary statistics. This table contains information about the distribution of key variables prior to corporate QE announcements, separately for eligible and ineligible corporate bonds. Outstanding amounts are measured in EUR million, and all remaining variables in percentage points.

(a) Pre-CSPP: September 2015 – February 2016

	Amount outstanding		Credit spread		CDS-bond basis	
	ineligible	eligible	ineligible	eligible	ineligible	eligible
Mean	242	650	1.05	1.12	-0.18	-0.29
SD	630	509	0.76	0.52	0.56	0.38
p10	10	70	0.27	0.61	-0.76	-0.68
p50	35	600	0.92	1.04	-0.18	-0.31
p90	750	1,200	1.94	1.77	0.43	0.11

(b) Pre-PEPP: September 2019 – February 2020

	Amount outstanding		Credit spread		CDS-bond basis	
	ineligible	eligible	ineligible	eligible	ineligible	eligible
Mean	165	611	1.10	0.88	-0.54	-0.32
SD	320	782	0.61	0.49	0.43	0.41
p10	10	20	0.57	0.34	-1.07	-0.82
p50	34	500	0.97	0.80	-0.53	-0.32
p90	575	1,250	1.81	1.50	-0.03	0.12

Table 9: The effect of the CSPP and the PEPP on corporate bond spreads. This table displays the results of estimating equation (18) for different outcome variables related to bond yields. The first row of each panel contains difference-in-differences estimates of the price impact of the respective corporate QE program. By construction, the difference between the estimated impact on CDS spreads (column 3) and credit spreads (column 2) equals the estimated impact on the CDS-bond basis (column 4).

(a) CSPP: September 2015 – September 2016

	(1) Bond Yield	(2) Credit Spread	(3) CDS Spread	(4) CDS - Bond Basis
Post=1 × CSPP eligible=1	-0.255***	-0.223***	-0.0659***	0.157***
	(0.0152)	(0.0149)	(0.0115)	(0.0133)
CSPP eligible=1	-0.0154	-0.0293***	-0.173***	-0.143***
	(0.0113)	(0.0111)	(0.00857)	(0.00986)
Time FE	✓	✓	✓	✓
Rating x Maturity FE	✓	✓	✓	✓
R^2	0.53	0.39	0.44	0.11
Observations	38,357	38,357	38,357	38,357

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) PEPP: September 2019 – September 2020

	(1) Bond Yield	(2) Credit Spread	(3) CDS Spread	(4) CDS - Bond Basis
Post=1 × PEPP eligible=1	-0.0545***	-0.0498***	0.0428***	0.0926***
	(0.0109)	(0.0109)	(0.00829)	(0.00948)
PEPP eligible=1	-0.279***	-0.280***	-0.0333***	0.247***
	(0.00837)	(0.00838)	(0.00635)	(0.00726)
Time FE	✓	✓	✓	✓
Rating x Maturity FE	✓	✓	✓	✓
R^2	0.52	0.49	0.40	0.24
Observations	42,490	42,490	42,490	42,490

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: The effect of corporate QE on sectoral corporate bond holdings. This table displays the results of estimating equation (19) separately for five holdings sectors: Banks, mutual funds, insurance companies & pension funds, others (incl. households and non-financial corporations), and rest of the world (i.e., non-euro area holdings estimated as the residual). The dependent variable has been rescaled to be measured in basis points. Standard errors are clustered at the firm and quarter level.

(a) CSPP: 2015q1 – 2016q4

	Dependent variable: Portfolio share				
	(1) Banks	(2) MF	(3) ICPF	(4) Other	(5) RoW
Post=1 × CSPP eligible=1	-0.338	0.297**	-0.0164	-0.444***	-0.408
	(0.189)	(0.0822)	(0.0719)	(0.0912)	(0.253)
CSPP eligible=1	-2.529**	-0.964*	0.345	-1.427**	1.709*
	(0.660)	(0.363)	(0.411)	(0.348)	(0.654)
Holder country x Time FE	✓	✓	✓	✓	✓
Rating x Maturity FE	✓	✓	✓	✓	✓
R^2	0.29	0.22	0.25	0.15	0.02
Observations	45,863	71,314	74,807	74,289	20,340

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) PEPP: 2019q1 – 2020q4

	Dependent variable: Portfolio share				
	(1) Banks	(2) MF	(3) ICPF	(4) Other	(5) RoW
Post=1 × PEPP eligible=1	-0.380*	0.253***	-0.224**	0.143**	-0.282
	(0.159)	(0.0441)	(0.0518)	(0.0394)	(0.253)
PEPP eligible=1	-0.316	-1.483***	-0.188	-1.426***	3.359**
	(0.620)	(0.227)	(0.240)	(0.264)	(1.092)
Holder country x Time FE	✓	✓	✓	✓	✓
Rating x Maturity FE	✓	✓	✓	✓	✓
R^2	0.33	0.22	0.22	0.16	0.07
Observations	55,582	106,540	115,522	81,059	21,114

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Appendix A. Proofs

Appendix A.1. Portfolio Allocation

We first prove that investor portfolio allocation is

$$\boldsymbol{x}_{it} = \frac{1}{a_{it}} \Sigma_t^{-1} \left(\boldsymbol{\mu_t} + \boldsymbol{s_{it}} \right) \tag{A.1}$$

where $\boldsymbol{\mu} = \mathbb{E}_t[\boldsymbol{r}_{t+1}]$, $\Sigma_t = Var(\boldsymbol{r}_{t+1})$, and $a_{it} = \gamma_{it} w_{it}$.

Then the objective becomes:

$$\max_{\mathbf{x}_{it}} \quad w_{it} \left(1 + r_t(f) + \mathbf{x}_{it}^\top (\boldsymbol{\mu}_t + \mathbf{s}_{it}) \right) - \frac{\gamma_{it}}{2} w_{it}^2 \mathbf{x}_{it}^\top \boldsymbol{\Sigma}_t \mathbf{x}_{it}$$

Taking first-order condition

$$w_{it}(\boldsymbol{\mu}_t + \mathbf{s}_{it}) - a_{it} w_{it} \boldsymbol{\Sigma}_t \mathbf{x}_{it} = 0$$

Solving for $\mathbf{x}_{it}$

$$\boxed{\mathbf{x}_{it} = \frac{1}{a_{it}} \boldsymbol{\Sigma}_t^{-1} (\boldsymbol{\mu}_t + \mathbf{s}_{it})}$$

Appendix A.2. Linear demand functions

We know that

$$\mathbf{x}_{it} = \frac{1}{a_t} \Sigma_t^{-1} \left(\boldsymbol{\mu}_t + Z_t \boldsymbol{\lambda}_{it} \right)$$
$$\mathbf{x}_{mt} = \frac{1}{a_t} \Sigma_t^{-1} \left(\boldsymbol{\mu}_t + Z_t \bar{\boldsymbol{\lambda}}_t \right)$$

Hence, investors' portfolio tilts from the market portfolio can be written as

$$\mathbf{x}_{it} - \mathbf{x}_{mt} = \frac{1}{a_t} \Sigma_t^{-1} Z_t \left(\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t \right)$$

The linear factor model for returns, implies that

$$\Sigma_t = \boldsymbol{\delta}_t^\top \Sigma_f \boldsymbol{\delta}_t + \Sigma_u$$

Using the Woodbury matrix identity, we have:

$$\Sigma_t^{-1} = \Sigma_u^{-1} - \Sigma_u^{-1} \boldsymbol{\delta}_t^\top \left(\Sigma_f^{-1} + \boldsymbol{\delta}_t \Sigma_u^{-1} \boldsymbol{\delta}_t^\top \right)^{-1} \boldsymbol{\delta}_t \Sigma_u^{-1}$$

Therefore:

$$\begin{aligned} \mathbf{x}_{it} - \mathbf{x}_{mt} &= \frac{1}{a_t} \Sigma_u^{-1} \left[\mathbf{I} - \boldsymbol{\delta}_t^\top \left(\Sigma_f^{-1} + \boldsymbol{\delta}_t \Sigma_u^{-1} \boldsymbol{\delta}_t^\top \right)^{-1} \boldsymbol{\delta}_t \Sigma_u^{-1} \right] Z_t (\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t) \\ &= \frac{1}{a_t} \Sigma_u^{-1} \left[Z_t (\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t) - \boldsymbol{\delta}_t^\top \boldsymbol{\kappa}_{it} \right] \end{aligned}$$

where

$$\boldsymbol{\kappa}_{it} = \left(\Sigma_f^{-1} + \boldsymbol{\delta}_t \Sigma_u^{-1} \boldsymbol{\delta}_t^\top \right)^{-1} \boldsymbol{\delta}_t \Sigma_u^{-1} Z_t (\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t)$$

Focusing on asset n, we have:

$$x_{it}(n) - x_{mt}(n) = \frac{1}{a_t \, \sigma_t(n)^2} \left[Z_t(n) (\boldsymbol{\lambda}_{it} - \bar{\boldsymbol{\lambda}}_t) - \boldsymbol{\delta}_t(n)^\top \boldsymbol{\kappa}_{it} \right]$$

Appendix A.3. Equilibrium expected returns

Now we want to show that excess expected returns can be written as:

$$\boldsymbol{\mu}_t = \boldsymbol{\beta}_t \mu_{mt} - \left(Z_t - \tilde{Z}_{mt} \right) \bar{\boldsymbol{\lambda}}_t \tag{A.2}$$

where $\beta_t = \frac{1}{\sigma_{mt}^2} \Sigma_t \boldsymbol{x}_{mt}$ and $\tilde{Z}_{mt} = Z_{mt} \beta_t$

Assume that $a_{it} = a_t$ for all agents and allow $\tilde{w}_{it} = \frac{w_{it}}{w_t}$ where w_t is total wealth. By market clearing, the weights in the market portfolio can be written as

$$\boldsymbol{x}_{mt} = \int_i \tilde{w}_{it} \boldsymbol{x}_{it} di$$

Replacing the optimal portfolio allocation, we have

$$\begin{aligned}\boldsymbol{x}_{mt} &= \int_i \tilde{w}_{it}\boldsymbol{x}_{it}di = \int_i \tilde{w}_{it}\cdot\frac{1}{a_t}\Sigma_t^{-1}\left(\boldsymbol{\mu}_t+\boldsymbol{s}_{it}\right)di \\ &= \frac{1}{a_t}\Sigma_t^{-1}\left(\boldsymbol{\mu}_t + Z_t\int_i \tilde{w}_{it}\boldsymbol{\lambda}_{it}di\right)\end{aligned}$$

So then

$$\boldsymbol{x}_{mt} = \frac{1}{a_t}\Sigma_t^{-1}\left(\boldsymbol{\mu}_t + Z_t\bar{\boldsymbol{\lambda}}_t\right), \quad \bar{\boldsymbol{\lambda}}_t = \int_i \tilde{w}_{it}\boldsymbol{\lambda}_{it}di \tag{A.3}$$

Rearranging this, we find then

$$\boldsymbol{\mu}_t = a_t\Sigma_t\boldsymbol{x}_{mt} - Z_t\bar{\boldsymbol{\lambda}}_t \tag{A.4}$$

Premultiply $\boldsymbol{x}_{mt}^\top$, the weights of the market portfolio, and set $\boldsymbol{x}_{mt}^\top Z_t = Z_{mt}^\top$:

$$\mu_{mt} = a_t\sigma_{mt}^2 - Z_{mt}^\top\bar{\boldsymbol{\lambda}}_t \tag{A.5}$$

where μ_{mt} and σ_{mt}^2 are the mean and variance of the market portfolio. This allows us to phrase the agent's relative risk aversion in terms of market primitives:

$$a_t = \frac{\mu_{mt} + Z_{mt}^\top\bar{\boldsymbol{\lambda}}_t}{\sigma_{mt}^2}$$

Plugging it in Eq. (A.4), we have

$$\begin{aligned}\boldsymbol{\mu}_t &= \frac{\mu_{mt} + Z_{mt}^\top\bar{\boldsymbol{\lambda}}_t}{\sigma_{mt}^2}\cdot\Sigma_t\boldsymbol{x}_{mt} - Z_t\bar{\boldsymbol{\lambda}}_t \\ &= \frac{\mu_{mt}}{\sigma_{mt}^2}\Sigma_t\boldsymbol{x}_{mt} + \frac{Z_{mt}^\top\bar{\boldsymbol{\lambda}}_t}{\sigma_{mt}^2}\Sigma_t\boldsymbol{x}_{mt} - Z_t\bar{\boldsymbol{\lambda}}_t \\ &= \frac{\mu_{mt}}{\sigma_{mt}^2}\Sigma_t\boldsymbol{x}_{mt} - \left(Z_t - \frac{Z_{mt}^\top\Sigma_t\boldsymbol{x}_{mt}}{\sigma_{mt}^2}\right)\bar{\boldsymbol{\lambda}}_t\end{aligned}$$

Hence

$$\boldsymbol{\mu}_t = \boldsymbol{\beta}_t\mu_{mt} - \left(Z_t - \tilde{Z}_{mt}\right)\bar{\boldsymbol{\lambda}}_t \tag{A.6}$$

where $\beta_t = \frac{1}{\sigma_{mt}^2}\Sigma_t\boldsymbol{x}_{mt}$ and $\tilde{Z}_{mt} = \beta_t Z_{mt}^\top$

If $Z_{mt}^\top = 0$, i.e., the average service flow is zero,

$$\boxed{\boldsymbol{\mu}_t = \boldsymbol{\beta}_t\mu_{mt} - Z_t\bar{\boldsymbol{\lambda}}_t} \tag{A.7}$$

Appendix A.4. Model Predictions

Proposition 1 (Service-Driven Portfolio Rebalancing)**.** *Consider two investors i and j with heterogeneous valuations for service k. Investor i exhibits a larger portfolio rebalancing than investor j in response to a marginal change in the service k for asset (n), i.e. a perturbation in $z_t^k(n)$,*

$$\frac{\partial \mathbf{x}_{it}}{\partial z_t^k(n)} > \frac{\partial \mathbf{x}_{jt}}{\partial z_t^k(n)},$$

if and only if

$$\lambda_{it}^k > \lambda_{jt}^k.$$

Proof. From equation (4), the portfolio choice of investor $\ell \in \{i, j\}$ is

$$\mathbf{x}_{\ell t} = \frac{1}{a_t} \Sigma_t^{-1}\big(\mu_t + Z_t \lambda_{\ell t}\big).$$

Differentiating with respect to $z_t^k(n)$ yields

$$\frac{\partial \mathbf{x}_{\ell t}}{\partial z_t^k(n)} = \frac{1}{a_t} \Sigma_t^{-1}\left(\frac{\partial \mu_t}{\partial z_t^k(n)} + \lambda_{\ell t}^k \, e_n\right),$$

where e_n is the unit vector selecting the n-th asset.

Taking the difference between investors i and j:

$$\frac{\partial \mathbf{x}_{it}}{\partial z_t^k(n)} - \frac{\partial \mathbf{x}_{jt}}{\partial z_t^k(n)} = \frac{1}{a_t} \Sigma_t^{-1}\Big((\lambda_{it}^k - \lambda_{jt}^k) e_n\Big).$$

Since the common term $\frac{\partial \mu_t}{\partial z_t^k(n)}$ cancels, the inequality between rebalancing responses is determined entirely by the difference in valuations $\lambda_{it}^k - \lambda_{jt}^k$. Hence, investor i exhibits a strictly larger rebalancing in asset (n) if and only if $\lambda_{it}^k > \lambda_{jt}^k$. □

Proposition 2 (Service Preference and Convenience Yield)**.** *Consider two assets n and m with service characteristics $Z_t^k(n) > Z_t^k(m)$ for service k. Everything else equal, if the aggregate preference for service k increases, then the convenience yield of the asset with higher service provision increases more than the asset with lower service provision.*

Formally:

$$Z_t^k(n) > Z_t^k(m) \text{ and } \Delta\bar{\lambda}_t(k) > 0 \implies \Delta cy_t(n) > \Delta cy_t(m)$$

Proof. From equation (9), the convenience yield of asset j is:

$$cy_t(j) = Z_t^k(j)\bar{\lambda}_t(k) + \sum_{l \neq k} Z_t^l(j)\bar{\lambda}_t(l)$$

When the aggregate preference for service k changes by $\Delta\bar{\lambda}_t(k)$, holding all other service valuations constant ($\Delta\bar{\lambda}_t(l) = 0$ for $l \neq k$), the change in convenience yield for asset j is:

$$\Delta cy_t(j) = Z_t^k(j)\Delta\bar{\lambda}_t(k)$$

The difference in convenience yield changes between assets n and m is:

$$\Delta cy_t(n) - \Delta cy_t(m) = \left[Z_t^k(n) - Z_t^k(m)\right]\Delta\bar{\lambda}_t(k)$$

Since by assumption $Z_t^k(n) > Z_t^k(m)$ and $\Delta\bar{\lambda}_t(k) > 0$:

$$\Delta cy_t(n) - \Delta cy_t(m) = \left[Z_t^k(n) - Z_t^k(m)\right]\Delta\bar{\lambda}_t(k) > 0$$

Therefore:

$$\Delta cy_t(n) > \Delta cy_t(m)$$

This result holds for any positive change in aggregate service valuation, regardless of magnitude. □

Appendix B. Extra Descriptive Information

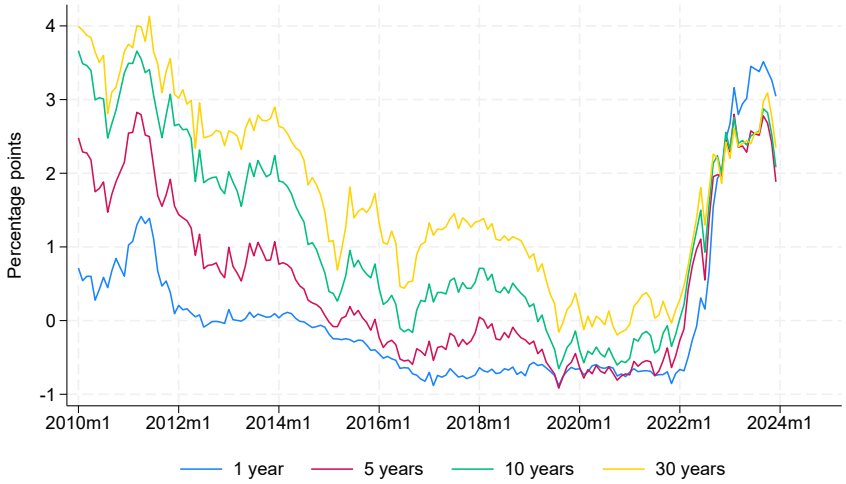


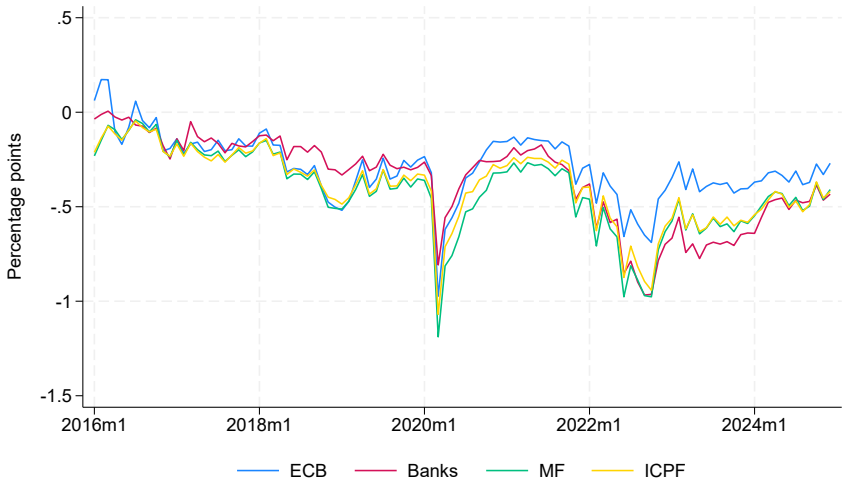
Figure B.11: ECB benchmark interest rates for different maturities. This plot presents the time series of the benchmark interest rate for 1Y, 5Y,10Y, and 30Y maturity. The ECB benchmark interest rate is provided under the Euro area yield curves estimation and is used as an approximate measure of risk-free rate in the Euro area. It is estimated daily by using the AAA-rated euro area central government bonds.

Appendix C. Heterogeneity in convenience yields across investors

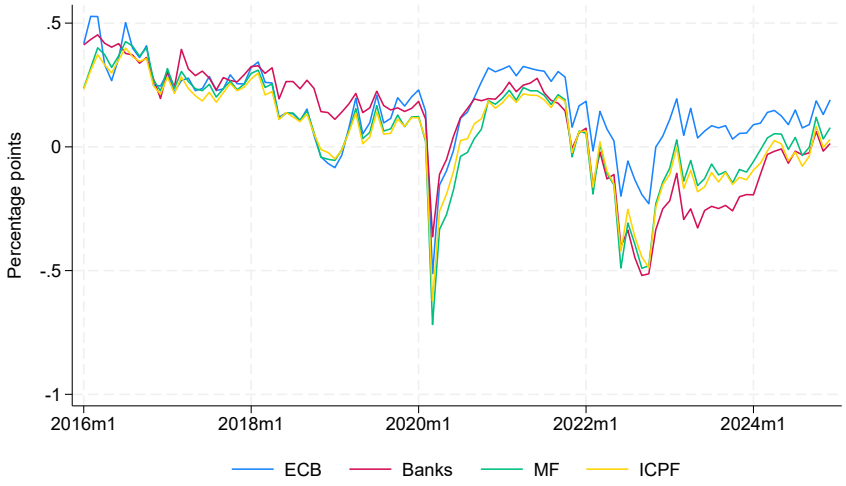
Table C.11 and Figure C.12 contain the average CDS-bond basis for each investor sector's corporate bond portfolio.

Table C.11: CDS-bond basis by investor sector This table contains distributional summary statistics of the CDS-bond basis (calculated by subtracting a bond's credit spread from its CDS spread), separately for each investor type's portfolio. All moments are obtained by weighting observations by nominal holdings.

	Mean	SD	Min	p10	p25	p50	p75	p90	Max
ECB	-0.34	0.33	-3.02	-0.69	-0.51	-0.34	-0.17	-0.01	2.13
Banks	-0.34	0.48	-3.05	-0.91	-0.59	-0.32	-0.09	0.16	2.65
ICPF	-0.37	0.41	-3.05	-0.85	-0.56	-0.35	-0.14	0.05	2.65
MF	-0.42	0.46	-3.05	-0.96	-0.63	-0.39	-0.17	0.04	2.56
Other	-0.47	0.47	-3.05	-1.04	-0.70	-0.44	-0.19	0.02	2.65
RoW	-0.24	0.42	-3.05	-0.70	-0.41	-0.18	-0.06	0.14	2.65



(a) CDS-bond basis of portfolios of different investor classes



(b) CDS-bond basis of portfolios of different investor classes after absorbing Rating x Maturity FE

Figure C.12: Value-weighted average CDS-bond basis of each investor sector's corporate bond portfolio Panel (a) of this plot presents the average CDS-bond basis (weighted by nominal holdings) of each investor sector's corporate bond portfolio. Panel (b) plots the average residual from a regression of the CDS-bond basis on rating x maturity dummies for each investor sector, again weighted by nominal holdings.

Appendix D. Sovelcy II Regulation Details

Table below shows the stress parameter calculation in accordance to Article 176 of the Solvency II Directive 2009/138/EC.

Table D.12: Credit Quality Step Stress Parameters by Duration

Duration (dur_i)	$stress_i$	Credit quality step											
		0		1		2		3		4		5 and 6	
		a_i	b_i	a_i	b_i	a_i	b_i	a_i	b_i	a_i	b_i	a_i	b_i
up to 5	$b_i \cdot dur_i$	—	0.9%	—	1.1%	—	1.4%	—	2.5%	—	4.5%	—	7.5%
More than 5 and up to 10	$a_i + b_i \cdot (dur_i - 5)$	4.5%	0.5%	5.5%	0.6%	7.0%	0.7%	12.5%	1.5%	22.5%	2.5%	37.5%	4.2%
More than 10 and up to 15	$a_i + b_i \cdot (dur_i - 10)$	7.0%	0.5%	8.4%	0.5%	10.5%	0.5%	20.0%	1.0%	35.0%	1.8%	58.5%	0.5%
More than 15 and up to 20	$a_i + b_i \cdot (dur_i - 15)$	9.5%	0.5%	10.9%	0.5%	13.0%	0.5%	25.0%	1.0%	44.0%	0.5%	61.0%	0.5%
More than 20	$\min[a_i + b_i \cdot (dur_i - 20); 1]$	12.0%	0.5%	13.4%	0.5%	15.5%	0.5%	30.0%	0.5%	46.5%	0.5%	63.5%	0.5%

Furthermore, Article 180 paragraph 2 determines specific stress calculations for certain bonds. In particular, exposures in the form of bonds and loans to the following shall be assigned a risk factor $stress_i$ of 0 %:

(a) the European Central Bank;

(b) Member States' central government and central banks denominated and funded in the domestic currency of that central government and the central bank;

(c) multilateral development banks referred to in paragraph 2 of Article 117 of Regulation (EU) No 575/2013;

(d) international organisations referred to in Article 118 of Regulation (EU) No 575/2013.

Furthermore, exposures in the form of bonds and loans that are fully, unconditionally, and irrevocably guaranteed by one of the counterparties mentioned in points (a) to (d), where the guarantee meets the requirements set out in Article 215, shall also be assigned a risk factor stress of 0%.

Appendix E. Extra results on the decomposition of convenience yields

In this section we propose a different regression to decompose convenience yields. For each point in time, we run the following cross-section regression

$$b_t(n) = \alpha_t + \sum_k \lambda_{kt} z_{kt}(n) + \varepsilon_t(n) \tag{E.1}$$

Notice that our model predicts that $\alpha_t = 0, \forall t$. However, this equality is not necessarily upheld in a simple OLS regression. We therefore interpret the difference, $-\alpha_t - z_t(T)^\top \boldsymbol{\lambda}_t$, as the average value of other services omitted from the model. The plots below show the results.

Appendix F. Evidence from portfolio sorting on holdings share

Table F.13: Annualized descriptive statistics for long-short portfolios. On the top panel, portfolios are sorted by holdings. On the bottom panel, portfolios are sorted by holding, maturity, and rating.

	Single Sorted Portfolios		
Investor	Mean	SD	SR
Banks	-1.821	2.988	-0.610
ECB	-0.890	2.724	-0.327
ICPF	-0.645	2.730	-0.236
MF	1.198	2.719	0.441
Other	-0.299	1.868	-0.160
RoW	0.604	1.919	0.315
Market	2.438	3.367	0.724

	Triple Sorted Portfolios		
Investor	Mean	SD	SR
Banks	-0.430	3.289	-0.131
ECB	0.167	1.580	0.106
ICPF	-0.905	3.115	-0.290
MF	0.307	3.004	0.102
Other	-0.374	2.681	-0.139
RoW	1.131	3.249	0.348

Table F.14: Regression Analysis of Single-Sorted Portfolios. This table presents the coefficients obtained from a CAPM regression for portfolios sorted based on holdings across different investor classes. Panel A excludes the eight-week Covid-19 disruption period in March and April 2020, while Panel B incorporates these weeks with an additional dummy variable to account for the pandemic's impact. The term *Combination* refers to an equally weighted portfolio of the Banks, Insurance Companies, Pension Funds (ICPF), and Mutual Funds (MF) portfolios.

	Panel A: Excluding Covid period				
	Banks	ICPF	MF	RoW	Combination (Banks+ICPF+MF)
	(1)	(2)	(3)	(4)	(5)
α	−0.001	−0.024**	0.016*	0.017**	−0.003
	(0.007)	(0.010)	(0.010)	(0.007)	(0.003)
β_m	−0.836***	−0.261***	0.542***	0.214***	−0.185***
	(0.026)	(0.037)	(0.035)	(0.027)	(0.011)
β_{term}	0.124***	0.476***	−0.365***	−0.290***	0.078***
	(0.012)	(0.018)	(0.017)	(0.013)	(0.005)
Observations	356	356	356	356	356
R^2	0.765	0.689	0.579	0.592	0.484
Adjusted R^2	0.764	0.687	0.576	0.590	0.481

	Panel B: All periods with Covid dummy				
α	−0.003	−0.027**	0.019*	0.020**	−0.004
	(0.008)	(0.012)	(0.011)	(0.008)	(0.003)
$\beta_{m,\text{No Covid}}$	−0.834***	−0.259***	0.540***	0.212***	−0.184***
	(0.030)	(0.043)	(0.041)	(0.030)	(0.012)
$\beta_{term,\text{No Covid}}$	0.124***	0.476***	−0.365***	−0.290***	0.078***
	(0.014)	(0.021)	(0.020)	(0.015)	(0.006)
$\beta_{m,\text{Covid}}$	−0.841***	−0.513***	0.756***	0.491***	−0.200***
	(0.037)	(0.054)	(0.052)	(0.038)	(0.015)
$\beta_{term,\text{Covid}}$	−0.156**	0.265**	−0.147	−0.177**	−0.012
	(0.070)	(0.103)	(0.098)	(0.072)	(0.029)
Observations	364	364	364	364	364
R^2	0.871	0.669	0.696	0.669	0.677
Adjusted R^2	0.870	0.665	0.692	0.666	0.674

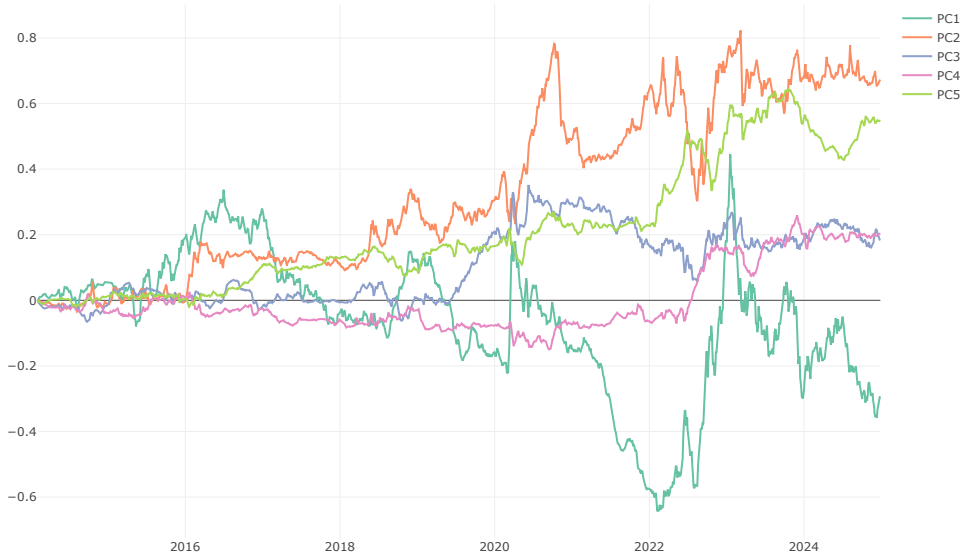
Note: *p<0.1; **p<0.05; ***p<0.01

Table F.15: Regression Analysis of Triple-Sorted Portfolios. This table presents the coefficients obtained from a CAPM regression for portfolios sorted based on holdings, maturity, and credit ratings across different investor classes. In this table we do not control for the Covid period. The term *Combination* refers to an equally weighted portfolio of the Banks, Insurance Companies, Pension Funds (ICPF), and Mutual Funds (MF) portfolios.

	No Covid treatment				
	Banks	ICPF	MF	RoW	Combination (Banks + ICPF + MF)
	(1)	(2)	(3)	(4)	(5)
α	0.0005	−0.010	−0.003	0.016**	−0.004
	(0.008)	(0.008)	(0.007)	(0.008)	(0.004)
β_m	−0.235***	−0.231***	0.228***	0.179***	−0.079***
	(0.019)	(0.019)	(0.018)	(0.020)	(0.009)
β_{term}	0.047***	0.069***	−0.050***	−0.063***	0.022***
	(0.013)	(0.013)	(0.012)	(0.014)	(0.006)
Observations	364	364	364	364	364
R^2	0.303	0.285	0.322	0.177	0.175
Adjusted R^2	0.299	0.281	0.318	0.172	0.171

Appendix G. Principle Component Analysis

(a) Cumulative Returns of the Top 5 Principal Components



(b) Cumulative Variance Explained by the Top 5 Principal Components

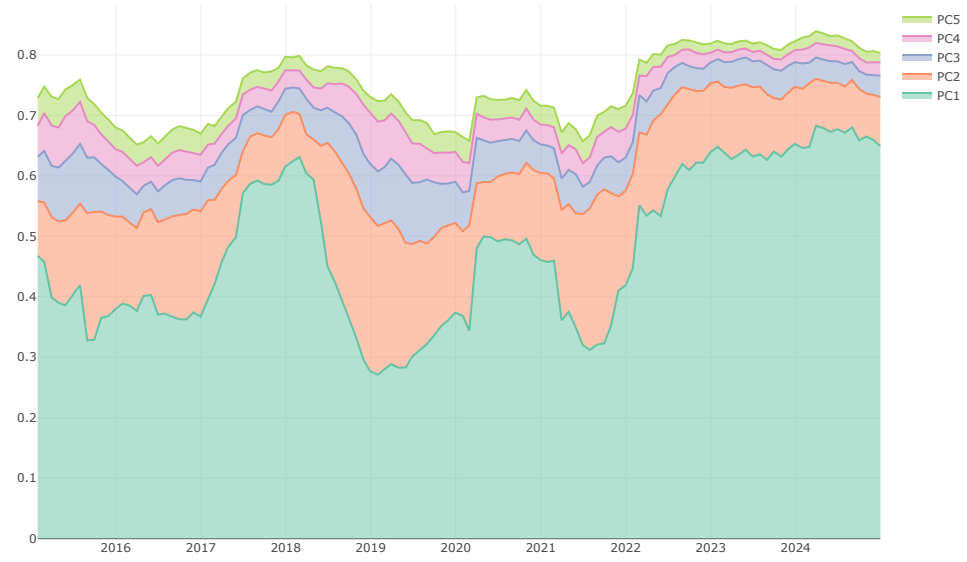


Figure G.13: Top 5 Principal Components. This figure shows a time series view of the top 5 principal components. The top panel represents the time series cumulative returns of the top 5 principal components and the bottom panel is the variance contribution of each principal component.

Appendix H. Extra Results for Corporate QE

Table H.16: The effect of CSPP on corporate bond spreads. This table displays the results of estimating equation (18) where the outcome variables is a bond's credit spread. The first row contains difference-in-differences estimates of the price impact of CSPP. The different columns refer to different sets of fixed effects. The time period is September 2015 – September 2016.

	Dependent variable: Credit Spread				
	(1)	(2)	(3)	(4)	(5)
Post=1 × CSPP eligible=1	-0.223***	-0.250***	-0.249***	-0.201***	-0.227***
	(0.0149)	(0.00693)	(0.00693)	(0.0152)	(0.00685)
CSPP eligible=1	-0.0293***	0.324***	0.336***	-0.0407***	0.305***
	(0.0111)	(0.0313)	(0.0312)	(0.0111)	(0.0303)
Time FE	✓	✓	✓		
ISIN FE		✓	✓		✓
Rating x Maturity FE	✓		✓		
Rating x Maturity x Time FE				✓	✓
R^2	0.39	0.89	0.89	0.40	0.90
Observations	38,357	38,148	38,148	38,352	38,142

Standard errors in parentheses

Sample period: Sep 2015 – Sep 2016

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

Table H.17: The effect of CSPP on CDS spreads. This table displays the results of estimating equation (18) where the outcome variables is a bond's CDS spread. The first row contains difference-in-differences estimates of the price impact of CSPP. The different columns refer to different sets of fixed effects. The time period is September 2015 – September 2016.

	Dependent variable: CDS Spread				
	(1)	(2)	(3)	(4)	(5)
Post=1 × CSPP eligible=1	-0.0659***	-0.0988***	-0.0987***	-0.0635***	-0.0951***
	(0.0115)	(0.00479)	(0.00479)	(0.0117)	(0.00459)
CSPP eligible=1	-0.173***	0.0807***	0.0797***	-0.173***	0.0651***
	(0.00857)	(0.0216)	(0.0216)	(0.00858)	(0.0203)
Time FE	✓	✓	✓		
ISIN FE		✓	✓		✓
Rating x Maturity FE	✓		✓		
Rating x Maturity x Time FE				✓	✓
R^2	0.44	0.92	0.92	0.45	0.93
Observations	38,357	38,148	38,148	38,352	38,142

Standard errors in parentheses

Sample period: Sep 2015 – Sep 2016

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

Table H.18: The effect of CSPP on the CDS-bond basis. This table displays the results of estimating equation (18) where the outcome variables is a bond's CDS-bond basis. The first row contains difference-in-differences estimates of the price impact of CSPP. The different columns refer to different sets of fixed effects. The time period is September 2015 – September 2016.

	Dependent variable: CDS - Bond Basis				
	(1)	(2)	(3)	(4)	(5)
Post=1 × CSPP eligible=1	0.157***	0.151***	0.151***	0.138***	0.132***
	(0.0133)	(0.00714)	(0.00715)	(0.0136)	(0.00719)
CSPP eligible=1	-0.143***	-0.243***	-0.256***	-0.133***	-0.239***
	(0.00986)	(0.0322)	(0.0323)	(0.00996)	(0.0318)
Time FE	✓	✓	✓		
ISIN FE		✓	✓		✓
Rating x Maturity FE	✓		✓		
Rating x Maturity x Time FE				✓	✓
R^2	0.11	0.79	0.79	0.12	0.80
Observations	38,357	38,148	38,148	38,352	38,142

Standard errors in parentheses

Sample period: Sep 2015 – Sep 2016

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

Table H.19: The effect of PEPP on corporate bond spreads. This table displays the results of estimating equation (18) where the outcome variables is a bond's credit spread. The first row contains difference-in-differences estimates of the price impact of PEPP. The different columns refer to different sets of fixed effects. The time period is September 2019 – September 2020.

	Dependent variable: Credit Spread				
	(1)	(2)	(3)	(4)	(5)
Post=1 × PEPP eligible=1	-0.0498***	-0.00236	-0.0130**	-0.0436***	-0.0447***
	(0.0109)	(0.00640)	(0.00639)	(0.0111)	(0.00603)
PEPP eligible=1	-0.280***	-0.181***	0.0369	-0.286***	0.318***
	(0.00838)	(0.0368)	(0.0385)	(0.00832)	(0.0353)
Time FE	✓	✓	✓		
ISIN FE		✓	✓		✓
Rating x Maturity FE	✓		✓		
Rating x Maturity x Time FE				✓	✓
R^2	0.49	0.86	0.86	0.53	0.89
Observations	42,490	42,245	42,245	42,490	42,245

Standard errors in parentheses

Sample period: Sep 2019 – Sep 2020

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

Appendix H.1. Parallel trends

To assess the validity of the parallel trends assumption and provide evidence of the dynamic impact of both ECB packages for different time periods, we set up a Granger causality test, as suggested in Angrist and Pischke [2009]. We split the *Post* dummy into monthly dummies and run the following specification:

$$y_t(n) = \sum_{\tau} \theta_{0,\tau} \times \mathbb{1}_{\tau=t} \times Eligible_t(n) + \alpha_{R\times M} + \alpha_t + \epsilon_t(n) \tag{H.1}$$

Table H.20: The effect of PEPP on CDS spreads. This table displays the results of estimating equation (18) where the outcome variables is a bond's CDS spread. The first row contains difference-in-differences estimates of the price impact of PEPP. The different columns refer to different sets of fixed effects. The time period is September 2019 – September 2020.

	Dependent variable: CDS Spread				
	(1)	(2)	(3)	(4)	(5)
Post=1 × PEPP eligible=1	0.0428***	0.0808***	0.0745***	0.0783***	0.0728***
	(0.00829)	(0.00418)	(0.00418)	(0.00839)	(0.00387)
PEPP eligible=1	-0.0333***	-0.334***	-0.199***	-0.0541***	0.00706
	(0.00635)	(0.0240)	(0.0252)	(0.00627)	(0.0226)
Time FE	✓	✓	✓		
ISIN FE		✓	✓		✓
Rating x Maturity FE	✓		✓		
Rating x Maturity x Time FE				✓	✓
R^2	0.40	0.87	0.88	0.45	0.91
Observations	42,490	42,245	42,245	42,490	42,245

Standard errors in parentheses

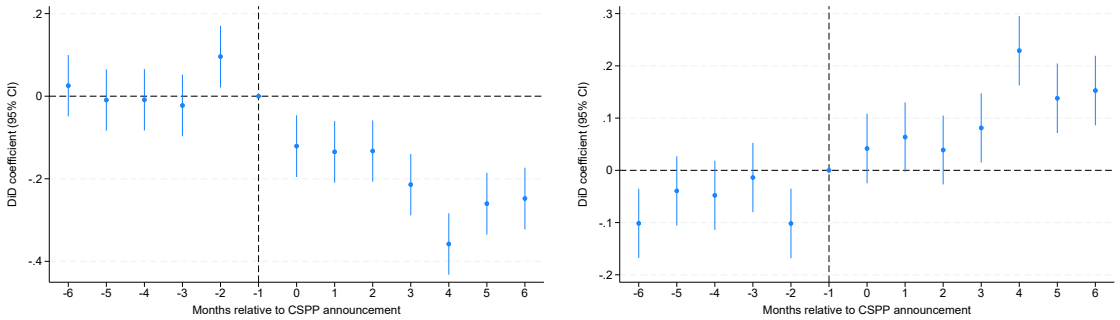
Sample period: Sep 2019 – Sep 2020

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

We chose the month before the program announcement as reference date. Figure H.14 shows the dynamic DiD coefficient estimates with 95% confidence intervals for the two events (CSPP and PEPP) for the credit spread (left-hand side) and for the CDS-Bond basis (right-hand side).

The impact of the two programs on the credit spread is clear. We observe that all coefficients are not statistically significant and close to zero until the month before the program announcement, whereas they become negative and statistically significant in the months that follow. The fact that we do not observe significant differences in the pre-period is strong evidence that the parallel trends assumption holds.

(a) CSPP: September 2015 – September 2016



(b) PEPP: September 2019 – September 2020

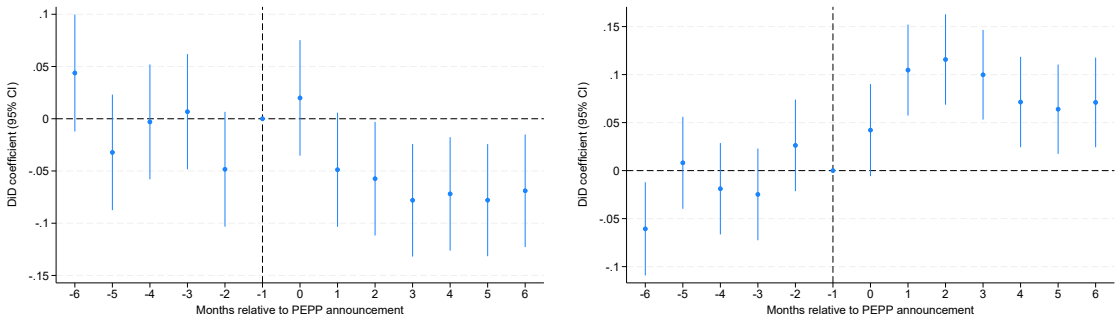


Figure H.14: DiD coefficients around the CSPP and the PEPP announcement. This figure contains the monthly point estimates in equation (H.1) where the dependent variables are credit spreads (left-hand panel) and the CDS-bond basis (right-hand panel).

Table H.21: The effect of PEPP on the CDS-bond basis. This table displays the results of estimating equation (18) where the outcome variables is a bond's CDS-bond basis. The first row contains difference-in-differences estimates of the price impact of PEPP. The different columns refer to different sets of fixed effects. The time period is September 2019 – September 2020.

	Dependent variable: CDS - Bond Basis				
	(1)	(2)	(3)	(4)	(5)
Post=1 × PEPP eligible=1	0.0926***	0.0831***	0.0875***	0.122***	0.118***
	(0.00948)	(0.00546)	(0.00549)	(0.00991)	(0.00555)
PEPP eligible=1	0.247***	-0.153***	-0.236***	0.232***	-0.311***
	(0.00726)	(0.0314)	(0.0331)	(0.00741)	(0.0325)
Time FE	✓	✓	✓		
ISIN FE		✓	✓		✓
Rating x Maturity FE	✓		✓		
Rating x Maturity x Time FE				✓	✓
R^2	0.24	0.80	0.80	0.26	0.81
Observations	42,490	42,245	42,245	42,490	42,245

Standard errors in parentheses

Sample period: Sep 2019 – Sep 2020

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

Regarding the CDS-Bond basis, we observe a positive significant result after the announcement of the CSPP, but no effect in the pre-period.

Appendix I. ECB Collateral Eligibility

Appendix I.1. A snapshot of ECB haircuts as 06/29/2023

Table I.22: ECB haircuts for different bond categories. This table contains the haircuts that the ECB applies to the market value of securities pledged as collateral. The maximum amount a bank can borrow against a given amount of collateral is (100-haircut)% times the market value of the pledged security. The collateral framework is periodically reviewed and changes to the haircut schedule are not unusual. Per Guideline ECB/2022/49 the schedule below is effective as of 29 June 2023.

Rating	Residual Maturity	Central government		Local gov. + covered bonds		NFC		FC	
		Fix/Float	Zero	Fix/Float	Zero	Fix/Float	Zero	Fix/Float	Zero
AAA-A	0-1y	0.5	0.5	1.0	1.0	1.0	1.0	7.5	7.5
	1-3y	1.0	2.0	1.5	2.5	2.0	3.0	10.0	11.5
	3-5y	1.5	2.5	2.5	3.5	3.0	4.5	12.0	13.0
	5-7y	2.0	3.0	3.5	4.5	4.5	6.0	14.0	15.0
	7-10y	3.0	4.0	4.5	6.5	6.0	8.0	16.0	17.5
	10-15y	4.0	5.0	6.5	8.5	7.5	10.0	18.0	22.5
	15-30y	5.0	6.0	8.0	11.5	9.0	13.0	21.0	25.0
	>30y	6.0	9.0	10.0	13.0	11.0	16.0	24.0	31.5
BBB	0-1y	5.0	5.0	5.5	5.5	6.5	6.5	11.5	11.5
	1-3y	6.0	7.0	7.5	10.5	9.5	12.0	18.5	20.0
	3-5y	8.5	10.0	11.0	16.0	13.0	18.0	23.0	27.0
	5-7y	10.0	11.5	12.5	17.0	15.0	21.5	25.5	29.5
	7-10y	11.5	13.0	14.0	21.0	17.0	23.5	26.5	31.5
	10-15y	12.5	14.0	17.0	25.5	19.5	28.0	28.5	35.0
	15-30y	13.5	15.0	20.0	28.5	22.0	31.0	31.5	39.0
	>30y	14.0	17.0	22.0	32.5	25.0	35.5	34.5	43.0

Appendix I.2. The Change of Eligibility of Subordinated Unsecured Bank Bonds

The ultimate cause of the change in ECB collateral eligibility of senior unsecured bank bonds in December 2018 is the Directive of the European Union 2014/59/EU, also called the Bank Recovery and Resolution Directive (BRRD). Among other things, the directive required banks to increase their total loss-absorbing capital (TLAC) and comply with the new minimum requirement for own funds and eligible liabilities (MREL), so that a significant

share of liabilities could be written down before public funds be used in the recovery of a failing bank. In other words, banks had to issue more "bail-in-able" securities that are subordinated to deposits, covered liabilities, and other senior liabilities such as wages and taxes.

Importantly, the directive allowed three ways of implementing the new rules, leaving it open to member states to decide which approach they preferred:

- *Contractual subordination*, where the subordination is explicitly stated in the bond's terms. This effectively amounts to the creation of an entirely new asset class, sometimes called *senior non-preferred* liabilities. France and Spain were among the early adopters of this option.

- *Structural subordination*, which applies only to banks with a holding structure: Debt issued by a holding company is automatically structurally subordinated to debt issued by the operating company. This applied mostly to banks from the UK, Belgium, Switzerland, and the Netherlands.

- *Statutory subordination*, where all senior bank bonds would be subordinated by law, through a modification of national insolvency laws. Germany was the only member state to take this route.

Regardless of which approach was taken, subordinated uncovered bank bonds (sUBB), even if called "senior", are more risky than plain-vanilla senior bank debt by construction. Any exposure to potential bail-in losses during a bank's resolution could jeopardize the ECB's authority and even create conflicts of interest. This is what motivated the ECB to reconsider its collateral framework and, in particular, which bank bonds it should accept as collateral going forward. The most immediate solution would have been to simply stop accepting all subordinated UBB. However, this would have put German banks at a significant disadvantage. While, for example, French banks could have issued both senior preferred and senior non-preferred UBB (the former of which would have been eligible for collateral),

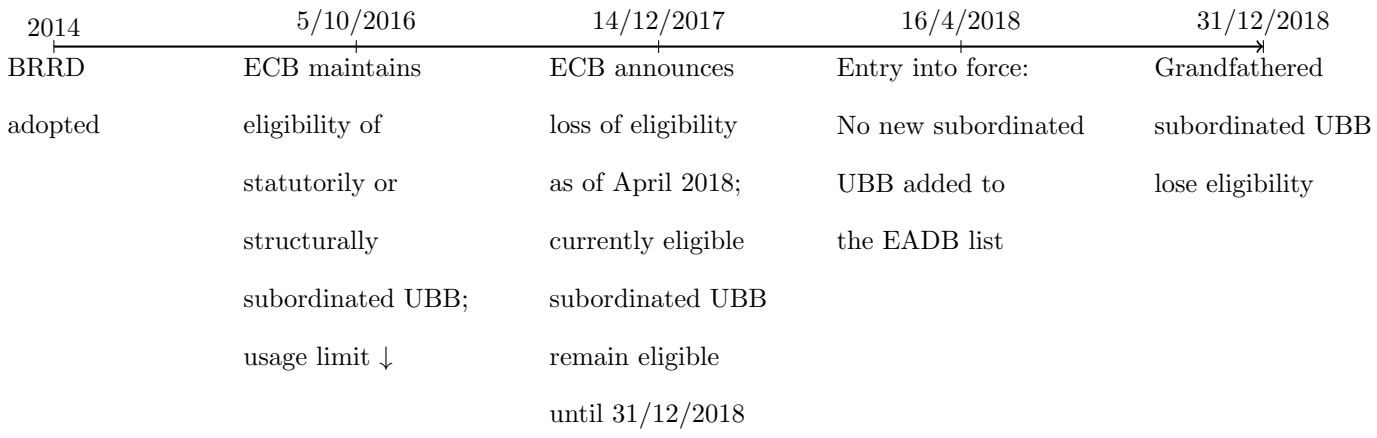


Figure I.15: Timeline of events

German banks could not have issued any ECB-eligible UBB anymore because of statutory subordination.

That is why, on October 5th, 2016 the ECB announced to *maintain* the eligibility of statutorily or structurally subordinated UBB for the time being until member states would converge to a harmonized approach. Without this temporary waiver, the sUBB in question would have become ineligible as of January 1st, 2017. Obviously, the main beneficiaries of this decision were German banks and bank holding companies which could now continue to issue ECB-eligible sUBB which, at the same time, counted towards the issuer's MREL requirement. In other words, for a while, German sUBB enjoyed the best of both worlds.[26]

However, on December 14th, 2017, the ECB announced the end of this exception: As of April 2018, no new subordinated UBB would be eligible for collateral anymore (with the exception of government-guaranteed bonds). To ease the transition, the ECB adopted a grandfathering approach for those subordinated UBB that were still eligible at the time of the announcement. Those securities would maintain their eligibility until December 31st, 2018. We summarize the most important events in Figure I.15.

[26]However, the ECB lowered the usage limit of sUBB from 5% to 2.5%, i.e. the value of sUBB pledged as collateral by a bank could not exceed 2.5% of its total pledged collateral.

Eventually, to level the playing field, the German Banking Act (Kreditwesengesetz) was amended to adopt the contractual subordination option as well.[27] This allowed German banks to issue both senior preferred and senior non-preferred bonds as of July 21st, 2018.

As further evidence of our interpretation of ECB collateral eligibility as a service that banks value, Figure I.16 plots the average CDS-bond basis of senior preferred vs. senior non-preferred bonds. Note that the series only starts in 2018, after senior non-preferred bonds and, even more importantly, their corresponding CDS contracts, had been widely introduced. The plot clearly shows that senior preferred bank bonds (which are generally eligible for collateral at the ECB) have a higher CDS-bond basis than (ineligible) senior non-preferred bank bonds, even after we account for the different default risk of each asset class (by using the seniority-appropriate CDS spread when calculating the CDS-bond basis).

[27] See section 46f paragraphs 6, 7, and 9 KWG.

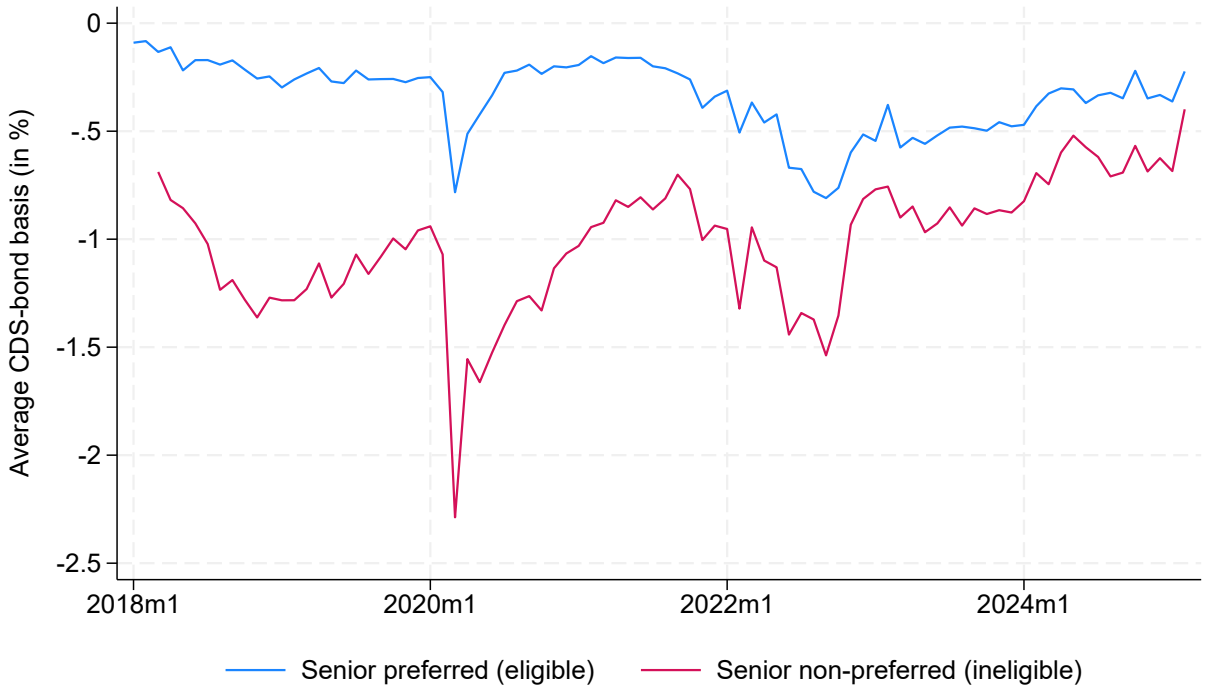


Figure I.16: Average CDS-bond basis of bank bonds of different seniority. This plot displays the average CDS-bond basis of senior preferred bank bonds (blue) vs. that of senior non-preferred bank bonds (pink). The former are generally collateral-eligible, the latter are not. To obtain the average basis, observations are weighted by outstanding amounts. Note that because the two debt classes have different seniority, the CDS spreads used to calculate the CDS-bond basis are also different.