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# From Multiplicative to Additive Growth: Redefining TFP in the European Framework

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# Abstract

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In a recent paper, Thomas Philippon argues that total factor productivity (TFP) has historically followed an additive rather than an exponential growth path. Exponential TFP modelling is part of the fiscal and macroeconomic surveillance toolbox at the European level. The corresponding state-space model and its Bayesian estimation are part of the Commonly Agreed Method (CAM) for the estimation of potential output growth. Given the high relevance of the CAM for economic policy, we propose a model that introduces the idea of additive growth through a simple transformation of the data, while maintaining the structure of the state-space model and the estimation procedure. The adaptation of the current estimation methodology used by the European Commission and member states of the European Union (1) improves the forecast error in the long run and (2) obtains reliable estimates of the short-run gap. Using US data and data for the 6 largest European countries, we are able to reduce the RMSFE by 35 percent on average for various forecast horizons compared to the CAM.

**Keywords:** Forecasting, Time Series, Aggregate Productivity, TFP Growth
**JELs:** C32, C53, D24, E66, O47

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# 1 Introduction

In a recent paper, Philippon (2022) argues that total factor productivity (TFP) can be better described as a process involving additive fixed increments rather than exponential growth with fixed growth rates. The additive model performs extremely well with US long-run data, and is shown to be superior to the exponential growth model in a number of other countries.

Regrading short-run forecasting, the differences between an additive and an exponential model are inconsequential; however with increasing forecast horizon, the differences between the two models get substantial.

In 2024, the fiscal surveillance in the European Union (EU) was reformed. Long-run projections for fiscal sustainability have come under scrutiny. This implies a shift in the focus of macroeconomic analysis and forecasting. While business cycle analysis to calculate structural budget balances at the current edge was the main focus in former years, the long-term potential growth now carries more weight. The question arises whether this shift should be reflected in the methods applied by the European Commission and the member states of the EU for medium and long-run forecasts.

Both, European Commission and the member states of the EU, use the so-called Commonly Agreed Method (CAM) for the purpose of potential output estimations and medium to long-run forecasting. The CAM is based on the production function approach. Capital, labour and TFP follow their own independent models. In this paper, we focus on the TFP since it shows – as it is constructed as a residual – the largest revisions, even in the short to medium term (Boysen-Hogrefe and Hoffmann, 2024). This stands in contrast to the modeling of the capital stock and potential labor, which incorporates multiple economic variables and the theoretical relationships between them. TFP estimation is based on the model described by Planas, Roeger, and Rossi (2013). The state-space model considers log TFP to be an observable variable. Assuming that changes in log TFP are approximately constant implies exponential growth in levels. This assumptions follows, not least, from standard exogenous growth theory and from endogenous growth models such as Romer (1986). A Bayesian estimation is conducted for the model and the POWG deliberates on the priors. In principle, this TFP model can provide projections for any forecast horizon. However, Philippon's results may suggest that, in the long run, a model implying exponential growth may be unsuitable. Conversely, the additive model with a fixed increment discussed in Philippon (2022) lacks the flexibility to capture the business cycle in most of the European countries. Actually, a major advantage of the Planas, Roeger, and Rossi (2013) model is that short run dynamics are included via an indicator measuring capacity utilization.

For this reason, we propose modifying the state-space model in the CAM. For this purpose, we do not take logs, but instead rescale the TFP so that the first two moments of the log TFP are met. This rescaling enables us to use the same estimation routine as in the current CAM. Following the estimation of the trend TFP, the results are rescaled back. We can demonstrate that the proposed modification would have provided more accurate long-run forecasts in recent decades and that the revisions would have been smaller compared to the state-space model with log TFP. Furthermore, our adaptation is straightforward to implement, as it requires neither changes to the underlying model structure nor adjustments to the assumed priors. This increases the likelihood of adoption by policymakers, such as the European Commission. In addition, we show that essential in-sample characteristics of the original CAM model are invariant to our modification. Most notably, it preserves the estimated TFP gaps, implying that past economic assessments based on the existing CAM methodology need not be revised.

Longer run forecasts are often found to be too optimistic (Estefania-Flores et al., 2022), the exponential modeling of the TFP may one reason for this. Since the corresponding forecast errors can have a relevant impact on public budgeting and economic policy (Ademmer and Boysen-Hogrefe, 2022; Beaudry and Willems, 2022), the paper contributes to the question how to achieve reliable fiscal planning with the goal of sustainable public finances.

The remainder of the paper is structured as follows. Section 2 covers additive growth, while section 3 presents the TFP model applied in the CAM and the modification proposed in this paper. Sections 4 and 5 are devoted to the presentation of the data and the results. Section 6 concludes.

## 2 Additive Growth

In standard growth theory with exogenous productivity growth, TFP, denoted by $SR_t$, is assumed to follow a constant or highly persistent growth rate, $g$, in logs:

$$sr_{t+\tau} = g\tau + sr_t, \tag{1}$$

with $\tau > 0$ and $sr_t = \log SR_t$. Thereby, TFP follows an exponential growth path in levels, i.e.,

$$SR_{t+\tau} = (1+g)^{\tau} SR_t. \tag{2}$$

Endogenous growth models such as Romer (1986) also imply multiplicative and exponential growth, respectively.

In contrast, Philippon (2022) suggest on the bases of the datasets provided by Fernald (2014) and Bergeaud, Cette, and Lecat (2016) including 23 countries and 123 years that TFP growths with fixed increments $b$:

$$SR_{t+\tau} = b\tau + SR_t. \tag{3}$$

The fixed increments are country-specific and remain constant over long periods of time. Structural breaks in $b$ are triggered by major discoveries such as the introduction of electricity.[1] That means that TFP increases linearly in levels. Still, labour productivity is convex in time and livings standards are rising at an accelerating pace (Philippon, 2022). Sampi (2024) also finds evidence of additive growth for most high-income countries, although the evidence for middle-income countries is limited. Assuming that productivity growth is linear, this partly resolves the productivity growth puzzle, as fixed increments translate into declining productivity growth rates.

In economic theory, innovations are the main driver of productivity growth (Romer, 1990). Philippon (2022) argues that previous inventions boost productivity but do not necessarily stimulate (the likelihood of) new discoveries. This is either because the sequence of discoveries

[1] A generalized long time model is $\mathbb{E}[SR_{t+1} - SR_t] = (1-p)b_t + p\xi SR_t$ with probably of a regime change $p \in [0,1]$ and multiplicative parameter $\xi$. This specification nests both, additive and multiplicative growth (Philippon, 2022). Either a major new discovery, such as the invention and application of artificial intelligence, or improvements in the allocation of talents, such a the rise of women investors, may represent a potential break point (Charles I. Jones, 2023).

is linear or bounded, i.e., an invention yields only a limited number of downstream benefits. Or it is because the sequence itself is not indefinite, implying that inter-temporal spillovers are limited. Moreover, knowledge can become outdated (Alston and Pardey, 2022; Pfeiffer, Varga, and Veld, 2024). As a consequence, the current stock of knowledge does not influence future TFP growth. And a constant increment leads to decreasing TFP growth rates. This finding is consistent with the extant literature on the productivity growth slowdown, which posits that there are departures from exponential growth theory (e.g. Bloom et al., 2020; Charles I Jones, 2017; Pfeiffer, Varga, and Veld, 2024). Diminishing marginal returns in the innovation process could be a key driver: discoveries may be harder to find. Then, exponential growth requires exponentially increasing research effort to counteract slowing productivity (Bloom et al., 2020; B. F. Jones, 2009; Kruse-Andersen, 2023).

# 3 Econometric Approach

In this section, we briefly outline the trend TFP estimation of the EU Commonly Agreed Method (CAM) along with our adjustments. We also describe the evaluation procedure.

## 3.1 Commonly Agreed Method

On EU and country level, potential output is estimated by the CAM. The estimate of potential output, $YPOT$, builds on a Cobb-Douglas production function approach,

$$YPOT = TFPT \cdot LP^{\alpha} \cdot K^{1-\alpha}, \tag{4}$$

where $TFPT$ is the trend TFP estimate, $LP$ is potential labour, $K$ is the capital stock, and $\alpha$ is the elasticity of labour.[2] The three inputs, labour, capital, and TFP, are estimated by three different and independent models. The unobserved component model to describe TFP is based on Planas, Roeger, and Rossi (2013). In the measurement equations, *log* TFP is considered as a observable variable, denoted by $sr_t$.[3] TFP is separated into a trend component $p_t$ and a cycle $c_t$. The cycle itself depends on a capacity utilization indicator, $cu_t$, to exploit the theoretical link between TFP and capacity utilization: While the economy's capacities are fully utilised and productivity increases in times of high aggregate demand, the opposite holds during a negative output gap. Subsequently, the model can better distinguish between business cycle and growth and thereby reduces revisions of TFP estimations, especially at the current edge (Planas, Roeger, and Rossi, 2013, Graff and Sturm, 2012, D'Auria et al., 2010, and Turner et al., 2016).[4] The European Commission uses the Capacity-Utilization-and-Business-Sentiment (CUBS) indicator as a proxy for $cu_t$. The CUBS is constructed as a weighted average of a direct measure of capacity utilization in industry and two business sentiment indicators regrading the capacity utilization in services and in the construction sector (Havik et al., 2014). The error term $e_{cu.t}$ is modeled as a mean-zero AR(1) to allow for persistent deviations between CUBS,

[2] In section 3.1, we stick to the variable labels of Havik et al. (2014).

[3] The usage of *log* is indicated below by the use of lower case letters, e.g., $\log SR_t = sr_t$.

[4] It is even possible to add more survey data to further reduce revisions, e.g., Carstensen, Kießner, and Rossian (2024).

$cu_t$, and the cycle, $c_t$. Thus, the measurement equations are

$$sr_t = p_t + c_t \tag{5}$$

$$cu_t = \mu_{cu} + \beta c_t + e_{cu,t} \tag{6}$$

$$e_{cu,t} = \delta_{cu} e_{cu,t-1} + a_{cu,t}, \qquad a_{cu,t} \overset{\text{iid}}{\sim} \mathcal{N}(0, V_{cu}), \tag{7}$$

with $|\delta_{cu}| < 1$. The trend component of TFP, $p_t$, in which we are interested, follows a random walk with slope $\mu_t$. The slope is defined as an AR(1) process with intercept. Therefore, as $t \longrightarrow T$ for a sufficiently large $T$, $\Delta p_t$ converges to unconditional mean growth rate, implying exponential growth of TFP in levels (mean-reversion property). The description of the cycle, $c_t$, completes the state equations. The cycle is assumed to follow a mean-zero AR(2) process with periodicity $\tau > 0$ and amplitude $A \in [0, 1]$:

$$\Delta p_t = \mu_{t-1} \tag{8}$$

$$\mu_t = \omega(1-\rho) + \rho\mu_{t-1} + a_{\mu.t}, \qquad a_{\mu,t} \overset{\text{iid}}{\sim} \mathcal{N}(0, V_\mu) \tag{9}$$

$$c_t = 2Acos\left(\frac{2\pi}{\tau}\right) c_{t-1} - A^2 c_{t-2} + a_{c,t}, \qquad a_{c,t} \overset{\text{iid}}{\sim} \mathcal{N}(0, V_c), \tag{10}$$

where $|\rho| < 1$.

The CAM is estimated using a Metropolis-within-Gibbs sampler. By employing a Bayesian approach, it is possible to overcome stability issues that can arise with maximum likelihood.[5] The priors are aligned with those provided by the European Commission and remain unchanged.[6]

### 3.2 Adjusted CAM

To align the CAM with the idea of Additive Growth, we propose an adjusted methodology. In contrast to the conventional approach, which applies a logarithmic transformation to the Solow residuals ($SR$), this adjustment avoids log-linearization altogether. Instead, it introduces a moment-based rescaling of the untransformed data to align it with the statistical properties required for the CAM estimation and its associated priors. Specifically, the original Solow residuals $SR_u$ are standardized and shifted using the transformation

$$SR_{scale} = \frac{SR_u - \mu_u}{\sigma_u} \cdot \sigma_{log} + \mu_{log}, \tag{11}$$

where $(\mu_u, \sigma_u > 0)$ denote the mean and standard deviation of the untransformed SR, and $(\mu_{\text{log}}, \sigma_{\text{log}} > 0)$ represent the corresponding moments of the log-transformed residuals. This transformation ensures that the scaled series retains distributional properties similar to the logarithmized data, thereby enabling consistent application of the CAM and its priors. After estimating the trend TFP component via the CAM, the results are rescaled back to the original scale of the untransformed data to facilitate interpretation. This adjusted procedure preserves the benefits of the CAM framework while mitigating the exponential growth assumption implicitly made by the log transformation.

By including Solow residual data in levels rather than in logs, we redefine the mean-reversion property implied by equation 9. In the log specification, the TFP trend converges to a constant

[5] Havik et al. (2014) provides more details.

[6] The prior distributions can be found in the AMECO data base following circabc.europa.eu.

growth rate as $t \to T$ for a sufficiently large $T$. Similarly, when specified in levels, the TFP trend converges to a constant increment, directly linking to the notion of additive growth. Furthermore, these increments are not fixed. Insetad, they are allowed to converge gradually due to the auto-regressive component – either from below during a recovery or from above during a boom. Compared to a linear trend with fixed increment, this modeling assumption offers two advantages: First, it introduces flexibility into the TFP trend. While a linear trend smooths over recessions and booms, our specification allows for a degree of procycality, yielding more accurate and resolvable output gap estimates, comparing to other estimates such as survey indicators (Planas, Roeger, and Rossi, 2013). Second, this flexibility is bounded, as the trend still converges to a constant increment in the long run.

As a benchmark, we estimate trend TFP using the standard CAM approach based on log-transformed Solow residuals, referred to as CAM (*log*). In addition to the CAM-based methods, we include a simple linear trend model, denoted as *lin*. This specification corresponds to the main approach employed by Philippon (2022), wherein trend TFP evolves deterministically over time. By including both CAM and linear trend approaches, we aim to capture a range of assumptions about the nature of TFP dynamics, from purely deterministic to richly stochastic.

### 3.3 Forecast Experiment

To evaluate the forecasting performance of the different trend TFP estimation methods, we conduct an quasi-real-time out-of-sample forecast experiment based on an expanding window approach. For each iteration, the model is re-estimated using all available data up to time $t$, and forecasts are generated for horizons $h \in \{1, 5, 10\}$. It is important to note that forecast errors, particularly at medium- and long-term horizons, tend to exhibit serial correlation due to the overlapping nature of the forecast windows and the persistent structure of macroeconomic variables. Therefore, we restrict Diebold-Mariano (DM) tests for predictive accuracy to horizons $h \in \{1, 5\}$. Since TFP is a latent variable, it is generally not possible to compare predictions with its true values to assess forecast accuracy. Instead, we rely on the most recent estimate from the CAM model (*log*) for the year 2026 as a proxy.

A special emphasis is placed on the horizon $T+20$, which corresponds to the minimum forecast length required under the European Union's revised fiscal surveillance framework. However, given the limited availability of observations that extend far enough beyond the end of the estimation window, we are unable to compute meaningful forecast error statistics for this horizon. Consequently, we restrict our analysis of the $T + 20$ forecasts to a graphical comparison across models. This qualitative assessment provides insights into the longer-run implications of each trend estimation method, despite the absence of a formal quantitative evaluation at such extended horizons. Nevertheless, the results corresponding to the horizon $T + 10$ should offer a quantitative indication of model performances at longer ranges, and thus provide a useful benchmark.

### 3.4 Revisions and Procyclicality

Besides the forecast accuracy, we are interested in the magnitude of the revisions in a real-time setting. Assessing the magnitude of the revisions also allows us to examine potential procyclicality. Although the CAM is designed to extract the TFP trend component of TFP, analyses indicate that its trend estimate exhibit cyclical behavior (Boysen-Hogrefe and Hoffmann, 2024).

Revisions are defined as the difference between consecutive estimates of the same vintage, with step size $k \geq 1$. We denote revisions at time $s+k$ for period $t$ as $R_t^{s+k}$, with $t = 1, \ldots, T$, $s = 1, \ldots S$, and $s \geq t$. They are defined as follows:

$$R_t^{s+k} = \widehat{SR}_t^{s+k} - \widehat{SR}_t^{s}, \tag{12}$$

where $\widehat{SR}_t^{s}$ represents the estimate of the TFP trend for period $t$, made at time $s$. For simplicity and in line with Carstensen, Kießner, and Rossian (2024) and Planas, Roeger, and Rossi (2013), we focus on one- and four-step-revisions ($k = 1, 4$) and $t = s-2, s-1, \ldots, s+2$ in our analysis. By summing over s, we compute the root mean squared error as a summary measure of the magnitude of revisions and define it for clarity as

$$RMSR_t = \sqrt{\frac{1}{S-k} \sum_{s=1}^{S-k} \left(R_t^{s+1}\right)^2}. \tag{13}$$

Similar to Theil's U, we compare the RMSR of a model with its benchmark on a relative scale:

$$RR_t = \frac{RMSR_t^m}{RMSR_t^b}, \tag{14}$$

where $RMSR_t^m$ and $RMSR_t^b$ represent the mean revisions for model $m$ and its benchmark $b$, respectively. The CAM serves as our benchmark model.

# 4 Data and Stylized Facts

We assess the forecasting performance via data from the European Commission's AMECO database. Solow residuals, which proxy for total factor productivity (TFP), and capacity utilization indicators (CUBS), are obtained form this source. The sample covers the United States and the six largest European economies – Germany, France, Italy, Spain, the Netherlands, and the United Kingdom – over the period from 1980 to 2026. This time frame allows us to capture both long-run growth dynamics and cyclical variations in productivity.

During the sample periods, TFP tends to follow a linear trend in levels (Figure 1). This observation is consistent with the additive growth hypothesis, where productivity evolves along a deterministic linear path. Alternatively, the data may also be reconciled with an exponential growth model punctuated by recurrent structural breaks, suggesting periods of regime change or persistent shocks. Importantly, there are notable differences in the TFP trajectories between the United States and the European economies. In line with the results of Philippon (2022), deviations from the linear trend in Europe may reflect a catch-up effect. These transatlantic differences – or more precisely, differences between countries at and below the productivity frontier – highlight the importance of modeling flexibility, such as that offered by the CAM framework, when estimating and interpreting productivity trends across heterogeneous economies. This is especially relevant given that the most recent slowdown in TFP growth in Europe appears more pronounced than would be expected at the end of a typical catch-up period (Philippon, 2022). There a several possible channels for this difference, e.g., a misallocation of factors in low-income countries as Restuccia and Rogerson (2017) argue. For southern European countries such as Portugal and Spain, Reis (2013) links the slowdown in productivity growth following their entry into the Euro area to a misallocation of substantial capital inflows. Gopinath et al.

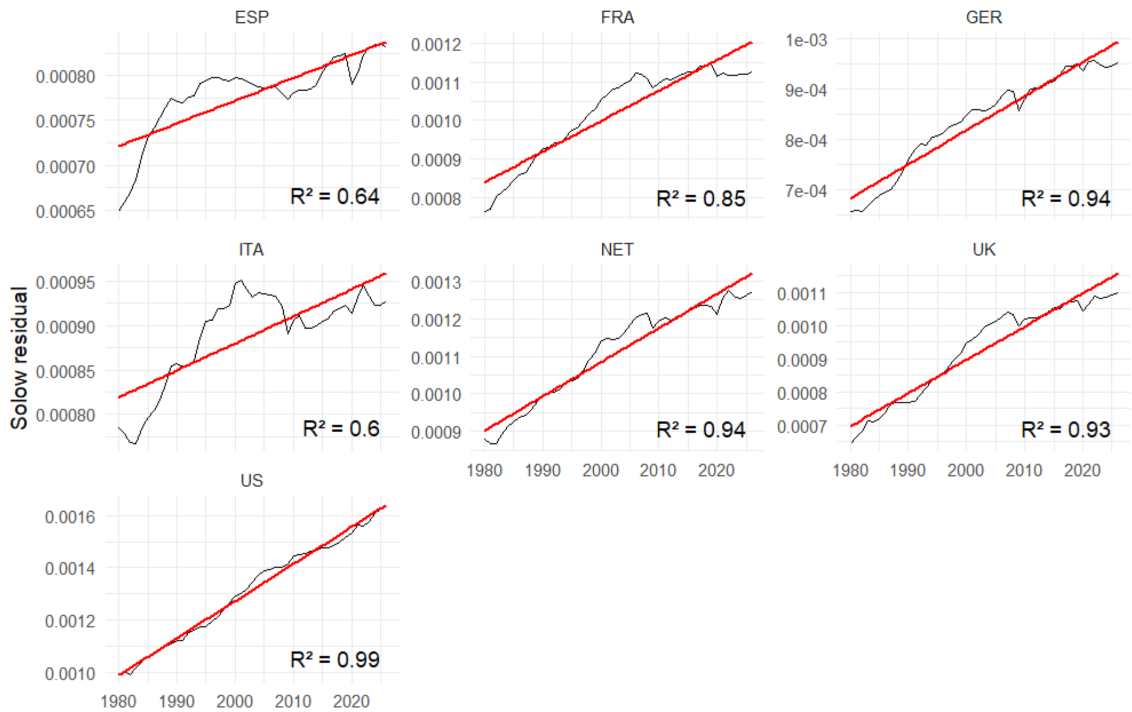


Figure 1: Solow Residual data

*Note:* The Solow residual data (black) spans the years 1980-2026. A linear regression line (red) is included to illustrate the deviation of the observed data from a purely additive growth path.

(2017) arrive at a similar conclusion, identifying misallocation in Spain and Italy, but not in France or Germany.

For the revision analysis, we use real-time data on Solow residuals and the CUBS for the same five EU countries – Germany, France, Italy, Spain, and the Netherlands – provided by Carstensen, Kießner, and Rossian (2024). The authors also collected the data from the European Commission's AMECO database. Since the CUBS indicator was first published in 2009, they constructed pseudo-real-time vintages for the years 2005 to 2008. The dataset includes two projections per year (spring and autumn), beginning with the autumn forecast of 2005 and ending with the autumn forecast of 2021.

To avoid structural breaks, we rescale the real-time data. For all vintages, we set the 1990 value equal to the 1990 value of the last vintage, autumn 2021. By multiplying of the year- and vintage-specific growth rates, we obtain smoothed time series. Although the smoothing methodology requires arbitrary assumptions such as the year to fix, other smoothing approaches yield similar results.[7]

[7] An alternative smoothing approach is to compute the ratio of 10-year averages of TFP values between the last and another vintage. Multiplying by this ratio also generates a smooth time series. In practice, both smoothing methodologies yield almost identical results.

# 5 Results

## 5.1 TFP Cycles

The in-sample estimates of the TFP gap under the adjusted CAM specification (*skal*) are nearly indistinguishable from those obtained using the standard CAM with log-transformed residuals (*log*), across all countries in the sample. This close alignment suggests that the proposed transformation preserves the core dynamics captured by the original CAM approach. In contrast, the linear trend specification (*lin*) yields systematically different gap estimates, often diverging significantly from those implied by the CAM framework. These differences underscore the limitations of purely deterministic models in capturing cyclical fluctuations in productivity.

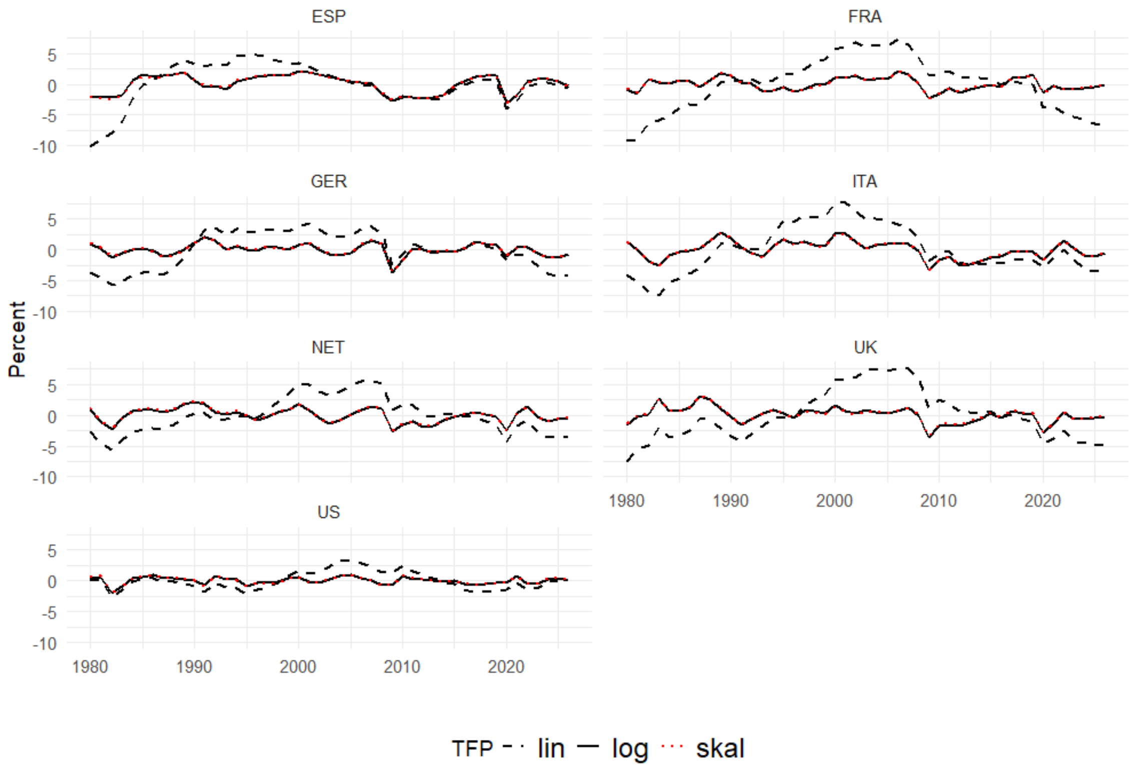


Figure 2: TFP cycles

*Note:* TFP cycles for several countries based on the CAM (*log*, slid line), adjusted CAM (*skal*, red dotted line), and linear model (*lin*, dashed line). Models are estimated over 1980-2026.

Crucially, our adjusted method (*skal*) succeeds in preserving the gap structure of the standard CAM while avoiding the potentially problematic logarithmic transformation. As a result, the adoption of *skal* does not imply any need to 'rewrite economic history': historical TFP gap estimates remain stable and consistent with previous findings, while the model gains in flexibility and applicability, particularly in cases where the log transformation may be inappropriate.

## 5.2 Forecast Performance

We evaluate the three models using root mean squared forecast errors (RMSFE) at horizons $h \in \{1, 5, 10\}$, and report Theil's $U$ statistics relative to the benchmark CAM with log-transformed residuals (*log*). Theil's $U$ values below one indicate superior forecast accuracy compared to the benchmark.

The results reveal a clear distinction between the two alternative specifications. The adjusted CAM (*skal*) consistently outperforms the benchmark across countries and horizons, with Theil's $U$ values typically well below one – particularly at medium and longer horizons ($h \in \{5, 10\}$, Table 1). As expected, the forecast accuracy of the adjusted CAM increases with the forecast horizon, as the difference between linear and exponential growth becomes substantial for large $h$. More surprisingly, even one-year-ahead Theil's U is smaller than one for almost all countries. Spain is the exception here. Nevertheless, the forecast accuracy increases by around 30 percent across the country sample. For larger time horizons, the average increase in accuracy is around 35 percent for $h = 5$ and 40 percent for $h = 10$. Despite the small number of observations, a DM-test supports a significantly better forecast accuracy for horizon $h = 1$. Due to the lack of observations, the difference between the projections becomes less significant for the medium-term ($h = 5$). Latest for the long term, $h = 10$, the sample size is too low to deliver interpretable results for the DM-test.

The results suggests that the *skal* transformation retains the desirable properties of the original CAM – the TFP cycle remains nearly untouched – while offering improved forecast accuracy. By contrast, the linear trend model (*lin*) performs significantly worse, with Theil's $U$ values often exceeding one by large margins, especially at shorter horizons, where short-run fluctuations are more relevant. The exception are the USA for medium and large horizons and the Netherlands as well as the UK for large horizons. These differences underscore the importance of preserving a model-based estimate of cyclical TFP dynamics for accurate projection – especially for short-term dynamics.

Furthermore, the level of improvement varies between the countries and depends on the degree of linearity of the Solow residual data (Figure 3). For the US, where Solow residuals follow a linear trend almost entirely (Figure 1), Theil's U is smallest. That is also the reason while the linear trend (*lin*) performs best for the US and large forecast horizons. In contrast, countries with a smaller degree of linearity within their Solow residuals such as Italy show a higher Theil's U, i.e., a smaller improvement of the forecast accuracy due to the scaling.

For the European fiscal surveillance, even larger forecast horizons are needed (at least $T + 20$). While an assessment of out-of-sample forecast errors reaches its limits due to the lack of observations, a graphical analysis might support previous findings. Therefore, we create projections for all three models (*log*, *skal*, and *lin*) with ex post data up the years 2000, 2010, and 2020 and compare it with the current estimate of the TFP trend (*Actual*). The results emphasize the previous findings: For large horizons, the adjusted CAM would have provided more accurate projections (Figure 4). Nevertheless, an upward bias seems to be present in all models: compared to the current trend TFP estimation, all three predictions would have been too optimistic.

### 5.3 Revision Analysis

For the purpose of fiscal planning it is not just the accuracy but also the stability of forecasts that matters. In this context, minimizing model revisions is essential. To asses this aspect, we compare our adjusted CAM with the current version by shifting the evaluation setting from pseudo-real-time to real-time, thereby allowing for data revisions. We examine a subsample of

Table 1: RMSFE and Theil's U for $h \in \{1, 5, 10\}$

| | | **GER** | **FRA** | **ESP** | **ITA** | **NET** | **UK** | **US** |
|---|---|---|---|---|---|---|---|---|
| | | | | | $h = 1$ | | | |
| $TFP_{\text{log}}$ | RMSFE $\times 10^{10}$ | 1.98 | 6.46 | **0.47** | 1.92 | 3.46 | 6.75 | 2.75 |
| $TFP_{\text{skal}}$ | RMSFE $\times 10^{10}$ | 1.18*** | 5.16** | 0.50 | 1.72*** | 2.09*** | 3.20*** | 1.51** |
| | Theil's U | **0.60** | **0.80** | 1.06 | **0.90** | **0.60** | **0.47** | **0.55** |
| $TFP_{\text{lin}}$ | RMSFE $\times 10^{10}$ | 9.48*** | 34.41*** | 8.64*** | 16.12*** | 13.91*** | 19.54*** | 4.90* |
| | Theil's U | 4.79 | 5.33 | 18.27 | 8.39 | 4.02 | 2.89 | 1.78 |
| 26 observations | | | | | | | | |
| | | | | | $h = 5$ | | | |
| $TFP_{\text{log}}$ | RMSFE $\times 10^{8}$ | 0.14 | 0.40 | 0.02 | 0.12 | 0.25 | 0.45 | 0.19 |
| $TFP_{\text{skal}}$ | RMSFE $\times 10^{8}$ | 0.07** | 0.29 | 0.02 | 0.10* | 0.15 | 0.22 | 0.10 |
| | Theil's U | **0.51** | **0.74** | **0.90** | **0.86** | **0.59** | **0.49** | **0.52** |
| $TFP_{\text{lin}}$ | RMSFE $\times 10^{8}$ | 0.23 | 0.81 | 0.18 | 0.44** | 0.35 | 0.48 | 0.11 |
| | Theil's U | 1.64 | 2.04 | 9.08 | 3.69 | 1.42 | 1.08 | 0.57 |
| 22 observations | | | | | | | | |
| | | | | | $h = 10$ | | | |
| $TFP_{\text{log}}$ | RMSFE $\times 10^{8}$ | 0.54 | 1.76 | 0.05 | 0.45 | 1.20 | 2.01 | 0.78 |
| $TFP_{\text{skal}}$ | RMSFE $\times 10^{8}$ | 0.22 | 1.17 | 0.03 | 0.36 | 0.67 | 0.90 | 0.30 |
| | Theil's U | **0.41** | **0.66** | **0.68** | **0.81** | **0.56** | **0.45** | 0.39 |
| $TFP_{\text{lin}}$ | RMSFE $\times 10^{8}$ | 0.54 | 1.83 | 0.37 | 1.12 | 0.87 | 1.11 | 0.20 |
| | Theil's U | 1.00 | 1.04 | 7.46 | 2.49 | 0.72 | 0.55 | **0.26** |
| 17 observations | | | | | | | | |

*Note:* Root Mean Squared Forecast Errors are scaled to standardised powers of ten. Theil's U measures the relative forecast accuracy compared to the variant *log*. Bold values indicate the best forecast accuracy for the specific country and forecast horizon. Models are estimated over 1980-2026. Due to the large autocorrelation of errors for large forecast horizons, a Diebold-Mariano test is left out for $h = 10$.

*Significance levels:* Stars indicate statistically significant differences based on the Diebold-Mariano test for predictive accuracy: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

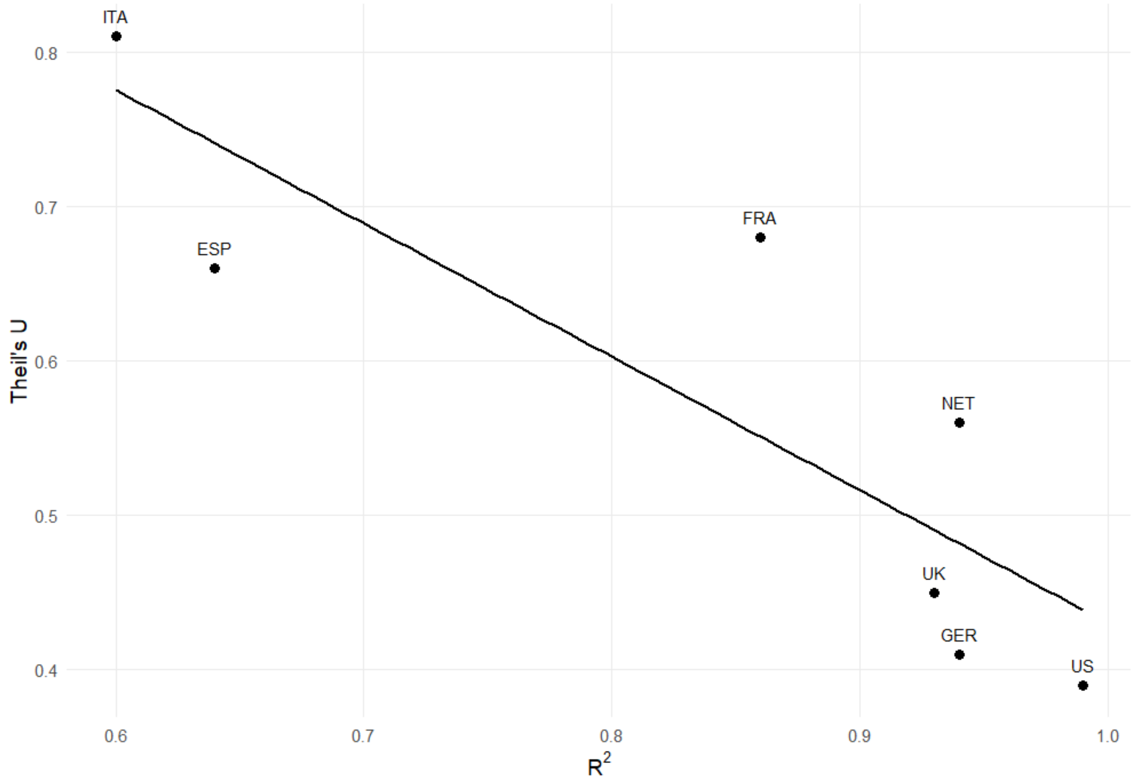


Figure 3: Linearity and forecast performance

*Note:* Linear regression of the Theil's U of the adjusted CAM (*skal*) (c.f. Table 1) on the $R^2$ of the Solow residual data (c.f. Figure 1).

the years from 2005 to 2019 out of the years from 1980 to 2023 for which TFP is estimated. This choice shall guarantee an a sufficient large base sample for model estimates. We compute the one-step ($k = 1$, left panel) and four-step ($k = 4$, right panel) revisions and observe a almost identical revision pattern of the CAM (*log*) and the adjusted CAM (*skal*) (Figure 5).[8] The linear model reveals a very similar but less diverse revision pattern, at least for the one-step revisions. The revisions of all three models seem to follow the output gap and are thereby procyclical. This becomes particularly clear in the case $k = 4$. The output gap is estimated as the deviation of the CUBS indicator which captures the aggregated capacity utilization from its mean. Consequently, the German TFP trend estimates are revised downward in 2007 due to the financial crisis and in 2019 due to the energy crisis.

To quantitatively analyze the revisions, we compute the *RMSR*, as defined in equation 13, for horizons $h \in \{-2, -1, \ldots, 2\}$. This means we evaluate the revisions for the last *ex post* year of the latent TFP (where the vintage year coincides with the estimated year, i.e., $h = 0$), as well as for the two years preceding and following that year. Once again, we distinguish between two cases: one-step ($k = 1$) and four-step ($k = 4$) revisions.

For Germany and France, the *RMSR* rises steadily with $h$ (Table 2). For France, the benchmark *RMSR* values are larger than those in Germany. For both countries, the adjusted

[8] The same figures for France, Spain, Italy, and the Netherlands can be found in appendix B. The same pattern is evident in every country.

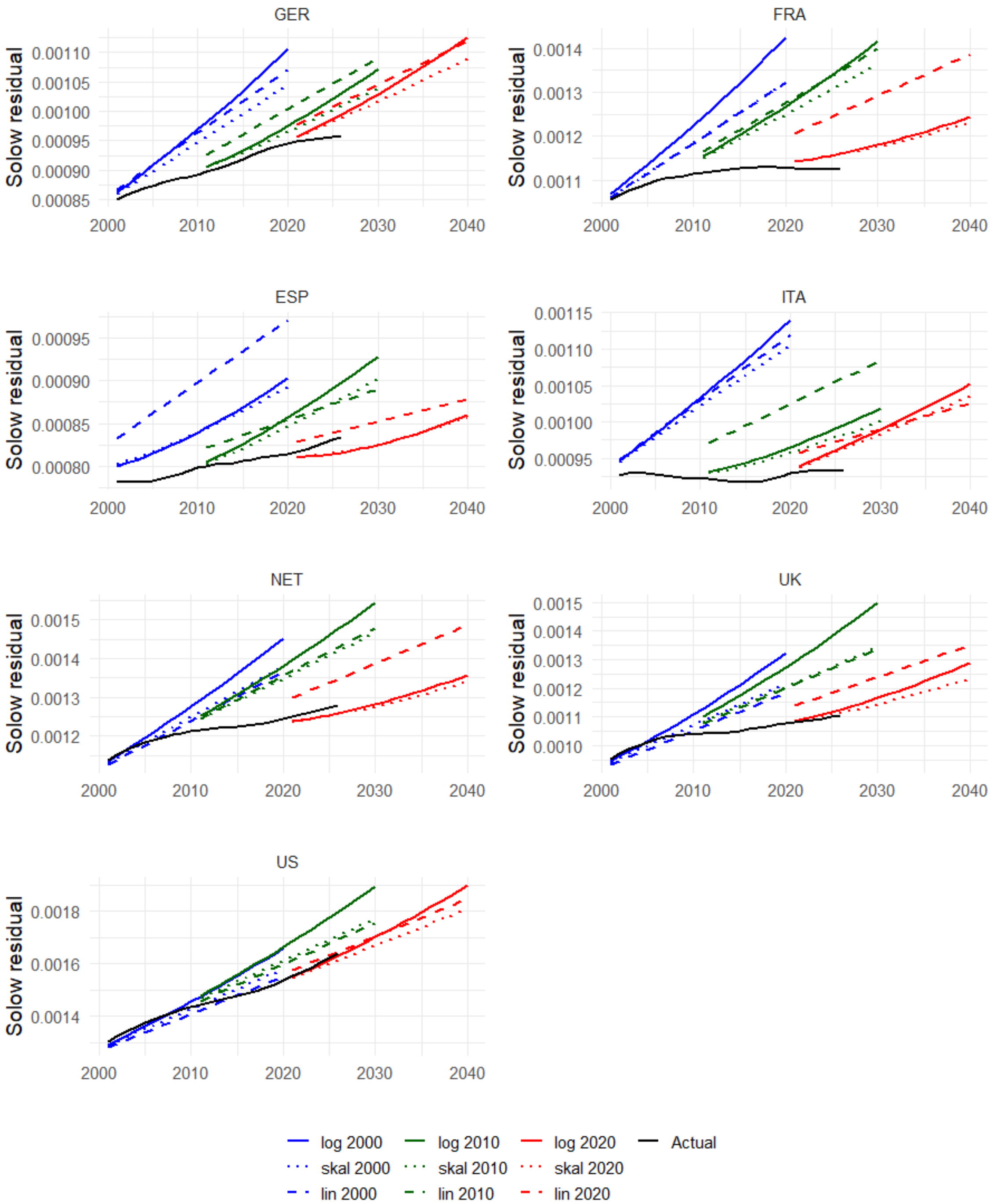


Figure 4: Out-of-sample predictions for $T + 20$

*Note:* Out-of-sample predictions for the years 2000 (blue), 2010 (green), and 2020 (red) are made 20 years in advance for Germany, Spain, France, Italy, the Netherlands, the UK, and the US using the CAM (*log*, solid line), adjusted CAM (*skal*, dotted line), and linear model (*lin*, dashed line). The true values of the latent TFP are taken as the most recent estimate from the CAM.

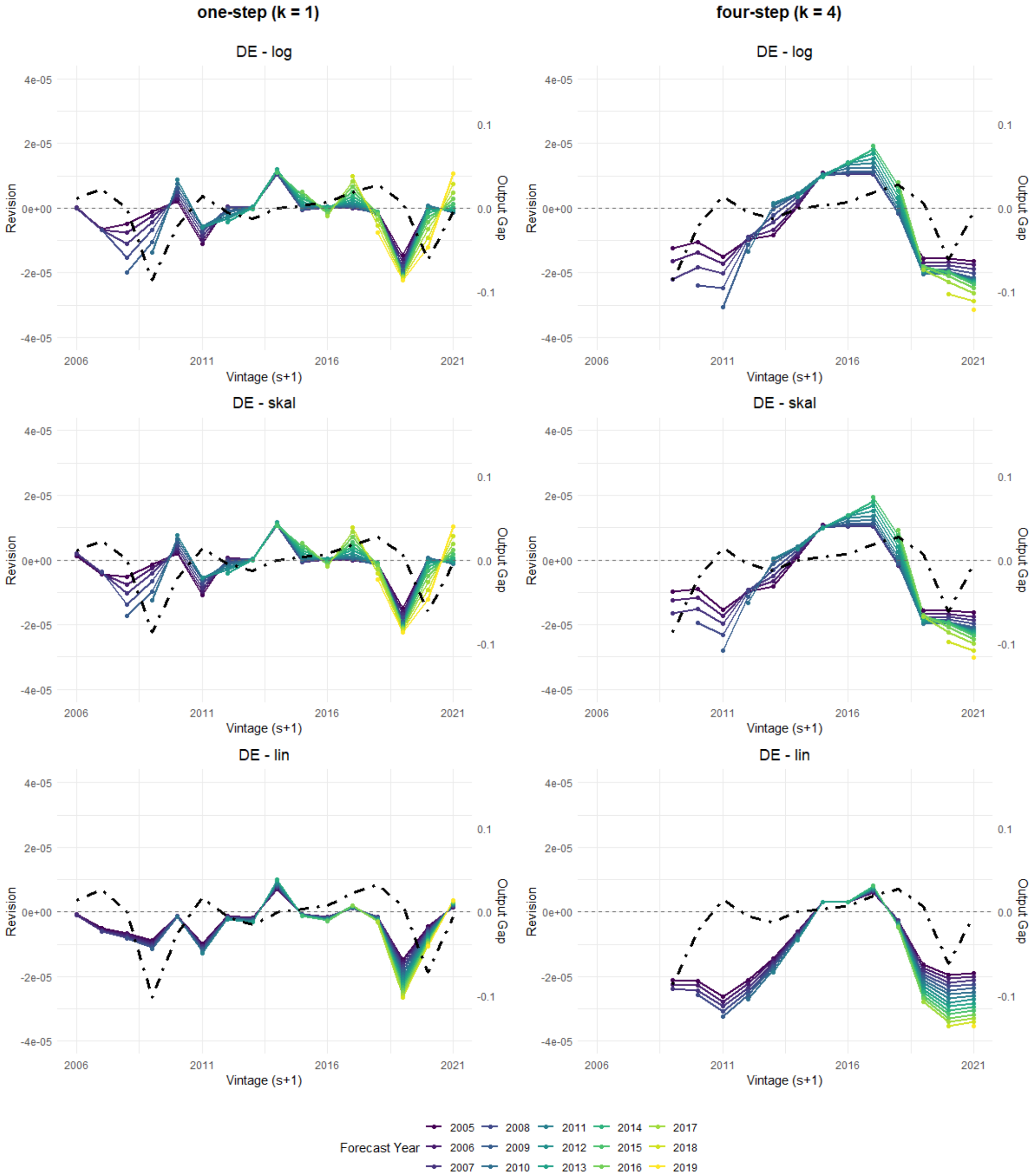


Figure 5: Revisions for vintages from 2006 to 2021 in Germany

*Note:* The figure shows how the TFP estimates for Germany of the years from 2005 to 2021 (the forecast year, colored lines) change throughout the various vintages (2006 to 2021). The results are presented for all three models. The revisions, $R_t^{s+k}$, as defined in equation 12, are shown for $k = 1$ (one-step revisions, left panel) and $k = 4$ (four-step revisions, right panel). Aligning the revisions with the output gap (black, dot-dashed line on the right-hand axis) suggests procyclicality. The output gap is estimated as the deviation of the CUBS indicator from the most recent vintage (2021) from its mean.

Table 2: RMSR and relative revisions

| | | | one-step ($k = 1$) | | | | | four-step ($k = 4$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $h$ | $-2$ | $-1$ | 0 | 1 | 2 | $-2$ | $-1$ | 0 | 1 | 2 |
| GER | $TFP_{\text{log}}$ | RMSR $\times 10^5$ | 0.72 | 0.80 | 0.91 | 1.07 | 1.23 | 1.30 | 1.38 | 1.50 | 1.69 | 1.96 |
| | $TFP_{\text{skal}}$ | RMSR $\times 10^5$ | 0.72 | 0.78 | 0.88 | 1.01 | 1.14 | 1.28 | 1.35 | 1.45 | 1.60 | 1.80 |
| | | RR | **0.99** | **0.98** | 0.96 | 0.94 | 0.93 | **0.99** | **0.98** | **0.96** | **0.95** | **0.92** |
| | $TFP_{\text{lin}}$ | RMSR $\times 10^5$ | 0.80 | 0.83 | 0.86 | 0.89 | 0.92 | 1.91 | 2.00 | 2.09 | 2.19 | 2.28 |
| | | RR | 1.10 | 1.04 | **0.94** | **0.83** | **0.75** | 1.47 | 1.45 | 1.39 | 1.29 | 1.17 |
| FRA | $TFP_{\text{log}}$ | RMSR $\times 10^5$ | 1.56 | 1.66 | 1.77 | 1.90 | 2.04 | 2.30 | 2.45 | 2.66 | 2.93 | 3.26 |
| | $TFP_{\text{skal}}$ | RMSR $\times 10^5$ | 1.47 | 1.54 | 1.62 | 1.72 | 1.83 | 2.27 | 2.30 | 2.38 | 2.50 | 2.68 |
| | | RR | 0.95 | 0.93 | 0.91 | 0.90 | 0.90 | **0.99** | **0.94** | **0.89** | **0.85** | **0.82** |
| | $TFP_{\text{lin}}$ | RMSR $\times 10^5$ | 1.46 | 1.53 | 1.60 | 1.66 | 1.73 | 2.63 | 2.77 | 2.91 | 3.06 | 3.20 |
| | | RR | **0.94** | **0.92** | **0.90** | **0.87** | **0.85** | 1.14 | 1.13 | 1.10 | 1.04 | 0.98 |
| ESP | $TFP_{\text{log}}$ | RMSR $\times 10^5$ | **0.79** | 0.82 | 0.87 | 0.94 | 1.02 | **1.72** | 1.77 | 1.85 | 1.98 | 2.12 |
| | $TFP_{\text{skal}}$ | RMSR $\times 10^5$ | 0.79 | 0.82 | 0.86 | 0.92 | 1.00 | 1.72 | 1.76 | 1.82 | 1.92 | 2.04 |
| | | RR | **1.00** | **0.99** | **0.99** | **0.98** | **0.98** | **1.00** | **0.99** | **0.99** | **0.97** | **0.96** |
| | $TFP_{\text{lin}}$ | RMSR $\times 10^5$ | 0.86 | 0.90 | 0.94 | 0.98 | 1.02 | 1.89 | 1.98 | 2.07 | 2.16 | 2.25 |
| | | RR | 1.09 | 1.10 | 1.08 | 1.04 | 1.00 | 1.10 | 1.12 | 1.12 | 1.09 | 1.06 |
| ITA | $TFP_{\text{log}}$ | RMSR $\times 10^5$ | 0.40 | 0.55 | 0.73 | 0.93 | 1.12 | 0.57 | 0.71 | 0.88 | 1.08 | 1.30 |
| | $TFP_{\text{skal}}$ | RMSR $\times 10^5$ | 0.38 | 0.53 | 0.71 | 0.90 | 1.09 | 0.56 | 0.69 | 0.86 | 1.05 | 1.27 |
| | | RR | **0.97** | **0.97** | 0.97 | 0.98 | 0.98 | **0.98** | **0.98** | **0.98** | **0.98** | **0.98** |
| | $TFP_{\text{lin}}$ | RMSR $\times 10^5$ | 0.59 | 0.63 | 0.66 | 0.69 | 0.72 | 1.86 | 1.97 | 2.09 | 2.20 | 2.32 |
| | | RR | 1.50 | 1.15 | **0.90** | **0.74** | **0.65** | 3.24 | 2.77 | 2.36 | 2.05 | 1.79 |
| NET | $TFP_{\text{log}}$ | RMSR $\times 10^5$ | **2.07** | **2.21** | **2.37** | 2.57 | 2.79 | 3.91 | 4.21 | 4.58 | 5.03 | 5.55 |
| | $TFP_{\text{skal}}$ | RMSR $\times 10^5$ | 2.12 | 2.26 | 2.43 | 2.62 | 2.82 | 3.86 | 4.16 | 4.55 | 5.00 | 5.50 |
| | | RR | 1.02 | 1.02 | 1.02 | 1.02 | 1.01 | **0.99** | **0.99** | **0.99** | **0.99** | 0.99 |
| | $TFP_{\text{lin}}$ | RMSR $\times 10^5$ | 2.18 | 2.29 | 2.39 | 2.50 | 2.60 | 4.59 | 4.80 | 5.02 | 5.23 | 5.45 |
| | | RR | 1.05 | 1.04 | 1.01 | **0.97** | **0.93** | 1.17 | 1.14 | 1.10 | 1.04 | **0.98** |
| Observations | | | | | 16 | | | | | 12 | | |

*Note:* Root Mean Squared Revisions (*RMSR*), as defined in equation 13, are scaled to standardised powers of ten. One-step ($k = 1$) and four-step ($k = 4$) revisions are computed. *RR* measures the relative revisions compared to the baseline model log as defined in equation 14. Bold values indicate the minimum revision for each forecast horizon, defined as $h = t - s$. Since $t \in \{s-2, s-1, \ldots, s+2\}$, it follows that $h \in \{-2, -1, \ldots, 2\}$. Models are estimated over 1980–2023.

CAM (*skal*) consistently reduces the revisions, with $RR < 1$ for all $h$ and $k$. The results suggest a greater robustness, particularly at longer forecast horizons, in two respects. First, $RR$ declines steadily with $h$, reaching values of 0.93 for $k = 1$ and 0.92 for $k = 4$ in the case of Germany. For the French data, the $RR$ falls even further to 0.90 for $k = 1$ and 0.82 for $k = 4$. This implies that even in the short term, defined as two-years-ahead forecast, the revisions of French TFP projections are reduced by around 20 percent when comparing today's projection with that made four years later. Second, as already observed in the previous example, the gains for the four-step revisions are larger than the ones of the one-step revisions. In the four-step case, it even consistently achieves the lowest $RMSR$ of all three methodologies for both countries. This is particularly important for policymakers which rely on long-term stable forecasts.

The linear model performs worse than the benchmark CAM at short horizons, i.e., $RR > 1$ for $h \in \{-2, -1\}$, but improves substantially for longer horizons ($h \geq 0$), with $RR$ dropping to 0.75 at $h = 2$ in the German data. For France, the linear model reduces revisions across all $h$. However, this holds only for the one-step case. With respect to the four-step revisions, the linear models performs almost consistently worse than both the benchmark and the adjusted CAM. This means that while the linear model may yield smaller revisions than the benchmark between yearly projections, both CAM specifications produce lower revisions from a long-term perspective.

Spain and Italy exhibit the lowest benchmark $RMSR$ values in the country sample. The adjusted CAM slightly reduces the revisions across the board, with $RR \in (0.97, 1)$. The linear model performs worse than both the benchmark and the adjusted CAM across horizons in these two countries. In the one-step case and for $h \geq 0$, the linear models performs best for the Italian data ($RR = 0.65$ at $h = 2$).

The Netherlands stand out with the largest benchmark $RMSR$ among countries. The adjusted CAM performs almost identical to the benchmark CAM, with $RR \approx 1.02$ for the one-step case ($k = 1$) and $RR \approx 0.99$ for the four-step case ($k = 4$). The linear model again performs worse than both the benchmark and adjusted CAM with the exception of $h \geq 1$ in the one-step case and $h = 2$ in the four-step case.

Overall, the adjusted CAM provides clear improvements in terms of revision robustness for Germany and France, while Spain and Italy show moderate gains. In contrast, there is neither an improvement nor a deterioration for the Dutch data. The model thus appears to represent a conservative modification with respect to revisions, giving modest improvement in most countries, with most $RR < 1$. This holds particularly for the four-step case, in which the adjusted CAM performs best across all countries. This implies that the adjusted CAM produces the most robust TFP projections from a long-term perspective. Furthermore, the gains in robustness increase steadily with the forecast horizon $h$. This suggests that the advantages of the adjusted CAM relative to the benchmark CAM become even more pronounced in the long run. This finding is important, as 10-step revisions cannot be reliably assessed due to data limitations. The linear model also yield more stable projections at larger horizons, particularly for Germany, France, Italy, and the Netherlands. Only Spain shows no improvements. However, the linear model tends to produce larger revisions at the current edge and, overall, performs worse across horizons than both the benchmark and the adjusted CAM in the four-step case.

## 6 Conclusion

Recent evidence points more convincingly towards a linear, rather than exponential, trajectory of TFP growth. In line with this, we propose a simple adjustment of the current CAM framework. The adjusted specification (*skal*) preserves the essential in-sample characteristics of the original CAM model. Most notably, it maintains the estimated TFP gaps, implying that there is no need to revise or reinterpret past economic assessments based on the existing CAM methodology.

While the forecast gains may appear in some cases modest in absolute terms, they are present across all major European economies in our sample. Especially at longer horizons, forecasts generated by the *skal* specification tend to be systematically closer to realized outcomes than those produced by either the benchmark CAM (*log*) or the linear trend model (*lin*). On average, the adjusted CAM improves forecast performance by approximately 30 percent relative to the benchmark in the short term ($h = 1$) and 40 percent in the long term ($h = 10$). In a real-time data setting, the adjusted CAM exhibits forecast revisions that are smaller than or equal to those of the benchmark CAM. This holds particularly for revisions conducted at four year intervals, in which the adjusted CAM performs best across all countries. Furthermore, the gains in robustness increase steadily with the forecast horizon $h$. This suggests that the advantages of the adjusted CAM relative to the benchmark CAM become even more pronounced in the long run. The linear model reduces revisions relative to the benchmark CAM only for large horizons and in a year-to-year comparison. However overall, the model performs worse across horizons than both the benchmark and the adjusted CAM from a long-term perspective. This finding suggests that the linear model lacks the necessary modeling flexibility, such as that offered by the CAM framework, needed to estimate productivity trends across heterogeneous economies. While the linear model generates reasonable long-run TFP trajectories for the US, its forecast performance for the diverse European countries is generally worse than that of the benchmark. This flexibility is particularly relevant, as the slowdown in TFP growth in Europe appears more pronounced than would typically be anticipated at the conclusion of a standard catch-up period.

As a practical consequence of adopting Additive Growth, both productivity levels and growth rates are lower than under exponential growth in the current methodology. Whereas the benchmark CAM assumes an average yearly TFP increase of 0.80 percent over the next 20 years, the adjusted CAM assumes 0.65 percent. This downward adjustment has direct implications for the fiscal framework: lower potential growth reduces the scope for debt reduction through growth alone and may require more cautious assumptions budgetary planning.

# Appendix

## A Procyclicality

Table 3: Procyclicality

| | | $h = -2$ | $h = -1$ | $h = 0$ | $h = 1$ | $h = 2$ |
|---|---|---|---|---|---|---|
| GER | $TFP_{\text{log}}$ | 0.11 | 0.05 | -0.05 | -0.19 | -0.27 |
| | $TFP_{\text{skal}}$ | 0.09 | 0.03 | -0.05 | -0.18 | -0.26 |
| | $TFP_{\text{lin}}$ | -0.03 | -0.03 | -0.04 | -0.04 | -0.05 |
| FRA | $TFP_{\text{log}}$ | 0.08 | 0.08 | 0.07 | 0.05 | 0.03 |
| | $TFP_{\text{skal}}$ | 0.07 | 0.07 | 0.06 | 0.03 | 0.00 |
| | $TFP_{\text{lin}}$ | 0.08 | 0.08 | 0.09 | 0.09 | 0.09 |
| ESP | $TFP_{\text{log}}$ | -0.41 | -0.36 | -0.28 | -0.21 | -0.12 |
| | $TFP_{\text{skal}}$ | -0.41 | -0.36 | -0.28 | -0.19 | -0.10 |
| | $TFP_{\text{lin}}$ | -0.40 | -0.40 | -0.40 | -0.39 | -0.39 |
| ITA | $TFP_{\text{log}}$ | 0.30 | 0.25 | 0.19 | 0.15 | 0.13 |
| | $TFP_{\text{skal}}$ | 0.32 | 0.26 | 0.19 | 0.15 | 0.13 |
| | $TFP_{\text{lin}}$ | -0.09 | -0.10 | -0.10 | -0.11 | -0.11 |
| NET | $TFP_{\text{log}}$ | 0.17 | 0.17 | 0.16 | 0.14 | 0.11 |
| | $TFP_{\text{skal}}$ | 0.17 | 0.17 | 0.16 | 0.14 | 0.12 |
| | $TFP_{\text{lin}}$ | 0.12 | 0.13 | 0.13 | 0.14 | 0.14 |
| 16 observations | | | | | | |

*Note:* The procyclicality is measured as correlation (ranging from 0 to 1) between the revisions of the estimated TFP trend for each horizon and the output gap. The latter is estimated as the deviation of the CUBS indicator from the most recent vintage (2021) from its mean. Bold values indicate the smallest correlation in absolute terms for each forecast horizon and country.

## B Revisions

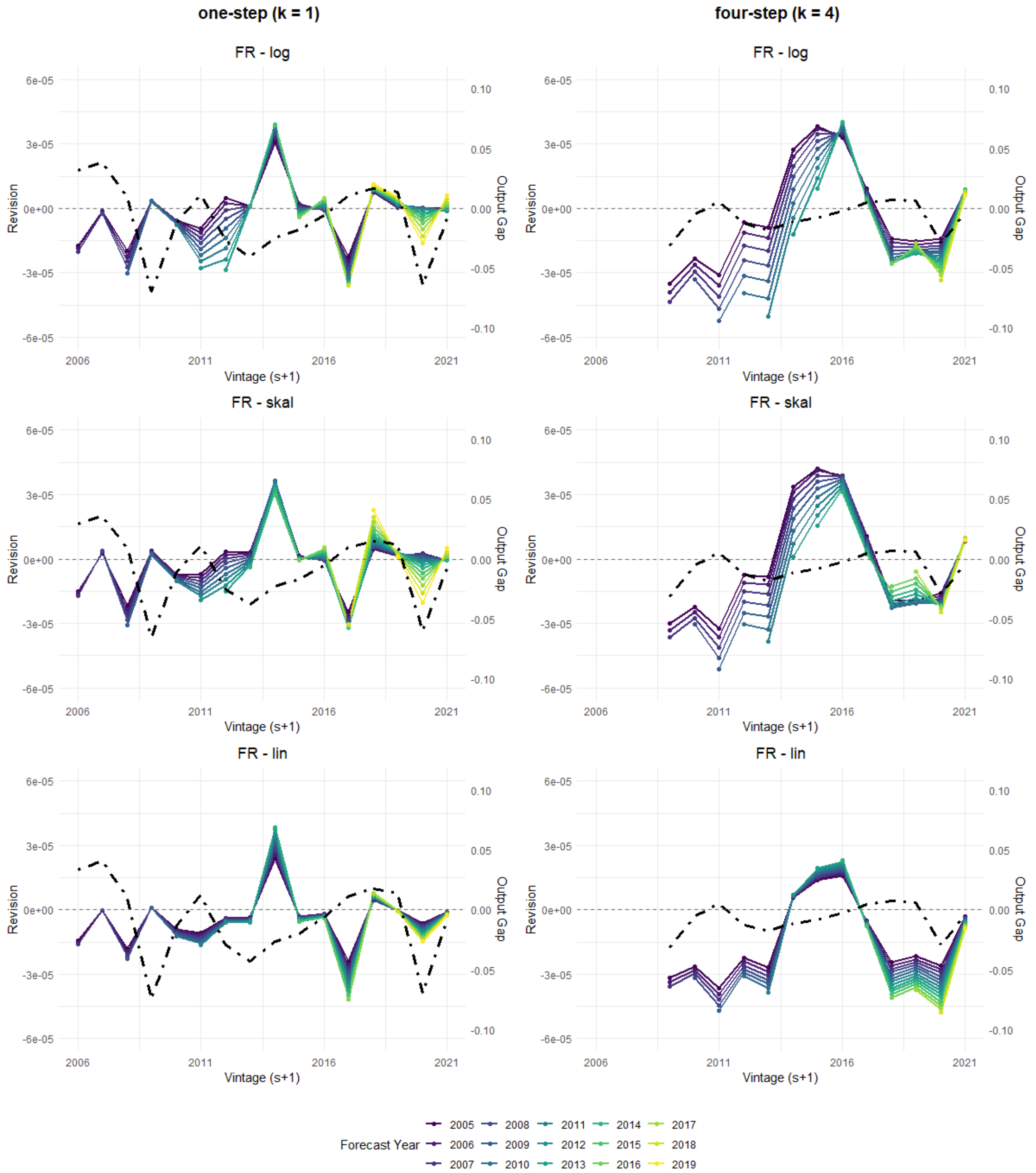


Figure 6: Revisions for vintages from 2006 to 2021 in France

*Note:* The figure shows how the TFP estimates for France of the years from 2005 to 2021 (the forecast year, colored lines) change throughout the various vintages (2006 to 2021). The results are presented for all three models. The revisions, $R_t^{s+1}$, are defined in equation 12 with $s = t$. Aligning the revisions with the output gap (black, dot-dashed line on the right-hand axis) suggests procyclicality. The output gap is estimated as the deviation of the CUBS indicator from the most recent vintage (2021) from its mean.

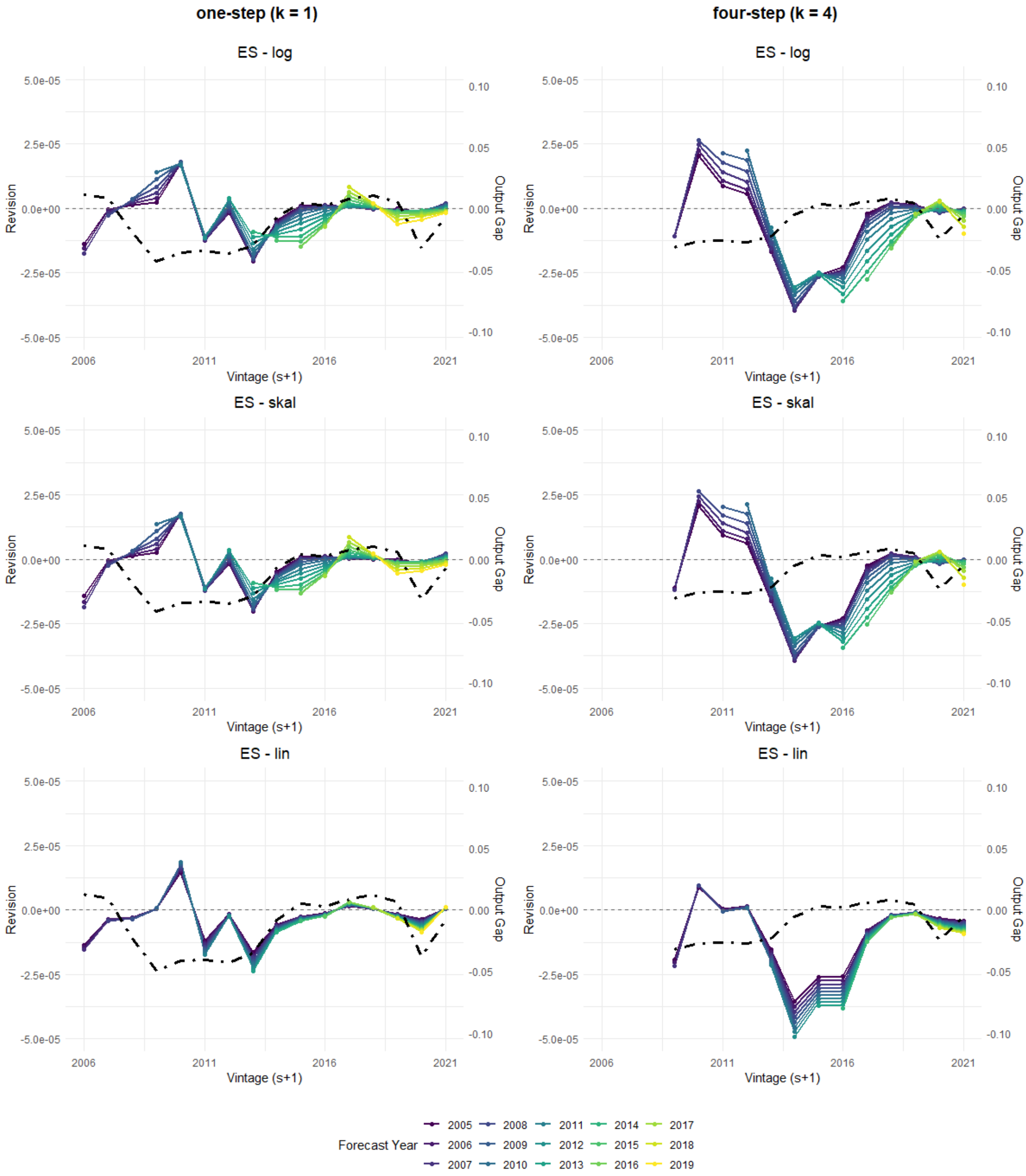


Figure 7: Revisions for vintages from 2006 to 2021 in Spain

*Note:* The figure shows how the TFP estimates for Spain of the years from 2005 to 2021 (the forecast year, colored lines) change throughout the various vintages (2006 to 2021). The results are presented for all three models. The revisions, $R_t^{s+1}$, are defined in equation 12 with $s = t$. Aligning the revisions with the output gap (black, dot-dashed line on the right-hand axis) suggests procyclicality. The output gap is estimated as the deviation of the CUBS indicator from the most recent vintage (2021) from its mean.

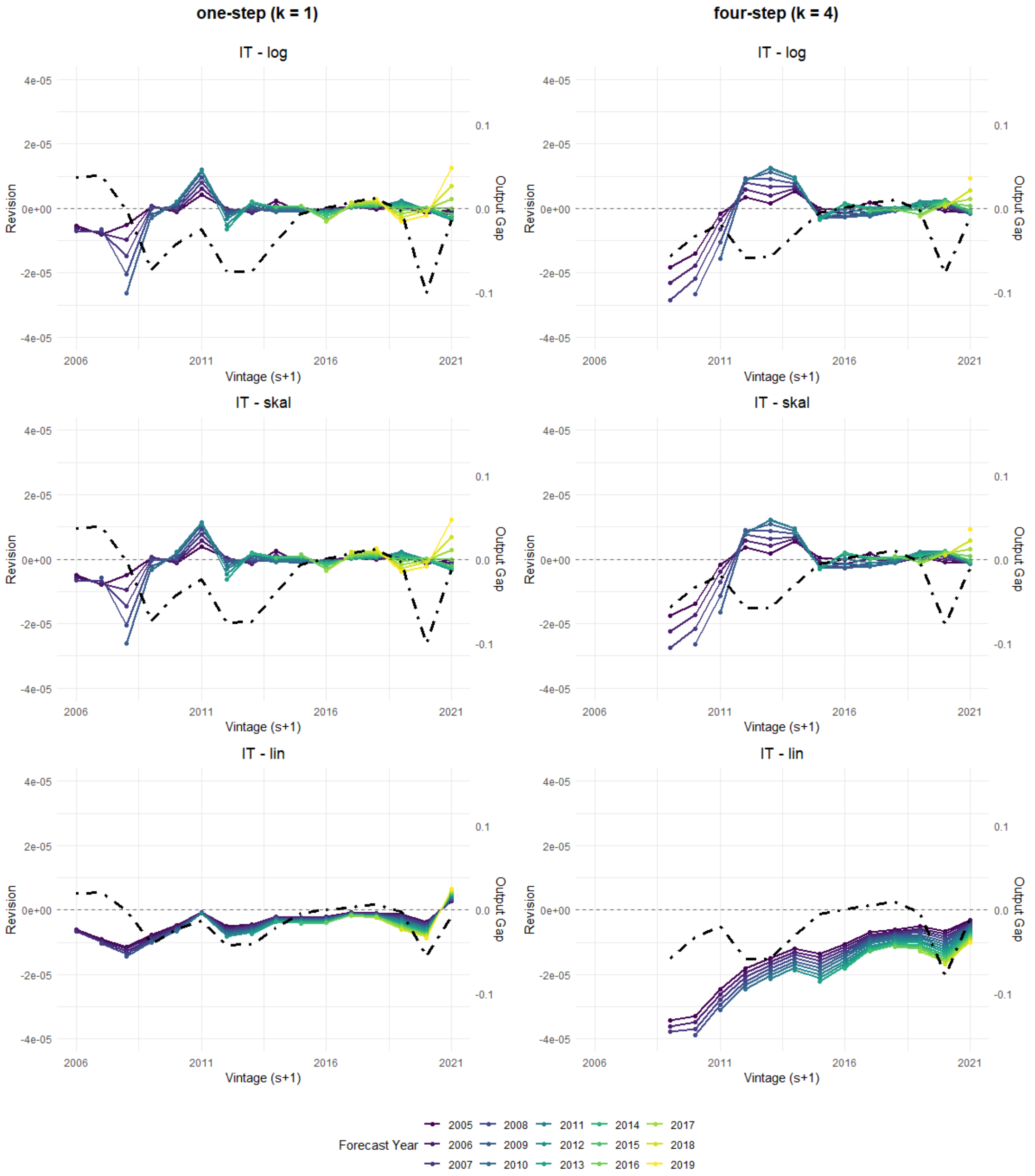


Figure 8: Revisions for vintages from 2006 to 2021 in Italy

*Note:* The figure shows how the TFP estimates for Italy of the years from 2005 to 2021 (the forecast year, colored lines) change throughout the various vintages (2006 to 2021). The results are presented for all three models. The revisions, $R_t^{s+1}$, are defined in equation 12 with $s = t$. Aligning the revisions with the output gap (black, dot-dashed line on the right-hand axis) suggests procyclicality. The output gap is estimated as the deviation of the CUBS indicator from the most recent vintage (2021) from its mean.

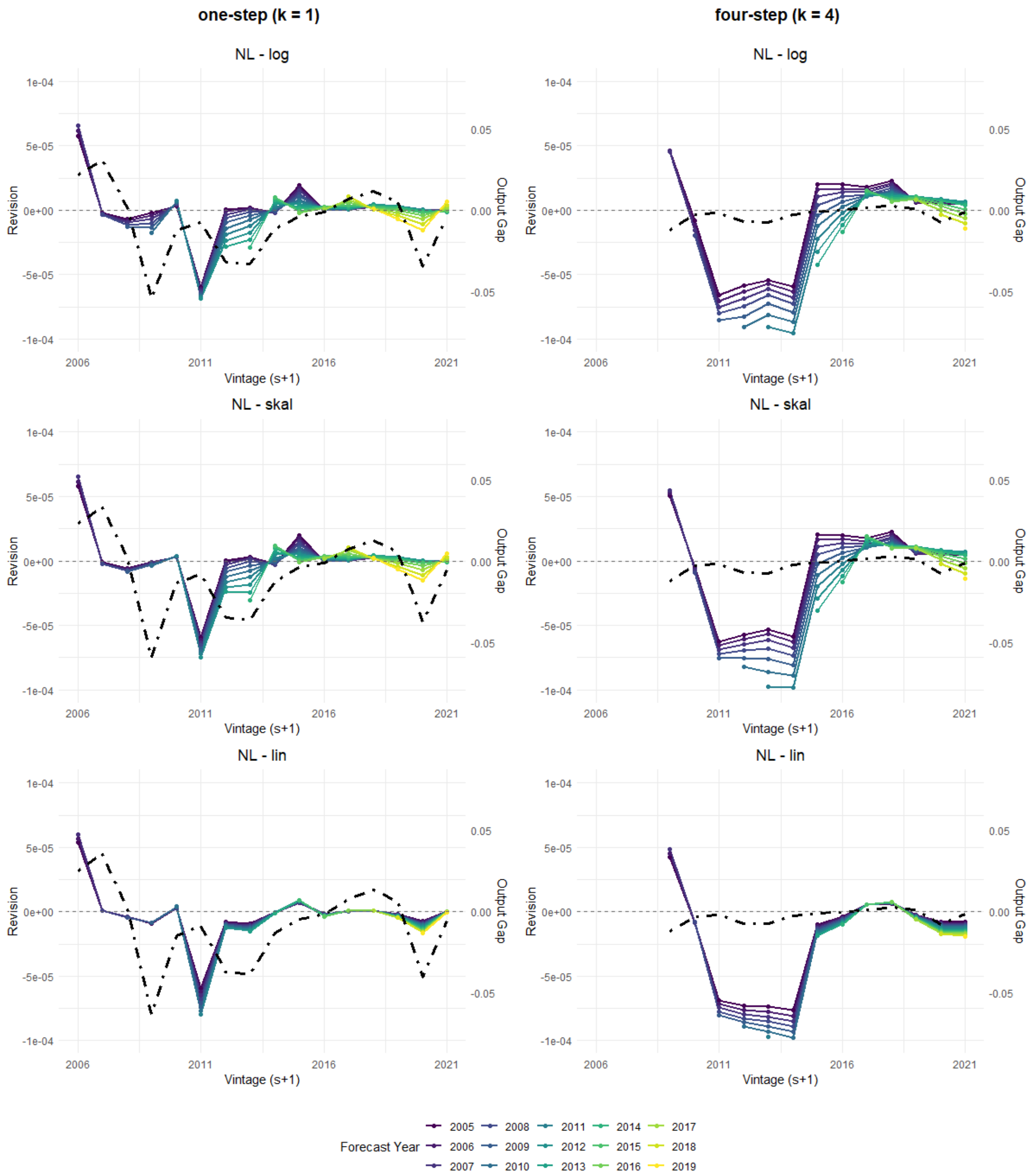


Figure 9: Revisions for vintages from 2006 to 2021 in the Netherlands

*Note:* The figure shows how the TFP estimates for the Netherlands of the years from 2005 to 2021 (the forecast year, colored lines) change throughout the various vintages (2006 to 2021). The results are presented for all three models. The revisions, $R_t^{s+1}$, are defined in equation 12 with $s = t$. Aligning the revisions with the output gap (black, dot-dashed line on the right-hand axis) suggests procyclicality. The output gap is estimated as the deviation of the CUBS indicator from the most recent vintage (2021) from its mean.

# C Revisions of the Moments

This appendix reports additional results on the revisions of the first two moments of the Solow residuals. Those are needed for the rescaling of the data (Equation 11). The figures illustrate how these moments evolve across data vintages and countries.

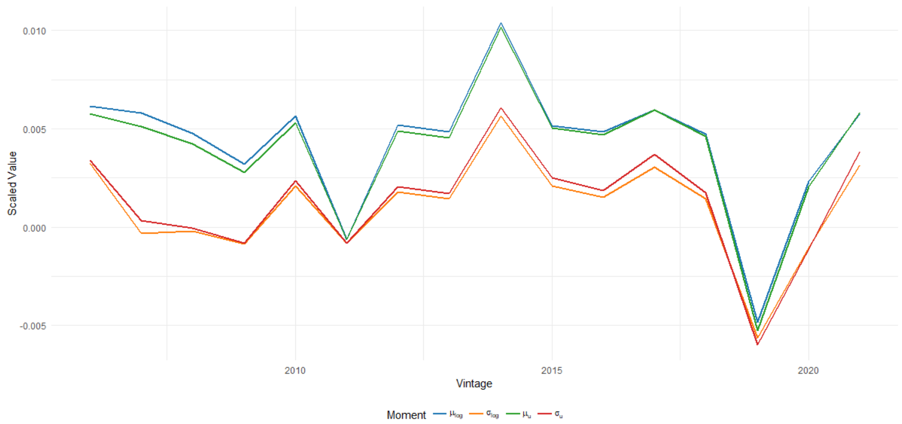


Figure 10: Revisions of the moments for vintages from 2006 to 2021 in Germany
*Note:* The first two moments of the Solow residual data are denoted as $(\mu_u, \sigma_u > 0)$. $(\mu_{\log}, \sigma_{\log} > 0)$ represent the corresponding moments of the log-transformed residuals.

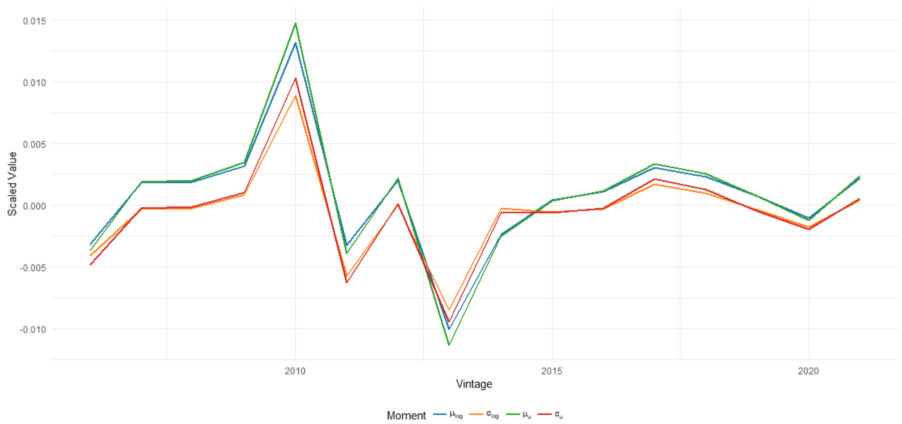


Figure 11: Revisions of the moments for vintages from 2006 to 2021 in Spain
*Note:* The first two moments of the Solow residual data are denoted as $(\mu_u, \sigma_u > 0)$. $(\mu_{\log}, \sigma_{\log} > 0)$ represent the corresponding moments of the log-transformed residuals.

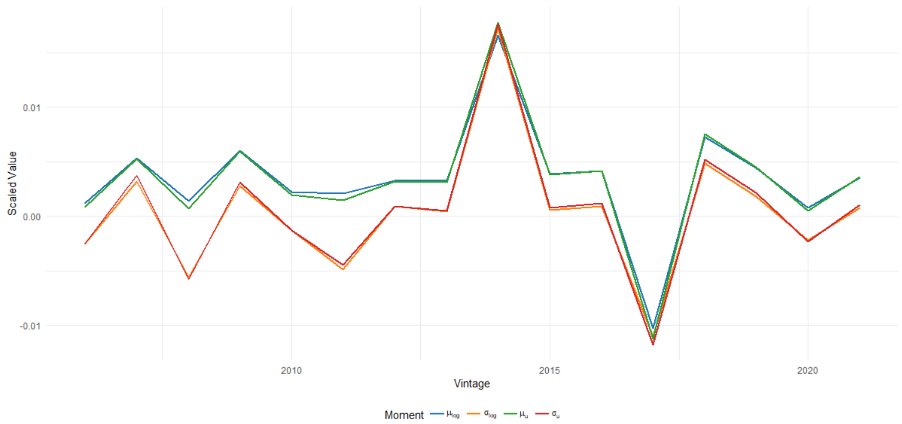


Figure 12: Revisions of the moments for vintages from 2006 to 2021 in France

*Note:* The first two moments of the Solow residual data are denoted as $(\mu_u, \sigma_u > 0)$. $(\mu_{\log}, \sigma_{\log} > 0)$ represent the corresponding moments of the log-transformed residuals.

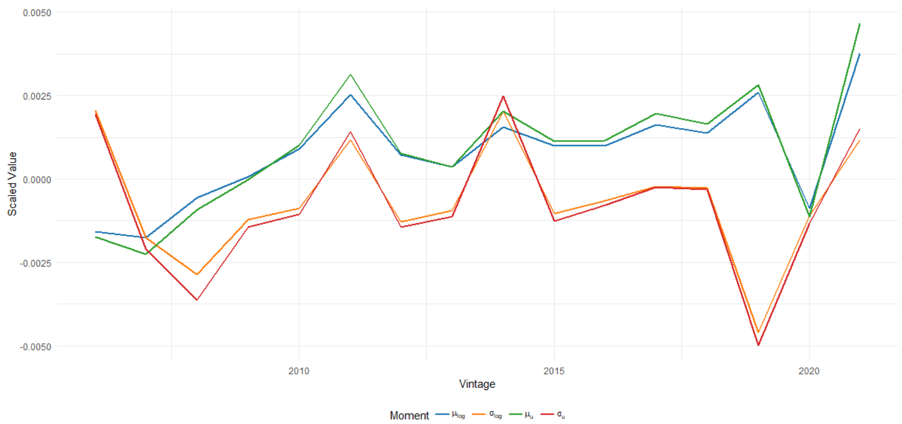


Figure 13: Revisions of the moments for vintages from 2006 to 2021 in Italy

*Note:* The first two moments of the Solow residual data are denoted as $(\mu_u, \sigma_u > 0)$. $(\mu_{\log}, \sigma_{\log} > 0)$ represent the corresponding moments of the log-transformed residuals.

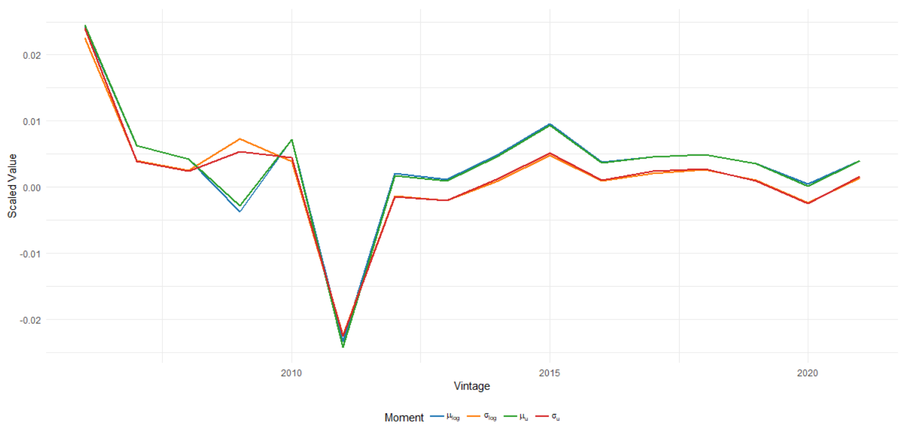


Figure 14: Revisions of the moments for vintages from 2006 to 2021 in the Netherlands
*Note:* The first two moments of the Solow residual data are denoted as $(\mu_u, \sigma_u > 0)$. $(\mu_{\log}, \sigma_{\log} > 0)$ represent the corresponding moments of the log-transformed residuals.

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