

## BUSINESS ANALYTICS WORKING PAPER SERIES

## Corrected Forecast Combinations

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January 15, 2026

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This paper proposes corrected forecast combinations when the original combined forecast errors are serially dependent. Motivated by the classic Bates and Granger (1969) example, we show that combined forecast errors can be strongly autocorrelated and that a simple correction – adding a fraction of the previous combined error to the next-period combined forecast – can deliver sizable improvements in forecast accuracy, often exceeding the original gains from combining. We formalize the approach within the conditional-risk framework of Gibbs and Vasnev (2024), in which the combined error decomposes into a predictable component (measurable at the forecast origin) and an innovation. We then link this correction to efficient estimation of combination weights under time-series dependence via GLS, allowing joint estimation of weights and an error-covariance structure. Using the U.S. Survey of Professional Forecasters for major macroeconomic indices across various subsamples (including pre/post-2000, GFC, and COVID), we find that a parsimonious correction of the mean forecast with a coefficient around 0.5 is a robust starting point and often yields material improvements in forecast accuracy. For optimal-weight forecasts, the correction substantially mitigates the forecast combination puzzle by turning poorly performing out-of-sample optimal-weight combinations into competitive forecasts.

**Keywords:** Monetary policy indicators, China, forecast combination, optimal weights.

**JEL Codes:** C53, C22, E37

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# Corrected Forecast Combinations

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## Abstract

This paper proposes corrected forecast combinations when the original combined forecast errors are serially dependent. Motivated by the classic [Bates and Granger \(1969\)](#) example, we show that combined forecast errors can be strongly autocorrelated and that a simple correction—adding a fraction of the previous combined error to the next-period combined forecast—can deliver sizable improvements in forecast accuracy, often exceeding the original gains from combining. We formalize the approach within the conditional-risk framework of [Gibbs and Vasnev \(2024\)](#), in which the combined error decomposes into a predictable component (measurable at the forecast origin) and an innovation. We then link this correction to efficient estimation of combination weights under time-series dependence via GLS, allowing joint estimation of weights and an error-covariance structure. Using the U.S. Survey of Professional Forecasters for major macroeconomic indices across various subsamples (including pre/post-2000, GFC, and COVID), we find that a parsimonious correction of the mean forecast with a coefficient around 0.5 is a robust starting point and often yields material improvements in forecast accuracy. For optimal-weight forecasts, the correction substantially mitigates the forecast combination puzzle by turning poorly performing out-of-sample optimal-weight combinations into competitive forecasts.

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# 1 Introduction

Consider the motivating example from [Bates and Granger \(1969\)](#), in which the passenger miles flown in 1953 were predicted by two models, exponential smoothing (ES) and Box-Jenkins' ARIMA model (BJ), as well as by their equally weighted (EW) combination, reproduced in [Table 1](#). The final line in the table reports the mean squared forecasting error (MSFE). The final column presents our contribution, explained below.

**Table 1:** Errors in forecasts (actual less estimated) of passenger miles flown, 1953.

Month	Brown's exponential smoothing forecast errors	Box-Jenkins adaptive forecasting errors	Combined forecast ( $\frac{1}{2}$ Brown + $\frac{1}{2}$ Box-Jenkins) errors	Corrected combined forecast errors
Jan.	1	-3	-1	-2.375
Feb.	6	-10	-2	-1.5
March	18	24	21	22
April	18	22	20	9.5
May	3	-9	-3	-13
June	-17	-22	-19.5	-18
July	-24	10	-7	2.75
Aug.	-16	2	-7	-3.5
Sept.	-12	-11	-11.5	-8
Oct.	-9	-10	-9.5	-3.75
Nov.	-12	-12	-12	-7.25
Dec.	-13	-7	-10	-4
MSFE	196	188	150	103

*Note.* The first four columns are a replication of [Table 1](#) from [Bates and Granger \(1969\)](#) except that the title of the last line is changed from 'Variance of errors' to MSFE. Corrected combined forecast errors in the final column are equal to the combined forecast errors  $-0.5 \times$  combined forecast errors from the previous period, e.g., for Feb.  $-1.5 = -2 - 0.5 \times (-1)$ . To correct the Jan. observation, we used the December 1952 error, which is 2.75, from [Barnard \(1963\)](#).

This motivating example, showing that the average of two forecasts is better than the individual forecasts, started the area of forecast combination, with a multitude of papers appearing every year; see [Wang et al. \(2023\)](#) for the latest over 50-year review. One simple fact, however, remained overlooked over all these years: the errors of the combined forecast exhibit strong autocorrelation of around 54%. This information can be used in different ways, but the simplest option is to correct the combined forecast with the error from the previous period, i.e., if we denote the actual observation  $y_t$  at time  $t$ , the combined forecast  $f_{t|t-1}^{EW}$  based

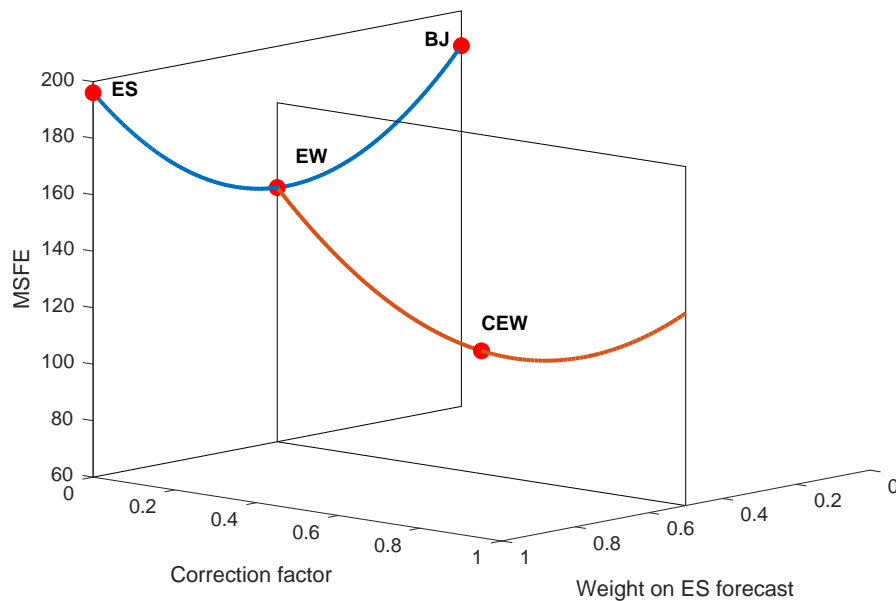
on the information available at time  $t - 1$ , and its error  $e_{t|t-1}^{\text{EW}} = y_t - f_{t|t-1}^{\text{EW}}$  observable at time  $t$ , then the combined forecast for the next period  $t + 1$  can be corrected using

$$f_{t+1|t}^{\text{CEW}} = f_{t+1|t}^{\text{EW}} + 0.5 e_{t|t-1}^{\text{EW}}$$

(where we use the correction of 0.5 for simplicity) and its error is

$$e_{t+1|t}^{\text{CEW}} = y_{t+1} - f_{t+1|t}^{\text{CEW}} = e_{t+1|t}^{\text{EW}} - 0.5 e_{t|t-1}^{\text{EW}},$$

which is reported in the final column in Table 1. What is surprising is that correcting for first-order autocorrelation yields even greater improvement than the original combination. Specifically, the change in MSFE from the best individual forecast to the combination (from 188 to 150) is a 20% reduction, while the change in MSFE from the combination to the corrected combination (from 150 to 103) is a 31% reduction.



**Figure 1:** Improvements from combination (EW) and correction (CEW) in the motivating example from [Bates and Granger \(1969\)](#). Points ES and BJ correspond to the original Brown’s exponential smoothing and Box-Jenkins forecasts.

Figure 1 depicts this improvement. The back plane shows the performance of two original forecasts, ES and BJ, and the equally weighted combination, EW. The quadratic curve in this plane passing through all three points has been studied in [Claeskens et al. \(2016\)](#) and

holds only when a fixed weight (such as 0.5) is used. Once we correct EW, a new dimension emerges: the plane corresponding to changes in the correction factor. It also contains a new curve that starts at EW and illustrates the improvements achieved by using a fixed correction factor, such as 0.5, which yields point CEW on that curve. The improvement in MSFE from the correction, i.e., from EW to CEW, is visually larger than the improvement from the combination, i.e., from ES or BJ to EW, in line with the numerical results in Table 1.

This motivating example shows that, although the vast forecast combination literature operates in the back plane and has made substantial progress over the years, see Wang et al. (2023), a new dimension focusing on the properties of the combined forecast can be highly beneficial.

Furthermore, the optimal forecasting weights introduced by Bates and Granger (1969) exhibit poor empirical performance, leading to the forecast combination puzzle of Stock and Watson (2004): “repeated finding that simple combination forecasts outperform sophisticated adaptive combination methods in empirical applications”. The optimal weight problem can be estimated using ordinary least squares (OLS) in a linear regression, as noted by Granger and Ramanathan (1984). However, as many textbooks show, autocorrelated errors in regression models make OLS estimators inefficient, potentially leading to undesirable consequences. Generalized least squares (GLS) estimation is more efficient than OLS in the presence of autocorrelated errors, a point recently reiterated by Poojari et al. (2025). By focusing on the properties of the combined optimal forecast, we should be able to shed more light on the forecast combination puzzle.

The paper is organized as follows. Section 2 formalizes our idea with the correction of the mean (2.1) and the optimal forecast (2.2) via the two-step procedure used in the motivating example, before calling on the conditional framework of Gibbs and Vasnev (2024) in Subsection 2.3 that allows simultaneous estimation of the optimal weights and the correction factor. We also provide a generalization of our approach via GLS in Subsection 2.4. The empirical illustration using the U.S. Survey of Professional Forecasters is presented in Section 3. Finally, Section 4 concludes.

## 2 Theory

Assume that we wish to forecast  $y_{T+h} \in \mathbb{R}$  using the vector of  $h$ -step-ahead forecasts  $\mathbf{f}_{T+h|T} = (f_{1,T+h|T}, f_{2,T+h|T}, \dots, f_{n,T+h|T})' \in \mathbb{R}^n$ . Following [Giacomini and White \(2006\)](#), we assume that  $y_t$  may follow a complex process marked by measurement issues, structural changes, and nonstationarity induced by distribution changes. Following [Aiolfi and Timmermann \(2006\)](#), we map all forecasts to the real number line and limit our analysis to linear combinations with weights  $\mathbf{w} = (w_1, w_2, \dots, w_n)' \in \mathbb{R}^n$  to produce the combined forecast  $f_{c,T+h|T} = \mathbf{w}' \mathbf{f}_{T+h|T}$ . We denote the vector of forecasting errors as  $\mathbf{e}_{T+h|T} = y_{T+h} \boldsymbol{\iota} - \mathbf{f}_{T+h|T}$ , where  $\boldsymbol{\iota}$  is a vector of ones, and the error of the combined forecast as  $e_{c,T+h|T} = y_{T+h} - f_{c,T+h|T} = \mathbf{w}' \mathbf{e}_{T+h|T}$ .

We first formalize the correction to the mean forecast used in the motivating example. We then embed it in the conditional framework of [Gibbs and Vasnev \(2024\)](#) and conclude with the generalization.

### 2.1 Correction of the mean forecast

Let us consider the equal weights  $\mathbf{w}^{\text{EW}} = \boldsymbol{\iota}/n$  (where  $\boldsymbol{\iota}$  is a  $n \times 1$  vector of ones), a generalization of the motivating example with two forecasts in the introduction. The combined forecast  $f_{T+h|T}^{\text{EW}} = \boldsymbol{\iota}' \mathbf{f}_{T+h|T}/n$  and the corresponding forecasting error  $e_{T+h|T}^{\text{EW}} = y_{t+h} - f_{T+h|T}^{\text{EW}}$  can be corrected using a correction factor  $b_T^{\text{EW}}$  available at time  $T$  to produce the corrected combined forecast  $f_{T+h|T}^{\text{CEW}} = f_{T+h|T}^{\text{EW}} + b_T^{\text{EW}}$ . In our motivating example,  $b_T^{\text{EW}} = 0.5 e_{T|T-1}^{\text{EW}}$  with  $h = 1$ , a simple function of the previous forecasting error. However, a general correction  $b_T^{\text{EW}}(I_T, \boldsymbol{\gamma})$  that involves information  $I_T$ , including additional variables, and parameters  $\boldsymbol{\gamma}$  is also possible and presented in [Section 2.4](#). Here, we show a simple possibility of estimating one parameter.

When dealing with the simple correction  $b_T^{\text{EW}} = \gamma e_{T|T-1}^{\text{EW}}$ , it seems that the correction factor of 0.5 is a reliable starting point in many applications, but with sufficient data available, one can use historical data to find the optimal correction. In each period  $t$ , one needs to solve the optimization

$$\hat{\gamma}_t = \arg \min_{\gamma} \sum_{\tau=t_0}^{t-h} [y_{\tau+h|\tau} - (f_{\tau+h|\tau}^{\text{EW}} + \gamma e_{\tau|\tau-h}^{\text{EW}})]^2 \quad (1)$$

and use the historically optimal (in the period  $[t_0, t]$ ) factor  $\hat{\gamma}_t$  to correct forecast  $f_{t+h|t}^{\text{CEW}} = f_{t+h|t}^{\text{EW}} + \hat{\gamma}_t e_{t|t-h}^{\text{EW}}$  at the future moment  $t + h$ .

The optimal correction, in terms of the mean squared error (MSE), is achieved by  $b_T^{\text{EW}} = \text{E}(e_{T+h|T}^{\text{EW}}|I_T)$  as given by the following theorem.

**Theorem 1** *Given the additional available information  $I_T$ , the corrected forecast  $f_{T+h|T}^{\text{CEW}}$  using  $b_T^{\text{EW}} = \text{E}(e_{T+h|T}^{\text{EW}}|I_T)$  achieves lower conditional and unconditional MSE, i.e.,*

$$\text{E}[(e_{T+h|T}^{\text{EW}})^2|I_T] \geq \text{E}[(e_{T+h|T}^{\text{CEW}})^2|I_T] \text{ and } \text{E}[(e_{T+h|T}^{\text{EW}})^2] \geq \text{E}[(e_{T+h|T}^{\text{CEW}})^2].$$

**Proof** Since  $y_{T+1} = f_{T+h|T}^{\text{EW}} + e_{T+h|T}^{\text{EW}} = f_{T+h|T}^{\text{EW}} + b_T^{\text{EW}} + \xi_{T+h}^{\text{EW}}$ , where  $\xi_{T+h}^{\text{EW}} = e_{T+h|T}^{\text{EW}} - \text{E}(e_{T+h|T}^{\text{EW}}|I_T)$ , then the corrected combined forecast error  $e_{T+h|T}^{\text{CEW}} = y_{T+1} - f_{T+h|T}^{\text{CEW}} = e_{T+h|T}^{\text{EW}} - b_T^{\text{EW}} = \xi_{T+h}^{\text{EW}}$  has zero conditional mean and achieves lower conditional MSE as

$$\begin{aligned} \text{E}[(e_{T+h|T}^{\text{EW}})^2|I_T] &= \text{E}[(b_T^{\text{EW}} + \xi_{T+h}^{\text{EW}})^2|I_T] = (b_T^{\text{EW}})^2 + \text{E}[(\xi_{T+h}^{\text{EW}})^2|I_T] \\ &\geq \text{E}[(\xi_{T+h}^{\text{EW}})^2|I_T] = \text{E}[(e_{T+h|T}^{\text{CEW}})^2|I_T] \end{aligned}$$

and by taking the unconditional expectation, we have the same inequality for the unconditional MSE,  $\text{E}[(e_{T+h|T}^{\text{EW}})^2] \geq \text{E}[(e_{T+h|T}^{\text{CEW}})^2]$ . ■

In applications, one needs to specify how to model  $b_T^{\text{EW}} = \text{E}(e_{T+h|T}^{\text{EW}}|I_T)$  and estimate it, which will affect the MSE. Therefore, keeping the model simple and minimizing additional estimation, as in our motivating example, should be a favorable correction strategy.

## 2.2 Correction of the (unconditionally) optimal forecast

We now turn our attention to the optimal weights. Assuming that the loss function  $L(\cdot)$  depends only on  $e_{c,T+h|T}$ , the classical *unconditionally* optimal weights solve the problem

$$\min_{\mathbf{w}} \text{E}[L(e_{c,T+h|T})]. \quad (2)$$

Under mean squared error loss,  $L(e) = e^2$ , only the first two conditional moments influence the optimal weights, and the optimization problem can be solved explicitly. We also assume that the forecasts are unbiased,  $E(\mathbf{e}_{T+h|T}) = \mathbf{0}$ ; thus, we solve the optimization problem (2) subject to the restriction that the weights sum up to one,  $\mathbf{w}'\boldsymbol{\iota} = 1$ , which produces the optimal weights of [Bates and Granger \(1969\)](#)

$$\mathbf{w}^{\text{BG}} = \frac{\Sigma^{-1}\boldsymbol{\iota}}{\boldsymbol{\iota}'\Sigma^{-1}\boldsymbol{\iota}}, \quad (3)$$

where  $\Sigma = E[\mathbf{e}_{T+h|T}\mathbf{e}'_{T+h|T}]$ , and the optimal BG forecast  $f_{T+h|T}^{\text{BG}} = (\mathbf{w}^{\text{BG}})'\mathbf{f}_{T+h|T}$ . The existence of the first two moments of the errors,  $\mathbf{e}_{T+h|T}$ , is sufficient for the results derived in this section to be valid under our general data assumptions.

If a suitable correction  $b_T^{\text{BG}}$  is available, then the conditional and unconditional inequalities for the reduction in error will hold for the corrected BG forecast  $f_{T+h|T}^{\text{CBG}} = f_{T+h|T}^{\text{BG}} + b_T^{\text{BG}} = (\mathbf{w}^{\text{BG}})'\mathbf{f}_{T+h|T} + b_T^{\text{BG}}$ , as stated in the following theorem.

**Theorem 2** *Given the additional available information  $I_T$ , the corrected forecast  $f_{T+h|T}^{\text{CBG}}$  using  $b_T^{\text{BG}} = E(e_{T+h|T}^{\text{BG}}|I_T)$  achieves lower conditional and unconditional MSE, i.e.,*

$$E[(e_{T+h|T}^{\text{BG}})^2|I_T] \geq E[(e_{T+h|T}^{\text{CBG}})^2|I_T] \text{ and } E[(e_{T+h|T}^{\text{BG}})^2] \geq E[(e_{T+h|T}^{\text{CBG}})^2].$$

**Proof** The same as before. ■

In fact, any other combination (not necessarily optimal) or even the original individual forecasts can be corrected in a similar manner to improve performance. All previous corrections were two-step procedures, in which the original forecasts were combined in the first step and corrected in the second step.

The correction term, such as  $b_T^{\text{EW}}$  or  $b_T^{\text{BG}}$ , will generally depend on a vector of unknown parameters  $\boldsymbol{\gamma} \in \mathbb{R}^k$  that need to be estimated or selected. From now on, we explicitly denote this dependence as  $b_T^{\text{EW}}(\boldsymbol{\gamma})$  or  $b_T^{\text{BG}}(\boldsymbol{\gamma})$ . In our motivating example in the introduction, this is a scalar first-order autoregressive parameter, and its value is simply set to 0.5. However, if  $\boldsymbol{\gamma}$  is estimated, then the two-step procedure is the simplest option, i.e., given the weights,  $\mathbf{w}^{\text{EW}}$ ,

$\mathbf{w}^{\text{BG}}$  (or any other chosen weights) and their corresponding combinations  $f_{T+h|T}^{\text{EW}}$ ,  $f_{T+h|T}^{\text{BG}}$ , we can use the corresponding combined forecasting errors to estimate  $\gamma$  and correct the combined forecast  $f_{T+h|T}^{\text{CZZ}} = f_{T+h|T}^{\text{ZZ}} + b_T^{\text{ZZ}}(\hat{\gamma}^{\text{ZZ}})$ , where ZZ stands for EW, BG or any other combination that one decides to use. This procedure may be effective in many situations due to its simplicity.

### 2.3 Conditional Framework of Gibbs and Vasnev (2024)

One expects benefits from jointly estimating  $\mathbf{w}$  and  $\gamma$ , at least in theory, so we now turn our attention to a one-step procedure in which weights and corrections are determined simultaneously. Given  $I_T$ , the *conditionally* optimal combination weights of Gibbs and Vasnev (2024) solve the problem

$$\min_{\mathbf{w}} \text{E}[L(e_{c,T+h|T})|I_T]. \quad (4)$$

For the conditional expectation in the optimization (4) to be well defined, one must specify how the conditional information is used. While Gibbs and Vasnev (2024) used  $I_T$ , the information set available at time  $T$ , to extract the conditional bias of individual models producing the conditionally optimal weights, we will focus on the combined error.

We assume that the combined forecast error,  $e_{c,T+h|T}$ , can be decomposed into two parts,  $e_{c,T+h|T} = b_T + \xi_{T+h}$ , where  $b_T = \text{E}(e_{c,T+h|T}|I_T)$  and  $\text{E}(\xi_{T+h}|I_T) = 0$ . A simple example where this decomposition arises naturally is when forecasting errors exhibit autocorrelation, as in our motivating example in the introduction. In this case, the information set  $I_T$  consists of previous forecasting errors, i.e.,  $I_T = \{e_{c,T|T-1}\}$ , and the conditional bias follows a first-order autoregressive model  $e_{c,T+1|T} = \gamma e_{c,T|T-1} + \xi_{T+1}$  (for  $h = 1$ ), with  $b_T = \gamma e_{c,T|T-1}$  and the remainder  $\xi_{T+1} = e_{c,T+1|T} - \gamma e_{c,T|T-1}$ .

We now approach the optimal weight problem by noting that, as Granger and Ramanathan (1984) observed, the unconditional optimal weights can be estimated using ordinary least squares (OLS) in the linear regression

$$y_{t+h} = w_1 f_{1,t+h|t} + \dots + w_n f_{n,t+h|t} + e_{c,t+h|t}, \quad t = 1, \dots, T-h \quad (5)$$

subject to the restriction  $w_1 + \dots + w_n = 1$ . The implicit assumption is that  $e_{c,t+h|t}$  are independent and identically distributed (*iid*). If the errors are correlated, i.e., the *iid* assumption does not hold, then the OLS estimator,  $\hat{\mathbf{w}}^{\text{OLS}}$  (and its corresponding forecast  $f_{T+h|T}^{\text{OLS}}$ ), remains unbiased and consistent but is not necessarily efficient. We can therefore estimate the corrected forecast combination using

$$y_{t+h} = w_1 f_{1,t+h|t} + \dots + w_n f_{n,t+h|t} + \gamma [y_t - (w_1 f_{1,t|t-h} + \dots + w_n f_{n,t|t-h})] + \xi_{t+h},$$

which is equivalent to

$$y_{t+h} - \gamma y_t = w_1 (f_{1,t+h|t} - \gamma f_{1,t|t-h}) + \dots + w_n (f_{n,t+h|t} - \gamma f_{n,t|t-h}) + \xi_{t+h}.$$

Poojari et al. (2025) refer to this transformation as the Hildreth–Lu method and also present other alternatives that may be more attractive. We will focus on the simple version and the corresponding estimators  $(\hat{\mathbf{w}}^{\text{GLS}}, \hat{\gamma}^{\text{GLS}})$ , which can be used to combine and correct at the same time

$$f_{T+h|T}^{\text{GLS}} = (\hat{\mathbf{w}}^{\text{GLS}})' \mathbf{f}_{T+h|T} + \hat{\gamma}^{\text{GLS}} (y_T - (\hat{\mathbf{w}}^{\text{GLS}})' \mathbf{f}_{T|T-h}). \quad (6)$$

When considering the forecasting errors,  $e_{T+h|T}^{\text{OLS}} = y_T - f_{T+h|T}^{\text{OLS}}$  and  $e_{T+h|T}^{\text{GLS}} = y_T - f_{T+h|T}^{\text{GLS}}$ , one naturally expects the GLS to perform better. This result is formalized by the following theorem.

**Theorem 3** *The conditionally optimal forecast achieves lower conditional and unconditional MSE, i.e.,*

$$\mathbb{E}[(e_{T+h|T}^{\text{OLS}})^2 | I_T] \geq \mathbb{E}[(e_{T+h|T}^{\text{GLS}})^2 | I_T] \text{ and } \mathbb{E}[(e_{T+h|T}^{\text{OLS}})^2] \geq \mathbb{E}[(e_{T+h|T}^{\text{GLS}})^2].$$

**Proof** See Theorem 1 of Gibbs and Vasnev (2024). ■

## 2.4 Generalization

We now extend our approach to allow general time-series dependence in the forecasting error term. Let  $\mathbf{y} = (y_{1+h}, \dots, y_T)'$ ,  $\mathbf{F} = (\mathbf{f}_{1+h|1}, \dots, \mathbf{f}_{T|T-h})'$ ,  $\mathbf{f}_{t+h|t} = (f_{1,t+h|t}, \dots, f_{n,t+h|t})'$ , and  $\mathbf{e}_c = (e_{c,1+h|1}, \dots, e_{c,T|T-h})'$ . In matrix notation, we write the model (5) as  $\mathbf{y} = \mathbf{F}\mathbf{w} + \mathbf{e}_c$ . The time-series dependence in the forecasting errors can be modeled with a general covariance matrix  $E[\mathbf{e}_c \mathbf{e}_c'] = \Omega(\boldsymbol{\gamma})$ . Suppose that  $\mathbf{e}_c$  follows a stationary ARMA( $p, q$ ) process and that  $\Omega(\boldsymbol{\gamma})$  is known. Then we solve the following optimization problem

$$\min_{\mathbf{w}} (\mathbf{y} - \mathbf{F}\mathbf{w})' \Omega^{-1}(\boldsymbol{\gamma}) (\mathbf{y} - \mathbf{F}\mathbf{w}) \quad (7)$$

subject to the restriction  $\mathbf{w}'\boldsymbol{\iota} = 1$ , which produces the optimal weights

$$\mathbf{w}^{\text{opt}} = \frac{\tilde{\Sigma}^{-1}\boldsymbol{\iota}}{\boldsymbol{\iota}'\tilde{\Sigma}^{-1}\boldsymbol{\iota}}, \quad (8)$$

where  $\tilde{\Sigma} = \tilde{\mathbf{e}}' \tilde{\mathbf{e}}$ ,  $\tilde{\mathbf{e}} = \Omega^{-1/2}(\boldsymbol{\gamma})\mathbf{e}$ , and  $\mathbf{e} = (\mathbf{y}\boldsymbol{\iota}' - \mathbf{F})$ .

In practice,  $\Omega(\boldsymbol{\gamma})$  is unknown, but the efficient generalized least squares ( $\hat{\mathbf{w}}^{\text{GLS}}, \hat{\boldsymbol{\gamma}}^{\text{GLS}}$ ) can be estimated simultaneously using the maximum likelihood estimation (MLE) method proposed by [Harvey and Phillips \(1979\)](#) or a two-step procedure proposed by [Zinde-Walsh and Galbraith \(1991\)](#). Let  $R(\mathbf{w}) = (\mathbf{y} - \mathbf{F}\mathbf{w})' \Omega^{-1}(\boldsymbol{\gamma}) (\mathbf{y} - \mathbf{F}\mathbf{w})$  and  $R_n(\mathbf{w}) = (\mathbf{y} - \mathbf{F}\mathbf{w})' \Omega^{-1}(\hat{\boldsymbol{\gamma}}) (\mathbf{y} - \mathbf{F}\mathbf{w})$  denote the theoretical and empirical risks, respectively. They differ only in the use of the true parameter  $\boldsymbol{\gamma}$  versus its estimator  $\hat{\boldsymbol{\gamma}}$ . The following theorem shows that the theoretical minimum risk  $R(\mathbf{w}^{\text{opt}})$  and the empirical GLS risk  $R_n(\hat{\mathbf{w}}^{\text{GLS}})$  are approximately equal as long as the covariance matrix estimate  $\Omega^{-1}(\hat{\boldsymbol{\gamma}})$  is close to the true value  $\Omega(\boldsymbol{\gamma})$ .

**Theorem 4** *Let  $a_T = \|\mathbf{e}'(\Omega^{-1}(\hat{\boldsymbol{\gamma}}) - \Omega^{-1}(\boldsymbol{\gamma}))\mathbf{e}\|_{\infty}$ . Suppose that  $\|\mathbf{w}\|_1 \leq c$ , then, we have*

$$\begin{aligned} |R(\mathbf{w}^{\text{opt}}) - R_n(\hat{\mathbf{w}}^{\text{GLS}})| &\leq a_T c^2, \\ |R(\hat{\mathbf{w}}^{\text{GLS}}) - R_n(\hat{\mathbf{w}}^{\text{GLS}})| &\leq a_T c^2, \\ |R(\hat{\mathbf{w}}^{\text{GLS}}) - R(\mathbf{w}^{\text{opt}})| &\leq 2a_T c^2. \end{aligned}$$

**Proof** Under the restriction  $\mathbf{w}'\boldsymbol{\iota} = 1$ , we have  $\mathbf{e}_c = \mathbf{y} - \mathbf{F}\mathbf{w} = \mathbf{y}\boldsymbol{\iota}'\mathbf{w} - \mathbf{F}\mathbf{w} = (\mathbf{y}\boldsymbol{\iota}' - \mathbf{F})\mathbf{w} = \mathbf{e}\mathbf{w}$ . Therefore, we can rewrite the theoretical and empirical risks as  $R(\mathbf{w}) = \mathbf{w}'\mathbf{e}'\Omega^{-1}(\boldsymbol{\gamma})\mathbf{e}\mathbf{w}$  and  $R_n(\mathbf{w}) = \mathbf{w}'\mathbf{e}'\Omega^{-1}(\hat{\boldsymbol{\gamma}})\mathbf{e}\mathbf{w}$ , respectively. Following a similar argument to the proof of Theorem 1 of Fan et al. (2012), we can show the results. ■

While our theory allows for general correction, parsimonious models often deliver good forecasts in practice. Therefore, the practical advice is to use simple corrections, as in our motivating example in the introduction, before adding complexity and estimation variability that could harm forecasting performance.

### 3 Empirical illustration: The US Survey of Professional Forecasters

The analysis uses individual-level forecasts from the U.S. Survey of Professional Forecasters (SPF), conducted quarterly by the Federal Reserve Bank of Philadelphia. The SPF collects forecasts from a panel of professional economists for a range of key U.S. macroeconomic variables across multiple horizons. We focus on one-step-ahead forecasts ( $h = 1$ ) and four major macroeconomic indicators: the civilian unemployment rate (UNEMP), real gross domestic product (RGDP), industrial production growth (INDPROD), and consumer price inflation (CPI). The data were accessed in October 2025<sup>1</sup>. Figure 2 presents a graphical overview of the data.

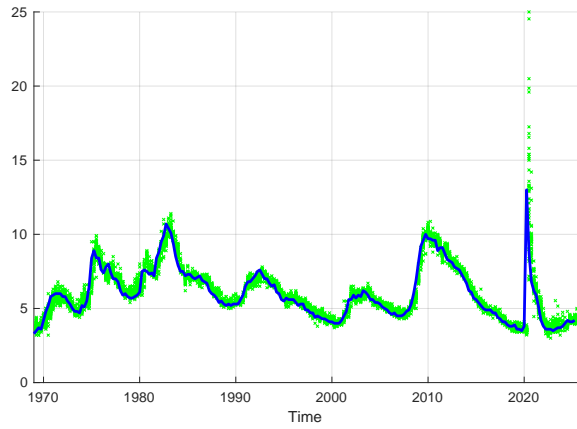
#### 3.1 Corrected Mean Forecast

We first investigate the performance of the corrected mean forecast in our data. Because we have several indicators, we introduce a subscript to distinguish among them, making the correction specific to each indicator

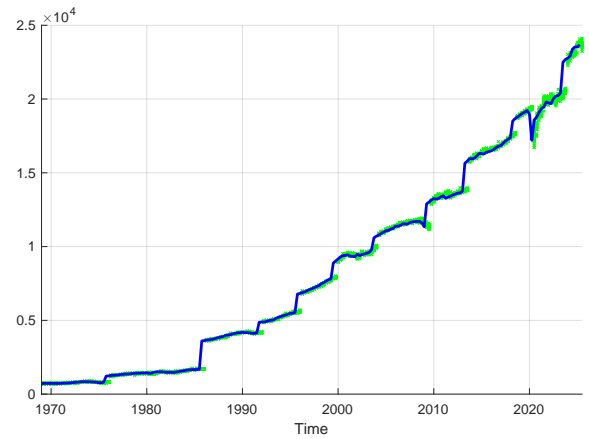
$$f_{i,T+1|T}^{\text{CEW}} = f_{i,T+1|T}^{\text{EW}} + \gamma_i e_{i,T|T-1}^{\text{EW}}, \quad (9)$$

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<sup>1</sup><https://www.philadelphiafed.org/surveys-and-data/data-files>



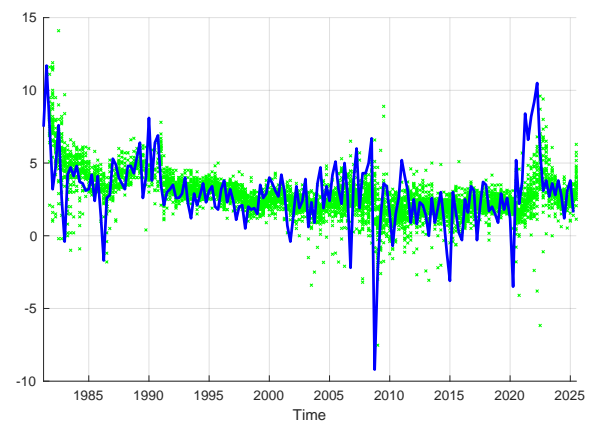
(a) UNEMP



(b) RGDP



(c) INDPROD



(d) CPI

**Figure 2:** Four major macroeconomic indicators considered in the empirical study. The line represents the actual realizations of each macroeconomic variable, while the light crosses represent the individual expert forecasts from the US SPF.

where  $i \in \{\text{UNEMP}, \text{RGDP}, \text{INDPROD}, \text{CPI}\}$ . The forecasts and correction elements remain the same as before, but with the additional subscript  $i$ . To assess the effects of events such as the global financial crisis (GFC) and the COVID pandemic, as well as performance in historical and more recent periods, we consider the periods specified in Table 2.

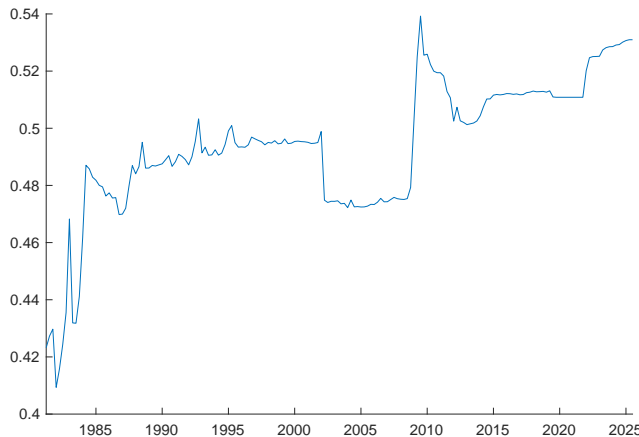
Period	Description
1969Q1–2025Q2	complete (CPI data starts in 1981Q3)
1969Q1–2025Q2*	complete (excl. COVID, CPI data starts in 1981Q3)
1969Q1–1999Q4	before 2000 (CPI data starts in 1981Q3)
2000Q1–2025Q2	after 2000
2000Q1–2025Q2*	after 2000 (excl. COVID)
2000Q1–2008Q4	before GFC
2000Q1–2019Q4	before COVID
2010Q1–2019Q4	between GFC and COVID
2022Q1–2025Q2	after COVID

**Table 2:** Period definitions and descriptions.

Table 3 shows the relative root mean squared forecasting errors (RMSFE) across different periods and various correction factors, with the different panes corresponding to UNEMP, RGDP, INDPROD, and CPI. The results are relative to the original mean forecast for each row. Let us consider the UNEMP results in the first pane. The COVID period is characterized by large outliers that are propagated by the correction (9), as shown in Figure 2a. Therefore, when the period 2020-2022 is included in the evaluation, it is better to use the original mean forecast, i.e., all values in the rows corresponding to 1969Q1-2025Q2 and 2000Q1-2025Q2 are greater than one, and the optimal correction parameter is  $\gamma_i = 0$  (no correction). However, once this relatively short period is excluded from the evaluation, the optimal correction is in the neighbourhood of 0.5 (used in the motivating example in the introduction) for 1969Q1-2025Q2\*, 2000Q1-2025Q2\*, and all other periods. This treatment of the COVID period aligns with the ‘set to missing’ approach of Hyndman and Rostami-Tabar (2025) and is sufficient for our purposes; however, other approaches can also be used.

It appears that a correction factor of 0.5 is a reliable starting point for our application; however, with sufficient historical data, one can use historical data to determine the optimal correction factor via the simple optimization procedure (1) introduced earlier, with the additional stabilizing restriction  $-1 < \hat{\gamma}_{i,t} < 1$ . The final column in Table 3 shows this possibility.

As in the evaluation, the COVID period is detrimental to correction, so the values corresponding to COVID are excluded from the sum in (1). The correction with the historically optimal correction factor is beneficial in all periods (once COVID is excluded). Moreover, the estimated corrected factor  $\hat{\gamma}_{i,t}$  delivers the performance close to the optimal fixed correction factor. In fact, the estimated correction factor is very stable for most of the period, ranging between 0.4 and 0.54, as can be seen in Figure 3.



**Figure 3:** Historically optimal correction factor for UNEMP computed using the past available data and used for the mean forecast correction.

The results for RGDP are more pronounced. Even with the COVID period included, we observe around a 10% improvement from the correction in the 1969Q1–2025Q2 period, and this improvement increases once COVID is excluded from the evaluation in 1969Q1–2025Q2\*. In all periods considered, the correction is beneficial, i.e., the minimum relative RMSFE is substantially less than 1 in all rows when a fixed correction factor is used. Again, a correction factor of around 0.5 delivers good performance in all cases. When using the historically optimal correction factor, as given in the last column, performance drops only marginally (with the largest deterioration in the distant 1969Q1–1999Q4 period), and the corrected mean forecast always outperforms the mean. The results for INDPROD further strengthen support for the fixed correction factor of 0.5, with only a marginal drop in performance when using the historically optimal correction factor across all periods.

CPI is challenging to forecast, see [Gibbs and Vasnev \(2024\)](#), and beating simple benchmarks, such as a simple average or random walk variations, by more than a few percent is

notoriously difficult. Keeping this in mind, we can examine the CPI results that diverge from other indicators. The correction yields only minor improvements over the mean forecasts, and the best results are achieved with a correction factor close to 0.3. The important exception is the most recent period after COVID, 2022Q1–2025Q2, where the fixed factor 0.5 yields a 30% improvement. Again, estimating the historically optimal correction factor affects performance only marginally, except for the recent 2022Q1–2025Q2 period, where the drop is more substantial, yet the final results are 16% better than the original mean forecast.

### 3.2 Corrected Optimal Forecast

We now turn to the correction of the optimal forecast. The main difficulty here is that the SPF is highly unbalanced, with many forecasters skipping periods, new forecasters joining the panel, and old ones dropping out, making the computation of the correlation matrix  $\Sigma$  for the optimal weights (3) challenging. For this reason, we limit our demonstration to UNEMP for the period 2000Q1–2019Q4, before COVID. We further select 6 forecasters with at least 70 observations (out of 80). Even with this restriction, there are only a few time periods in which all of them submit their forecasts. We therefore need to implement a simple imputation using their previously submitted forecasts for the missing periods. Other forms of imputation that prevent data leakage (i.e., using future information to impute the past) are also possible, see [Ahn et al. \(2022\)](#), but since a relatively small number of observations are missing, the final results should not be sensitive. The precision of the individual forecasts is reported in the top section of Table 4.

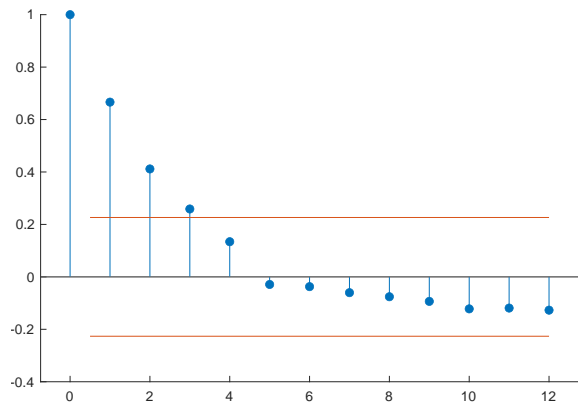
The bottom part of Table 4 reports the precision of the combination methods. The simple mean of the forecasts outperforms each individual forecast (except one), consistent with the vast empirical literature; see, for example, [Wang et al. \(2023\)](#). The errors of the mean forecast exhibit high autocorrelation, as shown in Figure 4a. Applying a correction factor  $\gamma_i = 0.5$  yields close to a 50% improvement, which increases by another 5% when using the optimal fixed correction factor  $\gamma_i = 0.65$ . Estimating the historically optimal correction factor slightly deteriorates forecasting performance but still provides a sizable improvement of close to 45%

over the original mean forecast. As expected, the correction removes the autocorrelation in the forecasting errors, as shown in Figure 4b.

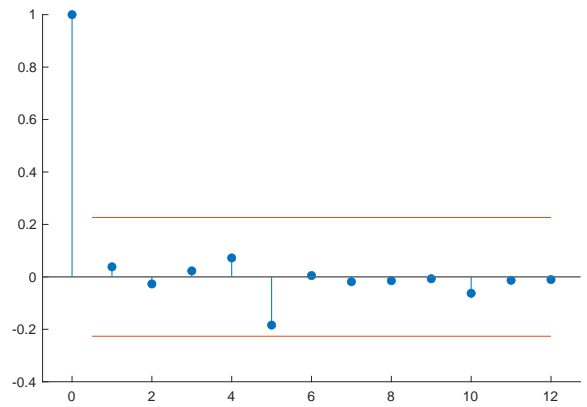
When running the restricted regression (5) of Granger and Ramanathan (1984) over the full period 2000Q1–2019Q4, the optimal (in-sample) weights improve upon equal weights by construction. However, a more realistic approach is to use only the available observations  $[t_0, t]$  to estimate the optimal (out-of-sample) weights and then use them to forecast  $t + 1$ . The performance of this approach corresponds to the optimal combination in Table 4. The optimal combination is slightly worse than the mean forecast, which is consistent with the vast empirical literature on the forecast combination puzzle, see Claeskens et al. (2016). The optimal forecast can be corrected using the default fixed factor 0.5, the optimal fixed factor 0.7, or a historically optimal factor  $-1 < \hat{\gamma}_{i,t} < 1$ . All options outperform the mean forecast, which partially addresses the forecast combination puzzle, i.e., the corrected optimal forecast now performs better than the mean forecast, as expected by theory but often violated in practice. The improvements are dramatic, with the default  $\gamma_i = 0.5$  correction performing more than 40% better than the mean. The optimal fixed correction factor  $\gamma_i = 0.7$  further improves performance by another 3.5%. Estimating the historical correction factor diminishes the improvement, yielding results similar to the default correction with  $\gamma_i = 0.5$ .

Finally, the last row of Table 4 reports the case in which the estimation of the optimal weights and the correction factor is done simultaneously via GLS, as given by equation (6) in Section 2.3. This one-step procedure yields better results than the two-step forecasts analyzed in the previous paragraph because it is more efficient. Its performance is almost catching up to the corrected mean forecast using the default correction factor of 0.5. Our practical recommendation is to use the corrected mean forecast until further research reveals insights into the modified forecasting puzzle: the corrected optimal forecast is better than the mean forecast, yet it is still outperformed by the corrected mean forecast. However, the GLS forecast is now a formidable contender and might outperform the corrected mean forecast in some applications.

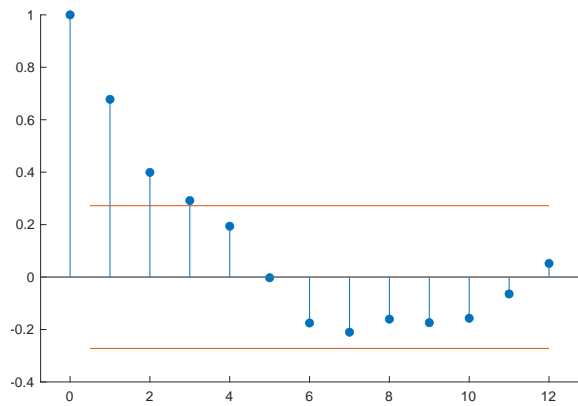
Figure 4 investigates the autocorrelation of the regression forecasting errors. The OLS



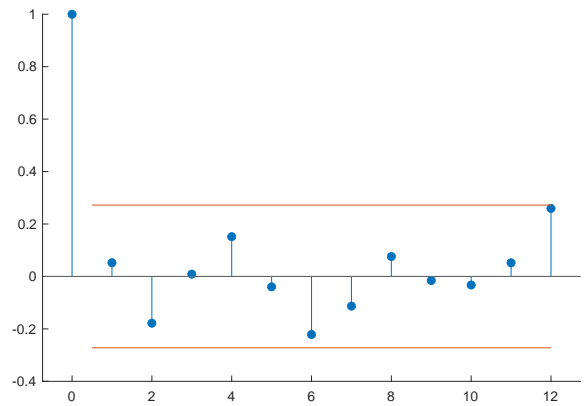
(a) Mean forecast errors



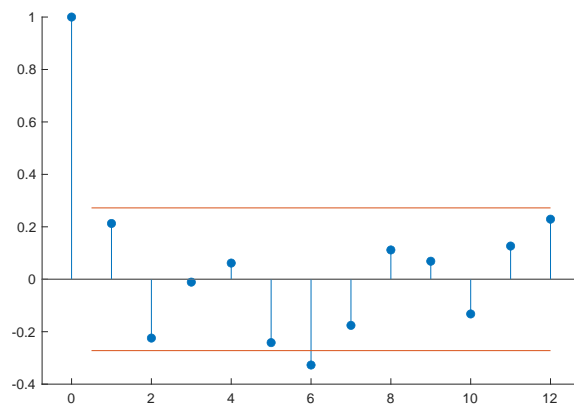
(b) Corrected mean forecast errors (correction factor 0.65)



(c) OLS regression forecast errors



(d) Corrected OLS regression forecast errors with historically optimal correction factor



(e) GLS regression forecast errors

**Figure 4:** Autocorrelation of the forecast errors.

regression, which is equivalent to the optimal weights of [Bates and Granger \(1969\)](#), produces forecasting errors that exhibit significant autocorrelation at multiple lags, as shown in [Figure 4c](#). Correcting the OLS forecast removes this autocorrelation, as shown in [Figure 4d](#). The same result is obtained by estimating the weight and correction simultaneously via GLS, as shown in [Figure 4e](#).

## 4 Conclusion

This paper shows that an important and largely overlooked source of forecast improvement lies not in refining combination weights, but in correcting combined forecasts when their errors are serially dependent. Building on the classic [Bates and Granger \(1969\)](#) example, we demonstrate that combined forecast errors often exhibit substantial autocorrelation and that exploiting this predictability can deliver gains that exceed those achieved by forecast combination itself. We formalize this idea within the conditional-risk framework of [Gibbs and Vasnev \(2024\)](#) and link forecast correction to efficient estimation of combination weights under time-series dependence using GLS. Empirical evidence from the U.S. Survey of Professional Forecasters across multiple variables and subsamples strongly supports the effectiveness of this approach.

A central empirical finding is the robustness of a simple, easily implementable correction: adding a fraction of the previous combined forecast error to the next-period combined forecast. Across most variables and subsamples—excluding periods dominated by extreme structural disruptions such as COVID—a correction factor near 0.5 consistently yields sizable improvements in forecast accuracy. The gains from this parsimonious adjustment are comparable to those from estimating historically optimal correction factors, while avoiding additional estimation uncertainty. As a result, the corrected mean forecast is a practical and robust default choice for applied forecasting.

The correction perspective also offers new insight into the forecast combination puzzle. Although optimal-weight combinations estimated via OLS often perform poorly out of sample, correcting these forecasts substantially improves their accuracy and frequently restores their

theoretical advantage over simple averages. Jointly estimating weights and the correction factor via GLS further improves efficiency and eliminates residual autocorrelation in forecast errors, although in our application, the corrected mean forecast remains highly competitive.

These findings point to a promising and largely unexplored direction for future research. We encourage researchers to give explicit attention to the time-series properties of combined forecast errors and to treat forecast correction as a complementary dimension to forecast combination. Rather than replacing existing techniques, correction can be naturally integrated into the multitude of established combination methods, as well as newer approaches, including machine-learning-based forecast ensembles. Incorporating simple correction mechanisms into both classical and modern forecasting frameworks has the potential to deliver substantial accuracy gains at minimal additional cost, and we view this as a fertile area for further theoretical and empirical work.

## Code availability

The code for the motivating example and the empirical investigation is available at <https://github.com/a-vasnev/GLS>.

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Period	Fixed correction factor										valid. hist.
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
UNEMP											
1969Q1–2025Q2	1.01	1.04	1.07	1.11	1.16	1.21	1.27	1.33	1.40	1.47	1.16
1969Q1–2025Q2*	0.95	0.91	0.88	<b>0.86</b>	0.86	0.86	0.88	0.90	0.94	0.99	0.86
1969Q1–1999Q4	0.95	0.92	0.89	0.87	<b>0.87</b>	0.87	0.89	0.92	0.96	1.00	0.87
2000Q1–2025Q2	1.02	1.05	1.09	1.14	1.19	1.25	1.32	1.39	1.46	1.53	1.20
2000Q1–2025Q2*	0.95	0.90	0.86	0.84	<b>0.83</b>	0.83	0.84	0.87	0.90	0.95	0.83
2000Q1–2008Q4	0.97	0.94	0.92	0.90	0.89	<b>0.89</b>	0.89	0.91	0.92	0.95	0.90
2000Q1–2019Q4	0.95	0.90	0.87	0.85	0.83	<b>0.83</b>	0.84	0.87	0.90	0.94	0.84
2010Q1–2019Q4	0.97	0.95	0.94	<b>0.93</b>	0.94	0.96	0.99	1.03	1.08	1.13	0.95
2022Q1–2025Q2	0.91	0.84	0.79	0.75	<b>0.74</b>	0.75	0.79	0.85	0.92	1.00	0.74
RGDP											
1969Q1–2025Q2	0.96	0.93	0.91	<b>0.90</b>	0.90	0.92	0.94	0.97	1.01	1.06	0.94
1969Q1–2025Q2*	0.95	0.91	0.88	0.86	<b>0.85</b>	0.86	0.87	0.90	0.93	0.98	0.90
1969Q1–1999Q4	0.95	0.91	0.88	0.86	0.85	<b>0.85</b>	0.86	0.88	0.91	0.95	0.95
2000Q1–2025Q2	0.96	0.94	0.92	<b>0.92</b>	0.92	0.94	0.97	1.01	1.05	1.11	0.94
2000Q1–2025Q2*	0.95	0.91	0.88	0.86	<b>0.86</b>	0.86	0.88	0.91	0.95	0.99	0.87
2000Q1–2008Q4	0.95	0.91	<b>0.89</b>	0.89	0.91	0.95	1.01	1.08	1.16	1.25	0.94
2000Q1–2019Q4	0.95	0.92	0.89	0.87	<b>0.87</b>	0.88	0.90	0.93	0.97	1.02	0.89
2010Q1–2019Q4	0.95	0.91	0.88	0.86	<b>0.85</b>	0.85	0.87	0.89	0.93	0.97	0.87
2022Q1–2025Q2	0.95	0.90	0.87	0.85	0.83	<b>0.83</b>	0.84	0.87	0.90	0.94	0.85
INDPROD											
1969Q1–2025Q2	0.95	0.91	0.88	0.86	<b>0.85</b>	0.86	0.87	0.90	0.93	0.98	0.86
1969Q1–2025Q2*	0.95	0.91	0.88	0.86	<b>0.85</b>	0.85	0.86	0.89	0.92	0.97	0.85
1969Q1–1999Q4	0.95	0.91	0.88	0.86	<b>0.85</b>	0.85	0.87	0.89	0.93	0.97	0.86
2000Q1–2025Q2	0.95	0.92	0.89	0.88	<b>0.87</b>	0.88	0.90	0.92	0.96	1.01	0.88
2000Q1–2025Q2*	0.95	0.91	0.87	0.85	<b>0.84</b>	0.84	0.85	0.87	0.91	0.95	0.84
2000Q1–2008Q4	0.95	0.91	0.87	0.85	0.84	<b>0.83</b>	0.85	0.87	0.90	0.94	0.84
2000Q1–2019Q4	0.95	0.90	0.87	0.85	0.84	<b>0.84</b>	0.85	0.87	0.90	0.95	0.84
2010Q1–2019Q4	0.96	0.93	0.90	0.89	<b>0.89</b>	0.90	0.92	0.96	1.00	1.05	0.89
2022Q1–2025Q2	0.97	0.96	<b>0.95</b>	0.96	0.97	1.00	1.03	1.08	1.13	1.18	0.98
CPI											
1981Q3–2025Q2	0.98	0.96	<b>0.96</b>	0.97	0.99	1.01	1.05	1.09	1.14	1.20	0.97
1981Q3–2025Q2*	0.98	0.97	<b>0.97</b>	0.98	1.00	1.03	1.07	1.12	1.17	1.23	0.98
1981Q3–1999Q4	0.98	0.97	<b>0.97</b>	0.98	1.00	1.03	1.07	1.11	1.17	1.23	0.97
2000Q1–2025Q2	0.98	0.96	<b>0.96</b>	0.97	0.98	1.01	1.04	1.09	1.14	1.20	0.97
2000Q1–2025Q2*	0.98	0.97	<b>0.97</b>	0.98	1.00	1.03	1.07	1.12	1.17	1.24	0.98
2000Q1–2008Q4	1.01	1.02	1.04	1.06	1.08	1.11	1.15	1.18	1.22	1.26	1.03
2000Q1–2019Q4	<b>0.99</b>	0.99	1.01	1.03	1.06	1.10	1.15	1.20	1.26	1.32	1.01
2010Q1–2019Q4	0.98	0.97	<b>0.96</b>	0.97	0.99	1.02	1.06	1.11	1.16	1.22	0.97
2022Q1–2025Q2	0.92	0.85	0.79	0.74	0.70	<b>0.69</b>	0.69	0.71	0.75	0.80	0.84

**Table 3:** Relative RMSFE for UNEMP, RGDP, INDPROD, and CPI across different periods (relative to the original mean forecast). The fixed correction factor is varied from 0 to 1 in increments of 0.1 (0 corresponds to the original mean forecast). The last column shows the result for the cross-validated historical correction factor (excluding the COVID period from validation). The minimum value (based on the full precision) that improves on the mean forecast in each row (across the fixed factor) is bold.

Note: \* indicates that the COVID period (2020Q1–2022Q4) was excluded from evaluation.

Forecasts	MSFE	relative MSFE
Individual forecasts		
ID 421	0.1557	0.9956
ID 426	0.1736	1.1104
ID 484	0.3679	2.3534
ID 504	0.1681	1.0750
ID 510	0.1948	1.2460
ID 518	0.2255	1.4422
Combinations		
Mean Forecast	0.1563	1.0000
– corrected with $\gamma = 0.5$	0.0802	0.5132
– corrected with $\gamma = 0.65$ (fixed opt.)	0.0729	0.4663
– corrected with hist. opt. factor	0.0878	0.5613
Optimal Combination (via restr. OLS)	0.1613	1.0315
– corrected with $\gamma = 0.5$	0.0915	0.5850
– corrected with $\gamma = 0.7$ (fixed opt.)	0.0860	0.5502
– corrected with hist. opt. factor	0.0914	0.5846
One-step combination and correction (via restricted GLS)	0.0825	0.5275

**Table 4:** Mean Squared Forecasting Errors (MSFE) and relative (to the mean forecast) MSFE for individual forecasts and combinations. The evaluation is done over the period starting from 2006, when all methods deliver a forecast, as the out-of-sample optimal combination and GLS require an initial sample to start the estimation procedure.