

# Pre-Tax Corporate Profits Forecasts for the US Economy: An unresolved Challenge

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## Research Article

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# **Pre-Tax Corporate Profits Forecasts for the US Economy: An unresolved Challenge**

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**JEL codes:** D53, D81, D84, D91, G12, G17, G41.

**Abstract:** This study examines forecasts of corporate profits in the US economy. The specific subject of forecast is the percentage change in pre-tax corporate profits compared to the previous year. These forecasts are available for the period from 1990 to 2024. The forecasts encompass a range of 24 different forecast horizons, spanning from 24 months to one month. The finding that the mean forecast error does not decrease with a shorter forecast horizon is particularly surprising. This contradicts previous empirical findings and is unique in the field of macroeconomic forecasts. Furthermore, the findings indicate that forecasters tend to herd, underestimate the variability of reality, and are by no means overly optimistic.

## Introduction

Earnings forecasts are a key component of fundamental stock analysis. In order to estimate the price potential of stocks, the current stock price is often compared with the intrinsic value of the stock. The intrinsic value of a stock corresponds to the sum of all discounted future cash flows generated by the stock. A shareholder benefits from dividend payments and increases in the stock price. A company's profits can be distributed or retained. Distributed profits correspond to dividend payments. Retained earnings increase the value of the company, which is reflected in corresponding price increases. A company's profits thus reflect the streams of benefits that accrue to shareholders. Consequently, determining the intrinsic value of a share therefore necessitates the forecast of future profits (cf. Capstaff et al., 1995).

Not least because of their great practical significance for stock investments, earnings forecasts have been reviewed for reliability for decades. Several hundred studies deal exclusively with earnings forecasts by financial analysts. Other studies examine the earnings forecasts of the management of the respective stock corporations.

Most analysts examine a limited number of industries, or, in some cases, a single industry only (see, for example, Myring & Wrege, 2009). They usually focus on a small number of companies of outstanding importance. They compile all publicly available information on the business development of these companies. They also strive to establish contacts with company representatives in order to learn about new products, new business strategies, new business areas, etc. at an early stage. Finally, they summarize all the information and use it to generate profit forecasts.

Analyst activities of this kind guide actively oriented portfolio management in the selection of promising stocks (stock picking). However, stock picking is not everything. Over the past five decades, even the large, established stock markets have experienced phases of very unfavorable price developments. Portfolios based on very good stock picking, for example, showed a performance of only -20%, while the corresponding stock market suffered a performance of -40%. Stock picking would then be considered enormously successful, but the overall investment result would still have to be regarded as disappointing. For this reason, active portfolio management generally involves asset allocation in addition to stock picking. Asset allocation refers to the distribution of the investment volume across different asset classes and different economies. The great importance of asset allocation for investment success is emphasized, for example, by Ibbotson & Kaplan (2000). In order to successfully allocate the funds to be invested in stocks or other corporate investments across different economies, it is necessary to prepare corporate earnings forecasts for entire economies. Earnings forecasts at such a high level of aggregation are a major challenge. Information about

a breakthrough in a company's product development helps analysts to prepare a good profit forecast for that company. However, such information is almost irrelevant for the further development of corporate profits of an entire economy. For this reason, corporate profit forecasts for entire economies are generally prepared by macro analysts who also deal with growth forecasts, inflation forecasts, interest rate forecasts, exchange rate forecasts, and similar issues. These highly aggregated profit forecasts are the key to a successful asset allocation in the context of active portfolio management.

In this study, we focus on aggregated corporate profit forecasts for the US economy. The forecasts are taken from the journal "Consensus Forecasts" and are available on a monthly basis for the period from 1990 to 2024. The forecasters are primarily large, well-known US banks, investment companies, and economic research institutes. The forecasts predict the percentage change in pre-tax corporate profits compared to the previous year. These forecasts refer to the current year and the following year. Since the forecasts are made on a monthly basis, there are a total of 24 different forecast horizons, ranging from 24 months to one month. We examine whether – and, if so, to what extent – the mean absolute percentage error (MAPE) decreases as the forecast horizon is reduced. This is to be expected, as the forecast task is generally easier to accomplish when the forecast horizon is shorter. Furthermore, the forecasts are checked for any overoptimism on the part of the forecasters, and the dispersion of the forecasts is examined in more detail.

The findings reveal that the average forecast error does not diminish with decreasing forecast horizon. Forecasts with a 24-month forecast horizon are, on average, almost exactly at the same error level as forecasts with only a one-month forecast horizon. This result is particularly noteworthy given that other forecast items (gross domestic product, producer price index, consumer price index, housing starts, and many others) show very significant reductions in forecast errors as the forecast horizon decreases. In addition, it can be seen that the average variance of the forecasts diminishes as the forecast horizon decreases. Analysts are therefore becoming increasingly unanimous, but forecast errors are not decreasing. This is a clear sign of herd behavior among analysts. Finally, it becomes evident that forecasters underestimate the variability of reality and are by no means prone to optimism.

We present some thoughts on the causes of these surprising findings and highlight the necessary consequences for portfolio management decisions.

## Literature review

The reliability of earnings forecasts made by financial analysts has been examined for decades. Early studies include Cragg & Malkiel (1968), Elton & Gruber (1972), Barefield & Comiskey (1975), Basi et al. (1976), Richards (1976), Brown & Rozeff (1978), Crichfield et al. (1978), Imhoff (1978), Ruland (1978), Barefield et al. (1979), and Givoly & Lakonishok (1980).

The exact nature of the subject of the forecast varies considerably. Most studies refer to US companies (see, for example, Lim, 2025; Mamatzakis & Bagntasarian, 2020; Mande & Son, 2012; Ertimur et al., 2011; Aiolfi et al., 2010; Avramov et al., 2009; Kwag & Small, 2007; Hong & Kubik, 2003; Machuga et al., 2002; Brown, 2001; Ely & Mande, 1996; Abarbanell & Bernard, 1992) or British companies (see, for example, Constantinou et al., 2003; Hussain, 1997; Patz, 1989). Some studies also make international comparisons of forecast accuracy (see, for example, André et al., 2016; Athavale et al., 2013; Lim et al., 2013; Yu, 2010; Coën et al., 2009; Bae et al., 2008; Black & Carnes, 2006; Beckers et al., 2004; Hope, 2003; Rothovius, 2003; Claus & Thomas, 2001; Capstaff et al., 2001; Firth & Gift, 1999). More recently, there has been an increase in research examining forecasts for the profits of Chinese and other Asian companies (see, for example, Tang et al., 2025; Wang et al., 2024; Zhang & Luo, 2024; Liu et al., 2023; Luo & Wu, 2022; Wang et al., 2022; Wang et al., 2021; Hu et al., 2021; Ding et al., 2021; Hou & Gao, 2021; Hou et al., 2018; Yu & Wang, 2018; Wu et al., 2018; Liu, 2017; Huang & Wright, 2015; Wang et al., 2015; Kubota et al., 2010; Loh & Mian, 2003; Eng & Teo, 1999; Jaggi & Jain, 1998; Lui, 1992).

The majority of studies consider earnings in US dollars per share or, where applicable, in other currencies per share (see, for example, Huang et al., 2017; Barron et al., 2008; Stickel, 1993; Brous & Kini, 1993; Mendenhall, 1991; Stickel, 1990). However, the change in earnings as a percentage compared to the previous year is rarely discussed.

There are studies that examine earnings forecasts with a consistent forecast horizon (see, for example, Bochkay & Levine, 2019; Amiram et al., 2018; Hussain, 1997). Other studies consider earnings forecasts with different forecast horizons (see, for example, Cordeiro & Kent, 2001). Some studies explicitly compare earnings forecasts with different forecast horizons. These studies demonstrate that, in general, the shorter the forecast horizon, the smaller the forecast errors (see, for example, Sougiannis & Yaekura, 2001; De Bondt & Forbes, 1999; Capstaff et al., 1998; Das, 1998; Das & Saudagaran, 1998; Jaggi & Jain, 1998; Sinha et al., 1997; Lys & Soo, 1995; Kross et al., 1990; Patz, 1989; O'Brien, 1988; Brown et al., 1987a; Brown et al., 1987b; Brown et al., 1985). These clear indications of a positive correlation between the forecast horizon and forecast error are incorporated into hypotheses 1 and 2 of

the present study. The exact formulation of hypotheses 1 and 2 can be found in the following chapter.

Many different approaches are employed to assess the success of forecasts. Some studies apply the unbiasedness test (see, for example, Keane & Runkle, 1998; Ackert & Hunter, 1994; Kang et al., 1994; Ackert & Hunter, 1993; Klein, 1990; Givoly, 1985; Klein, 1990). The unbiasedness test usually yields unfavorable results. However, earnings forecasts occasionally prove to be unbiased (cf. Dick-Nielsen et al., 2022). The efficiency test is also used to evaluate earnings forecasts (cf. e.g. Elgers & Lo, 1994). In the efficiency test, earnings forecasts often prove to be valid (cf. e.g. Basu & Markov, 2004; Lys & Sohn, 1990). In some studies, however, earnings forecasts also fail the efficiency test (see, for example, Ahmed et al., 2005; Ali et al., 1992; Abarbanell, 1991). The test for overreaction/underreaction to changes in analysts' forecasts (De Bondt & Thaler, 1990) is also frequently used (see, for example, Smith Raedy et al., 2006; Easterwood & Nutt, 1999; O'Hanlon & Whiddett, 1991). Another way of assessment compares analyst forecasts with forecasts which are generated using simple statistical models, such as ARIMA or random walk models (see, for example, Dreman & Berry, 1995; Brown, 1996; Imhoff & Paré, 1982; Fried & Givoly, 1982). In some studies, analysts perform well (see, for example, Wild & Kwon, 1994; Chatfield et al., 1989; Patz, 1989; O'Brien, 1988; Brown et al., 1987b). In other studies, analysts fail to meet this benchmark (see, for example, Harris & Wang, 2019; Bradshaw et al., 2012; Lacina et al., 2011; Harris, 1999; Kodde & Schreuder, 1984). Ball & Ghysels (2018) demonstrate that forecasts derived from complex statistical models are often more accurate than those made by analysts. A comparison with naive forecasts is also made (see, for example, Lacina et al., 2011). Bradshaw et al. (2012) show that the earnings forecasts considered prove to be less reliable than the corresponding naive forecasts. Finally, some studies raise the question of whether earnings forecasts are suitable for contributing to successful stock price forecasts and/or successful investment decisions (see, for example, Kothari et al., 2016; Wieland, 2011; Dugar & Nathan, 1995; Jennings, 1987). It is often found that analysts' earnings forecasts (or their dispersion) are indeed suitable for successfully predicting stock price developments and/or making successful investment decisions (see, for example, Feldman et al., 2019; Barth & Hutton, 2004; Han & Manry, 2000; Bandyopadhyay et al., 1995). In other studies, earnings forecasts prove to be less suitable in this regard (see, for example, Hall & Tacon, 2010).

Some studies compare the success of different forecasters (see, for example, Hsu & Chiao, 2011). Comparisons are often made between analysts' earnings forecasts on the one hand and management's earnings forecasts on the other (see, for example, Brown & Zhou, 2015; Kim & Song, 2015; Hutton et al., 2012; Bartley & Cameron, 1991; Bathke et al., 1991; Baginski & Hassell, 1990; Hassel & Jennings, 1986; Waymire, 1986; Schreuder & Klaassen, 1984). It

is only rarely discussed whether business economists or macroeconomists have prepared the profit forecasts. The business perspective focuses on individual companies. The profit development of a particular company is determined in order to be able to adequately assess the attractiveness of the relevant stock. The macroeconomic perspective tends to focus on the corporate profit development of an entire stock market or even an entire economy. Hope & Kang (2005) find that profit forecasts become less accurate when there is a greater degree of macroeconomic uncertainty. Amiram et al. (2018) point out that earnings forecasts are better managed in an environment of market uncertainty when macroeconomists are involved in their preparation. We will return to this particularly interesting aspect in the discussion chapter.

Many studies address the variance in forecasts made by different analysts (see, for example, Ajinkya et al., 1991; Ajinkya & Gift, 1985). This aspect is particularly interesting when the change in variance over time, i.e., with a shorter forecast horizon, is discussed (see, for example, Spiwoks, 2009; Wallmeier, 2005). This is often followed by the question of possible herd behavior among analysts (see, for example, De Bondt & Forbes, 1999). We address this aspect in our third hypothesis. The exact formulation of hypothesis 3 can be found in the subsequent chapter.

Ogburn (1934) showed that forecasters very often underestimate the variability of reality. This results in the dispersion of actual events being greater than the dispersion of forecasts. This circumstance has not yet been investigated in connection with profit forecasts. We pursue this aspect in the context of the fourth hypothesis. The exact formulation of hypothesis 4 can be found in the following chapter.

Many studies on the success of analysts in forecasting earnings developments discuss some novel ideas about the possible causes of successful or unsuccessful forecasts. For example, it is assumed that analysts may "fall in love" with the stocks they observe, which can cloud their judgment (see, for example, Chopra, 1998). Occasionally, the tendency towards herd behavior is discussed (see, for example, Jiao, 2024; Keskek et al., 2014; Cooper et al., 2001; Hong et al., 2000). The presence of overconfidence among analysts is also discussed as a disruptive element (see, for example, Friesen & Weller, 2006). Anchoring heuristics (see, for example, Cen et al., 2013; Amir & Ganzach, 1998) or cognitive dissonance (see, for example, Friesen & Weller, 2006) can prevent analysts from making appropriate corrections to their forecasts when conditions change. Azevedo et al. (2021) see considerable potential for improving earnings forecasts in combating analysts' sluggishness with respect to information in recent stock price movements.

There is debate as to whether analysts are really striving to produce the best possible earnings forecasts (see, for example, Berger et al., 2019; Brown et al., 2015; Chan et al., 2007;

Trueman, 1990) or whether they want to buy access to management information with the help of overly optimistic forecasts (see, for example, Eames & Glover, 2003; Lim, 2001). Hutton (2005) points out that close contact between analysts and management can contribute to fewer errors in earnings forecasts. The experience of analysts is addressed by Mikhail et al. (2003). They find that more experienced analysts produce better earnings forecasts (see also Call et al., 2021; Clement et al., 2007; Clement, 1999; Mikhail et al., 1997). Jacob et al. (1999) come to the opposite conclusion.

Corporate transparency could also play a role in the success of forecasts. Abarbanell & Lehavy (2003a) see corporate earnings management and the strategic handling of earnings information as a reason for significant forecasting errors by analysts (see also Wilson & Wu, 2011). Abernathy et al. (2013) find that the higher the accounting expertise of companies' audit committees, the lower the forecasting errors in earnings forecasts (for similar conclusions, see Bochkay & Levine, 2019; Behn et al., 2008; Barron et al., 1999; Lang & Lundholm, 1996). Noh et al. (2017) emphasize the importance of auditors for the success of analysts' earnings forecasts (see also Rouhou et al., 2015; Xie et al., 2012). Aboud et al. (2018) see an influence of accounting standards on the accuracy of earnings forecasts (see also Bratten et al., 2023; Bradshaw et al., 2018; André et al., 2016; Rouhou et al., 2015; Garrido-Miralles & Sanabria-García, 2014; Horton et al., 2013; Cotter et al., 2012; Glaum et al., 2011; Hodgdon et al., 2008; Mensah et al., 2004; Hope, 2003; Machuga et al., 2002; Ashbaugh & Pincus, 2001; Peek, 2001; Basu et al., 1998; Maines et al., 1997; Brown, 1983). Lehavy et al. (2011) find that the more readable the annual report (Form 10-K) is, the more accurate the analysts' earnings forecasts are. Yu (2010) points out that companies with comprehensive corporate governance disclosures in their annual reports receive accurate and less scattered earnings forecasts from financial analysts (see also Yu & Wang, 2018).

Call et al. (2009) show that earnings forecasts are more accurate when forecasters also prepare cash flow forecasts. Keung (2010) assumes that earnings forecasts are more accurate when analysts also prepare sales forecasts at the same time (see also Kim & Prather-Kinsey, 2010). Ciftci et al. (2016) see potential for improvement in earnings forecasts if the cost structures of companies are taken into account more precisely (see also Weiss, 2010). Furthermore, it is emphasized that the further development of earnings is more difficult to forecast in loss phases than in profit phases (see, for example, Ciccone, 2005). Barron et al. (2002) highlight the problem of intangible assets, particularly in R&D-intensive companies (see also Chakravarty & Grewal, 2016; Wang & Alam, 2007; Gu & Wang, 2005). Anagnostopoulou (2010) notes that reporting R&D activities and R&D successes in the balance sheet leads to lower profit forecast errors by analysts. Orens & Lybaert (2007) emphasize that the use of non-financial corporate information (e.g., about internal structures) can contribute to an

improvement in analysts' earnings forecasts. Luo & Wu (2022) find that the availability of ESG ratings increases the accuracy of analysts' earnings forecasts by reducing information risks.

Datta et al. (2011) show that analysts' profit forecasts are more accurate for companies with significant market power than for companies without such outstanding market power (cf. similar findings in Patz, 1989). Dunn & Nathan (1998) find that the extent of diversification of business areas within a company has an impact on the accuracy of earnings forecasts (see also Lee et al., 2013). Miller & Sedor (2014) discuss the influence of a company's stock price, and Walther & Willis (2013) discuss the influence of investor sentiment on analysts' earnings forecasts (see also Wu et al., 2018). O'Brien (1990) demonstrates that the ease with which earnings trends can be forecast varies across different industries.

Hou & Gao (2021) posit that a high degree of economic freedom tends to result in more precise earnings forecasts (see also Wang et al., 2021). Le et al. (2024) find that an elevated degree of economic policy uncertainty contributes to amplified forecast errors and augmented dispersion in earnings forecasts.

Datta et al. (2022) find that analysts are more capable of assessing the profit performance of companies with female chief executive officers (CEOs) than companies with male CEOs (see Gul et al., 2013, for similar findings). Mamatzakis & Bagntasarian (2020) conclude that the structure of management compensation has an impact on the accuracy of analysts' earnings forecasts.

Hunton & McEwen (1997) identify an influence of cognitive information search strategies on the accuracy of analysts' earnings forecasts. Hou et al. (2018) find that analysts occupying more central positions in information networks tend to produce more accurate earnings forecasts. Confucian culture is also discussed as an element that can improve earnings forecasts (see, for example, Zhao & Li, 2024). We will return to some of these ideas in the discussion chapter.

There is considerable debate as to whether earnings forecasts are characterized by optimism or pessimism (see, for example, Veenman & Verwijmeren, 2018; Hribar & McInnis, 2011; Dolvin et al., 2009; Groyberg et al., 2008; Jung, 2005; Loh & Mian, 2003; Butler & Lang, 1991). Some studies show a systematic overestimation of profit development, which is mostly regarded as a sign of optimism or overoptimism (see, for example, Lehmer et al., 2022; Bradshaw et al., 2016; Lambert et al., 2015; Kwag & Small, 2007; Wallmeier, 2005; Helbok & Walker, 2004; Huberts & Fuller, 1995; Brown, 1997; Hwang et al., 1996). Other studies show a systematic underestimation of profit development, which is then interpreted as pessimism on the part of analysts (see, for example, Black & Carnes, 2006). Findings on the distribution of

forecast errors in earnings forecasts can be found, for example, in Cohen & Lys (2003) and Abarbanell & Lehavy (2003b). This aspect leads us to the fifth hypothesis. The exact formulation of the fifth hypothesis can be found in the following chapter.

Brief overviews of some of these and other aspects that can influence the accuracy of profit forecasts are provided by Rahman et al. (2019), Stotz (2016), Ramnath et al. (2008), and Schipper (1991).

## **Hypotheses, data, and methods**

In this study, we focus on corporate profit forecasts for the US economy. The forecasts are taken from the journal "Consensus Forecasts" and are available on a monthly basis for the period from 1990 to 2024. The forecasters are primarily large, well-known US banks, investment companies, and economic research institutes. The forecasts predict the percentage change in pre-tax corporate profits compared to the previous year. These forecasts refer to the respective current year and the subsequent year.

At the beginning of a month, forecasters are asked by "Consensus Forecasts" for their estimates. Unlike in Guttman (2010), in this case the forecasters have no influence on the timing of the submission of their profit forecasts. The forecast item under consideration is the percentage change in corporate profits compared to the previous year. This figure is calculated at the end of the year in comparison with the end of the previous year. So if a forecaster is asked at the beginning of January 2023 what percentage change in profits he expects for 2024, the forecast horizon is 24 months (from the beginning of January 2023 to the end of December 2024). If the forecaster is asked about the same issue at the beginning of February, the forecast horizon has decreased by one month and is now 23 months (from the beginning of February 2023 to the end of December 2024). Forecasters are asked not only about their assessments for the following year, but also about their assessments for the current year. The forecast requested at the beginning of January 2024 then refers to the end of December 2024 and thus has a forecast horizon of twelve months. At the beginning of February, the forecast for the current year has a remaining forecast horizon of eleven months. At the beginning of December, the forecast for the current year has a forecast horizon of only one month. This results in 24 different forecast horizons (from 24 months to one month).

As the forecast horizon decreases, the forecasting task generally becomes easier. The outcome of a basketball game between the Los Angeles Lakers and the Denver Nuggets is easier to predict in the final minutes of the fourth quarter than in the first minutes of the first quarter. The average temperature for a year is easier to forecast in November than in January of the same year. The yield of a wheat field is easier to forecast in mid-June than in early April. This is simply because, over time, more and more factors that are important for assessing the situation become apparent. If an important player for the Denver Nuggets gets injured in the third quarter and the L.A. Lakers are leading 104-79 with two minutes left in the game, it is no longer difficult to predict who will win. If January and February have been unusually mild and there has been a prolonged heatwave in the summer, it is no longer difficult to predict a high average annual temperature towards the end of the year. If there have been severe

thunderstorms with dramatic hail damage to fields at the beginning of June, it is no longer difficult to predict a below-average wheat harvest in mid-June.

This so-called horizon effect also applies to economic issues. When forecasting economic growth for a year, little information is available in January. For example, sentiment and leading indicators can be used. In December of the same year, however, the preliminary GDP growth rates for the first and second quarters are already available. Initial estimates for the third quarter are also usually already known. Accordingly, forecast errors in December are likely to be much lower than in January. The same situation applies to profit forecasts. Many companies report their profit development on a quarterly basis. Consequently, as the forecast horizon decreases, the amount of information available that provides clues about the situation to be forecast increases.

The special data structure presented here should also help to reduce forecast errors as the forecast horizon shortens. Since the percentage change in corporate profits is forecast compared to the previous year, forecasts of more than one year forecast horizon (forecast horizons of 24 months to 13 months) present a double challenge. In order to be able to forecast the percentage change in profits in the following year, forecasters must assess not only the coming year but also the current year. Only if the development of the current year is accurately forecast, the necessary basis for estimating the percentage change in the following year is available. Forecasts of more than one year forecast horizon are therefore twice as difficult to manage as intra-year forecasts.

The gradual increase in the level of information over time, the particular difficulty of forecasts of more than one year forecast horizon, and a large number of empirical findings in previous studies (see chapter Literature review) lead to the first hypothesis.

Hypothesis 1: The average forecast error of US corporate profits forecasts decreases statistically significantly as the forecast horizon decreases.

Null hypothesis 1: The average forecast error of US corporate profits forecasts does not decrease statistically significantly as the forecast horizon decreases.

To measure the forecast error, a scale should be used in which overestimates and underestimates do not cancel each other out. Consequently, it appears rational to employ an absolute forecast error measure. In addition, the forecast error measure should take into account different magnitudes of actual events. Forecasting a profit increase of +108% when the actual value is +100% is less serious than forecasting +10% when the actual value is +2%. In both cases, the actual value is overestimated by 8 percentage points. However, in the first

case, the forecast error is insignificant in relation to the magnitude of the actual event. In the second case, profit growth is overestimated by a factor of five. The percentage changes in corporate profits can vary quite significantly over different periods of time. In some years, there is a significant increase in profits. In other years, there are only minor changes. In order to make such different starting situations comparable, it makes sense to use a relative forecast error measure. We therefore rely on the frequently used forecast error measure of the mean absolute percentage error (MAPE). The MAPE is used, for example, by Conroy & Harris (1995), Conroy & Harris (1987), Waymire (1986), and Kodde & Schreuder (1984).

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{A_i - F_i}{A_i} \right| \cdot 100\%$$

With: MAPE = Mean Absolute Percentage Error; A = Actual Event; F = Forecast.

Whether the expected decline in forecast errors with a gradual shortening of the forecast horizon is actually statistically significant is determined using Kendall's tau, whereby the correlation test is designed as a one-sided test.

It can be assumed that forecasting corporate earnings trends in the US economy poses a challenge comparable to that of other US macro forecasts. Therefore, we expect a gradual decline in average forecast errors (MAPE) not only for profit forecasts, but also for economic forecasts (gross domestic product, industrial production, business investment, personal consumption, housing starts, auto & light truck sales, employment costs) and for inflation forecasts (consumer price index, producer price index, core personal consumption expenditures price index [core PCE prices]) with a gradual shortening of the forecast horizon. This consideration leads to the second hypothesis.

Hypothesis 2: The development of average forecast errors with a gradual shortening of the forecast horizon for US corporate profit forecasts does not differ from other US macro forecasts.

Null hypothesis 2: The development of average forecast errors with a gradual shortening of the forecast horizon for US corporate profit forecasts differs from other US macro forecasts.

The macro forecast data is also sourced from the journal "Consensus Forecasts." It is available on a monthly basis for the period from 1990 to 2024. Only the publication of the forecasts for core PCE prices was started later by "Consensus Forecasts." They are available for the period from 2018 to 2024. Like the corporate profit forecasts, the other macro forecasts are primarily provided by large US banks, investment companies, and research institutes. They also have

forecast horizons ranging from 24 months to one month. The same tools are used for data analysis as for testing hypothesis 1.

If the forecast error gradually decreases as the forecast horizon shortens, it can also be expected that the dispersion of the pre-tax corporate profit forecasts of the various analysts will decrease as the forecast horizon shortens. With a long forecast horizon, estimates can vary greatly. Over time, as the information base becomes more and more solid, analysts' forecasts should gradually become more accurate. As a result, analysts' forecasts will gradually converge. The dispersion of forecasts will decrease. This leads to the third hypothesis.

Hypothesis 3: The average dispersion of US corporate profit forecasts made by different forecasters decreases statistically significantly as the forecast horizon shortens.

Null hypothesis 3: The average dispersion of US corporate profit forecasts made by different forecasters does not decrease statistically significantly as the forecast horizon shortens.

Whether this is a statistically significant reduction in dispersion is again determined using Kendall's tau, whereby the correlation is tested with a one-sided hypothesis.

Ogburn (1934) pointed out that forecasters often underestimate the variability of reality. The dispersion of forecasts is thus significantly lower than the dispersion of actual events. This leads to the fourth hypothesis.

Hypothesis 4: The variance of corporate profit forecasts is significantly lower than the variance of the actual percentage change in corporate profits in the US economy.

Null hypothesis 4: The variance of corporate profit forecasts is not significantly lower than the variance of the actual percentage change in corporate profits in the US economy.

This hypothesis is tested using the Brown-Forsythe test and cluster bootstrapping.

A large number of studies on profit forecasts observe overoptimism among forecasters (see chapter Literature review). These observations lead to the fifth hypothesis.

Hypothesis 5: The forecasts of US corporate profit growth are significantly higher in their central tendency (median) than the corresponding actual corporate profit growth in the US economy.

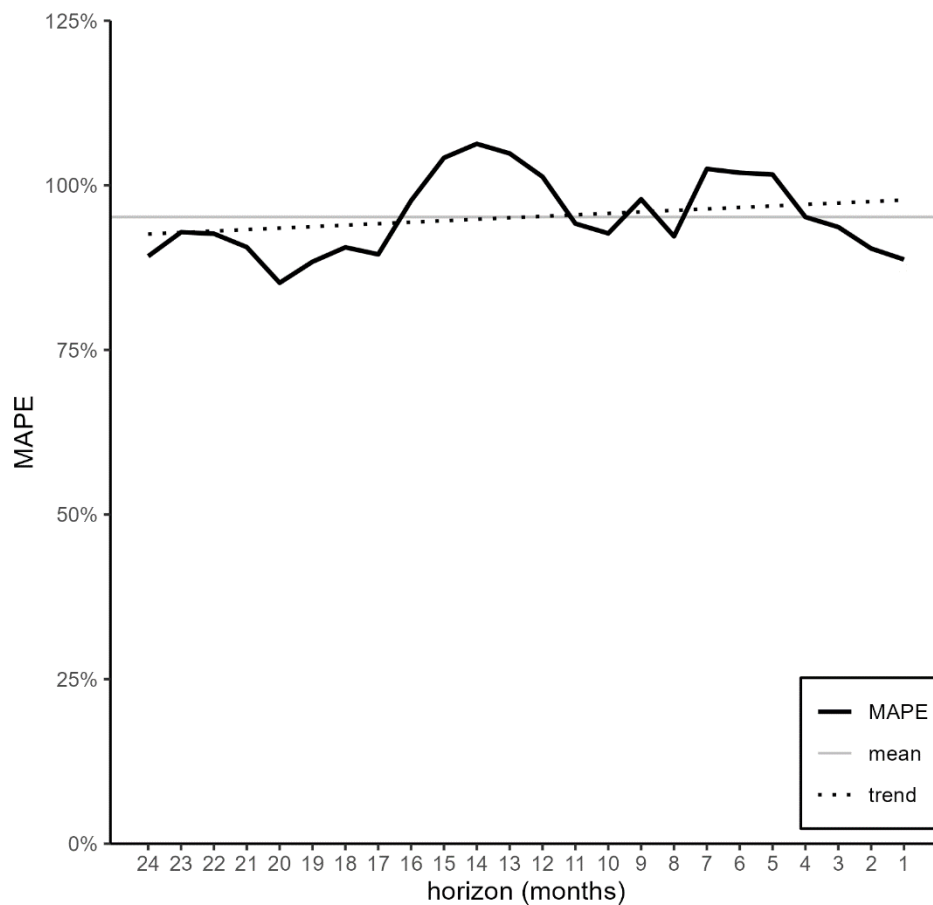
Null hypothesis 5: The forecasts of US corporate profit growth are not significantly higher in their central tendency (median) than the corresponding actual corporate profit growth in the US economy.

This hypothesis is tested using the Wilcoxon signed-rank test.

## Results

Over time, more and more relevant facts become known. Many companies report their profits on a quarterly basis. Therefore, the shorter the forecast horizon, the smaller the forecast errors should be. In addition, forecasts of more than one year forecast horizon (forecast horizons of 24 months to 13 months) pose a double challenge compared to intra-year forecasts (forecast horizons of 12 months to one month). In the case of forecasts of more than one year forecast horizon, the current year must first be forecast in order to determine a basis for the percentage change in profits in the following year. Only then can analysts turn their attention to the forecast for the following year. Both aspects (gradually increasing information and easier handling of intra-year forecasts) should contribute to a decrease in the average forecast error as the forecast horizon shortens. However, this effect does not occur (see Figure 1 and Table 1).

**Figure 1:** Average forecast errors in US corporate profit forecasts from 1990 to 2024 depending on the forecast horizon



With: MAPE = Mean Absolute Percentage Error.

**Table 1:** Average forecast errors in US corporate profit forecasts from 1990 to 2024 depending on the forecast horizon

| Forecast horizon                          | MAPE    | Forecast horizon       | MAPE    |
|-------------------------------------------|---------|------------------------|---------|
| 24 months                                 | 89.23%  | 12 months              | 101.30% |
| 23 months                                 | 92.88%  | 11 months              | 94.18%  |
| 22 months                                 | 92.65%  | 10 months              | 92.70%  |
| 21 months                                 | 90.61%  | 9 months               | 97.88%  |
| 20 months                                 | 85.19%  | 8 months               | 92.25%  |
| 19 months                                 | 88.39%  | 7 months               | 102.49% |
| 18 months                                 | 90.58%  | 6 months               | 101.91% |
| 17 months                                 | 89.51%  | 5 months               | 101.64% |
| 16 months                                 | 97.67%  | 4 months               | 95.18%  |
| 15 months                                 | 104.18% | 3 months               | 93.66%  |
| 14 months                                 | 106.30% | 2 months               | 90.40%  |
| 13 months                                 | 104.84% | 1 month                | 88.73%  |
| Average across all forecast horizons      |         | 95.18%                 |         |
| Regression line                           |         | $y = 0.9798 - 0.0022x$ |         |
| Kendall's tau                             |         | -0.138                 |         |
| p-value (one-sided, alternative: greater) |         | 0.831                  |         |

With: MAPE = Mean Absolute Percentage Error.

The extent of the average forecast errors is surprisingly large. On average across all forecast horizons and on average for the years 1990 to 2024, the mean absolute percentage error (MAPE) reaches a level of 95.18%. If profits actually increase by 40.0%, the average forecast is 78.07% [ $40\% \cdot (1 + 0.9518)$ ] or 1.93% [ $40\% \cdot (1 - 0.9518)$ ]. There is no way around the conclusion that this represents a very high level of error.

Even more surprising, however, is that the gradual shortening of the forecast horizon does not lead to a reduction in average forecast errors. While forecasts with a 24-month forecast horizon have an average MAPE of 89.23% for the years 1990 to 2024, forecasts with only a one-month forecast horizon have a MAPE of 88.73%. The minimum can be observed for the 20-month forecast horizon, where the average forecast error (MAPE) is 85.19%. If a regression line is added to Figure 1, it shows a negative slope of -0.0022. This is also reflected in Kendall's tau of -0.138. A negative slope of the regression line or a negative Kendall's tau means that the shorter the forecast horizon, the higher the forecast error tends to be.

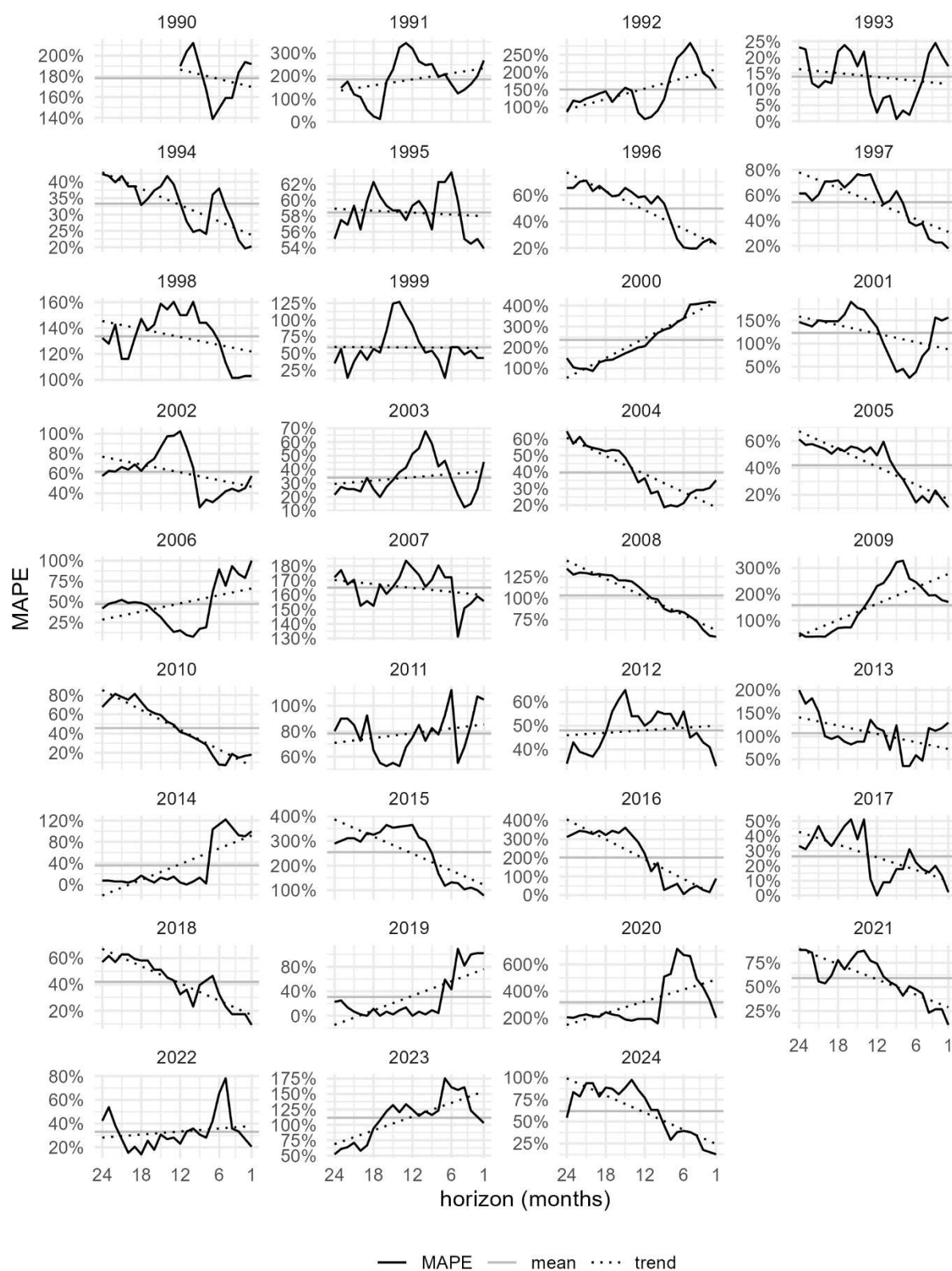
We performed these calculations on the basis of consensus forecasts. Ramnath et al. (2005) show that consensus forecasts have an advantage over the forecasts of individual forecasters in terms of forecast accuracy. Nevertheless, we also looked at the results obtained when all individual forecasts are included. In this case, the MAPE must first be determined for each of the 35 years (1990-2024) for each forecast horizon. Then the respective average of the 35 MAPE results per forecast horizon is determined. However, this produces a largely consistent picture. Kendall's tau is 0.011. The p-value (one-sided, alternative: greater) is 0.470.

If we summarize the results of the consensus forecasts on the one hand and the results of all individual forecasts on the other, it becomes clear that the forecast errors do not change significantly as the forecast horizon shortens. Depending on the data cut, there is an insignificant weak negative correlation (Kendall's tau = -0.138; p-value = 0.831) or an insignificant weak positive correlation (Kendall's tau = 0.011; p-value = 0.470). In any case, it is a very surprising result that the forecast error does not decrease significantly as the forecast horizon shortens.

Therefore, null hypothesis 1 cannot be rejected. This means that the average forecast errors do not decrease statistically significantly as the forecast horizon shortens.

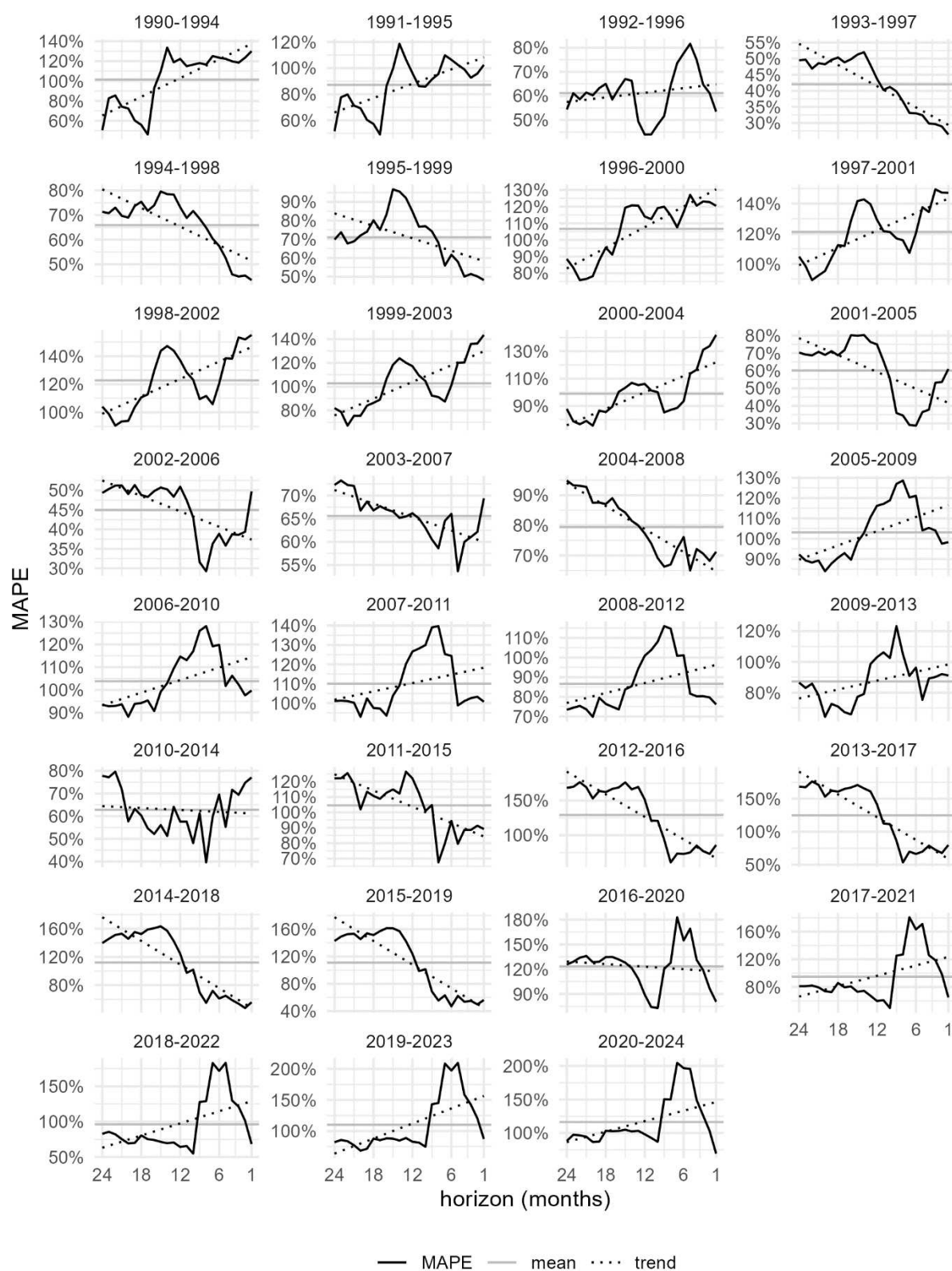
Looking at individual years and rolling five-year periods shows that phases in which forecast errors decrease as the forecast horizon shortens alternate with phases in which forecast errors increase as the forecast horizon shortens (see Figures 2 and 3). Therefore, on a long-term average (1990-2024), there is no significant reduction in forecast error as the forecast horizon shortens.

**Figure 2:** Average forecast errors in US earnings forecasts depending on the forecast horizon for the individual years 1990 to 2024



With: MAPE = Mean Absolute Percentage Error.

**Figure 3:** Average forecast errors in US earnings forecasts depending on the forecast horizon for revolving five-year periods from 1990 to 2024



With: MAPE = Mean Absolute Percentage Error.

The correlation between forecast errors and the forecast horizon varies considerably depending on the time periods considered. If well-known crisis years such as 2000 to 2002 (bursting of the dot-com bubble), 2008 to 2009 (major banking, capital market, and economic crisis following the bankruptcy of Lehman Brothers), and 2020 (COVID-19 pandemic) are not included in the analysis, a Kendall's tau of 0.478 and a p-value of  $<0.001$  result when all analysts' forecasts are taken into account. If only the consensus forecasts are taken into account, again excluding the crisis years, Kendall's tau is 0.514 with a p-value of  $<0.001$ . Outside of crisis years, there is thus a clear improvement in forecast quality as the forecast horizon decreases. However, when the analysis is restricted to the crisis years, no enhancement in forecast quality is observed with a diminishing forecast horizon, irrespective of whether all individual forecasts are considered (Kendall's tau = -0.754; p-value = 1) or when the consensus forecasts are taken into account (Kendall's tau = -0.739; p-value = 1).

If the latter correlations for the crisis years are tested exploratively using a left-sided correlation test (alternative: smaller), this is indeed found to be statistically highly significant, both when considering all forecasts (p-value  $< 0.001$ ) and when considering the consensus forecasts (p-value  $< 0.001$ ). It can therefore be concluded that in crisis years, forecast errors actually increase as the forecast horizon shortens.

Naturally, crises occur unexpectedly. But even when a crisis has already become apparent, analysts often fail to respond appropriately to this new situation. One possible interpretation could be that analysts underestimate the duration and impact of crises, so that shortening the forecast horizon actually leads to an increase in forecast errors (see also the review of hypothesis 5 and, in particular, Figure 11). Since these results fall outside the scope of this study and are therefore only exploratory in nature, further research is needed to examine the role of economic crises in the accuracy of earnings forecasts in more detail.

Finally, it should be emphasized that an increase in forecast errors with a declining forecast horizon is by no means only observed in crisis years. For example, in 1991, 1992, 2006, 2014, 2019, and 2023, forecast errors also tend to increase as the forecast horizon shortens (Figure 2).

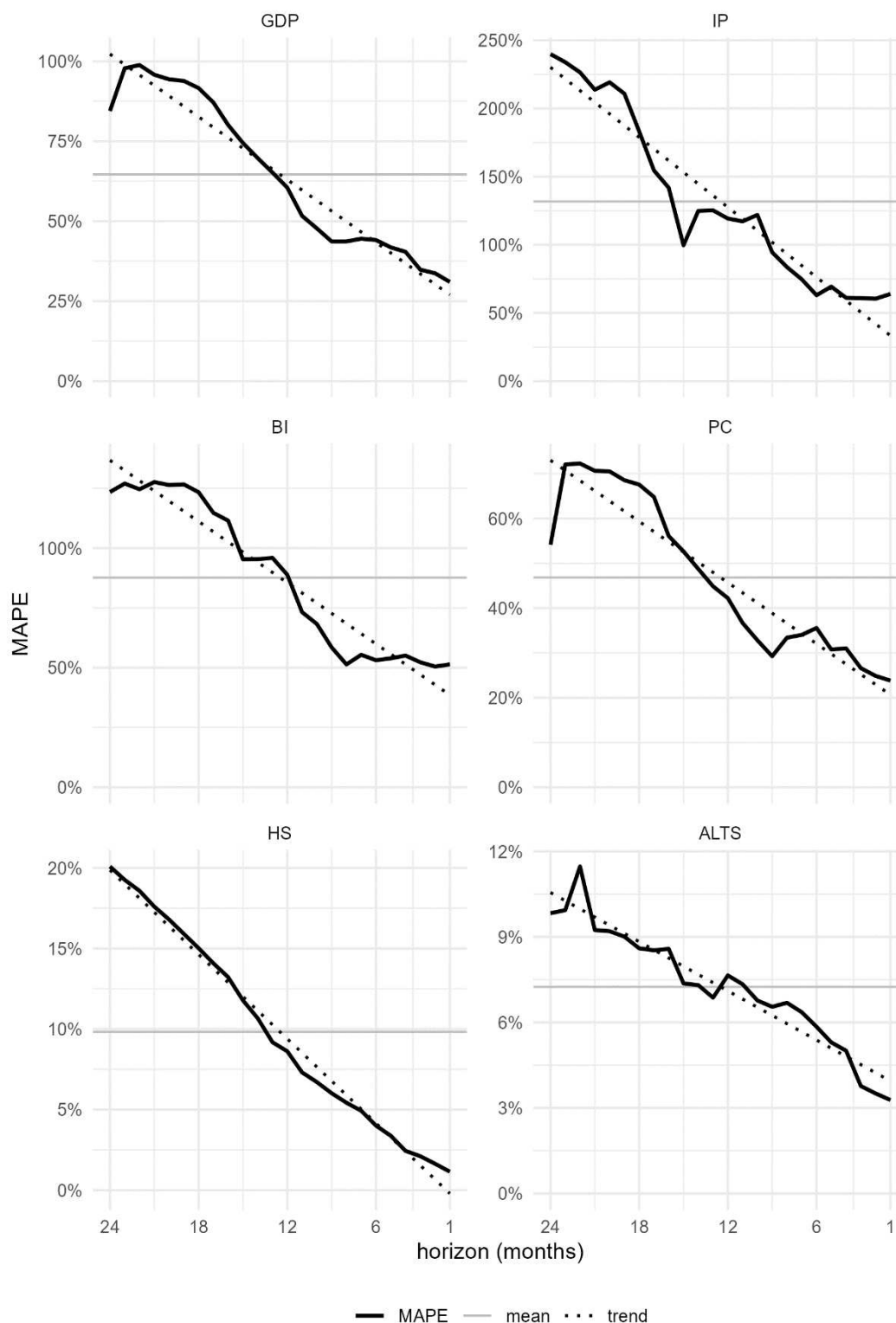
However, one caveat must be noted. The data aggregation required for correlation analysis using Kendall's tau and the associated reduction of information to only one data point per forecast horizon increases the probability of type II errors. The lower test power is particularly problematic in the case of insignificant results. This determines how likely it is that an actual correlation can be detected at all. Conversely, this is much less of a problem, as the risk of a type I error when using non-parametric methods such as Kendall's correlation is determined solely by the choice of alpha.

There is undoubtedly a dependency between forecasts that refer to the same year. In order to be able to examine the relationship between forecast errors and forecast horizons without first aggregating to a single value per forecast horizon, cluster bootstrapping was performed as a robustness test. To this end, several complete clusters (based on the forecast years) are randomly extracted from the data in 10,000 iterations and the Kendall correlation of the forecasts contained therein is calculated. Since the confidence interval is of primary interest here and the results so far paint a mixed picture, this was carried out as a two-sided test. Looking at the consensus forecasts, cluster bootstrapping yields a 95% confidence interval of -0.050 to 0.155, an average Kendall's tau of 0.049 (original data: 0.046), and an empirical p-value of 0.542.

In summary, it can be said that there is insufficient evidence to reject null hypothesis 1 for the entire period from 1990 to 2024. In the case of corporate profit forecasts, there is therefore no improvement in forecast quality as the forecast horizon gradually shortens. If there is a correlation, it is very weak and, despite supplementary robustness tests using cluster bootstrapping, lies below the detection limit of the statistical methods used.

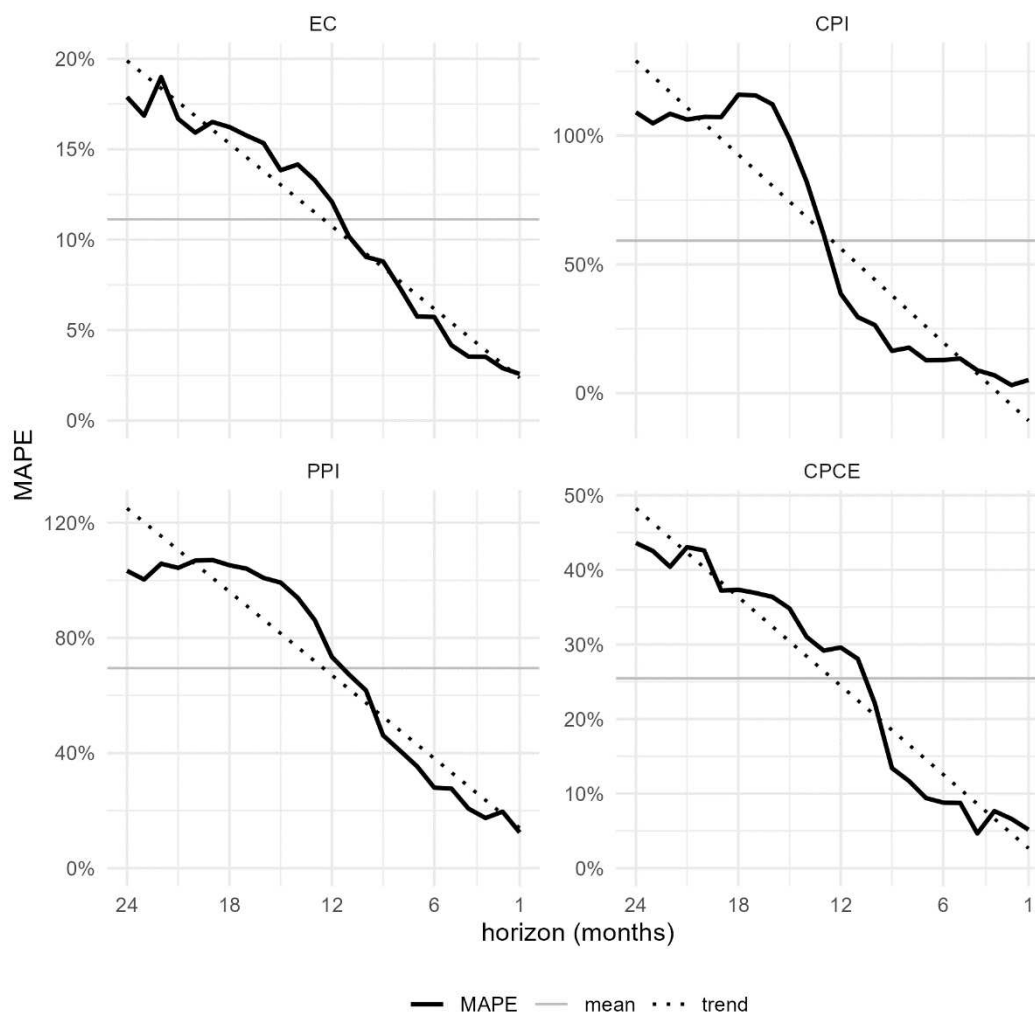
Against the backdrop of these surprising findings, it is particularly interesting to examine the relationship between forecast horizons and forecast errors in other macro forecasts.

**Figure 4:** Average forecast errors in US macro forecasts from 1990 to 2024 depending on the forecast horizon – Part 1



With: MAPE = Mean Absolute Percentage Error; GDP = Gross Domestic Product; IP = Industrial Production; BI = Business Investment; PC = Personal Consumption; HS = Housing Starts; ALTS = Auto & Light Truck Sales.

**Figure 5:** Average forecast errors in US macro forecasts from 1990 to 2024 depending on the forecast horizon – Part 2



With: MAPE = Mean Absolute Percentage Error; EC = Employment Costs; CPI = Consumer Price Index; PPI = Producer Price Index; CPCE = Core PCE Prices (excluding food & energy).

**Table 2:** Average forecast errors in US macro forecasts from 1990 to 2024 depending on the forecast horizon – Part 1

| Forecast horizon in months                | MAPE GDP forecasts     | MAPE IP forecasts      | MAPE BI forecasts      | MAPE PC forecasts      | MAPE HS forecasts       |
|-------------------------------------------|------------------------|------------------------|------------------------|------------------------|-------------------------|
| 24                                        | 84.47%                 | 239.84%                | 123.43%                | 54.14%                 | 20.09%                  |
| 23                                        | 97.82%                 | 233.89%                | 126.98%                | 72.07%                 | 19.26%                  |
| 22                                        | 98.83%                 | 226.44%                | 124.60%                | 72.28%                 | 18.58%                  |
| 21                                        | 95.79%                 | 213.72%                | 127.60%                | 70.65%                 | 17.60%                  |
| 20                                        | 94.37%                 | 219.17%                | 126.35%                | 70.52%                 | 16.80%                  |
| 19                                        | 93.86%                 | 210.82%                | 126.64%                | 68.56%                 | 15.91%                  |
| 18                                        | 91.63%                 | 183.21%                | 123.36%                | 67.58%                 | 15.02%                  |
| 17                                        | 87.11%                 | 154.53%                | 114.72%                | 64.82%                 | 14.08%                  |
| 16                                        | 80.08%                 | 141.83%                | 111.48%                | 56.09%                 | 13.22%                  |
| 15                                        | 74.45%                 | 99.65%                 | 95.30%                 | 52.67%                 | 11.78%                  |
| 14                                        | 69.72%                 | 124.86%                | 95.38%                 | 48.75%                 | 10.67%                  |
| 13                                        | 65.21%                 | 125.25%                | 95.91%                 | 44.87%                 | 9.18%                   |
| 12                                        | 60.49%                 | 119.25%                | 88.86%                 | 42.23%                 | 8.62%                   |
| 11                                        | 51.66%                 | 117.21%                | 73.23%                 | 36.68%                 | 7.31%                   |
| 10                                        | 47.76%                 | 121.93%                | 68.28%                 | 32.83%                 | 6.71%                   |
| 9                                         | 43.67%                 | 94.49%                 | 58.51%                 | 29.27%                 | 6.02%                   |
| 8                                         | 43.68%                 | 83.65%                 | 51.38%                 | 33.41%                 | 5.43%                   |
| 7                                         | 44.53%                 | 74.70%                 | 55.40%                 | 34.03%                 | 4.93%                   |
| 6                                         | 44.12%                 | 63.03%                 | 53.13%                 | 35.58%                 | 4.01%                   |
| 5                                         | 41.83%                 | 69.33%                 | 53.93%                 | 30.76%                 | 3.38%                   |
| 4                                         | 40.43%                 | 61.12%                 | 55.07%                 | 31.03%                 | 2.44%                   |
| 3                                         | 34.84%                 | 60.93%                 | 52.28%                 | 26.61%                 | 2.11%                   |
| 2                                         | 33.73%                 | 60.46%                 | 50.49%                 | 24.87%                 | 1.64%                   |
| 1                                         | 31.02%                 | 63.93%                 | 51.40%                 | 23.83%                 | 1.15%                   |
| Average of all forecast horizons          | 64.63%                 | 131.80%                | 87.65%                 | 46.84%                 | 9.83%                   |
| Regression line                           | $y = 0.2374 + 0.0327x$ | $y = 0.2487 + 0.0855x$ | $y = 0.3434 + 0.0426x$ | $y = 0.1840 + 0.0227x$ | $y = -0.0108 + 0.0087x$ |
| Kendall's tau                             | 0.906                  | 0.899                  | 0.833                  | 0.848                  | 1.000                   |
| p-value (one-sided, alternative: greater) | <0.001                 | <0.001                 | <0.001                 | <0.001                 | <0.001                  |

With: MAPE = Mean Absolute Percentage Error; GDP = Gross Domestic Product; IP = Industrial Production; BI = Business Investment; PC = Personal Consumption; HS = Housing Starts.

**Table 3:** Average forecast errors in US macro forecasts from 1990 to 2024 depending on the forecast horizon – Part 2

| Forecast horizon in months                | MAPE<br>ALTS<br>forecasts | MAPE<br>EC<br>forecasts | MAPE<br>CPI<br>forecasts | MAPE<br>PPI<br>forecasts | MAPE<br>CPCE<br>forecasts |
|-------------------------------------------|---------------------------|-------------------------|--------------------------|--------------------------|---------------------------|
| 24                                        | 9.83%                     | 17.89%                  | 109.09%                  | 103.35%                  | 43.62%                    |
| 23                                        | 9.94%                     | 16.86%                  | 104.81%                  | 100.30%                  | 42.53%                    |
| 22                                        | 11.47%                    | 18.99%                  | 108.53%                  | 105.79%                  | 40.42%                    |
| 21                                        | 9.24%                     | 16.68%                  | 106.29%                  | 104.36%                  | 43.06%                    |
| 20                                        | 9.20%                     | 15.92%                  | 107.33%                  | 106.89%                  | 42.60%                    |
| 19                                        | 9.01%                     | 16.51%                  | 107.27%                  | 107.11%                  | 37.22%                    |
| 18                                        | 8.60%                     | 16.23%                  | 115.92%                  | 105.27%                  | 37.34%                    |
| 17                                        | 8.53%                     | 15.76%                  | 115.71%                  | 104.08%                  | 36.91%                    |
| 16                                        | 8.58%                     | 15.34%                  | 112.21%                  | 100.86%                  | 36.38%                    |
| 15                                        | 7.37%                     | 13.84%                  | 98.74%                   | 99.24%                   | 34.83%                    |
| 14                                        | 7.31%                     | 14.16%                  | 82.21%                   | 93.96%                   | 31.02%                    |
| 13                                        | 6.87%                     | 13.29%                  | 61.61%                   | 86.20%                   | 29.18%                    |
| 12                                        | 7.65%                     | 12.10%                  | 38.63%                   | 73.43%                   | 29.60%                    |
| 11                                        | 7.34%                     | 10.18%                  | 29.54%                   | 67.33%                   | 28.07%                    |
| 10                                        | 6.77%                     | 9.05%                   | 26.45%                   | 61.76%                   | 22.08%                    |
| 9                                         | 6.55%                     | 8.80%                   | 16.43%                   | 46.17%                   | 13.42%                    |
| 8                                         | 6.69%                     | 7.32%                   | 17.68%                   | 40.80%                   | 11.69%                    |
| 7                                         | 6.36%                     | 5.75%                   | 12.78%                   | 35.34%                   | 9.40%                     |
| 6                                         | 5.85%                     | 5.73%                   | 12.87%                   | 27.97%                   | 8.80%                     |
| 5                                         | 5.30%                     | 4.17%                   | 13.43%                   | 27.70%                   | 8.75%                     |
| 4                                         | 5.01%                     | 3.54%                   | 8.88%                    | 20.71%                   | 4.66%                     |
| 3                                         | 3.77%                     | 3.53%                   | 6.95%                    | 17.44%                   | 7.66%                     |
| 2                                         | 3.51%                     | 2.90%                   | 3.12%                    | 19.66%                   | 6.62%                     |
| 1                                         | 3.28%                     | 2.58%                   | 5.10%                    | 12.42%                   | 5.16%                     |
| Average of all forecast horizons          | 7.25%                     | 11.13%                  | 59.23%                   | 69.51%                   | 25.46%                    |
| Regression line                           | $y = 0.0366 + 0.0029x$    | $y = 0.0160 + 0.0076x$  | $y = -0.1674 + 0.0608x$  | $y = 0.0916 + 0.0483x$   | $y = 0.0069 + 0.0198x$    |
| Kendall's tau                             | 0.928                     | 0.964                   | 0.790                    | 0.855                    | 0.935                     |
| p-value (one-sided, alternative: greater) | <0.001                    | <0.001                  | <0.001                   | <0.001                   | <0.001                    |

With: MAPE = Mean Absolute Percentage Error; ALTS = Auto & Light Truck Sales; EC = Employment Costs; CPI = Consumer Price Index; PPI = Producer Price Index; CPCE = Core PCE Prices (excluding food & energy).

It is evident that for the other US macro forecasts, the forecast error decreases significantly as the forecast horizon shortens. This applies equally to the forecasts for gross domestic product, industrial production, business investment, personal consumption, housing starts, auto & light truck sales, employment costs, consumer price index, producer price index, and core PCE prices. Without exception, the gradually improving level of information leads to the observation that forecasts with shorter forecast horizons are, on average, significantly more accurate than the corresponding forecasts with longer forecast horizons (see Figure 4 and Figure 5 as well as Table 2 and Table 3). These results prove to be statistically highly significant without exception. We also used consensus forecasts for this analysis. These forecasts are available for all forecast items for the period from 1990 to 2024. The only exception is core PCE prices, which have only been published by the journal "Consensus Forecasts" since June 2018.

Based on the available results, null hypothesis 2 cannot be rejected. This means that there is a remarkable difference between US pre-tax corporate profits forecasts on the one hand and the other US macro forecasts considered on the other. For the other macro forecasts, correlation values for Kendall's tau between 0.790 and 1.000 can be observed across the board. This applies to the entire period (i.e., including all crisis years) and thus represents a reliable correlation, unlike the forecasts for US corporate profits. The average error level for the shortest forecast horizon of one month is also significantly higher for US corporate profits forecasts at 88.73% than for any of the other forecast items examined.

However, US corporate profits forecasts stand out in particular because they are the only forecast item for which shortening the forecast horizon does not lead to a reduction in the average forecast error (MAPE) when viewed holistically over the period 1990-2024. Excluding crisis years, a substantial decrease in forecast errors is observed when the forecast horizon is reduced. However, even in this case, the correlation remains significantly weaker compared to other forecast items.

The average variance in earnings forecasts changes as the forecast horizons gradually shorten. For forecast horizons of 24 months to 18 months, analysts seem to become increasingly experimental and opinionated. While the average variance is 11.91 for a forecast horizon of 24 months, it reaches its maximum of 20.75 for a forecast horizon of 18 months. From there, the average variances gradually decline, albeit with fluctuations. The minimum average variance is 2.94. It is reached at the one-month forecast horizon (see Figure 6 and Table 4). Of course, all forecasts from all analysts are required for this analysis. There can be no restriction to consensus forecasts here, as the focus is on the deviations in the estimates of the individual analysts. The following data evaluation method was used for this purpose: First, the variance of all analysts' forecasts is measured separately for each year and for each

forecast horizon. Then, the average variance per forecast horizon is determined. The average variance of 11.91 for the 24-month forecast horizon (see Table 4) is calculated from the arithmetic mean of the 35 variances for the years 1990 to 2024.

**Figure 6:** Average variances in US corporate profits forecasts by analysts depending on the forecast horizon

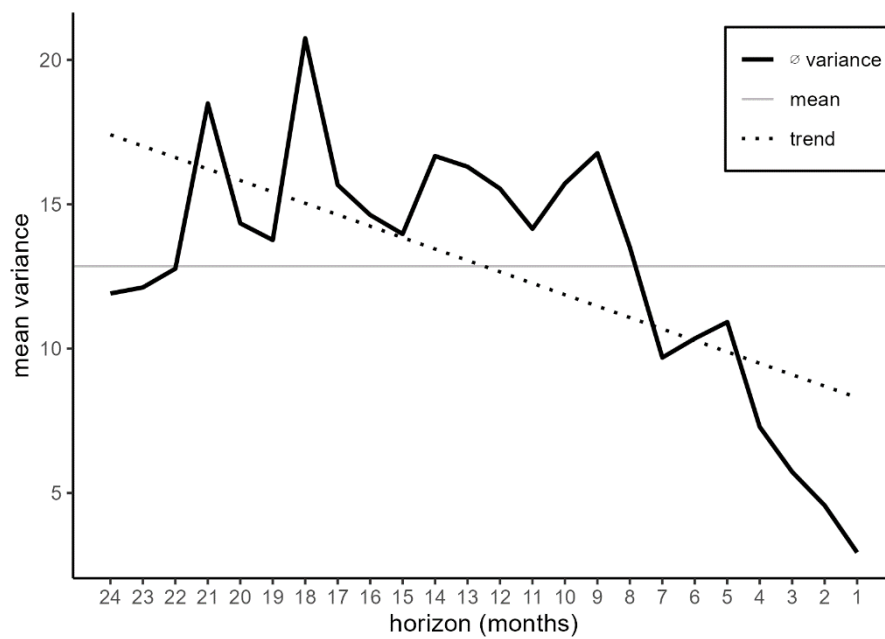


**Table 4:** Average variances in US corporate profits forecasts by analysts depending on the forecast horizon

| Forecast horizon                          | Ø Variance | Forecast horizon       | Ø Variance |
|-------------------------------------------|------------|------------------------|------------|
| 24 months                                 | 11.91      | 12 months              | 15.54      |
| 23 months                                 | 12.12      | 11 months              | 14.15      |
| 22 months                                 | 12.77      | 10 months              | 15.72      |
| 21 months                                 | 18.49      | 9 months               | 16.77      |
| 20 months                                 | 14.34      | 8 months               | 13.51      |
| 19 months                                 | 13.76      | 7 months               | 9.69       |
| 18 months                                 | 20.75      | 6 months               | 10.35      |
| 17 months                                 | 15.67      | 5 months               | 10.92      |
| 16 months                                 | 14.63      | 4 months               | 7.29       |
| 15 months                                 | 13.97      | 3 months               | 5.73       |
| 14 months                                 | 16.67      | 2 months               | 4.57       |
| 13 months                                 | 16.30      | 1 month                | 2.94       |
| Average across all forecast horizons      |            |                        | 12.86      |
| Regression line                           |            | $y = 7.9092 + 0.3958x$ |            |
| Kendall's tau                             |            |                        | 0.355      |
| p-value (one-sided, alternative: greater) |            |                        | 0.007      |

Null hypothesis 3 must be rejected. This means that the average dispersion of the forecasts made by the different forecasters decreases as the forecast horizon shortens. Kendall's tau is 0.355. The p-value of 0.007 shows that, with a probability of error of < 1%, the average variances decrease significantly as the forecast horizon shortens. However, it is particularly interesting to see how this finding came about.

If analysts develop increasingly accurate forecasts over time, it follows that their forecasts must converge more and more. However, it appears that such an improvement does not occur with US corporate earnings forecasts as the forecast horizon shortens (see Figure 1 and Table 1). It is therefore very surprising to see that the average variances of the forecasts gradually decrease as the forecast horizon shortens.

Let's assume that a group of seven motorcyclists meet in Boston. They agree to ride to Providence and meet at Russell's Ice Cream at a certain time. The motorcyclists love to ride on small side roads. However, there are hardly any road signs on small side roads. So they have to rely on their knowledge of the area. They neither agree to ride in convoy, nor do they

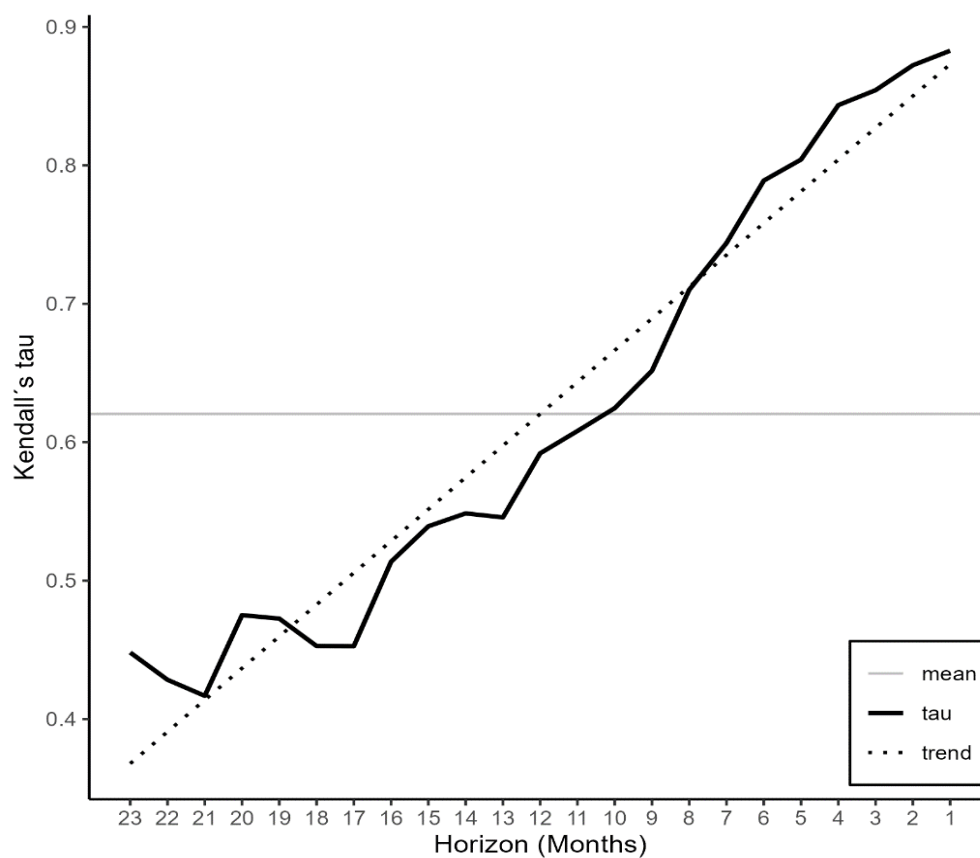
agree that everyone will ride on their own. If all seven motorcyclists arrive at Russell's Ice Cream in Providence at the agreed time, there are two possibilities: 1. All seven motorcyclists are very familiar with the roads between Boston and Providence. Accordingly, they could all have found their way completely independently of each other (no herd behavior). 2. However, it is also possible that one of the seven motorcyclists knows the area well and sets off. The other six motorcyclists are less familiar with the area and simply follow the first one (herd behavior).

Let's assume that the seven motorcyclists agreed to meet in Providence, but all seven arrive in Rockport at the agreed time and drink iced coffee at Russell's Ice Cream. In this case, there are no longer two possible interpretations. If the seven motorcyclists had been traveling independently without any knowledge of the area, one might have ended up in Salem, one in Worcester, one in New Bedford, one in Woonsocket, one in Taunton, one in Attleboro, and one in Framingham. The fact that they all arrived in Rockport instead can only be explained by one of the motorcyclists getting completely lost and the other six motorcyclists following him (herd behavior).

Similarly, the behavior of financial analysts can now be interpreted as a clear case of herd behavior. If they were to arrive at increasingly accurate forecasts as the forecast horizon shortened, it would be difficult to interpret the decreasing average variances. It could be that the analysts are independently developing increasingly better forecasts and that their forecasts are gradually approaching the actual value (no herd behavior). This would explain the declining average variances with a shorter forecast horizon. However, it is also possible that only one forecaster is gradually developing increasingly accurate forecasts and the other analysts are imitating his or her forecasts (herd behavior).

Barron & Stuerke (1998) point out that a high dispersion of profit forecasts indicates a high degree of uncertainty. As the forecast horizon shortens, the dispersion of forecasts becomes increasingly smaller amid fluctuations. The degree of uncertainty thus decreases, but the degree of ignorance (measured by the forecast error) does not. However, if the forecasts do not become more accurate as the forecast horizon shortens, but at the same time the average variances continue to decline, then the only plausible explanation is that analysts deliberately align their forecasts with each other as the forecast horizon shortens. This is clearly a case of intentional herding.

**Figure 7:** Kendall correlation of all analyst forecasts (excluding consensus forecasts) with the previous month's consensus forecast by forecast horizon

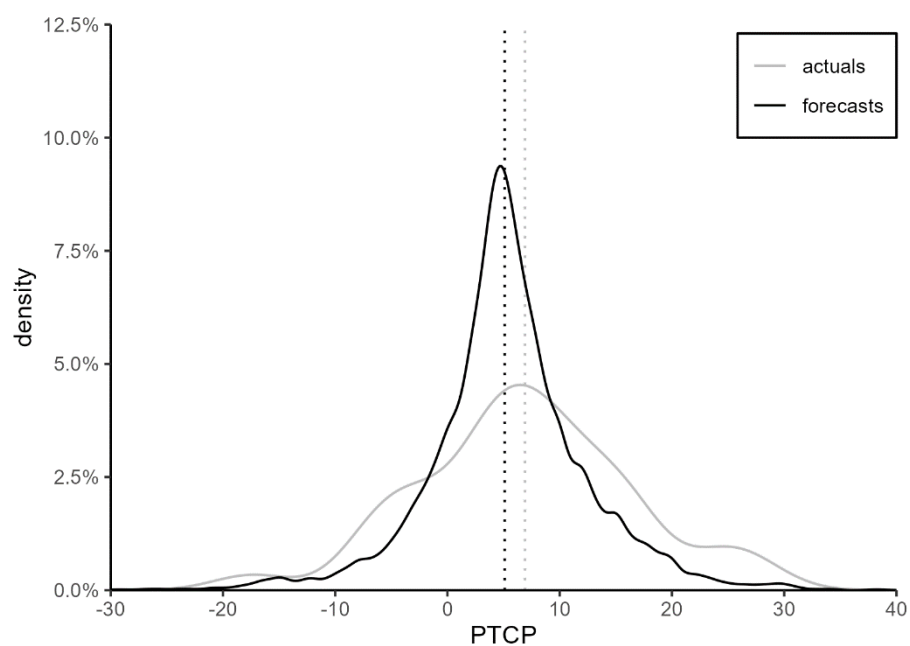


This finding is clearly confirmed when the influence of the previous month's consensus forecast on all analyst forecasts is examined using Kendall's tau (Figure 7). In fact, a significant correlation with the consensus forecast of the respective previous month can be established for all forecast horizons from 23 months to one month. Therefore, the correlations shown in Figure 7 can be considered as valid estimates. As the forecast horizon gradually shortens, the orientation towards the consensus forecast of the previous month (observable majority opinion) becomes increasingly stronger. With a forecast horizon of only one month, analyst forecasts on average from 1990 to 2024 are very strongly oriented towards the consensus forecast of the previous month (Kendall's tau = 0.883; p-value < 0.001). This increasing orientation of analysts towards the observable majority opinion leads step by step to an ever-greater convergence of forecasts – but without this being associated with a significant reduction in forecast errors. The tendency for forecasts to be increasingly based on the previous month's consensus forecast as the forecast horizon shortens can also be considered significant (Kendall's tau = -0.921; p-value < 0.001). As the forecast horizon shortens, the

influence of the previous month's consensus can indeed be observed to increase. However, it should be noted that the correlation values (Kendall's tau) used for this calculation, despite their significance, are themselves only estimates. In addition, it should be noted that the results presented in this paragraph are purely exploratory in nature and therefore no general conclusions should be derived from them. However, they can be understood as an impetus for further research efforts.

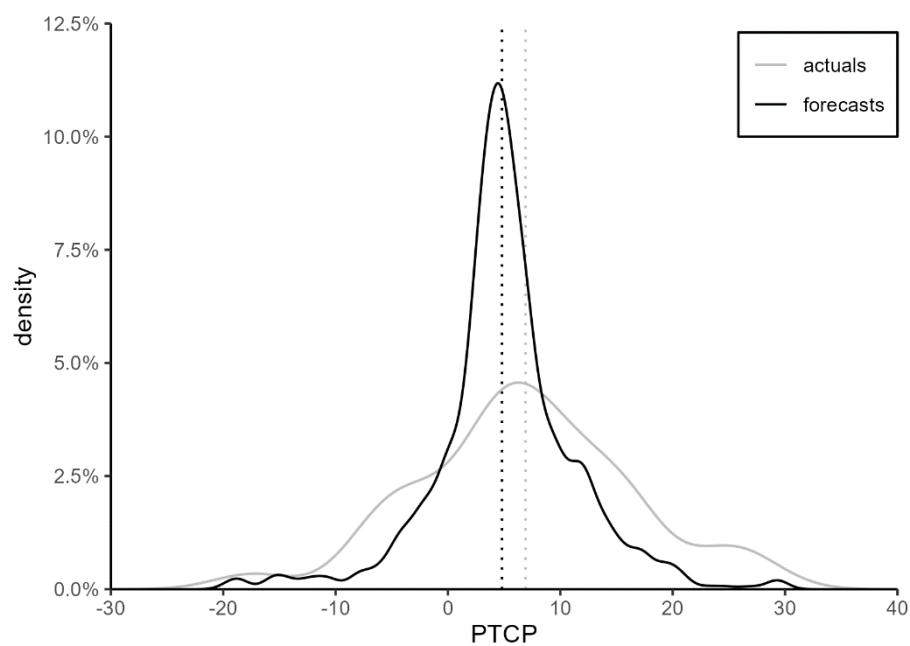
Ogburn (1934) points out that forecasters often underestimate the variability of reality. This contributes to the dispersion of actual events being significantly greater than the dispersion of forecasts. This is also evident in US corporate profits forecasts. Both when looking at all forecasts (Figure 8) and when looking exclusively at consensus forecasts (Figure 9), it becomes apparent that forecasts are more strongly oriented towards what analysts consider to be normal or usual. As a result, the variance of actual events is noticeably higher than the variance of forecasts (for similar findings, see Helbok & Walker, 2004). For all forecasts (Figure 8), the variance is 50.66. For the consensus forecasts (Figure 9), the variance is 39.24. However, the average dispersion of the actual values is significantly greater. The variance of the actual events is 92.52 (Figure 8 and Figure 9). The Brown-Forsythe test, taking all forecasts into account (data basis as in Figure 8), shows that the variances of the forecasts and the actual values are significantly different ( $p\text{-value} = 0.005$ ).

**Figure 8:** Distribution of all US corporate profits forecasts and distribution of actual events



With PTCP = pre-tax corporate profits in % compared to the previous year.

**Figure 9:** Distribution of consensus forecasts for US corporate profits and distribution of actual events



With PTCP = pre-tax corporate profits in % compared to the previous year.

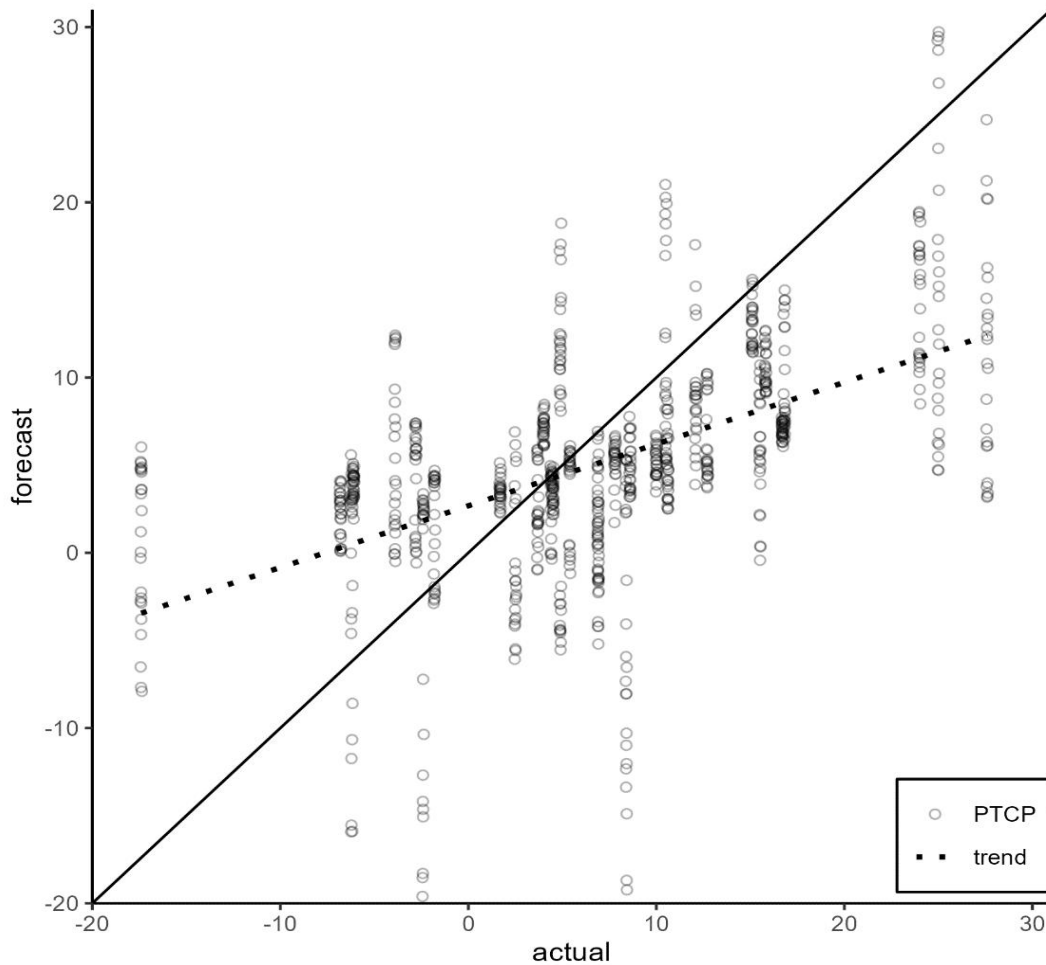
However, since the Brown-Forsythe test requires independent observations but there are cluster relationships between the forecasts (several forecasts refer to the same forecast year), the data for the Brown-Forsythe test first had to be aggregated to a single value per year. To do this, the data was first grouped by forecast year and forecast horizon, and the arithmetic mean of the forecasts was determined. The average for each year to be forecast was then calculated. When aggregated as described here, the consensus forecasts (data basis as in Figure 9) lead to almost identical aggregated values as when all forecasts are taken into account, except for small rounding differences. Accordingly, a Brown-Forsythe test on this basis provides an identical assessment ( $p\text{-value} = 0.005$ ).

It should be noted that, by definition, the aggregation of forecasts leads to a reduction in the variance of the forecast data series. The Brown-Forsythe test without prior aggregation based on the raw data, taking all forecasts into account (data basis as in Figure 8), produces a comparable picture ( $p\text{-value} = 0.007$ ), but should be interpreted with caution due to the violation of the assumption of independent observations. Since consensus forecasts represent the average of the individual forecasts per forecast horizon and forecast year, they generally also exhibit lower variance than individual forecasts, which means that a Brown-Forsythe test on this basis (data basis as in Figure 9; without the additional aggregation described above) does not lead to a different assessment ( $p\text{-value} < 0.001$ ). However, the assumption of independent observations is violated here too, which can lead to misjudgments.

In order to be able to fairly compare the variances of the forecasts and the actual values despite the problems associated with the cluster structure, even without the variance-reducing aggregation of the forecasts, cluster bootstrapping of the raw data is also performed. To this end, several complete clusters (based on the forecast years) are randomly extracted from the data in 10,000 iterations, and the variances of the forecasts contained therein and the corresponding actual values are compared by determining their difference (variance of the forecasts - variance of the actual values). Since cluster bootstrapping – unlike the Brown-Forsythe test – allows for a one-sided test to be performed, it was carried out as such (alternative: smaller) in accordance with our hypothesis 4. When considering all forecasts (data basis as in Figure 8), cluster bootstrapping results in a left-sided 95% confidence interval that lies completely below -11.34, an average variance difference of -42.34 (original data: -41.86), and an empirical  $p\text{-value}$  of 0.011. If only the consensus forecasts (data basis as in Figure 9) are considered, the left-sided 95% confidence interval is completely below -22.84, the average variance difference is -53.79 (original data: -53.29) and the empirical  $p\text{-value}$  is  $<0.001$ .

Overall, the results are consistent across the different methods and very robust, so that the findings can be considered reliable. The forecasts show less variability than the actual events.

**Figure 10:** Prediction-realization diagram



With PTCP = pre-tax corporate profits in % compared to the previous year.

The same situation can also be illustrated using a prediction-realization diagram (cf. Theil, 1958) (Figure 10). It can be seen that small actual events tend to be overestimated and large actual events tend to be underestimated. Unbiased forecasts should be arranged around the angle bisector. However, the regression line resulting from the scatter plot of the pairs of values from forecasts and actual events is noticeably flatter than the angle bisector. Figure 10 is based on the consensus forecasts. However, a corresponding representation with all analyst forecasts shows identical characteristics. Thus, the prediction-realization diagram also demonstrates that the dispersion of actual events is greater than the dispersion of forecasts because large actual rates of change – both negative and positive – are rarely captured by the forecasts.

Null hypothesis 4 must therefore be rejected. This means that the forecasts show less variation than the actual events. Analysts underestimate the variability of reality. Ogburn (1934)

interprets this circumstance as an expression of the conservative attitude of forecasters. They lack imagination and/or courage. They cannot imagine all the serious changes that could occur. Or, if they can imagine them, they do not dare to reflect the expected serious changes in their forecasts.

The medians of the distributions of actual US earnings developments and the corresponding forecasts in Figures 8 and 9 clearly show that analysts are too cautious. They underestimate earnings growth. Between 1990 and 2024, US corporate profits rose by a median of 6.90% per year (gray dotted line in Figures 8 and 9). However, the forecasts of all analysts predict a median annual increase in US corporate profits of only 5.10% for that period (black dotted line in Figure 8). The consensus forecasts even predict a median annual profit growth of only 4.80% for the same timeframe (black dotted line in Figure 9). This results in a difference of -1.80 percentage points between the median of all forecasts (see Figure 8) and the median of actual events, as well as a difference of -2.10 percentage points between the median of consensus forecasts (see Figure 9) and that of actual events. The results are even more serious when looking at the median of the paired differences compared to the actual events, which is -2.40 percentage points for all forecasts (data basis as in Figure 8) and -2.70 percentage points for the consensus forecasts (data basis as in Figure 9).

The Wilcoxon signed-rank test examines such differences in the central tendency of the distributions, more precisely in the so-called pseudo-median of the differences. However, in order to fulfill the assumption of independence of the observations for the test, the forecasts were aggregated in advance to a single value per year. To do this, the median of the forecasts was first calculated for each forecast year and forecast horizon, and then the arithmetic mean was determined from these results for each forecast year. The second aggregation step is deliberately performed using the arithmetic mean instead of the median, as otherwise the probability of ties in the Wilcoxon signed-rank test would be increased, which could impair the test quality. In addition, the upstream calculation of the median already minimizes the risk of outliers and asymmetric distributions to a large extent.

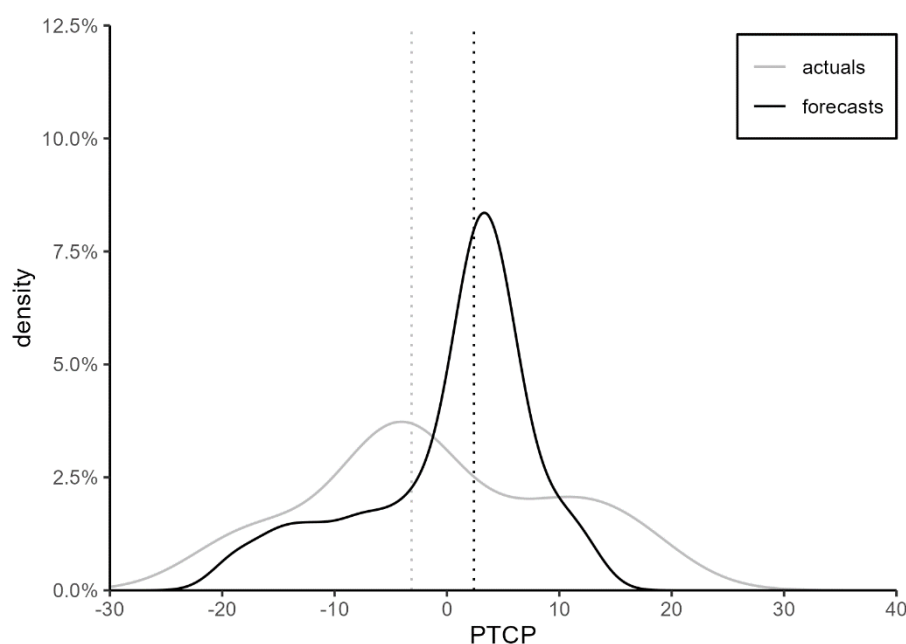
The Wilcoxon signed-rank test (alternative: greater) shows that the central tendency (pseudo-median) of the aggregated forecasts, taking all forecasts into account (data basis as in Figure 8), is not significantly greater than the central tendency (pseudo-median) of the corresponding actual events (p-value = 0.955). If, following the same logic, only the consensus forecasts (data basis as in Figure 9) are considered – here, by definition, the first aggregation step is omitted – there is also no significant difference (p-value = 0.956). Consequently, there is no evidence to suggest that forecasters tend to be overly optimistic. Looking at the distributions in Figures

8 and 9, as well as the medians and their differences, which were determined on the same basis in each case, the impression is rather that forecasters tend to be pessimistic.

This is not the case in crisis situations. If we look at the analysts' forecasts for the years 2000 to 2002 (bursting of the dot-com bubble), 2008 to 2009 (major banking, capital market, and economic crisis following the bankruptcy of Lehman Brothers), and 2020 (COVID-19 pandemic), there appears to have been an overestimation of profit developments (Figure 11).

However, this observation is probably not evidence of over-optimism, but rather due to the fact that analysts did not see the crises coming and/or misjudged their duration. In the Wilcoxon signed-rank test (alternative: greater; basis: aggregated values), this is also not significant ( $p\text{-value} = 0.500$ ), which may be due to the very small sample size (only 6 years) and the associated low test power – or simply to the fact that there is no stable relation in these years.

**Figure 11:** Distribution of consensus forecasts for US corporate profits and distribution of actual events for the crisis years 2000 to 2002, 2008 to 2009, and 2020



With: PTCP = Pre-Tax Corporate Profits in % compared to the previous year.

A possible tendency towards pessimism in the overall assessment (1990–2024) is surprising in light of hypothesis 5, although it is not an entirely new observation (see, for example, Black & Carnes, 2006). In fact, a Wilcoxon signed-rank test with reversed test direction (alternative: smaller) yields a  $p\text{-value}$  of 0.047 for the overall period. Since this result contradicts our

previously formulated hypothesis 5, it should be understood as purely exploratory, as should the results presented below on this issue, and as an indication for further research efforts.

If we assume pessimism on the part of the analysts and want to conduct a more detailed investigation taking into account the cluster structure in addition to the Wilcoxon signed-rank test, cluster bootstrapping can be performed based on the raw data. In order to follow the basic logic of the Wilcoxon signed-rank test, it makes sense to consider the median of the paired differences here as well. To do this, we first determine the difference between the forecasts and their corresponding actual events. Then, several complete clusters (based on the forecast years) are randomly drawn from the data in 10,000 iterations and the median of the differences is determined. The resulting distribution of the median of the differences, when considering all individual forecasts (data basis as in Figure 8), exhibits an average of -2.33 percentage points (original data -2.40 percentage points), the left-sided 95% confidence interval is completely below -0.20, and an empirical p-value of 0.039 is obtained. If only consensus forecasts are considered (data basis as in Figure 9), the median of the differences averages -2.61 percentage points (original data: -2.70 percentage points), the left-sided 95% confidence interval is completely below -0.60, and the empirical p-value is 0.023.

If we remove the crisis years 2000 to 2002, 2008 to 2009, and 2020 from the analysis, the picture becomes even clearer. When all forecasts are taken into account, the median of the differences in this case averages -2.70 percentage points (original data: -2.80 percentage points), the left-sided 95% confidence interval is completely below -0.80, and the empirical p-value is 0.011. If only the consensus forecasts are taken into account, excluding the crisis years, the average median of the differences is -2.86 percentage points (original data: -3.00 percentage points), the left-sided 95% confidence interval is completely below -1.10, and the empirical p-value is 0.006.

The results of this exploratory analysis of possible pessimism among analysts can therefore be considered robust in the present data set. In crisis situations, however, this effect does not appear to exist, which is plausible given the surprising occurrence of crises.

In summary, null hypothesis 5 cannot be rejected. Contrary to the findings of several previous studies (see the Literature review chapter), financial analysts do not tend towards optimism or overoptimism. Rather, there are strong indications that forecasters may tend towards pessimism, which could be examined in more detail in future studies on earnings forecasts.

## Discussion

The accuracy of forecasts for the development of corporate earnings in the US is disappointing. The mean absolute percentage error (MAPE) averages 95.18% across all forecast horizons and for the period from 1990 to 2024 (based on consensus forecasts).

Even more serious, however, is the fact that the average forecast error does not decrease significantly as the forecast horizon shortens. While the forecast error (MAPE) for a 24-month forecast horizon averages 89.23% for the years 1990 to 2024, the corresponding value for a forecast horizon of only one month is 88.73% (based on consensus forecasts). The minimum is for a forecast horizon of 20 months. There, the mean absolute percentage error (MAPE) is at 85.19%. If a regression line is drawn in the scatter plot of the mean forecast errors for all 24 forecast horizons, the result exhibits even a negative slope (Figure 1). This is also reflected in Kendall's tau of -0.138.

These are very surprising findings, which differ greatly from previous empirical results (see the chapter Literature review) and which also clearly contradict reasonable preliminary considerations. This also contrasts sharply with other macro forecasts that focus on economic development and inflation (see Figure 4 and Figure 5). For these forecast variables, there are statistically highly significant declines in forecast errors as the forecast horizons gradually shorten (see Table 2 and Table 3).

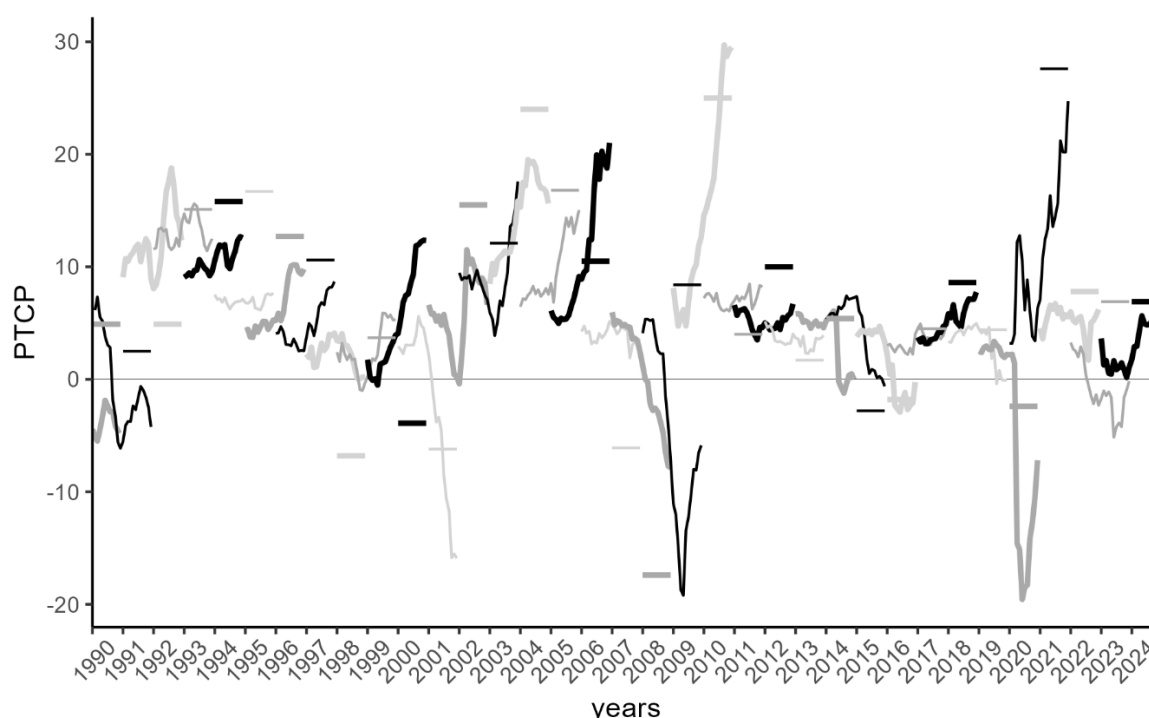
What distinguishes the development of US profits from the development of other macro data? Why are analysts able to cope with other macro forecasts (measured by the decline in average forecast errors with a declining forecast horizon) but fail spectacularly when it comes to forecasting the profit development of US companies?

Brown & Mohammad (2010) show that analysts' abilities are by no means limited to specific companies. This means that successful forecasters of earnings trends should be able to make good forecasts not only for specific companies, but also for aggregated earnings trends. Why are many forecasters able to predict the profits of individual companies with increasing accuracy as the forecast horizon decreases, while macro forecasters are unable to do so?

The development of profits in an economy is not an event which is independent of other economic developments (see, for example, Sharpe & Gil de Rubio Cruz, 2024). Economic developments in particular have an impact on profit development. If other economic data is predicted with increasing accuracy by macro forecasters as the forecast horizon decreases, why is this not reflected at all in profit forecasts?

Overconfidence and/or cognitive dissonance could contribute to analysts' reluctance to adjust their forecasts to new information over time in a necessary manner.

**Figure 12:** Development of consensus forecasts with a reduction in the forecast horizon from 24 months to one month for the years 1990 to 2024



With: PTCP = Pre-Tax Corporate Profits in % compared to the previous year.

Note: 24-month forecasts to one-month forecasts, actual events as horizontal lines; revolving hues and line thicknesses to distinguish between the different years to be forecast.

However, there is clearly no such inertia here. Figure 12 shows that some significant adjustments have been made over time. In 1991, the profits of US companies rose by 2.50% compared to the previous year (first black horizontal line on the left in Figure 12). The thin black line, which begins at the start of 1990 and runs until the end of 1991, indicates the corresponding consensus forecasts with a gradually shortening forecast horizon. At the beginning of 1990, earnings growth of +6.16% was forecast for 1991. By the end of 1990, the forecasts for 1991 had been gradually revised downwards, finally reaching -6.14% towards the end of 1990. They were then revised upwards again, reaching -0.63% in August 1991. After that, the forecasts were revised downwards again, reaching -4.23% in December 1991. There are very strong forecast corrections for US earnings development in 2001, 2009, 2010, 2020,

and 2021. However, even these adjustments do not always go in the right direction. Therefore, there is no evidence of analysts being slow to adjust their forecasts.

There is clearly a significant tendency among forecasters to follow the herd. This can be seen when looking at the declining average variance of forecasts with a declining forecast horizon (Figure 6), without any improvement in forecast quality (Figure 1). However, this tendency to herd behavior leads to an improvement in forecasts with a declining forecast horizon in some years and to a deterioration in other years (see Figure 2). The tendency to herd behavior alone therefore does not explain why only the forecasts for US earnings development with a declining forecast horizon are not accompanied by declining average forecast errors.

The time series of US companies' pre-tax corporate profits is a data series that takes a considerable amount of time to compile. As a result, data revisions often occur even after a longer period of time. Is this the reason why macro forecasters find it particularly difficult to produce reliable forecasts? This is hardly likely. The collection of GDP data is also a complex undertaking. Here, data revisions often occur after a considerable period of time as well. Nevertheless, the forecast errors of GDP forecasts gradually decrease as the forecast horizon shortens. The publication of pre-tax corporate profits takes even longer than the publication of GDP data. Nonetheless, the level of relevant information continues to rise as the forecast horizon shortens, so that a gradual decline in forecast errors as the forecast horizon shortens would be expected.

Is the cause of the findings presented here professional arrogance on the part of macro forecasters? It is usually macroeconomists who prepare macro forecasts. Forecasting corporate profits is the domain of business economists. Is this why macroeconomists perhaps do not take profit forecasts seriously? It should perhaps be noted that forecasters are not obliged to forecast US profit developments, nor are they obliged to publish these forecasts in the journal "Consensus Forecasts." If macroeconomists believe that the subject of the forecast is irrelevant and unimportant, then one would expect them to refrain from making and publishing such forecasts. Therefore, this is not a convincing approach to explaining the empirical findings.

The background to the research results presented is probably even more serious. If a basketball expert cannot predict the outcome of basketball games one minute before the end of the game any better than one minute after the start of the game over a period of 35 years, there is only one plausible explanation: he does not watch the games or he completely ignores what happens during the game. This would be a case of denial of reality. The analysts who predicted the change in corporate earnings growth in the US from 1990 to 2024 were

apparently unwilling, on average, to take note of the additional relevant information that emerged step by step. They denied reality.

This finding has fatal consequences for asset allocation decisions. If the forecasters of corporate earnings growth for the world's largest and most important economy, which also has the world's largest and most important stock market, deny the reality, then these forecasts cannot be used as a basis for a reasonable allocation of money to be invested across different national stock markets. Studies on the reliability of stock index forecasts confirm this finding. It is not possible to reliably forecast the index performance of various stock markets (see, for example, Filiz et al. 2021; Fujiwara et al., 2013; Spiwoks & Hein, 2007; Benke, 2006; Spiwoks, 2004; Fraser & MacDonald, 1993; Lakonishok, 1980). The poor quality of earnings forecasts could be a decisive factor in this.

What consequences do these findings have for portfolio managers? Active portfolio management that involves asset allocation in addition to stock picking is doomed to failure given the poor quality of forecasts. This circumstance is also likely to have contributed to the fact that passive investment instruments such as exchange-traded funds (ETF) have gained considerable attention and investment volume over the past 25 years. Portfolio managers who pursue active investment strategies therefore seem a little like the alchemists of the present day, working on the impossible task of turning lead into gold. If it does not become easier to forecast corporate earnings growth in major economies in the future, it will be virtually impossible to make systematically successful asset allocation decisions for active portfolio management strategies.

Lacina et al. (2011, p. 97) emphasize „that analysts' long-term earnings forecasts should be used with caution by researchers and practitioners“. This wording must presumably be regarded as a euphemism.

## Summary

This study examines forecasts for corporate earnings growth in the US economy. The subject of the forecast is the percentage change in pre-tax corporate profits compared to the previous year. These forecasts are available for the period from 1990 to 2024. They are published monthly in the journal "Consensus Forecasts". Each actual event is forecast 24 times – starting with a forecast horizon of 24 months and ending with a forecast horizon of one month. The analysis of the forecast data has essentially yielded the following results:

1. Overall, the forecasts are quite inaccurate. The mean absolute percentage error (MAPE) is 95.18% on average across all forecast horizons and on average for the years 1990 to 2024. If profits actually increase by 40.0%, the average forecast is therefore 78.07% or 1.93%. This is a disillusioning level of inaccuracy.
2. The average forecast errors do not decrease significantly as the forecast horizon decreases. While the forecast error (MAPE) for a 24-month forecast horizon averages 89.23% for the years 1990 to 2024, the corresponding value for a forecast horizon of only one month is 88.73%. If a regression line is drawn through the scatter plot of the average forecast errors for all 24 forecast horizons, the result exhibits even a negative slope of -0.0022 which is also reflected in Kendall's tau of -0.138. This is a surprising finding that clearly contradicts previous empirical results and reasonable preliminary considerations.
3. It appears that the forecasts for the development of US profits are an exception in the canon of other US macro forecasts. For forecasts of gross domestic product, industrial production, business investments, personal consumption, housing starts, auto & light truck sales, employment costs, consumer price index, producer price index, and core PCE prices (excluding food & energy), the forecast error decreases significantly as the forecast horizon shortens.
4. Although forecasts of US earnings growth do not become more accurate as the forecast horizon shortens, the average variances decrease significantly as the forecast horizon shortens. They reach their minimum at a forecast horizon of one month. Forecasters are therefore becoming increasingly unanimous, but without advancing to more accurate forecasts. This finding is interpreted as a clear indication of herd behavior among analysts.
5. The variability of reality is underestimated by forecasters. The distribution of forecasts shows significantly less dispersion than the distribution of actual events.
6. The forecasts examined do not show any over-optimism. Instead, they are too cautious. Based on the median values analyzed, actual earnings growth is underestimated for the years 1990 to 2024.

7. The poor quality of the aggregated earnings forecasts could be a major reason why previous studies on stock index forecasts have also led to very disillusioning results. Active portfolio management strategies are therefore not very promising. Passive investment strategies remain the method of choice for the time being.

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### **Statement on the use of artificial intelligence (AI)**

**No** artificial intelligence was used in the literature review, the evaluation of previous studies, the formulation of the research question, the selection of research data, the selection of research methods, the data analysis, the interpretation of the research results, or the formulation of the study.

Since none of the six authors are native speakers of US English or British English, we decided to use the AI application DeepL to iron out any linguistic errors, especially with prepositions. AI was used in this study for this purpose only.