

# Central Bank Asset Purchases and Auction Cycles Revisited: New Evidence from the Euro Area\*

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## Abstract

This study provides new evidence on the relationship between unconventional monetary policy and auction cycles in the euro area. Using proprietary data on purchases of public sector securities implemented by the Eurosystem, the paper examines the flow effects of asset purchase programmes on 10-year government bond yields in secondary markets around dates of public debt auctions. The findings indicate that Eurosystem's asset purchase flows mitigate yield cycles during auction periods and counteract the amplification impact of market volatility. The dampening effect of central bank asset purchases on auction cycles is more sizeable and precisely estimated for purchases of securities with medium-term maturities and in jurisdictions with relatively lower credit ratings. The analysis has broader implications for monetary policy and market functioning in the euro area.

**JEL Classification:** E52, E58, G12, G14.

**Keywords:** Unconventional monetary policy; Public debt auctions; Bond yields; Flow effects; Eurosystem.

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## Non-technical summary

The operations of debt management offices (DMOs) and central banks are interlinked in their impact on the functioning of bond markets. On the one hand, by overseeing the issuance of public debt via auctions and syndications, DMOs play an essential role in maintaining the health and efficiency of government bond markets. On the other hand, central banks may influence price dynamics in these markets, most notably through their asset purchase programmes.

This paper sheds new light on the interconnected impact of DMOs' and central banks' operations on government bond markets by tackling the following research questions. Are the government bond yields in secondary markets sensitive to the occurrence of public debt auctions? If so, do central bank asset purchases affect how bond yield movements around auction dates?

To answer these questions, the study builds on a strand of the literature that has assessed whether the issuance of government debt in primary markets generates “auction cycles” (e.g., [Sigaux 2018](#); [Beetsma et al. 2018b](#); [van Spronsen and Beetsma 2022](#)). Auction cycles are present when secondary market yields rise in anticipation of a debt auction and fall thereafter, generating an inverted V-shaped pattern around auction dates.

Drawing from an extensive dataset spanning the 1999-2022 period, the study focuses on the 10-year government debt across nine jurisdictions in the euro area. Using internal proprietary data on daily transactions of central government debt implemented by the Eurosystem, the paper examines the flow effects of asset purchase programmes on 10-year government bond yields in secondary markets around dates of public debt auctions.

The findings show that central bank asset purchases contribute to mitigating yield cycles around public debt auctions and counteract the amplification impact that market volatility has on yield fluctuations around auction dates. The dampening effect of central bank asset purchases on auction cycles is more sizeable and

precisely estimated for purchases of securities with medium-term residual maturities (from 2 to 9 years).

The main results are driven by the lower-rated countries in the sample.

The evidence provided in the paper adds to a broader literature on the flow effects of Eurosystem's asset purchases. The findings underscore the importance of ongoing monitoring of yield cycles around auction dates. Such monitoring may offer valuable insights into bond market functioning in the current context of monetary policy normalisation and central bank balance sheet reduction in the euro area.

# 1 Introduction

The impact of central bank asset purchases on government bond markets is a focal point of economic and financial research. The conduct of large-scale asset purchases by central banks can directly and indirectly impact the performance, volatility, and yield curves of sovereign bonds, affecting the borrowing costs of governments (e.g., [D’Amico and King 2013](#); [Altavilla et al. 2015](#); [Eser and Schwaab 2016](#); [Arrata and Nguyen 2017](#); [De Santis and Holm-Hadulla 2020](#)) and influencing their funding strategies and fiscal policy decisions (e.g., [Greenwood et al. 2014](#); [Plessen-Mátyás et al. 2021](#)).

Government bond markets, in turn, constitute a key element in the transmission of monetary policy. Distortions in this core market segment can propagate through the financial system, potentially leading to unintended consequences for monetary policy effectiveness and, ultimately, for financial and macroeconomic stability (e.g., [Acharya et al. 2014](#); [Broner et al. 2014](#); [De Santis 2014](#); [Ehrmann and Fratzscher 2017](#)). This underlines the importance of maintaining well-functioning government bond markets.

Debt management offices (DMOs) play a crucial role in this regard. DMOs are entities that are operationally responsible for public debt management, including the conduct of auctions and syndications to issue government debt. They do not only serve to meet the financing needs of governments, but also shape the structure and liquidity of government bond markets, both of which can impact monetary policy transmission. Thus, an analysis of the market impact of public debt auctions conducted by DMOs can provide valuable insights for both monetary and fiscal policymakers.

This paper provides an empirical examination on this topic, addressing the following research questions. Are government bond yields in euro area secondary markets sensitive to government debt auctions? If so, do central bank asset purchases shape yield sensitivity around auction dates? To answer these questions, I build on a strand of the literature that has assessed whether the issuance of government debt in primary markets generates “auction cycles” (e.g., [Beetsma et al. 2016](#); [Sigaux 2018](#); [Beetsma et al. 2018b](#)). Auction

cycles are present when secondary market yields rise in anticipation of a debt auction and fall thereafter, generating an inverted V-shaped pattern around auction dates.

The article tackles these research questions by analysing a comprehensive dataset spanning the 1999-2022 period. The analysis is based on primary and secondary market data for the 10-year government debt in nine euro area countries. A novel dataset is employed to obtain information about auctions in the euro area (e.g., auction date, issuer country, maturity of issued security). To assess the impact of Eurosystem's asset purchases on government bond yields around auction dates, I use internal proprietary data on daily transactions of central government debt implemented by the Eurosystem in the context of the Securities Markets Programme (SMP), the Public Sector Purchase Programme (PSPP) and the Pandemic Emergency Purchase Programme (PEPP).

The paper provides new evidence on the effects of Eurosystem's asset purchases on secondary market yields around public debt auction dates. The analysis builds on previous research based on lower-frequency data on central bank asset purchases and a shorter analysis period ([van Spronsen and Beetsma 2022](#)). The results show that purchase flows dampen the magnitude of auction cycles and counteract the amplification impact of market volatility on yield shifts during auction periods.

The evidence from heterogeneity tests expands the picture of these findings. First, disaggregating Eurosystem's purchase flows into different brackets of maturity of targeted securities reveals that purchases of bonds with medium-term maturities (from 2 to 9 years) are most effective in mitigating auction cycles for the 10-year public debt. Second, the analysis of cross-country heterogeneity indicates that the main results are driven by the lower-rated countries in the sample. Third, the findings suggest that there is some variation in the effects of purchase flows across programmes. Consistent with the evidence provided by [Eser and Schwaab \(2016\)](#), SMP purchase flows during the sovereign debt crisis exhibit a positive and significant correlation with yield changes around auction dates. On the contrary and in line with the expectations, PSPP and

PEPP purchase flows are more negatively correlated with yield fluctuations during auction periods.

Taken together, these results provide new evidence about auction cycles in Europe and contribute to a larger literature on the flow effects of central bank asset purchases on bond markets. As I highlight in the conclusion, the findings have broader implications for monetary policy and market functioning in the euro area.

The next section provides a literature review on auction cycles. Section 3 presents the data and methods employed in the analysis. Section 4 offers descriptive evidence about auction cycles in the euro area. Section 5 presents the results of the econometric analysis. Section 6 discusses the findings from the heterogeneity tests. The final section draws conclusions and points to further avenues for research.

## 2 Auction cycles and unconventional monetary policy

Governments rely on auctions and syndications to issue public debt. The dates of public debt auctions are determined in advance by euro area DMOs and are listed in the EU national issuance calendar<sup>1</sup>. Primary dealers are the main participants in these auctions.

Primary dealers are financial intermediaries that, generally in exchange for specific privileges, agree to perform specific obligations or functions in the operation of markets for government securities (Arnone and Iden 2003). They are strongly incentivised to participate and bid in government debt auctions, thereby underwriting the issuance of public sector securities. Primary dealers play a crucial role in financial markets by serving as a conduit for the government's financing needs. These financial institutions are the heart of the phenomenon of auction cycles.

Auction cycles are defined by the presence of an inverted V-shaped pattern in secondary market yields around primary auctions. That is, government bond yields rise in the run-up to the date of the auction and

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<sup>1</sup>See: [https://economic-financial-committee.europa.eu/efc-sub-committee-eu-sovereign-debt-markets/issuance-calendar/national-issuance-information\\_en](https://economic-financial-committee.europa.eu/efc-sub-committee-eu-sovereign-debt-markets/issuance-calendar/national-issuance-information_en).

fall back to their original level after the auction.

Theoretically, the literature has explained this phenomenon in light of the constraints and incentives faced by primary dealers. Their limited risk-bearing capacities and inventory management operations are seen as key mechanisms driving auction cycles ([Beetsma et al. 2016](#); [Beetsma et al. 2018b](#); [van Spronsen and Beetsma 2022](#)). Prior to a new debt auction, primary dealers face the need to free up space in their trading portfolios. To do so, they reduce their position in instruments with a high return correlation with the security set to be auctioned. This action results in a drop in secondary market prices in the days preceding the auction date. Moreover, selling pressures influence the price at which the new debt is obtained due to the significant interchangeability between the instruments sold prior to the auction and the newly auctioned debt. In the days following the auction, primary dealers sell the newly acquired bonds on to their customers, and the downward pressures on the secondary market fade away.

This theoretical framework generates several testable predictions. First, in contexts of higher market volatility, the risk-bearing capacity of primary dealers shrinks, due to the stronger weight of value-at-risk metrics and higher risk aversion associated with higher uncertainty. Therefore, when market volatility is higher, primary dealer risk aversion implies a larger pre-auction sale of substitutable instruments, resulting in a larger auction cycle ([Beetsma et al. 2016](#)).

Second, central bank asset purchases can alleviate the cycle by (partly) absorbing the additional supply of substitutable instruments in the secondary market ([van Spronsen and Beetsma 2022](#)). This expectation is supported by several analyses on the price effects of central bank bond purchases ([D'Amico and King 2013](#); [Arrata and Nguyen 2017](#); [De Santis and Holm-Hadulla 2020](#)).

Third, when market volatility is higher, central bank interventions may have a stronger dampening effect on the auction cycle, leading to smaller variations in secondary market yields around auction dates ([van Spronsen and Beetsma 2022](#)). This hypothesis is supported, for instance, by evidence from the pandemic

period in the euro area, which points to stronger “flow effects” of central bank asset purchases under the stressed market conditions and high volatility environment that characterised the initial phase of the PEPP (Altavilla et al. 2021).

Empirically, previous research has provided evidence of auction cycles taking place across different jurisdictions. Fleming and Rosenberg (2007) and Lou et al. (2013) focus on auction cycles in the US. Beetsma et al. (2016) detect auction cycles for government debt in Italy, but not in Germany, during the European sovereign debt crisis. Sigaux (2018) confirms the price fall of public debt during the run-up to Italian treasury auctions. The literature has also shown that this phenomenon is triggered by both domestic and foreign government debt auctions, and finds evidence that price movements around auctions are larger when market volatility is higher (Beetsma et al. 2018b). Importantly, studies in this area provide estimates of a non-negligible impact of auction cycles on debt-servicing costs<sup>2</sup> and do not reject the hypothesis of symmetry in secondary market price movements before and after the auctions.

Research on the impact of central bank asset purchases on yield cycles around auctions is still limited. An important exception is the study by van Spronsen and Beetsma (2022). Their paper provides evidence that Eurosystem’s asset purchases reduce the presence of auction cycles for euro area government debt. This effect tends to be larger when market volatility is higher, implying that, if central banks were to time their purchases to periods with high market volatility, average debt-servicing costs may be reduced for euro area governments.

Nonetheless, several questions remain open about auction cycles and unconventional monetary policy in the euro area. This paper aims to extend the analysis by tackling the following aspects that are left unaddressed by previous research.

First, the studies on the euro area cited above rely on auction data only up to 2017. Therefore, they

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<sup>2</sup>For instance, for the issue of an Italian five-year bond in the period from mid-2007 to early 2013, Beetsma et al. (2016) calculate an auction-induced additional issuance cost of almost 11 million euros, while the additional annual cost associated with a complete roll-over of the outstanding debt amounts to almost 1.3 billion euros



provide only a partial picture of auction cycles and central bank asset purchases in Europe.

Second, from a methodological standpoint, the study by [van Spronsen and Beetsma \(2022\)](#) suffers from structural limitations related to the data on Eurosystem’s asset purchases used for the analysis. As the authors do not have access to granular data on central bank asset purchases in the euro area, their empirical strategy relies on the interpolation of low-frequency stock data of holdings of Eurosystem national central banks (NCBs) to obtain series at the daily frequency<sup>3</sup>. This can raise issues of measurement error that may threaten the validity of the estimates.

Third, relying on proxies of Eurosystem’s asset purchases based on aggregate data on NCBs’ holdings poses additional limitations from a substantive perspective. For one thing, this does not allow researchers to investigate possible heterogeneous effects across types of purchases that may drive the average effects of unconventional monetary policy on auction cycles. For another, high-frequency granular data is crucial to obtain a reliable picture of the flow effects of Eurosystem’s asset purchases and disentangle them from the possible effects of future and cumulated past purchases (i.e., “stock effects”). This point has received attention by other studies making use of the same high-frequency data to evaluate the flow effects of Eurosystem’s asset purchases on bond prices. (e.g., [Arrata and Nguyen 2017](#); [De Santis and Holm-Hadulla 2020](#)).

Altogether, these elements motivate further investigation of the relationship between central bank asset purchases and auction cycles in the euro area. To do so, I employ more precise high-frequency data on Eurosystem’s asset purchases and consider an extended analysis period. In the next section, I describe the data and variables of my analysis.

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<sup>3</sup>To construct series of government debt purchases at the daily frequency, [van Spronsen and Beetsma \(2022\)](#) retrieve data on government debt holdings reported on the balance sheets of NCBs from the ECB’s Statistical Data Warehouse (SDW). These are reported only on a monthly basis. They thus construct daily series by evenly distributing monthly changes in NCBs’ debt holdings over all days in each month, excluding the blackout period of the Eurosystem’s purchases occurring on domestic auction and pre-auction days.

### 3 Data and construction of variables

The empirical analysis in this paper is based on primary and secondary government debt market data of Austria, Belgium, Finland, France, Germany, Italy, the Netherlands, Portugal, and Spain. This country sample includes nine out of the eleven jurisdictions that have been members of the euro area since its start in 1999. The other two initial members, Ireland and Luxembourg, are not included in the analysis due to incompleteness of publicly available data on government debt auctions. Following previous studies, for each country, I investigate the 10-year government bonds, as this is generally the most liquid and most frequently auctioned type of public debt.

The sample starts on 1 January 1999 and ends on 31 December 2022. The dataset extends an additional five years beyond what was utilised in prior research ([van Spronsen and Beetsma 2022](#)). Importantly, this extended time frame spans the entire net purchase phase of both the PSPP and PEPP<sup>4</sup>.

The next two subsections describe the primary and secondary market data in detail.

#### 3.1 Primary market data

*Government debt auctions.* Information about auctions in the euro area (e.g., auction date, issuer country, and maturity of security) is obtained from an internal ECB dataset based on public data automatically compiled from various DMO websites. The retrieved data is augmented further with the Eligible Assets Database (EADB) and internal databases to fill possible gaps in published DMO information. The dataset is periodically updated and covers the entire 1999-2022 period, thus providing the opportunity to extend the time frame of the analysis to the post-2017 period.

The dataset includes information on the maturity of securities issued with each auction. Exploiting this information, I isolate all the auctions with which DMOs issued a 10-year instrument. More specifically, I

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<sup>4</sup>The Eurosystem first discontinued net purchases and moved to reinvestment phase under the PEPP at the end of March 2022. This was then followed by halting net purchases under the APP as of July 2022.

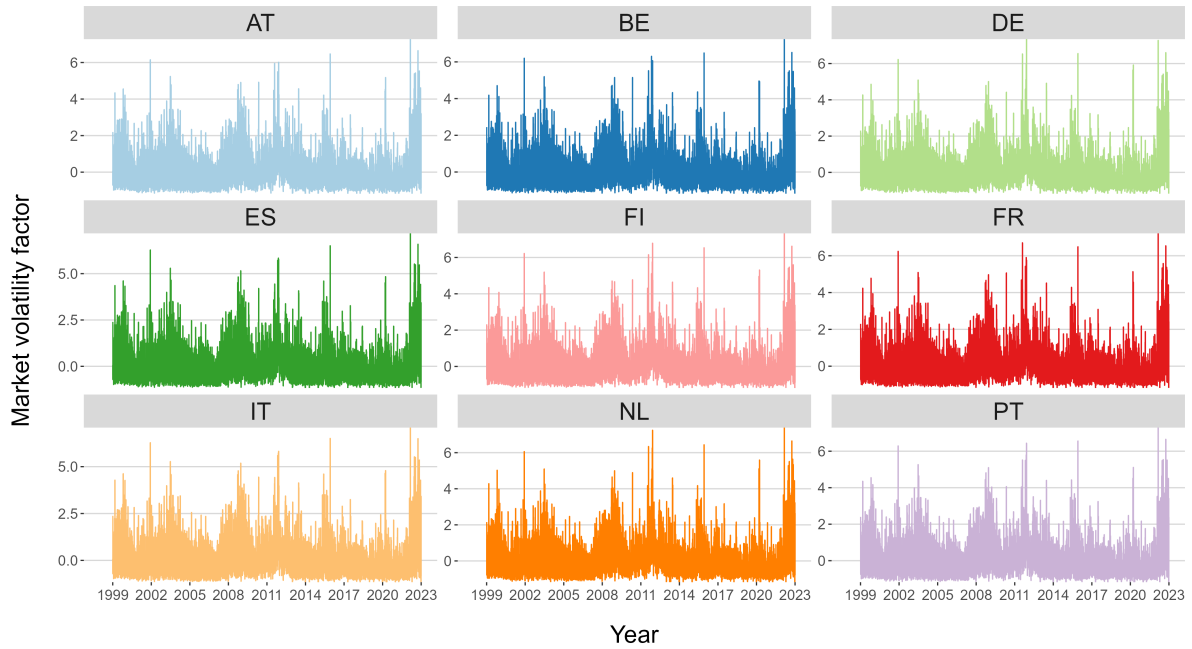
focus on all auctions for instruments with a maturity between 8.5 and 11.5 years. Table A.1 in Appendix A reports the distribution of 10-year auctions by country. In total, the dataset contains 1605 auction dates.

### 3.2 Secondary market data

*Government bond yields.* I retrieve information about 10-year government bond yields in secondary markets from Refinitiv Datastream and make use end-of-day quotes. Table A.2 in the Appendix reports summary statistics for daily secondary market yield levels in percentage and yield changes in basis points.

*Market volatility.* Following [van Spronsen and Beetsma \(2022\)](#), to study how volatility in government bond markets affects yield cycles around auctions, I use a factor model to extract a volatility metric based on variations in 10-year government bond yields. More specifically, I extract the first factor of the absolute deviations from the mean of the individual countries' differenced yield series. To ensure that this market volatility measure can be treated as exogenous in the analysis, for each country  $i$ , the factor model is estimated on all countries except  $i$  (i.e.,  $\forall j \in \{1, 2, \dots, 9\} \wedge j \neq i$ ). Figure 1 displays the country-specific evolution of the market volatility factor over the entire time frame of the analysis. As expected, high-volatility episodes are observed in particular between 2008 and 2012, and in the second half of 2022, after the start of the ECB's monetary policy normalisation process.

Figure 1: Market volatility factor (1999-2022)



NOTES: This figure shows the daily government bond market volatility factor by country. Daily volatility in government bond markets is based on the first factor derived from a factor model of the absolute deviations from the mean of individual differenced series of 10-year government bond yields. For each country  $i$  the factor model is estimated on all countries except  $i$ .

*Control variables.* In my analyses, I introduce a set of financial control variables capturing risk sentiment and market conditions. Specifically, I include information on the euro short-term rate<sup>5</sup>, the Euro Stoxx 50 Index, the Euro Stoxx Banks Index, and the Euro Stoxx 50 Volatility Index (VSTOXX)<sup>6</sup>. These variables are retrieved from the ECB's Statistical Data Warehouse (SDW). Table A.2 in the Appendix reports summary statistics for both their levels and differences.

### 3.3 Data on Eurosystem's asset purchases

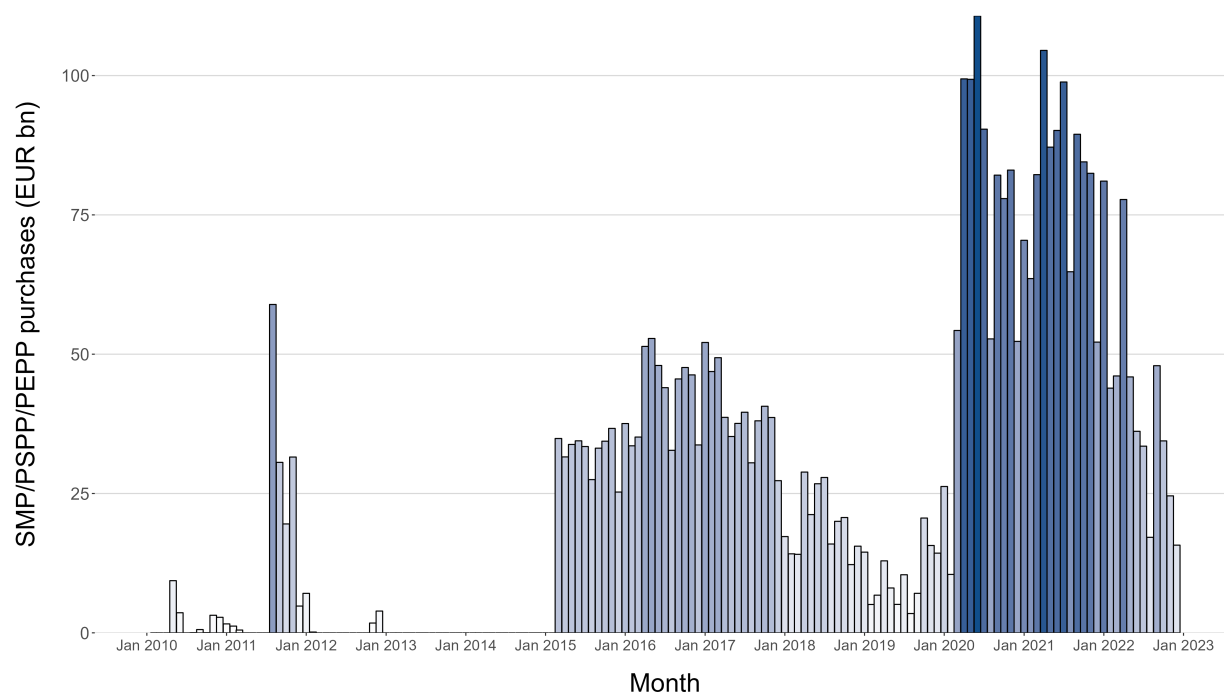
*Purchase flows.* To measure flows of central bank asset purchases, I use internal proprietary data on daily transactions implemented by the Eurosystem in the context of the SMP, the PSPP and the PEPP on the

<sup>5</sup>I use data on the Euro Overnight Index Average (EONIA) until 31 December 2021 and on the euro short-term rate (ESTR) from 1 January 2022.

<sup>6</sup>This is the same set of control variables employed in the analysis by [van Spronsen and Beetsma \(2022\)](#).

central government debt of each of the nine euro area countries in the analysis. Proprietary data on the Eurosystem's public sector purchases has already been employed in previous studies on the impact of asset purchases on government bond markets by researchers at the ECB and the NCBs of the Eurosystem (e.g., Ghysels et al. 2014; Arrata and Nguyen 2017; De Santis and Holm-Hadulla 2020; Arrata et al. 2020).

Figure 2: Monthly volumes of Eurosystem's public sector purchases (2010-2022)



NOTES: This figure displays the nominal amounts of the monthly purchases of central government debt securities implemented by the Eurosystem under the SMP, PSPP and PEPP. The variation in the colour scale is related to the size of the monthly volumes.

The data on Eurosystem's transactions is at the security level, and features the date, the nominal amount and the price at which each transaction was settled. For each security, I have information about its ISIN code, maturity and coupon. Based on this information, I aggregate the nominal amounts of purchased securities at the daily level and by country. This allows me to generate country-specific daily series of Eurosystem's net purchases of public sector securities. Figure 2 shows the monthly evolution of public sector purchases under the SMP, PSPP and PEPP. For reasons of confidentiality, the daily series of the Eurosystem's asset

purchases by country can not be shown.

*Floating supply.* In addition to a variable capturing flow effects of central bank asset purchases, I construct a control variable to gauge possible stock effects of the Eurosystem’s purchase programmes. This variable aims to assess the influence of the realised purchases implemented by the Eurosystem, and does so by considering the amount of government debt securities available for trading in the secondary market.

I start from the assumption that, until March 2023, the Eurosystem reinvested redemptions, therefore its stock of asset holdings grew steadily over the entire time frame of the analysis. This affects the volume of an instrument actually available for trading, which may, in turn, affect the servicing cost of new government debt. Similar to the approach adopted by [van Spronsen and Beetsma \(2022\)](#), I therefore construct a proxy variable of “floating supply” , defined as the difference between the level of outstanding euro-denominated long-term central government debt at time  $t$  ( $Outstanding_{i,t}$ ) minus the cumulative purchases of long-term public sector securities implemented by the Eurosystem from day 0 up to time  $t$  ( $\sum_{d=0}^t LongTermFlows_{i,d}$ ). I define long-term public securities as all securities with a residual maturity greater than 8.5 years. More formally, the floating supply variable is constructed as follows:

$$FloatingSupply_{i,t} = Outstanding_{i,t} - \sum_{d=0}^t LongTermFlows_{i,d} \quad (1)$$

The information on the outstanding euro-denominated long-term central government debt for each country is obtained from SDW and has quarterly frequency. To adapt this information to the daily structure of the dataset, I linearly interpolate the quarterly data to obtain series at the daily frequency.

## 4 Descriptive analysis

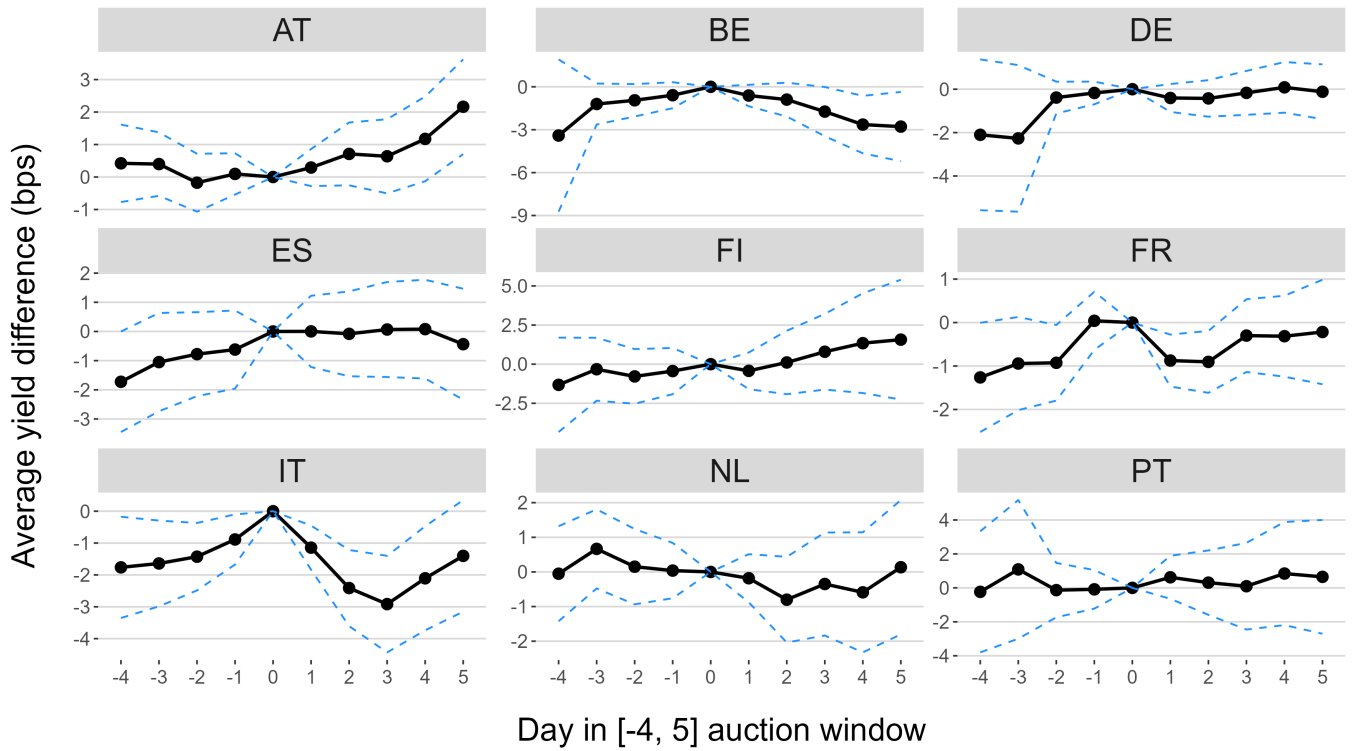
This section sets the stage for the ensuing regression analysis by presenting an event study on the trends of secondary market yields around auction dates. This is akin to the event studies carried out by [Lou et al.](#)

(2013), who provide evidence of an inverted V-shaped pattern in secondary market yields around auction dates in the US, as well as [Beetsma et al. \(2016\)](#), [Beetsma et al. \(2018b\)](#) and [van Spronsen and Beetsma \(2022\)](#), who present similar findings for euro area countries.

The event window extends from four trading days prior to the auction day and continues for five trading days after the auction. Figure 3 displays the average, computed over the entire sample period, of the difference in secondary market yields ( $y_t - y_0$ ), measured from the close of the auction day (marked as subscript 0) to the end of any given day  $t$ . Furthermore, the figure shows 95% confidence intervals.

It is possible to observe that the cyclical pattern of yields movements is more evident in certain jurisdictions than others. This is clearly the case for Italy, where the characteristic surge in the secondary market yield before the auction, followed by a drop after the auction, is evident. France and Belgium also exhibit approximately symmetric patterns of auction cycles. Spain, Germany and Finland exhibit minimal cycles with a more asymmetric structure, characterised by surges of 10-year yields in the days preceding the auction, not followed by meaningful drops thereafter. Austria and Portugal do not present evident cyclical patterns.

Figure 3: Event study - yield differences (1999-2022)

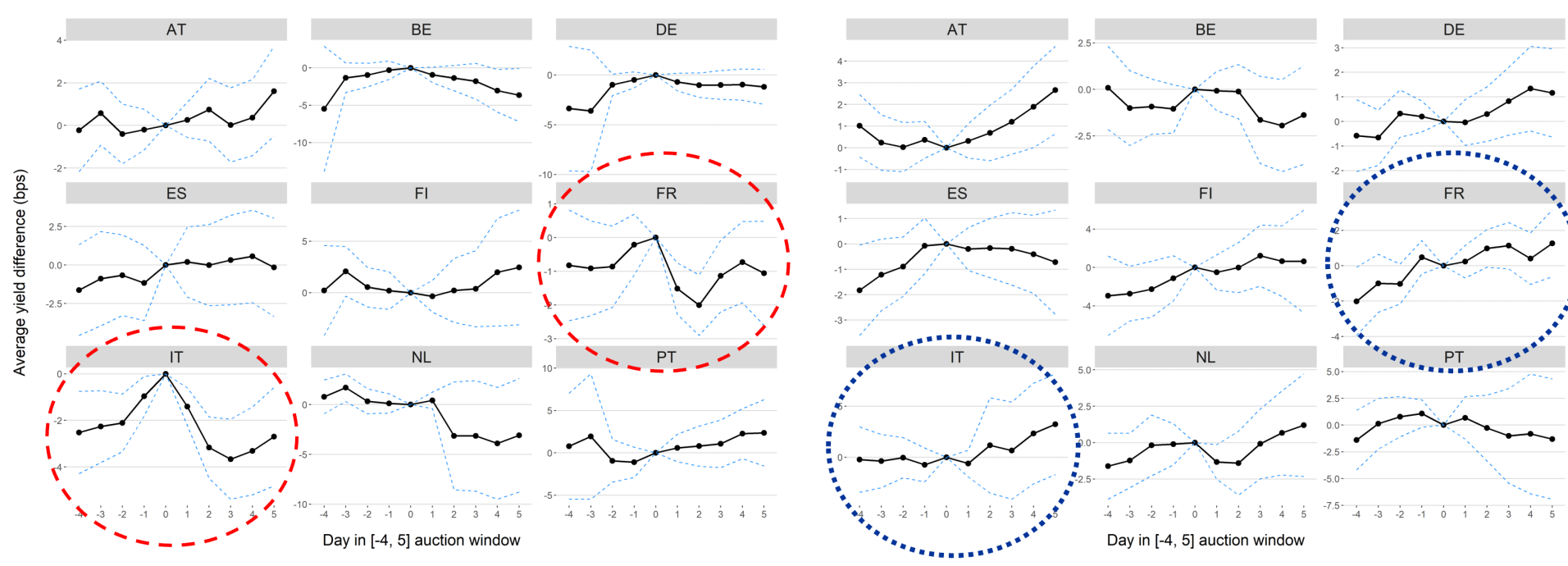


NOTES: This figure displays 10-year government bond yield difference around auction dates. Mean differences show 95% confidence intervals.

As a next step, I perform the same descriptive analysis to compare auction cycles before and after the start of the PSPP in 2015. Figure 4 shows the results for, respectively, the 1994-2014 subsample period (LHS panel) and the 2015-2022 subsample (RHS panel). This picture of heterogeneity across time periods highlights that auction cycles patterns are much more pronounced in the pre-PSPP period. This is especially the case for Italy and France, as highlighted in the chart. While these two jurisdictions exhibit a rather symmetric structure of yield cycles around public debt auctions before 2015, symmetry disappears after the start of the PSPP and the pattern becomes almost flat.



Figure 4: Event study (LHS: 1999-2014; RHS: 2015-2022)



NOTES: This figure displays 10-year government bond yield difference around auction dates. Mean differences show 95% confidence intervals.

This raises the question whether these changes in yield movements in the auction window are driven by the purchases of public sector securities implemented by the Eurosystem. The next sections presents a more comprehensive empirical assessment to tackle this question.

## 5 Econometric analysis

In this section, I employ panel regression analyses to examine the relationship between the Eurosystem's asset purchases and secondary market yield cycles around public debt auctions.

Auction dates for the coming year are determined beforehand. This makes the occurrence of an auction a plausibly exogenous event. The cornerstone of my econometric analysis is the estimation of the effect of domestic auctions and Eurosystem's asset purchases on country-specific changes in secondary market yields. In line with previous research, I do so by using dummies for each of the ten days around auctions and interact these with measures of market volatility, purchase flows and floating supply discussed in Section 3. This is described more formally in the following subsection.

### 5.1 Baseline regression

I use fixed-effects panel regression models, initially imposing that the effects of auction cycles, market volatility and purchase flows are uniform across the countries in my sample. Following the approach adopted by [van Spronsen and Beetsma \(2022\)](#), my baseline regression specification is:

$$\begin{aligned}
\Delta y_{i,t} = & \alpha_i + \phi \Delta y_{i,t-1} + \sum_{k=-4}^5 \beta_k a_{i,t-k} \\
& + \gamma_1 Flows_{i,t} + \gamma_2 MktVol_{i,t} + \gamma_3 FloatingSupply_{i,t} \\
& + \sum_{k=-4}^5 a_{i,t-k} \cdot (\zeta_{1k} Flows_{i,t} + \zeta_{2k} MktVol_{i,t} + \zeta_{3k} FloatingSupply_{i,t}) \\
& + \eta Flows_{i,t} \cdot MktVol_{i,t} + \sum_{k=-4}^5 a_{i,t-k} \cdot (\theta_k Flows_{i,t} \cdot MktVol_{i,t}) \\
& + \Delta z'_{t-1} \kappa + \sum_{k=-4}^5 \lambda_k a_{j,t-k} + \epsilon_{i,t}
\end{aligned} \tag{2}$$

In this model,  $i$  indexes country panels and  $t$  indexes time.  $\Delta y_{i,t}$  is the dependent variable, namely the daily change in the 10-year government bond yield.  $\alpha_i$  is a country-specific intercept.  $a_{i,t-k}$  are daily dummies for each of the days falling within the  $[-4, 5]$  window around a domestic public debt auction, and  $\beta_k$  (with  $k \in \{-4, -3, \dots, 5\}$ ) are their coefficients.  $Flows_{i,t}$ ,  $MktVol_{i,t}$  and  $FloatingSupply_{i,t}$  are the three variables of interest on, respectively, daily purchase flows, market volatility and floating debt supply, with the respective coefficients  $\gamma_{1-3}$ . The daily dummies are interacted with the variables of interest, and  $\zeta_{1-3k}$  are the coefficients of these interaction terms.

In addition to that, as in [van Spronsen and Beetsma \(2022\)](#), I estimate an interaction term between purchase flows and market volatility for the days within the auction window, whose coefficient is  $\theta_k$ .  $\eta$  is the coefficient of the interaction between flows and volatility taken separately.  $\kappa$  is a vector of coefficients for the financial control variables in  $\Delta z_{t-1}$ , namely the lagged changes in the EONIA/ESTR, Euro Stoxx 50 Index, Euro Stoxx Banks Index, and VSTOXX.  $a_{j,t-k}$ , with coefficients  $\sum_{k=-4}^5 \lambda_k$ , are daily dummies to control for foreign auctions. Each of these dummies takes value 1 for each day falling within the  $[-4, 5]$  window around an auction occurring in country  $j$ , with  $j \in \{1, 2, \dots, 9\} \wedge j \neq i$ .  $\epsilon_{i,t}$  is the error term.

In equation 2, the summation accounts for the final four days preceding each auction ( $-4 \leq k < 0$ ), the auction day itself ( $k = 0$ ), and the initial five days succeeding the auction ( $0 < k \leq 5$ ), resulting in ten

dummy variables for domestic auctions. The reason for this modelling choice is that the expected pattern of an auction cycle is distinguished by an upward trend in the secondary market yield before the auction and a subsequent decline post-auction. Consequently, to test the null hypothesis of absence of a domestic auction cycle, I consider the following linear combination of coefficients:

$$H0 : AC \equiv \sum_{k=-4}^0 \beta_k - \sum_{k=1}^5 \beta_k = 0 \quad (3)$$

In a similar vein, to study the effects of asset purchases and volatility on yield changes, I rely on the following tests:

$$H0 : AC \ x \ Flows \equiv \sum_{k=-4}^0 \zeta_{1k} - \sum_{k=1}^5 \zeta_{1k} = 0 \quad (4)$$

$$H0 : AC \ x \ MktVol \equiv \sum_{k=-4}^0 \zeta_{2k} - \sum_{k=1}^5 \zeta_{2k} = 0 \quad (5)$$

$$H0 : AC \ x \ FloatingSupply \equiv \sum_{k=-4}^0 \zeta_{3k} - \sum_{k=1}^5 \zeta_{3k} = 0 \quad (6)$$

$$H0 : AC \ x \ Flows \ x \ MktVol \equiv \sum_{k=-4}^0 \theta_k - \sum_{k=1}^5 \theta_k = 0 \quad (7)$$

Finally, to assess whether the structure of auction cycles in the euro area is symmetric, I test whether the absolute value of the sum of differences in government bond yields in the run-up to an auction is different

from the absolute value of the sum of post-auction yield differences. More formally, I test the following hypothesis:

$$H0 : \textit{Symmetry AC} \equiv \left| \sum_{k=-4}^0 \beta_k \right| = \left| \sum_{k=1}^5 \beta_k \right| \quad (8)$$

Below I present results from two types of estimations. The first one makes use of robust standard errors and is consistent with the model employed by [van Spronsen and Beetsma \(2022\)](#). The other uses panel-corrected standard errors (PCSE) ([Beck and Katz 1995](#)). In this latter case, when computing the estimates of the variance-covariance matrix, the disturbances are assumed to be, by default, heteroskedastic (i.e., each panel has its own variance) and contemporaneously correlated across panels (i.e., each pair of panels has its own covariance). This method is particularly beneficial when dealing with large sample sizes. As the number of units grows, so does the efficiency of PCSE, making it a more robust tool for statistical analysis than non-corrected standard errors. The next subsection presents the results from this baseline model.

## 5.2 Results

I start by replicating the results obtained by [van Spronsen and Beetsma \(2022\)](#), who made use of less granular data on Eurosystem’s asset purchases. To this end, columns 1-3 of table 1 report the results of a model with robust standard errors and the same variables and sample periods considered in the baseline regressions in their study ([van Spronsen and Beetsma 2022](#), p. 190)<sup>7</sup>. The table also presents the Born-Breitung statistic for serial correlation ([Born and Breitung 2016](#)), which is robust against heteroskedasticity in the time dimension.

Column 1 reports the panel estimates of *AC* and the interaction terms with the key independent variables of interest (i.e., *MktVol<sub>i,t</sub>*, *Flows<sub>i,t</sub>* and their interaction) using the full sample considered by the authors,

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<sup>7</sup>The only difference is that my analysis does not consider market volatility, central bank asset purchases and floating supply interacted with foreign auction dummies. Nonetheless, this does not affect qualitatively the picture of consistency between the two sets of results.

from January 1999 to December 2017. Columns 2 and 3 present the estimates for the APP subsample period in their study, from May 2010 to December 2017. Column 3 adds the floating supply variable as a control.

Columns 4, 5 and 6 perform the same exercise on the extended sample of my analysis. Column 4 uses the full sample in my dataset, spanning the period from January 1999 to December 2022. Columns 5 and 6 consider the APP subsample period, from May 2010 to December 2022.

Table 1: Static fixed-effect regression model with robust standard errors

Sample	(1) vS&B full	(2) vS&B APP	(3) VS&B APP	(4) Full	(5) APP	(6) APP
AC	2.305** (0.944)	3.228 (1.830)	2.857 (2.811)	2.089* (1.078)	2.545 (1.771)	1.492 (2.016)
x MktVol	2.967** (1.083)	5.424 (3.169)	5.357 (3.215)	2.565 (1.381)	3.641 (2.713)	3.671 (2.741)
x Flows	-6.699* (3.298)	-7.822** (3.278)	-8.463** (2.897)	-5.583 (3.097)	-6.268 (3.920)	-7.484 (5.132)
x MktVol x Flows	-9.252 (7.275)	-12.964 (7.906)	-12.560 (7.866)	-6.125 (6.172)	-7.572 (6.561)	-7.532 (6.405)
x Floating Supply			0.054 (0.380)			0.153 (0.245)
Symmetry AC	0.732 (0.669)	1.370 (0.902)	2.434 (1.739)	0.904 (0.809)	1.398 (1.086)	1.492 (2.016)
Observations	43,425	17,937	17,991	55,179	29,745	29,745
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
BB stat	1.342	2.035	2.030	1.617	2.295	2.292
BB p-value	0.180	0.0418	0.0423	0.106	0.0217	0.0219

NOTES: This table presents estimates from the baseline static regression model with robust standard errors in parentheses. Column 1 reports estimates based on a regression considering the full sample used by [van Spronsen and Beetsma \(2022\)](#) (January 1999 - December 2017). Columns 2 and 3 are based on the APP subsample period in [van Spronsen and Beetsma \(2022\)](#) (May 2010 - December 2017). Column 4 reports estimates based on the full sample in this study (January 1999 - December 2022). Columns 5 and 6 are based on the APP subsample period in this study (May 2010 - December 2022). Definitions of AC, AC x Flows, AC x MktVol, AC x Flows x MktVol, AC x Floating Supply and Symmetry AC are given in equations 3, 4, 5, 7, 6 and 8. BB = Born-Breitung statistic for serial correlation. \*, \*\*, \*\*\* indicate the 10%, 5%, and 1% significance levels, respectively.

In the analysis, a unit variation in the yield change variable corresponds to a one basis point variation in the 10-year yield. The market volatility factor is centred around zero and a unit increase corresponds to an increase by one standard deviation. For the purchase flow variable, a unit variation corresponds to an

increase by €1 billion in the nominal amount of central bank purchases. For the floating supply variable, a unit increase corresponds to an increase by €100 billion in the stock of floating debt.

The estimates displayed in columns 1-3 are consistent with the results in [van Spronsen and Beetsma \(2022\)](#), with a significant impact of purchase flows on yield changes around auctions in the period up to December 2017. When considering the two sets of results, the occurrence of an auction is associated with an increase in yields during the auction window in a range between 2 and 4.8 bps. In both studies, the coefficients range from 2.1 to 5.4 bps yield increase for a unit increase in market volatility and between 6.7 bps and 9 bps yield decrease for €1 billion increase in purchase flows.

A more sizeable difference in the size of the interaction between  $MktVol_{i,t}$  and  $Flows_{i,t}$  is present, with that being greater in absolute values in my estimation, but in both studies this appears not to be statistically significant when considering the full sample of countries. The coefficient of the floating supply measure is negative in [van Spronsen and Beetsma \(2022\)](#) and close to zero here, but not statistically significant in either case. The null hypothesis of symmetry of auction cycles, testing the significance of the difference between absolute value of the sum of pre-auction yield differences (i.e.,  $|\sum_{k=-4}^0 \beta_k|$ ) and the absolute value of the post-auction differences (i.e.,  $|\sum_{k=1}^5 \beta_k|$ ), is generally not rejected. In both cases, the results of the Born-Breitung statistic point to potential issues of serial correlation when considering the APP subsample period.

Extending the time frame of the analysis to include the 2017-2022 period does not substantially change the size of the coefficients, but highlights the presence of greater uncertainty associated with the estimates when using robust standard errors. Columns 4-6 show that, with the exception of  $AC$  in the full sample, the estimates do not reach conventional levels of statistical significance. However, this picture changes when employing PCSE, as shown in table 2.

Table 2: Static fixed-effect regression model with panel-corrected standard errors

Sample	(1) Full	(2) Full	(3) APP	(4) APP
AC	2.089*** (0.511)	0.456 (0.867)	2.545*** (0.763)	1.492 (1.304)
x MktVol	2.565*** (0.509)	2.553*** (0.509)	3.641*** (0.728)	3.671*** (0.728)
x Flows	-5.583*** (1.679)	-7.869*** (1.833)	-6.268*** (2.013)	-7.484*** (2.152)
x MktVol x Flows	-6.125*** (1.614)	-5.934*** (1.612)	-7.572*** (1.989)	-7.532*** (1.985)
x Floating Supply		0.258*** (0.100)		0.153 (0.134)
Symmetry AC	0.904 (0.579)	0.456 (0.867)	1.398 (0.930)	1.492 (1.304)
Observations	55,179	55,179	29,745	29,745
Control variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
BB stat	1.617	1.610	2.295	2.292
BB p-value	0.106	0.107	0.0217	0.0219

NOTES: This table presents estimates from the baseline static regression model with panel-corrected standard errors (PCSE) in parentheses. Columns 1 and 2 report estimates based on the full sample in this study (January 1999 - December 2022). Columns 3 and 4 are based on the APP subsample period in this study (May 2010 - December 2022). Definitions of AC, AC x Flows, AC x MktVol, AC x Flows x MktVol, AC x Floating Supply and Symmetry AC are given in equations 3, 4, 5, 7, 6 and 8. BB = Born-Breitung statistic for serial correlation. \*, \*\*, \*\*\* indicate the 10%, 5%, and 1% significance levels, respectively.

The estimates based on PCSE point to the statistical significance of the market volatility and purchase flow variables. Specifically, a unit increase in the market volatility factor is estimated to increase yields around auctions by around 2.5 bps in the full sample specification, and by around 3.6 bps in the specification considering the APP subsample period up to December 2022. €1 billion increase in sovereign debt purchases is associated with an average reduction in 10-year government bond yields around auctions by 5.6 bps in the more parsimonious specification based on the full sample, and around 6.3 bps when taking into account the APP subsample period. Moreover, the interaction between market volatility and purchase flows also appears to be statistically significance across specifications, pointing to a stronger impact of purchase flows in times of high market stress.



The evidence on the relevance of the floating supply is more mixed, with this variable being significant in the full sample, but not in the APP period. However, the introduction of this variable affects the size and significance of the auction dummies, with the coefficient of  $AC$  displaying greater magnitude and statistical significance in the absence of the floating supply control. Again, the null hypothesis of the symmetry of the auction cycle is not rejected.

Taken together, these results confirm that Eurosystem's asset purchases mitigate yield cycles during auction periods and counteract the amplification impact of market volatility. The analysis detects a substantial difference in the picture of statistical significance generated by the estimation based on robust standard errors compared to that based on PCSE. The robust estimator of variance produces much larger standard errors, potentially pointing to a few large observations driving the results. At the same type, PCSE are more appropriate to model the dynamics of contemporaneous correlations across panels and are specifically designed for large panels, such as the one employed in this study. For the following analyses, I therefore present results based on both types of variance estimators in all the tables, while sticking to the more conservative option of robust standard errors for the visualisations in Section 6.

Before moving to the heterogeneity analysis in the next section, as a key test to check the robustness of these results, I replicate them making use of an econometric model that addresses a potential shortcoming of the baseline regressions. As shown by the results of the Born-Breitung statistic in tables 1 and 2, it is not possible to reject the hypothesis of serial correlation for all the specifications estimated with my baseline model. This suggests that a dynamic, rather than a static, panel data model may be preferable. The inclusion of an autoregressive term of the dependent variable may mitigate this potential issue of serial correlation.

Following this line of reasoning, in table B.3 in Appendix B, I present the baseline results making use of a dynamic model with an autoregressive term of the dependent variable. The results are qualitatively

unchanged. The magnitude of the coefficients and their statistical significance is broadly in line with those shown in tables 1 and 2. With this model framework, the Born-Breitung statistic does not exhibit statistical significance in any of the specifications.

Resorting to the baseline model, in the next section, I relax the assumption of homogenous effects across the following three dimensions: a) type of central bank purchases, based on the residual maturity of targeted securities; b) country groups, based on different credit ratings; c) purchase programmes, based on their different periods of implementation.

## 6 Heterogeneity tests

In this section, I modify the initial assumption that the effects of auction cycles, market volatility and Eurosystem's asset purchases on secondary market yields are distributed uniformly across different dimensions.

First, given the presence of blackout restrictions limiting the type of purchases that the Eurosystem can implement during auction windows, it is by no means clear whether the effects of unconventional monetary policy on auction cycles are driven by the purchase of securities in the 10-year maturity space or by public sector securities with different maturities. Moreover, the European sovereign debt crisis and the tensions at the onset of the pandemic have shown that concerns about the allocation of new debt tend to be greater in lower-rated countries compared to those with high ratings, and especially so in times of crisis. Therefore, it is reasonable to expect some cross-maturity, cross-country and cross-programme variation in the degree of sensitivity of secondary market yields to auctions and central bank purchases conducted during auction windows.

I start by grouping public sector purchases across different residual maturity brackets. I consider the following categories. The first one covers short-term securities, with a residual maturity below 2 years. The second bracket includes purchases of securities with medium-term maturity, ranging from 2 to 8.5 years. The

third bracket isolates purchases of 10-year securities and (consistent with the definition of 10-year auctions provided in Section 3.1) considers purchases of securities with a maturity from 8.5 to 11.5 years. The fourth bracket covers purchases of long-term securities, with maturities from 11.5 to 20 years. The final bracket includes purchases of very long-term government bonds, with maturities above 20 years.

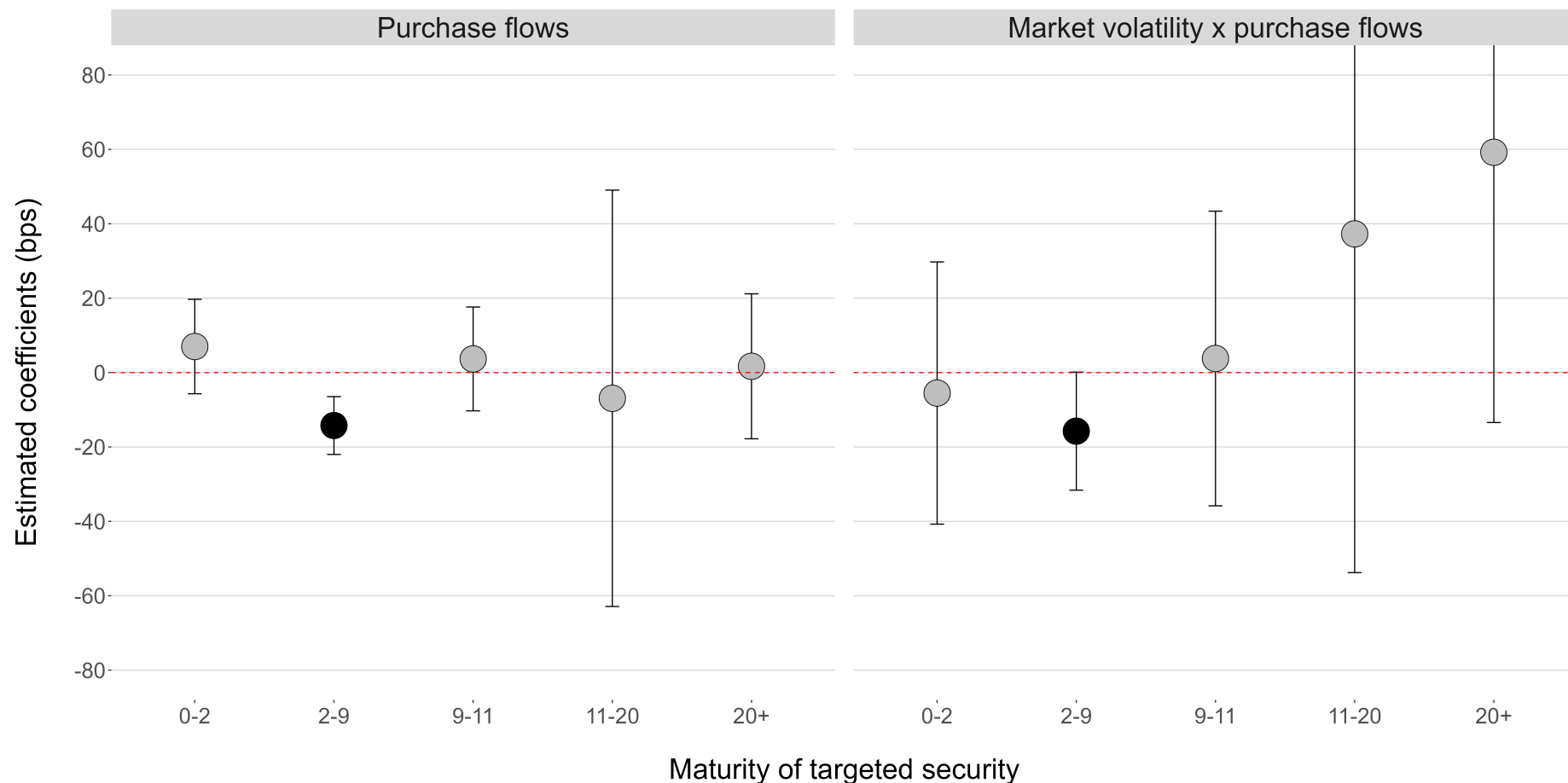
To investigate the presence of heterogeneous effects by purchase type, I disaggregate the purchase flow variable into volumes of purchases for these different categories, and run regressions including each category, interacted with the auction window dummies and the market volatility factor. The estimation is based on the baseline model (defined as in equation 2) and includes the full set of variables.

The coefficients for the interactive terms of interest are shown in figure 5. The left-hand side panel visualises the coefficients of the purchase type categories interacted with the auction dummies only. The right-hand side panel shows the coefficients of their interaction adding market volatility. The 90% confidence intervals are based on robust standard errors. Table B.4 in the Appendix presents the full set of results of the estimation based on both robust standard errors and PCSE.

The findings in the left-hand side panel suggest that the main effects are driven by purchases of securities outside the 10-year maturity space. The only category for which the coefficient is estimated to be negative and statistically significant at conventional levels is the 2-9 maturity bracket, focusing on purchases of medium-term public sector securities. The effect appears to be amplified in times of high market stress.

This result may be consistent with the presence of restrictions to the purchase of 10-year securities around auctions, which limit the volume of transactions targeting these securities during auction windows. This can explain the relatively small, positive and insignificant coefficient of 10-year purchases. More substantial uncertainty is associated with long-term purchases.

Figure 5: Heterogenous effects of purchase flows by maturity of targeted security

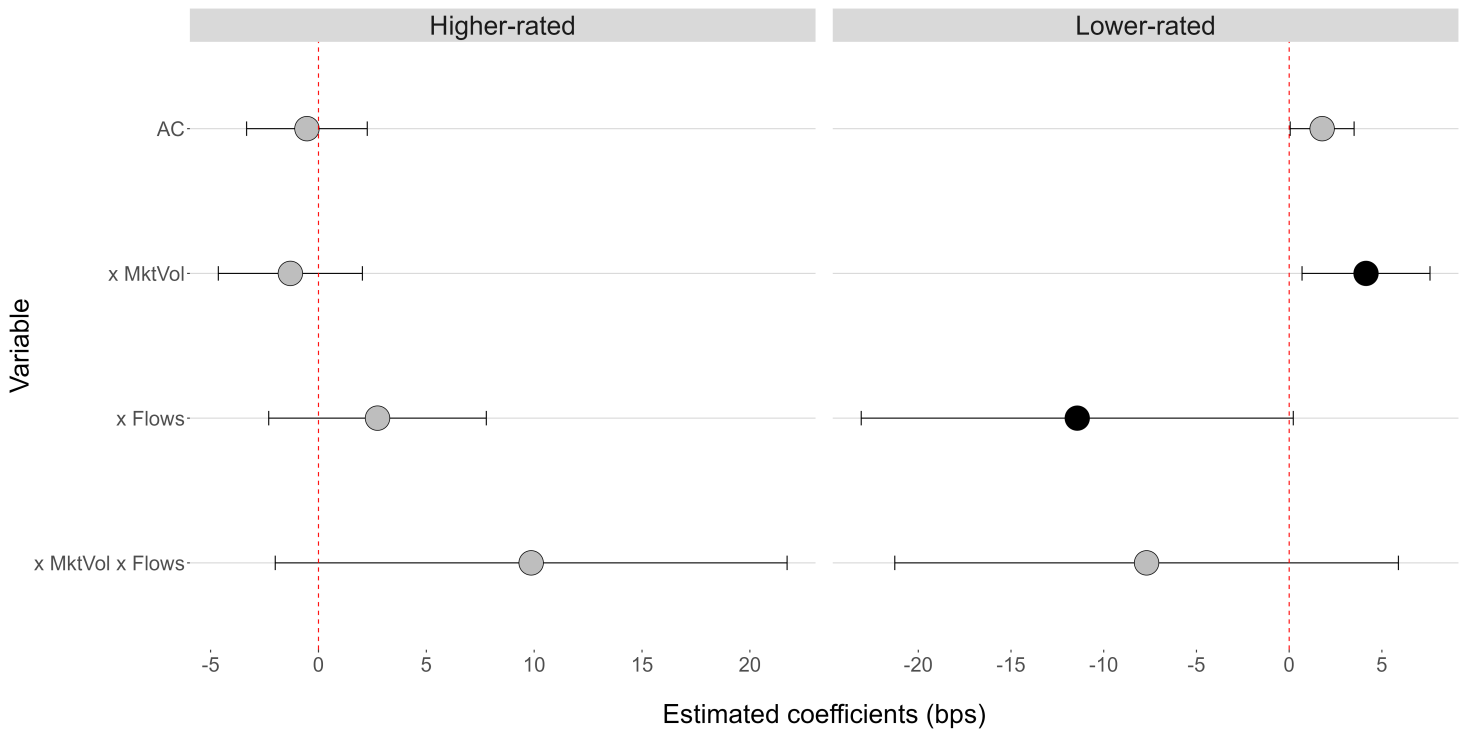


NOTES: This figure displays estimates from the baseline model (defined as in equation 2) and obtained by interacting auction dummies with the purchase flow variable disaggregated by the maturity of targeted securities. Estimates are based on the full sample period. The 0-2 maturity bracket considers purchases of securities with maturity below 2 years. The 2-9 bracket includes purchases of securities with maturity from 2 up to 8.5 years. The 9-11 bracket includes purchases of securities from 8.5- to 11.5-year maturity. The 11-20 bracket covers maturities from 11.5 to 20 years. The 20+ considers maturities above 20 years. 90% confidence intervals are based on robust standard errors. Coefficients marked in black approach conventional levels of statistical significance. The estimated coefficients, together with both robust and panel-corrected standard errors, are reported in table B.4.

To explore effect variation across countries, I group the jurisdictions in my sample into two clusters: those with higher credit ratings and those with lower credit ratings. In doing so, I follow the approach adopted by [van Spronsen and Beetsma \(2022\)](#), who classify countries with an average rating of AAA (Germany and the Netherlands) or near-AAA (Austria and Finland) over the time frame of their analysis into a “higher-rated” cluster. The remaining ones are grouped into a “lower-rated” cluster. Based on this classification, I split the sample into two groups and estimate the baseline model separately for the two country clusters.

Figure 6 visualises these split-sample estimates of the key variables of interest, with confidence intervals based on robust standard errors. The full results are reported in table B.5. The findings confirm that the flow effects of central bank purchases on yield movements around auction dates are driven by lower-rated countries. The effect is stronger for higher levels of the market volatility factor, although the interaction between purchase flows and volatility is estimated to be not statistically significant. For higher-rated countries, the sign of the coefficients is the opposite and the results are not statistically significant.

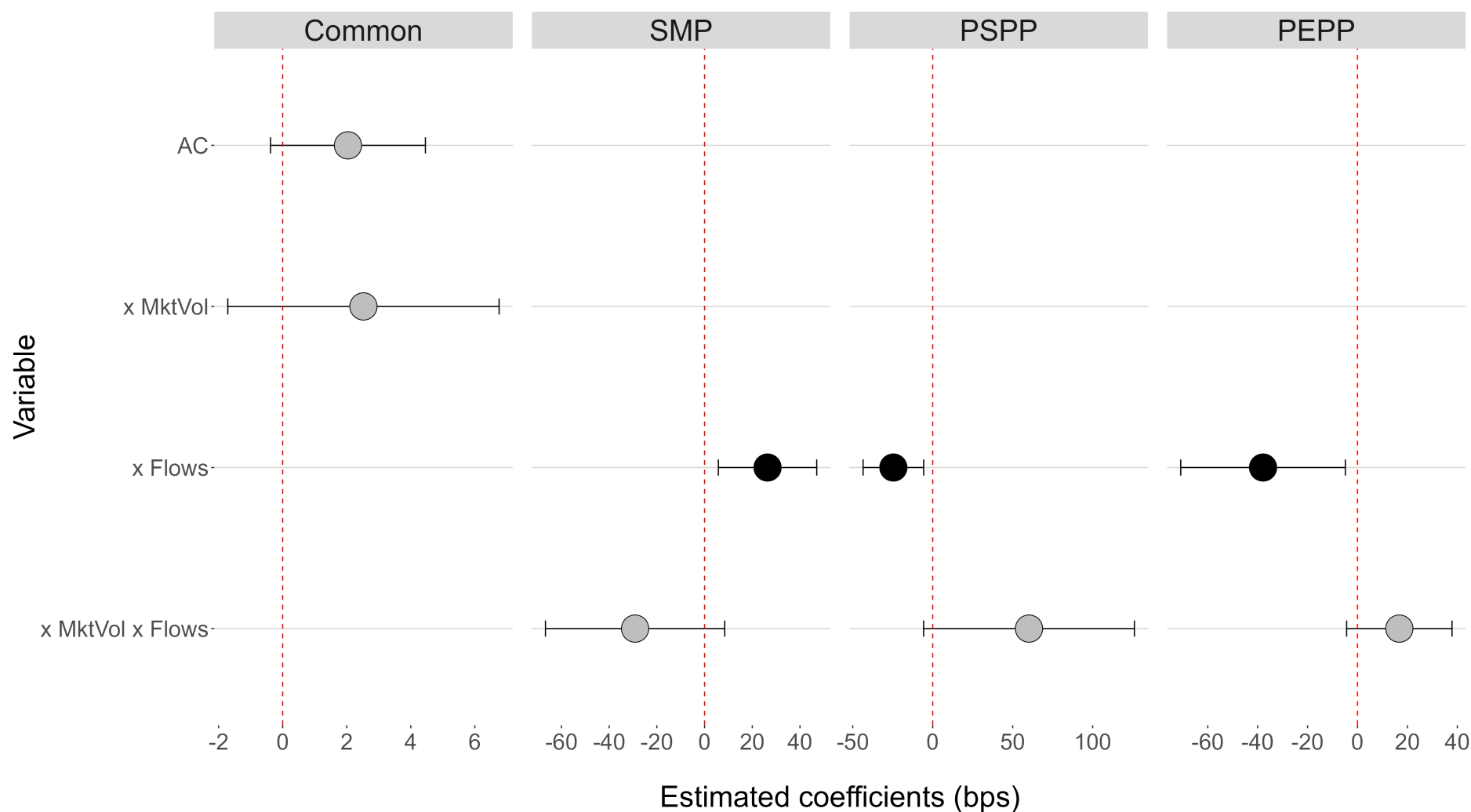
Figure 6: Heterogenous effects across country groups



NOTES: This figure displays estimates from the baseline model (defined as in equation 2) and obtained by splitting the sample of countries between higher-rated (i.e., Austria, Germany, Finland and the Netherlands) and lower-rated (i.e., Belgium, France, Italy, Portugal and Spain) jurisdictions. Estimates are based on the full sample period. 90% Confidence intervals are based on robust standard errors. Coefficients marked in black approach conventional levels of statistical significance. The estimated coefficients, together with both robust and panel-corrected standard errors, are reported in table B.5.

Finally, I relax the assumption of homogenous effects across purchase programmes. To do so, I interact the flow variable with two dummy variables for, respectively, the PSPP period and the PEPP period. The first variable takes value 1 in the period from 1 March 2015, when the PSPP started, to 18 March 2020, when the PEPP was announced. The second variable takes value 1 from 18 March 2020 until the end of December 2022. The estimates of the flow variable when both the PSPP and the PEPP dummies take value 0 can be attributed to SMP purchases implemented before 1 March 2015.

Figure 7: Heterogenous effects across purchase programmes (lower-rated countries)



NOTES: This figure displays estimates from the baseline model (defined as in equation 2) obtained by interacting the purchase flow variable with purchase programme-specific dummies. The PSPP dummy takes value 1 for observations from 1 March 2015 to 18 March 2020. The PEPP dummy takes value 1 for observations from 18 March 2020 to 31 December 2022. Flow effects when these two dummy variables are set to 0 can be attributed to the SMP programme and are indicated accordingly. Estimates are based on the full sample period. 90% confidence intervals are based on robust standard errors. Coefficients marked in black approach conventional levels of statistical significance. The estimated coefficients, together with both robust and panel-corrected standard errors, are reported in table B.4.

Figure 7 visualises the estimates of this cross-programme heterogeneity test for lower-rated countries. I focus on lower-rated jurisdictions as the previous analysis has shown that this is the country cluster that primarily drives the flow effects of asset purchases on auction cycles. The full set of results is presented in table B.6 in the Appendix.

The flow estimates not interacted with purchase-specific dummies and attributable to the SMP period exhibit a positive and significant correlation between central bank asset purchases and yield changes around auction dates. This is consistent with the evidence provided by [Eser and Schwaab \(2016\)](#), who document that yield changes and SMP purchase amounts at a daily frequency are positively correlated for most SMP countries when interventions took place. At the same time, when interacting SMP flows with volatility, the estimated coefficient is negative, albeit not statistically significant. Given the large variations in bond yields during the sovereign debt crisis, the estimated coefficients are large in absolute values.

The results for PSPP and PEPP flows should be interpreted in light of the non-interacted estimates, given the additive nature of interaction terms. Compared to SMP, PSPP and PEPP purchases exhibit significantly more negative flow effects. Importantly, the estimated coefficients for PSPP and PEPP flows are larger in absolute terms than that of SMP, pointing to an overall negative impact of these flows when the market volatility factor is around its mean value of 0.

The large positive, but insignificant, coefficient of the interaction between PSPP flows and market volatility is partly justified by the fact that, during the 2015-2020 period, volatility was low and the average value of the market volatility factor is negative over that period. Regarding the interaction between PEPP flows and market volatility, it is important to note that the magnitude of the absolute value of the estimated coefficient is lower than that of the negative SMP estimate. Thus, the sum of the two still points to an overall negative, albeit insignificant, effect of purchase flows in times of higher volatility during the PEPP period.



Altogether, these findings suggest that the flow effects detected in the baseline estimation are driven by PSPP and PEPP flows when market volatility is around its average value. In line with the baseline results, the evidence about the state-contingent nature of purchase flows is more mixed, with greater uncertainty surrounding the negative effects of flows of asset purchases in times of higher volatility in the conservative estimation with robust standard errors.

In the next section, I turn to the conclusions and highlight the implications of the analysis for monetary policy and market functioning in the euro area.

## 7 Conclusion

This paper has offered new evidence on the relationship between unconventional monetary policy and yield cycles around public debt auctions in the euro area. Making use of proprietary data on purchases of public sector securities implemented by the Eurosystem, the analysis has extended the picture on the effects of central bank asset purchases on auction cycles provided by previous research ([van Spronsen and Beetsma 2022](#)).

The mitigating effects of central bank asset purchases on yield fluctuations around auction dates have been estimated to be, on average, in line with previous findings in terms of magnitude. When relying on a robust covariance matrix to base inferences on, the extension of the analysis period up to 2022 reveals more uncertainty associated with the estimates compared to the 1999-2017 subsample considered by previous research. However, the estimates are highly statistically significant when employing PCSE, which can account for contemporaneous correlations across panels and are commonly used to model large panel datasets.

Additional analyses highlight the presence of substantial heterogeneity of these effects. The effects of asset purchases on auction cycles are more sizeable and statistically significant for purchases of bonds with medium-term maturities (from 2 to 9 years). These effects are concentrated in the lower-rated countries of

the sample and driven by PSPP and PEPP flows when market volatility is at normal levels. Flow effects tend to be stronger when volatility is higher, but they are less precisely estimated in specifications based on robust standard errors.

Taken together, these findings have several potentially relevant implications for monetary policy and market functioning in the euro area. First, the evidence provided in the paper adds to a broader literature on the flow effects of Eurosystem's asset purchases (e.g., [Eser and Schwaab 2016](#); [Arrata and Nguyen 2017](#); [De Santis and Holm-Hadulla 2020](#)). The mitigating impact of purchase flows on auction cycles can be seen as a channel of transmission of monetary policy under the past accommodative stance of the ECB. Purchase flows contributed to transmission via lower debt-servicing costs for euro area DMOs and smoothened bond market volatility around auction dates.

Second, while the time frame of this paper's analysis is not sufficiently extended to draw meaningful conclusions about the post-pandemic period, the results also suggest that the auction cycle phenomenon warrants monitoring in times of high inflation, rising interest rates and heightened bond market volatility. At the time of writing, the ECB is pursuing a strategy of monetary policy normalisation to tackle unprecedented price pressures experienced in the euro area. In this context, the ECB has been raising its key interest rates at the fastest pace ever experienced in the history of the euro and has been significantly reducing its balance sheet, including via the partial reduction (from March to June 2023) and discontinuation (as of July 2023) of reinvestments of maturing securities under the APP. Bond market volatility has increased significantly since the start of the Russian invasion of Ukraine in February 2022. Moreover, the end of APP reinvestments implies the end of PSPP purchase flows and an increase in the share of bond supply unabsorbed by the Eurosystem.

The presence of higher volatility, reduced purchase flows and increasing floating supply may lead primary dealers to manage their inventories more actively, generating more pronounced fluctuations of government

bond yields around auction dates. Thus, a dedicated monitoring of secondary market yield dynamics around public debt auctions can provide useful indications about bond market functioning in the current context of monetary policy normalisation. This is especially relevant in light of the evidence that greater secondary market yield cycles tend to be associated with sovereign bond auctions with lower bid-to-cover ratios ([Beetsma et al. 2018a](#)).

Future research may extend the analysis of this paper in several interesting directions. Two are especially worth highlighting. First, for the reasons outlined above, a detailed assessment of auction cycles in the post-pandemic regime is warranted as new data come in and the ECB moves to the discontinuation of APP reinvestments. Second, building on examples from previous research on the impact of central bank asset purchases on bond markets (e.g., [De Santis and Holm-Hadulla 2020](#)), future efforts should be directed to designing more advanced causal identification strategies for the empirical assessment of the effects of purchase flows on yield cycles around auction dates.

## References

- Acharya, V. V., I. Drechsler, and P. Schnabl (2014). A Pyrrhic Victory? Bank Bailouts and Sovereign Credit Risk. *The Journal of Finance* 69(6), 2689–2739.
- Altavilla, C., G. Carboni, and R. Motto (2015). Asset Purchase Programmes and Financial Markets: Lessons from the Euro Area. *ECB Working Paper No. 1864*. Available at: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1864.en.pdf>.
- Altavilla, C., W. Lemke, T. Linzert, J. Tapking, and J. von Landesberger (2021). Assessing the Efficacy, Efficiency and Potential Side Effects of the ECB’s Monetary Policy Instruments since 2014. *ECB Occasional Paper No. 278*. Available at: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2293~41f7613883.en.pdf>.
- Arnone, M. and G. Iden (2003). Primary Dealers in Government Securities: Policy issues and Selected Countries’ Experience. *IMF Working Paper No. 03/45*. Available at: <https://www.imf.org/external/pubs/ft/wp/2003/wp0345.pdf>.
- Arrata, W. and B. Nguyen (2017). Price Impact of Bond Supply Shocks: Evidence from the Eurosystem’s Asset Purchase Program. *Banque de France Working Paper No. 623*. Available at: [https://blocnotesdeleco.banque-france.fr/sites/default/files/medias/documents/document-de-travail-623\\_2017-03.pdf](https://blocnotesdeleco.banque-france.fr/sites/default/files/medias/documents/document-de-travail-623_2017-03.pdf).
- Arrata, W., B. Nguyen, I. Rahmouni-Rousseau, and M. Vari (2020). The Scarcity Effect of QE on Repo Rates: Evidence from the Euro Area. *Journal of Financial Economics* 137, 837–856.
- Beck, N. and J. N. Katz (1995). What to do (and not to do) with Time-Series Cross-Section Data. *Econometric Reviews* 89(3), 634–647.
- Beetsma, R., M. Giuliodori, F. de Jong, and D. Widiyanto (2016). Price Effects of Sovereign Debt Auctions in the Eurozone: The Role of the Crisis. *Journal of Financial Intermediation* 25, 30–53.
- Beetsma, R., M. Giuliodori, J. Hanson, and F. de Jong (2018a). Bid-to-Cover and Yield Changes around Public Debt Auctions in the Euro Area. *Journal of Banking and Finance* 87, 118–134.
- Beetsma, R., M. Giuliodori, J. Hanson, and F. de Jong (2018b). Cross-Border Auction Cycle Effects of Sovereign Bond Issuance in the Euro Area. *Journal of Money, Credit and Banking* 50(7), 1401–1440.
- Born, B. and J. Breitung (2016). Testing for Serial Correlation in Fixed-Effects Panel Data Models. *Econometric Reviews* 35(7), 1290–1316.
- Broner, F., A. Erce, A. Martin, and J. Ventura (2014). Sovereign Debt Markets in Turbulent Times: Creditor Discrimination and Crowding-Out Effects. *Journal of Monetary Economics* 61, 114–142.
- D’Amico, S. and T. B. King (2013). Flow and Stock Effects of Large-Scale Treasury Purchases: Evidence on the Importance of Local Supply. *Journal of Financial Economics* 108(2), 425–448.
- De Santis, R. and F. Holm-Hadulla (2020). Flow Effects of Central Bank Asset Purchases on Sovereign Bond Prices: Evidence from a Natural Experiment. *Journal of Money, Credit and Banking* 52(6), 1467–1491.
- De Santis, R. A. (2014). The Euro Area Sovereign Debt crisis: Identifying Flight-to-Liquidity and the Spillover Mechanisms. *Journal of Empirical Finance* 26, 150–170.
- Ehrmann, M. and M. Fratzscher (2017). Euro Area Government Bonds – Fragmentation and Contagion During the Sovereign Debt Crisis. *Journal of Empirical Finance* 70, 26–44.
- Eser, F. and B. Schwaab (2016). Evaluating the Impact of Unconventional Monetary Policy Measures: Empirical Evidence from the ECB’s Securities Markets Programme. *Journal of Financial Economics* 119(1), 147–167.

- Fleming, M. J. and J. V. Rosenberg (2007). How Do Treasury Dealers Manage Their Positions? *Federal Reserve Bank of New York Staff Report No. 299*. Available at: [https://www.newyorkfed.org/medialibrary/media/research/staff\\_reports/sr299.pdf](https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr299.pdf).
- Ghysels, E., J. Idier, S. Manganelli, and O. Vergote (2014). A High Frequency Assessment of the ECB Securities Markets Programme. *ECB Working Paper No. 1642*. Available at: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1642.pdf>.
- Greenwood, R., S. G. Hanson, J. S. Rudolph, and L. H. Summers (2014). Government Debt Management at the Zero Lower Bound. *Working Paper 5, Hutchins Center on Fiscal and Monetary Policy at Brookings*. Available at: [https://www.brookings.edu/wp-content/uploads/2016/06/30\\_government\\_debt\\_management\\_zlb.pdf](https://www.brookings.edu/wp-content/uploads/2016/06/30_government_debt_management_zlb.pdf).
- Lou, D., H. Yan, and J. Zhang (2013). Anticipated and Repeated Shocks in Liquid Markets. *Review of Financial Studies* 26, 1891–1912.
- Plessen-Mátyás, K., C. Kaufmann, and J. von Landesberger (2021). Funding Behaviour of Debt Management Offices and the ECB’s Public Sector Purchase Programme. *ECB Working Paper No. 2552*. Available at: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2552~9335019d0c.de.pdf?2a22d05953158d955d8ef2ec4cfd0a95>.
- Sigaux, J.-D. (2018). Trading ahead of Treasury Auctions. *ECB Working Paper No. 2208*. Available at: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2208.en.pdf>.
- van Spronsen, J. and R. Beetsma (2022). Unconventional Monetary Policy and Auction Cycles of Eurozone Sovereign Debt. *Journal of Money, Credit and Banking* 54(1), 169–202.

# Appendix

## A Summary statistics

Table A.1: Number of 10-year public debt auctions by country

	(1)	(2)	(3)
Sample	Full	Pre-APP	APP
AT	194	54	140
BE	146	52	94
DE	233	73	160
ES	250	81	169
FI	35	11	24
FR	249	110	139
IT	284	130	154
NL	107	48	59
PT	107	46	61
Total	1605	605	1000

NOTES: This table presents the number of auctions across the nine jurisdictions considered in the analysis. Column 1 shows the number of all auctions taking place in the full sample (January 1999 - December 2022). Column 2 shows the number of auctions taking place in the pre-APP subsample period (January 1999 - April 2010). Column 3 reports the number of auctions taking place in the APP subsample period (May 2010 - December 2022).

Table A.2: Summary statistics for financial variables

	(1)		(2)		(3)	
Sample	Full		Pre-APP		APP	
	Mean	SD	Mean	SD	Mean	SD
Yield level (%)	3.00	1.98	4.37	0.66	1.78	1.97
Yield difference (bps)	-0.01	5.87	-0.01	4.67	-0.01	6.76
Market volatility factor	0.00	0.97	-0.00	0.93	0.00	1.00
SMP/PSPP/PEPP flows (bn)	0.07	0.21	0.00	0.00	0.14	0.27
Floating supply (trn)	0.53	0.50	0.40	0.36	0.66	0.57
EONIA/ESTR level	1.31	1.71	2.86	1.19	-0.07	0.45
EONIA/ESTR difference	-0.00	0.09	-0.00	0.12	0.00	0.06
Euro Stoxx 50 Volatility Index level	23.91	9.43	25.97	10.66	22.07	7.73
Euro Stoxx 50 Volatility Index difference	0.00	1.80	0.00	1.78	-0.00	1.81
Euro Stoxx 50 Index level	3329.43	684.91	3468.17	830.20	3205.40	489.59
Euro Stoxx 50 Index difference	0.04	44.60	-0.25	49.71	0.30	39.47
Euro Stoxx Banks Index level	198.22	108.51	295.21	83.20	115.23	31.41
Euro Stoxx Banks Index difference	-0.03	3.37	-0.03	4.32	-0.03	2.27
Observations	56349		26604		29745	

NOTES: This table reports summary statistics (mean and standard deviation) for the financial variables employed in the analysis. Column 1 shows summary statistics for the full sample (January 1999 - December 2022). Column 2 reports summary statistics for the pre-APP subsample period (January 1999 - April 2010). Column 3 reports summary statistics for the APP subsample period (May 2010 - December 2022).

## B Additional analyses

Table B.3: Dynamic regression models with robust and panel-corrected standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	APP	APP	Full	APP	APP
Std. errors	Robust	Robust	Robust	PCSE	PCSE	PCSE
$\Delta y_{i,t-1}$	0.053** (0.022)	0.091*** (0.010)	0.091*** (0.010)	0.053*** (0.008)	0.091*** (0.010)	0.091*** (0.010)
AC	1.973* (1.018)	2.285 (1.626)	1.357 (1.901)	1.973*** (0.511)	2.285*** (0.760)	1.357 (1.298)
x MktVol	2.548* (1.361)	3.656 (2.655)	3.689 (2.681)	2.548*** (0.509)	3.656*** (0.725)	3.689*** (0.725)
x Flows	-5.229* (2.805)	-5.549 (3.444)	-6.626 (4.551)	-5.229*** (1.678)	-5.549*** (2.008)	-6.626*** (2.147)
x MktVol x Flows	-6.006 (6.155)	-7.458 (6.574)	-7.423 (6.418)	-6.006*** (1.613)	-7.458*** (1.983)	-7.423*** (1.979)
x Floating Supply			0.135 (0.229)			0.135 (0.133)
Symmetry AC	0.861 (0.759)	1.290 (0.973)	1.357 (1.901)	0.861 (0.578)	1.290 (0.926)	1.357 (1.298)
Observations	55,179	29,745	29,745	55,179	29,745	29,745
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No
BB stat	-0.0574	0.0392	0.0527	-0.0574	0.0392	0.0527
BB p-value	0.954	0.969	0.958	0.954	0.969	0.958

NOTES: This table presents estimates from a dynamic regression model. Columns 1, 2 and 3 report estimates based on the specification with robust standard errors (in parentheses). Columns 4, 5 and 6 report estimates based on the specification with panel-corrected standard errors (in parentheses). Columns 1 and 4 are based on the full sample in this study (January 1999 - December 2022). Columns 2, 3, 5 and 6 are based on the APP subsample period in this study (May 2010 - December 2022). Definitions of AC, AC x Flows, AC x MktVol, AC x Flows x MktVol, AC x Floating Supply and Symmetry AC are given in equations 3, 4, 5, 7, 6 and 8. BB = Born-Breitung statistic for serial correlation. \*, \*\*, \*\*\* indicate the 10%, 5%, and 1% significance levels, respectively.

Table B.4: Heterogeneity across maturities of purchased securities

Std. errors	(1) Robust	(2) PCSE
AC	0.480 (1.096)	0.480 (0.869)
x MktVol	1.813 (1.504)	1.813*** (0.518)
x 0-2	7.001 (6.825)	7.001 (5.786)
x 2-9	-14.236*** (4.182)	-14.236** (5.823)
x 9-11	3.664 (7.504)	3.664 (13.826)
x 11-20	-6.922 (30.100)	-6.922 (17.325)
x 20+	1.686 (10.480)	1.686 (20.155)
x MktVol x 0-2	-5.502 (18.957)	-5.502 (6.902)
x MktVol x 2-9	-15.749 (8.533)	-15.749*** (5.500)
x MktVol x 9-11	3.784 (21.300)	3.784 (14.267)
x MktVol x 11-20	37.279 (48.969)	37.279** (17.321)
x MktVol x 20+	59.215 (39.063)	59.215*** (22.752)
x Floating Supply	0.235 (0.185)	0.235** (0.101)
Observations	55,179	55,179
Control Variables	Yes	Yes
Country FE	Yes	Yes

NOTES: This table presents estimates from the baseline model (defined as in equation 2) with purchases disaggregated across maturity brackets of the targeted securities. Column 1 reports estimates based on the specification with robust standard errors (in parentheses). Column 2 report estimates based on the specification with panel-corrected standard errors (in parentheses). Estimates are based on the full sample period. The 0-2 maturity bracket considers purchases of securities with maturity below 2 years. The 2-9 bracket includes purchases of securities with maturity from 2 up to 8.5 years. The 9-11 bracket includes purchases of securities from 8.5- to 11.5-year maturity. The 11-20 bracket covers maturities from 11.5 to 20 years. The 20+ considers maturities above 20 years. \*, \*\*, \*\*\* indicate the 10%, 5%, and 1% significance levels, respectively.



Table B.5: Heterogeneity across country groups

	(1)	(2)	(3)	(4)
Sample	Higher-rated	Lower-rated	Higher-rated	Lower-rated
Std. errors	Robust	Robust	PCSE	PCSE
AC	-0.534 (1.188)	1.778* (0.808)	-0.534 (0.964)	1.778 (1.374)
x MktVol	-1.303 (1.419)	4.144* (1.618)	-1.303* (0.705)	4.144*** (0.680)
x Flows	2.738 (2.143)	-11.428 (5.464)	2.738 (2.485)	-11.428*** (2.704)
x MktVol x Flows	9.860 (5.042)	-7.689 (6.369)	9.860*** (2.755)	-7.689*** (2.043)
x Floating Supply	-0.031 (0.103)	0.254 (0.184)	-0.031 (0.152)	0.254* (0.142)
Observations	24,524	30,655	24,524	30,655
Control Variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

NOTES: This table presents estimates from the baseline model (defined as in equation 2) and obtained by splitting the sample of countries between higher-rated (i.e., Austria, Germany, Finland and the Netherlands) and lower-rated (i.e., Belgium, France, Italy, Portugal and Spain) jurisdictions. Estimates are based on the full sample period. Columns 1 and 2 report estimates based on the specification with robust standard errors (in parentheses). Columns 3 and 4 report estimates based on the specification with panel-corrected standard errors (in parentheses). Columns 1 and 3 report estimates for higher-rated countries. Columns 2 and 4 report estimates for lower-rated countries. \*, \*\*, \*\*\* indicate the 10%, 5%, and 1% significance levels, respectively.

Table B.6: Heterogeneity across purchase programmes (lower-rated countries)

Std. errors	(1) Robust	(2) PCSE
AC	2.066 (1.098)	2.066 (1.398)
xMktVol	2.525 (1.983)	2.525*** (0.790)
x SMP Flows	26.319* (9.707)	26.319* (13.833)
x MktVol x SMP Flows	-29.097 (17.624)	-29.097*** (10.884)
x PSPP Flows	-30.331** (10.523)	-30.331* (15.657)
x MktVol x PSPP Flows	43.831 (22.263)	43.831*** (13.974)
x PEPP Flows	-34.360* (12.982)	-34.360** (14.701)
x MktVol x PEPP Flows	22.494 (13.517)	22.494* (11.667)
x Floating Supply	0.175 (0.215)	0.175 (0.143)
Observations	30,655	30,655
Control Variables	Yes	Yes
Country FE	Yes	Yes

NOTES: This table displays estimates from the baseline model (defined as in equation 2) and obtained by interacting the purchase flow variable with purchase programme-specific dummies. The PSPP dummy takes value 1 for observations from 1 March 2015 to 18 March 2020. The PEPP dummy takes value 1 for observations from 18 March 2020 to 31 December 2022. Flow effects when these two dummy variables are set to 0 can be attributed to the SMP programme and are indicated accordingly. Estimates are based on the sample of lower-rated countries and the full sample period. Columns 1 reports estimates based on the specification with robust standard errors (in parentheses). Columns 2 reports estimates based on the specification with panel-corrected standard errors (in parentheses). \*, \*\*, \*\*\* indicate the 10%, 5%, and 1% significance levels, respectively.