Geographic Representation and Information Capacity in the European Union*

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Abstract

International organizations (IOs) must decide between prioritizing qualifications or geographic representation of member states when recruiting staff. Many IOs assume a trade-off between expertise and representation, where the former increases capacity and the latter increases legitimacy. However, this paper provides evidence that geographic representation can enhance bureaucratic information capacity. Using the European Commission's Directorate-General for Economic and Financial Affairs as a case study, I provide evidence that increasing representation of bureaucrats from a member state increases the accuracy of that state's economic forecasts. This effect, which I call "national expertise," decreases as member state representation within the Commission increases and is most pronounced for large economies. These findings highlight that prioritizing geographic balance in IOs may positively impact both legitimacy and capacity.

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1 Introduction

International organizations (IOs) typically have large bureaucracies that handle the day-to-day operations of the organization, and these bureaucracies have a large influence on the ability of IOs to achieve their goals (Eckhard and Ege 2017). To staff these bureaucracies, IOs must hire staff from the pool of applicants that come from the member states of the IO. Ideally, the staff recruited for positions at an IO would be representative of the member states that the IO commits to working with. However, in reality it is often difficult to achieve perfect representation for each member state. This may be because of competitiveness of the IOs wages compared to member state wages, or because educational and professional opportunities are unevenly distributed across member states. Therefore, these organizations typically must decide whether they will prioritize hiring to maximize representation of members states (geographic representation) or based on qualifications of applicants alone. Some organizations, like the IMF and the World Bank, prioritize qualifications and focus on hiring candidates from top university programs (Yi-chong and Weller 2018). The European Union, on the other hand, explicitly prioritizes a geographic balance of staff members, although it qualifies that deviations from geographically representative guidelines are sometimes "necessary to prevent the risk of inefficiencies" (Commission 2018).

The idea that there is a trade-off between bureaucratic capacity and geographic representation in international organizations (IOs) implies that geographic representation, while important for reasons of legitimacy and representation, has little to no effect on enhancing the capacity of these organizations. However, the importance of the knowledge, expertise, and connections bureaucrats have for their home states (first nationality) is understudied in the literature. IOs need to be informed on the political, economic, and cultural background of many (often vastly distinct) states in order to be effective. Nationals of a member state, therefore, will have an advantage when it comes to monitoring and implementing policy in their own state. Thus, IOs with geographically diverse and representative staff will have workers with "national expertise" from each member state, while an IO that does not have a representative staff will lack national expertise for some of its member states. This paper examines whether higher levels of national expertise lead to better information capacity.

I estimate the effect of national expertise on IO capacity in the context of the European Commission, the executive branch of the EU. The Commission oversees the implementation and administration of EU policies through various policy departments known as Directorates-General (DGs). The DG for Economic and Financial Affairs (ECFIN), is tasked with conducting and publishing economic forecasts to monitor market conditions in EU member states. ECFIN relies on the expertise of its diverse staff, who come from all member states, to produce accurate forecasts essential for monitoring economic conditions and potential violations of EU economic criteria (European Commision,) . These forecasts are published biannually and are publicly available going back to 2011. I use the accuracy of these forecasts as a proxy for the information capacity of ECFIN. This measure of capacity is best suited for my analysis, because measures that rely on the academic or professional qualifications of bureaucrats in the commission arguably do not capture ECFIN's ability to be effective at its goals.

To proxy national expertise, I use first nationalities of ECFIN staff. I find that increasing national expertise leads to more accurate economic forecasts. In substantive terms, the effect of hiring an additional national to ECFIN leads to a 2.5-2.6% increase in revenue forecast accuracy and a 1.8-3.1% increase in expenditure forecast accuracy in the member state of the staff member's nationality. The effect of national expertise on forecast accuracy is strongest for member states with large economies and for those that are less wealthy. However, suggestive evidence indicates that even forecasts for small and wealthy EU member states can benefit, to some extent, from national expertise.

These findings provide evidence that the national affiliation of IO staff members plays a meaningful role, contributing to the growing literature on how staff characteristics shape key organizational functions (Clark and Zucker 2024; Lang, Wellner, and Kentikelenis 2024). They also advance our understanding of the sources of IO forecast errors (Eicher and Kawai 2023) by highlighting the advantages associated with national expertise. Finally, the results offer preliminary insights into representation, an underexplored dimension of IO staffing that warrants greater scholarly attention.

This paper proceeds as follows. In section 2, I provide an overview on research that touches on bureaucratic capacity in IOs, and I explain the Commission's bureaucratic system. In section 3, I describe my empirical expectations given the theory I present. I then outline my empirical strategy and the model specification used in my analysis. Finally, section 4 shows the main results of this analysis along with interaction models that provide more detail about where national expertise is most effective.

2 Bureaucratic Capacity in IOs

It is widely acknowledged that the bureaucracies of IOs do influence policy making and governance decisions (Ege and Bauer 2013; Eckhard and Ege 2017; Clark and Zucker 2024; Lang, Wellner, and Kentikelenis 2024), so it is important to understand the factors that help these organizations function effectively. Research in international relations and public administration that examines the capacities of IOs typically focuses on the credentials of leaders (Kille 2013; Murdoch, Trondal, and Gänzle 2014) or on the degree of independence IOs have from their constituent member countries (Hawkins et al. 2006). While these topics are worthy of study, they may reflect differences in organizational preferences (e.g., hiring preferences, reliance on member countries, etc.) more than the underlying capacity of an IO to achieve its goals. IOs need to be able to collect taxes, monitor member quotas, and carry out borrowing arrangements in order to fund themselves. They also need to be able to monitor the economic and political conditions of member countries in order to enforce policies. This type of capacity is sometimes referred to as "information capacity" in the state capacity literature (Brambor et al. 2020).

Some research has been done examining the relationship between geographic representation (sometimes called "passport diversity") and bureaucratic expertise in IOs. In the context of the EU specifically, there is evidence that European Commission recruitment competitions that have nationality as a criterion put less emphasis on expertise requirements (Christensen 2015) and that recruitment has become more generalist over time as geographic representation has become more important to the Commission (Christensen, Bekerom, and Voet 2017). However, as mentioned in the previous paragraph, changes in recruitment practices is an imperfect measure of the underlying capacity of the Commission.

Scholars have long argued that bureaucracies must be somewhat representative of their constituencies in order to be seen as legitimate (Tilly 1975; Weber, Roth, and Wittich 1978; Hood and Lodge 2006). Recent research shows evidence that this might not need to come at the expense of expertise or efficiency. Pérez-Durán and Bravo-Laguna (2019) find that EU agencies (different from DGs) that are designed to be inclusive of member states do not have fewer experts with scientific training. Additionally, in a large meta-analysis of public administration research on representative bureaucracies in the US, Ding, Lu, and Riccucci (2021) find that bureaucracies that work to hire staff that are demographically similar to the constituencies they serve can "bolster performance and productivity." The question of whether and to what extent representation matters in other contexts, like IOs, has not been examined.

2.1 Capacity in the EU

The European Commission is the executive branch or secretariat of the EU, and it is the largest employer in the EU. The Commission is responsible for implementing and administrating EU policies. To do so, the Commission relies on bureaucrats' expertise in order to fulfill its administrative duties efficiently and accurately. However, the Commission is also fundamentally committed to having a workforce that is representative in order "to be close to the citizens and to reflect the diversity of Member States" (Commission 2018).

The Commission recruits people to hire as staff through open recruitment competitions. For administrator positions, applicants first pass an array of tests that measure verbal and numerical skills, abstract reasoning, and situational judgement. Applicants who pass this pre-selection process are then asked to do case studies, group exercises, and interviews. After this second stage, those who are deemed capable of working at the Commission are put on a reserve list, which means they are eligible to be hired by any of the European institutions (Christensen 2015; EPSO 2010).

The Commission is comprised of many policy departments (DGs) that are responsible for overseeing the executive functions of the EU, which includes proposing, implementing, and managing EU policy. The EU has many laws that require states to follow economic guidelines. As the Commission must ensure these laws are being followed across member states, it is important for the Commission to have accurate data about the economic conditions of member states that are gathered independently from member states themselves. It is also important for the EU to have accurate forecasts on member country budgets, as countries that are in danger of violating economic criteria are to be put under surveillance (e.g., European Commission (2024)). These forecasts are also taken seriously in European financial markets. Section C in the online appendix shows that government bond yields react to forecasts released by ECFIN (with joint significance tests showing a p-value of 0.001).

The DG for Economic and Financial Affairs (ECFIN) is responsible for conducting and publishing these forecasts and their accompanying reports (Economic and Financial Affairs - European Commission 2025). ECFIN's staff is mostly comprised of administrator-level positions and includes staff members from almost every EU member state every year.[1] Because these forecasts are important for the EU, there is a large incentive for ECFIN to make forecasts that are as accurate as possible. This accuracy depends on both the economic modeling knowledge and field knowledge of ECFIN staff [2] (European Commision,). Thus, if economic forecasts improve because of changes in the composition of staff, it should be attributable to ECFIN's higher capacity.

It is important to note that ECFIN staff are not typically assigned to work solely on their own state's economic analyses and forecasts. This is typically done to avoid potential conflicts of interest with work done in the Commission (Kassim 2013). To illustrate, I examine the nationalities of heads of ECFIN subdivisions that focus on specific member economies in the July 2024 official EU directory. There are three such direc-

1. Occasionally there is no one from Luxembourg on staff at ECFIN. See figure 1 for more details.
2. ECFIN has a unit specifically in charge of economic forecasts (ECFIN.A.3, Economic situation, forecasts, business and consumer surveys), but the work that goes into making accurate forecasts will be a combination of the work of many staff throughout the DG.

Table 1: Nationalities of Unit Heads and Directors

Position	Surname	Surname Nationality
ECFIN.E, Director	Friis	Denmark
Belgium, France, Luxembourg	Yaniz Igal	Spain
Estonia, Latvia, Lithuania, Netherlands	Griesse	Norway
Bulgaria, Romania, Sweden	D'Souza	Ireland†
ECFIN.F, Director	Tholoniat	France
Austria, Cyprus, Germany	Masselink	Netherlands
Finland, Greece	Lendvai	Hungary
Croatia, Spain	Giudice	Italy
Hungary, Slovenia	Ciobanu	Romania†
ECFIN.G, Director	Grilo	Portugal*
Czechia, Poland, Slovakia	D'Elia	Italy
Denmark, Ireland, Portugal	Woehlbier	Germany
Italy, Malta	Kutos	Austria

*Director whose nationality is in their directorate
†Highest surname density in non-EU country, so I show highest density within EU

torates (ECFIN E, F, and G), which are broken down further to units that focus on 2-4 member countries. I use **forebears.io** to find the country where the surname has the highest density to approximate the nationality of the administrators. As shown in table 1, only one of the three subdivision directors is in charge of a sub-division that includes her nationality, and none of the unit heads are over a unit that includes their nationality.

The fact that ECFIN does not typically assign staff to work on their own state's economic forecasts is important. If staff were assigned to work only on their home state's economy, the connection between staff nationalities and informational capacity would be simple, i.e. adding resources to a specific forecast makes the forecast better. Knowing that staff are not assigned to units based on their first nationality, the effect of national expertise points more to how their expertise helps contribute to accurate forecasts by maintaining a diversity of national expertise throughout the directorate.

Using forecast accuracy to operationalize state capacity has been used in the context of American bureaucratic politics (Krause, Lewis, and Douglas 2006) and is desirable for at least two reasons. First, ECFIN publishes forecasts on many economic indicators for all member countries twice a year, and this data is publicly available on their website as early as 2011. For other measures of bureaucratic capacity (e.g. educational attainment of

ECFIN employees or recruitment procedures), getting coverage this comprehensive would be difficult and costly, if not impossible. Second, ECFIN is incentivized to minimize error for all member countries. This is in contrast to other potential measures of capacity (e.g. policy implementation), which may have different outcomes across member states for reasons other than the bureaucratic capacity of ECFIN or any other DG (e.g. preferences about where to focus implementation efforts). Thus, economic forecast accuracy serves as a robust measure of capacity for ECFIN.

3 Empirical Strategy

3.1 Expectations

IOs must decide whether to prioritize geographic representation in hiring. If the distribution of highly qualified candidates differs across member states, IOs must prioritize representation of qualifications. Some organizations, like the IMF and the World Bank, insist on recruiting only "super experts" to their staff, which generally means hiring PhD graduates of top universities in the US and the UK (Yi-chong and Weller 2018). This typically results in large geographic imbalances. For example, from 2017 to 2022 over 40% of the IMF's contributors and senior officers (A9 - A15/A15) and the majority of senior managers and above (A14/15 - B5) were from the US, Canada, or Western Europe (IMF 2024), which are less than 19% of the 191 IMF member countries. The Commission, on the other hand, requires geographic balance to be considered in recruiting and releases recommendations on the percentage of staff DGs should have from each member country. Do these requirements result in a lower functioning bureaucracy in the Commission?

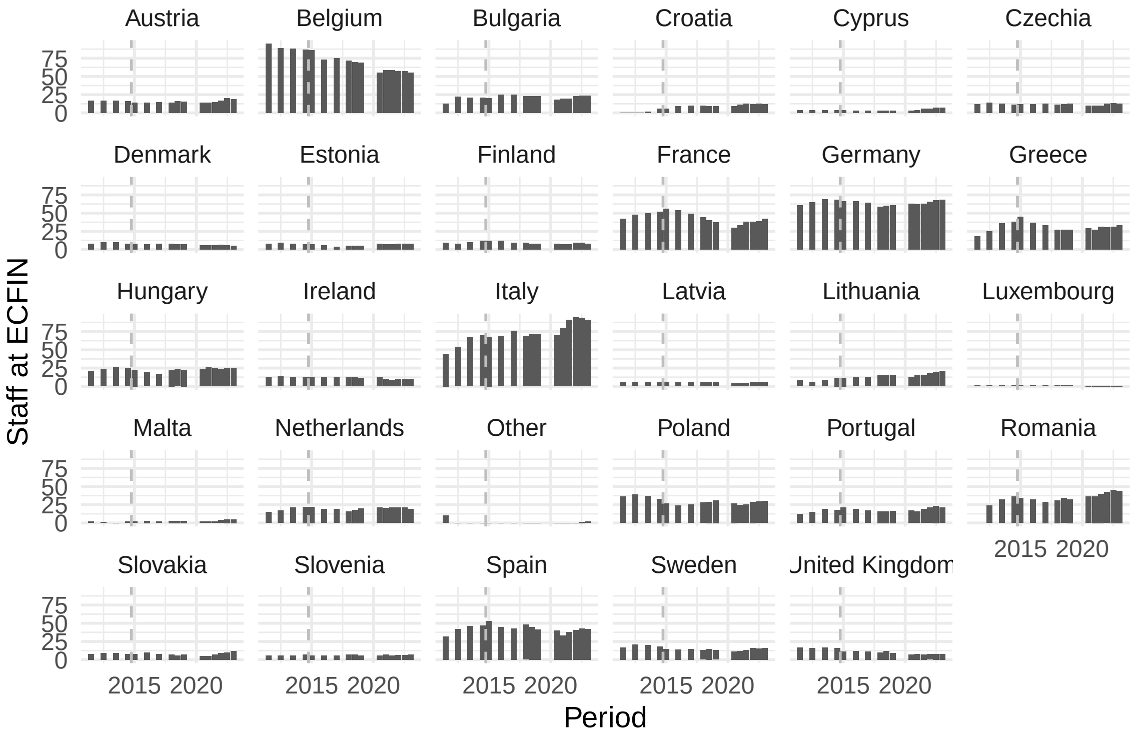
I argue that having a representative workforce is beneficial for the functioning of ECFIN, given that the EU needs accurate information on each member state in order to function well. Obtaining information on the economies of member states will be least costly for staff that have connections and familiarity with the economic systems in these states. For example, many ECFIN staff previously worked in the financial sector or central bank of their home state.[3] Additionally, familiarity with the history, language, and current events of the state will be beneficial. This expertise that staff members have of their own states means they can easily help with forecasts pertaining to their home state, even if they are not assigned to work exclusively on their home economy (as is often the case). Thus, having staff that are representative of the EU's member states could lead to more accurate forecasts. On the other hand, staff from countries with less advanced university education systems or less professional opportunities may be less experienced to take on the tasks that are required to generate accurate forecasts.

To test this empirically, I use data from the Commission to see whether the "national expertise" that staff have results in more accurate forecasts. I proxy national expertise as the first nationality of staff members at ECFIN. Using first nationality is a conservative measure of national expertise, as staff may have multiple nationalities or other ties to member states that are not their first nationality. Therefore, the results from my analysis will likely be a conservative measure of the effect of national expertise on the capacity of ECFIN.

As an illustrative example, consider the effect of hiring a highly skilled Irish staff member to ECFIN. If there is a significant relationship between hiring an Irish staff member to ECFIN (i.e. increased "Irish expertise") and improved Ireland economic forecast accuracy (controlling for the size/composition of ECFIN and other country specific factors), this would be evidence that the expertise the Irish staff member brings to Irish forecasts improves Irish-specific capacity. If this effect holds across all staff members, this suggests that having geographic representation as a factor in recruiting may be an important factor in building and maintaining information capacity at ECFIN. If there is no significant relationship as described above, then I would not find evidence that national expertise matters for bureaucratic capacity at ECFIN.

3. Based on the author's convenience sample of ECFIN employees with up-to-date LinkedIn profiles.

Figure 1: ECFIN Employees by Nationality Over Time



3.2 Data

To investigate the impact of local knowledge on bureaucratic capacity in the EC, I collect data on the first nationality of employees by DG from 2011 to 2022 from the Commission's Human Resources DG. The data from 2011-2014 include official employees and temporary employees, while the data from 2015-2022 includes official, temporary, and contract employees. Figure 1 shows the time trends of how many employees from each member country are employed at ECFIN, where to the right of the dashed line is when contract employees were added to the population.[4]

I use data from the annual macro-economic (AMECO) database to create forecast accuracy variables. The database has released forecasts at least twice yearly since 2011 and includes short-term forecasts made by ECFIN. These novel forecasts are released in May and November of every year. Every release contains end-of-year (EOY) and 1-year forecasts on economic indicators of interest for all EU member states, as well as

4. For the purposes of this paper, only the primary nationalities of ECFIN staff are presented. The full dataset can be obtained from the author upon request.

some non-EU states. The forecasts released in November also include 2-year forecasts. Economic indicators for both revenue and expenditure are included in the forecasts. In my analysis, I exclude indicators that are aggregates of other indicators (e.g. total revenue, lending, etc.). I also exclude variables that are included in AMECO for only part of the sample. Table 2 shows the list of economic indicators from forecasts used in my analysis, categorized as either revenue or expenditure. See section A in the online appendix for a full list of economic indicators, including those that are excluded from my analysis.

Table 2: Economic Indicators used in Forecasts

Revenue	Actual social contributions received, Capital taxes, Capital transfers received, Current tax burden, Current taxes on income and wealth (direct taxes), Gross disposable income, general government, Gross saving, Imputed social contributions, Net disposable income, Net saving, Net social contributions received, Other current revenue including sales, Other current revenue, Taxes linked to imports and production (indirect taxes), Total tax burden excluding imputed social security contributions, Total tax burden including imputed social security contributions
Expenditure	Capital transfers paid, Collective consumption expenditure, Compensation of employees, Final consumption expenditure of general government, Gross fixed capital formation, Interest, Intermediate consumption, Other current expenditure, Social benefits other than social transfers in kind, Social transfers in kind supplied to households via market producers, Subsidies

I calculate the error of each forecast using the true values of these indicators in the AMECO database. I use the May 2014 AMECO database for 2011-2013 and the May 2024 for November 2014 - 2023. (I use two different databases because the accounting system changed from ESA 1995 to ESA 2010 in November 2014). The unit of this error variable is millions of Euro. I also include time-varying controls for population (yearly data from World Bank, linearly interpolated for the second half of the year), GDP (quarterly data from Eurostat, average for first and second half of the year), and GDP per capita (calculated using the two variables above).

3.3 Model

To estimate the effect of national expertise on capacity, the equation of interest is given by

$$log(y_{ifct}^2) = \beta_1 NE_{ct} + \Theta X + \Gamma_{ifct} + \epsilon_{ifct} \tag{1}$$

where i represents economic indicators, f indicates the year being forecasted (e.g. EOY or 1-year forecast), c represents member countries, and t represents the time period in which the forecast was made. y_{ict} is the forecast error variable described above. I use squared error to measure inaccuracy broadly rather than differentiating between positive or negative errors, and I log transform the squared error to account for differences in the sizes of economies (and outliers therein) and to approximate a normal distribution. NE (National Expertise) is the number of employees at ECFIN that are of first nationality c at time t. X is a matrix of observables, namely population (logged), GDP (logged), and GDP per capita. I log transform population and GDP in order to approximate normal distributions in these control variables. Γ_{ifct} represents a matrix fixed effects included for economic indicator, forecast period, member country, and the time period in which the forecast is made.

GDP and population are used as controls to roughly proxy the size and/or complexity of an economy. While the country fixed effects control for average country differences in economies, adding these variables allows me to also control for changes in economies over time. Including GDP per capita in the model roughly controls for the wealth of countries over time, which could control for differences in a country's workforce over time. Economic indicator fixed effects control for the differences in how difficult individual indicators may be to forecast as well as differences in scale (i.e. direct taxes will be a larger quantity than capital taxes in most countries). Forecast year fixed effects will control for the differences in difficulty of forecast periods (i.e. longer vs. shorter term forecasts). Country fixed effects control for country specific factors, such as the amount of economic experts that could work at ECFIN. Finally, time fixed effects will control for EU-wide time varying changes. Importantly, this will control for the total number of ECFIN staff in each time period as well as the differences in reporting contracted staff workers that occurs after 2014.

The coefficient of interest is β_1, which I argue is the effect of national expertise on ECFIN information capacity. This coefficient represents the effect of adding one more national from a member state to ECFIN on the member state's forecast accuracy. As the outcome variable is logged, this will be in terms of the percent of error for a given member state's forecasts. For example, if $\beta_1 = -0.015$, then adding a national to ECFIN will have the effect of a 1.5% reduction in forecast error. It is important to note that this effect is an average for all member states and all economic indicators. Therefore, it is possible that the effect is heterogeneous across member states or economic indicators. I address this in section 4.4.

4 Results

4.1 Main model

Table 3 and figure 2 show the results of the main model using six alternative specifications. Model 1 shows the estimates for revenue forecasts and model 2 shows expenditure forecasts. Panel A includes all forecast periods, Panel B excludes EOY forecasts that were made in November, and Panel C excludes all EOY forecasts. All models include fixed effects for economic indicator, period being forecast, member country, and the time period in which the forecast was made. The standard errors are clustered by country.

A negative coefficient for national expertise indicates that national expertise *increases* forecast accuracy, since the outcome is forecast error squared. All models in all panels show a negative coefficient for National Expertise. For each estimate except for model 2 panel A, these coefficients are significant at $\alpha = 0.05$. The coefficient in Model 2, Panel A is significant for $\alpha = 0.1$ ($p = 0.09$), but in Panels B and C the estimates are significant at $\alpha = 0.01$ and the magnitudes are larger. Since I expect EOY forecasts to be more straightforward than longer-term forecasts, it is intuitive that national expertise plays a larger role in longer-term forecasts.

The effects estimated in table 3 do not show the average effect of increasing the size of ECFIN staff, as time fixed effects control for the total size of ECFIN in any given time period. These results are robust to removing time periods that may have been affected by COVID-19 uncertainty. They are also robust to filling in periods with missing ECFIN data using linear and spline interpolation (see section D in the online appendix). Country fixed effects control for any systematic (time-invariant) differences in ECFIN staff. GDP, population, and GDP per capita roughly control for the size and wealth of a member economy. This may control for changes in quality of recruits over time, which the country fixed effects do not control for.

The point estimate of the effect of national expertise on revenue forecast accuracy is quite stable across models (between -0.021 and -0.023), while the magnitude of the effect in expenditure models varies from -0.020 and -0.033. As the outcome variable is log transformed, the interpretation of these coefficients is that national expertise leads to a decrease in a member state's revenue forecast error by 2.4-2.6% and expenditure forecast error by 1.8-3.1%. To understand these coefficients substantively, I will use Ireland as an example. In 2023, Ireland's total revenue was €123.71 billion and its total expenditure was €115.39 billion. Applying the coefficients in Panel B for models 1 and 2, adding an Irish staff member to ECFIN would translate to a revenue forecast that is more accurate by €2.97 billion and an expenditure forecast that is more accurate by €2.54 billion.

4.2 Randomization Inference

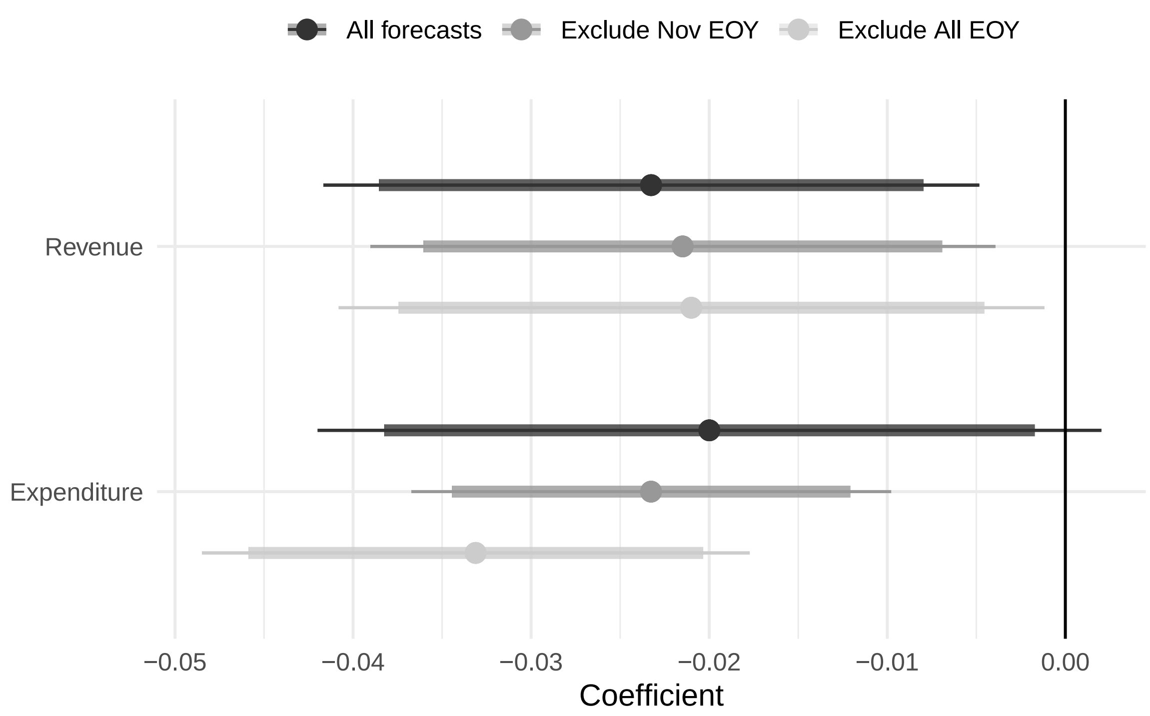
The models in Table 3 show the results of ECFIN staff on their own member state's forecasts, but they do not take into account that the work ECFIN staff do will most likely improve other member states' forecasts as well. While I control for the general size of ECFIN staff, it is possible that the model is not picking up national expertise but rather something more broad. This could be knowledge of a specific region within Europe, familiarity with countries that have similar economic systems, or ties between higher education systems across countries. If this were the case, then strict geographic

Table 3: Effect of National Expertise on Member State Forecast Accuracy

Dependent Variable:	Log Error Squared	
Forecasts Category:	Revenue	Expenditure
Model:	(1)	(2)
Panel A: All forecasts		
National Expertise	-0.023**	-0.020*
	(0.009)	(0.011)
Observations	12,504	9,990
R^2	0.680	0.604
Within R^2	0.005	0.006
Panel B: Excluding EOY Forecasts made in November		
National Expertise	-0.021**	-0.023***
	(0.009)	(0.007)
Observations	9,603	7,679
R^2	0.686	0.612
Within R^2	0.004	0.005
Panel C: Excluding EOY Forecasts		
National Expertise	-0.021**	-0.033***
	(0.010)	(0.007)
Observations	6,997	5,588
R^2	0.689	0.617
Within R^2	0.004	0.008

Clustered (country) standard-errors in parentheses
Fixed effects: econ. indicator, period, state, forecast year
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Figure 2: National Expertise Effect on Revenue and Expenditure Forecasts

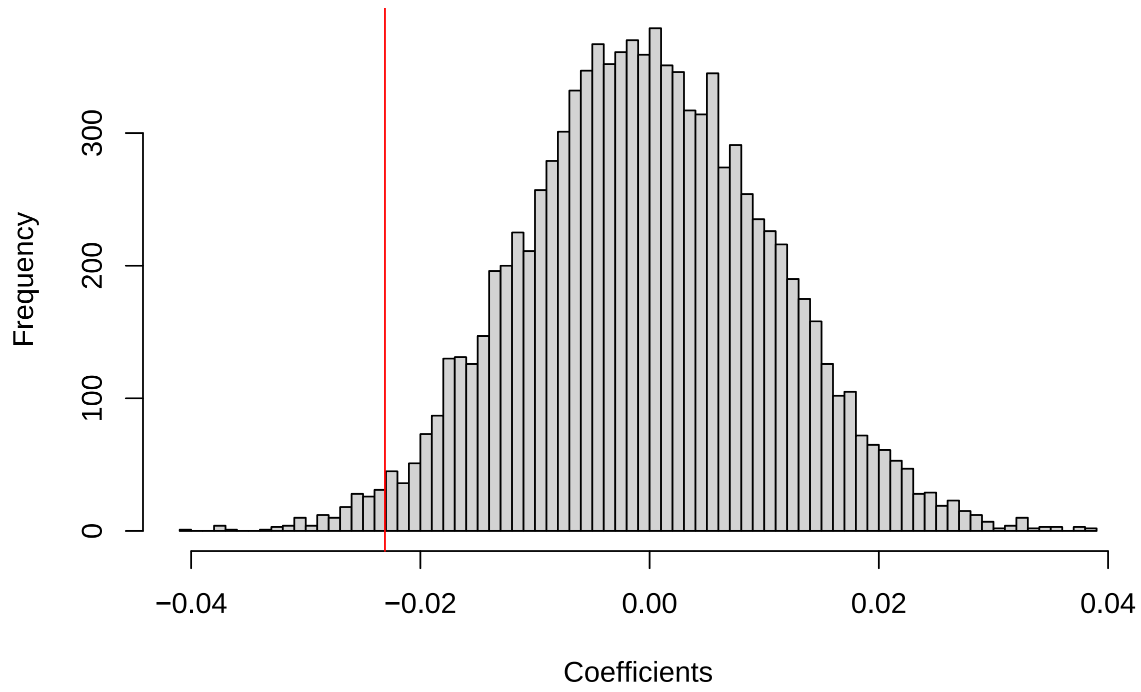


representation would not be crucial for improving capacity.

To make sure the effect I estimate is not one of these broader factors, I conduct a Monte Carlo simulation in which I randomly assign ECFIN staff members to EU state forecasts, using a combined model specification that includes both revenue and expenditure 1- and 2-year forecasts. In other words, I conduct simulations in which the staff of a certain nationality are randomly linked to the forecasts of a potentially different member state. If national expertise doesn't matter, or matters less than some other factor related to nationality, then randomly assigned ECFIN nationalities should have similar coefficients as the main model. However, if national expertise does matter, the main model's coefficient should be one of the most extreme compared to the simulations. This is similar to a Fischer sharp null hypothesis, but I run only 10,000 iterations in a MC simulation instead of going through the whole universe of nationality and member state forecast pairings.

Figure 3 graphically shows the results of the MC simulation, where the vertical red line indicates the coefficient from the combined model. The coefficient from the main model is

Figure 3: MC Simulations of Staff-Member State Forecast Pairings



smaller (i.e. more negative) than almost 99% of the simulated coefficients (sharp p-value for one sided test= 0.014). Thus, I have sufficient evidence to reject the null hypothesis that broader factors than nationality are driving the results in the model.

4.3 Marginal Effects

The main model shows the general effect of national expertise on forecast accuracy. However, this is effect is likely to be dependent on the current level of representation from a given member state. Member states that are already well represented would likely see much smaller gains in forecast accuracy from an additional staff member being added to ECFIN and vice-versa. Thus, the effect of adding an additional national to ECFIN should be larger if the member state was previously underrepresented and smaller if the state was previously overrepresented. In other words, I expect the effect of national expertise to be decreasing in member states' representation.

To test this expectation, I compare the actual ECFIN staff representation for a given member state to the level of representation suggested by the Commission's guide rate. In a 2018 Report from the Commission (Commission 2018), guidelines are given for the percentage of Commission staff that should be employed from each member state, called "guiding rates." Based on the details from Annex 5 of the report, I find that these percentages are calculated by taking the average of three proportions: country's population as a percent of the EU's population, the percent of seats the country has in the European Parliament, and the percent of seats the country has on the European council. When I calculate this for the year 2017 (as in the report), my calculation is nearly perfectly correlated with the reported guiding rates (Pearson's $r = 0.98$). The slight difference seems to come from the report's rounding of percentages to the nearest tenth of a percentage point, while I do no such rounding.

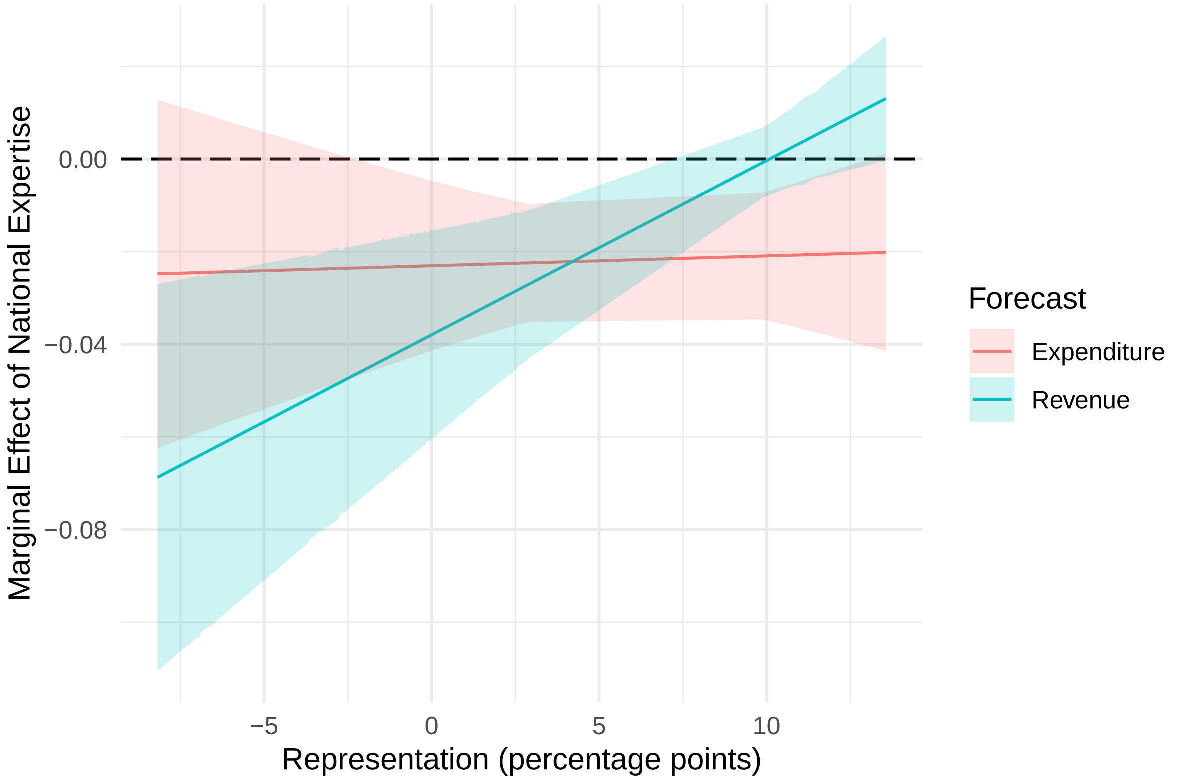
I run the forecast models that exclude EOY forecasts made in November (Table 2, Panel B models) with the addition of a new variable I call *Representation*. This variable is the guiding rate for a member state (calculated as described in the previous paragraph) substracted from the percentage of ECFIN staff from said member state. Formally, the model can be written as

$$\begin{aligned} \log(y^2_{ifct}) = &\beta_1 NE_{ct} + \beta_2 Representation_{c,t} + \beta_3 NE_{ct} * Representation_{ct} \\ &+ \Theta X + \Gamma_{ifct} + \epsilon_{ifct} \end{aligned} \tag{2}$$

This is identical to (1), with the addition of $Representation_c t$ and the interaction $NE_{ct} * Representation_{ct}$ in the model. The estimate of interest is the marginal effect of national expertise, which is the partial derivative of the equation with respect to NE. Formally, $\frac{\partial y}{\partial x_1} = \beta_1 + \beta_3 Representation_{ct}$.

Figure 6 show the marginal effect described. Importantly, the effect of national expertise decreases in representation for both revenue and expenditure forecasts. For revenue forecasts, the effect goes from a large (-6.8%) and significant effect on forecast error for underrepresented member states (about -8 percentage points below the guiding rate) to an insignificant (and positive) effect on forecast error for member states that are highly

Figure 4: Marginal Effect of National Expertise by Country's Over/Under Representation

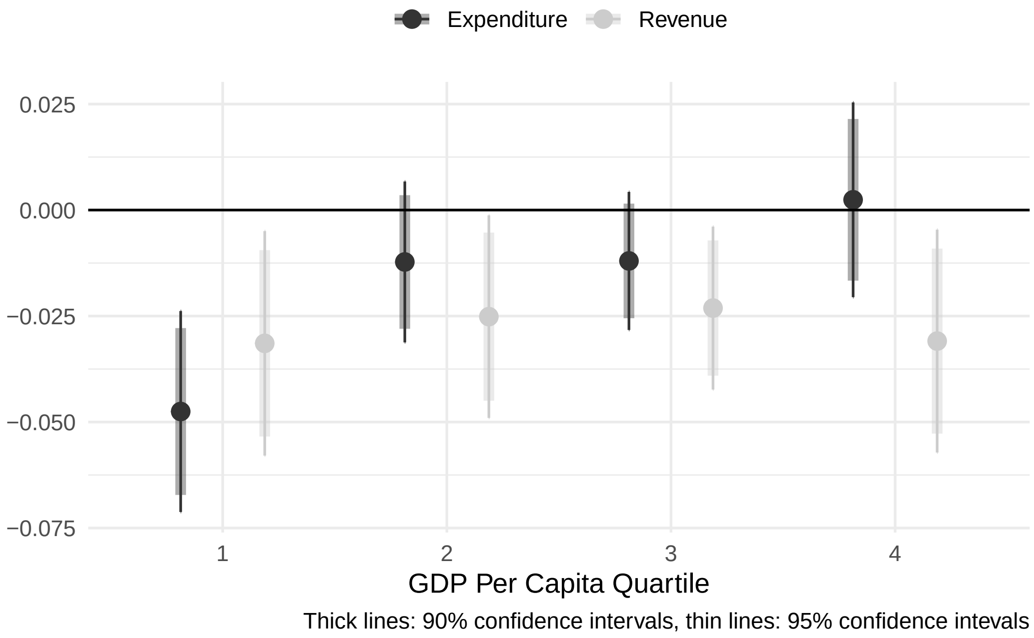


overrepresented (about 13 percentage points above the guiding rate). For expenditure forecasts, the decrease in the marginal effect of national expertise is much less dramatic (from -2.4% effect to -1.9% effect) and the interaction term is not statistically significant. Thus, it does seem that the effect of national expertise is decreases in a member state's representation, although this interaction effect is largely driven by the effect on revenue forecasts.

4.4 Interactive models

This section explores potential heterogeneity in the effect of national expertise across member states. First, national expertise may be helpful for less wealthy economies, but the effect might be negligible for wealthy countries with higher legibility, more predictable economic trends, or easily observable political and cultural environments. To address this, I re-run the models in Table 3 Panel 2 (which exclude EOY forecasts made in November) with an interaction for GDP per capita quartiles. Figure 5 shows this interaction, where the gray points show model 1 (Revenue) and black points show model 2 (Expenditure).

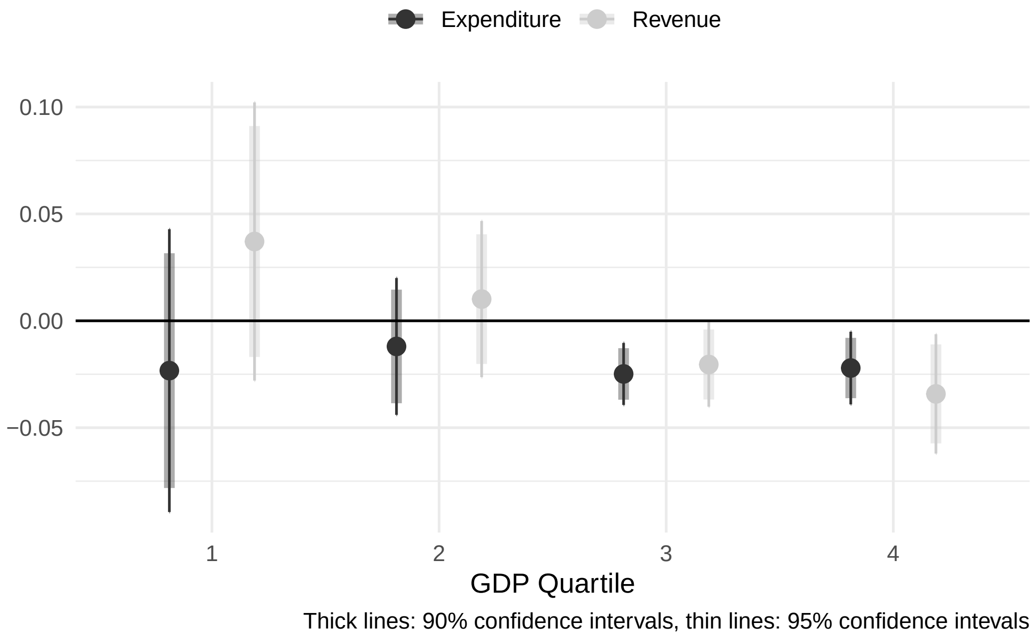
Figure 5: Marginal Effect of Expertise by GDP Per Capita



As Figure 5 shows, all but one of the point estimates are negative. For the least wealthy states (GDP per capita quartile 1), the effect is the largest and I reject the null hypothesis of no effect in both models. For all quartiles, point estimates for revenue models are negative and statistically significant at $\alpha = 0.05$. These estimates are also substantively large, ranging from a 2.2-3.6% increase in accuracy. For expenditure, the point estimates are generally closer to zero and imprecisely measured. However, the estimates are negative for all except the wealthiest quartile (where the estimate is 0.003). Taken together, these results suggest that even wealthy states can gain information capacity from more national expertise.

The effect of national expertise may also vary depending on the size of the economy of the member state. Larger economies are likely more difficult to forecast than small ones. To investigate this, I run the models in Table 3 panel B with an interaction for GDP quartile. The results of these models are shown in Figure 6. All but two point estimates are negative, although the estimates for smaller economies (quartiles 1 and 2) are imprecisely estimated. The revenue model coefficient for 1st quartile countries is positive and somewhat large (0.033), but it is very imprecisely estimated and not

Figure 6: Marginal Effect of Expertise by GDP



statistically different from any of the other revenue coefficients. The effect of national expertise on revenue increases for larger economies, while the effect on expenditure is roughly the same across quartiles. Thus, I find evidence that national expertise is most effective for larger economies, although this is largely driven by the effect on revenue forecasts.

5 Discussion and Conclusion

The European Commission is committed to having a staff that is geographically representative of its member states. Some argue that this means the Commission must sacrifice efficiency and expertise in order to achieve geographic representation (Yi-chong and Weller 2018). However, in this paper I show evidence that national expertise (operationalized by the number of employees with first nationality from a member state) increases forecast accuracy in ECFIN forecasts. Moreover, suggestive evidence shows that the effect of national expertise on forecasts decreases in the level of representation a country has at ECFIN, although the relationship is stronger for revenue forecasts than expenditure forecasts.

These results have important implications for recruitment decisions in IOs. First, the fact that the observed effect is strongest for underrepresented economies suggests that a lack of geographic representation may well have adverse effects on IOs information capacity. Second, the results speak to the problem of under-representation of large economies in the Commission (Michelmann 1978; Kassim 2013). Countries like France, Germany, and Spain are consistently underrepresented in ECFIN and the Commission in general (see section B in the online appendix). My results highlight the potential that this under-representation may have unintended consequences on information capacity.

While the findings presented in this paper constitute an important first step, a more systematic research agenda is needed to deepen our understanding of the relationship between geographic representation in IOs and their informational capacity. Because the empirical analysis focuses specifically on the European Commission, future work should investigate the extent to which these effects generalize across different organizational contexts. Comparative analyses across IOs with varying institutional designs, mandates, and staffing practices could shed light on whether the mechanisms identified here operate similarly elsewhere or are contingent on specific organizational features. Furthermore, this study does not explore how national expertise interacts with other forms of expertise that staff acquire during their tenure in IOs (Clark and Zucker 2024), nor does it address how personal biases may shape work that is less objective in nature (Lang, Wellner, and Kentikelenis 2024). These remain important avenues for future research.

Although this paper discusses potential mechanisms through which national expertise may influence forecast accuracy, it does not definitively establish how such expertise is applied in practice. Future research could more closely examine the processes through which national knowledge is mobilized within forecasting agencies, thereby clarifying how national affiliation contributes to organizational informational capacity. This may involve examining how information is shared across teams at ECFIN and other IO forecasting departments. By unpacking these mechanisms, subsequent work can advance a more precise understanding of the micro-level channels through which staff composition shapes

IO performance.

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Online Appendix

Geographic Representation and Information Capacity in International Organizations

Appendix A Economic Indicators

The list below shows all of the indicators included in the revenue and expenditure categories, as well as the indicators that were excluded from the analysis.

- Revenue
  - Actual social contributions received
  - Capital taxes
  - Capital transfers received
  - Current tax burden
  - Current taxes on income and wealth (direct taxes)
  - Gross disposable income, general government
  - Gross saving
  - Imputed social contributions
  - Net disposable income
  - Net saving
  - Net social contributions received
  - Other current revenue including sales
  - Other current revenue
  - Taxes linked to imports and production (indirect taxes)
- Expenditure
  - Capital transfers paid
  - Collective consumption expenditure
  - Compensation of employees
  - Final consumption expenditure of general government
  - Gross fixed capital formation

- Interest
- Intermediate consumption
- Other current expenditure
- Social benefits other than social transfers in kind
- Social transfers in kind supplied to households via market producers
- Subsidies

• Indicators that are sums of other indicators (excluded)

- Total current expenditure excluding interest
- Total current expenditure
- Total current revenue
- Total expenditure excluding interest
- Total expenditure
- Total revenue
- Net lending (+) or net borrowing (-) excluding gross fixed capital formation
- Net lending (+) or net borrowing (-) excluding interest
- Net lending (+) or net borrowing (-)
- Total tax burden excluding imputed social security contributions
- Total tax burden including imputed social security contributions

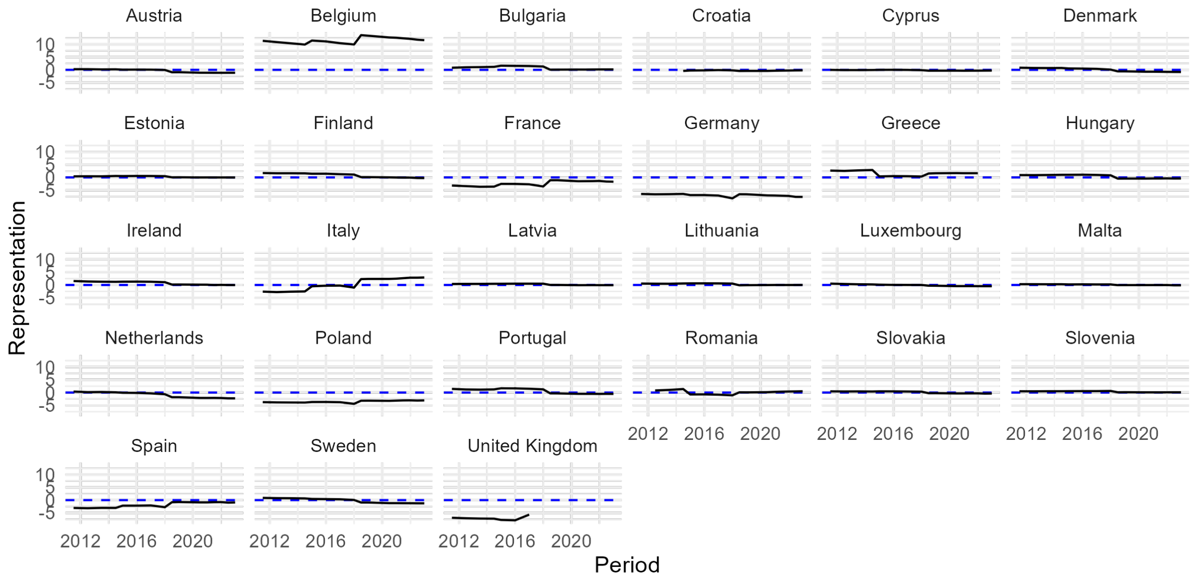
• Included in ESA 1995, not included in ESA 2010 (excluded)

- Social contributions received (Revenue)
- Implicit interest rate (Expenditure)

• Included in ESA 2010, not included in ESA 1995 (excluded)

- Other capital expenditure, including capital transfers (Expenditure)
- Social transfers in kind (Expenditure)

Figure 1: Over- and Under-Representation at ECFIN



Appendix B Representation at ECFIN

Figure 1 shows the over- and under- representation for each member state from 2011 to 2022. The dotted line at $y = 0$ represents the guiding rate as specified by the Commission in a 2018 report (Commission 2018). Note that large economies like Germany, France, and Spain are under-represented during the whole period. Additionally, Belgium and the United Kingdom (during the period it was part of the EU) stand out as outliers in their levels of representation.

Appendix C Forecasts and Financial Markets

In this section, I show that increased capacity has a measurable effect on member state economies by estimating whether the information provided by ECFIN forecasts affects government bond markets in member states. As mentioned above, the forecasts released by ECFIN are part of the AMECO database, which releases forecasts at least twice a year since 2011. The database contains economic forecasts for all EU member states, so the information from the forecasts is shared for all member countries on the same day at the same time. Therefore, I can test whether the changes in government bond yields can be predicted by changes in ECFIN forecasts in an analysis similar to a difference-in-differences model.

To measure changes in bond yields, I obtain government bond yields from Investing.com, a website that has historical data for almost all EU member states for the whole span of my analysis.[1] The outcome variable of interest is the week over week percentage change in bond yield. I collect these week over week changes for seven days before and after the forecasts are released.

I also create variables that show the update in information that the forecasts give. These are created by taking the difference between the previous forecast and the current forecast for a given time period. For example, the EOY forecast update in May is the difference between the November 1-year forecast and the May EOY forecast. If a member state's total expenditure for a given year was forecasted to be €100 billion in November of the previous year, but in May of the next year is forecasted to be €105 billion, then the update is €5 billion. For the weeks before the forecasts are released, this variable is equal to zero. I create this variable using the forecasts for total government revenue, total government expenditure, and net lending. These are aggregate economic indicators that are sums of the economic indicators used in the main analysis. See Eurostat (2021) for the breakdown of these indicators.

I also include a dummy variable that indicates whether the observations are pre- or post- forecast to control for factors that might differ from earlier and later weeks that is not related to the forecasts being released. Additionally, country and time (whether the observations are around the May or November forecast releases) fixed effects are added to control for country-specific factors and time trends. Note that country fixed effects will control for differences in magnitude of updates (i.e. larger updates for larger economies and smaller updates for smaller economies).

Thus, the model is the following:

$$y_{it} = \beta_1 * Post + \beta_2 * X_{it} + \gamma_i + \delta_t$$

where y_{it} is the percentage change in the current week's yield from the previous week's

1. Cyprus only has bonds data since 2016.

yield, $Post$ is the binary variable indicating whether the week is before or after the forecasts have been released, X_{it} is a matrix of of the update variables described above, and γ_i and δ_t are country and time (month) fixed effects. I include total revenue, total expenditure, and net lending updates separately, as well as a model with both revenue and expenditure. I do not include lending with other updates, as lending is simply total revenue minus total expenditure.

Table 1 shows the models described above. Model 1 shows the combined revenue and expenditure model, which includes EOY and 1 year forecast updates for both total revenue and total expenditure. While only the expenditure 1 year update's coefficient is significant, the joint significance of all update variables is significant at $\alpha = 0.01$. Additionally, the joint significance for revenue updates is significant at $\alpha = 0.01$ and the joint significance of expenditure updates is significant at $\alpha = 0.1$. The significance for revenue holds when I remove expenditure updates from the model, but the significance for expenditure does not hold when I remove revenue from the model. Finally, in model 4 lending updates are jointly significant at $p = 0.001$.

As I expect that markets respond to the aggregate information received from the forecasts more than any single variable, model 1's joint significance tests are the most relevant to the question of whether bonds markets respond to ECFIN forecasts. Thus, I reject the null hypothesis that forecasts have no effect on government bonds, which suggests that these forecasts have an actual impact on markets. Based on these results and the results from the paper, this shows evidence that the forecasts released by ECFIN are taken seriously by financial markets.

Appendix D Interpolation

The main results presented in the paper are robust to interpolation of ECFIN (the number of staff from country predicted) to fill in missing periods. The main results are replicated with linear interpolation of ECFIN in Table 2, with virtually no difference in effect size or significance level. I also replicate the results with spline interpolation of ECFIN, shown

Table 1: The Effect of ECFIN Forecasts on Government Bonds

Dependent Variable:	% Change in Yield from Previous Week			
Model:	(1)	(2)	(3)	(4)
Post Forecast Release	0.601	0.570	0.597	0.464
	(0.390)	(0.356)	(0.389)	(0.313)
EOY update, revenue	0.005	0.008		
	(0.015)	(0.020)		
1 year update, revenue	-0.008	-0.009		
	(0.014)	(0.017)		
EOY update, expenditure	-0.007		-0.006	
	(0.005)		(0.005)	
1 year update, expenditure	0.006**		0.003	
	(0.003)		(0.002)	
EOY update, lending				0.007
				(0.005)
1 year update, lending				-0.009*
				(0.005)
Revenue Joint Significance	p = 0.00***	p = 0.07*	NA	NA
Expenditure Joint Significance	p = 0.04**	NA	p = 0.33	NA
Rev and Exp Joint Significance	p = 0.00***	NA	NA	NA
Lending Joint Significance	NA	NA	NA	p = 0.06*
Fixed-effects				
Time	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Fit statistics				
Observations	292	292	292	338
R^2	0.135	0.134	0.135	0.123
Within R^2	0.011	0.010	0.010	0.008

Clustered (country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Main Model with Linear Interpolation

Dependent Variable:	Log Forecast Error Squared	
Indicator Category:	Revenue	Expenditure
Model:	(1)	(2)
Panel A: All Forecasts		
National Expertise:	-0.023***	-0.020*
Linear Interpolation	(0.008)	(0.010)
Observations	18,785	14,998
R^2	0.672	0.603
Within R^2	0.005	0.007
Panel B: Excluding EOY Forecasts made in November		
National Expertise:	-0.024***	-0.023***
Linear Interpolation	(0.008)	(0.008)
Observations	14,389	11,490
R^2	0.676	0.610
Within R^2	0.005	0.006
Panel C: Excluding EOY Forecasts		
National Expertise:	-0.021**	-0.028***
Linear Interpolation	(0.009)	(0.007)
Observations	10,717	8,556
R^2	0.679	0.615
Within R^2	0.004	0.007

Clustered (country) standard-errors in parentheses. All models include country, time, forecast period, indicator fixed effects and controls for population, GDP, and GDP per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

in Table 3. As spline interpolation can sometimes result in negative values for ECFIN, in such cases I recode the variable to be zero. Again, the results from spline interpolation are very similar to the main results presented in the paper. This suggests that missingness of employment statistics is not systematic in a way that would bias my results.

Appendix E Removing the UK and Belgium from Analysis

After the UK officially notified the European Council of its intention to leave the European Union in 2017, the UK was not included in recruitment guiding rates (Commission 2018).

Table 3: Main Model with Spline Interpolation

Dependent Variable:	Log Forecast Error Squared	
Indicator Category:	Revenue	Expenditure
Model:	(1)	(2)
Panel A: All Forecasts		
National Expertise:	-0.021***	-0.019**
Spline Interpolation	(0.007)	(0.009)
Observations	18,785	14,998
R^2	0.672	0.603
Within R^2	0.005	0.007
Panel B: Excluding EOY Forecasts made in November		
National Expertise:	-0.021***	-0.022***
Linear Interpolation	(0.007)	(0.007)
Observations	14,389	11,490
R^2	0.676	0.610
Within R^2	0.005	0.006
Panel C: Excluding EOY Forecasts		
National Expertise:	-0.017**	-0.026***
Linear Interpolation	(0.008)	(0.006)
Observations	10,717	8,556
R^2	0.678	0.615
Within R^2	0.004	0.007

Clustered (country) standard-errors in parentheses. All models include country, time, forecast period, indicator fixed effects and controls for population, GDP, and GDP per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 4: Main Model, excluding UK and Belgium

Dependent Variable:	Log Forecast Error Squared	
Indicator Category:	Revenue	Expenditure
Model:	(1)	(2)
Panel A: All Forecasts		
National Expertise	-0.030**	-0.022
	(0.014)	(0.015)
Observations	11,738	9,407
R^2	0.682	0.599
Within R^2	0.006	0.008
Panel B: Excluding EOY Forecasts made in November		
National Expertise	-0.030**	-0.023**
	(0.011)	(0.010)
Observations	9,021	7,235
R^2	0.687	0.605
Within R^2	0.005	0.006
Panel C: Excluding EOY Forecasts		
National Expertise:	-0.031**	-0.030**
	(0.013)	(0.011)
Observations	6,568	5,261
R^2	0.691	0.607
Within R^2	0.006	0.008

Clustered (country) standard-errors in parentheses. All models include country, time, forecast period, indicator fixed effects and controls for population, GDP, and GDP per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Therefore, the UK was heavily under-represented for much of the period I examine. Additionally, since the Commission is physically in Brussels, Belgium is consistently heavily over-represented. Although country fixed effects will control for the differences in trends due to time-invariant country characteristics, in this section I also run the models with a subset of the data that excludes these member states in order to make sure the results are not being driven by either of these extreme cases.

Table 4 shows the results of this model.

Appendix F Removing Forecasts for/during COVID-19 from Analysis

COVID-19 and the ensuing global pandemic had unexpected effects on economies around the world that made it difficult to predict economic outcomes. To rule out the possibility that my results are driven by forecasts during the pandemic, I exclude any forecasts made for 2020 or 2021 and any forecasts made in 2020 or 2021. Table 5 shows the results of this model specification. Some of the magnitudes are smaller, and in panel C the estimate for model 1 is not significant at conventional significance levels. However, the point estimates in general are similar to the main model, and the substantive interpretation still points to national expertise improving forecast accuracy.

Table 5: Main Model, excluding COVID Pandemic Forecasts

Dependent Variable:	Log Forecast Error Squared	
Indicator Category:	Revenue	Expenditure
Model:	(1)	(2)
Panel A: All Forecasts		
National Expertise	-0.020***	-0.022**
	(0.007)	(0.010)
Observations	8,760	6,991
R^2	0.655	0.605
Within R^2	0.007	0.007
Panel B: Excluding EOY Forecasts made in November		
National Expertise	-0.017**	-0.022***
	(0.008)	(0.007)
Observations	6,610	5,282
R^2	0.662	0.608
Within R^2	0.005	0.005
Panel C: Excluding EOY Forecasts		
National Expertise:	-0.015	-0.032***
	(0.010)	(0.008)
Observations	4,374	3,488
R^2	0.658	0.621
Within R^2	0.006	0.007

Clustered (country) standard-errors in parentheses. All models include country, time, forecast period, indicator fixed effects and controls for population, GDP, and GDP per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

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