What Drives Monetary Preferences? Evidence from MEPs' Social Media Discourse on Cryptocurrencies and the Digital Euro

Gabriel Tailleur*

Abstract

This paper studies how ideology and economic conditions shape political preferences over digital money in the European Parliament. During the 9th Legislature, debates on cryptocurrency regulation and the ECB's central bank digital currency—the digital euro—created a rare opportunity to observe the politicization of money and assess whether it generates political polarization. Drawing on 2,523 tweets from 224 MEPs, we combine sentiment analysis with an unsupervised text-scaling model to identify the ideological and economic determinants of support for private and public digital money, to trace how these preferences are connected, and through which mechanisms. We document a mirror-image pattern: anti-elitism, right-wing economic positioning, and exposure to inflation increase support for cryptocurrencies, while the same drivers underpin opposition to the digital euro. The text-scaling analysis shows that discourse polarizes around privacy and fears of ECB mandate expansion, raising broader concerns about the political acceptability of the digital euro. Taken together, the findings indicate that debates over ECB legitimacy have crystallized into a new cleavage opposing public and private digital money.

KEYWORDS: *Political economy of central banking*; *Digital currencies*; *Textual analysis*; *Large Language Models*

JEL CLASSIFICATION: P16; E52

*University of Amiens, LEFMI, France. Contact: ga.tailleur@gmail.com

1 Introduction

Once regarded as a technocratic domain insulated from politics, central banks have become increasingly contested in the aftermath of the global financial crisis. Unconventional monetary policies and the rise of digital currencies have pushed money back into public debate and political arenas, turning it into a salient and politically charged issue. This politicization has recently crystallized around two monetary innovations: cryptocurrencies and central bank digital currencies (CBDCs). Cryptocurrencies emerged in explicit opposition to established financial and monetary institutions, offering private alternatives to public money. By contrast, the digital euro represents an institutional response aimed at reaffirming monetary sovereignty, yet it has also raised concerns among some politicians about potential overstretch of the European Central Bank (ECB) mandate. From a political economy perspective, the ECB therefore faces a dual challenge: securing political and public acceptance of the digital euro while limiting incentives to adopt or promote cryptocurrencies and other private alternatives. These tensions became especially visible in the European Parliament (EP). Although monetary issues rarely reach the floor, the 9th Legislature was an exception: both cryptocurrency regulation and the digital euro proposal entered the policymaking agenda and triggered intense political polarization, providing a rare window into how money becomes politicized in Europe.

In this article, we investigate the ideological and country-level drivers of political preferences toward cryptocurrencies and the digital euro. This raises a deeper puzzle: are preferences for private and public digital money systematically related, and if so, through what mechanisms? Unpacking this relationship is key to understanding how money becomes politicized, who drives this process, and what challenges it poses for monetary trust and the ECB's legitimacy. The overlap between the cryptocurrency and digital euro agendas in the 9th Legislature provides an opportunity to test whether the politicization of money translates into political polarization, and, if so, along which cleavages. To exploit this setting, we analyze 2,523 tweets from 224 Members of the European Parliament (MEPs) from 96 national political parties between 2019 and 2024, capturing parliamentary communication on both cryptocurrencies and the digital euro. Using text analysis techniques, we explore how parliamentarians' stances relate to ideology and macroeconomic conditions. We first employ sentiment analysis to measure MEPs' positions, relying on hand-coded annotations validated against large language models and lexicon-based classifiers. We complement this analysis with the Wordfish scaling model, which uncovers the rhetorical foundations of the political polarization over cryptocurrencies and the digital euro. Together, these approaches provide both quantitative estimates of preference determinants and qualitative insights into the mechanisms of monetary politicization.

We find that preferences toward digital money are jointly shaped by ideology and economic conditions.

Anti-elitism, right-wing economic positioning, and exposure to inflation are associated with greater support for cryptocurrencies and stronger opposition to the digital euro. A pro-European orientation reduces opposition to the digital euro but has no effect on cryptocurrency preferences. Among these predictors, left–right economic ideology has the largest substantive effect in the cryptocurrency sample, whereas anti-elitism is the strongest predictor of opposition to the digital euro. Importantly, polarization follows a mirror-image pattern: the same factors that predict support for cryptocurrencies also predict opposition to the digital euro. In addition, descriptive evidence on sentiment dynamics suggests that the politicization of the digital euro may amplify polarization around cryptocurrencies. The Wordfish scaling analysis points in the same direction. Supporters of cryptocurrencies rarely defend them on strictly monetary grounds; instead, they emphasize opposition to regulation and resistance to political interference in monetary affairs. In this context, support for cryptocurrencies appears to serve as a vehicle for criticizing the digital euro and, more generally, the expanding role of central banks. The word-scaling analysis further indicates that these divisions reflect competing views about markets and the state, as well as about the trade-off between privacy and political control.

Related literature. This paper contributes to several strands of research on the political economy of digital currencies and central banking. We first extend research on the political economy of cryptocurrencies, where most empirical studies have focused on individual adoption. Using survey data, Auer and Tercero-Lucas (2022) show that distrust in fiat money and commercial banks does not predict cryptocurrency use, contrary to Bitcoin's founding objective of providing an alternative to traditional financial institutions (Nakamoto, 2008; Chey, 2023). Still, cryptocurrencies remain ideologically charged. Steinmetz et al. (2021) find that most holders own digital assets for ideological rather than speculative reasons, though without specifying the content of these beliefs. Littrell et al. (2024) identify aversion to authoritarianism as an important determinant of adoption, while Ferguson et al. (2024) highlight the role of inflation hardship and conspiratorial beliefs. Yet, both studies report no systematic ideological or partisan divide among cryptocurrency holders. Our findings add to this literature by showing that preferences toward cryptocurrencies are deeply polarized at the policymaking level and structured along clear ideological dimensions, such as left/right and pro-/anti-elite orientations. More generally, by shifting from survey-based evidence on individual adoption to a text-as-data analysis of political discourse, we show how ideological and economic incentives shape the regulation of digital currencies.

Second, our results align with theoretical accounts that view cryptocurrencies as vehicles of contestation against monetary sovereignty. Bitcoin was conceived as 'digital cash' (Nakamoto, 2008; Luther, 2019), in explicit reaction to the discretionary policies of central banks. In this view, private monetary alternatives emerge as a logical consequence of a broader legitimacy crisis in money (Weber, 2016), and carry a strong

normative charge (De Filippi and Wright, 2018). We provide empirical evidence of this antagonistic relationship: at the policymaking level, support for cryptocurrencies is systematically associated with opposition to the central bank's digital currency. This divide is consistent with arguments that innovation and regulation operate as alternative strategies through which central banks seek to preserve monetary sovereignty against the rise of private digital money. In this context, Ba and Şen (2024) show that, unlike autocracies, liberal democracies face higher political costs when banning cryptocurrencies, and therefore tend to rely instead on regulatory containment or monetary innovation. The European case illustrates this pattern. In 2022, an amendment in the ECON Committee seeking to ban proof-of-work cryptocurrencies such as Bitcoin from regulated exchange platforms was ultimately rejected. Our paper builds on this insight by showing that CBDC development reflects both an institutional response to perceived threats to monetary sovereignty and a strategic attempt to limit dependence on private monetary alternatives. The Wordfish analysis further shows that MEPs themselves draw this connection, linking stricter cryptocurrency regulation to the political momentum behind the digital euro. This pattern echoes earlier work showing that the acceleration of CBDC projects was driven in large part by the rise of private cryptocurrencies (Kosse and Mattei, 2023).

Third, we contribute to the rapidly growing literature on CBDCs, which has so far remained largely theoretical and qualitative, with a primary focus on optimal design choices and the motivations behind their development. Central bank digital currencies are a new form of public money that, unlike commercial bank deposits, entail neither credit nor liquidity risk. They constitute a major monetary innovation whose design raises fundamental questions for financial stability, monetary policy, and the scope of central bank mandates (Quaglia and Verdun, 2025b). A common view presents CBDCs as technical instruments to modernize payments, adapt money to the 'digital age', and preserve monetary sovereignty amid declining cash use and the rise of private alternatives (EC, 2023; ECB, 2024). Recent research, however, emphasizes their political economy dimensions. From this perspective, the ECB's unusually rapid push toward a digital euro, despite its reputation as a risk-averse institution, suggests that political, institutional, and reputational incentives are central to its behavior (Moschella, 2024). First, institutional dynamics such as 'mission creep' (Pfister, 2024) and peer pressures following the development of Libra and the digital yuan generate strong diffusion pressures across central banks (Quaglia and Verdun, 2025a). For the ECB, Facebook's Libra project was a major catalyst that accelerated the digital euro agenda (Alonso-Robisco and Carbó, 2023). Second, fiscal and financial motivations matter: issuing a CBDC may preserve or increase seigniorage revenues as cash use declines (Pfister, 2024), while also generating transaction data that may be useful for limiting tax evasion and informal activity (Kim and Kwon, 2023; Auer et al., 2023). Third, CBDCs may enlarge the monetary policy toolkit by allowing central banks to move beyond the zero lower bound through negative interest rates (Barrdear and Kumhof, 2022) or programmable transfers to directly stimulate

demand (Davoodalhosseini, 2022). Finally, geopolitical motives have gained prominence, with the digital euro framed as a tool of European financial sovereignty aimed at reducing dependence on non-European payment systems amid growing international tensions (Westermeier, 2024; Quaglia and Verdun, 2025a; van 't Klooster et al., 2025). Moreover, previous research shows that central banks adapt their behavior to preserve or restore legitimacy. They may respond to political pressures by adopting unconventional policies aligned with governments' priorities (Moschella, 2024), or to negative public opinion by broadening their communication beyond their core mandate (Moschella et al., 2020). In this light, the digital euro can also be seen as an attempt by the ECB to restore legitimacy by reaffirming the public character of money and its connection with European citizens (Monnet, 2024). Building on this literature, our paper provides an empirical analysis of the political and economic determinants of policymakers' preferences toward the digital euro. It complements existing research by identifying the conditions under which a CBDC gains (or fails to gain) political support, a necessary condition for its eventual adoption by the European Parliament. The Wordfish analysis further illustrates these mechanisms by showing that opposition is driven primarily by concerns about anonymity and political discretion.

Finally, this paper also contributes to the literature on the political economy of central banking and monetary trust. Since the global financial crisis, public confidence in money and monetary institutions has been repeatedly challenged. Over the same period, central banks have accumulated new responsibilities and powers, including the potential issuance of digital currencies. This evolution has both reflected and intensified the politicization of money and of the ECB itself: monetary policy has become more salient in public debate, while the ECB is increasingly seen as deviating from a narrowly technocratic interpretation of its mandate (Tortola, 2020). The digital euro epitomizes this dual politicization, reflecting both the increased salience of monetary issues and concerns about mandate expansion. More broadly, central banks are no longer insulated from political contestation: periods of public distrust expose the ECB to blame for broader policy failures (Ferrara et al., 2022), while its independence is increasingly challenged by populist and anti-establishment politicians (Goodhart and Lastra, 2018). In this vein, Fraccaroli et al. (2022) show that eurosceptic MEPs tend to address ECB representatives more negatively during monetary dialogues. Our findings speak directly to these dynamics: anti-elitism stands out as the strongest predictor of opposition to the digital euro, consistent with broader skepticism toward ECB independence and the expansion of its mandate. More generally, our results highlight that money is not merely a technical instrument but an institution whose legitimacy is continuously contested and renegotiated. The polarization we document reveals a public-private monetary dialectic, in which competing normative visions of monetary order generate different expectations about the role of the central bank and the broader social and political implications of each monetary forms.

The rest of the paper is organized as follows. Section 2 motivates the use of X (formerly Twitter) to study political preferences and describes the data and methods. Section 3 presents descriptive evidence and the empirical strategy. Section 4 reports the main results and robustness checks, before turning to a Wordfish scaling analysis of the rhetorical mechanisms underlying polarization. Section 5 concludes.

2 Data and Text Analysis Methods

2.1 Social media textual data as a window into political preferences

Members of the European Parliament have few institutional channels to express their views on money and monetary policy. Parliamentary oversight of the ECB is largely confined to *monetary dialogues*, where representatives typically provide general, ex-post justifications. These exchanges place no direct constraints on ECB action, leaving the institution largely judge and party to its own conduct. Despite its formal independence, the ECB has increasingly been accused by some policymakers of playing politics (Monnet, 2024). These criticisms resonate in public opinion: monetary trust has weakened since the global financial crisis (Braun, 2016), and confidence in the ECB has declined over the past two decades (Bergbauer et al., 2020). Against this backdrop, alternative strategies are needed to study how MEPs position themselves on salient monetary issues. The 9th Legislature provides a rare opportunity to do so, as debates on cryptocurrencies and the digital euro both fell within the Parliament's legislative remit[1]. This overlap created a highly politicized setting in which MEPs actively communicated their positions, making posts on X (Twitter) a useful source for tracing political preferences

Prior research has shown that textual data are particularly useful for identifying political preferences when conventional indicators are less informative. This is especially true in our setting, where voting records provide limited leverage: votes on the digital euro have not yet taken place, while those on cryptocurrency regulation were largely consensus-driven, thereby masking the polarization observed in the ECON committee (see Figure 6 in the online Appendix, which reports a heatmap of amendment votes on the MiCA regulation). More generally, the strong role of eurogroup discipline in the EP (Servent and Roederer-Rynning, 2018) reduces the informational content of roll-call votes, whereas textual analysis has proven effective in uncovering intra-party heterogeneity in preferences (Proksch and Slapin, 2014; Lauderdale and Herzog, 2016). This informational advantage stems from both the richer expressive content of language compared to the binary nature of votes and the fact that MEPs may use social media to signal their *true* preferences outside formal parliamentary settings, such as plenary debates where group discipline is more binding (Silva and Proksch,

[1]Debates on the Markets in Crypto-Assets (MiCA) regulation and the digital euro legislative package were held within the same plenary sessions, making their interrelation a recurrent theme in parliamentary speeches.

2022). With 94% of Members of the European Parliament (MEPs) in the 9th Legislature using X[2], the platform has become a central channel through which they signal positions on salient issues (Daniel et al., 2019) and engage with otherwise distant constituencies (Scherpereel et al., 2017). In this light, tweets are increasingly used to infer MEPs' preferences and political positions through textual analysis. For instance, Nulty et al. (2016) show that sentiment analysis of tweets captures the main political cleavages in the EP, mirroring voting patterns while offering additional nuance from the richer informational content of texts. Finally, unlike episodic plenary debates, social media provides a continuous record of political communication, allowing us to trace sentiment dynamics and preference variation over the legislative term.

2.2 Data collection and presentation

We collected the X handles of all MEPs serving in the 9th Legislature and extracted tweets related to digital money using a multilingual keyword list. The list, reported in Section A.1 in the online Appendix, includes terms such as '*cryptocurrenc**', '*bitcoin*', '*digital euro*' or '*blockchain*', along with their stems in each of the EU27 languages[3]. To minimize false negatives, the keyword list is intentionally extensive, covering legislative references (MiCA and TFR) and related concepts (e.g., blockchain). Using the X API, we retrieved all tweets matching these keywords in either English or the MEPs' native languages. We then manually verified extracted tweets and removed false positives arising from polysemy[4]. Because the multilingual nature of MEP communication can affect the performance of sentiment and scaling models, we translated all tweets into English using the Google Translate API, following established practice (Vries, 2018; Proksch et al., 2019). Each tweets was then matched to the author's European Political Group (EPG), national party, nationality, and committee membership using official European Parliament records.

The Ninth Legislature comprises seven EPGs. The European People's Party (EPP), which brings together center-right Christian democratic parties, is the largest group in Parliament. The Progressive Alliance of Socialists and Democrats (S&D) is the second largest and represents the center-left. Renew Europe groups together liberal and centrist parties. On the right, the European Conservatives and Reformists (ECR) consists mainly of conservative parties and, during the 9th Legislature, often aligned in roll-call votes with Identity and Democracy (ID), the far-right group. Smaller groups include the Greens/European Free Alliance (Greens/EFA) and the radical left European United Left/Nordic Green Left (GUE/NGL).

[2]Author's calculation.

[3]We rely on the ECB's official translations of the terms 'cryptocurrency' and 'digital euro' provided on its digital euro presentation webpage, accessible at: https://www.ecb.europa.eu/euro/digital_euro/html/index.en.html.

[4]For instance, the term 'mica' is the acronym of the Markets in Crypto Assets regulation, but also refers to an unrelated political scandal in Ireland.

Table 1: Distribution of tweets per topic and eurogroup

Political group	N. of tweets	Crypto-currency	Digital euro	Other (e.g. libra)	N. of MEPs tweeting	N. of seats
Social-Democrats (S&D)	708	462	69	177	45	138
European People's Party (EPP)	560	328	93	139	55	179
Greens (Greens/EFA)	380	314	32	34	25	70
Renew Europe (Renew)	281	183	46	52	40	100
Identity and Democracy (ID)	254	100	117	37	28	69
European Conservatives and Reformists (ECR)	236	100	128	8	15	49
The Left (GUE/NGL)	90	61	15	14	11	37
Non-attached (NA)	14	6	3	5	5	63
Total	2,523	1,554	503	466	224	705

The final dataset comprises 2,523 tweets posted during the 9th Legislature (July 2019-July 2024). Table 1 reports their distribution across EPGs and topics. As expected, the two largest groups EPP and S&D account for the highest number of tweets, followed by the Greens, Renew Europe, ID, ECR, and The Left. Although the overall distribution of tweets broadly mirrors the distribution of seats across political groups, attention varies substantially across topics. This likely reflects differences in issue salience across party families' doctrinal orientations. ID and ECR, for example, are the only groups that tweet more about the digital euro (117 and 128 tweets, respectively) than about cryptocurrencies. By contrast, the Greens and Renew Europe devote comparatively less attention to the digital euro, suggesting that it occupies a less central place in their political agendas. Figure 7 in the online Appendix reports the distribution of tweets across member states. Germany, which has the largest representation in the European Parliament, accounts for the largest number of tweets, followed by France, the Netherlands, Spain, Greece, and the Czech Republic. At the other end of the distribution, smaller member states with fewer MEPs such as Lithuania, Luxembourg, Slovakia, and Croatia, account for the fewest tweets.

Of the 2,523 tweets, 1,554 concern cryptocurrencies, 503 concern the digital euro, and 466 refer to related topics such as blockchain or Facebook's Libra project. The dataset covers 224 MEPs, representing about 32% of the chamber. Naturally, not all parliamentarians publicly express positions on monetary issues, as communication tends to concentrate among those most involved in monetary and financial legislation or those for whom the topic is particularly salient. Finally, institutional features of the European Parliament, together with several empirical checks, mitigate potential concerns about sample composition. Legislative

responsibilities within each political group are organized by policy domain (Ringe, 2009), which makes committee members the most likely to communicate publicly on issues within their remit. These members also play a central role in shaping their group's policy line and, by doing so, influence the public stance adopted by their peers, contributing to the high cohesion observed within the main political groups (Servent and Roederer-Rynning, 2018). Our corpus reflects these institutional dynamics: it includes all ECON committee chairs, 38 of its 56 full members, and most substitutes. In addition, the distribution of tweets closely mirrors the balance of seats across political groups and aligns reasonably well with national representation. Several robustness checks based on alternative samples (Section 4.2) further suggest that the results are not driven by outlier groups or individual MEPs.

2.3 Sentiment analysis approaches

Broadly defined, sentiment analysis measures the attitude expressed in a text by one entity toward another (Algaba et al., 2020). Sentiment measures usually take the form of discrete polarity categories (positive, neutral, negative) or a continuous valence score (e.g., from -1 to +1). In the context of political communication, we treat tonality as a proxy for latent political preferences: parliamentarians use social media both to express opinions and to signal positions on salient issues. Consequently, a predominantly negative tonality is expected to reflect criticism or opposition, whereas positive tonality likely signals support for the issue under discussion. Sentiment analysis has been widely applied to political texts, including MEP speeches and tweets, to uncover politician's latent preferences (Fraccaroli et al., 2022; Nulty et al., 2016; Silva and Proksch, 2022). Early approaches relied on lexicons that assign fixed positive or negative scores to individual words. However, lexicon-based methods are insensitive to context and are therefore prone to misclassification, particularly in the presence of irony, negation, or domain-specific vocabulary not captured by the dictionary. More recently, generative language models have been shown to outperform lexicons by capturing such nuances. We therefore construct a hand-coded sentiment measure and validate it against four alternative classifiers: the Vader lexicon, the open-source Llama 3.1 model, and two GPT-4o classifications based on alternative prompting strategies.

2.3.1 Hand-coded annotations

Given the sample size, we manually classified each tweet into one of three categories: positive, neutral, or negative. A positive label indicates support for the cryptocurrencies or the digital euro, a negative label denotes criticism or opposition, and a neutral label applies to tweets that do not express a clear stance or merely report parliamentary activity. Manual classification allows us to capture irony, context, and

rhetorical nuance. It is therefore commonly used as a benchmark for validating automated approaches, although it is costly to replicate. We accordingly use it as the baseline outcome in our empirical analysis and validate it against four alternative sentiment classifications. The main results show strong convergence across classifiers, with the corresponding performance metrics reported in Table 5 in the online Appendix. Additional validation comes from the unsupervised Wordfish scaling analysis (Section 4.3), which yields patterns consistent with the hand-coded sentiment distribution.

2.3.2 Lexicon-based classification

As a first alternative classifier, we use the Vader lexicon (Hutto and Gilbert, 2014), a sentence-level dictionary containing roughly 9,000 words rated by ten independent annotators on a scale from -4 (extremely negative) to +4 (extremely positive). Originally developed for social media data, Vader has since been applied to other types of political and media texts, including newspaper articles (Shapiro et al., 2022) and parliamentary speeches (Fraccaroli et al., 2022). Unlike traditional Bag-of-Words lexicons, Vader incorporates heuristic rules to handle negation (e.g., *not*, *isn't*) and intensity modifiers (e.g., *very*, *extremely*, *!*). For example, '*this is good*' may receive a score of +1, whereas '*this is not good*' shifts to -1 due to negation. Intensity modifiers further amplify sentiment score in the direction of the detected tone. To ensure effective matching with our corpus, tweets were pre-processed by removing URLs, Twitter handles, newline characters, digits, and all non-alphanumeric characters except exclamation marks. Table A.4.1 in the online Appendix lists the 20 most frequent positive and negative terms matched by the lexicon.

For each tweet i, we compute the VADER sentiment score and normalize it as:

$$\text{Sentiment}_i = \frac{S_i}{\sqrt{S_i^2 + \alpha}}, \tag{1}$$

where S_i denotes the VADER compound score for tweet i, defined as the sum of token-level valence scores after VADER's heuristic adjustments for negation and intensifiers, and α is a normalization constant. The resulting measure is a score bounded between -1 and 1.

However, words may carry different connotations in political discourse than in general usage. For example, the term *lobby* receives a positive score in Vader, although in parliamentary debates it typically carries a neutral or negative connotation. To mitigate this issue, we excluded several problematic entries from the dictionary[5]. Section A.4.2 of the online Appendix reports the two most positive and two most negative tweets in both the cryptocurrency and digital euro samples, along with their Vader sentiment scores and GPT classifications. Extreme cases are generally well captured by Vader, with the exception of the two

[5]The following terms were removed from the list of positive terms: '*wealth*', '*rich*', '*speculative*', '*gain*', '*asset*', '*ban*', '*party*', '*growing*', '*lobby*'.

digital euro tweets that it classifies as positive. Both the LLM-based and hand-coded annotations instead classify these tweets as negative and neutral, respectively. This example illustrate the limitations of lexicon-based methods, which often misclassify texts with complex syntax or context-dependent meaning. Although useful for detecting broad tonal patterns, large language models provide more reliable classifications

2.3.3 Large language models (LLMs)

We complement the hand-coded and lexicon-based measures with sentiment classifications generated by large language models (GPT-4o and Llama 3.1), using both zero-shot and few-shot prompts. LLMs have become increasingly accessible and efficient for sentiment analysis (Korinek, 2023), with applications ranging from tweets (Algan et al., 2025) to central bank speeches (Leek and Bischl, 2025; Gambacorta et al., 2024) and Federal Reserve press releases (Hansen and Kazinnik, 2024). They are particularly efficient for capturing polarity shifts, speculation and irony (Wang et al., 2024), all of which are common in political communication. Empirical evidence further shows that GPT models outperform both fine-tuned smaller language models and alternative LLMs, especially in few-shot settings (Krugmann and Hartmann, 2024; Jha et al., 2024; Cook et al., 2023). However, proprietary models such as GPT-4 raise concerns about replicability (Ollion et al., 2024): closed models can generate greater variance across repeated queries in static tasks compared with locally run models (Barrie et al., 2025), and they are also subject to deprecation risk. Still, evidence suggests that in sentiment classification, prompt design has only limited influence on output variation (Zhang et al., 2023). To address these concerns, we also employ the open-source Llama 3.1 model. Performance metrics relative to the hand-coded annotations are reported in Table 5 of the Appendix, and Section A.2 documents the model parameters and prompts.

3 Empirical Approach

3.1 MEPs' attention and sentiment over time

Figure 1 illustrate how MEP attention, measured by tweet volume, reflects both static and dynamic incentives to signal positions on monetary issues. Peaks in attention coincide mainly with major legislative moments, including the plenary vote on MiCA (April 2023), the debate over a possible Bitcoin ban (March 2022)[6], and the European Commission's legislative proposal on the digital euro (June 2023). Exogenous events, such as the Bitcoin crash (May 2022) and the collapse of FTX (November 2022), also generated marked increases in activity.

[6]The March 2022 Bitcoin ban debate concerned an amendment to prohibit cryptocurrency transactions relying on energy-intensive networks, such as Bitcoin's Proof-of-Work (PoW) protocol. Supported by the Left and Greens, the amendment was narrowly rejected in the ECON committee (30–23).

The lower panel reports average sentiment scores for tweets on cryptocurrencies and the digital euro from 2021 onward, computed using the Vader lexicon. For readability, EPGs are aggregated into three broader blocs on the basis of the similarity of their sentiment levels documented in Section 3.2: left-leaning (GUE/NGL, S&D), center-right (EPP, Renew), and right-wing (ECR, ID). The Greens/EFA are shown separately because their sentiment profile differs from that of the broader left. Although generally aligned with other left-leaning groups, the Greens display increasingly favorable sentiment toward cryptocurrencies. This pattern, which we examine in greater detail in the next section (see Figures 2a and 3a), reflects substantial within-group heterogeneity driven by a small number of outlier MEPs whose positions diverge from both the Greens' dominant line and the broader left bloc.

Several partisan asymmetries are immediately visible. Sentiment toward cryptocurrencies among left-leaning groups declines steadily, with a pronounced drop in June 2023. By contrast, right-wing groups display broadly stable sentiment until mid-2023, after which sentiment becomes markedly more positive. Center-right sentiment remains consistently positive, at around 0.25, throughout the period. Turning to the digital euro, center-right MEPs become progressively more favorable over time, while left-leaning groups maintain positive sentiment throughout, with a peak around mid-2023. Right-wing sentiment, by contrast, declines steadily, from around 0.45 in early 2021 to values close to zero by 2024.

Interestingly, the European Commission's proposal for a digital euro triggered a polarization dynamic. From June 2023 onward, sentiment toward cryptocurrencies moves away from the center, with left- and right-wing groups evolving in opposite directions. This suggests that the digital euro's entry into the legislative arena (i.e., its politicization) may have amplified divisions over cryptocurrencies, pointing to an interdependence between the two debate. These patterns remain descriptive impressions and are examined more systematically in Section 4.

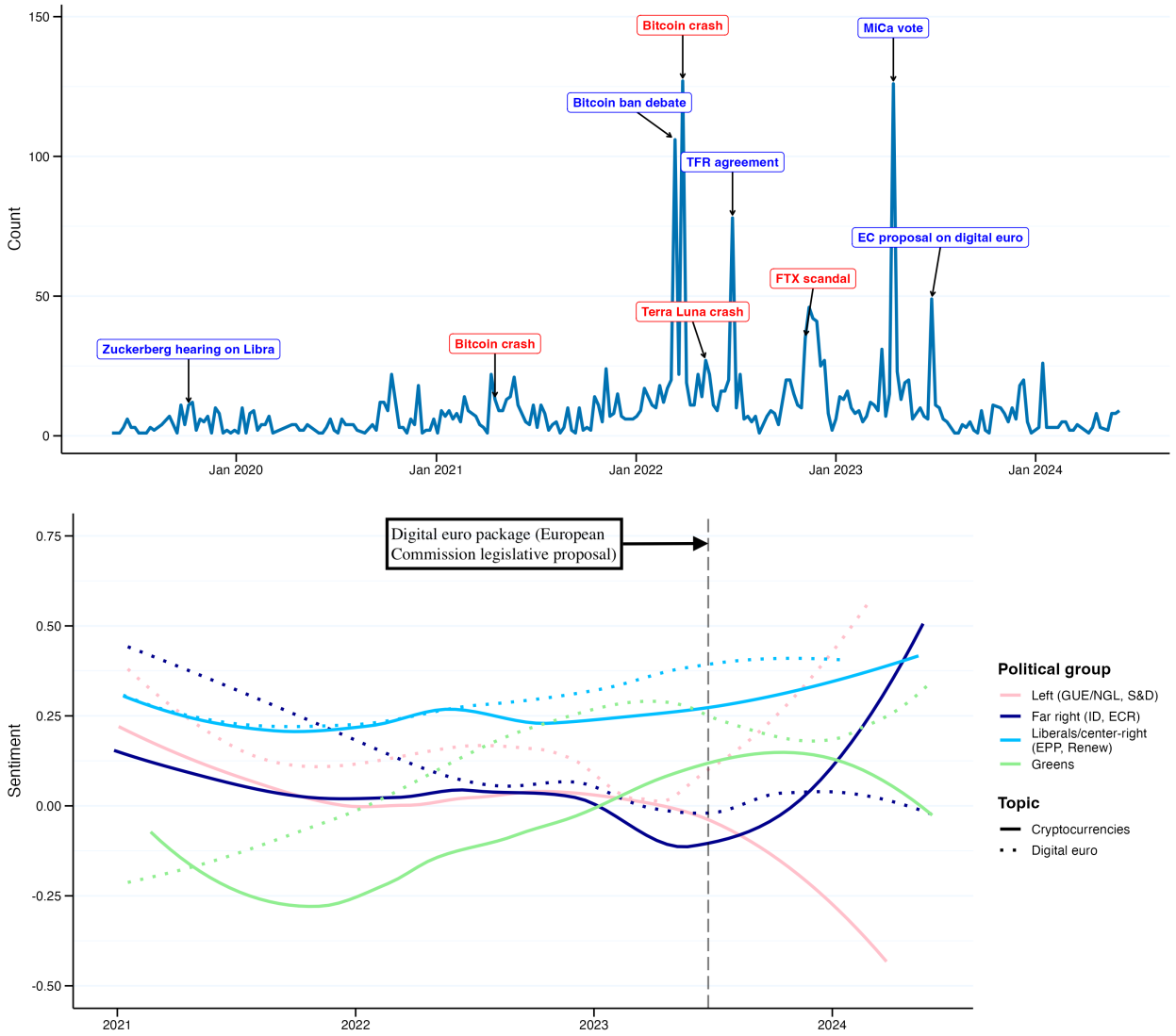
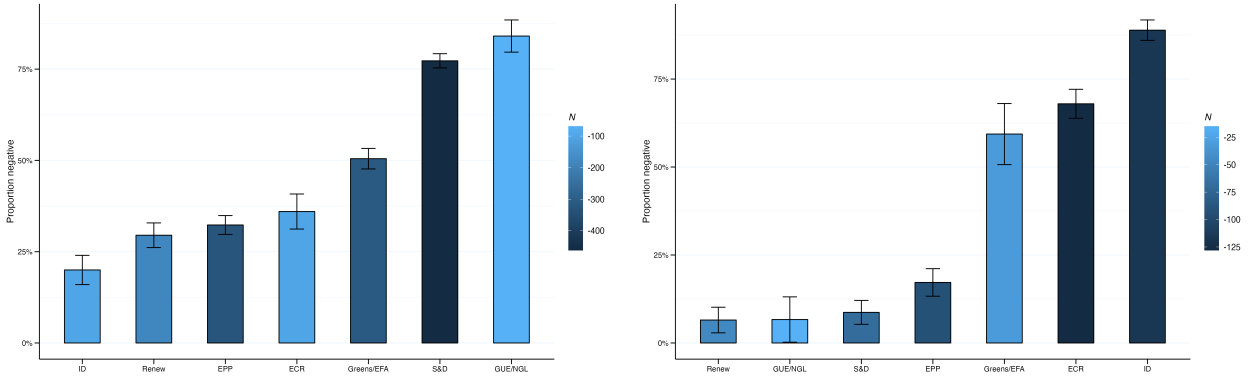


Figure 1: Weekly aggregated number of tweets and sentiment per political group. Notes: Top figure reports the weekly number of tweets related to cryptocurrencies and the digital euro. EU parliamentary events (blue) and external shocks (red) are indicated. Bottom figure shows the weekly average sentiment per political group, computed with the Vader lexicon. Solid (dashed) lines represent sentiment toward cryptocurrencies (digital euro). Left, center-right, and right-wing blocs are aggregated based on ideological and sentiment proximity. Curves are smoothed using local polynomial smoothing (LOESS).

3.2 Sentiment distribution across European political groups and party families

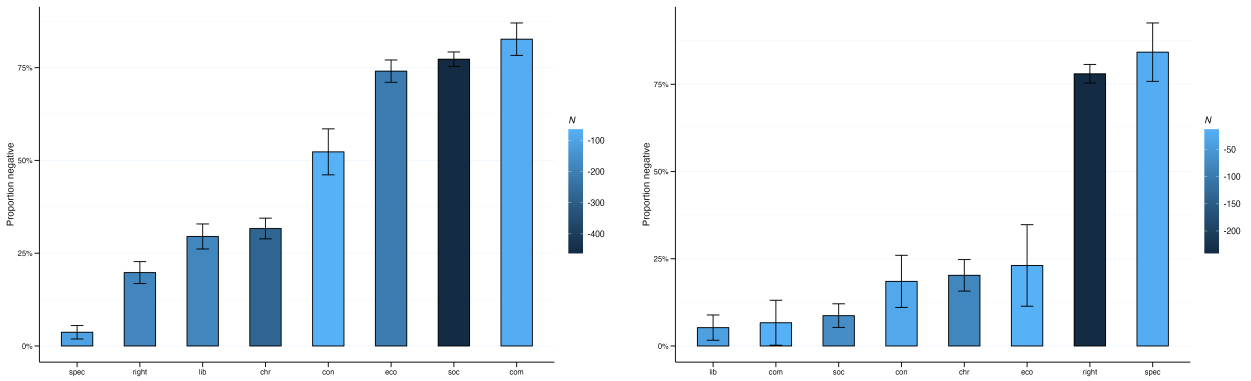
This section examines how sentiment toward cryptocurrencies and the digital euro varies across EPGs (Figure 2) and broader party families (Figure 3). Party families are derived from the ParlGov database (Döring et al., 2022), which classifies national parties into transnational groupings including communists, socialists, ecologists, liberals, christian-democrats, conservatives, the radical right, and a residual *special*

issue category for parties with ambiguous doctrinal profiles. Because national parties are generally more ideologically cohesive than EPGs, this classification provides finer ideological granularity, allowing us to capture the ideological diversity that persists within eurogroups and to also account for unaffiliated (non-attached) MEPs.



(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 2: Share of negative statements per European political group. *Notes:* Figure A (B) displays the results for the cryptocurrency (digital euro) corpus. Values are computed from the manual annotation. Bars indicate standard errors, and darker shades indicate a higher number of tweets.



(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 3: Share of negative statements by party family. *Notes*: General notes are as in Figure 2. Grouping by political family follows the classification of MEPs' national parties in the ParlGov database.

Sentiment is measured as the share of negative statements identified through manual annotations. Overall, the distributions point to a clear political polarization. Left-leaning MEPs display the highest share of negative stances on cryptocurrencies. By contrast, right-wing groups (ID, ECR) and *special issue* MEPs are the least negative, while Renew and the EPP average close to 30%. For the digital euro, the pattern is reversed: right-wing and *special issue* MEPs express mostly negative statements (80-85%), whereas all other groups remain broadly supportive, with average negativity rates between 5 and 25 percent. Within the right,

ECR is much closer to ID at the EPG level than their respective counterparts in the ParlGov classification, where conservatives and the radical right appear less proximate. More generally, the two figures show that left-leaning MEPs are consistently more critical of cryptocurrencies and more supportive of the digital euro, while right-wing groups adopt the opposite stance. Liberals and center-right parties occupy a more moderate position, with relatively low levels of negativity in both samples, especially for the digital euro. At both the EPG and party-family levels, sentiment distributions are broadly similar. One exception is the Greens/EFA EPG, which appears less negative toward cryptocurrencies and more negative toward the digital euro than its Parlgov party family counterpart, the Ecologists. This divergence reflects the presence of Pirate Party MEPs, whose pro-cryptocurrency and anti-CBDC positions differ sharply from both the Greens' dominant line and the broader left bloc[7].

This relationship between preferences over private (cryptocurrencies) and public (digital euro) money is consistent with theoretical expectations linking support for cryptocurrencies to distrust of central bank authority, especially among populist and right-wing politicians (Goodhart and Lastra, 2018). The political polarization is most visible at the extremes, but the distributions cannot be reduced to a simple left-right opposition. Notably, the two center-right groups do not simply invert their positions across monetary forms. Moreover, aggregation at the EPG or party-family level obscures within-group heterogeneity and prevents a systematic understanding of what drives polarization. The next section outlines the empirical strategy to identify the political and economic determinants of MEPs' preferences.

Finally, as shown in Section B of the online Appendix, sentiment distributions obtained with alternative classifiers (GPT, Llama, and Vader) closely replicate the hand-coded baseline shown in the figures, both in overall magnitude and in the relative ordering of groups. GPT and Llama produce almost identical distributions. Vader also captures the main pattern of polarization, although with larger standard errors and one notable anomaly: it understates support for cryptocurrencies by conflating criticism of regulation with criticism of the topic itself, which produces strongly negative scores for *special issue* MEPs in the cryptocurrency sample.

3.3 Logistic Regression Specification

To investigate the political and economic determinants of MEP sentiment, we estimate separate logistic regression models for the cryptocurrency and digital euro samples, using the same set of explanatory variables in both cases. The baseline specification is as follows:

[7] In Parlgov classification, Pirate MEPs are not categorized as ecologists but rather as special issue parties, due to their doctrinal ambiguity on standard ideological dimensions.

$$\text{logit}(\Pr(Y_{ipct}=1)) = \beta_0+\beta_1\text{Elite}_p+\beta_2\text{LR}_p+\beta_3\text{EU}_p+\beta_4\text{Trust}_{c,t}+\beta_5\text{Inflation}_{c,t-1}+\theta'\mathbf{X}_{pct}+\lambda'\mathbf{Z}_i+\mu_t+\pi_c \quad (2)$$

Where Y_{ipct} is a binary variable equal to one if MEP i, affiliated with national party p in country c, and at time t, expresses a negative stance in a given tweet, and zero otherwise (that is, for neutral or positive sentiment). Our baseline measure of sentiment Y_{ipct} is derived from hand-coded annotations. To assess robustness, we re-estimate the models using four alternative dependent variables: sentiment classifications produced by GPT-4o (zero-shot and few-shot), Llama 3.1 (few-shot), and the Vader lexicon. We also examine whether polarization also occurs on the opposite end of the sentiment distribution by re-estimating Equation 2 with a symmetric alternative dependent variable, $PosY_{ipct}$ equal to one if an MEP expresses a positive stance and zero otherwise. This allows us to assess whether the predictors are similarly associated with positive sentiment or whether their effects are asymmetric across the sentiment distribution.

The variables *Elite*, *LR* and *EU* are national party-level ideological indicators obtained from the 2019 wave of the Chapel Hill Expert Survey (Jolly et al., 2022). The variable *Elite* captures the anti-elite positioning of the MEP's national party on a continuous 10–point scale. Lower values indicate support for decision-making by political elites, whereas higher values reflect a more anti-establishment, people-centered orientation. This cleavage is often used as a minimalist measure of radical right populism (Subtil and Verger, 2024), rooted in the seminal framework of Mudde (2004). In this view, populism is understood as a rhetorical strategy framing political conflict as an irreconcilable opposition between two homogeneous and antagonistic groups: the *pure people* versus the *corrupt elite*. While populism is a multifaceted concept, anti-elitism plays a central role in its contemporary manifestations (Hameleers et al., 2018; Ernst et al., 2017).

The variable *LR* measures economic left-right positioning on a 0–10 point scale, with lower values denoting far-left preferences for state intervention and market regulation, and higher values denoting support for market liberalism, deregulation, and limited state intervention. *EU* captures the salience of European integration in a party's doctrine on a 10–point scale, with higher values denoting greater emphasis on European matters and low scores indicating that European integration is not an important issue. To account for the systematic tendency of anti-EU MEPs to adopt a more negative tone as a signal of opposition, the vector of controls X_{pct} includes a binary indicator for eurosceptic affiliation. The variable equals one if the speaker's national party is classified as eurosceptic in the PopuList database (Rooduijn et al., 2024), and zero otherwise.

We also include two macro-level covariates to account for the broader economic and institutional environment in which MEPs express their positions. The variable $Inflation_{c,t-1}$ measures the lagged monthly HICP inflation rate in country c, capturing delayed political reactions to domestic price dynamics. The second variable, $Trust_{c,t}$, measures net public trust in the ECB. Following Bergbauer et al. (2020), we compute

it as the difference between the percentage of respondents who *tend to trust* and those who *tend to distrust* the ECB, using five Eurobarometer survey waves (2019–2024). Because this net-trust measure is expressed in percentage points, we divide it by 10 so that a one-unit change corresponds to a 10–percentage-point shift in net trust, making its scale comparable to the CHES-based covariates. The resulting variable ranges from -10 to +10.

In addition to the eurosceptic indicator, the vector X_{pct} includes two time-varying political controls drawn from the Parlgov database (Döring et al., 2022), intended to capture strategic incentives shaping MEP communication. The first is a government participation dummy, equal to one if the MEP's national party is part of the governing coalition in country c at the time t, and zero otherwise. Governing parties may temper their rhetoric or avoid confrontational positions toward European institutions to preserve policy credibility. MEPs from governing parties also tend to align more closely with their national government's stance than with their EPG, reflecting the leverage of national executives (Costello and Thomson, 2016). The second control is an electoral-cycle dummy, equal to one if the observation falls within three months of a national election in the MEP's country c, and zero otherwise. The variable captures short-run electoral incentives, as MEPs may adjust their tone strategically when elections approach, either to appeal to key constituencies or to signal opposition.

The vector Z_i includes individual-level controls, namely a gender dummy and an indicator for whether the MEP sits on the Committee on Economic and Monetary Affairs (ECON). Because ECON oversees legislation on cryptocurrencies and the digital euro, its members are likely to be more informed and specialized (Servent and Roederer-Rynning, 2018), which may affect both the content and the tone of their communication.

Finally, we include year fixed effects μ_t to control for time-varying factors affecting MEP sentiment. External shocks of the kind shown in Figure 1, for example, may have shifted sentiment and attention across all political groups, generating common trends in the tone of communication. We also control for regional heterogeneity using an East-West dummy π_c, which equals one if the MEP's country belongs to the EU-15 (that is, member states that joined before the 2004 enlargement), and zero otherwise. This variable is intended to capture persistent political, economic and cultural differences across Europe's East-West divide (Schmitt, 2014; Epstein and Jacoby, 2014), which may shape how MEPs engage with monetary innovation and European regulation (Titova et al., 2021). In an alternative specification, we replace this regional control with country fixed effects to absorb unobserved national-level heterogeneity. Standard errors are clustered at the European Political Group (EPG) level, since MEPs within the same group share common institutional incentives (Hurka et al., 2015), including party discipline, peer-pressure effects and coordinated communication strategies.

4 Main results

This section presents the main results on the determinants of preferences toward cryptocurrencies and the digital euro. Section 4.1 reports estimates from the baseline specification (Equation 2) using five alternative sentiment measures as dependent variables. Section 4.2 then examines the robustness of the findings, while Section 4.3 studies the mechanisms underlying polarization through a Wordfish scaling of parliamentary rhetoric.

4.1 Attitudes towards digital currencies

Tables 2 and 3 report the benchmark regressions for cryptocurrencies and the digital euro. Column (1) uses the baseline hand-coded sentiment measure. Columns (2)–(4) replicate the specification using GPT-4o (zero-shot and few-shot prompting) and Llama 3.1 (few-shot) classifications. Across specifications, a negative coefficient implies that a higher value of the covariate is associated with a lower probability of expressing a negative stance toward the topic, and thus a greater support. Conversely, a positive coefficient denotes stronger opposition. Column (5) replaces the binary dependent variable with the continuous Vader sentiment score, estimated via OLS. Importantly, because the Vader and LLM-based sentiment measures are coded in opposite directions, substantively equivalent effects appear with opposite signs. The main results, reported in Columns (1)–(4), are stable across classifiers. Higher levels of anti-elitism, right-leaning economic ideology, lower trust in the ECB, and greater exposure to inflation are associated with lower opposition for cryptocurrencies and higher opposition to the digital euro. These results point to a common set of ideological and country-level determinants shaping preferences over both forms of digital money, but in opposite directions.

Figure 4, which reports average marginal effects, confirms the strong convergence across models. Coefficients based on the hand-coded measure and the three LLM-based classifiers align in sign, are of similar magnitude, with stable statistical significance. The only clear exception is the Vader lexicon (Column 5): in the digital euro sample its coefficients are not significant, and in the cryptocurrency sample the anti-elitism coefficient sign contradicts the logit estimates. This discrepancy likely reflects the limitations of the lexicon-based approach discussed in Section 2.3.2, and disappears once the robustness checks are applied (Section 4.2). Among LLMs, GPT-4o with zero-shot prompting yields somewhat less precise estimates, showing weaker alignment with the hand-coded benchmark than the few-shot specifications (see Table 5 in the online Appendix). In terms of statistical significance, anti-elitism, right-economic positioning, and inflation exposure are consistently significant at the 1-5 percent level in the cryptocurrency regressions, while ECB trust remains weaker but significant. In the digital euro regressions, anti-elitism and ECB trust remain

Table 2: MEP sentiment drivers on cryptocurrencies with alternative classifiers

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.262***	−0.083	−0.133**	−0.137**	−0.024***
	(0.071)	(0.059)	(0.052)	(0.058)	(0.008)
LR-econ	−0.550***	−0.221***	−0.315***	−0.347***	0.032***
	(0.153)	(0.071)	(0.099)	(0.131)	(0.009)
EU salience	−0.129	−0.094	−0.153	−0.150	0.032*
	(0.264)	(0.212)	(0.203)	(0.249)	(0.018)
Inflation (M-1)	−0.224***	−0.155***	−0.211***	−0.192***	0.018
	(0.085)	(0.039)	(0.061)	(0.064)	(0.012)
ECB trust	0.245***	0.104*	0.138*	0.123**	−0.011
	(0.086)	(0.059)	(0.074)	(0.056)	(0.008)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.234	0.092	0.157	0.15	
Observations	1,523	1,523	1,523	1,523	1,523
R^2					0.076
Adjusted R^2					0.066

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

strongly significant, whereas economic ideology and inflation fall within the 5-10 percent range. EU integration salience also becomes significant in all models except GPT-4o zero-shot. Importantly, the ECB-trust variable shows an interesting pattern in both samples but loses significance under most robustness checks.

Average marginal effects from the baseline specification in Column (1) indicate that, in the cryptocurrency sample, a one-unit increase in anti-elitism lowers the probability of expressing a negative stance by 4.6 percentage points, or roughly 10 points for a one-standard-deviation increase. Economic ideology has the largest effect: a one-unit rightward shift reduces the probability of a negative stance by 9.7 percentage points, equivalent to about 20 points for a one-standard-deviation change. Turning to inflation exposure, a one-unit increase lowers the likelihood of opposition by around 4 percentage points. By contrast, a one-unit increase in ECB trust raises the probability of a negative stance toward cryptocurrencies by about 9 points. In the digital euro regressions, the corresponding effects reverse sign. Anti-elitism is the strongest predictor of

Table 3: MEP sentiment drivers on the digital euro with alternative classifiers

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.467***	0.192***	0.323***	0.360**	−0.009
	(0.150)	(0.063)	(0.108)	(0.143)	(0.013)
LR-econ	0.307**	0.225*	0.183*	0.339**	−0.017
	(0.144)	(0.122)	(0.103)	(0.148)	(0.015)
EU salience	−0.533*	0.010	−0.463**	−0.501**	−0.017
	(0.294)	(0.150)	(0.206)	(0.233)	(0.028)
Inflation (M-1)	0.129	0.084**	0.330**	0.292*	0.002
	(0.103)	(0.034)	(0.153)	(0.154)	(0.017)
ECB trust	−0.417***	−0.132**	−0.256**	−0.396**	−0.006
	(0.115)	(0.060)	(0.128)	(0.177)	(0.013)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.358	0.142	0.326	0.343	
Observations	481	481	481	481	481
R^2					0.084
Adjusted R^2					0.052

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

opposition: a one-unit increase raises the probability of expressing a negative stance by 6.6 percentage points, or about 21 points for a one-standard-deviation change. The effect of the economic ideology is smaller, with a one-unit rightward shift increasing opposition by 4.4 percentage points. A one-unit increase in ECB trust reduces the probability of expressing a negative stance toward the digital euro by about 5.9 points. Finally, EU-integration salience lowers opposition by 7.6 points per unit, while remaining unrelated to attitudes toward cryptocurrencies.

A first result is the mirror-image structure of the two sets of regressions. Variables associated with support for cryptocurrencies are also associated with a higher likelihood of opposing the digital euro. This pattern suggests that preferences over private and public digital money are closely linked rather than formed independently. More broadly, it points to a public–private monetary divide structured around competing views of decentralization and centralization in money and payments, and thus around the proper role of

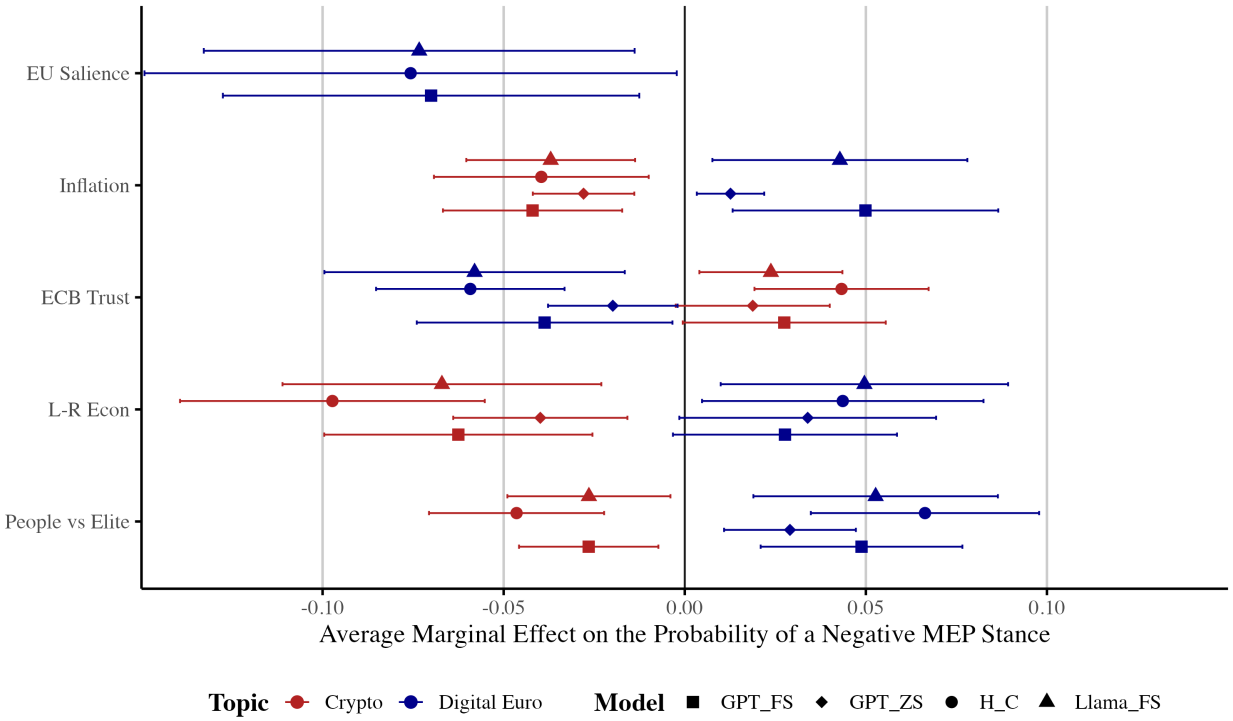


Figure 4: Average marginal effects on the probability of a negative MEP stance. **Notes**: Average marginal effects (AMEs) with 95% confidence intervals on the probability that an MEP adopts a negative stance towards cryptocurrency (red dot) and the digital euro (blue). Estimates are derived from the baseline regression model (Eq 2) and show the effects of selected independent variables, including EU issue salience, inflation, trust in the ECB, left-right economic ideology, and populist framing (people vs. elite). Negative values indicate that higher values of the covariate reduce the likelihood of a negative stance, while positive values indicate an increased probability. Robust standard errors are clustered at the eurogroup level. The effects displayed are significant at the 1%, 5%, or 10% levels. Results are presented separately for four sentiment classification models: GPT few-shot (GPT_FS), GPT zero-shot (GPT_ZS), Llama few-shot (Llama_FS), and the hand-coded baseline (H_C). Shapes differentiate models, while colors indicate policy topics.

the ECB. The results therefore indicate both that MEPs attach distinct normative meanings to the two monetary forms and that these competing views translate into political polarization along ideological and country-level lines.

A second result is that the magnitude of effects varies across topics. In the cryptocurrency regressions, right-leaning economic ideology is the strongest predictor of support, consistent with the sentiment divide documented in Section 3.2, which separates S&D and GUE/NGL from Renew, EPP, ID, and ECR. The result is robust to alternative ideological measures, including a general left-right scale (Tables 17 and 18 in the online Appendix) and positions on state intervention (Tables 19 and 20 in the online Appendix). This stands in contrast to studies of individual adoption, which typically find no effect of ideology or partisanship on cryptocurrency ownership (Littrell et al., 2024; Ferguson et al., 2024). One explanation is that public attitudes toward cryptocurrencies remain diffused, whereas among MEPs expressing support or opposition

reflects a programmatic view of monetary order and of the desired balance between markets and the state. In the digital euro regressions, by contrast, anti-elitism is the strongest predictor of opposition. The same variable is associated with support for cryptocurrencies, although with a smaller magnitude. This asymmetry is consistent with a broader populist contestation of the ECB's autonomy and legitimacy, which appears to be activated more strongly by the digital euro than by cryptocurrencies.

Ex ante, one might have expected no systematic relationship between attitudes toward cryptocurrencies and the digital euro. After all, cryptocurrencies could have been treated mainly as speculative investment assets, independently of CBDC design and its monetary and political implications. Instead, MEPs' positions along the anti-elitist cleavage echo the ideological origins of Bitcoin as a critique of state intervention, political intermediation, and centralized monetary control (Golumbia, 2017). Additionally, EU-integration salience reduces opposition to the digital euro but has no significant effect on attitudes toward cryptocurrencies, consistent with the idea that pro-integration views are specifically associated with support for European public monetary innovation. At the country level, higher inflation is associated with lower opposition to cryptocurrencies and greater opposition to the digital euro. Higher trust in the ECB correlates with lower opposition to the digital euro and greater opposition to cryptocurrencies, although this effect weakens in the robustness checks. These findings are line with Bergbauer et al. (2020), who show that trust in the ECB co-moves with perceptions of economic performance. In that perspective, when inflation undermines monetary trust, the digital euro may become a focal target of criticism, while cryptocurrencies serve as a symbolic alternative through which the ECB's authority is challenged.

The next section subjects these results to extensive robustness checks. Section 4.3 then turns to the rhetorical mechanisms underlying polarization in parliamentary discourse.

4.2 Robustness Checks on Main Results

This section examines the robustness of the main results. Specifically, we test (i) alternative sentiment measures, (ii) potential biases arising from topic composition, prolific MEPs, and neutral tweets, (iii) alternative specifications of ideological covariates and additional controls, and (iv) sensitivity to sample composition by excluding political groups iteratively. Across these tests, the main results remain stable. The main exception is the ECB-trust variable, whose effect weakens substantially in most specifications.

First, we examine whether results depend on the choice of sentiment classifier. As shown in Tables 2 and 3, estimates based on GPT-4o and Llama 3.1 closely track the hand-coded benchmark in both sign and statistical significance. Performance metrics reported in Table 5 in the Online Appendix further indicate that the results are not driven by classifier choice. In few-shot settings, both GPT-4o and Llama 3.1 achieve strong

F1 scores, around 0.80 in the cryptocurrency sample and close to 0.90 in the digital euro sample. GPT-4o in the zero-shot setting performs less well. The Vader lexicon diverges more clearly, which is consistent with the limitations of bag-of-words methods documented above. A related concern is that sentiment measures might capture a general communication style rather than issue-specific preferences. Radical-right parties, for instance, often adopt a systematically negative tone to elicit emotional resonance in the European Parliament (Subtil and Verger, 2024). The main results in Tables 2 and 3 mitigate this concern: the same covariates systematically reverse sign between cryptocurrency and digital euro samples, which is more consistent with substantive positioning than with generic negativity.

We next examine whether the results are sensitive to topic composition. In the cryptocurrency sample, tweets mentioning MiCA (Markets in Crypto-Assets) or TFR (Transfers of Funds Regulation) may express criticism of regulation rather than criticism of cryptocurrencies as such, a problem that is especially relevant for lexicon-based methods that do not account for context. Table 10 in the online Appendix addresses this issue by excluding the 292 tweets containing the strings 'mica' and 'tfr'. The results remain stable overall: the coefficient on anti-elitism strengthens, the coefficient on ECB trust weakens in the GPT-based models, and the misclassified anti-elite effect in Vader specification loses significance.

We also test whether the results are driven by a small number of highly active parliamentarians to avoid bias related to outlier behaviors. Section C of the online Appendix reports the 15 most active MEPs together with their average Vader sentiment scores. Excluding the five most active MEPs in each corpus (633 tweets in the cryptocurrency sample, 78 in the digital euro sample) leaves results robust (Tables 8 and 9). The coefficient on ECB trust becomes weaker, but anti-elitism becomes uniformly significant at the 1% level and its estimated effect increases in both samples.

A further concern is that neutral tweets may attenuate the contrast between support and opposition. To focus on tweets expressing an unambiguous stance, we re-estimate the benchmark regressions after excluding neutral tweets identified by GPT-4o, which account for 23% of the cryptocurrency sample and 25% of the digital euro sample. The results, reported in Section E of the online Appendix, remain stable, with somewhat stronger effects for anti-elitism. The same conclusion holds when neutral tweets are excluded on the basis of Llama classifications or hand-coded annotations.

We also examine whether polarization is symmetric by re-estimating the regressions with positive sentiment as the dependent variable. This exercise tests whether the same ideological and economic factors that predict opposition also predict support in the opposite direction, or whether the baseline results are driven mainly by one side of the sentiment distribution. If the latter were true, one would not expect a parallel structure in positive statements. Tables 13 and 14 of the online Appendix show that this is not the case for ideological variables: the coefficients are nearly symmetric to the baseline estimates, but with

opposite signs. The macro-level variables behave as expected in the cryptocurrency sample. In the digital euro sample, however, they are mostly insignificant and, in two specifications, do not reverse sign, likely because the number of positive observations is limited. Taken together, these results indicate that the main findings capture a genuine ideological divide across both ends of the sentiment distribution.

We then vary the specification of ideological covariates. Replacing the economic left-right scale with either a general left-right measure or a indicator of support for state intervention in the economy (both drawn from the CHES database and coded on 0–10 scales) yields similar results. Using the general left-right indicator (Tables 17 and 18 in the online Appendix) leaves the main findings unchanged, except that ECB trust loses significance in the non-hand-coded specifications of the cryptocurrency sample. The state-intervention variable ranges from 0 (strong support for extensive state intervention in the economy) to 10 (strong opposition to intervention). The corresponding regressions (Tables 19 and 20 in the online Appendix) show that higher values on this scale are associated with a lower probability of negative sentiment toward cryptocurrencies and a higher probability of negative sentiment toward the digital euro. The remaining coefficients are broadly stable and in some cases become stronger in both samples.

The results are also robust to additional controls. Adding a dummy for populist-party affiliation based on PopuList v3.0 (Rooduijn et al., 2024) leaves the coefficients essentially unchanged, suggesting that the anti-elitism result is not driven by a small number of extreme parties (Tables 21 and 22 in the online Appendix). We also estimate specifications with country fixed effects to absorb time-invariant national differences that may shape monetary preferences and patterns of communication independently of ideology or macroeconomic conditions. After dropping ECB trust to avoid multicollinearity with the country dummies, the country fixed-effects specifications again produce highly stable estimates reported in Tables 15 and 16 in the online Appendix.

Finally, we test the sensitivity of our results to influential political groups (online Appendix Section G). A natural concern is that the Identity and Democracy (ID) group's extreme stance may disproportionately influence the estimates. To address this, we exclude sequentially: first the most extreme groups (ID and then GUE/NGL), then the two largest groups (S&D and EPP), the center-right bloc (EPP and Renew). The main results remain largely unchanged. The coefficient on ECB trust loses significance for the digital euro when ID is excluded and for cryptocurrencies when S&D and EPP are removed. Inflation also loses significance in the GPT-ZS and Llama-FS specifications for the digital euro when ID is excluded. Aside from these cases, the pattern of results is stable throughout.

4.3 Rhetorical foundations of polarization

The previous section showed that inflation, anti-elitism and economic left-right positioning are associated with systematically opposed preferences toward cryptocurrencies and the digital euro. To investigate the rhetorical foundations of this polarization, we estimate separate Wordfish models for each corpus. This allows us to identify the linguistic mechanisms through which political conflict over digital money is expressed.

4.3.1 The Wordfish scaling model

Wordfish is an unsupervised text-scaling method that estimates latent political positions from word frequencies (Slapin and Proksch, 2008). It assumes that word counts follow a Poisson distribution and recovers latent positions by maximum likelihood:

$$y_{ij} \sim \text{Poisson}(\lambda_{ij}) \tag{3}$$

$$\lambda_{ij} = \exp(\alpha_i + \psi_j + \beta_j \cdot \omega_i) \tag{4}$$

where y_{ij} denotes the frequency with which MEP i uses the word j; α_i captures speaker fixed effects; ψ_j captures word fixed effects; β_j is the discrimination parameter measuring the extent to which word j differentiates positions along the latent dimension; and ω_i is the estimated latent position of MEP i. Political groups that rely on similar rhetorical repertoires are expected to cluster together on this dimension, whereas groups using opposing language should appear at opposite poles, indicating political antagonism. Originally developed for parliamentary speeches, Wordfish has also been applied to institutional reports (Diaf et al., 2022), ECB public addresses (Ferrara, 2020), and tweets (Aydogan et al., 2019).

The reliability of Wordfish estimates depends on careful document selection and pre-processing. Because the model extracts the dominant source of variation in word frequencies, identifying political polarization requires holding constant alternative sources of textual variation and heterogeneity unrelated to political preferences. Following Lauderdale and Herzog (2016), we focus on three main sources of variation: language, style, and topic. First, all tweets were translated into English. Second, we assume that word meanings remain sufficiently stable over the relatively short observation window (2019–2024) and within the standardized format of X communication. Third, topic consistency is addressed through the ex ante keyword-based selection of tweets and ex post validation of the corpus. Finally, because all texts are produced within the same institutional setting, we assume a sufficient degree of homogeneity in document generation (Bunea and Ibenskas, 2015).

4.3.2 Results

Figure 5a reports the estimated EPG ideal points on each topic dimension, while Figure 5b shows the lexical anchors of polarization underlying the scaling. The resulting configuration closely matches the sentiment distributions presented in Section 3.2. In the cryptocurrency corpus, GUE/NGL and S&D lie at one end of the dimension and are associated with stronger support for regulation, whereas Renew and EPP are located at the opposite end, consistent with a more market-oriented stance. The Greens/EFA cluster with ID and ECR, which points to a degree of rhetorical overlap and reflects the influence of Pirate MEPs within the ecologist group. In the digital euro corpus, the configuration is reversed: ID, ECR, and Greens/EFA are grouped on one side of the latent dimension, while S&D, GUE/NGL, EPP, and Renew cluster on the other end of the spectrum. The scaling suggests that political polarization cannot be reduced to a simple left-right opposition. Although left- and right-wing groups often occupy opposite poles, the center-right groups EPP and Renew shift across topic dimensions, aligning more closely with the right on cryptocurrencies and with the left on the digital euro.

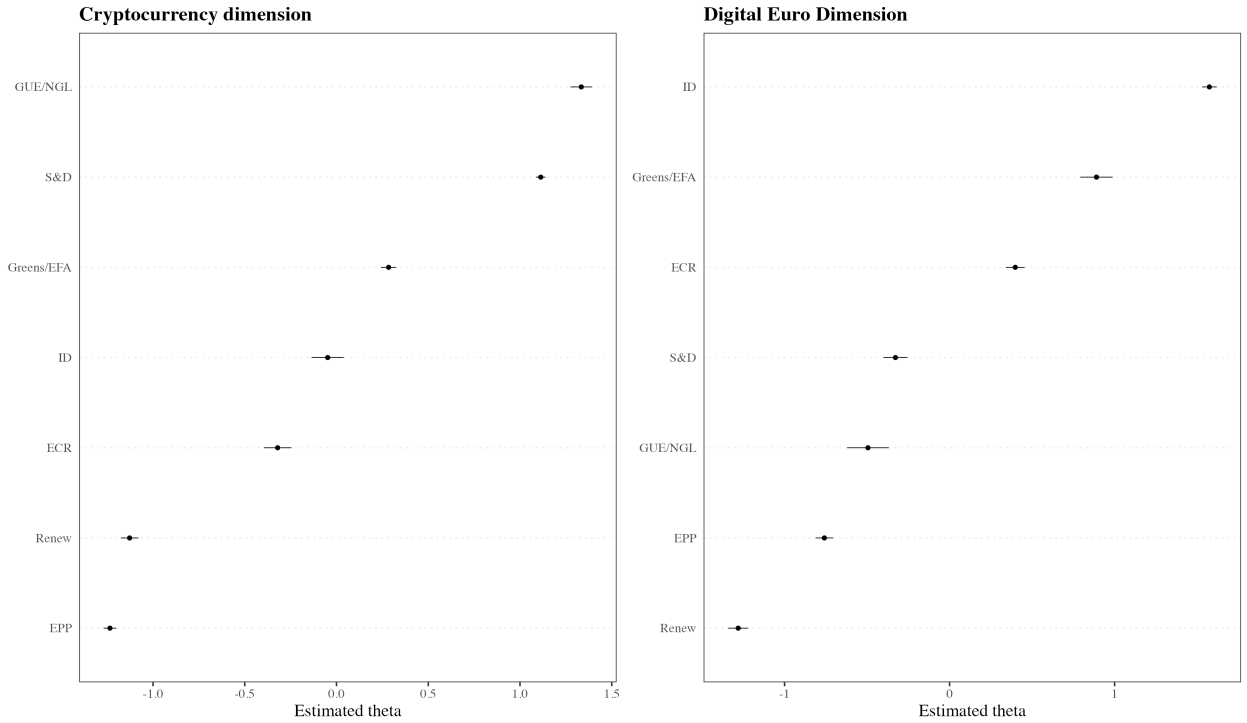
Figure 5b plots word weights on the vertical axis against word fixed effects on the horizontal axis, producing the familiar 'Eiffel Tower' shape. Words with high fixed effects and weights close to zero have limited discriminating power, as they are widely used across groups. This is the case, for example, for *crypto*, *bitcoin*, *regulation*, and *mica* in the cryptocurrency corpus, and for *digital euro* and *ecb* in the digital euro corpus. By contrast, words with lower fixed effects and more extreme weights are more informative, as they anchor the opposing rhetorical poles of the debate.

The scaling reveals clear antagonism in both corpora. In the cryptocurrency debate, some terms refer to the intrinsic features or supposed benefits of cryptocurrencies, such as *gold*, *freedom*, or *investment-friendly*. Yet the most discriminating terms relate less to these attributes than to regulation and perceived political interference. Terms such as *over-regulation*, *surveillance*, *elites*, *socialism*, and *dictatorship* are particularly salient. At the opposite pole, left leaning rhetoric emphasizes risk and disorder, with terms such as *scam*, *fraudulent*, *wild west*, *subprime*, and *dangerous*, alongside references to opponents associated with the *far right* and *anarchocapitalist* positions. In the digital euro debate, opposition is driven primarily by right-wing groups and is articulated through highly charged terms such as *totalitarian*, *social credit system*, *orwellian*, and *controlled*, together with repeated references to *surveillance* and *freedom*. A recurrent theme is the *programmability* of money, which reflects a central concern in the CBDC literature: the tension between the efficiency gains associated with new forms of monetary governance and the risks they may pose for individual freedoms and the scope of the ECB's mandate. References to *democratic*, *anonymously*, and *transparency* likewise point to the centrality of privacy concerns among digital euro opponents. By contrast, supporters

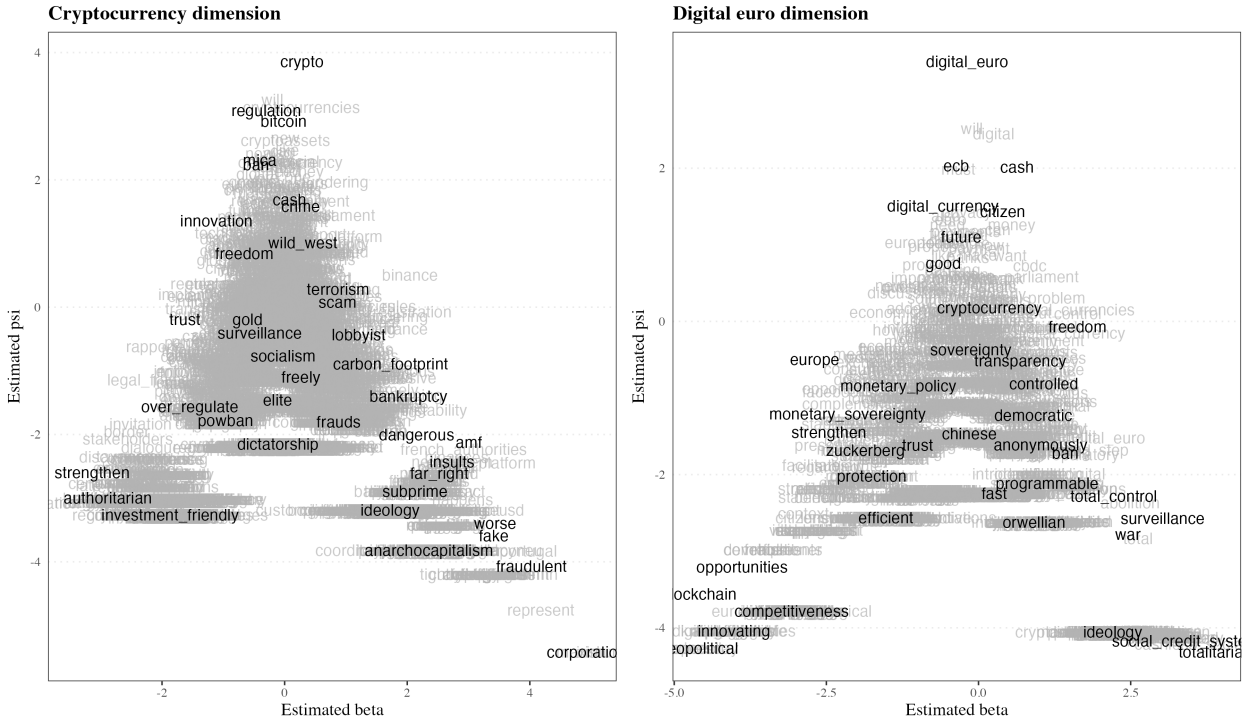
of the digital euro, mainly from the left and center-right, emphasize *competitiveness*, *efficiency*, *protection*, and *opportunities*, often together with references to *monetary sovereignty* and *geopolitics*. The term *ideology* is also highly discriminating in both corpora, combining a high weight and a low fixed effect. Interestingly, it appears in the rhetoric of opposing groups across the two dimensions. In the cryptocurrency debate, it is employed by left-leaning MEPs to refer to the ideological foundations of private money; in the digital euro debate, it is used by right-wing MEPs in connection with concerns about surveillance and control. In both cases, the term frames money as a normatively grounded institution with political implications rather than as a neutral technical innovation.

Taken together, the lexical anchors identified by Wordfish help clarify the preference structures documented in Section 4. Left and center-right groups support the digital euro on grounds of payment efficiency, consumer protection, and monetary sovereignty, presenting it as a part of a broader effort to strengthen Europe's payment infrastructure and to consolidate the ECB's role as a geopolitical actor. By contrast, right-wing groups are more favorable to cryptocurrencies and portray the digital euro as an instrument of ECB overreach, mandate expansion and political intervention. Notably, their discourse says relatively little about the intrinsic properties of cryptocurrencies. It focuses instead on opposition to regulation and to public institutions, suggesting that support for cryptocurrencies is often instrumental and serves as a vehicle for contesting the ECB rather than as an endorsement of private digital money as such. This interpretation is consistent with the sentiment trends, which show that polarization over cryptocurrencies intensifies once the digital euro becomes politically salient. Accordingly, the two debates are closely connected. The conflict between public and private forms of digital money appears to be embedded in broader ideological and economic cleavages shaped by competing societal visions.

Figure 5: Wordfish scaling and discriminant words in MEP communication.



(a) Ideal points (Wordfish estimates). Note: The coefficients are grouped by European political group, and the bars indicate the associated confidence intervals.



(b) Word weights vs. Word fixed effects.

5 Concluding Remarks

This paper investigates how ideology and economic conditions shape political preferences toward digital money, with a focus on cryptocurrencies and the digital euro. Combining sentiment analysis and Wordfish scaling on MEPs' tweets, it provides, to our knowledge, the first systematic account of how European legislators position themselves on these politically salient monetary innovations.

Three findings stand out. First, the descriptive evidence points to increasing political polarization over the course of the legislature, with the politicization of the digital euro coinciding with an amplified polarization of sentiment toward cryptocurrencies. Second, preferences toward the two monetary forms are driven by the same underlying factors, but in opposite directions. Anti-elitism, right-leaning economic ideology, and exposure to inflation are associated with stronger support for cryptocurrencies and stronger opposition to the digital euro. Third, the Wordfish analysis shows that these debates are structured by mistrust of elites and concerns about the expanding role of the ECB. The concentration of highly politicized terms in the digital euro debate suggests that the project elicits particularly strong opposition among right-wing populists and may therefore face substantial barriers to political acceptability.

Taken together, the results provide converging evidence that debates over the ECB's legitimacy and independence have crystallized around a new axis of conflict between private and public digital money. This divide is structured by competing views on the ECB's role and, more broadly, on the scope of political authority in monetary affairs. From this perspective, critics of the ECB treat the digital euro and the regulation of private cryptocurrencies as part of the same political process, both seen as expressions of mandate expansion. The debate over digital money in the European Parliament thus belongs to the political economy of central banking.

Our results also open several avenues for future research. A first step is to assess whether similar patterns arise in other democracies, notably in the United States, where monetary issues are also highly politicized. Another is to examine cross-country variation in the public acceptance of the digital euro and its relationship to national norms, informal economic activity, cash-use traditions, and payment habits. More broadly, further work on the relationship between cryptocurrencies and CBDCs could improve our understanding of the political and public acceptability of money, and the extent to which its regulation and design respond to political incentives.

Disclosure statement: No interest to declare.

Funding: No funding was received.

Data: The replication kit, including code and datasets, will soon be made available through the project's GitHub repository.

References

Algaba, A., Ardia, D., Bluteau, K., Borms, S., and Boudt, K. (2020). Econometrics Meets Sentiment: An Overview of Methodology and Applications. *Journal of Economic Surveys*, 34(3):512–547. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/joes.12370.

Algan, Y., Davoine, E., Renault, T., and Stantcheva, S. (2025). Emotions and policy views. *Harvard University Working Paper*.

Alonso-Robisco, A. and Carbó, J. M. (2023). Analysis of CBDC narrative by central banks using large language models. *Finance Research Letters*, 58:104643.

Auer, R., Cornelli, G., and Frost, J. (2023). Rise of the Central Bank Digital Currencies. *International Journal of Central Banking*, 19(4):185–214.

Auer, R. and Tercero-Lucas, D. (2022). Distrust or speculation? The socioeconomic drivers of U.S. cryptocurrency investments. *Journal of Financial Stability*, 62:101066.

Aydogan, A., Tuna, T., and Kadir Yildirim, A. (2019). Ideological Congruence and Social Media Text as Data. *Representation*, 55(2):159–178. _eprint: https://doi.org/10.1080/00344893.2019.1592012.

Ba, H.-L. and Şen, F. (2024). Explaining variation in national cryptocurrency regulation: implications for the global political economy. *Review of International Political Economy*, 31(5):1472–1495. _eprint: https://doi.org/10.1080/09692290.2024.2325403.

Barrdear, J. and Kumhof, M. (2022). The macroeconomics of central bank digital currencies. *Journal of Economic Dynamics and Control*, 142:104148.

Barrie, C., Palmer, A., and Spirling, A. (2025). Replication for Language Models. *Working paper*.

Bergbauer, S., Hernborg, N., Jamet, J.-F., and Persson, E. (2020). The reputation of the euro and the European Central Bank: interlinked or disconnected? *Journal of European Public Policy*, 27(8):1178–1194. _eprint: https://doi.org/10.1080/13501763.2020.1712463.

Braun, B. (2016). Speaking to the people? Money, trust, and central bank legitimacy in the age of quantitative easing. *Review of International Political Economy*, 23(6):1064–1092.

Bunea, A. and Ibenskas, R. (2015). Quantitative text analysis and the study of EU lobbying and interest groups. *European Union Politics*, 16(3):429–455.

Chey, H.-k. (2023). Cryptocurrencies and the IPE of money: an agenda for research. *Review of International Political Economy*, 30(4):1605–1620. _eprint: https://doi.org/10.1080/09692290.2022.2109188.

Cook, T. R., Kazinnik, S., Hansen, A. L., and McAdam, P. (2023). Evaluating Local Language Models: An Application to Financial Earnings Calls.

Costello, R. and Thomson, R. (2016). Bicameralism, nationality and party cohesion in the European Parliament. *Party Politics*, 22(6):773–783.

Daniel, W. T., Obholzer, L., and Hurka, S. (2019). Static and dynamic incentives for Twitter usage in the European Parliament. *Party Politics*, 25(6):771–781.

Davoodalhosseini, S. M. (2022). Central bank digital currency and monetary policy. *Journal of Economic Dynamics and Control*, 142:104150.

De Filippi, P. and Wright, A. (2018). *Blockchain and the Law*. Harvard University Press.

Diaf, S., Döpke, J., Fritsche, U., and Rockenbach, I. (2022). Sharks and minnows in a shoal of words: Measuring latent ideological positions based on text mining techniques. *European Journal of Political Economy*, 75:102179.

Döring, H., Huber, C., and Manow, P. (2022). ParlGov 2022 Release.

EC (2023). Proposal for a regulation of the european parliament and of the council on the establishment of a digital euro.

ECB (2024). Second progress report on a Digital Euro.

Epstein, R. A. and Jacoby, W. (2014). Eastern Enlargement Ten Years On: Transcending the East–West Divide? *JCMS: Journal of Common Market Studies*, 52(1):1–16. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcms.12089.

Ernst, N., Engesser, S., Büchel, F., Blassnig, S., and Esser, F. (2017). Extreme parties and populism: an analysis of Facebook and Twitter across six countries. *Information, Communication & Society*, 20(9):1347–1364. _eprint: https://doi.org/10.1080/1369118X.2017.1329333.

Ferguson, G., Haglin, K., and Jordan, S. (2024). The Personality and Politics of Cryptocurrency Investors. *American Politics Research*, 52(3):290–305.

Ferrara, F. M. (2020). The battle of ideas on the euro crisis: evidence from ECB inter-meeting speeches. *Journal of European Public Policy*, 27(10):1463–1486. _eprint: https://doi.org/10.1080/13501763.2019.1670231.

Ferrara, F. M., Masciandaro, D., Moschella, M., and Romelli, D. (2022). Political voice on monetary policy: Evidence from the parliamentary hearings of the European Central Bank. *European Journal of Political Economy*, 74:102143.

Fraccaroli, N., Giovannini, A., Jamet, J.-F., and Persson, E. (2022). Ideology and monetary policy. The role of political parties' stances in the European Central Bank's parliamentary hearings. *European Journal of Political Economy*, 74:102207.

Gambacorta, L., Kwon, B., Park, T., Patelli, P., and Zhu, S. (2024). CB-LMs: language models for central banking. *BIS Working Papers*, (1215).

Golumbia, D. (2017). The Politics of Bitcoin: Software as Right-wing Extremism. *Journal of Cultural Economy*, 10:1–3.

Goodhart, C. and Lastra, R. (2018). Populism and Central Bank Independence. *Open Economies Review*, 29(1):49–68.

Hameleers, M., Bos, L., Fawzi, N., Reinemann, C., Andreadis, I., Corbu, N., Schemer, C., Schulz, A., Shaefer, T., Aalberg, T., Axelsson, S., Berganza, R., Cremonesi, C., Dahlberg, S., de Vreese, C. H., Hess, A., Kartsounidou, E., Kasprowicz, D., Matthes, J., Negrea-Busuioc, E., Ringdal, S., Salgado, S., Sanders, K., Schmuck, D., Stromback, J., Suiter, J., Boomgaarden, H., Tenenboim-Weinblatt, K., and Weiss-Yaniv, N. (2018). Start Spreading the News: A Comparative Experiment on the Effects of Populist Communication on Political Engagement in Sixteen European Countries. *The International Journal of Press/Politics*, 23(4):517–538.

Hansen, A. L. and Kazinnik, S. (2024). Can ChatGPT Decipher Fedspeak?

Hurka, S., Kaeding, M., and Obholzer, L. (2015). Learning on the Job? EU Enlargement and the Assignment of (Shadow) Rapporteurships in the European Parliament. *JCMS: Journal of Common Market Studies*, 53(6):1230–1247. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcms.12270.

Hutto, C. and Gilbert, E. (2014). VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *Proceedings of the International AAAI Conference on Web and Social Media*, 8(1):216–225. Number: 1.

Jha, M., Qian, J., Weber, M., and Yang, B. (2024). ChatGPT and Corporate Policies.

Jolly, S., Bakker, R., Hooghe, L., Marks, G., Polk, J., Rovny, J., Steenbergen, M., and Vachudova, M. A. (2022). Chapel Hill Expert Survey trend file, 1999–2019. *Electoral Studies*, 75:102420.

Kim, Y. S. and Kwon, O. (2023). Central Bank Digital Currency, Credit Supply, and Financial Stability. *Journal of Money, Credit and Banking*, 55(1):297–321. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jmcb.12913.

Korinek, A. (2023). Generative AI for Economic Research: Use Cases and Implications for Economists. *Journal of Economic Literature*, 61(4):1281–1317.

Kosse, A. and Mattei, I. (2023). Making headway - Results of the 2022 BIS survey on central bank digital currencies and crypto. *BIS Papers*.

Krugmann, J. O. and Hartmann, J. (2024). Sentiment Analysis in the Age of Generative AI. *Customer Needs and Solutions*, 11(1):3.

Lauderdale, B. E. and Herzog, A. (2016). Measuring Political Positions from Legislative Speech. *Political Analysis*, 24(3):374–394.

Leek, L. and Bischl, S. (2025). How central bank independence shapes monetary policy communication: A Large Language Model application. *European Journal of Political Economy*, 87:102668.

Littrell, S., Klofstad, C., and Uscinski, J. E. (2024). The political, psychological, and social correlates of cryptocurrency ownership. *PLOS ONE*, 19(7):e0305178.

Luther, W. J. (2019). Getting off the ground: the case of bitcoin. *Journal of Institutional Economics*, 15(2):189–205.

Monnet, E. (2024). *Balance of Power: Central Banks and the Fate of Democracies*. University of Chicago Press, Chicago, IL.

Moschella, M. (2024). *Unexpected Revolutionaries: How Central Banks Made and Unmade Economic Orthodoxy*. Cornell University Press. Google-Books-ID: jAfmEAAAQBAJ.

Moschella, M., Pinto, L., and Martocchia Diodati, N. (2020). Let's speak more? How the ECB responds to public contestation. *Journal of European Public Policy*, 27(3):400–418. _eprint: https://doi.org/10.1080/13501763.2020.1712457.

Mudde, C. (2004). The Populist Zeitgeist. *Government and Opposition*, 39(4):541–563.

Nakamoto, S. (2008). Bitcoin : a peer-to-peer Electronic Cash System.

Nulty, P., Theocharis, Y., Popa, S. A., Parnet, O., and Benoit, K. (2016). Social media and political communication in the 2014 elections to the European Parliament. *Electoral Studies*, 44:429–444.

Ollion, E., Shen, R., Macanovic, A., and Chatelain, A. (2024). The dangers of using proprietary LLMs for research. *Nature Machine Intelligence*, 6(1):4–5.

Pfister, C. (2024). For a Political Economy of Central Bank Digital Currency. *Revue d'économie politique*, 134(4):525–551.

Proksch, S.-O., Lowe, W., Wäckerle, J., and Soroka, S. (2019). Multilingual Sentiment Analysis: A New Approach to Measuring Conflict in Legislative Speeches. *Legislative Studies Quarterly*, 44(1):97–131. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/lsq.12218.

Proksch, S.-O. and Slapin, J. B. (2014). *The Politics of Parliamentary Debate: Parties, Rebels and Representation*. Cambridge University Press, Cambridge.

Quaglia, L. and Verdun, A. (2025a). The geoeconomics of Central Banks Digital Currencies (CBDCs): the case of the European Central Bank (ECB). *New Political Economy*, 0(0):1–13. _eprint: https://doi.org/10.1080/13563467.2025.2504390.

Quaglia, L. and Verdun, A. (2025b). Introduction: the new political economy of central banks: reluctant Atlases? *New Political Economy*, 0(0):1–14. _eprint: https://doi.org/10.1080/13563467.2025.2504405.

Ringe, N. (2009). *Who Decides, and How?: Preferences, Uncertainty, and Policy Choice in the European Parliament*. Oxford University Press.

Rooduijn, M., Pirro, A. L. P., Halikiopoulou, D., Froio, C., Kessel, S. V., Lange, S. L. D., Mudde, C., and Taggart, P. (2024). The PopuList: A Database of Populist, Far-Left, and Far-Right Parties Using Expert-Informed Qualitative Comparative Classification (EiQCC). *British Journal of Political Science*, 54(3):969–978.

Scherpereel, J. A., Wohlgemuth, J., and Schmelzinger, M. (2017). The Adoption and Use of Twitter as a Representational Tool among Members of the European Parliament. *European Politics and Society*, 18(2):111–127. _eprint: https://doi.org/10.1080/23745118.2016.1151125.

Schmitt, H., editor (2014). *European Parliament Elections after Eastern Enlargement*. Routledge, London.

Servent, A. R. and Roederer-Rynning, C. (2018). The European Parliament: A Normal Parliament in a Polity of a Different Kind. In *Oxford Research Encyclopedia of Politics*.

Shapiro, A. H., Sudhof, M., and Wilson, D. J. (2022). Measuring news sentiment. *Journal of Econometrics*, 228(2):221–243.

Silva, B. C. and Proksch, S.-O. (2022). Politicians unleashed? Political communication on Twitter and in parliament in Western Europe. *Political Science Research and Methods*, 10(4):776–792.

Slapin, J. B. and Proksch, S.-O. (2008). A Scaling Model for Estimating Time-Series Party Positions from Texts. *American Journal of Political Science*, 52(3):705–722. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-5907.2008.00338.x.

Steinmetz, F., von Meduna, M., Ante, L., and Fiedler, I. (2021). Ownership, uses and perceptions of cryptocurrency: Results from a population survey. *Technological Forecasting and Social Change*, 173:121073.

Subtil, H. and Verger, V. (2024). Emotional Rhetoric and Rise of the Populism in the European Parliament. Note 108, Institute of Public Policies.

Titova, Y., Cornea, D., and Lemeunier, S. (2021). What Factors Keep Cash Alive in the European Union? *De Economist*, 169(3):291–317.

Tortola, P. D. (2020). The Politicization of the European Central Bank: What Is It, and How to Study It? *JCMS: Journal of Common Market Studies*, 58(3):501–513. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcms.12973.

van 't Klooster, J., Martino, E. D., and Monnet, E. (2025). Cryptomercantilism vs. Monetary Sovereignty.

Vries, C. E. D. (2018). *Euroscepticism and the Future of European Integration*. Oxford University Press. Google-Books-ID: fO9IDwAAQBAJ.

Wang, Z., Xie, Q., Feng, Y., Ding, Z., Yang, Z., and Xia, R. (2024). Is ChatGPT a Good Sentiment Analyzer? A Preliminary Study. arXiv:2304.04339 [cs].

Weber, B. (2016). Bitcoin and the legitimacy crisis of money. *Cambridge Journal of Economics*, 40(1):17–41.

Westermeier, C. (2024). The digital euro: a materialization of (in)security. *Review of International Political Economy*, 31(5):1569–1592. _eprint: https://doi.org/10.1080/09692290.2024.2345613.

Zhang, W., Deng, Y., Liu, B., Pan, S. J., and Bing, L. (2023). Sentiment Analysis in the Era of Large Language Models: A Reality Check. arXiv:2305.15005 [cs].

What Drives Monetary Preferences? Evidence from MEPs' Social Media Discourse on Cryptocurrencies and the Digital Euro

Gabriel Tailleur[††]

Online Appendix

[††]University of Amiens, France. Email: ga.tailleur@gmail.com

Table of Contents

A Replication Codebook

A.1 Extracting data and pre-processing

Table 4: List of cryptocurrency and digital euro filter terms

Language	Cryptocurrency Stem	Digital Euro Stem
English	Crypto*; cryptos; cryptocurrenc*; cryptoasset*	Digital euro; digitaleuro*; e-euro; cbdc; digital currenc*
English	Mica; tfr; nft; bitcoin; ethereum; blockchain; binance; ftx; stablecoin*; tether; coinbase	
French	cryptoactif*; cryptomonnaie*	Euro numérique; monnaie numérique
German	krypto*; Kryptowährung*; kryptos; kryptowerte; krypto-v*	Digital* euro; digitale währung*; digital* geld; digital* zentralbankgeld
Greek	Κρυπτο*· κρυπτονόμισμα· κρυπτογραφικό νόμισμα· κρυπτονομίσματα	Ψηφιακό ευρώ
Dutch	Cryptovalut*; cryptogeld; cryptoactiv*	Digitale euro; digitaal geld
Bulgarian	Криптовалута*; криптоактив*; крипто-актив*; крипто	Цифрово евро; дигитално евро
Croatian	Kripto*; kriptovalut*; kriptoaktiv*; kriptomovin*; kriptokovanica	Digitalni euro
Czech	Krypto*; Kryptoměn*; kryptovalut*	Digitáln* eur*; Digitální\euro
Danish	Krypto; kryptoaktiv*; kryptovalut*	Digitale euro; digital valut*
Estonian	Kruto*; Krüptovär*; krüptovara*	Digitaaleuro; digital euro
Finnish	Krypto; kryptovar*; kryptovaluut*	Digitaali* euro*; digitaali* valuut*
Hungarian	Kripto*; Kriptoeszköz*; kriptovalut*	Digitális euro*; digitális valuta
Irish	Criptea*; criptea-*; cripteam*	Euro digiteach
Italian	Cripto*; Criptoattiv*; criptomon*; cryptovalut*	Euro digitale*; valuta* digitale
Latvian	Kripto*; kriptomon*; kriptoakt*	Digital* euro; digital* eir*; digital* valut*
Lithuanian	Kripto*; kriptoturt*	Skaitmenin* eur*; skaitmenin̨* valiut*
Polish	Krypto*; kryptowalut*; kryptoakty*; walut* cyfrow*	Cyfrow* euro
Portuguese	Cripto*; cripto moeda*; cripto activ*; criptoativo*	Euro* digital*; moeda* digital*
Romanian	Cripto*; criptomoned*; cryptovalut*; criptovalut*	Euro digital*; moneda* digital*
Slovak	Krypto*; kryptomen*; kriptoaktiv*	Digitáln* eur*
Slovenian	Kripto*; kriptovalut*; kriptosredst*	Digitaln* euro; digitaln* evro
Spanish	Cripto*; criptomoneda*; criptomoneda*; cryptoactiv*	Euro* digital*; moneda* digital*
Swedish	Krypto*; kryptovalut*; kryptotillgån*	Digital valuta; centralbanksvaluta

A.2 LLM – Pipeline and prompts

We use the GPT-4o model (2024-05-13 version) via the OpenAI API, and the open-source Llama 3.1 model with 70B parameters (released by Meta in April 2024), both run on cloud-based computing resources. For both models, the temperature is set to zero, increasing determinism in outputs, though a small amount of variability remains, particularly for the proprietary model. As a result, results may not exactly replicate due to model updates and inherent response variation. Nonetheless, the overall classification patterns are

expected to remain consistent in a complete rerun. All prompt examples below refer to the cryptocurrency sample; we replace *cryptocurrency* with *digital euro* when applying the prompts to the digital euro sample.

Zero-shot Prompt

> *Tweet: {tweet}. What is the sentiment polarity related to the aspect {cryptocurrency} in this tweet? Answer positive, neutral or negative. Each tweet was posted by a member of the European Parliament expressing a stance on {cryptocurrencies}.*

Few-shot Prompt

Read this tweet related to the topic [cryptocurrency], posted by a member of the European Parliament: {tweet}.

Classify the tweet into one of the three categories: ['negative', 'neutral', 'positive'], based on whether the parliamentarian expresses a negative, neutral or positive stance towards cryptocurrencies. **Return only the label**.

Examples:

- **Example 1**: {Currencies cannot be privatized. Such privatization has taken place de facto and insidiously in recent years through Crypto Assets. We are now putting a stop to that. Cash must be preserved. #EPlenary.}
  - Label: **negative**
- **Example 2**: {The founder of FTX criticizes the excessive ecological footprint of bitcoin and believes that it is a financial asset and not a currency. He proposes to do without the proof of work to go towards the proof of stake. Exactly what we are asking for.}
  - Label: **negative**
- **Example 3**: {Cryptocurrencies: "Attack on the crypto space": How the EU's regulatory frenzy is hitting Bitcoin and Co.}
  - Label: **positive**
- **Example 4**: {Does @ecb loathe #Bitcoin? Yes, it's still volatile and the industry needs to mature. But the fact that many people prefer the freedom of a decentralized alternative, attractive as store of value, painfully shows the shortcomings of its own policies.}

  - Label: **positive**

- **Example 5**: {On next weeks #EPlenary agenda: Forcible deportation of Ukrainian children #Fit-for55 files: #ETS # CBAM # aviation Social climate fund halting deforestation #Crypto markets 2024 #EUbudget.}

  - Label: **neutral**

- **Example 6**: {Starting at 09:00h: the public hearing on #crypto and #blockchain in #taxation @EP_taxation. Make sure to tune in and hear what the experts have to say! @AlbertoGVale @andthiemann @demipreaux @RMueller_TaxTec.}

  - Label: **neutral**

A.3 LLM – Output Validity

Table 5: Performance metrics for negative stance classification of MEPs' tweets

	Cryptocurrency			Digital Euro		
	gpt-4o	llama-3.1	gpt-4o-zero-shot	gpt-4o	llama-3.1	gpt-4o-zero-shot
Accuracy	**0.8127**	0.8018	0.6802	0.8907	**0.9006**	0.7157
Precision	0.8557	**0.9034**	0.8361	0.8792	0.9269	**0.9273**
Recall	**0.7564**	0.6798	0.4554	**0.8903**	0.8565	0.4304
F1 Score	**0.8030**	0.7758	0.5896	0.8847	**0.8904**	0.5879

Note: The table reports classification performance of the LLMs relative to the hand-coded baseline for the cryptocurrency ($n = 1,554$) and digital euro ($n = 503$) datasets. Boldface indicates the best-performing model for each metric.

A.4 Lexicon descriptive statistics

A.4.1 Word occurrences

Table 6: Top 20 word occurrences

Positive word	Score	Occurrences	Negative word	Score	Occurrences
like	1.5	133	no	-1.2	123
innovation	1.6	101	fight	-1.6	56
good	1.9	100	risks	-1.1	49
energy	1.1	78	anti	-1.3	36
important	0.8	74	risk	-1.1	35
want	0.3	66	crime	-2.5	24
freedom	3.2	53	problem	-1.7	23
value	1.4	48	stop	-1.2	22
clear	1.6	47	criminal	-2.4	20
create	1.1	45	fraud	-2.8	19
great	3.1	41	avoid	-1.2	18
security	1.4	40	collapse	-2.2	17
support	1.7	37	attack	-2.1	16
thank	1.5	37	seriously	-0.7	16
thanks	1.9	37	terrorism	-3.6	16
better	1.9	35	wrong	-2.1	16
ensure	1.6	35	bad	-2.5	14
welcome	2.0	35	crash	-1.7	14
legal	0.5	33	threat	-2.4	14
well	1.1	33	war	-2.9	14

Note: The table shows the 20 VADER lexicon terms with the highest number of matches in our tweet dataset. Positive terms (Column 1) and negative terms (Column 4) are ranked by frequency. Reported values are VADER polarity scores and observed occurrences in the cryptocurrency and digital euro corpora.

A.4.2 Examples of tweets with extreme sentiment scores

We present the tweets with the highest positive and negative VADER scores for both the digital euro and cryptocurrency samples (eight tweets in total). Tweets are shown in their pre-processed form, except

where preprocessing would hinder comprehension. In those cases, removed words are included in brackets. For each tweet, we report the date, author, and European Political Group (EPG) affiliation, along with its Vader sentiment score and GPT few-shot classification. Lexicon-matched words appear in blue (positive) or red (negative). The underscore '_' signals where a negation flips the valence in Vader.

Two noteworthy misclassifications occur in the digital euro sample, where Vader assigns positive scores to tweets that GPT classifies as neutral or negative. The first results from repeated references to 'freedom', which Vader logically interpret as positive, even though in context, the MEP frames the digital euro as a threat to that freedom. The second is a standard political claiming tweet, in which an MEP highlights parliamentary activity. GPT correctly categorizes this as neutral, while Vader misclassifies it as positive.

Cryptocurrency corpus:

Soraya RODRÍGUEZ (Spain), Ciudadanos, Renew Europe Group, 27/01/2022:

Sexual exploitation and new technologies. From searching for victims on Facebook or Tinder, to laundering money in cryptocurrencies. Technology facilitates trafficking. But the essence of the crime remains: using deception and threat to enslave.

Vader sentiment score: **-0.97**. GPT classification: **negative**.

Ville NIINISTÖ (Finland), Vihreä Liitto – Gröna Förbundet, Group of the Greens/European Free Alliance, 02/01/2022:

Bitcoin alone destroyed all the energy savings that the world's electric cars could achieve. Not to mention the economic disadvantages, resource consumption and other problems it caused. Bitcoin and cryptos are the worst vanity of the moment. A pyramid scheme of global destruction.

Vader sentiment score: **-0.96**. GPT classification: **negative**.

Michiel HOOGEVEN (Netherlands), Juiste Antwoord21, European Conservatives and Reformists Group, 11/03/2021:

The ECB's buyback policy is creating historically low interest rates. More and more Dutch people are therefore choosing to save in Bitcoin. JA[21] stands for an open internet and individual economic freedom. We should embrace this innovation not immediately regulate it away.

Vader sentiment score: **0.94**. GPT classification: **positive**

Enikő GYORI (Hungary), Fidesz, European People's Party, 15/03/2022:

Yesterday in [@EP_Economics] we voted on MiCA, new rules for cryptocurrencies like bitcoin. Resisting

the push from the left, the new set of rules are innovation-friendly, establishing a clear framework to protect investors and ensure market integrity.

Vader sentiment score: **0.94**. GPT classification: **positive**

Digital euro corpus:

Marcel DE GRAAFF (Netherlands), Forum voor Democratie, Identity and Democracy Group, 06/11/2023:

Albert Camus, The Man in Revolt. Written in 1951. More topical than ever. No to vaccination, no to the slavery of digital money, no to state abduction of children, no to repopulation, no to the abuse of power. It is an inner revolt, an awakening.

Vader sentiment score: **-0.97**. GPT classification: **negative**

Christine ANDERSON (Germany), Alternative für Deutschland, Identity and Democracy, 21/12/2020:

Introduce the digital euro and abolish cash under the pretext of preventing terrorism, crime and more hygiene: no_ argument is low enough for the DDR2.0 fantasists to make their own control palatable to the citizens.

Vader sentiment score: **-0.91**. GPT classification: **negative**

Harald VILIMSKY (Austria), Freiheitliche Partei Österreichs, Identity and Democracy, 15/07/2021:

ECB Plan Digital Euro: Cash is freedom free of surveillance. Clear opposition to the gradual abolition of our financial freedom.

Vader sentiment score: **0.93**. GPT classification: **negative**

Frances FITZGERALD (Ireland), Fine Gael Party, European People's Party, 02/02/2022

A pleasure to welcome President of the Eurogroup, Minister [@Paschald] to [@EP_ Economics] this lunchtime. Constructive engagement on how the EU economy can deliver more for citizens post-covid. I also had the opportunity to question the Minister on the development of a digital euro.

Vader sentiment score: **0.91**. GPT classification: **neutral**

B Additional descriptive output

Figure 6: MiCA votes in the ECON committee

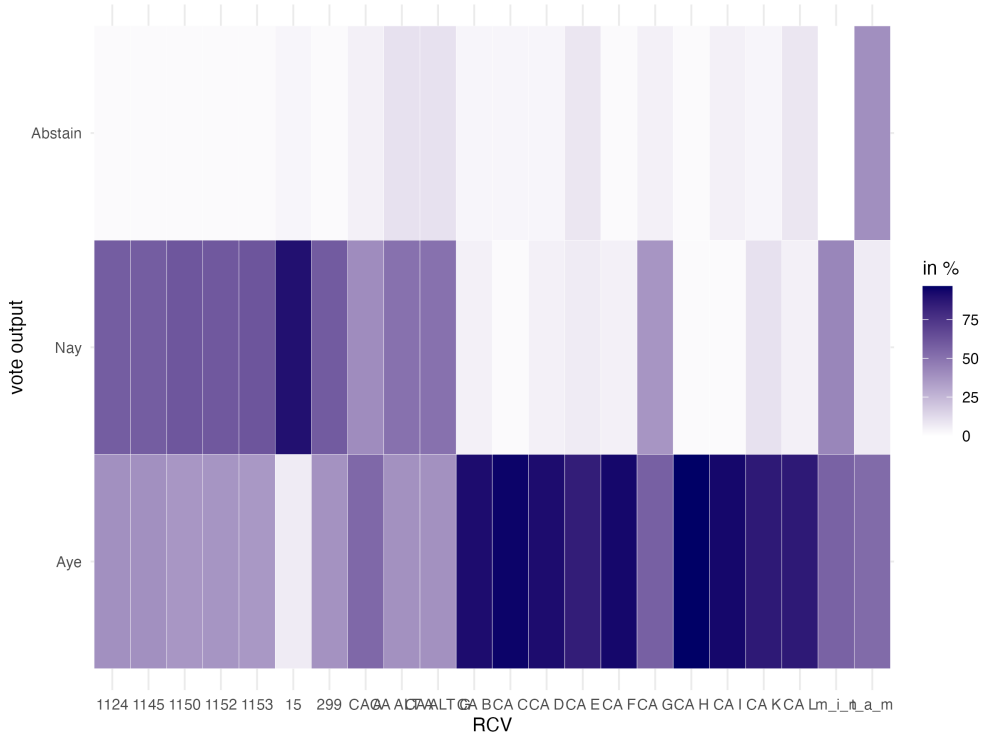


Figure 7: Distribution of MEPs tweets by country

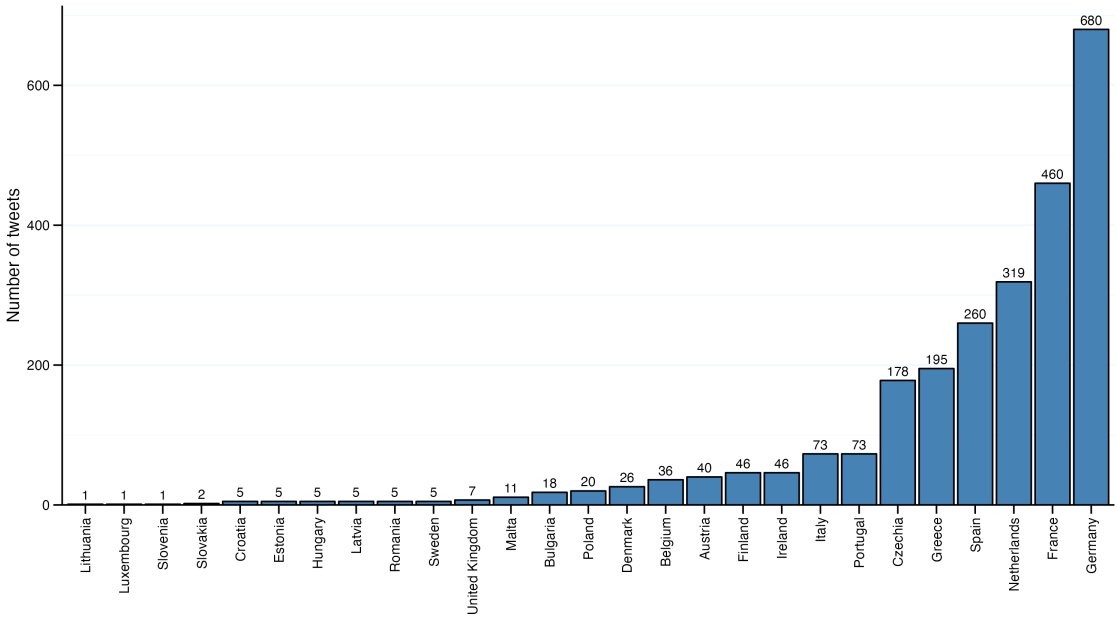
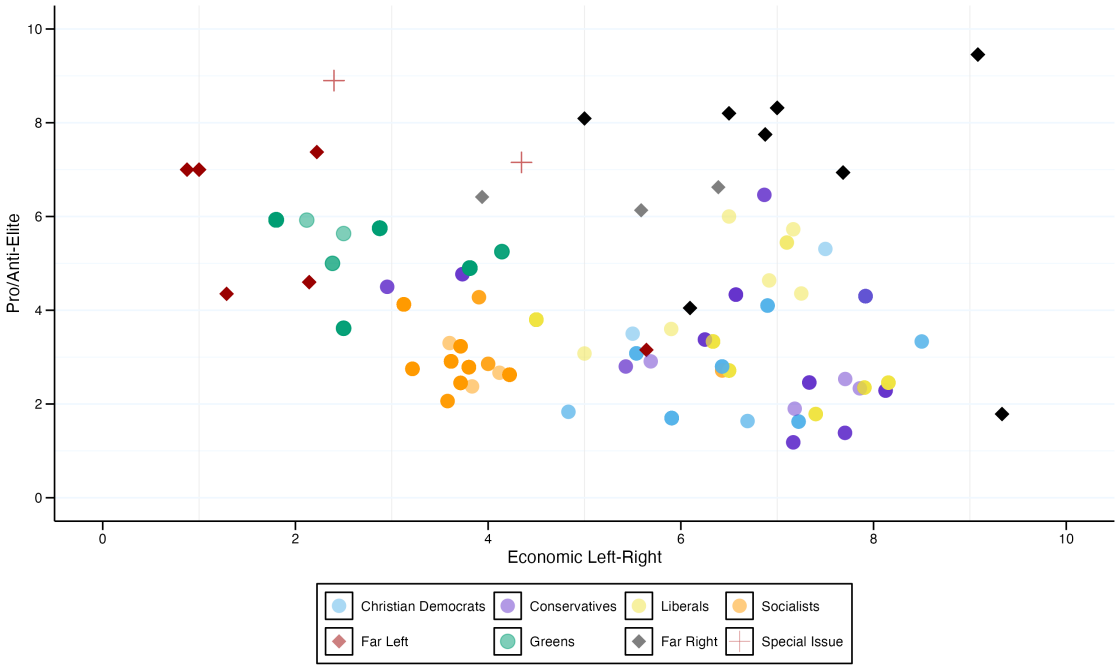
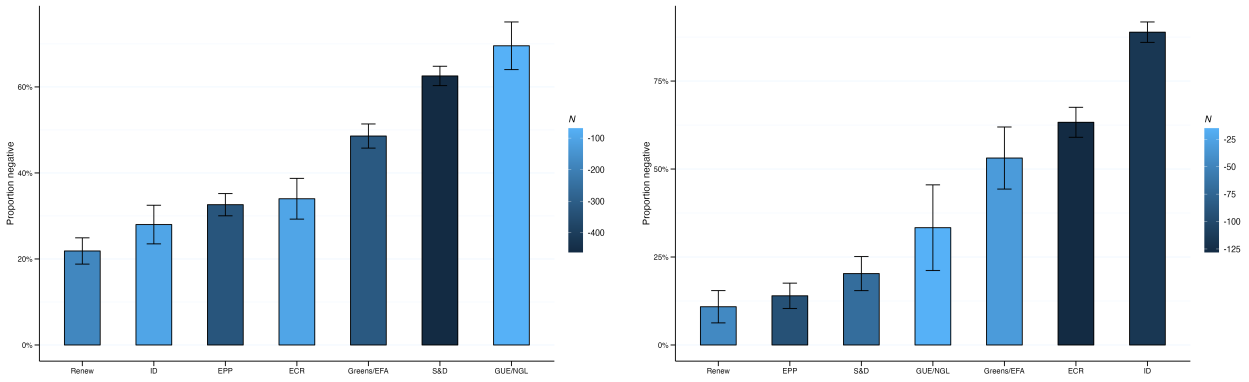


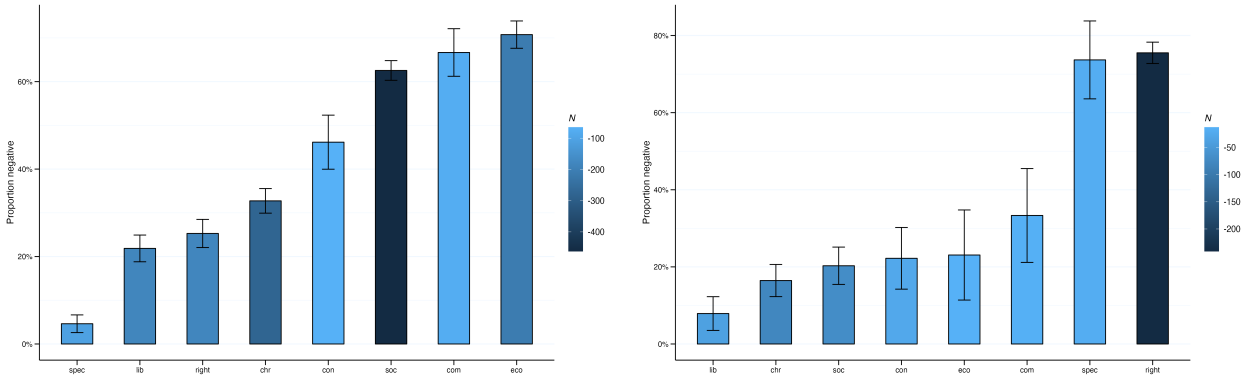
Figure 8: Ideological distribution of tweeting MEPs along the elite and left-right dimensions





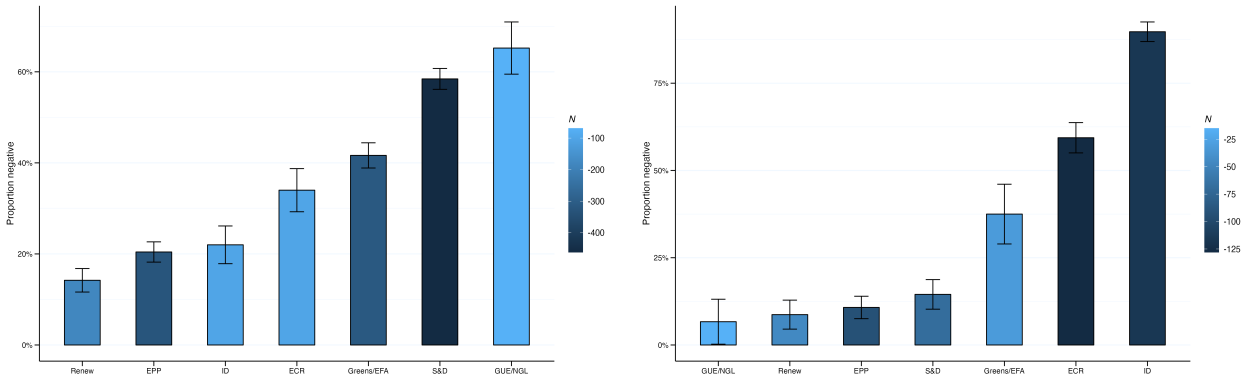
(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 9: GPT-4o share of negative statements by European political group.



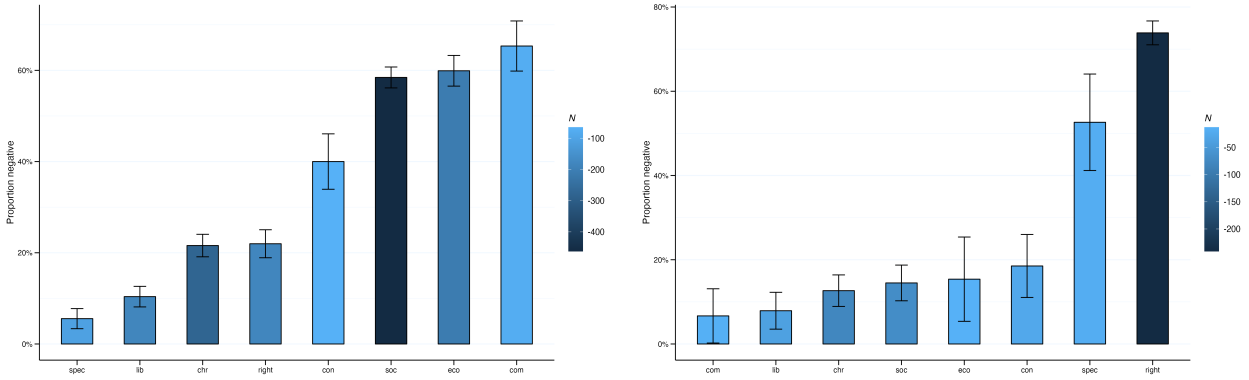
(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 10: GPT-4o share of negative statements by party family. Figure A (B) displays the results on the cryptocurrency (digital euro) corpus. The bars indicate the standard errors, whereas darker shades indicate a greater number of tweets posted



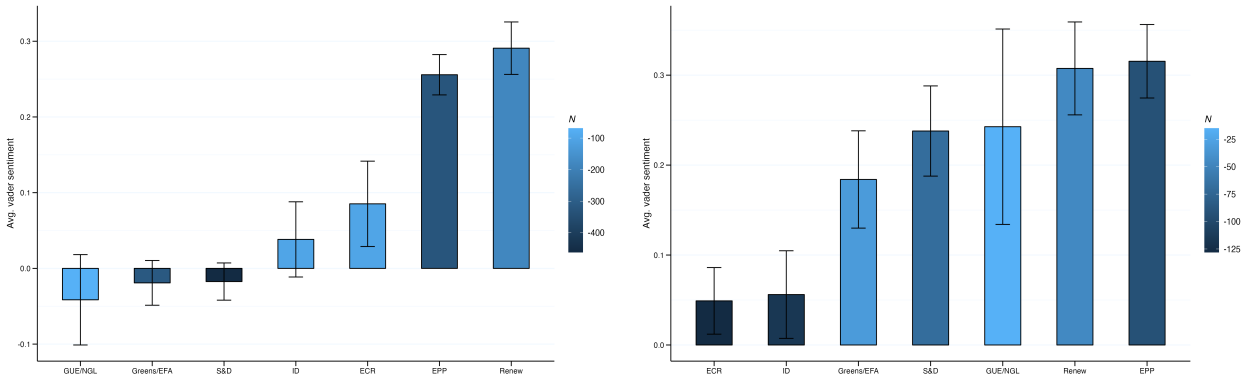
(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 11: Llama-3.1 share of negative statements by European political group.



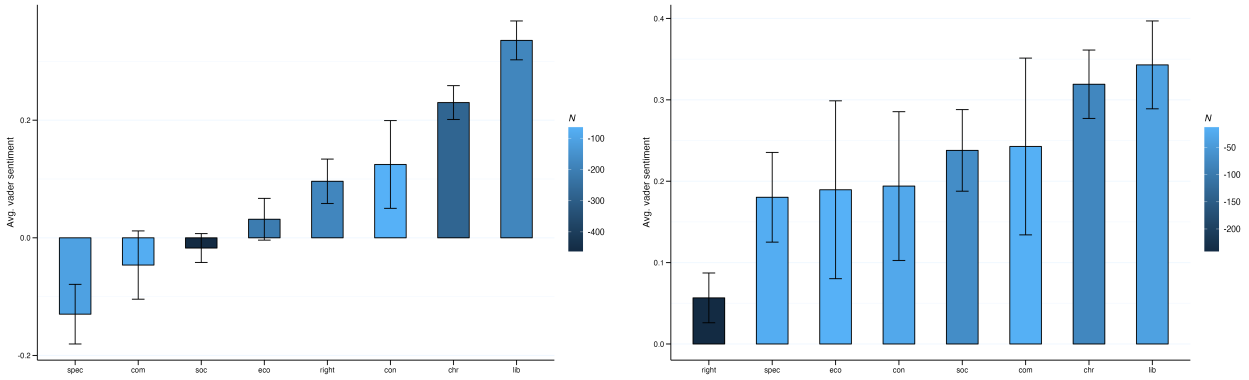
(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 12: Llama-3.1 share of negative statements by party family. Figure A (B) displays the results on the cryptocurrency (digital euro) corpus. The bars indicate the standard errors, whereas darker shades indicate a greater number of tweets posted



(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 13: Average Vader sentiment score by European political group.



(a) Cryptocurrency sentiment **(b)** Digital euro sentiment

Figure 14: Average Vader sentiment score by party family. Figure A (B) displays the results on the cryptocurrency (digital euro) corpus. Values are computed using the Vader lexicon and based on the weighting Eq. 1. The bars indicate the standard errors, whereas darker shades indicate a greater number of tweets posted.

C Robustness check: Without top tweeting accounts

Table 7 lists the 15 most active MEPs and their average Vader sentiment scores towards cryptocurrencies and the digital euro. Names shown in color mark the five most active MEPs in each corpus, who are excluded in the subsequent robustness check to ensure that results are not driven by specifically prolific speakers. Several cases merit comment. Stefan Berger (EPP), for instance, served as rapporteur for both the Markets in Crypto-Assets (MiCA) regulation and the digital euro legislative package. Ernest Urtasun (Greens/EFA) was lead rapporteur for the Transfer of Funds regulation (TFR). Eva Kaili (S&D) is an outlier: she exhibits a highly positive sentiment toward cryptocurrencies—unusual within the left bloc—but was expelled from her Eurogroup and national party in 2022 following a corruption scandal. Patrick Breyer and Mikulás Peksa, both members of the Greens/EFA eurogroup, record unusually positive sentiment scores on cryptocurrencies among Green MEPs. This reflects their affiliation with the Pirate Party, a source of significant intra-eurogroup heterogeneity within the Greens, as discussed in Sections 3.1 and 3.2.

Table 7: Twitter behavior and sentiment of the 15 most active MEPs

MEP name	EPG	Nationality	Tweets	**Cryptocurrencies**		**Digital euro**	
				N	Sentiment	N	Sentiment
Stefan BERGER*	EPP	Germany	316	219	0.19	47	0.26
Aurore LALUCQ	S&D	France	255	249	-0.12	0	*NA*
Eva KAILI	S&D	Greece	162	42	0.37	14	0.33
Ernest URTASUN	Greens	Spain	130	123	-0.18	2	0.17
Ondřej KOVAŘÍK	Renew	Czechia	108	88	0.09	15	0.31
Paul TANG	S&D	Netherlands	87	54	-0.15	29	0.18
Patrick BREYER	Greens	Germany	83	61	0.38	16	-0.06
Michiel HOOGEVEEN	ECR	Netherlands	81	13	0.37	67	-0.02
Dorien ROOKMAKER	ECR	Netherlands	76	44	0.17	31	-0.00
Christine ANDERSON	ID	Germany	44	17	0.16	21	-0.32
Ibán GARCÍA DEL BLANCO	S&D	Spain	44	31	-0.13	0	*NA*
Mikuláš PEKSA	Greens	Czechia	39	33	0.31	3	0.08
Stéphanie YON-COURTIN	Renew	France	39	23	0.02	13	0.36
Gunnar BECK	ID	Germany	36	23	0.37	13	-0.37
Markus FERBER	EPP	Germany	36	14	-0.00	19	0.17

Note: Names highlighted in red (blue) indicate top contributors on cryptocurrencies (digital euro) and are excluded from the datasets used in the subsequent robustness tests. Stefan Berger is indicated in red with a blue star, reflecting prominence in both categories.

Table 8: MEP sentiment drivers on cryptocurrencies excluding top MEPs

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.489***	−0.168***	−0.357***	−0.363***	−0.007
	(0.108)	(0.064)	(0.094)	(0.088)	(0.010)
LR-econ	−0.338***	−0.128**	−0.195**	−0.197*	0.018*
	(0.115)	(0.064)	(0.079)	(0.102)	(0.010)
EU salience	0.051	−0.109	0.001	−0.009	0.045**
	(0.244)	(0.180)	(0.185)	(0.268)	(0.021)
Inflation (M-1)	−0.203***	−0.131	−0.198***	−0.215***	0.015
	(0.063)	(0.093)	(0.055)	(0.069)	(0.014)
ECB trust	0.092*	0.029	0.035	0.038	0.006
	(0.050)	(0.079)	(0.069)	(0.074)	(0.011)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.237	0.087	0.158	0.151	
Observations	804	804	804	804	804
R^2					0.055
Adjusted R^2					0.036

Notes: Robust standard errors clustered at the eurogroup level are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9: MEP sentiment drivers on the digital euro excluding top MEPs

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.605***	0.243***	0.497***	0.627***	−0.013
	(0.185)	(0.085)	(0.108)	(0.161)	(0.015)
LR-econ	0.445**	0.243*	0.340***	0.550***	−0.023
	(0.189)	(0.139)	(0.110)	(0.149)	(0.017)
EU salience	−0.261	0.017	−0.244	−0.399	−0.015
	(0.415)	(0.218)	(0.325)	(0.367)	(0.030)
Inflation (M-1)	0.219	0.117*	0.781**	0.684*	−0.004
	(0.420)	(0.062)	(0.339)	(0.349)	(0.025)
ECB trust	−0.130	−0.162*	−0.139	−0.362***	0.001
	(0.147)	(0.095)	(0.152)	(0.134)	(0.016)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.504	0.188	0.47	0.514	
Observations	287	287	287	287	287
R^2					0.099
Adjusted R^2					0.046

Notes: Robust standard errors clustered at the eurogroup level are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D Robustness check: Limiting topic variability

To disentangle general attitudes toward cryptocurrencies from sentiment on cryptocurrency regulation, we omitted all tweets containing the substrings 'MICA' (Market in Crypto-Assets) or 'TFR' (Transfer of Funds Regulation), referring to legislative proposals adopted in the Ninth Legislature. This filter led to the removal of 292 tweets.

Table 10: MEP sentiment drivers on cryptocurrencies excluding regulation-related tweets

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.302***	−0.139**	−0.141**	−0.172**	−0.010
	(0.082)	(0.063)	(0.066)	(0.075)	(0.009)
LR-econ	−0.458***	−0.199***	−0.281***	−0.308**	0.029***
	(0.134)	(0.066)	(0.104)	(0.131)	(0.010)
EU salience	−0.108	−0.011	−0.117	−0.059	0.023
	(0.262)	(0.228)	(0.218)	(0.277)	(0.020)
Inflation (M-1)	−0.201***	−0.158***	−0.166***	−0.169**	0.022*
	(0.064)	(0.049)	(0.060)	(0.074)	(0.013)
ECB trust	0.204**	0.110	0.125	0.136*	−0.011
	(0.088)	(0.081)	(0.081)	(0.077)	(0.009)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.253	0.082	0.173	0.153	
Observations	1,231	1,231	1,231	1,231	1,231
R^2					0.061
Adjusted R^2					0.048

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E Robustness check: Treating neutral classifications as missing observations

To ensure that our sentiment capture only unequivocal positive or negative signals, we excluded all tweets that the GPT-4o few-shot classifier assigned a neutral label. In practice, this step led to the removal of approximately 23% of observations from the cryptocurrency tweet corpus and 25% from the digital euro corpus.

Table 11: MEP sentiment drivers on cryptocurrencies excluding neutral tweets

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	-0.405^{***}	-0.126^{**}	-0.231^{**}	-0.208^{**}	-0.027^{***}
	(0.115)	(0.062)	(0.093)	(0.099)	(0.010)
LR-econ	-0.745^{***}	-0.277^{***}	-0.459^{***}	-0.457^{**}	0.032^{***}
	(0.191)	(0.088)	(0.141)	(0.184)	(0.011)
EU salience	-0.172	-0.058	-0.121	-0.172	0.046^{**}
	(0.307)	(0.249)	(0.191)	(0.287)	(0.022)
Inflation (M-1)	-0.239^{**}	-0.174^{***}	-0.292^{***}	-0.211^{***}	0.019
	(0.096)	(0.062)	(0.076)	(0.080)	(0.014)
ECB trust	0.310^{***}	0.097	0.178^{*}	0.151^{***}	-0.010
	(0.079)	(0.069)	(0.092)	(0.058)	(0.011)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.299	0.099	0.198	0.185	
Observations	1,164	1,164	1,164	1,164	1,164
R^2					0.084
Adjusted R^2					0.071

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12: MEP sentiment drivers on the digital euro excluding neutral tweets

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.663***	0.252***	0.468***	0.439**	−0.010
	(0.196)	(0.066)	(0.145)	(0.173)	(0.016)
LR-econ	0.441***	0.276*	0.283*	0.375*	−0.015
	(0.133)	(0.154)	(0.162)	(0.208)	(0.022)
EU salience	−0.785**	−0.070	−0.551**	−0.575**	−0.028
	(0.365)	(0.159)	(0.267)	(0.284)	(0.036)
Inflation (M-1)	0.167	0.100	0.455***	0.418**	−0.005
	(0.111)	(0.090)	(0.158)	(0.189)	(0.021)
ECB trust	−0.608***	−0.121**	−0.261	−0.400*	−0.002
	(0.185)	(0.060)	(0.169)	(0.226)	(0.017)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.441	0.143	0.416	0.42	
Observations	362	362	362	362	362
R^2					0.120
Adjusted R^2					0.079

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

F Robustness check: Alternative specifications

F.1 Positive sentiment as a dependent variable

Table 13: MEP sentiment drivers on cryptocurrencies with positive sentiment as dependent variable

	Cryptocurrency model			
	H-C	GPT-ZS	GPT-FS	Llama-FS
	(1)	(2)	(3)	(4)
People/Elite	0.435***	0.069*	0.293***	0.213**
	(0.124)	(0.038)	(0.105)	(0.107)
LR-econ	0.722***	0.223***	0.458***	0.430***
	(0.179)	(0.076)	(0.136)	(0.152)
EU salience	0.069	0.037	0.003	0.054
	(0.201)	(0.131)	(0.171)	(0.173)
Inflation (M-1)	0.219***	0.085	0.252***	0.156**
	(0.073)	(0.052)	(0.056)	(0.073)
ECB trust	−0.236***	−0.088**	−0.194***	−0.134***
	(0.055)	(0.040)	(0.053)	(0.038)
Individual-level controls	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.284	0.057	0.137	
Observations	1,523	1,523	1,523	1,523

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 14: MEP sentiment drivers on the digital euro with positive sentiment as dependent variable

	Digital euro model			
	H-C	GPT-ZS	GPT-FS	Llama-FS
	(1)	(2)	(3)	(4)
People/Elite	-0.573^{***}	0.004	-0.335^{**}	-0.223^{**}
	(0.123)	(0.056)	(0.130)	(0.113)
LR-econ	-0.346^{***}	-0.074	-0.202	-0.325^{***}
	(0.122)	(0.066)	(0.135)	(0.108)
EU salience	0.528^{***}	-0.063	0.296	0.420^{***}
	(0.196)	(0.131)	(0.181)	(0.148)
Inflation (M-1)	0.097	0.085^{***}	0.116	-0.062
	(0.216)	(0.031)	(0.185)	(0.163)
ECB trust	0.234^{**}	-0.085^{**}	0.010	0.172
	(0.101)	(0.033)	(0.114)	(0.115)
Individual-level controls	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.365	0.044	0.176	
Observations	481	481	481	481

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

F.2 Model with country fixed effects

Table 15: MEP sentiment drivers on cryptocurrencies with country fixed-effects

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.277***	−0.061	−0.136**	−0.127**	−0.015**
	(0.073)	(0.078)	(0.056)	(0.050)	(0.007)
LR-econ	−0.522***	−0.191*	−0.207***	−0.280**	0.028**
	(0.168)	(0.106)	(0.052)	(0.111)	(0.013)
EU salience	0.111	−0.044	−0.043	0.017	0.033
	(0.283)	(0.219)	(0.120)	(0.185)	(0.027)
Inflation (M-1)	−0.217**	−0.149***	−0.205**	−0.178**	0.015
	(0.107)	(0.051)	(0.084)	(0.076)	(0.012)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.292	0.112	0.209	0.201	
Observations	1,513	1,513	1,513	1,513	1,513
R^2					0.096
Adjusted R^2					0.079

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 16: MEP sentiment drivers on the digital euro with country fixed-effects

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.450***	0.086	0.360***	0.342***	−0.016
	(0.135)	(0.062)	(0.096)	(0.116)	(0.012)
LR-econ	0.280***	0.219**	0.160*	0.247**	−0.015
	(0.085)	(0.104)	(0.085)	(0.110)	(0.016)
EU salience	−0.558*	0.045	−0.488***	−0.429*	−0.002
	(0.325)	(0.202)	(0.189)	(0.220)	(0.037)
Inflation (M-1)	0.085	0.059	0.313**	0.272*	−0.0001
	(0.073)	(0.039)	(0.143)	(0.141)	(0.017)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.405	0.167	0.349	0.381	
Observations	478	478	478	478	478
R^2					0.094
Adjusted R^2					0.046

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

F.3 Alternative left-right variable

Table 17: MEP sentiment drivers on cryptocurrencies with left-right general dimension

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.254***	−0.069	−0.108*	−0.121*	−0.024***
	(0.089)	(0.064)	(0.060)	(0.069)	(0.008)
LR-gen	−0.499***	−0.173**	−0.240***	−0.296**	0.030***
	(0.149)	(0.073)	(0.078)	(0.118)	(0.009)
EU salience	−0.171	−0.138	−0.209	−0.192	0.033*
	(0.247)	(0.206)	(0.185)	(0.232)	(0.018)
Inflation (M-1)	−0.212***	−0.154***	−0.205***	−0.187***	0.018
	(0.074)	(0.036)	(0.058)	(0.060)	(0.012)
ECB trust	0.203**	0.082	0.103	0.095	−0.008
	(0.096)	(0.067)	(0.081)	(0.063)	(0.008)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.224	0.087	0.147	0.143	
Observations	1,523	1,523	1,523	1,523	1,523
R^2					0.076
Adjusted R^2					0.066

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 18: MEP sentiment drivers on the digital euro with left-right general dimension

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.462***	0.216***	0.322***	0.371***	−0.009
	(0.141)	(0.068)	(0.100)	(0.128)	(0.013)
LR-gen	0.338***	0.308**	0.273***	0.442***	−0.018
	(0.128)	(0.134)	(0.073)	(0.111)	(0.015)
EU salience	−0.487*	0.049	−0.499**	−0.501**	−0.021
	(0.273)	(0.109)	(0.194)	(0.222)	(0.026)
Inflation (M-1)	0.107	0.074**	0.327**	0.281*	0.003
	(0.092)	(0.037)	(0.153)	(0.153)	(0.017)
ECB trust	−0.359***	−0.083***	−0.228**	−0.342***	−0.010
	(0.086)	(0.029)	(0.107)	(0.129)	(0.013)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.366	0.15	0.338	0.366	
Observations	481	481	481	481	481
R^2					0.084
Adjusted R^2					0.053

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

F.4 Economic interventionism

Table 19: MEP sentiment drivers on cryptocurrencies with economic intervention dimension

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.273***	−0.095*	−0.157***	−0.156***	−0.024***
	(0.066)	(0.057)	(0.050)	(0.054)	(0.008)
Econ interventionism	−0.548***	−0.234***	−0.352***	−0.370***	0.029***
	(0.113)	(0.058)	(0.081)	(0.107)	(0.009)
EU salience	−0.161	−0.104	−0.150	−0.160	0.036**
	(0.225)	(0.204)	(0.179)	(0.214)	(0.017)
Inflation (M-1)	−0.229***	−0.152***	−0.216***	−0.193***	0.017
	(0.083)	(0.040)	(0.059)	(0.061)	(0.012)
ECB trust	0.261***	0.115**	0.160**	0.140***	−0.011
	(0.075)	(0.057)	(0.069)	(0.046)	(0.008)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.247	0.095	0.169	0.159	
Observations	1,523	1,523	1,523	1,523	1,523
R^2					0.075
Adjusted R^2					0.065

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 20: MEP sentiment drivers on the digital euro with economic intervention dimension

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.440***	0.159***	0.307***	0.327**	−0.008
	(0.145)	(0.053)	(0.105)	(0.144)	(0.013)
Econ interventionism	0.283**	0.170*	0.128	0.253*	−0.006
	(0.116)	(0.099)	(0.100)	(0.141)	(0.014)
EU salience	−0.418*	0.120	−0.368**	−0.330*	−0.028
	(0.254)	(0.117)	(0.182)	(0.183)	(0.026)
Inflation (M-1)	0.130	0.078**	0.322**	0.281*	0.003
	(0.105)	(0.035)	(0.150)	(0.153)	(0.017)
ECB trust	−0.404***	−0.109*	−0.237*	−0.360**	−0.009
	(0.127)	(0.061)	(0.126)	(0.175)	(0.013)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.359	0.14	0.322	0.336	
Observations	481	481	481	481	481
R^2					0.081
Adjusted R^2					0.050

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

F.5 Controlling for populist national parties

Table 21: MEP sentiment drivers on cryptocurrencies with populist control

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.258***	−0.080	−0.161*	−0.132*	−0.037***
	(0.095)	(0.076)	(0.086)	(0.077)	(0.007)
LR-econ	−0.623***	−0.269***	−0.395***	−0.406***	0.014
	(0.104)	(0.075)	(0.055)	(0.074)	(0.010)
EU salience	0.045	−0.011	−0.041	−0.033	0.043**
	(0.204)	(0.150)	(0.163)	(0.186)	(0.018)
Inflation (M-1)	−0.230***	−0.157***	−0.213***	−0.195***	0.019
	(0.087)	(0.038)	(0.060)	(0.063)	(0.012)
ECB trust	0.281***	0.127***	0.167**	0.154***	−0.008
	(0.079)	(0.047)	(0.065)	(0.045)	(0.008)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Populist control	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.237	0.092	0.161	0.15	
Observations	1,523	1,523	1,523	1,523	1,523
R^2					0.081
Adjusted R^2					0.071

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 22: MEP sentiment drivers on the digital euro with populist control

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.478***	0.178**	0.334***	0.369**	−0.005
	(0.158)	(0.071)	(0.119)	(0.152)	(0.013)
LR-econ	0.314**	0.211*	0.185*	0.341**	−0.014
	(0.141)	(0.113)	(0.103)	(0.148)	(0.015)
EU salience	−0.537*	0.010	−0.455**	−0.492**	−0.023
	(0.297)	(0.151)	(0.207)	(0.229)	(0.029)
Inflation (M-1)	0.132	0.080**	0.334**	0.297*	0.003
	(0.106)	(0.036)	(0.158)	(0.160)	(0.017)
ECB trust	−0.417***	−0.128**	−0.252**	−0.391**	−0.007
	(0.114)	(0.064)	(0.128)	(0.176)	(0.013)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Populist control	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.358	0.142	0.325	0.343	
Observations	481	481	481	481	481
R^2					0.085
Adjusted R^2					0.054

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

G Robustness check: Removing eurogroups

G.1 Excluding Identity and Democracy MEPs

Table 23: MEP sentiment drivers on cryptocurrencies excluding ID eurogroup

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	-0.265^{***}	-0.097^{**}	-0.142^{***}	-0.141^{***}	-0.024^{***}
	(0.065)	(0.042)	(0.054)	(0.054)	(0.008)
LR-econ	-0.544^{***}	-0.254^{**}	-0.322^{***}	-0.350^{**}	0.033^{***}
	(0.159)	(0.101)	(0.123)	(0.149)	(0.010)
EU salience	-0.176	-0.077	-0.177	-0.171	0.029
	(0.264)	(0.235)	(0.216)	(0.262)	(0.019)
Inflation (M-1)	-0.214^{**}	-0.149^{***}	-0.222^{***}	-0.175^{***}	0.020^{*}
	(0.090)	(0.044)	(0.068)	(0.062)	(0.012)
ECB trust	0.252^{***}	0.133^{**}	0.158^{**}	0.133^{*}	-0.013
	(0.095)	(0.056)	(0.079)	(0.068)	(0.009)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.23	0.1	0.163	0.151	
Observations	1,424	1,424	1,424	1,424	1,424
R^2					0.080
Adjusted R^2					0.069

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 24: MEP sentiment drivers on the digital euro excluding ID eurogroup

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.403***	0.214***	0.252***	0.277**	−0.013
	(0.136)	(0.048)	(0.088)	(0.115)	(0.013)
LR-econ	0.300**	0.363**	0.176**	0.337***	−0.022
	(0.152)	(0.153)	(0.086)	(0.113)	(0.016)
EU salience	−0.377	0.183	−0.318	−0.264	−0.006
	(0.358)	(0.188)	(0.231)	(0.253)	(0.030)
Inflation (M-1)	−0.003	0.053	0.157**	0.117	0.004
	(0.056)	(0.109)	(0.075)	(0.118)	(0.019)
ECB trust	−0.264**	0.008	−0.077	−0.132	−0.005
	(0.108)	(0.034)	(0.085)	(0.107)	(0.015)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.3	0.17	0.279	0.261	
Observations	365	365	365	365	365
R^2					0.097
Adjusted R^2					0.055

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

G.2 Excluding European People's Party and Social Democrats MEPs

Table 25: MEP sentiment drivers on cryptocurrencies excluding EPP and S&D eurogroups

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.549***	−0.208*	−0.371***	−0.367***	−0.019
	(0.066)	(0.112)	(0.068)	(0.044)	(0.013)
LR-econ	−0.379***	−0.124*	−0.216**	−0.208*	0.013
	(0.121)	(0.066)	(0.091)	(0.115)	(0.011)
EU salience	0.016	−0.040	−0.142	−0.076	0.029
	(0.147)	(0.148)	(0.101)	(0.181)	(0.022)
Inflation (M-1)	−0.156***	−0.191**	−0.171***	−0.159**	0.015
	(0.037)	(0.084)	(0.065)	(0.081)	(0.015)
ECB trust	0.104	0.028	−0.012	0.061	−0.003
	(0.106)	(0.106)	(0.116)	(0.082)	(0.013)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.245	0.13	0.223	0.204	
Observations	747	747	747	747	747
R^2					0.095
Adjusted R^2					0.075

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 26: MEP sentiment drivers on the digital euro excluding EPP and S&D eurogroups

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.710***	0.323***	0.528***	0.579***	0.005
	(0.186)	(0.095)	(0.134)	(0.193)	(0.018)
LR-econ	0.498***	0.403***	0.382***	0.623***	−0.016
	(0.136)	(0.155)	(0.065)	(0.117)	(0.018)
EU salience	−0.984***	−0.158	−0.844***	−0.922***	−0.041
	(0.283)	(0.113)	(0.201)	(0.265)	(0.037)
Inflation (M-1)	0.192*	0.087**	0.397**	0.409*	−0.006
	(0.110)	(0.036)	(0.201)	(0.233)	(0.019)
ECB trust	−0.548***	−0.220***	−0.468***	−0.667***	−0.004
	(0.139)	(0.085)	(0.088)	(0.168)	(0.018)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.305	0.111	0.285	0.318	
Observations	329	329	329	329	329
R^2					0.086
Adjusted R^2					0.039

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

G.3 Excluding European People's Party and Renew Europe MEPs

Table 27: MEP sentiment drivers on cryptocurrencies excluding EPP and Renew eurogroups

	Cryptocurrency model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	−0.500***	−0.193**	−0.264***	−0.327***	−0.012
	(0.087)	(0.094)	(0.087)	(0.070)	(0.011)
LR-econ	−0.302**	−0.084***	−0.127*	−0.105	0.017
	(0.128)	(0.026)	(0.067)	(0.077)	(0.013)
EU salience	−0.077	−0.041	−0.286	−0.267	0.037
	(0.233)	(0.205)	(0.179)	(0.163)	(0.027)
Inflation (M-1)	−0.148***	−0.141***	−0.165***	−0.138***	0.018
	(0.029)	(0.036)	(0.051)	(0.049)	(0.013)
ECB trust	0.235***	0.107	0.110*	0.062	−0.010
	(0.075)	(0.074)	(0.064)	(0.057)	(0.011)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.331	0.068	0.206	0.169	
Observations	1,041	1,041	1,041	1,041	1,041
R^2					0.031
Adjusted R^2					0.016

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 28: MEP sentiment drivers on the digital euro excluding EPP and Renew eurogroups

	Digital euro model				
	logistic H-C	*logistic* GPT-ZS	*logistic* GPT-FS	*logistic* Llama-FS	*OLS* Vader
	(1)	(2)	(3)	(4)	(5)
People/Elite	0.639***	0.258***	0.347***	0.364***	−0.003
	(0.136)	(0.075)	(0.089)	(0.118)	(0.015)
LR-econ	0.550***	0.440***	0.343***	0.526***	−0.025
	(0.133)	(0.117)	(0.096)	(0.156)	(0.022)
EU salience	−1.071***	−0.273***	−0.760***	−0.805***	−0.021
	(0.279)	(0.079)	(0.164)	(0.234)	(0.040)
Inflation (M-1)	0.145	0.067**	0.356*	0.297*	0.001
	(0.111)	(0.028)	(0.193)	(0.179)	(0.019)
ECB trust	−0.491***	−0.164**	−0.302**	−0.488**	−0.004
	(0.137)	(0.077)	(0.137)	(0.205)	(0.016)
Individual-level controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
East/West FE	Yes	Yes	Yes	Yes	Yes
Pseudo-/R^2	0.338	0.121	0.238	0.274	
Observations	355	355	355	355	355
R^2					0.068
Adjusted R^2					0.024

Notes: Robust standard errors clustered at the eurogroup level are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.