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The life experience of central bankers and monetary policy decisions: a cross-country dataset

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Abstract

Using hand-collected data with biographical information on central bank governors and board members in over 200 countries, I obtain experience-based forecasts for GDP growth and inflation based on an adaptive learning model estimated from their lifetime macroeconomic data. I show life experience influences the monetary policy rates, even after accounting for other macroeconomics observables in the empirical Taylor rule. The role of personal experience is lower in advanced economies and for central bankers with treasury experience. Furthermore, life experience influences the tone of speeches for monetary policy, financial stability and climate concerns. Weather disasters experience reduces climate concerns and NGFS membership.

JEL Classification: D83; D84; E37; E50; E60; E70.

Keywords: Monetary policy; Fiscal policy; Experience effects; Forecasting; Learning; Beliefs.

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1 Introduction

Previous research shows that personal experience affects economic forecasts and investment decisions, even for highly skilled professionals such as financial analysts (Malmendier 2021) or central bank governors (Malmendier et al. 2021, Bordo and Istrefi 2023). Do central bankers' life experiences affect monetary policy decisions and inflation outcomes? Important determinants of monetary policy reaction functions are policy rules from observable inputs (e.g., Taylor rules or inflation targeting), as well as personal information and judgement held by policy makers (Hansen et al. 2014). Monetary policy decisions are ultimately decision under uncertainty and a significant discretionary component remains. Therefore, central bankers' personalities have a substantial influence on financial markets and the public (Kuttner and Posen 2010). This discretionary component can be thought of as reflecting preferences (Madeira and Madeira 2019, Madeira et al. 2023) or subjective expectations (Malmendier et al. 2021) which may be influenced by life experience. Previous work on this important question has been studied before for the FOMC members of the United States (Malmendier et al. 2021, Bordo and Istrefi 2023). This work seeks to extend this evidence across a broad range of countries with different historical experiences.

This work examines the role of life experience on monetary policy choices across more than 200 countries. I build a hand-collected dataset using online information from a variety of sources to document the mandate periods for central bankers. The analysis distinguishes term periods as chair, governor, deputy governor and board member.[1] Furthermore, I collect information on the birth date, country, gender, education, career experience, studies and professional experience in other countries for each central banker.

Using this information I characterize the education and professional experience across central bankers from different continents, as well as their experience of inflation, financial crises and disasters during the impressionable years (age 18 to 25). I then further summarize their life experience by calculating experience-based forecasts of inflation and real GDP growth for each central banker. The experience-based forecasts consist in a recursive learning linear model, which

[1] Chairs and governors coincide for most countries. There is a difference for multi-regional or supranational central banks, such as the US Federal Reserve, European Central Bank (ECB), Eastern Caribbean Central Bank (ECCB), Central Bank of West African States (BCEAO, from its acronym in French) and Bank of Central African States (BEAC, from its acronym in French). In this case the regional or national central bank presidents or governors are considered to be governors, but do not act in the role of chairs of monetary policy.

starts at age 18 and then adds new observations each period with a given weight (Malmendier et al. 2021). Note that the experience-based forecasts depend on the country and current time period of the forecast, but also on the birth date of each central banker. For this reason there is heterogeneity across central bankers within each time period and country, and therefore experience-based forecasts are not collinear with country and time fixed effects.

I then estimate panel linear regressions of the monetary policy rate in the style of Taylor rules (Taylor 1993, Clarida et al. 1999), including the experience-based forecasts of the central bankers (Malmendier et al. 2021). Besides the experience-based forecasts, the panel linear regressions account for country and time fixed effects and the previous inflation and GDP growth rates. These regressions show that experience-based forecasts of inflation are relevant for monetary policy decisions, even after accounting for country and time fixed effects and the conventional Taylor inputs such as the previous inflation and real GDP growth rates. The influence of personal experience-based inflation forecasts is lower in advanced economies and also for central bankers with experience as ministers of finance or secretaries of Treasury. I also find that the role of experience-based inflation forecasts is lower in advanced economies. Furthermore, I find central bankers with experience studying or working abroad give a lower weight to experience-based forecasts. The experience-based forecasts for real GDP growth, however, tend to have small coefficients. This is consistent either with central bankers focusing mostly on controlling inflation or with central bankers giving a lower role to the past in appraising current economic growth.

These results are robust to using annual or quarterly frequency data. Furthermore, the results are robust to using either the average central banker (chair, governors and board) for each monetary zone or just the experience-based forecasts of the chair. Using the average central banker for each country or supranational central bank is more appropriate if decisions are more based on a collegial approach (Ehrmann and Fratzscher 2007, Reis 2013). However, assigning a higher weight to the chair can be more appropriate due to its higher influence over the policy agenda and decisions (Riboni and Ruge-Murcia 2010, Bossu and Rossi 2019).

There is also the possibility that central bankers use diagnostic expectations, giving higher weight to forecast revisions (Bordalo et al. 2018, 2020). Forecast revisions are defined as the difference between the forecast for the current period with the recent information and the forecast for the current period based on the last period's information. To test the diagnostic expectations

I use two alternatives for obtaining the forecast revisions as an additional control: i) revisions of the experience-based forecasts; ii) using the entire time series of the macro outcomes to obtain the forecast revisions. The results show that the diagnostic expectations are significant at the quarterly frequency for year-on-year forecasts. However, the economic and statistical significance of the experience-based forecasts still remains statistically significant and stronger than the diagnostic expectations. Central bankers seem to give a negative weight to quarter-on-quarter forecast revisions, which may indicate a fear by central bankers in reacting to news on a very short term frequency. This result appears to reject central bankers as following naive and noisy short-term diagnostic expectations. These results are similar for both the samples of all central bankers and chairs only. This empirical exercise shows that experience-based learning appears to be more important than diagnostic expectations in the context of monetary policy decisions.

I then obtained the monetary policy tone (Apel et al. 2022) and financial sentiment (Correa et al. 2021) for 35,487 central bank speeches from the CBS dataset collected by Campiglio et al. 2025. I find that experience-based forecasts are statistically associated with hawkish monetary policy tones, as measured by the dictionary-based indexes from Apel et al. 2022. Furthermore, I find that higher experience-based forecasts of inflation and GDP growth are associated with more optimistic financial stability sentiment (Correa et al. 2021). This result makes sense, since higher growth and inflation should reduce financial stability risks associated with lower economic growth or tighter spreads. Finally, using EM-DAT to measure the number of deaths and affected people in the central bankers' countries during their impressionable years and the previous decade, I find that experience of natural disasters is associated with lower climate concerns in speeches from the database of Campiglio et al. 2025. Furthermore, past experience of natural disasters is associated with a later entry date into the Network for Greening the Financial System (NGFS) membership. These results are consistent with research in corporate finance, which shows that CEOs with experience of natural disasters are more risk-loving except in cases where their firm was especially affected (Bernile et al. 2017).

This work is closely related to Malmendier et al. 2021, who show that the inflation experience of the FOMC members influences their votes and the monetary policy rate (even after conditioning on traditional Taylor rule components). Bordo and Istrefi 2023 show that the birth year and university attended by FOMC members affect their hawkish-dovish leanings. Madeira et al. 2023 also find evidence that personal preferences affect US monetary policy, as shown by different reactions to supply and demand shocks across FOMC members. The main difference in this study relative to Malmendier et al. 2021 and Bordo and Istrefi 2023 is the international dimension. This article extends the analysis to a broad set of counties (advanced economies, emerging markets and developing economies). This helps to clarify how personal experience changes with less predictable policy settings such as those found in emerging markets (Frankel 2010). Even in the United States it took several decades before policy makers reached the current consensus on the importance of controlling inflation (Orphanides 2001, Primiceri 2006).

Finally, this work is also related to the broader literature of how policy makers and agents learn about the economy (Primiceri 2006, Baxa et al. 2013, Forbes et al. 2025). Primiceri 2006 shows that policy makers in the US had to learn about the economy, with inflation episodes being generated by underestimation of the natural unemployment rate and the persistence of inflation. This work tests similar learning hypotheses in a wider international setting. Malmendier 2021 shows that even sophisticated agents like financial analysts deviate substantially from rational expectations (Malmendier 2021). These findings have been replicated across financial analysts and professional forecasters for both financial and macroeconomic outcomes (Bordalo et al. 2020, Malmendier 2021). Previous research for the FOMC also finds that regional macroeconomic events (Bennani et al. 2018) and education-career profiles (Smales and Apergis 2016) appear to influence US monetary policy. Some studies have also shown that households can be slow learners of macro events (Madeira and Zafar 2015). The work also helps to provide further evidence on the debate between the use of discretion versus rules in central banking (Taylor 1993, Alesina and Stella 2010, Monti 2010).

This article is organized as follows. Section 2 summarizes the data collection process and the main variables in the biographical central bankers dataset. Section 3 lays out the methodology for estimating the experience-based forecasts and diagnostic expectations. It also specifies the panel Taylor rule with country and time fixed effects, the standard inputs of real GDP growth and inflation, and the experience-based forecasts. Section 4 shows the main results, showing that experience-based forecasts are significant predictors of monetary policy even accounting for other factors. I also test how the role of experience-based forecasts changes with central bank independence, Treasury or Ministry of Finance experience of the central bankers and PhD education.

Section 5 relates life experience to the tone of central bank speeches in terms of monetary policy, financial stability sentiment and climate concerns. Finally, section 6 concludes with a summary of the results and policy implications.

2 Data

2.1 Collecting data on central bankers

This work uses a hand-collected dataset of central bankers' birth dates, education and career backgrounds. The data was manually collected from online research by several research assistants and data typing professionals of different nationalities, which independently collected the same data in an exhaustive way between January 2020 and June 2025.[2] Besides online searches, central bank websites[3] and Wikipedia, I also used as additional sources the biographies available on Bloomberg and the book series "How countries supervise their banks, insurers and securities markets".[4]

In a first stage, I received five independent datasets from different research assistants, which were carefully reviewed for possible mistakes or incorrect entries. Differences among research assistants helps to obtain a more complete database[5] and to reduce discrepancies due to human error or errors in the online sources.[6] In case of discrepancies across cell entries made by different research

[2] Former research assistants helping with the online data collection had several country origins, including from Chile (Christian, Pilar, Ines, Francisco, Laura, Roberto), India (Naresh, Pramod), Pakistan (Eman, Sehrish) and Bangladesh (Farhad). Any research assistants were paid with my personal funds as freelancers and had no relationship with my current or former employers. None of my employers have responsibility in building the dataset.

[3] Central bank websites usually provide the names of the previous governors and board members, as well as short bios for the current governors and board members. However, official central bank websites usually do not provide information on age or birth date as this is considered to be personal information. Therefore, most of the birth date information comes from other online sources. The Central Bank of Costa Rica is one rare exception, since it publishes the complete CV of its board members, including their birth dates.

[4] From the book series, I used the editions of 1999, 2002, 2003, 2004, 2006, 2007, 2008, 2010, 2011 and 2013. The book series has been discontinued since, but Central Banking has continued part of the information from the book series in other publications.

[5] Knowledge of languages such as Spanish, Hindi and Arabic allows for different online searches, which helps to obtain a more exhaustive database. Also, research assistants of different languages and background may more easily recognize the gender of the names or whether a certain role should be classified as governor or deputy governor.

[6] Note that human errors can come from a variety of sources in manual data collection. One type of error is typing error, such as entering month 11 (November) instead of 1 (January) or exchanging birth month and birth year in different cells. Other type of typing error could be an incorrect exchange of digits, such as typing 1890 instead of 1980. Another type of human error could be to mistake the identity of the central banker with another reputable economist or professional with the same name. There can also be errors due to the online sources. For instance, on several occasions the news obituaries and Wikipedia may differ in the reported central banker's birth year or age by

assistants, I used the maximum mode across the assistants datasets to obtain a reliable value. The maximum mode is used, because in several cases it can be a more accurate description of the information.[7] To avoid mismatches, individuals across the different datasets for each research assistant are matched based on country, first and last names and either birth year or the starting year of the policy mandate. Names are formatted according to the algorithm built by Abramitzky et al. 2021.

In a second stage, to correct possible doubts, I requested one research assistant to make new searches for information in an exhaustive way for lists of names with incomplete data or suspected incorrect entries. This reviewing effort was performed on four occasions. In each time I obtained a new additional dataset that could be used to complete, cross-check and correct the previous datasets.

Furthermore, at a final reviewing stage, I used information from academic articles to review the dataset in terms of exhaustiveness and check values for some variables. From Dreher et al. 2010, I used information on 1,269 central bank governor mandates between 1955 and 2018, checking the names of the governors, beginning and end dates (year and month) of the mandates. Note that this dataset was updated by the authors several times since its first publication by Sturm and de Haan 2001. From Masciandaro et al. 2023, I used information on 2,323 central bankers with mandates between 2001 and 2018, comparing information on the name, gender, role,[8] appointment and end year of the mandates.[9] From Mishra and Reshef 2019, I used information on 128 central bank governors, which allowed to check the name, beginning and end year of mandate, and a dummy for previous experience in the private financial sector. From Ioannidou et al. 2023, I used information on 321 mandates of central bank governors, which allowed to check the name, appointment year and

one year or more. Even the most reliable of the online sources can show errors. For instance, Bloomberg lists Solomon Sekwakwa as Permanent Secretary at the Bank of Botswana, but he was Permanent Secretary at the Ministry of Finance. Mr. Sekwakwa did attend the monetary policy meetings at the Bank of Botswana, but in his capacity as a representative of the Ministry of Finance.

[7] For instance, if one research assistant reports that a given person had a professional background in banking or finance, then it could be that some of the assistants reporting a zero background did so due to a less exhaustive search or reading. Another case deals with the difference between the dates of appointment and the starting date of the mandate. For instance, even in highly cited sources, some articles mention Mario Draghi as starting as governor of the Bank of Italy in 2005. In this case, Draghi was appointed to be governor in December of 2005, but started his mandate in January of 2006.

[8] Note that the dataset of Masciandaro et al. 2023 includes also some heads of department at central banks, besides governors and board members.

[9] This information is not yet publicly available. It was kindly shared by the authors, whom I greatly thank for their generosity.

month of the persons. From Madeira and Madeira 2019, I checked the names and birth years for 151 members of the FOMC in the US. Finally, I checked the names and mandate periods (beginning and end year and months) with information from the voting records in the monetary policy meetings for Brazil, Chile, Colombia, Hungary, India, Japan, Mexico, Nigeria, Poland, Sweden, Thailand, United Kingdom and United States.

The dataset collected in this article, however, is more exhaustive in terms of the number of countries, central bankers and the range of variables collected. Previous academic articles outside of the US did not collect information on birth date, education[10] or on a wide range of career experience such as terms as Treasury Secretary or Minister of Finance. The dataset in this article collected some information on 5,023 central bankers (with roles as chair, governor, deputy governor or board member), among which there is complete information on birth date, education and other variables for 3,174 persons. The database includes 5,299 non-consecutive mandates (with consecutive mandates in the same role treated as a single period). Note that the same person can have had different mandates and even roles at different central banks.

The final dataset (plus the source datasets and codes used in building it) will be available online after the article is published in an academic journal to facilitate the work of future researchers. Furthermore, all the software codes (including data management and the empirical econometric analysis) will be made publicly available in a Mendeley Data link (after journal acceptance).

This subsection documents an extensive set of efforts undertaken to reduce possible errors and achieve the best possible results for future users of this dataset. Note that some degree of measurement error does not necessarily invalidate an empirical analysis, although it makes it harder to find statistical significance. Measurement error in endogenous variables implies higher standard errors, but not coefficient bias (Hausman 2001). Measurement error in the control variables tends to reduce the absolute size of the coefficients and make estimates less statistically significant. In this case, a statistically significant estimate in the empirical study implies that the true coefficient very likely has a higher absolute value and stronger statistical significance (Hausman 2001). Finally, one of the most adequate ways of reducing the implications of measurement error is to obtain independent measurements of the variables under study (Hausman 2001), a strategy which was adequately followed.

[10] Malmendier et al. 2021 and Bordo and Istrefi 2023 collected information on birth year and education, but this data effort is limited to the FOMC members in the United States.

2.2 Variables measured in the study

The information on the central bankers' demographics, mandates and professional careers includes a wide range of variables. These variables are summarized in Table 1. For clarity, I separate between the raw information that is manually collected from online sources and other variables which are calculated afterwards.

Among the variables collected directly from online sources, there is demographic information on country, as well as on birth dates and gender. Furthermore, I collected the dates and role of the mandate, with different periods assigned for roles as chair, president or governor, deputy governor and board member. Chair and governor are roles that usually coincide, but these can be different for multi-regional or multi-national central banks. For instance, the Federal Reserve System includes regional governors, who are not chairs of the monetary policy committee. The same applies for the governors of the national central banks of the eurozone, eastern Caribbean, west African states and central African states. For countries that control their own monetary policy, the role of chair and governor tends to coincide, except for regional governors.

I also collected information on the highest completed education and universities where the central bankers completed their higher education (BA or MA, MBA or MPA or law degrees, PhD). Finally, I collected information on the countries of work. Furthermore, I collected information on the professional career of the central bankers, such as countries where they worked, mandates in Treasury or Ministry of Finance, and dummies for whether they had experience in eight (non-exclusive) occupation types: industry; banking-finance; academia; government and state institutions; international organizations; audit and accounting; consulting; and military.

I then combined the personal information of the central bankers with other available datasets to obtain additional measures. For the universities of the central bankers, I classify these according to the country of study and whether it represents studies abroad, a dummy according to private ownership of the university (with religion affiliated schools often being private schools), an Ivy League Plus dummy (which covers the 13 US colleges considered to be Ivy League in an extensive concept of the term), and the type of university (whether it is a US freshwater or saltwater or other, a UK university, or from other countries). The role of the type of university has been emphasized for the FOMC by Bordo and Istrefi 2023. The popular press has also often emphasized the role of

Table 1: Summary of the main variables

Variables	Description
	Raw information collected
Identity and demographics	Birth information (birth country, year and month) and gender.
Mandate information	Start and end dates (year and month) and role (chair, governor, deputy, board).
Education	Highest education level (no BA, BA, MA/MPA or Law Degree, MBA, PhD).
	BA or MA; MBA, MS, JD or other; PhD (names for each university).
Countries of work	List of countries where the person worked.
Treasury/ministry experience	Dummy for whether the person was a Treasury secretary or Minister of Finance and the dates (year, month) in which such mandate happened.
Professional career	Dummies for work in industry, banking-finance, academia, government, international organizations, audit and accounting, consulting, military.
	Variables computed from the manually collected information
Other education info	The name of the individual universities for each degree is collected, then classified in terms of foreign studies (countries of study, dummy for studies abroad), private or public ownership (from Alper-Doger Scientific Index, Wikipedia or other source), type of university (US freshwater, saltwater, other, UK LSE, Cambridge, Oxford, or other), US Ivy League Plus dummy.
Crises during impressionable years (age 18 to 25)	Number of years lived during recession, sovereign debt, currency and banking crises. Weather disasters (events, deaths and affected persons).
Experience-based macroeconomic forecasts	Annual and quarterly forecasts for inflation and GDP growth using a recursive least squares AR model (see Malmendier et al. 2021). Learning starts at age 18 or the start date of the time series (if later than 18).

the Chicago school and its pro-market views in Latin America, although often in exaggerated terms (Edwards 2023). Private ownership is established according to the Alper-Doger Scientific Index, Wikipedia or other online sources such as university websites.

Using the central bankers' birth dates, I then summarize the experience of their impressionable years, which I define as between age 18 and 25. The concept of "impressionable age" is not an exact term in the psychological literature, with some including the childhood and teenage years in this concept. The impressionable years hypothesis suggests that core attitudes, beliefs, socialization preferences and personality crystallize during young adulthood, with people being more susceptible to remembering events from this age period (Krosnick and Alwin 1989). In this article, I use the period between age 18 and 25, in the same way as Bordo and Istrefi 2023. Furthermore, recent work on voting preferences shows that political attention starts to materialize at age 14 and then reach the peak tendency in young adulthood between ages 18 and 25 (Ghitza et al. 2023).[11] Therefore, research in economics (Bordo and Istrefi 2023), sociopolitical views (Krosnick and Alwin 1989) and voting preferences (Ghitza et al. 2023) seems to support an age range between 18 and 25 for the impressionable years period. An extended version of the impressionable years hypothesis could use an age range between 14 and 25 (Ghitza et al. 2023).

I then build the number of years spent in recessions or financial crises (banking crises, sovereign debt crises, currency crises) during the impressionable age period of each central banker. For this I use the list of financial crises from the Laeven and Valencia 2020 dataset for the period between 1970 to 2017, which is complemented with information from Nguyen et al. 2022 (with banking, sovereign debt and currency crises for the periods 1970-2019, 1960-2019 and 1950-2019) and from the Global Macro Database (Müller et al. 2025) for the period 1800-2019. The recession years are determined based on two consecutive quarters with negative real GDP growth for the country-year pairs with quarterly data. For the years before there is quarterly data, I use an annual negative GDP growth to classify whether a country faced a recession or not. The reason for using the annual criteria is that quarterly GDP time series for several countries do not stretch so far into the past.

Furthermore, I obtain information on weather disasters at the national level since 1900 using the EM-DAT database published by the Centre for Research on the Epidemiology of Disasters

[11] Ghitza et al. 2023 find the 14–24 age range is the most important for the formation of long-term presidential voting preferences. The weight of age experience systematically increases between age 14 and 18 and then remains at a peak point until age 24. Political events before age 14 have little impact. After 24 the age weight decreases.

(CRED).[12] Using the EM-DAT database, I calculate the average annual ratio of deaths as a fraction of the population during the impressionable years for each central banker.

Finally, using the central bankers' birth dates, I obtain their life experience macro forecasts in the same way as Malmendier and Nagel 2021. This methodology is explained in detail in the next section.

2.3 Observations, gender and age

I start by summarizing the number of central bankers in the dataset. Table 2 shows that the dataset has central bankers from countries across all continents. There are over five thousand central bankers in the dataset, around 60% of them with birth information. Around 44% of the central bankers with available birth date information are chairs of monetary policy. Note that due to their higher media status, it may be easier to find information for chairs than for other central bankers, therefore these may be over-represented in the sample with demographic information. Europe is the continent with the largest number of central bankers and countries represented. Restricting the sample to chairs with demographic information, the dataset includes 40 countries from Africa, 33 from the Americas, 49 from Asia, 52 from Europe and 9 from Oceania, with a total of 188 countries across the world. Note that the sample of chairs does not include national governors from multi-national monetary zones such as the European Central Bank (ECB), Eastern Caribbean Central Bank (ECCB), Central Bank of West African States (BCEAO, from its acronym in French) and Bank of Central African States (BEAC, from its acronym in French) or the regional governors from the US Federal Reserve.

Most central bankers are male, which represent 90.3% of the entire sample and 89.1% of those with demographic information. The fraction of 10.9% of women in the sample of central bankers with birth date information is similar to the sample used by Masciandaro et al. 2023, who find a share of 14% of female central bankers in their sample for 101 countries between 2001 and 2017. There are fewer women as governors, with women being 15.5% and 17.4% of the deputy governors and board members, respectively, but only 5.2% of the governors (using values from the sample with

[12] Note that the EM-DAT data coverage is not entirely exhaustive, especially for poorer economies. The EM-DAT coverage is especially low before 2000. However, I still use the EM-DAT reported weather disasters experienced by central bankers as a measure of their disaster experience, although with some measurement noise.

Table 2: Number of central bank governors or board members per country

Continent	Nr of Countries	minimum	p25	median	mean	p75	max	total
Chairs with available birth date information								
Africa	40	1	2	5	5	7	13	196
Americas	33	1	4	5	10	12	51	314
Asia	49	1	3	7	8	11	24	392
Europe	52	1	3	6	9	11	105	476
Oceania	9	1	1	2	4	4	12	34
World	183	1	2	5	8	10	105	1,412
All central bankers with available birth date information								
Africa	49	1	2	5	7	10	42	352
Americas	50	1	1	4	16	13	302	798
Asia	51	1	4	8	14	21	101	725
Europe	58	1	1	16	21	29	178	1,244
Oceania	9	1	1	2	6	5	29	55
World	217	1	2	6	15	17	302	3,174
All central bankers in the dataset (with or without birth date information)								
Africa	52	1	7	13	16	24	57	849
Americas	50	1	1	16	27	39	349	1,349
Asia	52	1	10	17	23	31	132	1,192
Europe	59	1	1	19	26	41	210	1,542
Oceania	9	1	4	9	10	11	30	91
World	222	1	5	15	23	30	349	5,023

Table 3: Fraction of female governors, deputy governors, board members and central bankers (% of sample of mandates)

Continent	Africa	Americas	Asia	Europe	Oceania	World
			Entire sample			
Governors	2.3	4.8	3.9	4.6	8.3	4.1
Deputy governors	5.6	13.0	15.4	21.4	0.0	15.8
Board members	16.2	11.8	9.4	20.2	26.7	15.5
Central bankers	6.0	8.0	7.4	14.3	10.4	9.7
		Sample of central bankers with birth date				
Governors	3.1	5.5	5.8	5.0	10.5	5.2
Deputy governors	6.9	10.4	16.3	23.5	0.0	17.4
Board members	18.6	9.9	9.9	20.4	28.6	15.5
Central bankers	7.0	7.9	8.8	14.8	13.1	10.9

Note: Central bankers include all the 3 roles. The board members category excludes those who are deputy governors and governors.

birth dates). Figure 1 shows the fraction of female central bankers by continent since 1990. The results show a positive trend in more female central bankers across all continents, except Asia. In Asia there was an increasing share of women until 2008 (which coincides with the Great Financial Crisis), with the female share reaching a peak close to 15% in 2008 and declining to below 10% and even lower after 2016. The appendix shows a figure with the evolution of female central bankers since 1960, but its pattern is a bit more volatile before 1990 since the lower numbers of female central bankers change frequently between zero and a positive fraction.

Most central bankers across the world are between age 40 and 63 at the starting time of their mandates, as shown by the percentiles 10 and 90 of starting age in Table 4. The age distribution is quite similar across genders and continents, as appropriate for high level leadership positions requiring substantial experience. Central bankers are slightly older in Asia and Oceania, presenting a median starting age of 54 and 53 years, respectively, which is 3 or 4 years older than the median age in Africa, the Americas and Europe.

Figure 1: Fraction of female central bankers by continent over time

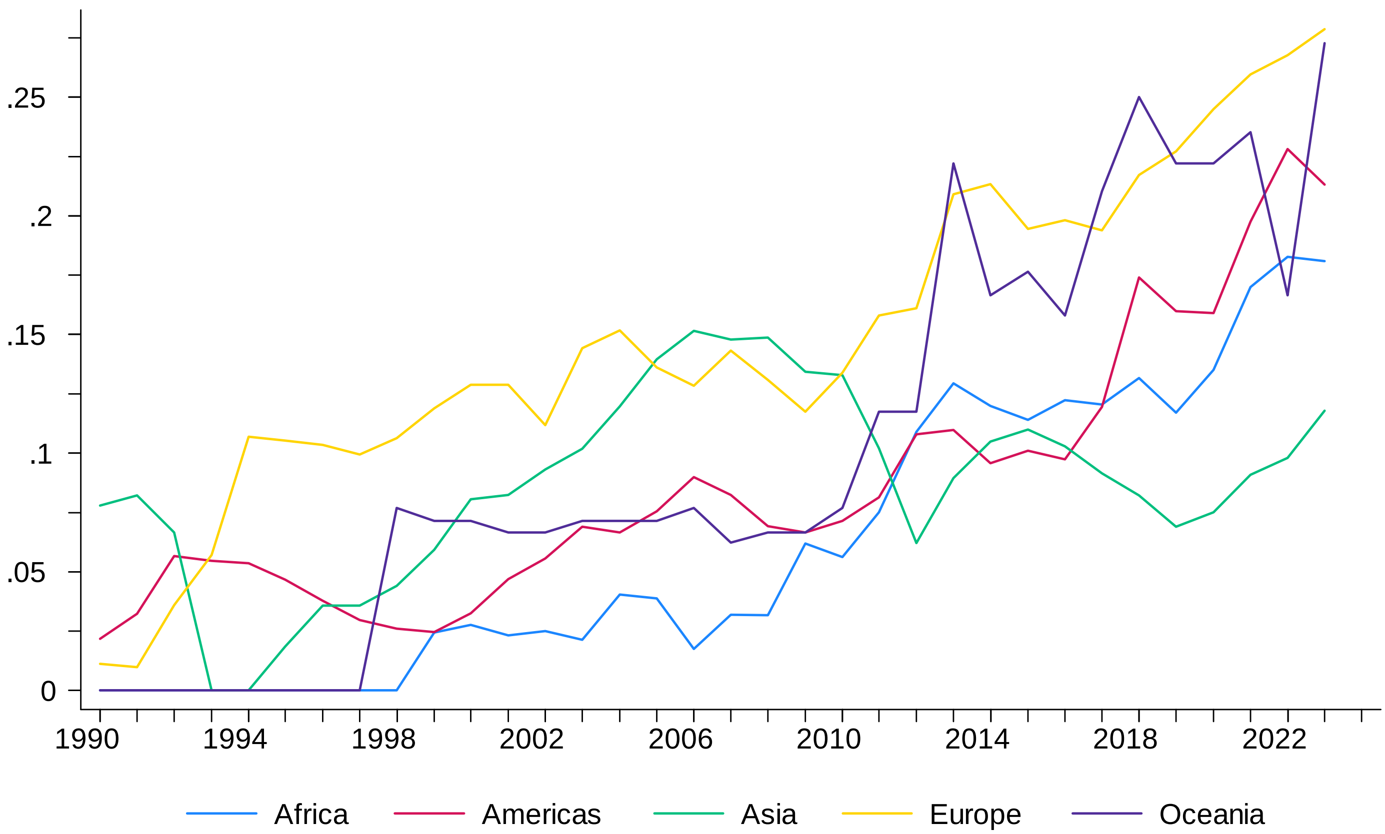


Table 4: Distribution of age (years) at the start of the first central bank mandate by sex and continent

Percentiles	Africa	Americas	Asia	Europe	Oceania	World
Male central bankers						
p10	37	40	40	39	44	39
p25	44	45	47	45	49	45
p50	50	51	54	52	54	52
p75	57	58	60	58	58	58
p90	63	63	65	63	64	63
Female central bankers						
p10	38	41	40	40	40	40
p25	44	46	48	45	50	45
p50	48	52	53	49	52	51
p75	57	57	58	56	59	57
p90	62	61	64	61	62	61
Both genders						
p10	38	40	40	40	44	40
p25	44	45	47	45	50	45
p50	50	51	54	51	53	52
p75	57	58	59	57	58	58
p90	62	63	65	62	63	63

The mean age of active central bankers has changed significantly over time, as shown in Figure 2.[13] There is a common trend across all continents for an increasing age since the mid 1990s. The mean age of Oceanian and African central bankers increased from just 50 in the mid-1990s to respectively 58 and 60 years in recent years. The mean age for American central bankers increased from 52 in 1980 to 59 in recent years. The mean age of European central bankers increased from 52 years in 2000 to 56 years in 2024. Asian central bankers' mean age increased from 53 to 60 years between 1995 and 2024.

Age trends between 1960 and 1980 favoured younger central bankers. African central bankers were much younger than their counterparts before 1980, perhaps as a result that many African central banks were only created after colonial independence in 1955. African central bankers presented a mean age between 42 and 47 years between 1960 and 1980. Oceanian central bankers, however, became younger during this period, with their mean age dropping from 55 to 60 years in the 1960s to just 47 in 1980. In Europe the mean age declined from around 60 years in the early 1970s to just 52 years by the mid 1990s.

2.4 Education and professional careers

The education and career background of central bankers is also quite diverse. The BA or MA degree and its university was found for 84% of the sample.[14] Furthermore, 40% of the sample has a PhD degree, which is fairly common across all continents. The fraction of PhDs is lower in Africa and Oceania with a value around 31%, while being 41% in Asia and above 44% in the Americas and Europe. Around 12.5% of the central bankers also have other post-graduate business, law or science degrees, such as MBAs, JDs, MPAs or MS. Most central bankers go to public colleges for their BA or MA, with only 23% graduating from private educational institutions. Around 35% of the PhDs come from private institutions. Private institutions represent the majority of the MBAs. American central bankers have the highest rate of private college degrees, whether for BA, MBA or PhD.

[13] Note that Figure 2 plots accounts for central bankers ageing over time during their mandates. Therefore, the age in each year differs from Table 4 which shows the age at the start of the mandate.

[14] Note that the absence of a BA or MA for individuals in the sample does not necessarily mean that those central bankers do not have college education. Most likely it means that I was unable to find the university and degree for those individuals.

Figure 2: Mean age of central bankers by continent over time

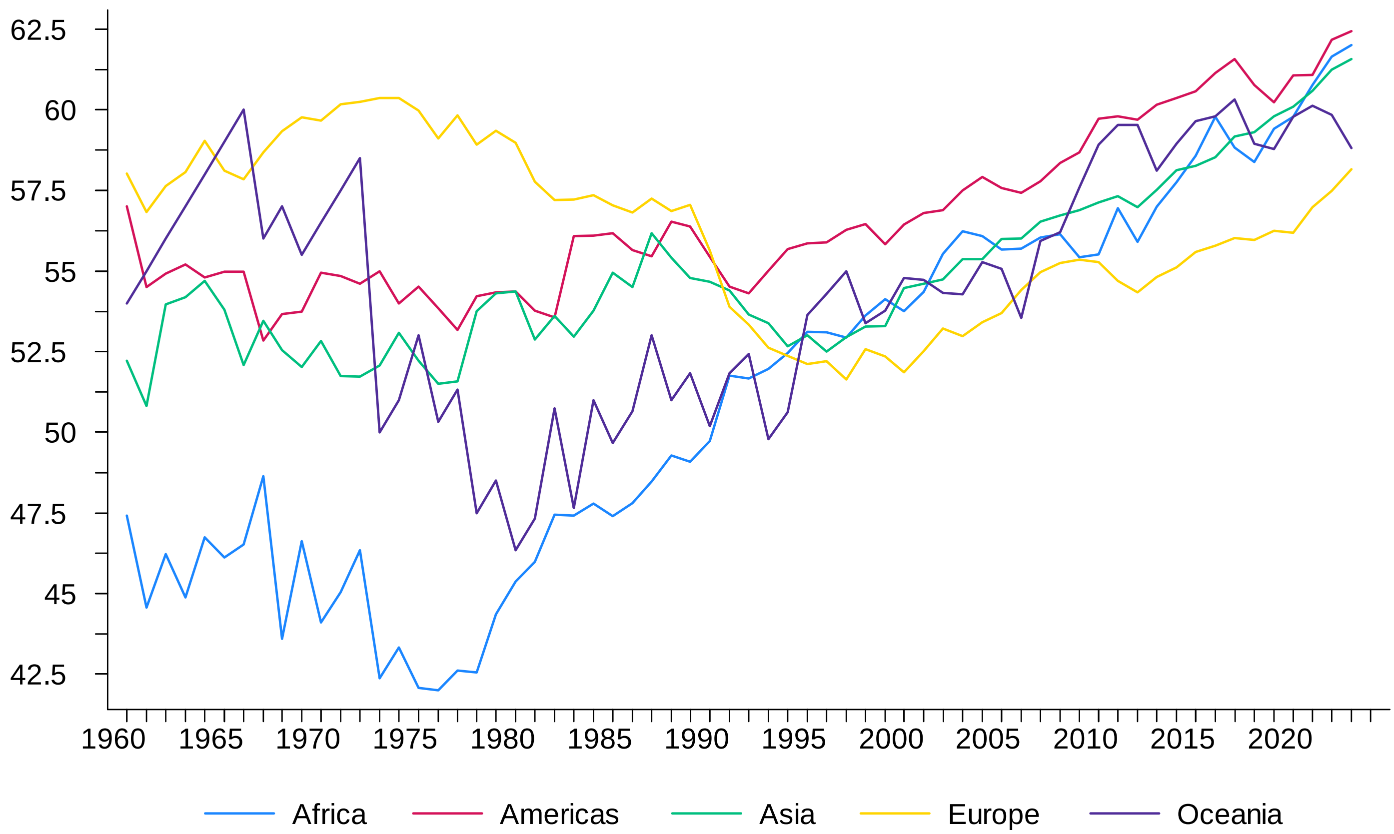


Table 5: Education and career background (% of all central bankers)

Continent	Africa	Americas	Asia	Europe	Oceania	World
Education degree (% of sample)						
BA or MA	86.1	92.0	86.5	76.6	92.5	84.1
MBA, JD, MPA, MS	15.4	12.1	15.4	8.6	4.2	11.7
PhD	29.9	38.8	40.7	44.6	31.9	40.4
Private educational institution (% of sample with a degree)						
BA or MA	15.4	46.5	28.4	11.8	0	27.9
MBA, JD, MPA, MS	21.4	69.2	58.1	41.2	0	54.5
PhD	32.6	54.3	35.5	12.5	57.1	34.2
Central bankers with mandates in Ministry of Finance (% of sample)						
Before Central Bank	13.4	13.2	14.9	12.1	3.6	13.0
After Central Bank	12.5	7.5	11.7	6.1	7.3	8.5
Either before or after	23.0	18.0	21.5	15.3	9.1	18.1
Before and after	2.0	2.1	4.3	2.2	1.8	2.6
Career background: multiple categories per person allowed (% of sample)						
Industry	9.0	12.2	7.9	18.3	32.6	13.5
Banking	79.2	72.1	78.1	70.1	81.8	73.7
Academy	24.5	39.9	31.3	44.3	29.2	37.8
Government/ Public A.	66.5	77.5	74.8	75.7	64.0	74.7
International Org.	28.8	29.4	22.9	22.9	23.4	25.3
Audit	5.3	5.2	3.5	3.7	0.0	4.2
Consulting	23.4	33.6	23.4	19.4	21.7	24.5
Military	0.6	3.5	0.8	0.7	2.2	1.5

Values as a % of the sample of all central bankers with reported birth date.

The fraction of PhDs in the sample has changed substantially over time, with PhDs increasing during the 1990s and early 2000s, but falling after 2010. Figure 3 shows that the fraction of PhDs increased significantly across all continents between 1990 and the early 2000s. In Africa the fraction of PhDs increased from below 10% in the early 1990s to close to 50% in 2012. In the Americas the increase in PhDs was quite steep, from less than 40% in 1990 to a peak of 65% by 2003. In Asia the fraction of PhDs increased from below 40% in 1990 to above 60% by 2008. In Europe the increase was achieved more quickly, from around 40% in the early 1990s to 60% by the late 1990s. Finally, the fraction of PhDs in Oceania has dropped from around 50% in 1990 to a low point around 20% between 1998 to 2005, before increasing again to almost 60% by 2019 and falling to below 40% in recent years. Oceania has fewer countries and also a lower number of people in the sample, therefore these sharp movements in gender (Figure 1), age (Figure 2) and education (Figure 3) can be due to just a few people. PhDs abroad in the US or UK increased significantly in Africa and the Americas during the 1990s, although these numbers fell in the Americas after 2005 and in Africa after 2010. Note that this fraction only counts PhDs abroad. It does not count central bankers from the US doing a PhD in the US, but it counts US citizens doing PhDs in the UK. Oceania also saw a rising trend in central bankers with PhDs in the US or UK since the early 2000s. PhDs in the US or UK have been relatively stable among Asian and European central bankers over the last 25 years.

A significant fraction of central bankers had careers as Treasury or Ministry of Finance officials either before or after their central bank mandate. Note that these statistics only include experience as minister, secretary or under-secretary in the Finance Ministry. Therefore, these numbers exclude central bankers with treasury experience in non-leadership roles, as well as other government appointed roles such as minister of the economy. Around 18% of the central bankers had mandates in Treasury or Finance, with 13% having a Ministry of Finance mandate before their central bank mandate and 9% afterwards. Therefore, there is a significant revolving door between the central bank and Ministry of Finance Ministry, which is present across all continents. Only 2.6% of the central bankers had such roles both before and after the central bank, perhaps because it is uncommon for a given political party to be in power for a period that covers at least 3 economic mandates (ministry of finance, central bank and ministry of finance again).

Africa has the highest fraction of central bankers with Ministry of Finance connections. Around

Figure 3: Fraction of central bankers with a PhD degree and with a PhD degree from the US or UK over time

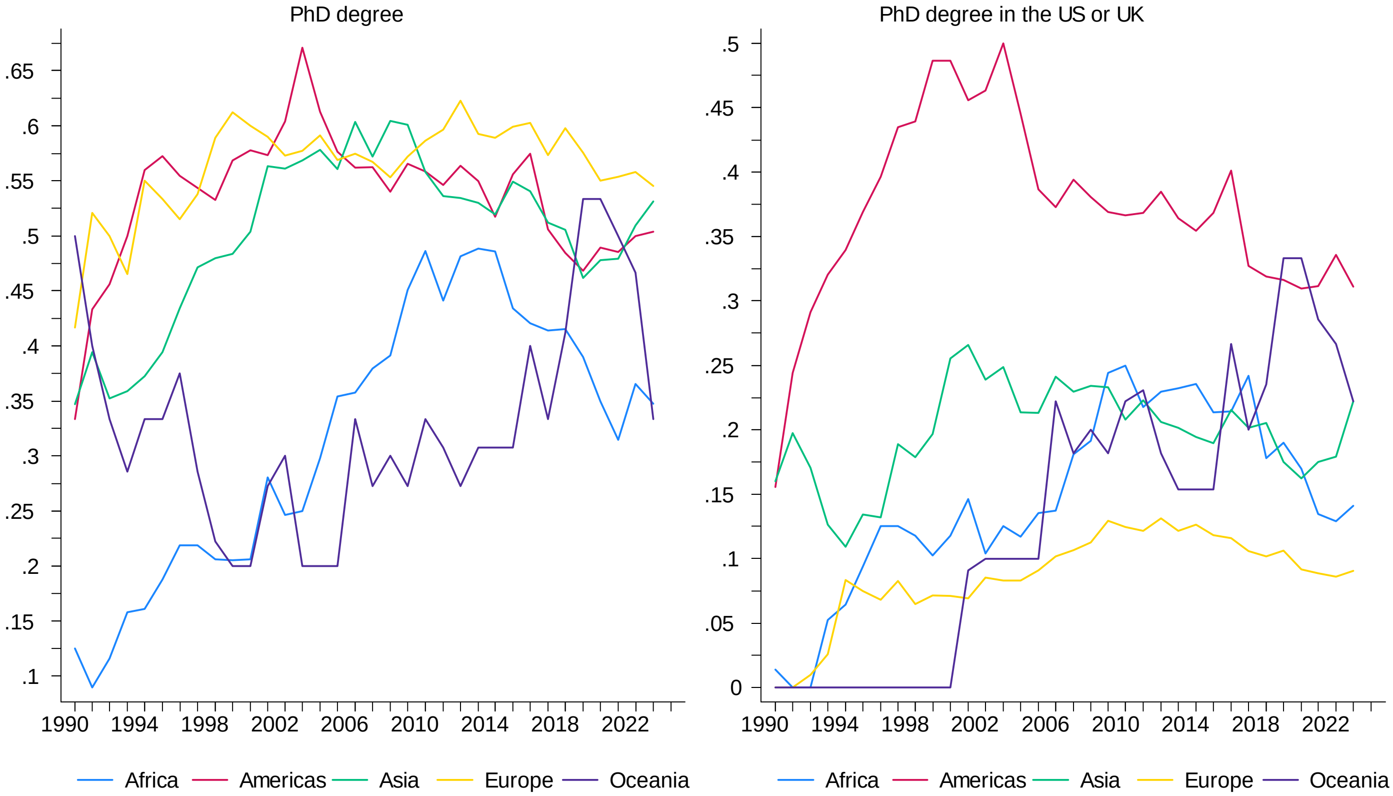
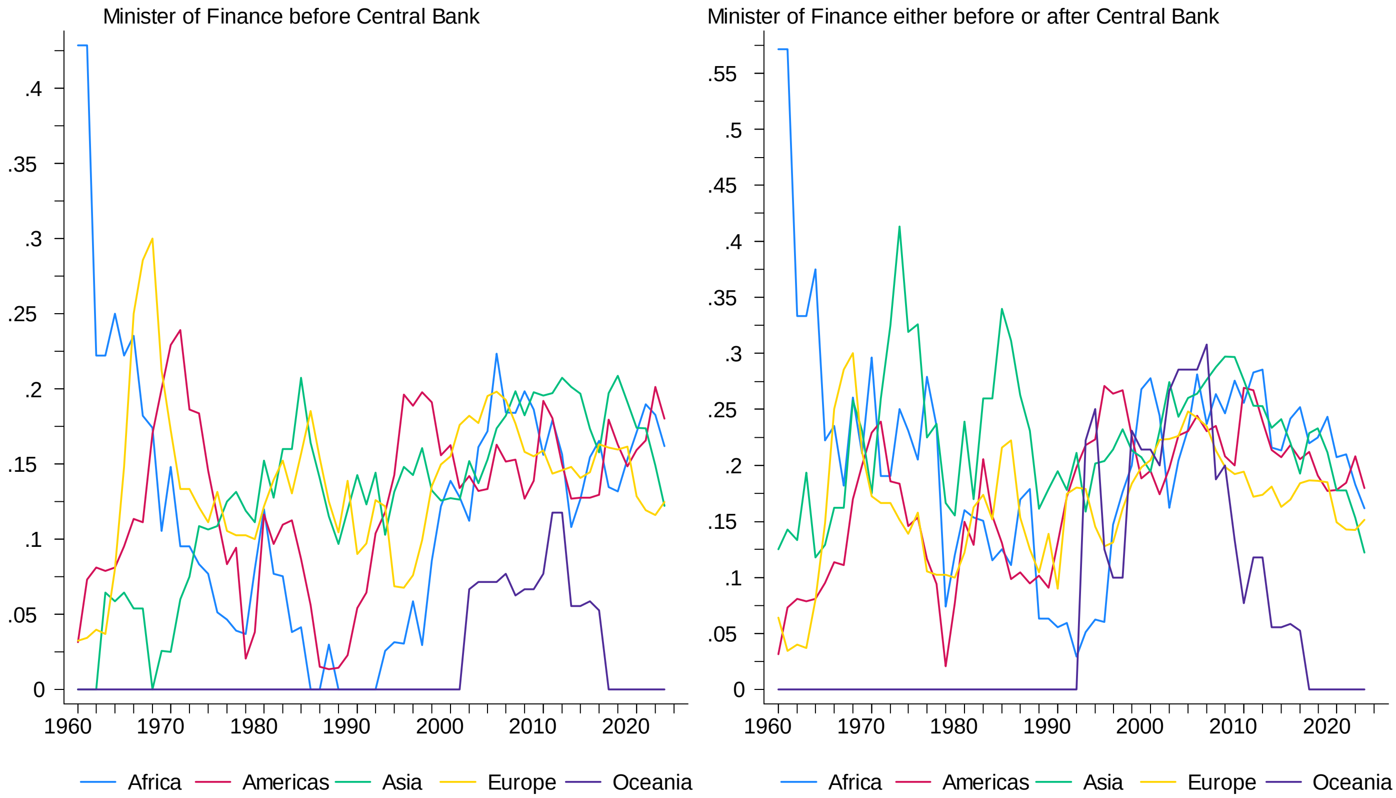


Figure 4: Fraction of central bankers with mandates in Treasury or Ministry of Finance over time



23% of African central bankers also had Ministry of Finance roles (before or after the central bank), a bit higher than the 21.5% in Asia and 18% in the Americas. However, Asia has a higher rate of central bankers who were Ministry of Finance officials before their central bank mandate, a fraction of 15% of the sample. Even Europe and Oceania, which have the lowest rates of central bankers with Ministry of Finance connections, show 15% and 9% of central bankers with Ministry of Finance mandates.

The fraction of central bankers with some Ministry of Finance mandate, either before or after the central bank has fluctuated significantly over time. It was higher in Europe and the Americas during the early 1970s, a period in which even in the US there was political pressure on monetary policy. Africa had a very high rate of central bankers with Ministry of Finance connections in the early 1960s, possibly because the central banks were new post-colonial institutions and there were few candidates available with the required experience and expertise. The fraction of central bankers with Ministry of Finance connections dropped across all continents during the 1980s and then increased again during the 2000s. The connection between central bankers and the Ministry of Finance, however, has fallen again since 2010, which could be a mark of increased concerns for central bank autonomy.

Finally, Table 5 also shows that professional careers of central bankers are diverse. Almost 74% of the sample has experience in banking (either in private or public institutions, including public commercial banks and central banks). A significant number of central bankers also had careers in academia (38%), international organizations (25%) or consulting (25%). There are fewer central bankers with background in industry (14%) and audit (4%). Furthermore, around 1.5% of the central bankers had some experience in the military. Military experience was common in countries that had communist regimes. For instance, Che Guevara was governor for the central bank of Cuba and a founding member of the CEMLA (Latin American Center for Monetary Studies) network of central bankers.

2.5 Macroeconomic data on real GDP growth, inflation and crises

The empirical analysis of the article requires long macroeconomic time series for several countries. For this reason, I matched data from several international organizations and academic teams. I use both quarterly and annual frequency time series because several countries only have quarterly data for the more recent decades. Having longer time series is especially important in this work, since the identification is given by generational differences. If time series are only available for recent years, then for some cases there is no difference between the life experience based forecasts for persons with 10 years of age difference or so.

Quarterly real GDP growth and inflation series in this article are presented both in terms of year-on-year (yoy) and quarter-on-quarter (qoq) series, with $y_{c,t}^{yoy} = \frac{I_{c,t}}{I_{c,t-4}} - 1$ and $y_{c,t}^{qoq} = 4(\frac{I_{c,t}}{I_{c,t-1}} - 1)$, with $I_{c,t}$ representing the real GDP or CPI indexes. Note that all the quarter-on-quarter series in the empirical analysis are used in a raw format. I do not apply any four-quarter moving average smoothness transformation or seasonal adjustment for quarter-on-quarter series. Therefore, the quarter-on-quarter time series represent the short-term quarterly fluctuations. Furthermore, the four-quarter moving average of the quarter-on-quarter time series tend to be highly correlated with the year-on-year series and would represent a less diverse exercise.

In terms of GDP growth, I obtained quarterly data from the OECD, IMF and Camous et al. 2025, with the order of preference in case of availability being OECD, IMF and Camous et al. 2025. Note that there are significant differences between IMF and OECD data at the quarterly frequency. Real GDP growth rates between both datasets show a correlation of 91.7% for year-on-year and 29.8% for quarter-on-quarter series. I preferred the OECD time series (when available) due to their lower volatility. For some countries the OECD and IMF series can have a correlation of 100%, so the difference between sources is not relevant for several of the major economies. In terms of the quarterly headline inflation rates, I used the following sources in order of preference: i) BIS, ii) IMF, iii) the global database of inflation (Ha et al. 2023) and iv) Camous et al. 2025.

In terms of annual real GDP growth and inflation rates, I used these sources in order of preference: i) World Bank, ii) IMF, iii) the Macrohistory database (Jordà, Schularick and Taylor 2017), iv) the Penn World Tables (Feenstra et al. 2015), and v) the Global Macro Database (Müller et al. 2025).

For the monetary policy rate panel time series, I use in order of preference the BIS and IMF datasets, for both quarterly and annual frequency.

Financial crises and recessions are only measured at the annual level. The data for financial crises (whether banking, currency, sovereign debt) come in order of preference from: i) Laeven and Valencia 2020, ii) Nguyen et al. 2022, and iii) the Global Macro Database (Müller et al. 2025).

Furthermore, I note that the monetary policy rates, headline inflation and real GDP growth rates are winsorized at both the bottom and top percentiles (i.e., percentiles 1 and 99). This winsorization does not affect most of the developed economies. For quarterly headline inflation rates, the percentile 1 and percentile 99 gives a range between -8.3% to 108.4% for year-on–year and between -16.4% and 111.8% for quarter-on-quarter series. For quarterly real GDP growth rates, the percentile 1 and percentile 99 gives a range between -9% to 14.8% for year-on–year and between -12.7% and 16.6% for quarter-on-quarter series. For annual series, the percentile 1 and percentile 99 gives a range between -13.6% to 166.7% for inflation and between -15.7% and 22.4% for real GDP growth series.

Therefore, most countries' time series are not at all affected by the winsorization. It is only the countries experiencing hyper-inflation or deep deflation periods that see their values winsorized.

Also, some countries both headline inflation and real GDP growth rate series can be affected by changes in base implemented by the national statistical offices and such statistical breaks are not properly accounted for by organizations collecting international data (Müller et al. 2025). The winsorization limits the effect of such statistical breaks which may be undetected in international datasets. Furthermore, the autoregressive (AR) experience-based learning model suggested by Malmendier et al. 2021 is a linear approximation and therefore would not be appropriate for testing expectations during hyper-inflation or deep deflation periods.

2.6 Central bank speeches: monetary policy tone and financial stability sentiment

I also use the central banker speeches (CBS) dataset collected by Campiglio et al. 2025. The CBS dataset (Campiglio et al. 2025) has 35,487 speeches, which are classified in terms of dummies for whether the speech mentions the climate change, green finance or carbon keywords. The CBS dataset also measures the fraction of words related to climate change, green finance or carbon in terms of the total words in the speech. Finally, I also consider a dummy variable for whether the speech mentions any of the climate keywords (climate change, green finance, carbon) and the total fraction related to all these climate keywords in the speech.

Furthermore, since the CBS dataset reports the translation of all speeches to English, I use their texts to classify each speech in terms of hawkish inflation or monetary policy tones, following the dictionary methodology of Apel et al. 2022. This gives a net hawkish inflation index associated with the keywords of "consumer prices", "inflation", "inflation rate" and "inflation expectations". The monetary policy tone is given by the sum of the net hawkish indexes obtained for inflation (with the keywords "consumer prices", "inflation", "inflation rate", "inflation expectations"), economic activity (with the keywords "consumer spending", "economic activity", "economic growth", "resource utilization") and employment (with the keywords "employment", "labor market", "unemployment"). I also obtain the financial stability sentiment (FSS) index, with higher values being associated with more pessimistic financial stability expressions. This FSS index is obtained with the dictionary methodology of Correa et al. 2021.

3 Methodology

3.1 Measuring life experience-based forecasts (EBF)

I utilize the learning-from-experience model of Malmendier and Nagel 2016 and Malmendier et al. 2021 to generate experience-based macroeconomic forecasts, using data observed after governors reach age 18. According to the exercises estimated for the US by Malmendier and Nagel 2016, the starting age has little influence and it makes little difference whether to start at age 10, 14 or 18. My baseline exercises use a starting point of age 18, which is more similar to the impressionable years concept from Bordo et al. 2023.

I focus on univariate models of macro outcomes in which agents forecast each variable based only on its previous realizations. Let x_t be a macroeconomic variable of interest, either headline inflation or real GDP growth or another variable. Each time series process is estimated separately for each country, therefore I omit the subscript c for simplicity. Agents perceive macroeconomic outcomes as an AR(1) process, and use data on experienced macro outcomes to estimate the AR(1) parameters and build forecasts. As agents experience new macro realizations, they update the AR(1) parameters and revise their forecasts. Therefore, the model provides a parsimonious way of considering how agents perceive the long-run mean and the persistence of shocks. For quarterly frequency the model is seasonally adjusted by adding 2 extra parameters for lags with 4 and 5 quarters (Malmendier et al. 2021):

1) $x_t = \alpha + \phi(x_{t-1}, x_{t-4}, x_{t-5}) + \eta_t$.

Let the constant and all the control variables used in forecasting be captured by the vector $h_{t-1} = (1, x_{t-1}, x_{t-4}, x_{t-5})$. For the case of annual frequency, the life experience based forecasts (EBF) are given by a similar AR(1) process, except that $h_{t-1} = (1, x_{t-1})$ due to the absence of seasonality.

The macroeconomic life experience-based forecasts are given by a simple weighted recursive least squares learning model of the observations in one's lifetime after age 18. Let s be the starting period of the agent's learning, which can be interpreted as the agents' cohort period for reaching adulthood. In this case, s is the maximum between the period in which the agent reaches age 18 and the start of the time series x. Agents estimate the parameters $b = (\alpha, \phi)'$ by weighting new information and past lifetime experience observed since period s:

2) $b_{t,s} = b_{t-1,s} + \gamma_{t,s} R_{t,s}^{-1} h_{t-1}(x_t - b'_{t-1,s} h_{t-1})$,

3) $R_{t,s} = R_{t-1,s} + \gamma_{t,s}(h_{t-1}h'_{t-1} - R_{t-1,s})$.

The experience-based forecast for an agent that starts learning at time s are obtained as:

4) $x^e_{t+1,s|t} = b'_{t,s} h_t$.

The learning parameter θ is similar to adaptive learning models, but it differs in the sense that learning declines over time instead of showing a constant gain. Following Malmendier and Nagel 2016, learning is calibrated as:

5) $\gamma_{t,s} = \begin{array}{c} \frac{\theta}{t-s} \text{ if } t-s \geq \theta \\ 1 \text{ if } t-s < \theta \end{array}$.

The parameter $\theta > 0$ is constant and determines how much weight the forecaster puts on recent data versus the distant past. $\theta = 1$ implies equal weighting of recent and past data, while $\theta > 1$ implies that recent data receives more weight than early experiences. In my baseline estimation I use $\theta = 3.044$, as estimated by Malmendier and Nagel 2016 for the cohorts of the representative survey of US households in the Michigan Survey of Consumers (MSC). Malmendier et al. 2021 also suggest using $\theta = 3.334$, since this was the estimate obtained for the sample of college graduates. A value of $\theta = 3.984$ was estimated by Madeira and Zafar 2015 for the median US household, using individual consumers expectations instead of cohort averages. According Madeira and Zafar 2015, the respondents of the MSC had updating parameters that would go from 3.430 (percentile 10 of the sample) to 4.533 (percentile 90).

The recursion starts in period $t = s + 1$, with $b_{s,s} = (x_s, 0, 0, 0)'$ and $R_{s,s} = h_s h'_s$. These initial conditions assume agents start their life with the naive prior that inflation and output growth are constant. For $\theta > 1$ past data gets down-weighted relatively fast, therefore the results are not very sensitive towards the initial prior for the first date of learning (Malmendier and Nagel 2016).

To be more comparable with the previous literature (Malmendier and Nagel 2016, Malmendier et al. 2021), I use the updating parameter value $\theta = 3.044$. However, in the appendix I show that the empirical results remain qualitatively similar for $\theta \in 1.5, 2.5, 3.0, 3.25, 3.5, 4.0, 4.5, 5.0$. For quarterly frequency, correlation is very high for experience based forecasts created with θ values between 3 and 3.5. In the case of annual frequency, I also tested θ values of 6.0 and 7.0.

The empirical analysis shows results for experience-based forecasts for year-on-year and quarter-on-quarter outcomes. The results are qualitatively similar, although the coefficients for quarter-on-quarter forecasts tend to be larger due to the higher volatility of quarter-on-quarter fluctuations. It is relevant to note that Malmendier et al. 2021, Malmendier and Nagel 2016 and Madeira and Zafar only used year-on-year quarterly experience-based forecasts. This article includes both types of inflation and GDP fluctuations for clarity and comparison.

3.2 Diagnostic expectations

I also test whether central bankers use a diagnostic expectations component (Bordalo et al. 2020) for determining monetary policy. The use of diagnostic expectations can be estimated by the coefficient given to forecast revisions for future outcomes ($FR_{t+1|t}$):

6) $FR_{t+1|t} = E_t(x_{t+1} \mid h_t) - E_{t-1}(x_{t+1} \mid h_{t-1})$.

For simplicity, let the vector of control variables be given by $h_{t-1} = (1, x_{t-1}, x_{t-4}, x_{t-5})$. . Testing diagnostic expectations depends on how the forecasts $E_t(x_{t+1} \mid h_t)$ and $E_{t-1}(x_{t+1} \mid h_{t-1})$ are modeled. The calibration of these revision forecasts again takes the form of a seasonally adjusted AR(1) for the expectation $E_t(x_{t+1} \mid h_t)$ and a local projection (Jorda and Taylor 2025) for two periods ahead for $E_{t-1}(x_{t+1} \mid h_{t-1})$.

For this I create two types of diagnostic forecasts, one diagnostic forecast based on the entire historical time series available and a second experience-based diagnostic expectation which is based on the experience-based forecasts. The first type of diagnostic expectation is given by

7) $FullTimeSeries\ Diagnostic_{t+1|t} = (\beta_{t+1|t} h_t) - (\beta_{t+1|t-1} h_{t-1})$,

with $\beta_{t+1|t}$ being obtained from a rolling regression that uses all data until time t (by estimating the regression $x_{t^*} = \beta_{t^*+1|t^*} h_{t^*-1}$, for all $t^* \leq t$) and similarly estimating a rolling regression that provides a forecast for two periods ahead as a local projection (by estimating the regression $x_{t^*} =$

$\beta_{t^*+1|t^*-1} h_{t^*-2}$, for all $t^* \leq t-1$). Therefore, the forecast revision $FullTimeSeries\ Diagnostic_{t+1|t}$ is obtained from rolling linear regressions that use all the historical time series available until time t and $t-1$.

The second type of forecast revision is given by similar experience-based forecasts as those proposed by Malmendier et al. 2021:

8) $EB\ Diagnostic_{t+1|t} = (b'_{t,s} h_t) - (\tilde{b}'_{t-1,s} h_{t-2})$,

with $b'_{t,s}$ given by the adaptive algorithm defined in equations 2) and 3) of the previous subsection. In this case, $\tilde{b}'_{t,s}$ is the equivalent to a local projection two periods ahead given by a lag of two periods and further controls for seasonality by weighting new information and past lifetime experience observed since period s:

9) $\tilde{b}_{t,s} = \tilde{b}_{t-1,s} + \gamma_{t,s} \tilde{R}^{-1}_{t,s} h_{t-2}(x_t - \tilde{b}'_{t-1,s} h_{t-2})$,

10) $\tilde{R}_{t,s} = \tilde{R}_{t-1,s} + \gamma_{t,s}(h_{t-2} h'_{t-2} - \tilde{R}_{t-1,s})$.

For simplicity, I use the same updating parameter $\theta = 3.044$ for these two period ahead linear projections based on experience. The recursion starts in period $t = s + 2$, with $\tilde{b}'_{t,s} = (x_s, 0, 0, 0)'$ and $\tilde{R}_{s,s} = h_s h'_s$. Therefore, the process is quite analogous to obtaining the experience-based forecasts for one period ahead (as shown in the previous subsection). Obtaining the forecast revision component for the diagnostic expectations in annual frequency data is similar, with the only difference that the control vector is defined as $h_{t-1} = (1, x_{t-1})$.

Instead of a local projection for two periods ahead to obtain $E_{t-1}(x_{t+1} \mid h_{t-1})$, an alternative would be to iterate the AR(1) on the expected value of the one period ahead forecast by using $E_{t-1}(x_{t+1} \mid \tilde{h}_{t-1} \equiv (1, \tilde{x}_t, x_{t-3}, x_{t-4}))$. However, the literature on local projections suggests that the local projections for two or more periods ahead has an improved bias-variance trade-off relative to the option of iterating an AR or VAR using the forecasts for one period ahead (Jorda and Taylor 2025). In any case, the results of obtaining forecast revisions based on a two period iteration of the AR model is shown in the appendix and the results are qualitatively similar.

3.3 Estimating a Taylor rule for monetary policy with experience-based forecasts

The baseline empirical model of the article will estimate a Taylor rule panel regression of the monetary policy rate ($i_{c,t}$) across countries c and time t:

11) $i_{c,t} = \beta(\pi_{c,t-1}, GDPgr_{c,t-1}, GDPgr^{HP}_{c,t-1}) + \gamma(\pi^{EB}_{c,t}, GDPgr^{EB}_{c,t}) + \alpha_c + \alpha_t + \varepsilon_{c,t},$

where the first coefficient vector β relates to the usual Taylor rule inputs of observed inflation ($\pi_{c,t-1}$), real GDP growth ($GDPgr_{c,t-1}$) and the Hodrick-Prescott cyclical component for the real GDP growth rate ($GDPgr^{HP}_{c,t-1}$) in the previous period. The second set of coefficients γ relates to the experience-based forecasts (hence denoted as EB) for inflation ($\pi^{EB}_{c,t}$) and real GDP growth ($GDPgr^{EB}_{c,t}$). Finally, I take into account fixed effects for countries (α_c) and time (α_t). The last term $\varepsilon_{c,t}$ is an idiosyncratic component (with mean zero) that represents all unobserved factors that affect monetary policy for country c at time t. Furthermore, I report robust Huber-White standard errors for all coefficients clustered at the country level.

The baseline regression can be expanded by including further controls for the diagnostic forecast revisions for inflation ($\pi^{Diag}_{c,t}$) and real GDP growth ($GDPgr^{Diag}_{c,t}$). Furthermore, an expanded empirical model can include interaction terms for the experience-based inflation forecasts ($\pi^{EB}_{c,t}$) with other relevant factors ($F_{c,t}$):

12) $i_{c,t} = \beta(\pi_{c,t-1}, GDPgr_{c,t-1}, GDPgr^{HP}_{c,t-1}) + \gamma(\pi^{EB}_{c,t}, GDPgr^{EB}_{c,t}, \pi^{Diag}_{c,t}, GDPgr^{Diag}_{c,t}) + \lambda((\pi^{EB}_{c,t}, \pi_{c,t-1}) \times F_{c,t}) + \alpha_c + \alpha_t + \varepsilon_{c,t}.$

The relevant factors for interaction ($F_{c,t}$) can be institutional measures, such as an index of central bank independence ($CBI_{c,t}$, taken from Romelli 2022, 2024). $F_{c,t}$ can also include relevant characteristics from the individuals that can influence their use of experience-based forecasts, such as a dummy for whether the central bankers played a role in the Ministry of Finance or Treasury (with $MinFin_{c,t}$ and $MinFinBefCB_{c,t}$ denoting dummies for any mandate in the Ministry of Finance and a Ministry of Finance mandate before the central bank period, respectively). Other relevant factors can be education such as dummies for PhD education ($PhD_{c,t}$) or a PhD abroad in the US or UK ($PhD^{US,UK}_{c,t}$).

Finally, I also include regressions which control for the lag value of the monetary policy rate, $i_{c,t-1}$. All results in this article remain similar, whether the lagged policy rate is included or not in the Taylor rule.

3.4 Using chair versus average national central banker characteristics

Note that individual characteristics of education and career experience and country level characteristics coincide perfectly for the case of a single decision maker, such as the chair of monetary policy. In this case, the country level characteristics match the individual characteristics of the chair individual i: $v_{c,t} = v_{i,c,t}$. The country variable v here can denote a wide set of individual specific variables, such as education, career experience-based forecasts and diagnostic forecast revisions: $v \in \pi^{EB}, GDPgr^{EB}, \pi^{Diag}, GDPgr^{Diag}, PhD, PhD^{US,UK}, MinFin, MinFinBefCB.$

Furthermore, I obtain other individual specific variables such as the central bank independence index for the countries where the central banker worked or studied. The central bank independence index of where the central banker worked is given by the average index of the foreign countries where the person worked: $CBI^{W}_{i,c*,t} = \frac{1}{n_{i,W}} \sum_{c \in W(i)} CBI_{i,c,t}$, with $W(i)$ and $n_{i,W}$ denoting the set and number of countries where i worked. In a similar way, the central bank independence index for the set of foreign countries where i studied is given by their average: $CBI^{S}_{i,c*,t} = \frac{1}{n_{i,S}} \sum_{c \in S(i)} CBI_{i,c,t}$, with $S(i)$ and $n_{i,S}$ denoting the set and number of countries where i studied.

For regressions with multiple central bankers per country (chair, deputy governor and other board members), there is not a coincidence between the individual central banker characteristics ($v_{i,c,t}$) and the country ones ($v_{c,t}$). Therefore, for the regressions with the sample of all the central bankers, the country characteristic is defined by the average across all central bankers of that period: $v_{c,t} = \frac{1}{n_{M,t}} \sum_{i \in M(c,t)} v_{i,c,t}$, with $M(c,t)$ and $n_{M,t}$ denoting the set and number of central bankers active for country c at time t.

Both options of using just chairs of monetary policy or the average of all the national central bankers have their disadvantages. Using the sample of chairs does not account for central banking involving decisions with a committee of multiple persons and views. However, using the average of the national central bankers also ignores that most research shows that the chair has an outsized influence relative to just an individual vote (Riboni and Ruge-Murcia 2010, Bordo and Istrefi

2023).[15] Even for the 12 member FOMC in the US, some estimates point towards a weight of 40% or 50% or higher for the individual chairs (Bordo and Istrefi 2023). In any case, all results in this article are qualitatively similar in both samples (all central bankers and chairs only).

3.5 Accounting for multi-national monetary policy zones

For simplicity, I use the subscript c for denoting a monetary policy zone. For the great majority of countries, the monetary policy zone is the same as the country. However, there are also supra-national monetary policy zones headed by central banks such as the ECB, ECCB, BCEAO and BEAC. The empirical analysis takes this into account by considering that c corresponds to a monetary policy zone. This means that once a country joins a multinational monetary zone, then its governors and board members are considered to be central bankers of the monetary policy zone. In this case, all the governors and board members within the monetary policy zone would be a part of the set $M(c,t)$. The regressions for the chairs would only consider the individual characteristics of the chair of the monetary policy zone and not those of its national central bank governors.

The option of considering a monetary policy zone as a single time series is taken, because the monetary policy zone has a common monetary policy interest rate $i_{c,t}$ for all its members. However, in the appendix I show regressions where all the countries of each multi-national zone are included separately, with c denoting each country (even if several countries share the same interest rate as dependent variable, $i_{c,t}$). The results are qualitatively very similar to the ones shown in the main article where each monetary policy zone is taken as a single time series. Therefore, the existence of multi-national monetary policy zones does not affect the results.

[15] The higher influence of the governor can be based on its prerrogative to set the agenda, propose the alternative policies for voting and conduct the discussion of the policy meetings (Riboni and Ruge-Murcia 2010). According to Bossu and Rossi 2019, 134 central banks (83% of the countries) follow a presidential model of management, with an executive management highly concentrated in the governor. Furthermore, the chair's power can be enhanced by a tradition for consensus (Riboni and Ruge-Murcia 2010) and a tighter influence over the central bank's staff and its reports (Bossu and Rossi 2019).

4 Does life experience affect monetary policy?

4.1 Evolution of experience-based forecasts and diagnostic expectations

To summarize the evolution of the experience-based forecasts explained in the previous section, Figure 5 shows the median across all central bankers in the sample for each continent over time. There is a large difference between median and mean for each continent in the case of inflation, because the mean inflation is strongly affected by the countries experiencing hyper-inflation in certain periods, such as Argentina, Hungary and Zimbabwe. The median experience-based forecasts for inflation show a global high inflation period in the 1970s (Ha et al. 2023). The 1970s inflation affected all continents, with Asia experiencing very high inflation for a brief period. The mid 1990s decade also saw inflation surges for the Americas and Africa. Additionally, Asia experienced a slower disinflation process relative to Europe and Oceania. Experience-based forecasts for real GDP growth have been declining across all continents over the decades. Large international crises, such as the European Monetary System (EMS) crisis in the early 1990s, the Asian Crisis in the late 1990s, the Great Financial Crisis (GFC) in 2008, the European Sovereign Debt Crisis and the Covid-19 pandemic had a clear effect in the real GDP growth forecasts.

Figure 6 summarizes the diagnostic forecast revisions obtained from the experience-based learning model, using the median forecast revisions across all central bankers in the sample. Again, there is a clear difference in median and mean diagnostic forecast revisions due to countries experiencing hyper-inflation periods. The inflation surge in the early and mid 1970s across all continents resulted in large forecast revisions based on the life experience of the median central banker. The post-pandemic period surge in inflation also implied large forecast revisions. Therefore, both the 1970s and 2020s inflation periods were not easy to be forecast by the median central banker and implied substantial revisions. Forecast revisions for the median central banker tend to be smaller for real GDP growth than for inflation. Oceania experienced the largest GDP growth forecast revisions during the 1970s. The median African central banker also had a large forecast revision in GDP growth in the post-pandemic period.

Figure 5: Experience-based forecasts for headline inflation and real GDP growth: median for the sample of all central bankers

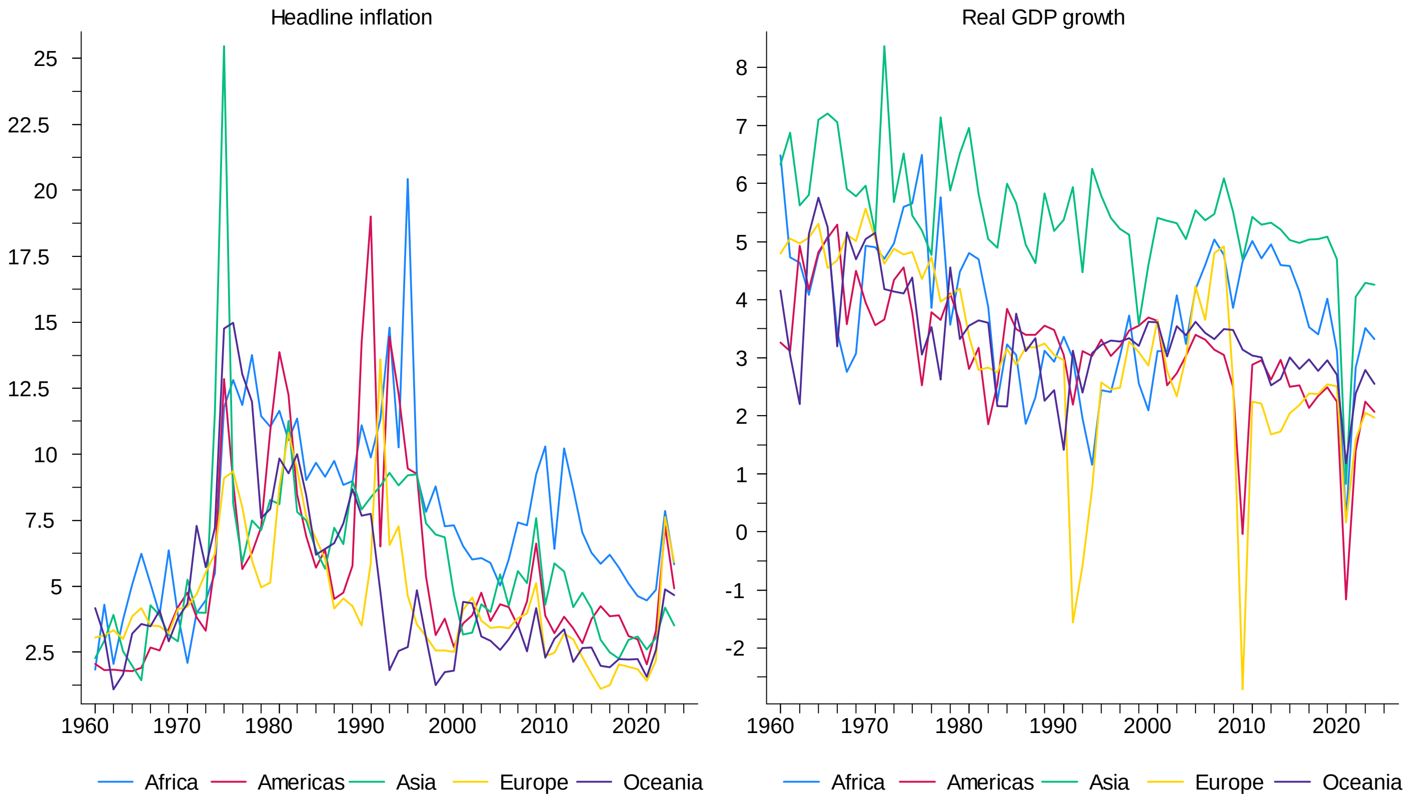
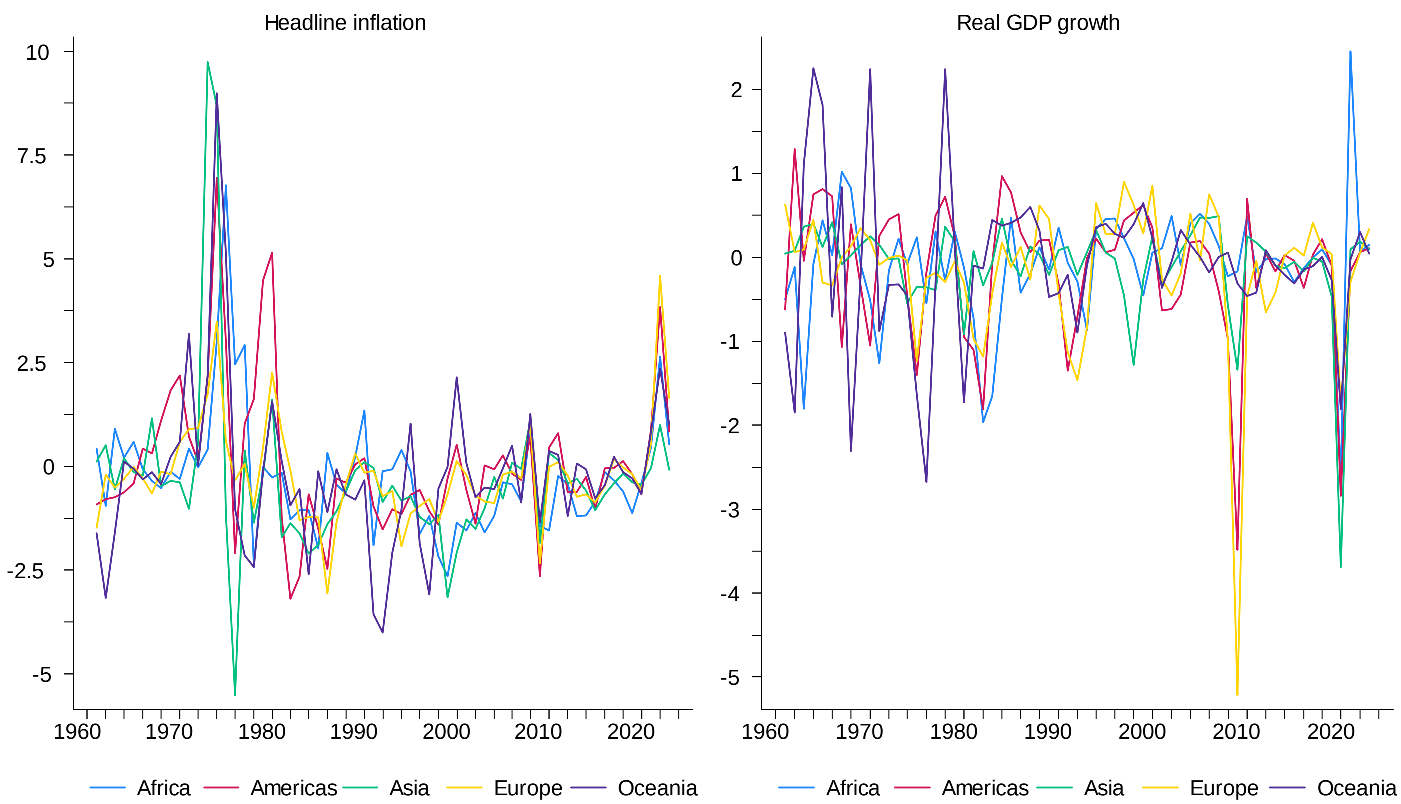


Figure 6: Diagnostic forecast revisions based on the local projection forecasts given by the experience-based learning AR model: median across all central bankers



4.2 Baseline results for the monetary policy rate rules

Now I summarize the baseline empirical model for the Taylor rule estimates with experience-based forecasts (see equation 11 in the previous section). Table 6 includes the results for both the samples of all central bankers and chairs only. The results are qualitatively similar in both samples. All regressions include both the previous real GDP growth and the lagged CPI inflation. In a few regressions, I also included the lag of the HP cyclical component for the real GDP growth. However, the HP cyclical GDP growth tends to have a small and statistically insignificant coefficient. Therefore, this inclusion is relatively unimportant and all results in this article remain robust to including or not the HP cyclical GDP growth.

EBF inflation is statistically significant at the 1% level across all specifications, whether with year-on-year, quarter-on-quarter or annual frequencies. The coefficients for year-on-year and quarter-on-quarter EBF inflation are always higher than the coefficients for the lagged inflation rate, whatever the specification (year-on-year, quarter-on-quarter, annual). This shows that experience-based forecasts have an impact on monetary policy decisions, even after accounting for the traditional Taylor rule inputs of inflation and growth. Central bankers with a lot of real time information may also be affected by the current macro variables. A robustness test in the appendix, however, shows that the role of personal experience-based forecasts of inflation remain high and statistically significant for all specifications (year on year, quarter on quarter, annual frequencies), even after including the inflation and real GDP growth for the current period.

The coefficients for both the real GDP growth ($GDPgr_{c,t-1}$) and the experience-based forecast of real GDP growth ($GDPgr^{EB}_{c,t}$) are negative, but only for the year-on-year specifications. This is against what is expected in a Taylor rule, since one should expect central bankers to increase interest rates after a surge in growth (which could indicate an overheated economy and a possible future increase in inflation). However, the coefficient for the reaction to experience-based growth forecasts is quite small, although statistically significant. Therefore, the interpretation is that monetary policy reacts little to the central bankers growth forecasts. Or perhaps central bankers believe that higher real GDP growth can in some cases be associated with positive supply shocks and therefore a future decrease in inflation. I also tested controls for the first-difference of the experience-based real GDP growth forecasts ($\Delta GDPgr^{EB}_{c,t} = GDPgr^{EB}_{c,t} - GDPgr^{EB}_{c,t-1}$), but the

Table 6: Quarterly panel regressions of the monetary policy rate based on the life experience (inflation and real GDP growth) forecasts

	Model 1	Model 2	Model 3	Model 1	Model 2	Model 1	Model 2
		year on year		quarter on quarter		annual	
Averages for the national monetary policy makers (chair, governors, board)							
HP GDP$_{c,t-1}$	0.309			0.0366		0.149	
	(0.197)			(0.0353)		(0.203)	
Inflation$_{c,t-1}$	0.234***	0.243***		0.194***	0.203***	0.00181	0.00279
	(0.0455)	(0.0442)		(0.0303)	(0.0265)	(0.0252)	(0.0242)
GDP growth$_{c,t-1}$	-0.242	0.00111		-0.0364	-0.00470	-0.0535	0.0539
	(0.172)	(0.0378)		(0.0345)	(0.00477)	(0.196)	(0.0582)
EBF Inflation$_{c,t}$	0.294***	0.299***	0.507***	0.337***	0.337***	0.260***	0.260***
	(0.0661)	(0.0675)	(0.0673)	(0.0516)	(0.0547)	(0.0758)	(0.0755)
EBF GDPgrowth$_{c,t}$	-0.0699**	-0.103**	-0.107*	-0.00488	-0.00911	0.0205	-0.0428
	(0.0301)	(0.0455)	(0.0545)	(0.00401)	(0.00602)	(0.107)	(0.0860)
Monetary Policy		-0.000104*			-0.000104*	-6.67e-05	-8.12e-05
Rate$_{c,t-1}$		(5.84e-05)			(5.65e-05)	(0.000223)	(0.000227)
Observations	8,318	8,267	8,343	8,348	8,297	2,641	2,641
R-squared	0.830	0.834	0.822	0.813	0.817	0.741	0.741
Only chairs' life experience							
HP GDP$_{c,t-1}$	0.326			0.0350		0.136	
	(0.208)			(0.0363)		(0.218)	
Inflation$_{c,t-1}$	0.239***	0.249***		0.201***	0.210***	0.000369	0.00113
	(0.0472)	(0.0458)		(0.0312)	(0.0271)	(0.0244)	(0.0234)
GDP growth$_{c,t-1}$	-0.253	0.00305		-0.0347	-0.00446	-0.0475	0.0497
	(0.179)	(0.0403)		(0.0354)	(0.00508)	(0.211)	(0.0647)
EBF Inflation$_{c,t}$	0.295***	0.300***	0.513***	0.336***	0.336***	0.270***	0.270***
	(0.0665)	(0.0680)	(0.0691)	(0.0525)	(0.0558)	(0.0805)	(0.0805)
EBF GDPgrowth$_{c,t}$	-0.0749**	-0.109**	-0.111*	-0.00515	-0.00924	0.0339	-0.0220
	(0.0327)	(0.0486)	(0.0565)	(0.00430)	(0.00624)	(0.121)	(0.0989)
Monetary Policy		-0.000104*			-0.000105*	-7.39e-06	-2.06e-05
Rate$_{c,t-1}$		(6.00e-05)			(5.80e-05)	(0.000231)	(0.000234)
Observations	7,709	7,661	7,752	7,768	7,720	2,416	2,416
R-squared	0.832	0.836	0.823	0.815	0.818	0.746	0.746

All regression include country and time fixed effects (omitted).
Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.

results were similar. These findings are consistent with central bankers being mostly concerned with the inflation goal.

All results are robust to using either the average national central banker or the chair samples. Therefore, the remainder of the article focuses only on the chairs sample.

4.3 Heterogeneity across different countries

Now I analyze the heterogeneous experiences of central bankers across emerging markets and developing economies (EMDEs), advanced economies (AEs), current OECD members, and current inflation targeting countries (ITs).[16] The results in Table 7 show that experience-based inflation forecasts are relevant for all country groups (EMDEs, AEs, OECD, ITs). However, for AEs the role of experience based forecasts has a much smaller coefficient. The monetary policy rate for AEs only increases 4 to 8 basis points for each 1% of personal experience-based inflation. This is much smaller than the 27 to 34 basis points estimated for the entire country sample (Table 6).

The persistence of the monetary policy rate is small in both EMDEs and ITs. However, monetary policy is substantially sticky in AEs, with the lag coefficient being 0.89 and 0.77 at the quarterly and annual frequencies. For OECD members, there is also some persistence of monetary policy, with a lag coefficient between 0.25 to 0.36.

The role of experience-based real GDP growth forecasts is small and statistically insignificant across all country groups, with the exception of year on year results for EMDEs. Again, this is consistent with central bankers across the world focusing mostly on the inflation goal.

4.4 How does life experience interact with central bank independence?

I now test how the role of experience-based forecasts changes with indexes of central bank independence. For this I include further controls using the central bank independence (CBI) index for the country of the central banker, the average foreign country where the central banker studied and worked. Again, the regressions show that experience-based forecasts for inflation are statistically significant,

[16] The ITs include the eurozone countries, Australia, Brazil, Canada, Chile, Colombia, Czechia, Hungary, Iceland, India, Indonesia, Israel, Japan, Mexico, New Zealand, Norway, Peru, Philippines, Romania, South Korea, South Africa, Sweden, Thailand, United States and United Kingdom.

Table 7: Quarterly panel regressions of the monetary policy rate based on the life experience (inflation and real GDP growth) forecasts across country groups:

Only chairs' life experience						
Country group		EMDEs			AEs	
Forecast type	yoy	qoq	annual	yoy	qoq	annual
$\text{Inflation}_{c,t}$	0.227***	0.233***	-0.00723	0.0128	0.0166***	-0.00701
	(0.0374)	(0.0284)	(0.0203)	(0.0194)	(0.00536)	(0.0143)
$\text{GDP growth}_{c,t}$	-0.0229	-0.00318	0.00740	0.0163*	0.00268	0.0560***
	(0.0517)	(0.00524)	(0.0697)	(0.00915)	(0.00272)	(0.0182)
$\text{EBF Inflation}_{c,t}$	0.330***	0.330***	0.283***	0.0574***	0.0379***	0.0760***
	(0.0813)	(0.0686)	(0.0772)	(0.0161)	(0.0117)	(0.0258)
$\text{EBF GDPgrowth}_{c,t}$	-0.173**	-0.00867	-0.0996	0.0150***	0.000888	0.0597
	(0.0685)	(0.00710)	(0.129)	(0.00535)	(0.00157)	(0.0414)
Monetary Policy	-0.000111	-0.000121	2.59e-05	0.892***	0.899***	0.771***
$\text{Rate}_{c,t-1}$	(7.73e-05)	(7.43e-05)	(0.000287)	(0.0256)	(0.0268)	(0.0366)
Observations	3,193	3,222	1,290	4,371	4,398	1,113
R-squared	0.847	0.835	0.754	0.964	0.964	0.921
Country group		OECD			Inflation targeting countries (ITs)	
Forecast type	yoy	qoq	annual	yoy	qoq	annual
$\text{Inflation}_{c,t}$	0.447***	0.152***	0.0448	0.244***	0.191***	0.0148***
	(0.0867)	(0.0403)	(0.0732)	(0.0290)	(0.0291)	(0.00357)
$\text{GDP growth}_{c,t}$	0.0496	0.0114*	0.0947*	0.0526	-0.0165	0.102
	(0.0438)	(0.00641)	(0.0468)	(0.0426)	(0.0109)	(0.0731)
$\text{EBF Inflation}_{c,t}$	0.0902***	0.304***	0.250***	0.226***	0.272***	0.247***
	(0.0292)	(0.0983)	(0.0558)	(0.0443)	(0.0295)	(0.0177)
$\text{EBF GDPgrowth}_{c,t}$	0.00240	-0.0210	0.00679	-0.0575	-0.0199	-0.122
	(0.0384)	(0.0189)	(0.0874)	(0.0392)	(0.0138)	(0.123)
Monetary Policy	0.248***	0.292***	0.363***	-3.78e-05**	-4.45e-05*	-0.000158
$\text{Rate}_{c,t-1}$	(0.0891)	(0.102)	(0.110)	(1.68e-05)	(2.36e-05)	(0.000104)
Observations	4,704	4,737	1,215	4,951	4,995	1,270
R-squared	0.911	0.898	0.901	0.884	0.851	0.875

All regression include country and time fixed effects (omitted).
Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.

whether at the year-on-year, quarter-on-quarter or annual specifications. The inclusion of the CBI index shows that previous inflation is more important for central banks with higher *de jure* independence, although there is only statistical significant for the quarter-on-quarter forecasts. The role of personal experience, however, is unrelated to central bank independence. This makes sense, since higher independence could mean the central bank focuses more on observable inflation, rather than discretionary components based on experience. Central bankers may also adopt professional behaviors observed in the countries where they studied. The central bank independence index is relevant both for the country of the central banker and the country where he or she studied (in the quarter on quarter specification).

The appendix shows interaction effects with PhD education, foreign PhD education in the US or UK, and whether the chairs studied or worked in a foreign country. I find no statistical significance for the year on year specification. For the quarter on quarter specification, I find that study or working abroad, studying or having worked abroad in the US or UK, and having worked abroad in the US or UK are associated with a stronger reliance on past inflation and a lower weight of personal experience-based forecasts. In the annual regressions, having worked abroad in the US or UK is also associated with a stronger reliance on past inflation. These results make sense, since professionals with broader experiences such as academic studies or work in foreign countries may be more open to relying on data rather than personal experience.

4.5 Ministry of Finance experience

As discussed in section 2, around 18% of the central bankers also had roles in the Ministry of Finance at some point of their career. Table 9 estimates the interaction of experience-based forecasts of inflation with dummies for Ministry of Finance experience. For the quarter on quarter specification, the Ministry of Finance career experience (whether before or after the central bank or just before) is negatively correlated with the weight of the experience-based inflation forecasts and positively associated with the previously observed inflation. Politically sensitive governors may give less weight to their personal opinions and more weight to objective inflation. However, this relationship is statistically significant at the year on year frequency and it differs qualitatively at the annual level.

Table 8: Quarterly panel regressions of the monetary policy rate based on life experience forecasts (chairs only) with central bank independence (CBI) interactions

	year on year			quarter on quarter			annual
	c*=c	c*=c(study)	c*=c(work)	c*=c	c*=c(study)	c*=c(work)	c*=c
Inflation$_{c,t-1}$	0.237***	0.240***	0.245***	0.206***	0.205***	0.207***	0.0119
	(0.0765)	(0.0499)	(0.0546)	(0.0253)	(0.0286)	(0.0290)	(0.0247)
GDP growth$_{c,t-1}$	0.0237	0.0103	0.00941	-0.00491	-0.00518	-0.00510	0.0360
	(0.0417)	(0.0433)	(0.0418)	(0.00537)	(0.00588)	(0.00573)	(0.0589)
EBF Inflation$_{c,t}$	0.206*	0.353***	0.334***	0.254***	0.363***	0.373***	0.256***
	(0.115)	(0.0962)	(0.0791)	(0.0563)	(0.0647)	(0.0635)	(0.0475)
EBF GDP	-0.116**	-0.117**	-0.119**	-0.00688	-0.00701	-0.00748	-0.0317
growth$_{c,t}$	(0.0496)	(0.0501)	(0.0518)	(0.00503)	(0.00548)	(0.00526)	(0.119)
CBI$_{c*,t}$	-7.039*	-0.453	0.443	-7.375*	-0.819	0.317	-11.58*
	(3.632)	(0.756)	(1.010)	(3.795)	(0.738)	(1.151)	(6.236)
CBI$_{c*,t}\times$	0.161	-0.00410	-0.0813	0.165***	0.125**	0.0801	-0.0144
Inflation$_{c,t-1}$	(0.218)	(0.163)	(0.358)	(0.0384)	(0.0584)	(0.0774)	(0.102)
CBI$_{c*,t}\times$	0.135	-0.0879	0.00333	0.0877	-0.104	-0.162	0.0700
EBF Inflation$_{c,t}$	(0.211)	(0.184)	(0.370)	(0.101)	(0.0826)	(0.132)	(0.238)
Monetary Policy	-7.97e-05*	-0.000118*	-0.000113*	-8.81e-05**	-0.000128**	-0.000116**	-0.000181
Rate$_{c,t-1}$	(4.15e-05)	(6.09e-05)	(5.85e-05)	(3.85e-05)	(6.17e-05)	(5.51e-05)	(0.000168)
Observations	7,158	7,158	7,158	7,210	7,210	7,210	2,129
R-squared	0.850	0.846	0.845	0.834	0.828	0.828	0.778

All regression include country and time fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

Table 9: Panel regressions of the monetary policy rate based on life experience forecasts (chairs only) with interactions for Ministers of Finance

	MinFinance is dummy for Minister of Finance:					
	before or after central bank			before central bank		
	yoy	qoq	annual	yoy	qoq	annual
Inflation$_{c,t-1}$	0.239***	0.212***	-0.00831	0.249***	0.208***	0.00714
	(0.0503)	(0.0263)	(0.0198)	(0.0478)	(0.0273)	(0.0229)
GDP growth$_{c,t-1}$	0.0124	-0.00418	0.0224	0.00315	-0.00466	0.0474
	(0.0396)	(0.00504)	(0.0543)	(0.0396)	(0.00517)	(0.0686)
EBF Inflation$_{c,t}$	0.340***	0.366***	0.348***	0.305***	0.343***	0.288***
	(0.0749)	(0.0658)	(0.0798)	(0.0733)	(0.0587)	(0.0875)
EBF GDPgrowth$_{c,t}$	-0.104**	-0.00785	0.0255	-0.110**	-0.00892	-0.0256
	(0.0461)	(0.00573)	(0.114)	(0.0491)	(0.00630)	(0.102)
MinFinance$_{c,t}$	0.127	0.275	1.365*	0.401	0.580	0.718
	(0.602)	(0.624)	(0.710)	(0.544)	(0.545)	(0.816)
MinFinance$_{c,t}\times$	0.143	0.103***	-0.427***	-0.0392	0.0697***	-0.124
Inflation$_{c,t-1}$	(0.181)	(0.0371)	(0.105)	(0.206)	(0.0201)	(0.141)
MinFinance$_{c,t}\times$	-0.286	-0.257*	0.128***	-0.0703	-0.198**	-0.0385
EBF Inflation$_{c,t}$	(0.203)	(0.134)	(0.0363)	(0.188)	(0.0848)	(0.0393)
Monetary Policy	-0.000113*	-0.000116**	-0.000266	-0.000109*	-0.000111*	-0.000233
Rate$_{c,t-1}$	(5.90e-05)	(5.76e-05)	(0.000221)	(6.23e-05)	(6.04e-05)	(0.000204)
Observations	7,661	7,720	2,416	7,661	7,720	2,416
R-squared	0.840	0.823	0.770	0.836	0.819	0.753

All regression include country and time fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

4.6 Experience-based forecasts and diagnosis expectations

I finish the section by showing that experience-based forecasts remain significant even after controlling for other behavioral theories, such as diagnostic expectations (Bordalo et al. 2020). Table 10 shows that the experience-based forecasts for inflation remain significant even after controlling for the diagnostic forecast revision component. This result is robust whether year-on-year or quarter-on-quarter forecasts are used. Therefore, personal life experience matters even after adding diagnostic forecast revisions as controls. It is also robust to whether diagnostic forecast revisions use the entire historical time series available ($FullTimeSeries\ Diagnostic_{c,t}$) or whether the forecast revisions use the experience-based learning model ($EB\ Diagnostic_{c,t}$).

The diagnostic revisions (whether EB or Full Time Series) for inflation have a positive weight and are statistically significant for the year-on-year specification. Central bankers give a negative weight to either diagnostic components (EB or Full Time Series) for the quarter-on-quarter specification. Perhaps, this is due to the volatility of the quarter-on-quarter indicators. This is consistent with central bankers giving some weight to diagnostic expectations if the components have some persistence (such as the year on year forecasts), but avoiding extra weight of noisy quarter on quarter forecast revisions.

I also find that the diagnostic revision (EB or Full Time Series) for GDP growth has a positive weight for the quarter-on-quarter forecasts. This result makes sense and it supports the idea that central bankers can increase interest rates if an unexpected positive shock to growth is observed.

5 Evidence from the tone of central bank speeches

5.1 Monetary policy tone and financial stability sentiment

Now I analyze the effect of the personal experience of central bankers on their speeches, as available from the CBS dataset. Both the net hawkish inflation and hawkish monetary policy indexes are standardized between -1 and 1, using the Apel et al. 2022. The Financial Stability Sentiment (FSS) is standardized as the ratio of net negative words (negative words minus positive ones) in terms

Table 10: Quarterly panel regressions of the monetary policy rate based on the life experience forecasts and diagnostic expectations

Type of diagnostic	*EB Diagnostic*$_{c,t}$			*FullTimeSeries Diagnostic*$_{c,t}$		
	yoy	qoq	annual	yoy	qoq	annual
Averages for the national monetary policy makers (governors, board)						
Inflation$_{c,t-1}$	0.342***	0.134***	-0.00325	0.324***	0.156***	-0.00318
	(0.0613)	(0.0330)	(0.0339)	(0.0473)	(0.0268)	(0.0288)
GDP growth$_{c,t-1}$	0.00625	-0.00892*	0.0393	-0.0141	-0.00717	0.0538
	(0.0411)	(0.00498)	(0.0596)	(0.0470)	(0.00505)	(0.0599)
EBF Inflation$_{c,t}$	0.205***	0.441***	0.270***	0.214***	0.419***	0.268***
	(0.0458)	(0.0681)	(0.0930)	(0.0493)	(0.0726)	(0.0856)
EBF GDPgrowth$_{c,t}$	-0.121**	-0.0208**	-0.0144	-0.0935**	-0.0153*	-0.0542
	(0.0493)	(0.00884)	(0.155)	(0.0426)	(0.00818)	(0.0914)
Diagnostic	0.169**	-0.187***	-0.00137	0.144***	-0.158***	0.00284
Inflation$_{c,t}$	(0.0830)	(0.0427)	(0.0498)	(0.0497)	(0.0396)	(0.00632)
Diagnostic	0.0151	0.00966**	-0.0422	-0.0107	0.00756*	0.558
GDPgrowth$_{c,t}$	(0.0175)	(0.00397)	(0.125)	(0.0198)	(0.00441)	(0.454)
Monetary Policy	-0.000110*	-0.000124**	-7.67e-05	-8.81e-05	-0.000150**	-7.07e-05
Rate$_{c,t-1}$	(6.20e-05)	(6.21e-05)	(0.000241)	(5.94e-05)	(6.47e-05)	(0.000241)
Observations	8,066	8,094	2,631	7,910	7,937	2,582
R-squared	0.836	0.829	0.735	0.835	0.828	0.734
Only chairs' life experience						
Inflation$_{c,t-1}$	0.353***	0.141***	0.000197	0.335***	0.163***	-0.00341
	(0.0642)	(0.0335)	(0.0323)	(0.0503)	(0.0274)	(0.0281)
GDP growth$_{c,t-1}$	0.00595	-0.00926*	0.0294	-0.0120	-0.00756	0.0472
	(0.0447)	(0.00544)	(0.0688)	(0.0510)	(0.00553)	(0.0676)
EBF Inflation$_{c,t}$	0.200***	0.439***	0.270***	0.209***	0.420***	0.275***
	(0.0459)	(0.0689)	(0.0989)	(0.0485)	(0.0741)	(0.0923)
EBF GDPgrowth$_{c,t}$	-0.126**	-0.0210**	0.0283	-0.0997**	-0.0159*	-0.0266
	(0.0523)	(0.00912)	(0.175)	(0.0449)	(0.00839)	(0.102)
Diagnostic	0.181**	-0.184***	0.0102	0.158***	-0.157***	0.00261
Inflation$_{c,t}$	(0.0845)	(0.0416)	(0.0502)	(0.0531)	(0.0399)	(0.00662)
Diagnostic	0.0112	0.00964**	-0.0713	-0.00986	0.00764*	0.227
GDPgrowth$_{c,t}$	(0.0193)	(0.00405)	(0.136)	(0.0215)	(0.00454)	(0.498)
Monetary Policy	-0.000110*	-0.000125*	-4.10e-05	-8.76e-05	-0.000152**	-8.38e-06
Rate$_{c,t-1}$	(6.35e-05)	(6.43e-05)	(0.000242)	(6.11e-05)	(6.67e-05)	(0.000245)
Observations	7,456	7,519	2,398	7,349	7,413	2,376
R-squared	0.838	0.829	0.739	0.837	0.829	0.738

All regression include country and time fixed effects (omitted).
Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.

of the total words in the text (Correa et al. 2021).[17] The results show that the experience-based forecasts for inflation are associated with higher hawkish tone in the speeches, especially for the year-on-year forecasts. This result makes sense, with higher inflation forecasts being associated with hawkish speeches. Note also that the past inflation and GDP growth rates are not statistically significant. Again, it shows that personal experience for central bankers seems to matter more than the previously observed outcomes.

The results also show that experience-based forecasts for real GDP growth rates are associated with less financial sentiment pessimism in speeches in the year on year specification. For the quarter on quarter specification, financial stability pessimism is negatively associated with higher observed real GDP growth in the previous period and positively associated with experience-based inflation forecasts. This also makes sense, as either higher inflation or lower growth can pose risks for financial stability.

5.2 Climate concerns

Now I analyze the effect of personal experience of natural disasters on the topic of speeches, using the CBS dataset (Campiglio et al. 2025). I use as measures of personal experience the average deaths, severity and number of affected people by weather disasters during the impressionable years (age 18 to 25) of the central banker (IA-Disaster_i) and in the average of the previous 10 years and the current year of the speech ($\text{RecentDisaster}_{i,t}$). The deaths, severity and affected people are measured as a fraction of the population. Severity is a summary measure of the damages of natural disasters, often used by the World Bank and IMF, which is being given by death+0.3affected people. Weather disasters includes the sum of coldwaves, droughts, floods, heatwaves, landslides, storms and wildfires for each country in a given year. To compute these variables, I use the EM-DAT database from CRED, with disasters available since 1900 (although the information can be more sparse and noisy before 2000).

Table 12 shows that central bankers with stronger personal experience of natural disasters during their impressionable years (IA-Disaster_i) and in the recent 11 years ($\text{RecentDisaster}_{i,t}$) have a lower probability of making a speech on the topic of climate change, green finance or carbon.

[17] Note that the results remain similar if this index is standardized between -1 and 1, by using the sum of negative and positive words in the denominator instead.

Table 11: Regressions of central bank speeches (in CBS database) based on the life experience forecasts (year on year "yoy" or quarter on quarter "qoq") of the speaker: hawkish inflation and monetary policy (sum of inflation, activity, employment) tones from Apel, Grimaldi & Hull 2022 and the financial stability sentiment of Correa et al. 2021.

	Apel, Grimaldi & Hull 2022				Correa et al. 2021	
	Hawkish inflation		Hawkish monetary policy		Financial Stability Sentiment	
	yoy	qoq	yoy	qoq	yoy	qoq
$\text{Inflation}_{c,t-1}$	-0.000552	0.00371	0.000166	0.00544*	8.07e-05	1.63e-05
	(0.00389)	(0.00293)	(0.00387)	(0.00300)	(8.00e-05)	(6.53e-05)
$\text{GDP growth}_{c,t-1}$	0.00235*	0.00176	0.00554***	0.00555***	-6.71e-05	-0.000149**
	(0.00126)	(0.00124)	(0.00159)	(0.00155)	(5.74e-05)	(6.30e-05)
$\text{EBF Inflation}_{c,t}$	0.00649**	0.00675	0.00729**	0.00420	-5.67e-06	0.000404*
	(0.00294)	(0.00603)	(0.00292)	(0.00634)	(9.74e-05)	(0.000211)
$\text{EBF GDPgrowth}_{c,t}$	-0.00169	-0.000231	-0.000721	-0.00103	-0.000163***	2.43e-05
	(0.00105)	(0.000615)	(0.00132)	(0.000986)	(4.37e-05)	(5.84e-05)
Observations	27,437	27,316	27,437	27,316	27,437	27,316
R-squared	0.071	0.071	0.061	0.061	0.154	0.154

All regression include country and year-quarter fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

Table 12: Effect of personal experience of weather disasters on speeches related to climate

	Dummy for speech with climate, green or carbon (linear probability model)			Fraction of words of climate, green or carbon in speech (linear model)		
	Disaster measure used			Disaster measure used		
Controls	Severity	Deaths	Affected	Severity	Deaths	Affected
IA-Disaster$_i$	-0.302***	-11.60***	-0.0907***	-0.00172***	-0.00269	-0.000517***
	(0.0413)	(3.994)	(0.0124)	(0.000342)	(0.0283)	(0.000103)
RecentDisaster$_{i,t}$	-0.705***	-106.3***	-0.212***	-0.00524***	-1.275***	-0.00157***
	(0.0547)	(36.43)	(0.0164)	(0.000663)	(0.293)	(0.000199)
ln($GDPpc$	-0.119***	-0.106***	-0.119***	-0.000417	-0.000220	-0.000416
$PPP_{c,t-1}$)	(0.0212)	(0.0219)	(0.0212)	(0.000280)	(0.000311)	(0.000280)
Real GDP	0.00570***	0.00534***	0.00571***	5.67e-06	2.86e-06	5.69e-06
growth$_{c,t-1}$	(0.000913)	(0.000922)	(0.000913)	(6.28e-06)	(6.32e-06)	(6.28e-06)
Observations	31,265	31,265	31,265	31,265	31,265	31,265
R-squared	0.570	0.567	0.570	0.135	0.131	0.135

Note: Severity is given by (deaths+0.3affected)/population.

All regression include country and year-quarter fixed effects (omitted).

Robust standard errors in ().

***,**,* denote 1%, 5%, 10% statistical significance.

Table 13: Effect of personal experience of weather disasters on making a speech (dummy variable) specific to climate change, green finance or carbon (linear probability model)

	Climate change speech		Green finance speech		Carbon speech	
	Disaster measure		Disaster measure		Disaster measure	
Controls	Severity	Deaths	Severity	Deaths	Severity	Deaths
IA-Disaster$_i$	-0.194***	-16.14***	-0.109***	3.572**	-0.137***	0.464
	(0.0359)	(3.557)	(0.0153)	(1.450)	(0.0221)	(2.176)
RecentDisaster$_{i,t}$	-0.493***	-64.57*	-0.233***	-83.75***	-0.324***	-45.60
	(0.0439)	(34.19)	(0.0306)	(13.72)	(0.0359)	(28.33)
$\ln(GDPpcPPP_{c,t-1})$	-0.195***	-0.191***	0.0673***	0.0776***	-0.0461***	-0.0370**
	(0.0182)	(0.0182)	(0.0124)	(0.0136)	(0.0171)	(0.0179)
Real GDP	0.00430***	0.00400***	-0.00227***	-0.00241***	0.00321***	0.00310***
growth$_{c,t-1}$	(0.000852)	(0.000863)	(0.000357)	(0.000359)	(0.000652)	(0.000659)
Observations	31,265	31,265	31,265	31,265	31,265	31,265
R-squared	0.513	0.512	0.082	0.080	0.406	0.405

Note: Severity is given by (deaths+0.3affected)/population.

All regression include country and year-quarter fixed effects (omitted).

Robust standard errors in ().

***,**,* denote 1%, 5%, 10% statistical significance.

This is robust to whether deaths, severity or affected people are used as a measure. Furthermore, central bankers with higher experience of weather disasters in terms of severity and affected people dedicate a lower fraction of words to the topics of climate change, green finance or carbon. This result seems to point that central bankers with stronger experience of weather disasters have lower concerns about the climate. This matches well with evidence from the corporate finance literature, which shows that CEOs with weather disaster experience tend to follow riskier strategies except if their companies were specifically affected by the past disasters (Bernile et al. 2017).

The same finding is confirmed for the analysis of the probability of making a speech on the separate topics of climate change, green finance and carbon. Table 13 shows that experience of disasters in the impressionable years (IA-Disaster$_i$) and recent period (RecentDisaster$_{i,t}$) are associated with a lower probability of making a speech on climate change, green finance and carbon. The only exception is that a higher experience of deaths by natural disasters in the impressionable years is associated with a higher probability of a speech dedicated to green finance. All coefficients are statistically significant and robust if the severity measure is used. Similar results are shown in the appendix for the fraction of words in the speech dedicated to each of these topics (climate change, green finance, carbon).

Furthermore, the appendix shows that central bankers with recent experience of weather disasters joined the NGFS network in a later year, as measured by the severity and people affected by the disasters. However, central bankers that observed a higher death rate from weather disasters in their impressionable years are more likely to join the NGFS at an earlier year. Again, this is consistent with the corporate finance literature that finds that experience of weather disasters makes CEOs less concerned about extreme events, except if the disaster implies serious damages (Bernile et al. 2017).[18]

6 Conclusion

Using a hand-collected dataset with cross-country biographical information on central bankers (chairs, governors, deputy governors, board members), I obtain experience-based forecasts for GDP growth and inflation based on an adaptive learning AR model estimated from their lifetime macroeconomic data (Malmendier et al. 2021). This new dataset provides a strong international evidence to the personal experience hypothesis found for the US (Malmendier et al. 2021, Bordo and Istrefi 2023). I expand upon their work by using international evidence and also by documenting the relevance of connections to government, education and studies abroad.

I find that life experience-based forecasts influence monetary policy rates. Each additional inflation percentage point in the year-on-year experience-based forecasts is associated with an

[18] On a cautionary note, it is relevant to acknowledge that the NGFS membership year analysis can be disturbed by omitted variables. The reason is that the regression for the NGFS membership is not a panel, since institutions only join the NGFS once (although some institutions may have decided to leave it later on). For this reason the NGFS membership regression does not include country fixed effects.

increase of 33 basis points in the monetary policy rate. This evidence is robust to the usual Taylor rule inputs for the past inflation and GDP growth and country and time fixed effects. Furthermore, the results are robust to using year-on-year or quarter-on-quarter forecasts. I also show that the evidence is found whether the sample of all central bankers (chairs, governors, deputy governors, board members) is used or for analysis limited to chairs of the monetary policy committee.

I find that central bankers across several country groups (inflation targeting central banks, OECD members, AEs, EMDEs) give a positive weight to personal experience of inflation in monetary policy setting. However, central bankers in advanced economies (AEs) give a much lower weight to personal experience-based forecasts, about 5 times less than in other economies. The monetary policy rate in AEs is associated with a change of only 4 to 8 basis points for each percentage point of personal inflation forecasts. Furthermore, I find that the monetary policy rate is much more persistent in AEs and OECD members, especially in AEs.

For the quarter on quarter specification, I find that central bankers that had official mandates in Treasury or Ministry of Finance tend to give higher weight to past inflation and less weight to their personal experience forecasts. Furthermore, central banks with higher central bank independence indexes in their countries or in the countries where they studied abroad also give higher weight to past observed inflation. For the case of higher central bank autonomy, it can be because more formal institutions give extra weight to the observable data. In the case of central bankers with experience in Treasury or Ministry of Finance, there can be a higher concern to base their choices also on observable data rather than on personal judgement.

PhD education increased among central bankers of all continents until the Great Financial Crisis (GFC), but this trend partially reversed since then. Age increased among central bankers of all continents since the early 1990s. The fraction of female central bankers has steadily increased since the early 1990s across all continents, except for Asia where the share of women has fallen after the GFC. For the quarter on quarter frequency, I find that studying or having worked abroad in the US or UK are associated with a stronger reliance on past inflation and a lower weight of personal experience-based forecasts. Therefore, professionals with broader experiences such as academic studies or work in foreign countries may be more open to relying on data rather than experience.

I also find that life experience influences the tone of speeches for monetary policy, financial stability and climate concerns. Inflation experience is more associated with hawkish tones in speeches, whether for inflation or overall monetary policy concerns. Experience based forecasts of inflation and GDP growth are also associated with higher and lower financial stability pessimism, respectively. This result makes sense because an economy with higher activity as measured by inflation and GDP growth may be less prone to financial system problems. Weather disasters experience reduces climate concerns in speeches and are associated with a delayed NGFS membership, with the exception of central bankers that saw weather disasters with high death rates in their impressionable years. These results are consistent with the corporate finance literature that shows that CEOs with experience of weather disasters implement riskier strategies, except if damages seriously affect them (Bernile et al. 2017).

Further research can analyse the effect of institutional frameworks, such as having a committee or board for monetary policy decisions, a single goal in terms of price stability, a dual goal that includes employment or financial stability, or the absence of an explicit inflation target.

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The life experience of central bankers and monetary policy decisions

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Abstract

This appendix provides additional summary statistics and robustness checks to the analysis in the main article. Figure A.1 shows the fraction of female central bankers since 1960. Figure A.2 shows the fraction of central bankers with PhDs since 1960. Tables A.1 to A.7 provide additional summary statistics on the number of observations, birth decade, impressionable years period, education, experience of financial crises and experience of weather disasters. The appendix also shows that experience of weather disasters is associated with a delayed NGFS membership (Table A.8), except for deaths experience during disasters in the impressionable years. Impressionable years or recent weather disaster experience is associated with lower fractions of words on the individual topics of climate change, green finance and carbon, except for experience of deaths in disasters during the impressionable years (Table A.9). Education, studies abroad or work abroad are associated with different weights for past inflation versus personal inflation experience on monetary policy decisions (Tables A.10, A.11 and A.12). Results are also robust if current observed inflation and GDP growth are included as controls (Table A.13). Regressions are robust to using different values of the updating parameter theta (Table A.14). Finally, Table A.15 shows that the results are robust to using all countries separately (instead of aggregating countries by monetary zone).

JEL Classification: D83; D84; E30; E37; E50; E70.

Keywords: Monetary policy; Experience effects; Forecasting; Learning; Beliefs.

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Figure A.1: Fraction of female central bankers by continent since 1960

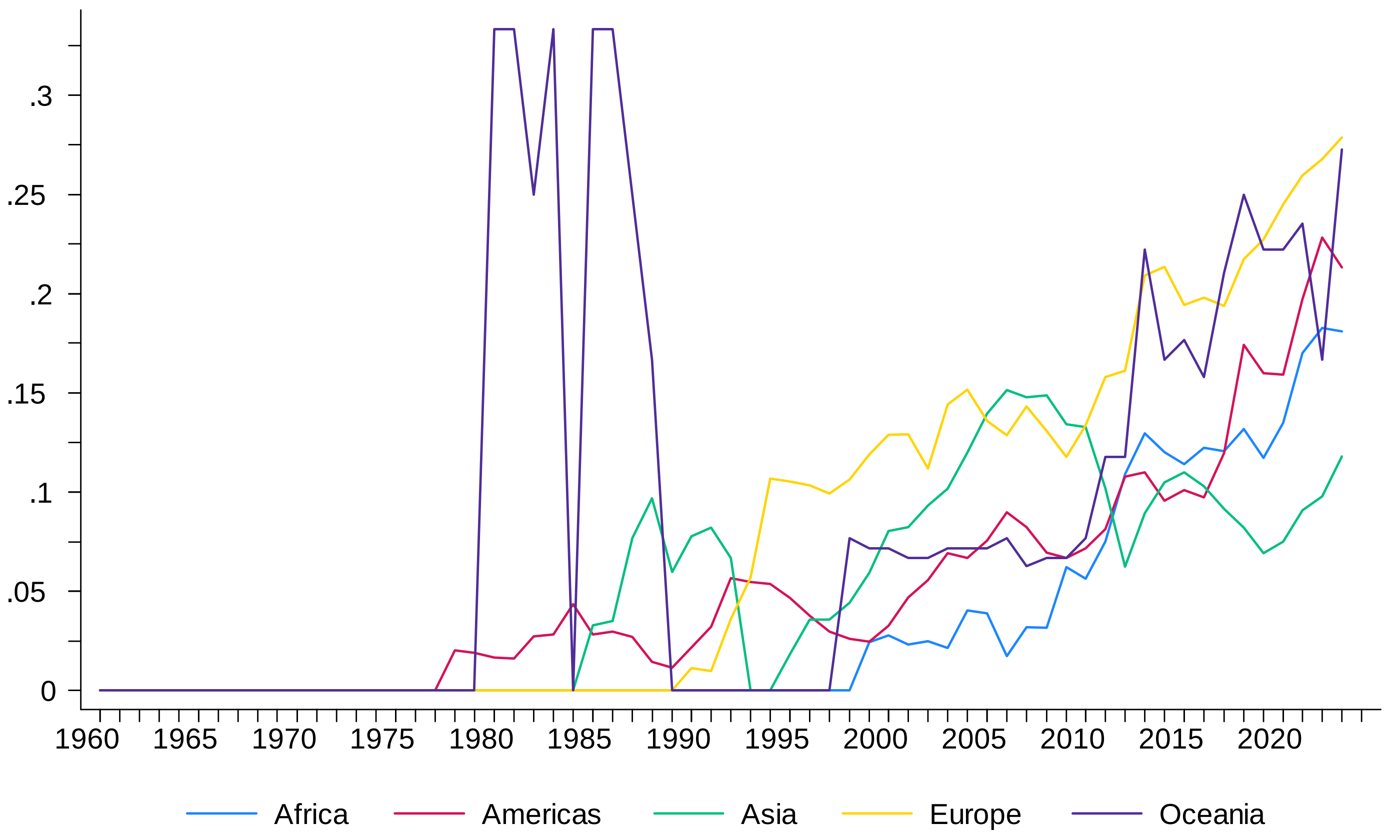

Figure A.2: Fraction of central bankers with a PhD degree and with a PhD degree from the US or UK since 1960

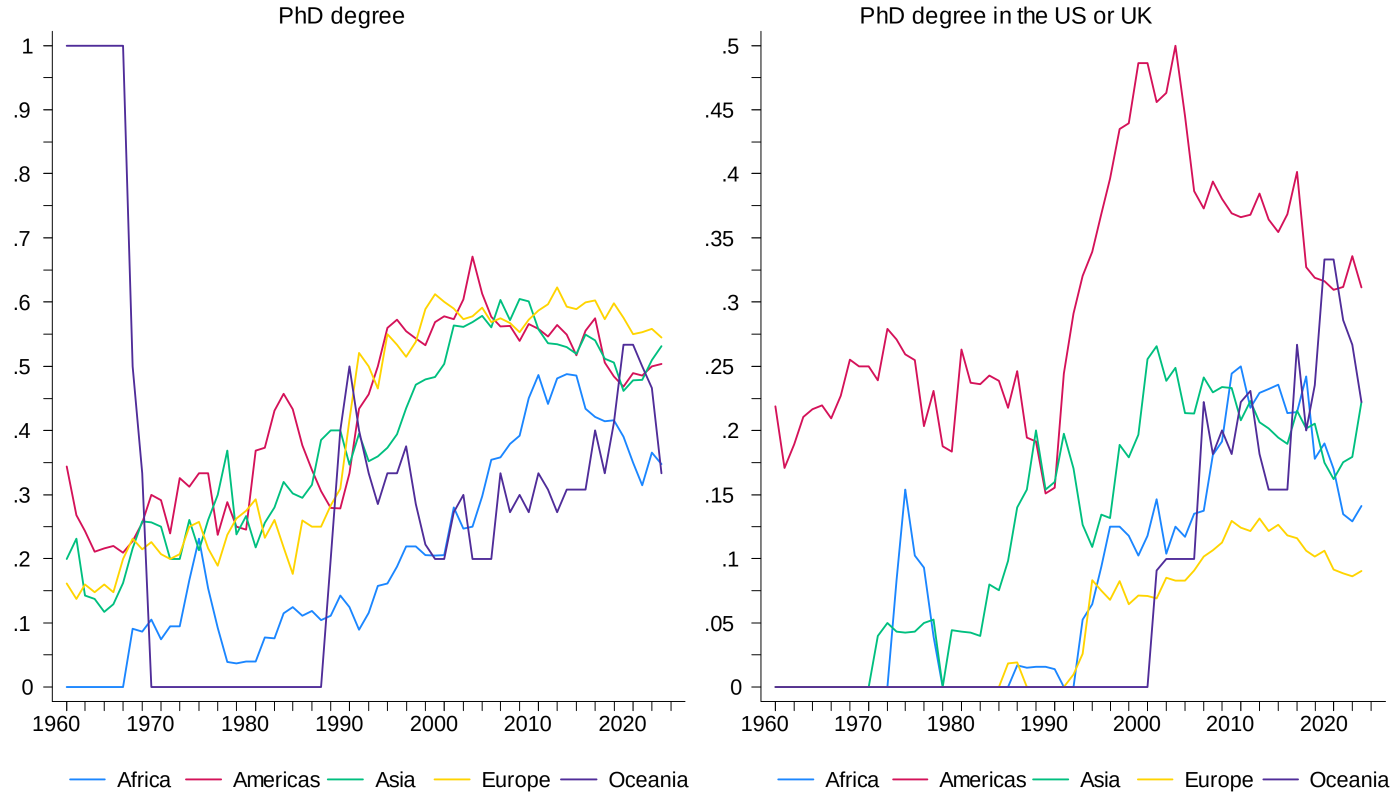

Table A.1: Top 11 countries with highest number of central bankers

(with birth date information)

Rank	Country	Persons	Country	Governors	Country	Chairs
1	USA	302	United Kingdom	105	United Kingdom	105
2	United Kingdom	178	USA	89	Argentina	51
3	India	101	Argentina	51	Brazil	42
4	Brazil	68	Brazil	42	Poland	27
5	Japan	68	Poland	27	Czech Republic	26
6	Switzerland	65	Czechia	26	Japan	24
7	Finland	64	Japan	24	Hungary	24
8	Argentina	58	Hungary	24	India	22
9	Belgium	57	India	22	Uruguay	22
10	Poland	56	Turkey	22	Turkey	22
11	Netherlands	56	Uruguay	22	Thailand	20

Table A.2: Education and career background in % of the 21st century sample (persons starting or ending their mandates after 2000)

Continent	Africa	Americas	Asia	Europe	Oceania	World
Education degree (% of sample)						
BA or MA	92.8	96.5	91.8	84.7	97.6	90.1
MBA, JD, MS, other	21.1	15.9	19.7	12.0	5.4	15.7
PhD	39.4	50.7	48.1	53.9	33.3	49.7
Private education institution (% of sample with a degree)						
BA or MA	16.4	40.2	27.9	12.2	0	23.3
MBA, JD, MS, other	23.1	72.0	56.0	37.5	0	51.9
PhD	30.2	53.3	34.4	12.9	57.1	32.8
Career background: multiple categories per person allowed (% of sample)						
Industry	11.6	13.7	9.5	22.1	40.0	16.2
Banking	83.3	76.4	77.6	68.7	93.0	74.6
Academy	32.9	49.8	36.6	54.9	32.4	46.4
Government/ Public A.	72.8	82.4	80.3	84.2	71.8	81.3
International Org.	32.9	34.1	27.9	28.4	30.6	30.1
Audit	4.2	5.9	4.3	4.2	0.0	4.5
Consulting	20.7	35.0	23.6	18.7	20.0	23.8
Military	0.5	0.5	0.5	0.6	2.9	0.6

Table A.3: Birth and impressionable age of the governors and board

Birth relative to Great Depression	Number of persons	Percent
Before the Great Depression	607	19.0
During Great Depression (1929-1939)	366	11.5
After the Great Depression	2218	69.5
Impressionable age (age 18 to 25)		
Before WW1	211	6.6
During WW1	89	2.8
After WW1 & before Great Depression	59	1.8
During Great Depression	110	3.4
During WW2	206	6.5
After WW2, before Great Inflation	0	0
During Great Inflation	1972	61.8
During Great Moderation	535	16.8
After the Great Financial Crisis	9	0.3

Note: latest period is the one that counts (if you lived years before the Great Inflation and also the Great Inflation, only the last one counts).

Table A.4: University category in % of the sample graduates

Type of University	BA	MBA	PhD
US freshwater	5.0	14.5	16.6
US saltwater	1.3	2.4	6.3
US other	9.3	9.3	6.5
Oxford, Cambridge, LSE	2.1	3.0	2.8
UK other	4.3	7.8	8.2
France	1.1	1.8	1.8
Germany	1.6	0.3	2.8
Canada	1.4	2.7	1.2
Spain	0.5		0.5
Italy	0.5		0.2
Australia	1.2		0.7
Russia	1.6	0.9	2.1
India	3.2	1.2	2.2
Africa	9.6	11.7	4.3
Americas other	13.2	7.5	6.1
Asia	17.3	18.7	9.7
Europe other	25.6	17.5	27.6
Oceania other	0.7	0.3	0.3
N/A	0.6	0.3	0.3

Table A.5: Central bankers work or study

experience in other countries (% of entire sample)

	Africa	Americas	Asia	Europe	Oceania	World
Worked abroad	5.7	9.5	13.5	6.2	16.4	8.8
Studied abroad	25.3	23.0	28.2	12.2	27.3	20.3
Studied in US or UK	19.0	20.7	25.9	11.1	21.8	18.0
Studied/worked in US or UK	21.6	22.9	31.0	16.0	32.7	22.1
Country where governors/board members worked (% of who worked abroad)						
USA or UK	85.7	93.9	94.3	88.7	70.6	90.5
USA	50.0	81.6	86.9	63.9	52.9	73.1
UK	38.1	16.3	13.9	30.8	17.6	22.6
France	4.8	1.0	0.8	4.5	0.0	2.4
Russia	0.0	0.0	4.1	1.5	0.0	1.7
Canada	4.8	3.1	0.0	1.5	11.8	2.2
Germany	0.0	0.0	0.0	5.3	0.0	1.7
Spain	0.0	1.0	0.0	0.0	0.0	0.2
Australia	0.0	0.0	1.6	0.0	17.6	1.2
Africa	4.8	0.0	0.0	0.0	0.0	0.5
Americas	54.8	84.7	86.9	64.7	64.7	75.0
Asia	0.0	3.1	1.6	0.8	5.9	1.7
Europe	47.6	19.4	18.9	45.9	17.6	30.6
Oceania	0.0	0.0	1.6	0.8	17.6	1.5

Table A.6: Mean years spent in economic crises during the impressionable age (18-25)

	Africa	Americas	Asia	Europe	Oceania	World
Recession	1.7	1.6	1.1	1.7	1.6	1.5
Banking crises	0.2	0.4	0.2	0.2	0.0	0.3
Currency Crises	0.5	1.0	0.6	0.3	0.1	0.6
Sovereign Debt Crises	1.8	0.9	0.4	0.3	0.0	0.7
Any crises	3.1	2.8	1.8	2.1	1.7	2.3
21st century sample						
	Africa	Americas	Asia	Europe	Oceania	World
Recession	1.8	1.6	1.1	1.7	1.7	1.5
Banking crises	0.3	0.6	0.2	0.3	0.0	0.3
Currency Crises	0.6	1.1	0.6	0.3	0.0	0.6
Sovereign Debt Crises	2.4	1.5	0.5	0.4	0.0	0.9
Any crises	3.6	3.1	1.9	2.1	1.7	2.4

Table A.7: Mean experience of natural disasters during the impressionable age (18-25)

	Africa	Americas	Asia	Europe	Oceania	World
All disasters (sum of deaths, affected and severity as % of population)						
Deaths	0.012	0.004	0.035	0.001	0.003	0.010
Affected	7.628	2.478	7.761	0.897	7.031	3.715
Severity	2.300	0.747	2.363	0.270	2.112	1.125
All disasters (as % of population) - 21st century period only						
Deaths	0.013	0.004	0.020	0.001	0.004	0.008
Affected	10.075	4.019	10.690	1.257	8.512	5.265
Severity	3.036	1.209	3.227	0.378	2.557	1.587

Severity is Deaths plus 0.3Affected

Table A.8: Linear model of membership entry in the NGFS based on governors' weather disasters experience: 2017=1, 2018=2, 2019=3, 2019=4, 2020=5, 2021=6, 2022 and later=7. (IA denotes the cumulative experience of the impressionable age 18 to 25 as a % of the population. Recent denotes the cumulative experience of the last 11 years.)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	WDis=Severity		WDis=Deaths		WDis=Affected	
IA-Dis$_i$	0.0760	0.112*	-20.35*	-12.01	0.0232	0.0340*
	(0.0557)	(0.0624)	(10.78)	(13.25)	(0.0168)	(0.0191)
Recent-Dis$_{i,t}$	-0.0280		-6.620		-0.00839	
	(0.0331)		(15.69)		(0.00992)	
$\ln(\frac{Recent-Dis_i}{IA-Dis_i})$		0.000501		0.00172		0.000759
		(0.000560)		(0.00133)		(0.000587)
$\ln(GDPpcPPP_{c,t-1})$	-0.804***	-0.546*	-0.915***	-0.844***	-0.802***	-0.529*
	(0.288)	(0.302)	(0.206)	(0.246)	(0.288)	(0.311)
Real GDP growth$_{c,t-1}$	0.0317	0.0383	0.0412	0.0594	0.0318	0.0419
	(0.0293)	(0.0302)	(0.0285)	(0.0373)	(0.0292)	(0.0302)
R-squared	71	64	71	60	71	59
Observations	0.222	0.203	0.250	0.321	0.222	0.200

Robust standard errors in ().

***,**,* denote 1%, 5%, 10% statistical significance.

Table A.9: Effect of personal experience of weather disasters on the fraction of speech words specific to climate change, green finance or carbon (linear model)

	Climate change speech		Green finance speech		Carbon speech	
Controls	Dis=Severity	Dis=Deaths	Dis=Severity	Dis=Deaths	Dis=Severity	Dis=Deaths
IA-Dis$_i$	-0.000634***	-0.0544***	-0.000146	0.0262***	-0.000145	0.0304***
	(0.000133)	(0.00897)	(0.000111)	(0.00896)	(0.000133)	(0.0103)
Recent-Dis$_{i,t}$	-0.00152***	-0.357**	-0.000748***	-0.127***	-0.00103***	-0.115*
	(0.000178)	(0.142)	(0.000225)	(0.0253)	(0.000249)	(0.0674)
$\ln(GDPpcPPP_{c,t-1})$	-0.000843***	-0.000826***	0.000367***	0.000414***	0.000263**	0.000325***
	(7.18e-05)	(6.85e-05)	(9.40e-05)	(0.000110)	(0.000105)	(0.000126)
Real GDP growth$_{c,t-1}$	2.63e-06	1.37e-06	-4.32e-06***	-4.39e-06***	1.86e-06	1.80e-06
	(2.81e-06)	(2.84e-06)	(1.34e-06)	(1.33e-06)	(1.77e-06)	(1.80e-06)
Observations	31,265	31,265	31,265	31,265	31,265	31,265
R-squared	0.135	0.134	0.056	0.053	0.121	0.119

All regression include country and year-quarter fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

Table A.10: Quarterly panel regressions of the monetary policy rate based on life experience forecasts (chairs only) with interactions for education and working abroad dummies (year on year fluctuations)

	I is interaction dummy for				
	PhD	PhD US/UK	Work US/UK	Study/work abroad	Study/work US,UK
Inflation$_{c,t-1}$	0.266***	0.251***	0.236***	0.236***	0.239***
	(0.0466)	(0.0509)	(0.0529)	(0.0543)	(0.0510)
GDP growth$_{c,t-1}$	0.00362	0.00286	0.00475	0.00325	0.00402
	(0.0419)	(0.0399)	(0.0398)	(0.0397)	(0.0398)
EBL Inflation$_{c,t}$	0.273**	0.294***	0.326***	0.341***	0.325***
	(0.105)	(0.0690)	(0.0800)	(0.0986)	(0.0741)
EBL GDPgrowth$_{c,t}$	-0.108**	-0.107**	-0.109**	-0.110**	-0.108**
	(0.0475)	(0.0488)	(0.0489)	(0.0483)	(0.0481)
I$_{c,t}$	-1.164***	-0.770	0.358	-0.269	0.354
	(0.426)	(0.634)	(0.609)	(0.396)	(0.570)
I$_{c,t}\times$	-0.102	-0.0500	0.236	0.0663	0.113
Inflation$_{c,t-1}$	(0.113)	(0.202)	(0.286)	(0.122)	(0.163)
I$_{c,t}\times$	0.115	0.0932	-0.312	-0.133	-0.195
EBL Inflation$_{c,t}$	(0.141)	(0.142)	(0.323)	(0.151)	(0.201)
Monetary Policy	-0.000102*	-0.000102	-9.00e-05*	-9.92e-05*	-8.87e-05*
Rate$_{c,t-1}$	(5.63e-05)	(6.33e-05)	(5.23e-05)	(5.66e-05)	(5.08e-05)
Observations	7,624	7,624	7,661	7,661	7,661
R-squared	0.838	0.836	0.837	0.838	0.837

All regression include country and time fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

Table A.11: Quarterly panel regressions of the monetary policy rate based on life experience forecasts (chairs only) with interactions for education and working abroad dummies (quarter on quarter fluctuations)

	I is interaction dummy for				
	PhD	PhD US/UK	Work US/UK	Study/work abroad	Study/work US,UK
$\text{Inflation}_{c,t-1}$	0.202***	0.209***	0.207***	0.203***	0.204***
	(0.0256)	(0.0237)	(0.0256)	(0.0251)	(0.0246)
GDP $\text{growth}_{c,t-1}$	-0.00470	-0.00442	-0.00475	-0.00441	-0.00461
	(0.00537)	(0.00504)	(0.00514)	(0.00529)	(0.00505)
EBL $\text{Inflation}_{c,t}$	0.316***	0.333***	0.354***	0.380***	0.359***
	(0.0738)	(0.0605)	(0.0591)	(0.0760)	(0.0598)
EBL $\text{GDPgrowth}_{c,t}$	-0.01000	-0.00933	-0.00949	-0.00962	-0.00952
	(0.00611)	(0.00625)	(0.00606)	(0.00609)	(0.00602)
$\text{I}_{c,t}$	-1.477***	-0.733	0.324	-0.306	0.413
	(0.445)	(1.133)	(0.696)	(0.420)	(0.666)
$\text{I}_{c,t}\times$	0.0812**	0.128	0.0866*	0.102***	0.0970**
$\text{Inflation}_{c,t-1}$	(0.0347)	(0.102)	(0.0447)	(0.0312)	(0.0418)
$\text{I}_{c,t}\times$	-0.0311	-0.0869	-0.172*	-0.189**	-0.194*
EBL $\text{Inflation}_{c,t}$	(0.0777)	(0.231)	(0.101)	(0.0814)	(0.0991)
Monetary Policy	-0.000122**	-0.000104*	-8.83e-05*	-9.92e-05*	-8.60e-05*
$\text{Rate}_{c,t-1}$	(5.77e-05)	(6.12e-05)	(5.09e-05)	(5.32e-05)	(4.94e-05)
Observations	7,683	7,683	7,720	7,720	7,720
R-squared	0.822	0.819	0.820	0.823	0.820

All regression include country and time fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

Table A.12: Annual panel regressions of the monetary policy rate based on life experience forecasts (chairs only) with interactions for education and working abroad dummies

	I is interaction dummy for				
	PhD	PhD US/UK	Work US/UK	Study/work abroad	Study/work US,UK
Inflation$_{c,t-1}$	0.00422	0.00184	-0.000756	-0.00771	0.00111
	(0.0202)	(0.0223)	(0.0244)	(0.0198)	(0.0233)
GDP growth$_{c,t-1}$	0.0561	0.0529	0.0477	0.0395	0.0492
	(0.0611)	(0.0630)	(0.0628)	(0.0542)	(0.0616)
EBL Inflation$_{c,t}$	0.264***	0.274***	0.269***	0.309***	0.273***
	(0.0861)	(0.0743)	(0.0842)	(0.0724)	(0.0790)
EBL GDPgrowth$_{c,t}$	-0.0229	-0.0102	-0.0311	-0.0104	-0.0138
	(0.101)	(0.0972)	(0.0983)	(0.108)	(0.108)
I$_{c,t}$	-1.165**	-0.852	-1.428	-0.113	-0.294
	(0.516)	(1.041)	(0.921)	(1.025)	(0.763)
I$_{c,t}\times$	0.0318	-0.401**	0.169**	-0.124	-0.0822
Inflation$_{c,t-1}$	(0.0778)	(0.161)	(0.0665)	(0.161)	(0.195)
I$_{c,t}\times$	-0.0202	0.445**	-0.0577	0.0323	0.0483
EBL Inflation$_{c,t}$	(0.0347)	(0.203)	(0.0690)	(0.0470)	(0.135)
Monetary Policy	7.66e-05	-2.60e-05	-0.000134	0.000182	-0.000181
Rate$_{c,t-1}$	(0.000259)	(0.000244)	(0.000736)	(0.000252)	(0.000795)
Observations	2,392	2,392	2,416	2,416	2,416
R-squared	0.748	0.750	0.747	0.750	0.746

All regression include country and time fixed effects (omitted).

Robust standard errors in (). Clusters by country.

***,**,* denote 1%, 5%, 10% statistical significance.

Table A.13: Quarterly panel regressions of the monetary policy rate based on the life experience (inflation and real GDP growth) forecasts

Regressions that include controls for current inflation and real GDP growth							
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 1	Model 2
		year on year		quarter on quarter		annual	
Averages for the national monetary policy makers (chair, governors, board)							
HP GDP$_{c,t-1}$	0.101*			-0.00466		0.0833**	
	(0.0542)			(0.00427)		(0.0402)	
Inflation$_{c,t}$	0.410***	0.402***	0.390***	0.143***	0.143***	-0.0156	0.000720
	(0.0953)	(0.0926)	(0.0967)	(0.0254)	(0.0254)	(0.0344)	(0.0272)
GDP growth$_{c,t}$	-0.0792	-0.0277	-0.0343	-0.00693	-0.00655	-0.0594	-0.110
	(0.0622)	(0.0527)	(0.0529)	(0.00452)	(0.00422)	(0.0651)	(0.0749)
EBF Inflation$_{c,t}$	0.123*	0.131*	0.132*	0.364***	0.364***	0.288***	0.240***
	(0.0729)	(0.0721)	(0.0716)	(0.0567)	(0.0568)	(0.0979)	(0.0750)
EBF GDPgrowth$_{c,t}$	-0.0667	-0.0778	-0.0825*	-0.00893	-0.00809	0.0536	0.124
	(0.0428)	(0.0472)	(0.0468)	(0.00607)	(0.00569)	(0.127)	(0.122)
Monetary Policy	-9.86e-05*	-9.79e-05*		-7.36e-05	-7.31e-05	2.04e-05	
Rate$_{c,t-1}$	(5.74e-05)	(5.72e-05)		(5.31e-05)	(5.29e-05)	(0.000144)	
Observations	8,270	8,270	8,343	8,300	8,300	2,641	2,773
R-squared	0.833	0.832	0.827	0.803	0.803	0.742	0.733
Only chairs' life experience							
HP GDP$_{c,t-1}$	0.107*			-0.00526		0.0709	
	(0.0593)			(0.00466)		(0.0448)	
Inflation$_{c,t}$	0.426***	0.417***	0.405***	0.153***	0.153***	-0.00945	0.00614
	(0.0979)	(0.0950)	(0.0992)	(0.0259)	(0.0259)	(0.0365)	(0.0288)
GDP growth$_{c,t}$	-0.0771	-0.0232	-0.0299	-0.00689	-0.00647	-0.0886	-0.131
	(0.0681)	(0.0588)	(0.0590)	(0.00486)	(0.00452)	(0.0720)	(0.0831)
EBF Inflation$_{c,t}$	0.113*	0.122*	0.122*	0.359***	0.360***	0.286***	0.237***
	(0.0689)	(0.0714)	(0.0712)	(0.0571)	(0.0572)	(0.106)	(0.0801)
EBF GDPgrowth$_{c,t}$	-0.0759	-0.0862*	-0.0908*	-0.00882	-0.00791	0.108	0.169
	(0.0459)	(0.0505)	(0.0499)	(0.00636)	(0.00587)	(0.137)	(0.130)
Monetary Policy	-9.91e-05*	-9.83e-05*		-7.49e-05	-7.43e-05	3.70e-05	
Rate$_{c,t-1}$	(5.87e-05)	(5.85e-05)		(5.42e-05)	(5.40e-05)	(0.000158)	
Observations	7,664	7,664	7,752	7,723	7,723	2,416	2,563
R-squared	0.834	0.834	0.829	0.804	0.804	0.746	0.734

All regression include country and time fixed effects (omitted).
Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.

Table A.14: Panel regressions (annual frequency) of the monetary policy rate based on the life experience forecasts: only chairs' life experience

Regressions with multiple values of the updating parameter theta					
$\theta =$	1.5	2.5	3	3.25	3.5
Inflation$_{c,t-1}$	0.0238	0.0186	0.0161	0.0155	0.0149
	(0.0228)	(0.0242)	(0.0249)	(0.0251)	(0.0252)
GDP growth$_{c,t-1}$	0.0605	0.0482	0.0453	0.0459	0.0468
	(0.0833)	(0.0738)	(0.0717)	(0.0716)	(0.0717)
EBF Inflation$_{c,t}$	0.256***	0.267***	0.272***	0.272***	0.272***
	(0.0830)	(0.0859)	(0.0867)	(0.0863)	(0.0857)
EBF GDPgrowth$_{c,t}$	0.0126	0.0676	0.0728	0.0686	0.0621
	(0.108)	(0.129)	(0.136)	(0.137)	(0.138)
Monetary Policy	-0.000363	-0.000329	-0.000311	-0.000296	-0.000286
Rate$_{c,t-1}$	(0.000221)	(0.000203)	(0.000193)	(0.000190)	(0.000187)
Observations	2,189	2,189	2,189	2,189	2,189
R-squared	0.764	0.768	0.771	0.771	0.772
$\theta =$	4	4.5	5	6	7
Inflation$_{c,t-1}$	0.0149	0.0148	0.0159	0.0230	0.0293
	(0.0251)	(0.0248)	(0.0242)	(0.0240)	(0.0255)
GDP growth$_{c,t-1}$	0.0510	0.0507	0.0501	0.0494	0.0489
	(0.0732)	(0.0748)	(0.0769)	(0.0804)	(0.0835)
EBF Inflation$_{c,t}$	0.268***	0.265***	0.259***	0.231***	0.208***
	(0.0832)	(0.0800)	(0.0755)	(0.0649)	(0.0614)
EBF GDPgrowth$_{c,t}$	0.0423	0.0387	0.0332	0.0199	0.00873
	(0.139)	(0.130)	(0.120)	(0.101)	(0.0870)
Monetary Policy	-0.000266	-0.000250	-0.000241	-0.000237	-0.000238
Rate$_{c,t-1}$	(0.000183)	(0.000183)	(0.000187)	(0.000217)	(0.000240)
Observations	2,189	2,189	2,189	2,189	2,189
R-squared	0.771	0.771	0.769	0.762	0.755

All regression include country and time fixed effects (omitted).
Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.

Table A.15: Quarterly panel regressions of the monetary policy rate based on the life experience (inflation and real GDP growth) forecasts

Regressions use all countries separately even if some countries are in the same monetary zone.							
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 1	Model 2
		year on year		quarter on quarter		annual	
Averages for the national monetary policy makers (chair, governors, board)							
HP $\text{GDP}_{c,t-1}$	0.233			0.0376		0.117	
	(0.150)			(0.0346)		(0.188)	
$\text{Inflation}_{c,t-1}$	0.221***	0.230***	0.221***	0.181***	0.188***	0.000881	0.00171
	(0.0443)	(0.0424)	(0.0440)	(0.0293)	(0.0256)	(0.0251)	(0.0240)
GDP $\text{growth}_{c,t-1}$	-0.190	-0.00997	-0.0153	-0.0372	-0.00445	-0.0379	0.0449
	(0.131)	(0.0321)	(0.0327)	(0.0340)	(0.00460)	(0.180)	(0.0536)
EBF $\text{Inflation}_{c,t}$	0.280***	0.284***	0.282***	0.318***	0.319***	0.249***	0.249***
	(0.0624)	(0.0635)	(0.0628)	(0.0496)	(0.0523)	(0.0726)	(0.0722)
EBF $\text{GDPgrowth}_{c,t}$	-0.0524**	-0.0814**	-0.0832**	-0.00408	-0.00826	0.0216	-0.0276
	(0.0247)	(0.0383)	(0.0376)	(0.00378)	(0.00572)	(0.0954)	(0.0809)
Monetary Policy		-0.000108*			-0.000104*	-0.000104	-0.000115
$\text{Rate}_{c,t-1}$		(5.53e-05)			(5.33e-05)	(0.000215)	(0.000220)
Observations	9,823	9,768	9,823	9,853	9,798	3,018	3,018
R-squared	0.836	0.841	0.835	0.819	0.823	0.751	0.751
Only chairs' life experience							
HP $\text{GDP}_{c,t-1}$	0.245			0.0371		0.104	
	(0.156)			(0.0358)		(0.201)	
$\text{Inflation}_{c,t-1}$	0.226***	0.236***	0.226***	0.188***	0.195***	-8.91e-05	0.000644
	(0.0457)	(0.0439)	(0.0455)	(0.0302)	(0.0263)	(0.0259)	(0.0248)
GDP $\text{growth}_{c,t-1}$	-0.195	-0.00575	-0.0114	-0.0364	-0.00421	-0.0317	0.0413
	(0.135)	(0.0338)	(0.0345)	(0.0351)	(0.00489)	(0.192)	(0.0581)
EBF $\text{Inflation}_{c,t}$	0.283***	0.287***	0.285***	0.321***	0.322***	0.247***	0.247***
	(0.0635)	(0.0646)	(0.0639)	(0.0506)	(0.0536)	(0.0745)	(0.0742)
EBF $\text{GDPgrowth}_{c,t}$	-0.0559**	-0.0856**	-0.0873**	-0.00427	-0.00840	0.0311	-0.0121
	(0.0267)	(0.0408)	(0.0401)	(0.00415)	(0.00603)	(0.107)	(0.0892)
Monetary Policy		-0.000108*			-0.000106*	-7.21e-05	-8.19e-05
$\text{Rate}_{c,t-1}$		(5.70e-05)			(5.51e-05)	(0.000227)	(0.000232)
Observations	9,230	9,177	9,230	9,289	9,236	2,809	2,809
R-squared	0.838	0.843	0.837	0.822	0.825	0.754	0.754

All regression include country and time fixed effects (omitted).
Robust standard errors in (). Clusters by country.
***,**,* denote 1%, 5%, 10% statistical significance.

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