Can Aggregate Special Items Aid in Predicting Future Inflation?

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Abstract: This study seeks to enhance the precision of inflation forecasting within Phillips Curve models by integrating 'special items' into the analysis. Recent strides in macro-accounting research underscore the substantive correlation between aggregate earnings and subsequent economic activity. Prior findings show that forecasts from the Survey of Professional Forecasters (SPF) do not fully incorporate the information available from aggregate earnings and it is primarily the 'Special Items' component of the aggregate earnings that is underestimated. We leverage the information content of this overlooked accounting variable, which responds to macro news shocks in a timely manner and mainly attributable to bad news, to study its impact on future inflation. While the preliminary results do not support the hypothesis that 'special items' improves the forecasting power of the baseline Phillips curve model, employing 'special items' as an indicator of economic slack yields results that align closely with those obtained using more conventional slack measurements.

Keywords: Macro-accounting; special items; inflation forecasting

1 Introduction

Accurate prediction of inflation holds significant importance for numerous economic stakeholders. Policymakers rely on this metric to determine optimal monetary policies, while businesses use it for investment, pricing decisions, and contract negotiations. Despite its importance, forecasting inflation remains a challenging task.

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Phillips curve models, relating some measure of real economic activity to inflation, predominantly used by macroeconomics to forecast inflation, have yielded mixed results, under-performing in some time periods and performing relatively well in others (Atkeson and Ohanian, 2001; Stock and Watson, 2008). While survey based forecasts appear to consistently be the best predictor of future inflation (Ang et.al, 2007; Faust and Wright, 2014). One possible explanation for this discrepancy relies on the assumption that survey information is not controlled in standard forecasting techniques, and thus adding surveys or new variables as part of the dataset used to construct aggregate macroeconomics components should improve a model's predictions.

Recent macro-accounting research has provided evidence that aggregate earnings and more specifically changes in special items can predict inflation via a change in a firm's investment response (Shivakumar et.al, 2017), and has also linked aggregate earnings news to future unemployment and real GDP (Hann et.al, 2021; Abdallah et.al, 2022).

Using quarterly data U.S data from 1991:Q4 to 2021:Q3, including the potential source of untapped information about firms' expectation contained in earnings reports, we examine the pseudo out-of-sample performance of a set of different forecasting procedures, with different slack variables, forecasting four different types of inflation measures (Median CPI, Core-CPI, Core-PCE, and Core-PPI). We present evidence that although incorporating aggregate special items in a standard Phillips curve model does not necessarily improve its prediction accuracy, it yields equivalent results relative to more commonly used measures of economic slack. We also report that in some cases, the Phillips curve provide more accurate forecasts than benchmark uni-variate models. Interestingly, we find that the best Phillips curve prediction of future inflation during the covid-19 induced recession is obtained when aggregate special items is used as a slack variable since the latter appears to be less affected by this recession than GDP or unemployment gaps. This finding motivates future use of accounting data in macroeconomic forecasting research.

The reminder of this paper proceeds as follows; section 2 provides important background information about accounting variables, and a potential mechanism relating aggregate special items and future inflation. In section 3, we summarize, and evaluate the existing literature in macro-accounting and inflation forecasting and explain how our research fits within the current research. Section 4 presents the data used in this project as well as descriptive statistics.Section 5, we describe the models used in the forecast evaluation and the methods. Section

7 presents the results, and in section 8, we discuss their implications, and conclude.

2 Institutional Background & Mechanism

In this section, we define important accounting concepts and describe the mechanism by which we think aggregate earnings and more specifically aggregate special items impact future inflation.

2.1 Aggregate Earnings

Following the accounting literature, we define aggregate earnings as a weighted average measure of earnings, as reported in income statements, for publicly listed companies in the US, where the weights are based on the market capitalization at the beginning of each quarter. Using the income approach to calculate GDP, aggregate earnings can be thought as a proxy for corporate profit [1]. However, unlike corporate profit, aggregate earnings is more likely to reflect information about bad economic news in a timely manner due to special items, an information discarded when constructing corporate profit (Abdallah and Carrabias, 2022).

2.2 Aggregate special items

Special items are a category of the income statement that reflects an unusual transaction or event which impacts a company's income but is not expected to recur regularly. The phenomenon of accounting conservatism, which leads to a higher degree of verification to recognize good news as gains than to recognize bad news as losses results in earnings reflecting bad news more quickly than good news and a major and often overlooked avenue through which earnings can recognize loss promptly is through special items. Abdalla et al. (2022) puts forth a proposition that the special items component of aggregate earnings contains significantly more information about future economic outcomes as

1 Aggregate earnings is not exactly equivalent to corporate profit due to the exclusion of privately held firms and the difference between accounting earnings and taxable income.

compared to aggregate earnings without special items because when bad news arrives, firms change their expectations about their assets' future cash flows and the expected losses are immediately recognized as special items. Consequently, firm's demand for investment in inventories, goods and services that are required to enhance a firm's operating capacity changes and this demand shift in turn impacts the prices of production in the short term due to the supply of these goods and services being inelastic.

Special items can further be broken down into various sub-types like in-process R&D, restructuring charges, asset write-offs, gain/loss, litigation gains/losses, merger and acquisition-related, goodwill write-off and extinguishment of debt (see Johnson et al.(2011) for an in-depth breakdown of the various components of special items). The Coumpustat dataset provides information about the Special Items subcomponents from 2001 onwards and for this period, the sub-items that turn out to be the most important are restructuring charges, goodwill write-offs, asset write-offs, and extinguishment of debt. Figure 1 shows the relative contribution of these sub-components to special items for the period 2001:Q1 to 2023:Q3. Restructuring charges contribute over 30 % to special item records but experience a structural change throughout our study with a decreasing trend in its contribution to special items. Asset write-offs too see a decrease in their contribution to special items with their contribution dropping below 10 % from well over 18%. Extinguishment of debt contributes over 10% to special items and goodwill write-offs for a significant period of our study remain below 10% contribution to special items. A noteworthy point here is that all of these subcomponents experience a spike during recessionary periods which is in line with previous findings that special items are better reflectors of bad news.

Figure 2 shows the magnitude of these sub-components. While goodwill write-offs may only contribute to less than 10% of special item instances, the magnitude of goodwill write-offs outweighs that of all other sub-items, especially during recessionary periods. The magnitude of goodwill write-offs during the Great Recession was north of 100 billion dollars. The rest of the above-mentioned sub items too experience steep increases in their magnitudes during contractionary periods.

3 Related Literature

Our contribution to the literature is twofold . First, we bridge macroeconomic and accounting research by incorporating accounting data in a standard inflation forecasting model used in the macroeconomic literature. Previous macro-accounting research have highlighted the connection between aggregate earnings ’news’ and nominal and real macroeconomic variables. Hann et.al (2021) finds that unexpected changes in aggregate earnings has a statistically significant predictive ability in job flows, where a shock to aggregate special items is associated with "job destruction"for up to one quarter ahead. However, the results rely on selection on observables that does not include important macro-variables such as a measure of economic slack. Abdallah and Carrabias (2022) provides evidence that special items have predictive power on real GDP by capturing firms’ expectation about the economy. To solve the endogeneity issue, the authors employ a vector autoregresssive model, however, they do not impose a structural form, making the interpretation of their impulse response functions difficult. Other research in this field have also found a link between aggregate earnings and nominal macro-variables. Shivakumar (2007) notices that aggregate earnings are correlated with future inflation, arguing that bad earnings news are driven by poor stock market returns which take the form of asset write downs. Konchitchki and Patatoukas (2014) documents that SPF survey respondents fail to fully incorporate aggregate earnings when making nominal GDP growth forecast. In a subsequent analysis, Shivakumar and Urcan (2017) using both selection on observables and VAR find that aggregate earnings changes appear to cause firms to update their investment, shifting the demand for investment causing prices to change, though the researcher only finds the effect to hold in the PPI index. We contribute to the literature by employing different specification of the Phillips curve, which provides a causal framework between some measure of economic activity and inflation.

Second, our work fits within the literature of inflation forecasting, which looks at a wide variety of model specifications. Atkeson and Ohanian (2001) show that over the period 1984-1999, a random walk provides a more accurate forecast than that of the Phillips curve. Ang et.al (2007) examine a large set of models and find that survey forecasts, as those reported by the SPF or the Michigan consumer survey, have the most accurate predictions, beating those from the random walk. Faust and Wright (2014) confirm those results, survey based forecasts outperform model based ones. Stock and Watson (2008) find that the performance of the Phillips curve depends on the time period; if the economy is far from its natural level of output Phillips curve forecasts are preferred over univariate models. Finally, Banbura and Bobeica (2023) argue that the Phillips curve provides a good inflation forecast in the euro-zone, and find that the best models are dependent on the slack measurement, where the more accurate forecasts rely on slack measures produced by the OECD. Our study contributes additional evidence indicating that, while univariate models such as the random walk remain challenging to surpass, certain specifications (i.e different slack measures) of the Phillips curve model yield forecast accuracy that is relatively comparable.

4 Data & Descriptive Statistics

4.1 Inflation rate

We select four core inflation measures: Median CPI, Core CPI, Core PCE, and Core PPI. The term 'core' indicates that the price indices exclude food and energy prices. CPI and PCE are commonly used indices to measure inflation. Median CPI provides another approach to capturing underlying inflation by eliminating both large and small price changes from its calculation. Additionally, we examine the producer price index, following the work of Shivakumar and Urcan (2017). The rationale behind forecasting underlying inflation rather than overall inflation is to filter out supply shocks or inflation not driven by price expectations and economic activity, as outlined by Balls and Mazumder (2011). We define the annualized quarterly inflation rate as follows:

$$\pi_t = 400 \cdot ln(\frac{P_t}{P_{t-1}})$$

where P_t corresponds to some price index P estimated at time t. We aim to forecast inflation next year (i.e for the next four quarters);

$$\pi^4_{t+4} = 100 \cdot ln(\frac{P_{t+4}}{P_t})$$

Figure 3 displays the inflation series for our four measures. They tend to move together, though Core PPI appears to be much more volatile than the rest, whereas inflation reported by Median CPI is quite stable, particularly post great recession.

4.2 Economic slack

The deviation from potential output is an essential parameter in the Phillips curve, our approach begins with the establishment of conventional measures for economic slack. Initially, we articulate slack in terms of output deviation from its natural level, achieved either through estimates from FRED or by employing the Hodrick-Prescott (HP) filter. Subsequently, we assess labor market tightness, considering either the percentage point deviation from NAIRU or the ratio of job openings to the number of unemployed workers. Both labor market tightness measures are constructed with the application of the HP filter to ensure stationarity. In Figure 4, we present the time series for our four standard indicators of economic activity, highlighting significant changes in each variable during the 2020 recession. It's important to note that, with the exception of the number of vacancies (i.e., job openings) calculated by Barnichon (2010) and available up to 2021:Q3, until now, the data stems from FRED and is seasonally adjusted.

We now proceed to derive the aggregate special items variable. Following Abdallah and Carrabias (2022), our initial step involves gathering quarterly accounting data from Compustat. Special items are then normalized by sales, and this variable is aggregated using value-weighted cross-sectional averages. The weights are determined by the market value of equity at the quarter's outset. We impose a requirement that firms must have sales of at least $1 million and select those with fiscal quarters concluding in March, June, September, and December. We exclude firms with earnings announcement dates occurring more than 45 days after the end of the fiscal quarter. Figure 5 illustrates the time series for our variable of interest. Notably, during economic downturns, the variable takes on negative values, indicating the promptness of adverse news. It is worth observing a slight decline in aggregate special items during the 2020 recession when compared to other measures of economic slack.

4.3 Survey Forecasts

We retrieved data from the Survey of Professional Forecasters (SPF) provided by the Federal Reserve Bank of Philadelphia. The dataset contains the 10-year CPI forecasts of inflation. Note our data starts on 1991:Q4. Data on PCE forecasts was omitted due to its limited availability. Figure 6 illustrates the anticipated inflation forecasts at time t. Notably, the long-term expectation of inflation remains stable especially post 2000, hovering around 2.5%, aligning closely with the official target set by the Fed in 2012. Thus, our data-set with no missing values for this project, ranges from 1991:Q4 to 2021:Q3.

5 Empirical Strategy

In this section, we introduce the models employed for inflation forecasting and outline the methodology used to assess their accuracy. Our objective is to put forth an updated Phillips curve; therefore, we compare a number Phillips curves based on single predictors to a set of standard benchmark uni-variate time series models.

5.1 The models

For our set of benchmark models, we start with the most naive forecast, namely the random walk model, as proposed by Atkeson and Ohanian (2001) where the forecast of inflation for the next four quarters is simply equal to the inflation observed in the last four quarters.

$$\pi^4_{t+4} = \pi^4_t + \varepsilon^4_{t+4} \tag{1}$$

Equation (1) represents the random walk model, where π^4_t is the annual inflation rate from P_{t-4} to P_t and ε^4_{t+4} the four step-ahead error term.

$$\phi_p(L) \cdot (\pi^4_{t+4} - \pi_t) = \alpha + \theta_q(L) \cdot \varepsilon^4_{t+4} \tag{2}$$

equation (2) represent the general form of an ARMA(p,q) model, where p and q are the order of its auto-regressive and moving average components respectively. Note that we are assuming that inflation is integrated of order 1, hence the first difference of the inflation measure.

We now turn our attention to a set of expectation augmented Phillips curve models. The first specification is a backward-looking Phillips curve, following Stock and Watson (2008);

$$\pi^4_{t+4} - \pi_t = \alpha + \phi(L) \cdot x_t + \theta(L) \cdot \Delta\pi_t + \varepsilon^4_{t+4} \tag{3}$$

This is an auto-regressive distributed lag model (ADL), where inflation for the next four quarters depend on inflation expectation which is expressed as a function of past inflation rates and x_t represent a measure of economic activity. Next, we have a forward-looking Phillips curve model, where inflation expectation is simply assumed to be equal to the mean CPI 10-year ahead SPF forecasts at time t and past expectations;

$$\pi^4_{t+4} - \pi^e_t = \alpha + \phi(L) \cdot x_t + \theta(L) \cdot \Delta\pi^e_t + \varepsilon^4_{t+4} \tag{4}$$

We denote π^e_t as the average 10-year ahead SPF forecast at time t. In this scenario, it is reasonable to anticipate that $\Delta\pi^e_t$ will be close to zero. It assumes that long-term inflation expectation is anchored, meaning that inflation expectation is firmly linked to a specific level, such as the target set by the Federal Reserve. This assumption aligns well with the time period under study (Sommer, 2002; Ball and Mazumder, 2011).

5.2 Pseudo out-of-sample forecast

In this paper, the period 1991Q4:2003Q4 is used for initial parameter estimation, where the degrees of lag polynomials represented by θ and ϕ are selected via the Bayesian information criterion (BIC) separately over the range of one to four lags.

We employ a recursive out-of-sample forecast starting in 2004:Q1 and ending in 2021:Q3, where we use the data available up to time t to estimate inflation from t to $t+4$. Our window used for estimating our models lengthen over time. We proceed to measure forecast accuracy by calculating the root mean squared errors (RMSE) of the forecast produced by each model. The RMSE is calculated as follows;

$$RMSE_{t_1,t_2} = \sqrt{\frac{1}{t_2 - t_1 + 1} \sum_{t_1}^{t_2} (\pi^4_{t+4} - \pi^4_{t+4|t})^2} \tag{5}$$

where t_1 and t_2 correspond to the first and last forecast period respectively, $\pi^4_{t+4|t}$ is the predicted value of π^4_{t+4} at time t. In order to make the results easier to interpret, we will report the RMSE relative to the ARMA benchmark, if a model outperforms model (2), its relative RMSE will be smaller than one, while if it under-performs the model's relative RMSE will be greater than one.

6 Results

In this section, we present the forecast performance of several models, discuss their relative performances and pay special attention to the different specifications of the Phillips curve model.

We begin by plotting the forecasts for each inflation measure from the backward-looking and forward-looking Phillips curves in figures 7 and 8 respectively. The models noticeably fail to predict inflation after the 2020 recession and covid-19 induced lockdown, predicting large negative changes in price levels, while the actual realized annual inflation rate over that period is increasing and positive. However, the Phillips curve employing aggregate special items as its measure of economic slack emerges as the model that most effectively predicts inflation over that period. Due to the large graphical discrepancy between the models' accuracy before and after 2021:Q1, we present the RMSE's for both the full pseudo out-of-sample period (i.e 2004:Q1 to 2021:Q3) and a sub-sample that excludes the aforementioned period (2004:Q1 to 2020:Q4) [2].

In tables 1 and 2, we report the RMSE's from the battery of models presented in section 5, relative to the RMSE's of the ARMA benchmark. Table 1 focuses on the backward-looking phillips curve models, we can observe that in the full out-of-sample period, the best auto-regressive distributed lag specification is with the inclusion of the aggregate special items variable. Frequently outperforming the ARMA benchmark, it is the preferred model when inflation is measured with the Core PPI. However, in most instances, the random walk remains the favored model. When examining the sub-sample, the ADL model with aggregate special items yields less promising results, nevertheless, they present intriguing findings. In certain cases, Phillips curve models manage to outperform our univariate benchmarks when inflation is measured with either Median CPI or Core CPI. This underscores the potential new relevance of

2 Note that by doing so, we are excluding forecasts impacted by the covid-19 recession, since we are predicting inflation for next year (i.e $t+4$), using data available at time t.

Phillips curve models in the inflation forecasting literature. Despite not being the preferred model, the Phillips curve with aggregate special items exhibits accuracy similar to that of other ADL specifications.

Table 2 presents the results for the ADL specification equivalent to model (4). Although none of the Phillips curve models are able to outperform the ARMA benchmark, the Phillips curve with aggregate special items is more precise than the random walk in the sub-sample when inflation is measured using Median CPI. Furthermore, for both Core CPI and Median CPI, the best Phillips curve specification is when we include the special items variable as our measure of economic activity.

Our results support previous findings in the literature; namely uni-variate time series model are hard to beat, and emphasizing the significant enhancement in standard Phillips curve forecasts when a specific slack measurement is chosen. Additionally, our study reveals that the inclusion of our novel slack variable, aggregate special items, in an auto-regressive distributed lag (ADL) framework either outperforms or yields comparable results to those obtained from more conventional multivariate models.

7 Conclusion

In this study, we evaluate the inflation forecasting efficacy of different Phillips curve specifications and univariate time series models, utilizing four distinct inflation measures and spanning two distinct out-of-sample periods (2004:Q1-2020:Q4 and 2004:Q1-2021:Q3). We establish an optimal Autoregressive Moving Average (ARMA) model as our benchmark for forecasting accuracy. Our findings carry significance within the ongoing discussion on the relevance of Phillips curve models in predicting inflation, as well as the exploration of the utility of special items in inflation forecasting.

Our results provide evidence for the crucial importance of choosing a suitable slack measure in a Phillips curve for accurate inflation prediction, emphasizing the important role that economic activity indicators play in inflation forecasting. Investigation of Autoregressive Distributed Lag (ARDL) Phillips curve models reveals that most of them have inadequate forecasting accuracy when post-COVID inflation is taken into account. Interestingly, the special item integrated Phillips Curve emerges as more successful at forecasting post-COVID inflation among the Phillips curve models assessed in a majority of cases. Consequently, the special items Phillips curve performs better than Phillips curves using different economic slack measures in most cases over the course of the whole out-of-sample period. When restricting our analysis to the pre covid period, though the special items Phillips curve rarely ranks highest in forecasting accuracy amongst Phillips curve models, it routinely performs comparably to Phillips curves using other known slack measures. This important finding highlights the informational value related to future macroeconomic variables contained within aggregate special items and this finding could be, under certain circumstances, used to improve forecasting accuracy of inflation, among other macroeconomic variables.

Another particularly interesting finding is that forward-looking Phillips curve models combined with special items outperform all other Phillips curve models in forecasting accuracy across both the out-of-sample periods that we work with. Our results corroborate previous findings that Phillips curve models generally face difficulties when competing with univariate time series models. But during the pre-COVID out-of-sample period, there are notable trends in some inflation metrics, like core PPI (Producer Price Index) and PCE (Personal Consumption Expenditure) where compared to the univariate time series models, backward-looking Phillips curve models show better forecasting accuracy.

Our results make a substantial contribution to the accounting literature's hypothesis that supports the idea that aggregate special items are important for determining the state of the economy. This validation lays the groundwork for future advancements in the field of macro accounting research, especially in the context of using aggregate special items for macroeconomic forecasting .

8 References

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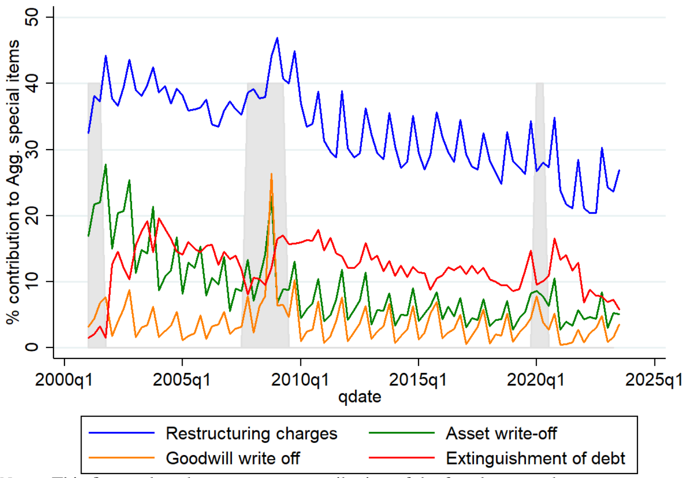
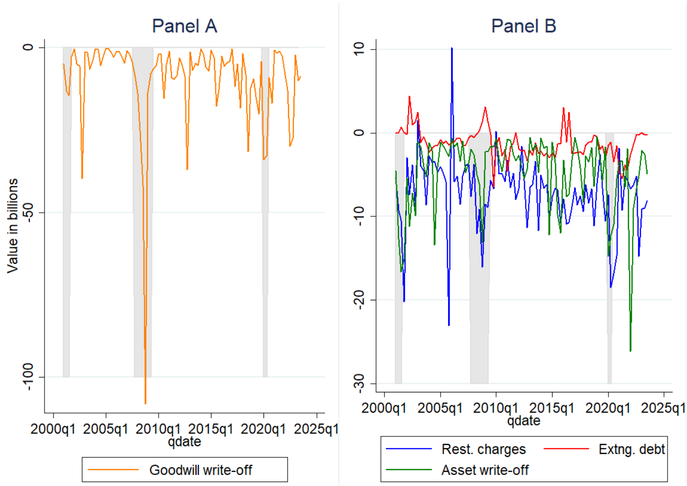
9 Graphs & tables

Fig. 1: Agg. special items decomposition (I)



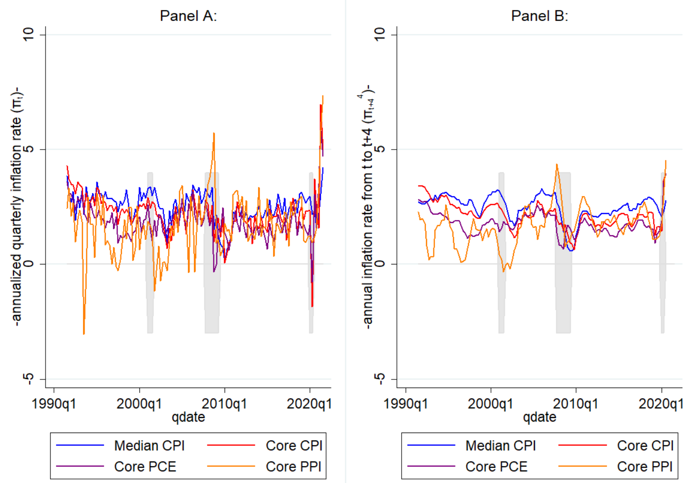
Notes: This figure plots the percentage contribution of the four largest sub-components to aggregate special items over time. Compustat only calculates the sub-items from 2000 onwards.The gray shaded areas represent recessionary periods identified by FRED.

Fig. 2: Agg. special items decomposition (II)



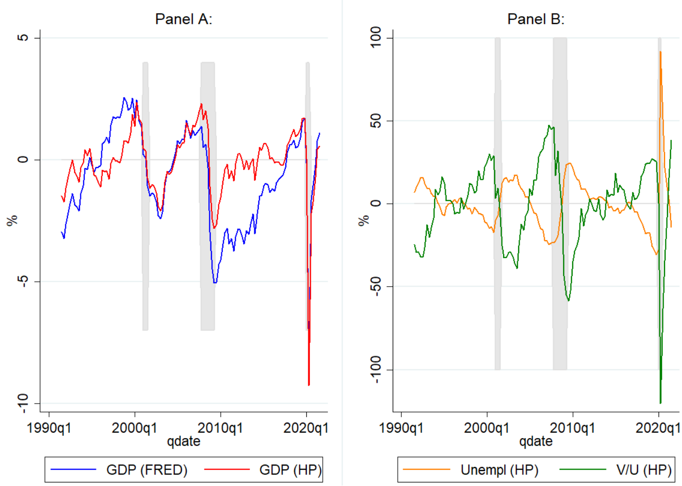
Notes: This figure plots the time series of the four largest sub-components of aggregate special items.

Fig. 3: Inflation series



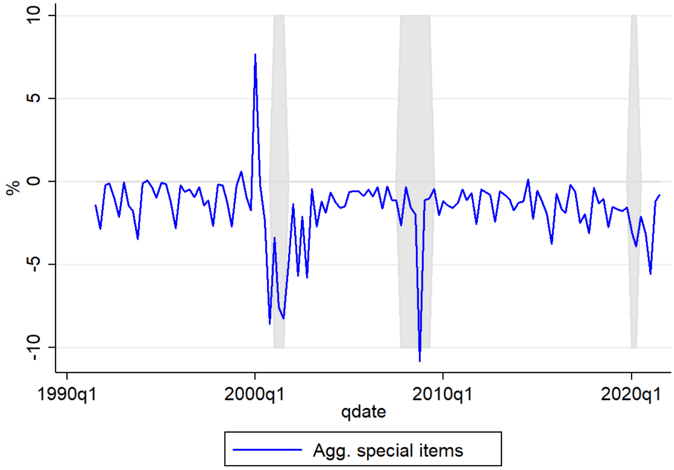
Notes: This figure plots the different measures for inflation. Panel A calculates the quaterly annualized inflation rate (i.e $\pi_t = 400 \cdot log(\frac{P_t}{P_{t-1}})$) and Panel B the annual inflation rate from t to t+4 (i.e $\pi^4_{t+4} = 100 \cdot log(\frac{P_{t+4}}{P_t})$).

Fig. 4: Economic slack series (I)



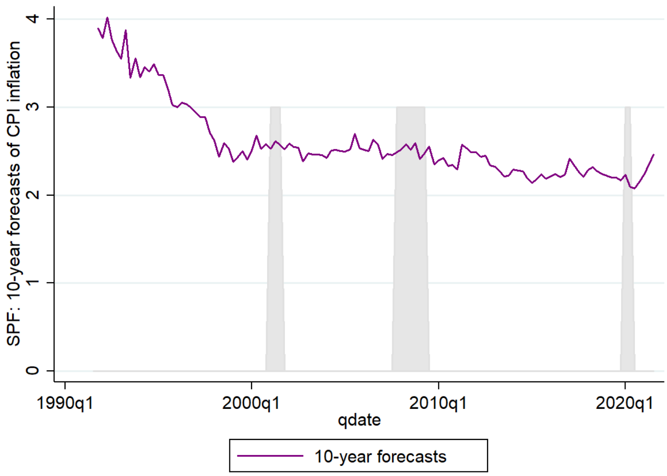
Notes: This figure represents the different standard measures for economic slack. Panel A represents the output gap expressed at the percent deviation of real GDP from its potential value. Panel B displays two measures of labor market tightness. The output gap, unemployment gap, and V/U are calculated via the Hodrick-Prescott filter with a smoothing parameter of 1600. The unemployment gap is the percent deviation of u-rate from its natural rate. Finally, V and U stand for vacancy and unemployment respectively and V/U is their ratio.

Fig. 5: Economic slack series (II)



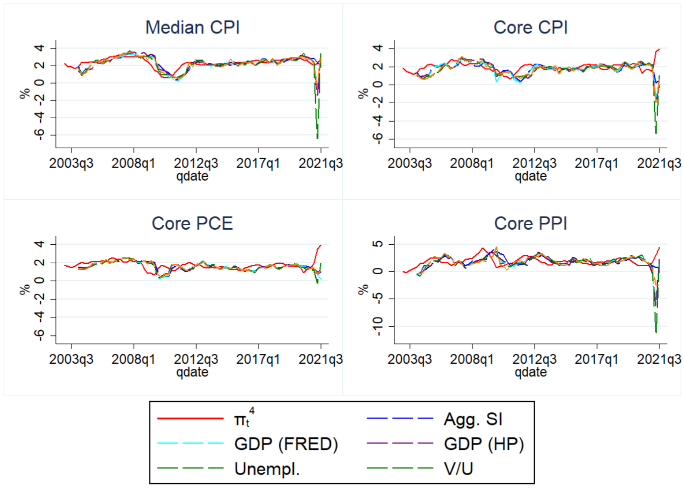
Notes: This graph represents the time series of aggregate special items. Aggregate special items is the value-weighted cross-sectional average of scaled quarterly firm-level special items with weights based on market value as of the beginning of the quarter.

Fig. 6: Long run SPF forecasts of inflation (CPI)



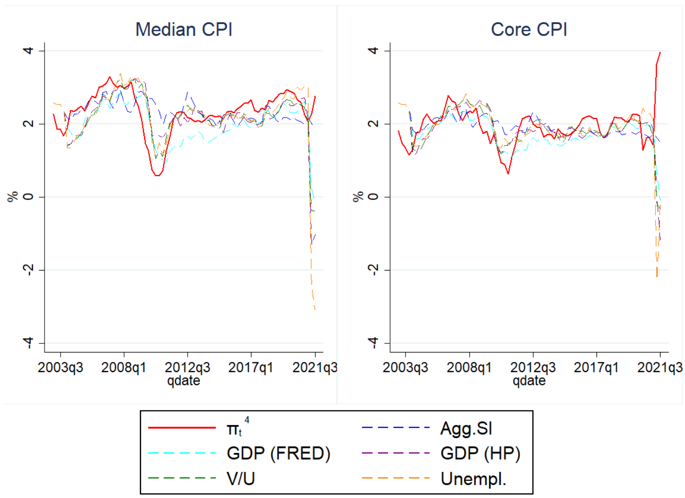
Notes: This graph represents the time series of the mean 10-year inflation forecasts from SPF.

Fig. 7: Forecasts of inflation based on model (3)



Notes: Each dotted line is a forecast corresponding to a specific version of the backward-looking Phillips curve (model (3)), the red line indicates the realized annual inflation.

Fig. 8: Forecasts of inflation based on model (4)



Notes: Each dotted line is a forecast corresponding to a specific version of the Phillips curve with anchored expectation (model (4)), the red line indicates the realized annual inflation.

Tab. 1: Forecasts of annual inflation (I)

		2004:Q1-2021Q3	2004:Q1 - 2020:Q4
		Relat. RMSE	Relat. RMSE
Median CPI	PC Agg. special items	1.06	1.06
	PC GDP gap (FRED)	1.21	1.02
	PC GDP gap (HP)	1.35	1.10
	PC Unempl. gap	2.19	**0.93**
	PC V/U	1.18	1.04
	R.W	1.15	1.18
	ARMA	**1**	1
Core CPI	PC Agg. special items	0.88	0.90
	PC GDP gap (FRED)	1.07	0.97
	PC GDP gap (HP)	1.10	0.97
	PC Unempl. gap	1.40	0.96
	PC V/U	1.08	0.95
	R.W	**0.71**	**0.85**
	ARMA	1	1
Core PCE	PC Agg. special items	0.86	0.81
	PC GDP gap (FRED)	0.95	0.85
	PC GDP gap (HP)	0.84	0.80
	PC Unempl. gap	0.91	0.81
	PC V/U	0.86	0.80
	R.W	**0.81**	**0.75**
	ARMA	1	1
Core PPI	PC Agg. special items	**0.95**	0.92
	PC GDP gap (FRED)	1.20	0.85
	PC GDP gap (HP)	1.26	**0.83**
	PC Unempl. gap	1.70	0.89
	PC V/U	1.24	0.92
	R.W	0.96	0.93
	ARMA	1	1

Notes: We forecast inflation over the next four quarters. Entries represent RMSEs, relative to the RMSE of the ARMA model, over the indicated sample period. Note that the Phillips curve models correspond to model (3).

Tab. 2: Forecasts of annual inflation (II)

		2004:Q1-2021Q3	2004:Q1 - 2020:Q4
		Relat. RMSE	Relat. RMSE
Median CPI	PC Agg. special items	1.24	1.28
	PC GDP gap (FRED)	1.86	1.76
	PC GDP gap (HP)	1.88	1.55
	PC Unempl. gap	2.31	1.59
	PC V/U	1.76	1.76
	R.W	1.15	1.32
	ARMA	**1**	**1**
Core CPI	PC Agg. special items	1.16	1.27
	PC GDP gap (FRED)	1.42	1.57
	PC GDP gap (HP)	1.47	1.45
	PC Unempl. gap	1.64	1.43
	PC V/U	1.43	1.43
	R.W	**0.71**	**0.85**
	ARMA	1	1

Notes: We forecast inflation over the next four quarters. Entries represent RMSEs, relative to the RMSE of the ARMA model, over the indicated sample period.Note that the Phillips curve models correspond to model (4).