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Do Inflation Expectations Granger Cause Inflation?

A VEC Model Approach

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Abstract: Being able to accurately predict future inflation is of great importance for a wide range of actors in the economy, as well as for the effectiveness of monetary policy decisions. In this thesis, we examine whether survey measures of inflation expectations contribute to more accurate inflation forecasts in Sweden. This is done by conducting forecasts using data between 2002Q1-2018Q1. Forecasts from two benchmark models, a univariate ARIMA model and a trivariate VAR model, are compared to three VEC models each - including the aggregated mean of inflation expectations as surveyed by NIER of both genders, men, and women, respectively. We find that the models including inflation expectations are all outperformed by the benchmark models, implying that none of the expectations series contribute to more accurate inflation forecasts in Sweden. However, our results suggest that the models including inflation expectations exhibit time-varying performance and that it is beneficial to integrate expectations into specific models during certain time frames.

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List of Abbreviations

ADF	Augmented Dickey-Fuller
AFE	Absolute Forecast Error
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BVAR	Bayesian Vector Autoregressive
CES	Consumer Expectations Survey
CPI	Consumer Price Index
CPIF	Consumer Price Index With Fixed Interest Rate
ECB	European Central Bank
ETS	Economic Tendency Survey
FE	Forecast Error
ML	Maximum Likelihood
NIER	National Institute of Economic Research
MA	Moving Average
ME	Mean Error
RMSE	Root Mean Square Error
RW	Random Walk
SPF	Survey of Professional Forecasters
VAR	Vector Autoregressive
VEC	Vector Error Correction

1 Introduction

Expectations of future inflation are of great importance to many actors in an economy, as well as to the effectiveness of monetary policy. Many central banks regularly announce forecasts of inflation and a large number of other key variables to support and motivate their monetary policy decisions. Furthermore, a variety of market actors, such as managers and retail investors, closely monitor various price movements as an element in shaping their expectations about the future. In addition, households and firms are affected by the inflation rate, not least since they have various nominal commitments (such as borrowing costs, labor wage contracts, and mortgage rates), and because of wages and social benefits often being tied to price developments. As can be seen, the general price level and inflation rate is an essential part to take into account in the many decisions made in a modern economy. Performing accurate forecasts of inflation is therefore of high value for households, firms, and policymakers, and not least for the effectiveness of monetary policy decisions. In this thesis, we investigate whether individuals' inflation expectations can be used as predictors to perform more accurate inflation forecasts, i.e., if these inflation expectations Granger cause inflation.

In Sweden, as well as in many other modern economies, the central bank's objective of monetary policy is to maintain a low and stable inflation rate (Riksbank, 2018). Monetary policy primarily influences the inflation rate by the Swedish Riksbank adjusting the policy rate. When the policy rate is adjusted, this mainly affects the inflation rate via changes in economic activity and trends in the exchange rate. Households' and firms' inflation expectations are crucial for the development of inflation since they adjust their decisions on setting prices and wages in accordance with these expectations. If the inflation is high, and this is incorporated into the expectations of households and firms, this could lead to price and wage spirals making the inflation entrenched at a high level. This mechanism makes it difficult to lower inflation again without a strongly rigorous monetary policy. When the central bank raises the policy rate and provides information about its predicted future level, such as when the Riksbank revises its forecast for a higher policy rate, it can create a dampening effect on the economy via expectations. The Riksbank therefore closely monitors inflation expectations and aim at employing a monetary policy that anchors the inflation expectations in the economy at the inflation target of 2 percent (Riksbank, 2023). It follows that the credibility of the Riksbank's inflation target can be inferred from inflation expectations. When long-term expectations are not well-anchored, it may indicate credibility issues with the inflation target.

It is accordingly of general interest to build on the understanding of how individuals' inflation expectations in Sweden relate to future inflation, and further investigate whether they contain useful information to incorporate when forecasting inflation. Therefore, as stated earlier, this thesis uses the concept of Granger causality to investigate whether data on individuals' inflation expectations contribute to more accurate inflation forecasts. The results can generate valuable implications for the main inflation forecasting institutions in Sweden, such as the Riksbank, the National Institute of Economic Research (NIER), and the Ministry of Finance, on whether to include the forecasting expectations of households in their models when conducting their forecasts.

Whether inflation expectations of different groups of individuals affect the accuracy of inflation forecasts has, to the best of our knowledge, not been studied. Therefore, we use data on individuals' inflation expectations disaggregated by gender in this thesis, to extend the analysis by assessing the potential impact of men's and women's inflation expectations on inflation in Sweden.

In our analysis, we conduct a forecasting exercise with quarterly data between 2002Q1-2018Q1. Forecasts by two benchmark models, a univariate autoregressive integrated moving average (ARIMA) model, and a trivariate vector autoregressive (VAR) model are compared to three vector error correction (VEC) models each - where data on inflation expectations of both genders, men, and women from the Economic Tendency Surveys (ETS) are respectively added as predictors of inflation. The forecasts are conducted for the period 2018Q2-2020Q1 and are compared to the forecasts of a random walk (RW) model to see whether they can be outperformed by these eight models.

Our results show that both models excluding the inflation expectations series outperform the models where inflation expectations are included. Hence, we find that in

Sweden, including individuals' inflation expectations in our models does not generate more accurate inflation forecasts. However, the six models including inflation expectations tend to perform more accurate forecasts with a longer forecast horizon than those excluding expectations. When comparing the various models incorporating inflation expectations with each other, we find that for the models excluding macro-financial indicators, the model including the expectations of men performs the most accurate forecasts. Nevertheless, the effect on the forecast accuracy only marginally differs when including the different inflation expectations series in the models including macro-financial indicators.

The remainder of this thesis is structured as follows. Section 2 provides a background on the formation of inflation expectations, and an overview of the existing literature on inflation forecasting in general and using inflation expectations, before the research question is specified. Section 3 describes the data included in the analysis and the selection and transformation of it. Section 4 details the econometric methodology and models used to generate inflation forecasts and describes how the comparisons between the models are conducted. Section 5 presents the results from the forecasting exercises carried out to answer the research question, followed by a sensitivity analysis in Section 6. Section 7 discusses the results. Lastly, Section 8 concludes the results and implications provided by the study.

2 Literature Review

Previous literature has enhanced our understanding of inflation predictors, including earlier theoretical work and a broad series of empirical studies on inflation forecasting. This section aims to provide an essential overview of the literature to accurately interpret and understand the analysis of this thesis. The review begins with a background on the formation of inflation expectations. This is followed by an overview of previous research on inflation forecasting in general, and using inflation expectations. The section ends with a formulation of the research question and contribution to the literature.

2.1 The Formation of Inflation Expectations

The literature on the formation of survey-based inflation expectations is relatively large. For inflation expectations to be rational, the rational expectations hypothesis states that they must be unbiased and efficient forecasts of inflation. Figlewski and Wachtel (1981) and Gramlich (1983) both find that the inflation expectations appear to be both biased and inefficient and hence reject the rational expectations hypothesis. The former paper finds that the adaptive expectations model describes expectations of inflation best. The rejection of the rational expectations hypothesis applied to the case of inflation expectations continues to be well documented in later studies.[1] Jonsson and Österholm (2012) study the properties of survey-based inflation expectations in Sweden, using data from Prospera. They find that Swedish inflation expectations are neither unbiased nor efficient forecasts of inflation. A common explanation is that individuals lack the required sophistication to form their expectations rationally while the hypothesis demands that individuals possess a lot of information. With information costs, the rational behavior of individuals may be selecting methods other than rational expectations.[2] Furthermore, Lack (2006) reasons that maintaining a low and stable inflation rate could have the unintended consequence of

[1] See, among others, Caskey (1985), Croushore (1993), Evans and Gulamani (1984), Frankel and Froot (1987), Jeong and Maddala (1996), Struth (1984), and Urich and Wachtel (1984). A significant exception to these studies is Keane and Runkle (1990), which consider data revisions and forecast error correlation across agents and fail to reject the hypothesis.

[2] See, among others, Brock and Hommes (1997), Brock and Hommes (1998), Evans and Ramey (1992), Evans and Honkapohja (2001), and Sargent (1993).

hindering critical analysis and rational expectations, both within and outside the central bank. Hence, in times of low and stable inflation, people may have more RW-like adaptive expectations.

Later studies provide empirical evidence for models where individuals face constraints on information processing in the case of forecasting macroeconomic variables, such as inflation. For example, Mankiw and Reis (2002) describe a model of 'sticky information' where individuals update their information infrequently and hence forecast based on information that might be outdated. Another recent finding is 'noisy information' models, see Maćkowiak and Wiederholt (2009), where individuals receive noisy signals of the true information state. Models like these allow heterogeneity across individuals in the frequency of when information is updated or in the information's noisiness. There is strong empirical evidence for the rejection of the rational expectations hypothesis by finding strong empirical support for heterogeneity in the formation of inflation expectations.[3] In short, individuals are shown to be rationally heterogeneous in the sense that each individual relies on different models, may have different information sets, or have different capacities for processing information.

Jonung (1981) studies the Swedish perceived and expected inflation rates, using data from NIER's ETS, and finds that sex and age are significantly related to perceptions and expectations of inflation. He reasons that the expectations are crucially determined by the individual's personal experience of changes in prices, i.e., the history of the purchasing power of money in their own favored consumption baskets. Jonung discusses the result by stating that women are reasonably more influenced by food prices than men since food prices rise more rapidly than prices in general, and women are responsible for the major share of food purchases. The empirical evidence on systematical differences between inflation expectations of men and women is well documented in a variety of countries, with women on average expecting a higher inflation rate.[4] Building on the literature of heterogeneity in inflation expectations, NIER (2014) analyze the forecast accuracy of

[3] See Blanchflower and MacCoille (2009), Branch (2004), Pfajfar (2013), and Pfajfar and Santoro (2010).

[4] See, among others, Binder and Rodrigue (2018), Blanchflower and MacCoille (2009), D'Acunto et al. (2020); D'Acunto et al. (2021); D'Acunto et al. (2022), Madeira and Zafar (2012), Leung (2009) and Souleles (2004).

Swedish inflation expectations on the consumer price index (CPI), using data on inflation expectations collected in ETS. They investigate a variety of groups' forecast performance by comparing the root mean square error (RMSE) of models including inflation expectations data from different groups. They find that the groups with the highest precision are individuals with post-secondary education, people aged 24-35 years, and men. The cause of the differences in forecast accuracy between the groups is not analyzed in their paper.

2.2 Forecasting Inflation in General

Forecasting inflation is difficult, in particular compared to other macroeconomic variables, as stated by, among others, Atkeson and Ohanian (2001), and Faust and Wright (2013). There is an abundance of literature looking at different methods and models for performing as accurate forecasts as possible in different economies. Making comparisons across papers in this literature is challenging since they study different sample periods in various economies, and use different inflation series and methods for various model comparisons, with the quantitative results depending crucially on these details. However, commonly used methods and models for forecasting inflation are described in this section by referring to former studies. One thing that we can state from the literature study is that an RW model is commonly used as a benchmark model when comparing various specifications of forecasting models.

Inflation forecasting models are frequently conducted using a Phillips curve approach. The Phillips curve is an economic model, first introduced in Phillips (1958). The theory states that the change in unemployment within an economy has a predictable effect on inflation. In its classical form, the Phillips curve illustrates a negative relationship between inflation and unemployment. This inverse relationship can be explained by an increased demand for labor making the pool of unemployed workers subsequently decrease. Therefore, firms must offer higher wages to attract workers, making inflation rise. Simultaneously, unemployment is reduced since the corporate cost of wages increases and companies forward the costs to consumers in the form of price increases. Another commonly used predictor is the interest rate, motivated by the economic theory called the Fisher effect. The Fisher effect was introduced in Fisher (1930), and describes the relationship between inflation and both real and nominal interest rates. In its classical form, the Fisher effect postulates that the nominal interest rate in any period equals the real interest rate plus the expected inflation rate. Accordingly, real interest rates drop as inflation rises, unless nominal rates rise at the same rate as inflation.

Whether the theory of the Phillips curve is applicable in practice and matches reality is a question that many researchers have tried to answer. Their results have often varied depending on what country and/or period is examined, while the applicability has been shown to depend crucially on the sample period.[5] Various extensions of this approach, so-called generalized Phillips curve models, are commonly used by including additional predictors as independent variables. For example, Stock and Watson (1999) consider several models over the 1970-1996 period and find that the Phillips curve-based models are the most reliable and accurate out-of-sample forecasts of U.S. inflation. Ang et al. (2007) later extend the analysis by considering no-arbitrage term structure models, non-linear forecasting models, and combined forecasts from different forecasting methods. They find that survey-based forecasts outperform the forecasts based on the Phillips curve, as well as ARIMA models, and using information in asset prices. We will get back to this in Section 2.3.

Concerns that are raised regarding the Phillips curve approach include its inability to capture parameter changes over time and handle large numbers of predictors, as stated by for example Koop and Korobilis (2012). A variety of other approaches have been proposed. For instance, an alternative approach is found in Primiceri (2005), using a VAR model including inflation, unemployment rate, and treasury bill rate. The study allows for the intercept and slope coefficients to drift slowly over time, with the parameters following RW with stochastic volatility. Further examples of studies constructing trivariate models with inflation, unemployment rate, and treasury bill yields are Cogley and Sargent (2001), Cogley and Sargent (2005), Del Negro and Primiceri (2015) and Ribba (2006).

[5] See, among others, Atkeson and Ohanian (2001), Fisher et al. (2002), and Sims (2002).

2.3 Forecasting Inflation Using Inflation Expectations

Faust and Wright (2013) conclude that forecasting inflation is difficult since various judgmental (institutions' or survey-based inflation expectations') or naïve (RW modeled) forecasts generally outperform the forecasts by more sophisticated time series models. Inflation expectations are often not explicitly included in models forecasting inflation.[6] Still, previous literature on the importance of survey expectations on inflation is fairly large and varies in their results, but commonly find improvements when using measures of inflation expectations in time series models forecasting inflation. Further, empirical evidence indicates that the ability of inflation expectations to predict inflation trends is impacted by varying economic regimes or may experience changes over time.[7]

Professional forecasts are commonly used as indicators of inflation expectations because of their wide accessibility across various economies and over extended time frames. This is particularly useful when assessing forecasting models, which generally require longer time samples for evaluation.[8] Nonetheless, as stated by for example Bańbura et al. (2021), professional forecasts have been repeatedly criticized as not representative of expectations in the economy at large. Other measures of inflation expectations are those of households and firms.[9] A counterargument is that the expectations of households and firms, and the ones derived from financial market prices, are subject to other pitfalls such as limited availability, measurement issues, or short sample.

Ang et al. (2007) forecast inflation using U.S. data for the period 1952-2002, and examine three inflation expectation surveys: the Livingstone Survey, the SPF, and the Michigan Survey. As previously mentioned, they find that out-of-sample survey-based

[6] Bańbura et al. (2021) discuss that this could be considered to partly depend on unavailable or only imperfect proxies of individuals' inflation expectations in a given economy, as well as the non-existing agreement regarding which measures of expectations are the most relevant. Another reason could be that observed measures of these expectations may not contribute any additional information to what is captured by other predictors of inflation.

[7] See, among others, Lack (2006), Mertens (2016), Mertens and Nason (2020), and Trehan (2015).

[8] Frequently used professional forecasts are the Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia, and the SPF conducted by the European Central Bank (ECB). See, among others, Bańbura et al. (2021), Bauer and McCarthy (2015), and Gil-Alana et al. (2012).

[9] Frequently used data on expectations of households and firms are the Survey of Consumers conducted by the University of Michigan's Survey Research Center (the Michigan Survey), the Swedish ETS conducted by NIER, and the Consumer Expectations Survey (CES) conducted by the ECB.

forecasts outperform a wide variety of time series models. In addition, they find that the strong performance of the survey-based forecasts extends to surveys dominating other models in forecast combination methods. Gil-Alana et al. (2012) use quarterly data from the period 1981-2008 and compare the four models presented in Ang et al. (2007) with an autoregressive fractionally integrated moving average (ARFIMA) model as well to confirm their findings. Both papers discuss that the strong success of survey-measured inflation expectations in forecasting inflation is likely explained by three factors. The first two are the expectations' capability to pool large amounts of information, and efficiently aggregate that information from many different sources. The third factor is the expectations' ability to quickly react and adapt to major changes and shocks in the economic environment and data generating process for inflation.

In a study by Lanne and Luoto (2017), the authors extend a non-causal autoregressive (AR) model and apply it to U.S. inflation. The study finds strong evidence in favor of non-causality in the inflation process, meaning that future inflation expectations played a significant role in determining current inflation levels. Trehan (2015) base two inflation forecast models on expectations from the American SPF and Michigan Survey and compare the accuracy of these with four time series models. He does this using data for two samples over the period 1996-2002 and 2003-2009. He finds that the survey-based forecasts have become less accurate, while inflation appears less persistent. Further, he states that it does not seem like households have learned about this change in the inflation process, since they appear to continue with their historical practice of placing a large weight on recent inflation data when forming inflation expectations. Bańbura et al. (2021) find that in the Euro area in 2001-2019, inflation expectations provided by the SPF or Consensus Economics forecasts do improve forecasts of inflation, while they are not improved when using inflation expectations of firms and households collected by the European Commission. They conclude this using a variety of time series models, different measures of inflation expectations, several economies, and two inflation indices and compare the accuracy of the models that include information on inflation expectations with those which do not.

Looking at the case of Sweden, Jonsson and Österholm (2012) compare the 1-year horizon forecast performance of the Prospera survey with that of the professional forecasting institution, NIER, using quarterly data from 1996 to 2009. They find that the survey-based forecasts are outperformed by NIER's forecast and, in addition, they are also typically worse predictors than simple AR models. Mossfeldt and Stockhammar (2016) conduct Swedish goods and services inflation forecasts with 1-, 2-, and 3-year horizons using three models with a mean-adjusted Bayesian VAR (BVAR) framework. They use quarterly data over the period 1996-2015 of Swedish goods and services inflation, resource utilization, labor costs, the nominal exchange rate, and inflation and price expectations from ETS. They find that their BVAR models including expectations, generally outperform a univariate model. Moving on with Swedish applications, Lindholm et al. (2020) use quarterly data over the period 1997-2017 to evaluate different inflation forecast approaches. These are model-based forecasts, survey-based forecasts using data from ETS and the Prospera Survey, judgmental forecasts from NIER, basic benchmark models for consumer price index with fixed interest rate (CPIF), and the method suggested by Faust and Wright (2013). The latter is found to be outperformed by all other models. The results of both Mossfeldt and Stockhammar (2016) and Lindholm et al. (2020) indicate that the conclusion made by Faust and Wright (2013), that time series models cannot outperform judgmental forecasts, is not valid in the case of Sweden. Although in Lindholm et al. (2020), the survey-based forecasts are found to perform poorly compared to the other models. Even the survey with the best forecasting precision estimates a far higher RMSE than most of the models.

Stockhammar and Österholm (2018) previously investigated whether inflation expectations Granger cause inflation in Sweden, using a sample of quarterly data from 1996 to 2016 and comparing different BVAR models. The first comparison is between a univariate model including CPI and a bivariate model including CPI and inflation expectations. The second comparison is between a trivariate model including CPI, unemployment rate, and 3-month treasury bill rate and a fourvariate model including inflation expectations as well. The inflation expectations are obtained from ETS and the Prospera survey. They find that the inclusion of inflation expectations in the models tends to improve forecast precision, i.e., inflation expectations Granger cause inflation. However, the impact is typically too small for reductions in the RMSE to be economically relevant. In a later study, Kladívko and Österholm (2020) use monthly data from ETS from January 1996 to August 2019 to analyze whether Swedish households can predict the direction of the inflation and unemployment rate. They find that households fail in forecasting the direction of inflation. Yet, they conclude that inflation has objectively been difficult to forecast over an extensive part of the analyzed sample, while the phrasing of the question in the survey and the answers available are somewhat problematic.

2.4 Research Question and Contribution

As declared in this literature review, there is reasonably large literature discussing the relevance of including inflation expectations when forecasting inflation, even in the case of Sweden, with varying results. It is therefore of our interest to build on the understanding of how inflation expectations relate to future inflation, and further investigate whether they should be taken into account when performing inflation forecasts. Building on the literature on inflation expectations in inflation forecasting, the main research question for this thesis is formulated as,

> *Do individuals' inflation expectations data contribute to more accurate forecasts of the Swedish inflation rate?*

We intend to contribute to the literature and knowledge regarding inflation expectations data and inflation forecasts as follows. Following Stockhammar and Österholm (2018), one reason for studying this issue in Sweden is that the country was an early adopter of inflation targeting, declaring the policy in 1993. We now apply more recent data on the case of Sweden, covering the period 2002Q1 to 2018Q1 and forecasting 2018Q2-2020Q1. Another reason for investigating the Swedish case is to analyze whether the main institutions performing inflation forecasts, such as the Riksbank, NIER, and the Ministry of Finance, should incorporate households' inflation expectations in their model-based forecasts. If our study finds that inflation expectations contribute with useful data when forecasting inflation in Sweden, it implies that these data should be included in their models.

As previously stated, there is extensive empirical evidence of individuals having heterogeneous expectations, with women systematically expecting higher inflation than men. Even so, former studies on households' inflation expectations' potential impact on inflation focus on the aggregated average of households' inflation expectations. An evaluation of how the inflation expectations of different groups of individuals affect the forecast accuracy when included in time series models has, to the best of our knowledge, not been made. By using data on inflation expectations aggregated on a gender level, we extend the analysis by investigating inflation expectations of men's and women's potential impact on inflation in Sweden. Moreover, we execute the analysis in the framework of VEC models, which have not previously been applied when assessing the Granger causality of survey-based inflation expectations on inflation outcomes.

3 Data

In this analysis, we consider data on quarterly macroeconomic time series from 2002Q1 to 2018Q1. Since the collected data are on different aggregation levels (see the data summary in Table 1), we rely on monthly data for the selected variables which are not reported quarterly and use the arithmetic mean as aggregation method. The inflation rate data cover the period 2002Q1-2020Q1 to enable a comparison between the predicted CPI values and the actual CPI outcomes, while data on all other variables cover the period 2002Q1-2018Q1.

The sample starts in 2002 since the primary variables of interest, i.e., the survey-based inflation expectations series, are only available from December 2001 onward. To facilitate the conversion of the data series from monthly to quarterly data (see Section 3.5), the observations from December 2001 are not included in the sample. The CPI sample ends in 2020Q1, which is the last quarter we perform forecasts for, because of the outbreak of the Covid-19 pandemic. The outbreak caused a time of high economic uncertainty, making it difficult to predict macroeconomic variables such as CPI, the unemployment rate, and the 3-month treasury bill rate for this period. In addition, economic uncertainty has been increasing again due to the Russian invasion of Ukraine in February 2022, and the related disorder in international markets. Since we aim to investigate whether inflation expectations Granger cause inflation, we limit the study to focus on the period before the Covid-19 pandemic and the Russian invasion of Ukraine to facilitate the interpretations and implications of our results. This section will begin with a discussion and motivation regarding the selection of variables, followed by closer descriptions of each selected variable. Lastly, the transformation of the data is explained.

3.1 Variable Selection

The selection of variables to include in the analysis is based on multiple criteria and closely follows the information set included by Stockhammar and Österholm (2018). One of the main criteria is that selected variables are commonly used in the previous inflation forecasting literature. Since the main aim of this thesis is to assess whether Swedish inflation expectations data can improve inflation forecasts, it is crucial to include data that have been extensively used in the past. This enables an evaluation of how the forecasting accuracy of specifications including inflation expectations data relates to the accuracy achieved when excluding these data. Additionally, it facilitates the comparability of this study to previous literature. Furthermore, only variables that can be theoretically and empirically motivated to help forecast the inflation rate are included (see Section 2). Intuitively, the selected variables have support from economic theory and previous empirical evidence to be related to the inflation rate. In addition, they all display a high degree of correlation with our inflation of inflation, CPI, in our specific sample. The correlation between CPI and the other selected variables is found in Appendix A, Table A.1.

Our data set includes six variables in total, which are categorized into three categories: measure of inflation, survey-based inflation expectations, and macro-financial indicators. A summary of the data used in this thesis, presenting the frequency, number of observations, transformation, and source of each variable, is displayed in Table 1. All six individual time series are plotted in Appendix A, Figure A.1.

Table 1: Data Summary

Variable	**Frequency**	**Observations**	**Transformation**	**Source**
CPI	Monthly	219	1^{st} diff	SS
Exp. CPI, BG	Monthly	195	1^{st} diff	NIER
Exp. CPI, M	Monthly	195	1^{st} diff	NIER
Exp. CPI, W	Monthly	195	1^{st} diff	NIER
Unemployment	Quarterly	65	1^{st} diff	SS
T-bill	Monthly	195	1^{st} diff	SS

Notes: The table provides summary statistics with information regarding the data used in this thesis. The columns show respectively the name, release frequency, number of observations, transformation for the model estimations, and source of the variables included in the analysis. In the presented order, the abbreviations for variable names refer to: CPI - Consumer Price Index, Exp. CPI, BG - Expected CPI of both genders, Exp. CPI, M - Expected CPI of men, Exp. CPI W - Expected CPI of women, Unemployment - Unemployment rate, T-bill - 3-month treasury bill rate. Lastly, the source abbreviations refer to: SS - Statistics Sweden, NIER - National Institute of Economic Research.

3.2 Measure of Inflation

The outcome variable in this thesis is the Swedish inflation rate, for which the year-on-year change in CPI is used as a measure. The index measures the average price trend for private domestic consumption in total, for a market basket of consumer goods and services, and is based on the prices consumers pay. CPI is the standard measure of compensation and inflation calculations in Sweden and is compiled and reported by Statistics Sweden. The index is constructed by using price notations for a selection of goods and services, so-called ‘representative products’. Prices are collected from a variety of categories, such as food, clothes, education, medical care, and transportation. CPI is published monthly, usually around 10–14 days after the end of the reported month (Statistics Sweden, 2023). Statistics Sweden’s construction of the index is described more closely in Appendix A, Section A.2. The data on Swedish CPI are used in a variety of contexts, mainly for compensation purposes and as a general measure of the households’ living costs trend, stabilization political purposes such as documentation for the Riksbank’s monetary policy, and to measure inflation- and price changes in financial analyses (Statistics Sweden, 2023).

Another measure of the inflation rate is HICP, harmonized index for consumer prices. This is used to measure consumer price inflation in the euro area and is an index for international comparisons of inflation (European Central Bank, 2023). In Sweden, HICP is mainly used to be able to compare the inflation rate with other countries and will therefore not be used as a measure in this thesis (Riksbank, 2022). In the U.S., a common measure of the inflation rate is PCE, the personal consumption expenditures price index. Since this is not an established measure in Sweden, it will not be considered in this thesis. Another alternative is CPIF, where the effect of changed mortgage rates is excluded. Since 2017, this is the inflation target variable by the Riksbank in Sweden (Riksbank, 2022). However, as seen in the overview of previous studies in Section 2, CPI is the most commonly applied measure of inflation by market practitioners and predictors. In addition, as it is the Swedish CPI the households are asked about in the inflation expectations survey, it is reasonable to use CPI as a measure of the inflation rate. Therefore, this thesis considers CPI as the most appropriate proxy for the inflation rate. The ‘headline’ CPI inflation rate is used, rather than the 'core' measure. The 'core' CPI excludes commodities in the basket of goods, such as food and energy prices, because of their high volatility. It is our perception that the 'headline' CPI, with these commodities included, is a more accurate measure of the Swedish inflation rate since it provides a more representative market basket of the average consumer.

In Figure 1, one can see that the year-on-year change in CPI (the blue line) has been relatively volatile over the sample period. Some periods worth mentioning are the great increase in CPI over the period 2005-2008, before the global financial crisis. The figure also displays a rapid fall to a CPI below −1 percent right before 2010, and an almost as radical increase around two years later, before decreasing again. In the period 2012-2016, CPI was around 0 percent before rising again to approach 2 percent.

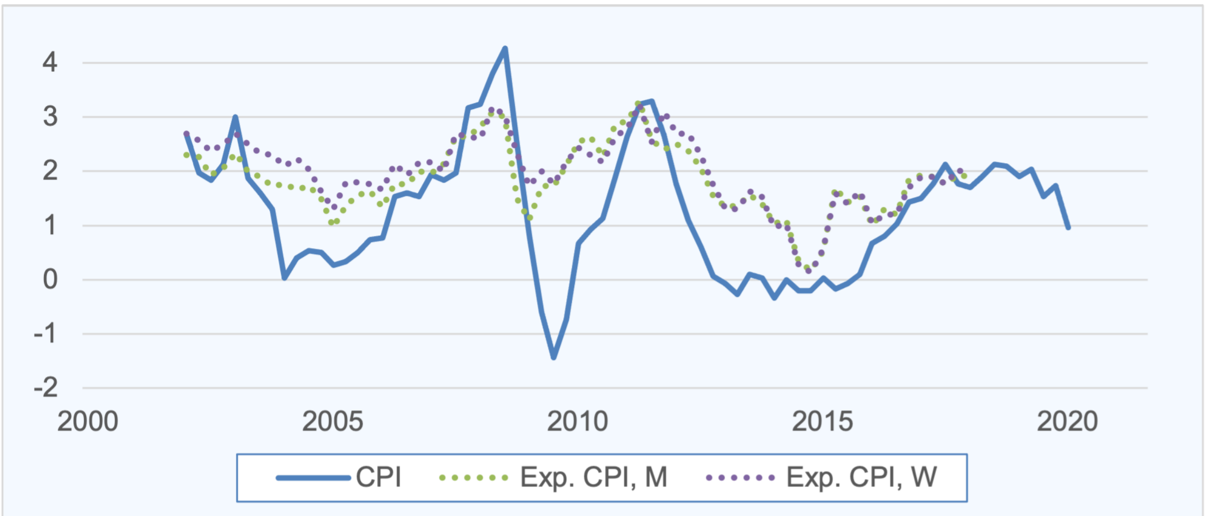


Figure 1: CPI and Expected CPI of Men and Women, 2002Q1-2020Q1

Notes: The figure displays quarterly data on the year-on-year percentage change in the Swedish headline CPI series (CPI), as well as the 1-year ahead inflation expectations series of men and women from ETS (Exp. CPI, where M = Men, W = Women). The latter are shown for the period 2002Q1-2018Q1, and the CPI series for 2002Q1-2020Q1. All three series have been converted from monthly to quarterly data using the arithmetic mean. All individual series, including the inflation expectations of both genders, can be found in Appendix A, Figure A.1. Sources: Statistics Sweden and NIER.

3.3 Survey-Based Inflation Expectations

Together with the Swedish CPI, the Swedish survey-based inflation expectations are at the center of the empirical analysis in this thesis. The forecasting properties of individuals' inflation expectations are assessed using Sweden's main survey – the ETS of households, constructed by NIER. ETS is a monthly selection survey, where answers from 1,500 individuals are collected. The questions asked are regarding the households' view on their finances and the Swedish economy, expectations on interest and inflation rates, and planned purchases of capital goods and savings. The question considering their inflation expectations is formulated as follows:

> *Compared with today, how much in percent do you think that prices will go up (i.e. the rate of inflation 12 months from now)?*

The results from the survey are reported at the end of the month, around a week after the data collection is finished. The results are reported in total for all households but also distributed by gender, age, and region of residence (NIER, 2023). A more detailed description of how the survey is conducted is found in Appendix A, Section A.2. Altogether, this thesis uses three series of monthly data on inflation expectations collected from the survey – the average inflation expectations of the households in total (both genders included), as well as men's and women's average inflation expectations.

The correlation between actual CPI and the inflation expectations series is positive in our sample (0.7394, 0.7156, and 0.7276 for the inflation expectations of both genders, men, and women respectively). The positive correlation can further be seen in Figure 1.[10] Both expectations series (the green dotted line for men and the purple dotted line for women) have a co-movement with actual CPI, although the expectations are generally less volatile and lay closer to the inflation target of 2 percent than actual CPI. One indicator of all series following the same pattern is, for example, that the series of inflation expectations increased substantially between 2005 and 2008. The figure shows that this increase in expectations is in line with the rise in actual CPI over the same period, although the

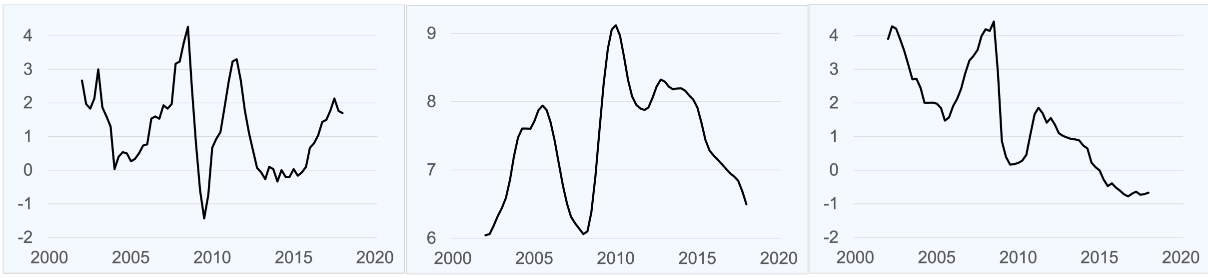
[10] The inflation expectations series of both genders are not included in Figure 1 but can, together with the individual series for all variables, be found in Appendix A, Figure A.1.

increase in actual CPI is more radical than any of the increases in expectations. In the same way, one can see a decrease in both inflation expectations series after the financial crisis until the end of 2014, while actual CPI fell faster and with a higher magnitude than the expectations before 2010, prior to another increase leading up to a match with expectations around 2012. As explained in Section 2.1, co-movement with actual CPI is to be expected for short-horizon inflation expectations like these from ETS, given the persistence of inflation.

Figure 1 also illustrates that there exist small differences between the inflation expectations of men and women in certain periods, with men generally having slightly lower expectations than women and being closer to the actual CPI. We see that the differences appear in periods where the actual CPI is more volatile, such as at the beginning of the sample until around 2007, and also during the financial crisis. However, the differences are generally very small, and even non-existing for a great part of the sample. Men having lower inflation expectations than women is consistent with the findings in previous research on inflation expectation (see more details in Section 2.1). Yet, since the differences are marginal in our sample, we might not expect one of the inflation expectations series to contribute to more accurate inflation forecasts than the other.

3.4 Macro-Financial Indicators

Two macroeconomic and financial variables are selected for the data set to capture the general economic conditions that potentially have an impact on Swedish consumer prices and the inflation rate. Standard macroeconomic models suggest that both the unemployment rate and the 3-month treasury bill rate are useful when predicting inflation (Cogley and Sargent, 2001; Primiceri, 2005; Ribba, 2006).



(a) CPI (b) Unemployment rate (c) T-bill

Figure 2: CPI, Unemployment Rate and 3-Month T-Bill, 2002Q1-2018Q1

Notes: The figure displays quarterly data on the year-on-year percentage change in the Swedish headline CPI series (panel a), as well as the unemployment rate for people aged 16-74 years (panel b), and the 3-month treasury bill rate (panel c) over the period 2002Q1-2018Q1. The CPI series and the treasury bill series have been converted from monthly to quarterly data using the arithmetic mean. All three individual series can be found in Appendix A, Figure A.1. Source: Statistics Sweden.

3.4.1 Unemployment Rate

As stated in Section 2.2, extensive previous literature applies a variety of extensions and variants of the Phillips curve when forecasting inflation. Therefore, we find it crucial to include a measure of the unemployment rate when constructing the inflation forecasts. Following, among others, Gil-Alana et al. (2012) and Stockhammar and Österholm (2018), the unemployment rate variable is selected in the data set as an activity measure of the economy. Seasonally adjusted quarterly data on the Swedish unemployment rate for people aged 16-74 years are obtained from the Labour Force Surveys by Statistics Sweden. The Labour Force Surveys is the only source of continuous data on total unemployment and represents the official unemployment rate (Statistics Sweden, n.d. a). The results from the surveys are reported at the end of January, April, July, and October (Statistics Sweden, n.d. b). For more information on the survey, see Appendix A, Section A.2.

One could consider the unemployment rate gap to be used as an alternative to the unemployment rate. However, following Stockhammar and Österholm (2018), we select the unemployment rate for this analysis since this variable is often used in previous research as a way to catch inflationary pressure (Cogley and Sargent, 2005; Primiceri, 2005). In addition, if the equilibrium unemployment rate changes slowly and marginally, which most studies suggest that it does, there is only a minor distinction between the two measures.

It can be noted from Figure 2 that the unemployment rate is generally negatively correlated with the CPI, as expected by the theory of the Phillips curve. We find that the correlation between these two variables is -0.6516 in our sample. The intuition behind is that in the short run, a declining unemployment rate indicates an increase in the labor demand, leading to upward pressure on wages. This pressure makes profit-maximizing firms raise the prices of their products as a response to rising labor costs.

3.4.2 3-Month Treasury Bill Rate

Regarding the financial indicator, the Swedish 3-month treasury bill rate is included. As mentioned initially in this section, this variable together with an activity measure such as the unemployment rate, is commonly used in previous research aiming at forecasting inflation.[11] Treasury bills are interest-bearing bonds that the state uses to borrow money. Monthly data on the 3-month treasury bill rate are obtained from Statistics Sweden, where the rates are calculated as a monthly average over the daily rates (Swedish National Debt Office, 2019). A further explanation of the 3-month treasury bill rate is found in Appendix A, Section A.2.

In our sample, we see a positive correlation between the 3-month treasury bill rate and CPI of 0.5748, which is in line with the anticipation of the Fisher effect. Figure 2 indicates a positive correlation between these two variables from the start of the sample period until the end of 2012. However, the treasury bill rate starts to fall at the end of 2012 and continues to do so throughout the sample, with some observations in 2018 as exceptions. From the first quarter of 2015 until the end of the sample, the treasury bill rate is negative. Simultaneously, the CPI falls from about 3 percent at the end of 2011 and stays around 0 in 2012-2015 before it starts to rise again in 2016. The two variables moving in different directions during this period can be explained by a more expansive monetary policy by the Swedish Riksbank. To support the rise in the underlying inflation and make CPIF approach the target of 2 percent, and for the long-term inflation expectations to be in line

[11] For additional references, see for example Ang et al. (2007), Bańbura et al. (2021), Gil-Alana et al. (2012), and Stockhammar and Österholm (2018).

with the inflation target, the Riksbank assessed that the monetary policy needed to be more expansive. To lower interest rates in general across the economy, the policy rate became negative for the first time in February 2015 and continued to be negative until the end of our sample period. Concurrently, the Riksbank began to purchase government bonds to increase the money supply in the economy and thereby drive inflation, see Riksbank (n.d.) This resulted in the 3-month treasury bill rate continuing to fall, and becoming negative.

3.5 Data Transformation

First of all, each data series (except the unemployment rate series) are converted from monthly to quarterly data using the arithmetic mean, causing the number of observations used in the model estimations to be 65 for each variable.

Time series methods are employed based on historical data to forecast the future. When forecasting, one needs to presume that the future will evolve like the past. If the past differs from the future in terms of distribution, the historical data will be improper when modeling the future. More generally, the probability distribution of the data is presumed to not change over time. The concept of stationarity formalizes this idea. If stationarity does not hold for the data generating process, a unit root is present, and the variable should be differenced to become stationary. The first difference in the variable y_t is defined as $\Delta y_t = y_t - y_{t-1}$, and the variable is said to be integrated of order one, $I(1)$.

The integration order of each variable is based on statistical pretesting results from the Augmented Dickey-Fuller (ADF) test. These test results will determine how the variables are transformed. The ADF test tests the null hypothesis of a unit root in the variable against the alternative of stationarity. This concept is explained further in Appendix A, Section A.3, where the results are also reported.

The results show that each data generating process has a unit root in level but not in first difference. Thus, each variable is integrated of order one, $I(1)$.

4 Empirical Methodology

There is a broad variety of methods to investigate whether inflation expectations have predictive power for inflation, as stated previously in the literature review in Section 2.3. In this thesis, we use three different model classes as frameworks when constructing our forecasting models. This includes the ARIMA model, the VAR model, and the VEC model. An overview of these models is illustrated in Table 2. In addition to comparing performance across the main specifications considered in this study, we follow much of the previous forecasting literature and compare the performance to an RW model as a benchmark.

We compute the forecasts by dividing the data set into two parts: An initial sample used for the model estimation, and a sample of the final observations used for forecast diagnostics. Our first part is the data sample of CPI, the survey-based inflation expectations, and the macro-financial indicators covering the period 2002Q1-2018Q1. Our second part is the data on CPI for the period 2018Q2-2020Q1, which are used to evaluate the performance of our inflation forecasts. Point forecasts are performed for the period 2018Q2-2020Q1, with a forecast horizon of 8 quarters ahead of 2018Q1. The last forecasts are performed for 2020Q1 because of the outbreak of the Covid-19 pandemic and the Russian invasion of Ukraine, as mentioned at the beginning of Section 3. However, the forecast horizon is extended to 12 quarters as a sensitivity analysis in Section 6.1.

The selected methods and model estimations are explained, presented, and discussed further in this section. The deviation between the predicted values and the actual outcome is reported and the forecasts are evaluated based on forecasting diagnostic methods which are explained at the end of this section, where also Granger causality is established and applied to the case of this thesis.

4.1 The Autoregressive Integrated Moving Average Model

The ARIMA model incorporates three components: the autoregressive model (AR), the differencing component (I), and the moving average model (MA). The AR component describes a time series as the linear relationship between the current value of a variable and its own lagged values, where p specifies the number of lags used in the model. An AR model of the p^{th} order is denoted AR(p) and takes the form of:

$$y_t = a_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \epsilon_t, \tag{1}$$

where the constant is denoted by a_0 and ϵ_t is white noise.

The MA component represents a time series as a linear combination of its past errors (residuals), where q specifies the number of residuals used in the model. An MA(q) process is defined as:

$$y_t = \sum_{i=0}^{q} \beta_i \epsilon_{t-i}, \quad \text{where} \quad \beta_0 = 1. \tag{2}$$

It is possible to combine an AR process and an MA process with a linear difference equation since the dependent variable often possesses characteristics of both. By doing so, we contain an autoregressive moving average (ARMA) process. The ARMA(p, q) model is defined as:

$$y_t = a_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=0}^{q} \beta_i \epsilon_{t-i}. \tag{3}$$

If the characteristic roots of (3) all lie inside the unit circle, y_t is denoted an ARMA model for y_t. However, if one or more characteristic roots of (3) lie outside the unit circle, the y_t sequence is an integrated process. If that is the case, it follows that (3) is instead an ARIMA model. In its general form, the ARIMA model is denoted ARIMA(p, d, q) where the AR process is of the p^{th} order, the time series are differenced d number of times, and the MA process is of the q^{th} order (Enders, 2014).

4.2 The Vector Autoregressive Model

VAR models are used to analyze the dynamic relationship for multivariate time series. The model considers the interdependence between the variables and their mutual interactions, which are captured by the lagged values of the same and other variables. We follow

Lütkepohl (2005) and consider the VAR model with p lags:

$$y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \epsilon_t, \tag{4}$$

where $y_t = (y_{1t}, \ldots, y_{Kt})'$ is a $(K \times 1)$ vector of observed values at time t, the A_i components are fixed $(K \times K)$ coefficient matrices, $v = (v_1, \ldots, v_K)'$ is a fixed $(K \times 1)$ vector of intercept terms allowing for the possibility of a nonzero mean $E(y_t)$. Lastly, $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Kt})'$ is a $(K \times 1)$ white noise innovation process. That is, $E(\epsilon_t) = 0$, $E(\epsilon_t \epsilon_t') = \Sigma_\epsilon$ and $E(\epsilon_t \epsilon_s') = 0$ for all $s \neq t$. Hence, Σ_ϵ is not diagonal and the error terms ϵ_t are correlated with each other.

The VAR(p) process in (4) is stable if the polynomial defined by $det(I_K - A_1 z - \cdots - A_p z^p)$ has no roots in and on the complex unit circle. Formally, y_t is stable if

$$det(I_K - A_1 z - \cdots - A_p z^p) \neq 0 \quad \text{for} \quad |z| \leq 1. \tag{5}$$

Moreover, for a univariate AR(1) process, defined as $y_t = \alpha y_{t-1} + u_t$, this property means that $1 - \alpha z \neq 0$ for $|z| \leq 1$ or, equivalently, $|\alpha| < 1$. A stable VAR(p) process, as seen in (4), is stationary. In other words, stability implies stationarity, which is why the stability condition in (5) is commonly called the 'stationarity condition' in the time series literature (Lütkepohl, 2005).

4.3 The Vector Error Correction Model

The VEC model is an extension of the VAR model explained above, and was introduced to capture the presence of cointegration among variables in a model. The nonstationary time series $y_t = (y_{1t}, \ldots, y_{Kt})'$ are said to be cointegrated if there is a linear combination of them that is stationary, $I(0)$. In other words, the variables share the same stochastic trend. Technically, the components of the vector $y_t = (y_{1t}, \ldots, y_{Kt})'$ are said to be cointegrated if there exist a $K \times 1$ vector $\beta = (\beta_1 + \beta_2 + \beta_K)'$ such that the linear combination is stationary $\beta' y_t = \beta_1 y_{1t} + \cdots + \beta_K y_{Kt} \sim I(0)$. The linear combination $\beta' y_t$ is often motivated by economic theory and is referred to as a long-run relationship between the variables. In the long run, cointegration assures that two or more variables move together, despite the fact that shocks may cause short-term deviations from this long-run relationship. In other words, the long-run equilibrium relationship between these $I(1)$ time series cannot drift too far apart, since economic forces will act to restore the equilibrium after a deviation.

A cointegrating relationship between one or two variables is determined using e.g. the Johansen test procedure. If the test finds a cointegrated relationship, the VAR representation is not the most suitable since the cointegrating relationship is not modeled. By reparameterizing the VAR model in levels as a VEC model, cointegrating relationships can be established. This method allows for the analysis of the original variables (or their logarithms) instead of the rates of change, while also accommodating nonstationary data (Lütkepohl, 2005).

Following Lütkepohl (2005), the K-dimensional VAR(p) model in (4) has r number of cointegrating relationships if $\mathbf{\Pi} = -(I_K - A_1 - \cdots - A_p)$ has rank r, where $\mathbf{\Pi}$ is the coefficient matrix of the cointegrating relationships. If one of the variables in the model deviates from long-run equilibrium, $\mathbf{\Pi}$ can be written as a matrix product $\boldsymbol{\alpha\beta'}$ where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are of dimension $(K \times r)$ and of rank r. The term $\boldsymbol{\alpha\beta'} y_t$ is hence defined as the error correction term. $\boldsymbol{\beta}$ is the cointegrating matrix as the columns contain the cointegrating vectors, and describe information about the equilibrium relationship between the variables (Lütkepohl, 2005). Furthermore, $\boldsymbol{\alpha}$ is referred to as the loading matrix, which describes the speed of adjustment back to equilibrium after a deviation. The larger the parameter is, the faster the variable returns after the previous period's deviation from long-run equilibrium (Enders, 2014).

If the $\mathbf{\Pi}$ matrix has rank $r = 0$, Δy_t should be modelled as a VAR($p-1$) representation in first differences. For $r = K$, $|-\mathbf{\Pi}| = |I_K - A_1 - \cdots - A_p| \neq 0$, y_t is a stable VAR(p) process with no unit roots. Furthermore, equation (4) can be rewritten on VEC form. Equation (6) shows that the only difference between the VAR and the VEC model is the error correction term, $\mathbf{\Pi} y_{t-1}$ (Lütkepohl, 2005).

$$\Delta y_t = \mathbf{\Pi} y_{t-1} + \mathbf{\Gamma_1} \Delta y_{t-1} + \cdots + \boldsymbol{\Gamma_{p-1}} \Delta y_{t-p+1} + u_t, \tag{6}$$

where

$$\boldsymbol{\Gamma_i} = -(A_{i+1} + \cdots + A_p), \quad i = 1, \ldots, p-1, \tag{7}$$

which is the coefficient matrix of the lags of differenced variables of y_t. By assumption, Δy_t is $I(0)$ (Lütkepohl, 2005).

4.4 Model Estimation

As mentioned in the introduction to this section, an overview of the eight models selected is displayed in Table 2, where their respective model class, variables included, number of lags, cointegration order, and the result from the Ljung-Box Q test is presented. As previously stated, we adhere to much of the former forecasting literature while evaluating the performance of our primary specifications to an RW model without a drift.

Table 2: Overview of Estimated Models

Model	$Model_{NC}^{NE}$	$Model_{NC}^{BG}$	$Model_{NC}^{M}$	$Model_{NC}^{W}$	$Model_{C}^{NE}$	$Model_{C}^{BG}$	$Model_{C}^{M}$	$Model_{C}^{W}$
Model class	ARIMA	VEC	VEC	VEC	VAR	VEC	VEC	VEC
CPI	x	x	x	x	x	x	x	x
Exp. CPI, BG		x				x		
Exp. CPI, M			x				x	
Exp. CPI, W				x				x
Unemployment					x	x	x	x
T-bill					x	x	x	x
Lags	0	4	4	4	4	4	4	4
Cointegrating order	N/A	1	1	1	0	1	1	1
Ljung-Box Q p-value	0.9775	0.6508	0.6722	0.4561	0.4597	0.4561	0.3044	0.4710

Notes: The table displays an overview of the models estimated in this analysis. The rows show respectively the model class, variables included in the model, cointegrating order, result from the Ljung-Box Q test, and the Johansen test statistic for each model. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators.

To begin with, the unit root tests explained in Section 3.5 show that all selected variables in our sample are integrated of order one, $I(1)$. As seen in Table 2, the first model, $Model_{NC}^{NE}$, only includes the CPI variable and is estimated using the ARIMA model class. More specifically, the model is estimated as an ARIMA in first difference with one MA component: ARIMA(0,1,1). The model selection is done by the widely used Bayesian information criterion (BIC).

To determine whether each multivariate model should be estimated as a VAR or VEC model, the Johansen test procedure explained in Section 4.3 is used. If the test shows that the model has one or more cointegrating relationship(s), a VEC model is estimated to account for the common stochastic trend between two or more variables. The Johansen test finds one (1) cointegrating relationship for all six models including inflation expectations ($Model^{BG}_{NC}$, $Model^{M}_{NC}$, $Model^{W}_{NC}$, $Model^{BG}_{C}$, $Model^{M}_{C}$, and $Model^{W}_{C}$). Therefore, we estimate these six models as VEC models using maximum likelihood (ML) estimation methods. The Johansen test does not find any cointegrating relationship(s) between the variables in $Model^{NE}_{C}$, hence it is estimated as a VAR model in first difference.

Since the data frequency of the variables is quarterly, all eight models except $Model^{NE}_{NC}$ in Table 2 are estimated with four lags, which is a commonly used number of lags in the previous inflation forecasting literature (see, among others, Lack (2006), and Stockhammar and Österholm (2018)). Furthermore, to ensure that the lag length is appropriate, all models are tested for remaining serial correlation in the residuals. To test the models for this, the Ljung-Box Q test statistic is calculated, which tests the null hypothesis of no remaining serial correlation in the error terms against the alternative of serial correlation. The corresponding p-value is presented in Table 2. As shown in the table, all models pass the test since the null hypothesis is not rejected, i.e., the lag order is high enough to eliminate serial correlation in the residuals.

4.5 Forecast Comparisons

To answer our research question of whether inflation expectations Granger cause the inflation rate, we must establish the concept of Granger causality in our forecast setting, which is discussed in this section. Further, the forecasting diagnostics methods that we use to assess the accuracy of the forecasts and make comparisons between the models are formulated.

4.5.1 Granger Causality

Granger causality is an econometric concept of causality based on prediction, applied to test whether one variable contains information that helps forecast another variable. So, rather than testing whether x_1 causes x_2, the Granger causality tests whether x_1 forecasts x_2. Intuitively, variable x_1 is said to Granger cause x_2 if x_1 contains information in past terms that helps forecast x_2 above and beyond the information contained in past terms of x_2 alone. The concept of Granger causality was developed in the 1960s, first proposed in Granger (1969), and has been widely used in economics since. Granger (1969) based the mathematical formulation of Granger causality on linear regression modeling of stochastic processes.

In this thesis, the concept of Granger causality will be applied to investigate whether Swedish inflation expectations are useful in the prediction of CPI inflation. If inflation forecasts based on past values of CPI and past values of inflation expectations are superior to forecasts of inflation based only on past values of CPI, inflation expectations are said to Granger cause inflation.

In the setting of this thesis, Granger causality requires that the forecast performance of models including inflation expectations is superior to a model excluding inflation expectations. As mentioned earlier, two comparisons will be made to investigate this. The first comparison is between the univariate ARIMA model of CPI inflation ($Model_{NC}^{NE}$) and three bivariate VEC models with CPI inflation and the various inflation expectations series ($Model_{NC}^{BG}$, $Model_{NC}^{M}$, and $Model_{NC}^{W}$). The second comparison is between the trivariate VAR model of CPI inflation, unemployment rate, and 3-month treasury bill ($Model_{C}^{NE}$) and three fourvariate models including the various inflation expectations series as well ($Model_{C}^{BG}$, $Model_{C}^{M}$, and $Model_{C}^{W}$). How Granger causality is tested in this setting is explained further in the next coming subsection.

4.5.2 Forecast Diagnostics Methods

In macroeconomics, an accurate prediction of inflation holds significant importance. As mentioned by Dellas et al. (2018), poor inflation forecasts destabilize output, undermine monetary policy under inflation targeting, and affect the costs of both short-term and long-term government borrowing. When the central bank makes FE, it may result in suboptimal policies that cause inefficient fluctuations in aggregate economic activity and inflation.

To investigate whether inflation expectations have predictive power when forecasting inflation, diagnostic checking and comparisons of the models are crucial. We do this by employing forecasting diagnostic methods to assess the accuracy of the forecasts. FE are defined as the positive or negative deviation of the predicted value of CPI ($\hat{\pi}_i$) from the actual value of CPI (π_i). The point forecasts have three different outcomes: The predicted value equals the actual value, the predicted value overestimates the actual value, or the predicted value underestimates the actual value. The two latter outcomes result in positive and negative FE respectively, i.e. the forecasts overpredict or underpredict the actual value of CPI.

We perform $h = 8$ number of point forecasts for each model. The first forecast diagnostics measure we use is the RMSE for each forecast model, defined as:

$$RMSE = \sqrt{\frac{1}{h}\sum_{i=1}^{h}(\hat{\pi}_i - \pi_i)^2}. \tag{8}$$

To get an understanding of the direction of the FE, we also compute the mean error (ME) for each model, defined as:

$$ME = \frac{1}{h}\sum_{i=1}^{h}\hat{\pi}_i - \pi_i. \tag{9}$$

The two loss functions RMSE and ME are different since the squaring of the differences in the RMSE function places greater emphasis on large errors. Further, we calculate an RMSE ratio as a forecast performance comparison between the benchmark models ($Model_{NC}^{NE}$ and $Model_{C}^{NE}$) and the models with an inflation expectations variable. In other words, the RMSE ratio is computed by dividing the RMSE for the bivariate models by the RMSE for the univariate model: $RMSE_{NC}^{NE}/RMSE_{NC}^{j}$ where $j = NE, BG, M, W$.

Further, we do the same procedure for the models where the macro-financial indicators are included, so the three fourvariate models are compared to the trivariate model: $RMSE_C^{NE}/RMSE_C^k$, where $k = NE, BG, M, W$. An RMSE ratio smaller than 1 signals that the benchmark model performs more accurate forecasts than a model where inflation expectations are included. It follows that a ratio larger than 1 implies that the model with an inflation expectations variable outperforms the benchmark model.

Lastly, we calculate the absolute forecast error (AFE) for the point forecasts from each model. The AFE is the absolute difference between the predicted forecast value for each model each quarter subtracted from the actual CPI: $|\hat{\pi}_i - \pi_i|$.

Since we perform inflation forecasts using time series models, we assume that the FE are symmetric. This assumption implies that the loss of underprediction and overprediction in terms of the commonly used loss functions RMSE and ME, is the same. However, as pointed out by Auffhammer (2007), this assumption does not hold in all settings. The monetary and political costs of under- and overprediction are probably not the same, meaning that the actual loss may be over- or underestimated if one assumes that the FE are symmetric while they are actually asymmetric.

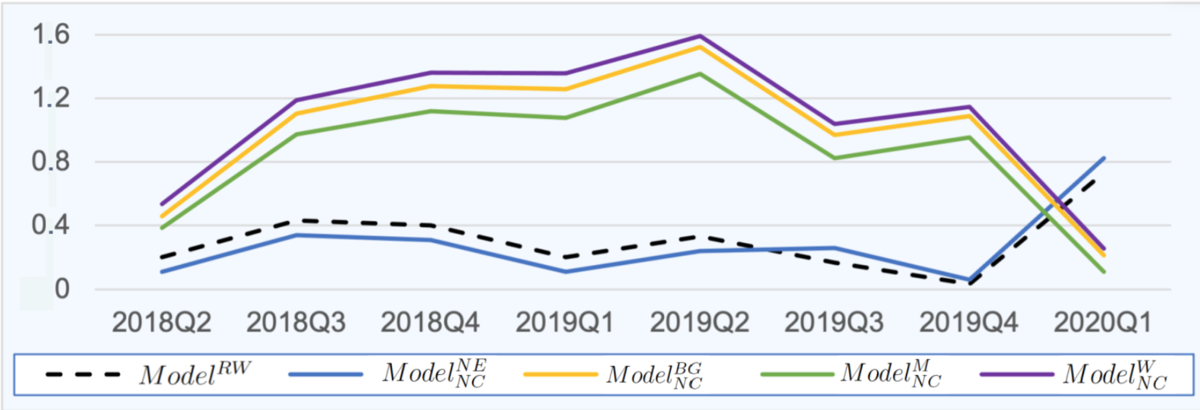
5 Results

In this section, the results from the inflation forecasts are presented for each estimated model. Further, the forecasting performance of the models including the inflation expectation series is compared to their respective benchmark models and $Model^{RW}$. We start with our first forecast comparison between the models excluding macro-financial indicators, followed by our second comparison between the models including these variables. The forecast performance of each model is evaluated using the forecast diagnostics methods described in Section 4.5.2. Table 3 reports the results of the forecast diagnostics measures: the RMSE, ME as well as the RMSE ratio for each model. The point forecasts for CPI from all models and the actual CPI over the forecasting period can be found in Appendix B, Table B.1.

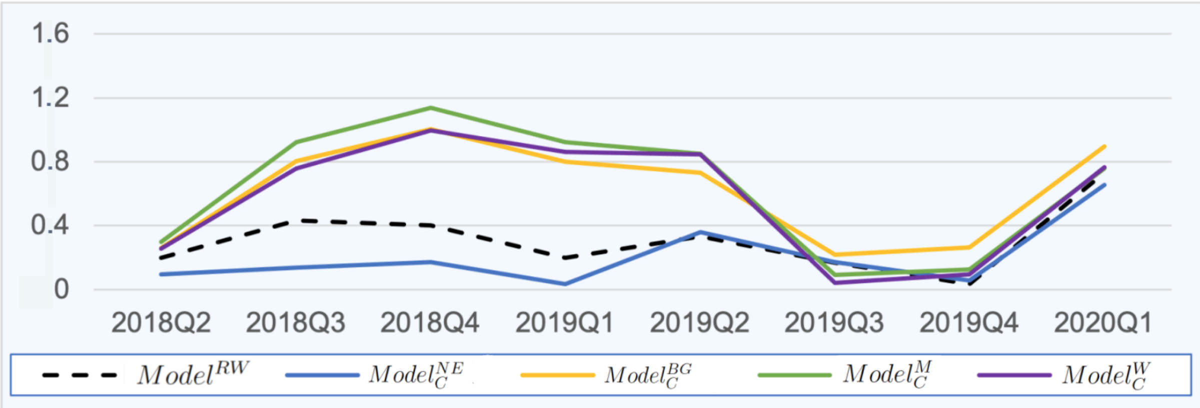
Table 3: Reported RMSE, ME and RMSE Ratio For All Estimated Forecasting Models

Model	RMSE	ME	Ratio
$Model^{RW}$	0.3717	-0.0875	N/A
$Model^{NE}_{NC}$	0.3613	0.0044	1
$Model^{BG}_{NC}$	1.0679	-0.9862	0.3383
$Model^{M}_{NC}$	0.9324	-0.8501	0.3875
$Model^{W}_{NC}$	1.1398	-1.0596	0.3170
$Model^{NE}_{C}$	0.2850	0.0353	1
$Model^{BG}_{C}$	0.6905	-0.2780	0.4128
$Model^{M}_{C}$	0.7420	-0.3948	0.3841
$Model^{W}_{C}$	0.6793	-0.3526	0.4196

Notes: Results from forecasting CPI for each quarter over the period 2018Q2-2020Q1. The RMSE is presented in the first column, followed by the ME to see the direction of the forecast errors. The RMSE ratios are calculated by dividing the RMSE for the benchmark model ($Model^{NE}_{NC}$ and $Model^{NE}_{C}$ respectively) with the RMSE for the models including inflation expectations respectively. A ratio greater than 1 indicates that the model with inflation expectations has a lower RMSE than the model without. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.



(a) AFE Excluding Macro-Financial Indicators



(b) AFE Including Macro-Financial Indicators

Figure 3: AFE From the Models, 2018Q2-2020Q1

Notes: AFE for each point forecast per quarter over the period 2018Q2-2020Q1 from the models. The AFE is the absolute difference between the predicted forecast value for each model each quarter subtracted from the actual CPI. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk. A table of the AFE from all models can be found in Appendix B, Table B.2.

5.1 Models Excluding Macro-Financial Indicators

We start with comparing the forecast accuracy of the ARIMA model including only CPI ($Model^{NE}_{NC}$) and the VEC models including CPI and inflation expectations ($Model^{BG}_{NC}$, $Model^{M}_{NC}$, and $Model^{W}_{NC}$) with each other and $Model^{RW}$. Beginning with the first column of Table 3, we find the lowest estimated RMSE for $Model^{NE}_{NC}$ (0.3613), closely followed by

$Model^{RW}$ (0.3717). The three VEC models including the inflation expectations series all perform less accurate forecasts. Out of these three models, the model including inflation expectations of men, $Model^{M}_{NC}$, performs the most accurate forecasts, with an estimated RMSE of 0.9324. When the inflation expectations variable for both genders is included in $Model^{BG}_{NC}$, the estimated RMSE increases to 1.0679, and for women in $Model^{W}_{NC}$, we find the highest estimated RMSE (1.1398). Another indicator of the models including inflation expectations being outperformed by the ARIMA model is found in the estimates in the third column in Table 3. In this, we see an RMSE ratio smaller than 1 for all three models including inflation expectations. Further, we can conclude that the ratios are far from 1 (0.3170 : 0.3875).

The ME estimates in Table 3 column 2 show that almost all models excluding macro-financial indicators estimate forecasts that, on average, underpredict the actual CPI. The exception is $Model^{NE}_{NC}$, which generally overpredicts the actual CPI. To understand the dimension of the errors, the range of the actual outcomes over the forecasting period is (0.9667 : 2.1333) (the point predicted CPI values from all models and the actual CPI over the forecasting period can be found in Appendix B, Table B.1). Hence, ME estimates of -0.9862, -0.8501, and -1.0596 in $Model^{BG}_{NC}$, $Model^{M}_{NC}$, and $Model^{W}_{NC}$ respectively are significantly high. However, $Model^{NE}_{NC}$ and $Model^{RW}$ show ME estimates close to zero (0.0044 and -0.0875 respectively), indicating accurate forecasting performance.

The performance comparisons are further illustrated in Figure 3, where the AFE for each model is plotted. A table of the AFE from all models can be found in Appendix B, Table B.2. Focusing on the models excluding macro-financial indicators (panel a), we see that the AFE of the models, including inflation expectations ($Model^{BG}_{NC}$, $Model^{M}_{NC}$, and $Model^{W}_{NC}$) follow each other closely. Moreover, $Model^{NE}_{NC}$ and $Model^{RW}$ overall show lower levels of AFE estimates and move in sync. The AFE of the models including inflation expectations are higher than of $Model^{NE}_{NC}$ and $Model^{RW}$ for all point forecasts except the last. Over time, the models including inflation expectations show shrinking AFE estimates and, as mentioned, outperform the other two models at the last point forecast.

To conclude, the results indicate that the ARIMA model including only CPI outperforms the models including inflation expectations, as well as $Model^{RW}$. In other words, the inclusion of any of the inflation expectation variables worsens the forecast performance compared to $Model^{NE}_{NC}$. We also find that $Model^{RW}$ and all models excluding macro-financial indicators, except $Model^{RW}$, generally underpredict the actual CPI. Out of the three models including inflation expectations, the model including inflation expectations of men, $Model^{M}_{NC}$, performs the most accurate forecasts.

5.2 Models Including Macro-Financial Indicators

Our second comparison is focused on the forecasts generated from the models where macro-financial indicators are added, where we compare the VAR model ($Model^{NE}_{C}$) with the VEC models including inflation expectations ($Model^{BG}_{C}$, $Model^{M}_{C}$, and $Model^{W}_{C}$). We see in the first column of Table 3 that the estimated RMSE are generally lower than for the models excluding macro-financial indicators. The estimated RMSE for $Model^{NE}_{C}$ is 0.2850 and increases with the inclusion of inflation expectations in $Model^{BG}_{C}$, $Model^{M}_{C}$, and $Model^{W}_{C}$. These three models have smaller differences between their estimated RMSE than the VEC models excluding macro-financial indicators, with the model including women's inflation expectations, $Model^{W}_{C}$, estimating the marginally lowest RMSE (0.6793). The lowest estimated RMSE is found for $Model^{M}_{C}$ including inflation expectations of men (0.7420), while the estimated RMSE for $Model^{BG}_{C}$ is 0.6905. An additional indicator of the model excluding inflation expectations outperforming the models including expectations is seen in the third column in Table 3. Our results show that all three models including inflation expectations have an RMSE ratio smaller than, and relatively far from, 1 (0.3841 : 0.4196).

The ME estimates in the second column in Table 3 show that all models but $Model^{NE}_{C}$ estimate forecasts that, on average, underpredict the actual CPI. The ME for the models including macro-financial indicators are generally lower than for those excluding them. As mentioned earlier, $Model^{RW}$ shows an ME estimate close to zero (-0.0875) which we now see that $Model^{NE}_{C}$ does as well (0.0353), indicating accurate forecasting performance.

We move on with our forecast comparisons by assessing the AFE between the models including macro-financial indicators in Figure 3 panel b. The graph shows that the AFE initially move in the opposite directions for the models including inflation expectations ($Model_C^{BG}$, $Model_C^{M}$, and $Model_C^{W}$) and the other two models ($Model_C^{NE}$ and $Model^{RW}$). We also see that the AFE for the models excluding inflation expectations have a lower AFE from the beginning of the forecasting period up until 2019Q2. However, in the point forecast for 2019Q3, the AFE estimates shrink for the models including inflation expectations, and all five models co-move from this point up to the last point forecast.

To conclude, we find the same implications in the second comparison as well - $Model_C^{NE}$ excluding inflation expectations outperforms the VEC models, as well as $Model^{RW}$ (and $Model_{NC}^{NE}$). Hence, including inflation expectations in the models (including as well as excluding macro-financial indicators) does not generate more accurate inflation forecasts. We also find that $Model_C^{NE}$ generally overpredicts the actual CPI, while the other models including macro-financial indicators generally underpredict the actual CPI. The difference in forecasting performance of the three models including inflation expectations is smaller in this case than when excluding macro-financial indicators, with the model including inflation expectations of women, $Model_C^{W}$, estimating slightly more accurate forecasts than the other two models.

Another finding that is important to point out is that the results from the two panels in Figure 3 indicate that the models including inflation expectations show poor short- and medium-term forecast performance. However, in the last half of the forecasting period, $Model_{NC}^{BG}$, $Model_{NC}^{M}$, and $Model_{NC}^{W}$ show reductions in AFE estimates and outperform the other two models at the last point forecast. The models including macro-financial indicators, $Model_C^{BG}$, $Model_C^{M}$, and $Model_C^{W}$ start to closely follow the pattern of the models excluding inflation expectations in the last point forecasts. These results indicate that the models including inflation expectations may perform better in the long run, compared to the models excluding inflation expectations, which appear to perform worse in the long run. To investigate our results' sensitivity for longer forecast horizons, we extend the horizon in Section 6.1.

6 Sensitivity Analysis

In this study, we execute forecast comparisons from a variety of models by making several choices and limitations. This section investigates the sensitivity of our results for such choices and limitations, and the data used. In particular, it aims to shed light on the sensitivity of the forecast horizon length and the external validity of our results on another sample.

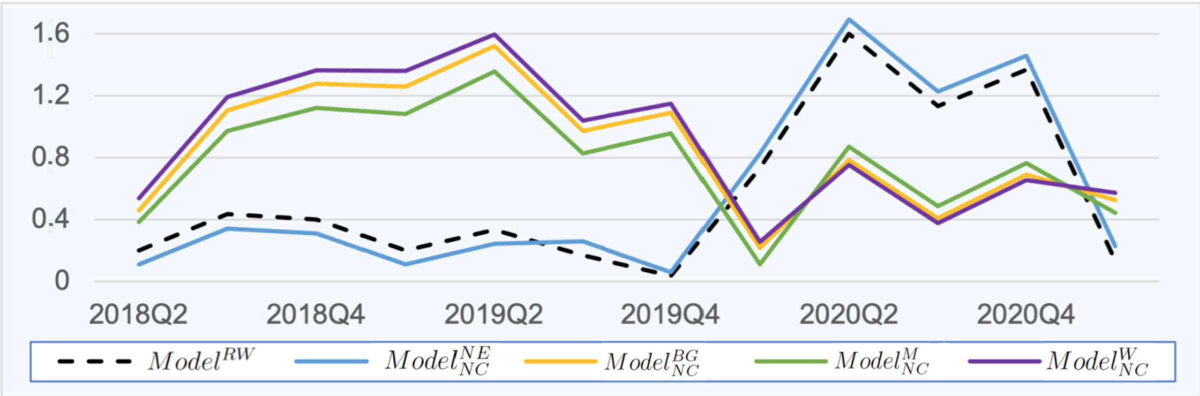
6.1 Extending the Forecast Horizon

As mentioned in the previous section, the results indicate that the models including inflation expectations are outperformed by the models excluding them. However, we saw in Figure 3 that the estimated AFE of the models including inflation expectations generally decrease at the end of the forecasting period. Simultaneously, we saw that the estimated AFE of the three models excluding inflation expectations ($Model^{RW}$, $Model^{NE}_{NC}$, and $Model^{NE}_{C}$) increase at the end of the forecast horizon. This finding implies that our models including inflation expectations might perform better in the long run, compared to the models excluding them. We extend the forecast horizon using the same sample as before to determine if our results are robust on longer horizons. We perform four additional point forecasts for each model for 2020Q2-2021Q1, with a forecast horizon of 12 quarters ahead of 2018Q1. Since the forecast horizon covers parts of the economic uncertainty period of the Covid-19 pandemic, with macroeconomic variables such as the inflation rate being difficult to predict, we expect the AFE estimates to be higher than in periods with lower uncertainty.

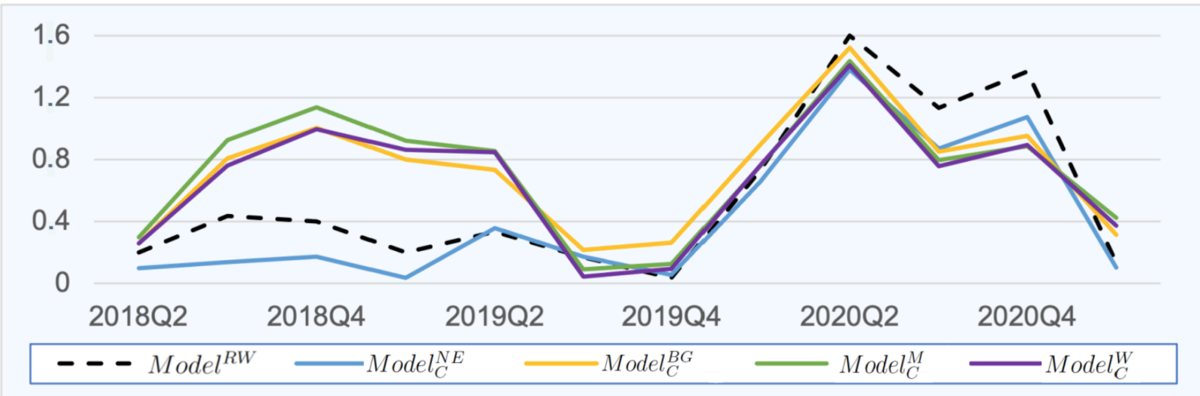
The results are presented in Figure 4, where the AFE for each model are plotted. Beginning with the models excluding macro-financial indicators (panel a), the AFE estimates for the models including inflation expectations stabilize at a lower level of AFE. Further, as indicated in the previous section, the AFE estimates of the models excluding inflation expectations generally increase at longer horizons. Moving to the models including macro-financial indicators (panel b), the AFE estimates of all models increase greatly for 2020Q2 and generally remain at a higher level onward, which is reasonable because of the

Covid-19 pandemic. However, the AFE estimates increase more over time for the models excluding inflation expectations. $Model_C^{NE}$ and $Model^{RW}$ outperform all other models in the short run but estimate high levels of AFE at the end of the forecasting period.

These results indicate that the comparative performance of models with and without inflation expectations fluctuates over time and that there are notable advantages to integrating inflation expectations into certain models during specific periods. This is especially true for the models excluding macro-financial indicators.



(a) AFE Excluding Macro-Financial Indicators



(b) AFE Including Macro-Financial Indicators

Figure 4: AFE From the Models With Extended Forecast Horizon, 2018Q2-2021Q1

Notes: AFE for each point forecast per quarter over the period 2018Q2-2021Q1 from the models respectively. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk. A table of the AFE from all models over the period 2020Q2-2021Q1 can be found in Appendix C, Table C.1.

6.2 The U.S.

As a robustness check, we estimate the models including the same variables over the same period as in the main Swedish case, but using U.S. data. Quarterly data on CPI, unemployment rate och 3-month treasury bill rate is obtained from FRED, and on survey-based inflation expectations from the Michigan Survey. The forecast horizon is again 8 quarters, and point forecasts are estimated over the period 2018Q2-2020Q1. Table 4 shows the results of the forecast diagnostics measures for each model respectively, i.e. the RMSE, ME, and RMSE ratio.

Table 4: Reported RMSE, ME and RMSE Ratio For All Estimated Forecasting Models With U.S. Data

Model	RMSE	ME	Ratio
$Model^{RW}$	0.6269	0.3250	N/A
$Model^{NE}_{NC}$	0.6044	0.1946	1
$Model^{BG}_{NC}$	0.7434	0.1865	0.8130
$Model^{M}_{NC}$	0.7400	0.2133	0.8167
$Model^{W}_{NC}$	0.7682	0.2387	0.7867
$Model^{NE}_{C}$	0.6267	0.3541	1
$Model^{BG}_{C}$	0.6826	0.4579	0.9181
$Model^{M}_{C}$	0.6829	0.4785	0.9177
$Model^{W}_{C}$	0.6849	0.4515	0.9149

Notes: Results from forecasting CPI for each quarter over the period 2018Q2-2020Q1, using U.S. data. The RMSE is presented in the first column, followed by the ME to see the direction of the forecast errors. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.

Looking at the first column in Table 4, we see that $Model^{NE}_{NC}$ has the lowest estimated RMSE (0.6044), closely followed by $Model^{NE}_{C}$ (0.6267), and $Model^{RW}$ (0.6269) when using U.S. data. In other words, both models excluding inflation expectations outperform the models including them, as well as $Model^{RW}$, which is in line with our Swedish results. Another indicator of this can be seen in the third column, where we see that all RMSE ratios of the models including inflation expectations are less than 1.

In the second column of Table 4, we see that all models on average overpredict the actual CPI. This is different from the Swedish case, where all models except $Model_{NC}^{NE}$ and $Model_{C}^{NE}$ on average underpredict actual CPI. The range of the actual CPI over the forecast period is (1.2333 : 2.9667) (the point forecasts for CPI from all models and the actual CPI over the forecasting period, as well as the AFE for all forecasts, can be found in Appendix C, Table C.2 and C.3). The ME range is (0.1865 : 0.4785), which is lower than in the Swedish case, while the range of the actual CPI is higher than in the Swedish case.

7 Discussion

This section first summarizes the main findings of including individuals' inflation expectations in model-based forecasts in Sweden and relates these to previous literature. The validity and limitations of the chosen method, setting, and sample are then discussed. This is followed by a discussion of the policy implications of our study's results.

In our study, the ARIMA model ($Model_{NC}^{NE}$) and the VAR model ($Model_{C}^{NE}$) both outperform all models including inflation expectations. These results imply that the survey measures of individuals' inflation expectations studied in this thesis seem to have limited value for enhancing model-based forecasts of Swedish inflation. On the one hand, our results can be regarded as conflicting with earlier findings, which indicate that inflation expectations can be of great use when forecasting inflation.[12] On the other hand, even though we find no improvements in the forecast accuracy when including inflation expectations, our results are relatively in line with the closely related study by Stockhammar and Österholm (2018). They find reductions in the RMSE when including inflation expectations series in their forecast models, but conclude that these are generally too small to be economically relevant.

Regarding the external validity of our study, we find that using the same models and sample with U.S. data results in the same implications. Both in the Swedish and the U.S. case, the models including inflation expectations are outperformed by the models excluding these series.

Further, we find that the models including the inflation expectations series generally perform more accurate forecasts at a longer forecast horizon, while the opposite is true for the models excluding expectations. This suggests that the relative effectiveness of models incorporating inflation expectations compared to those without, varies over time. Moreover, incorporating inflation expectations into certain models during specific time frames can offer significant benefits. The finding is in line with previous literature indicating that inflation expectations' ability to predict inflation trends could vary over time periods.[13]

[12] See, among others, Ang et al. (2007), Faust and Wright (2013), Gil-Alana et al. (2012), Lanne and Luoto (2017), and Mossfeldt and Stockhammar (2016).

[13] See, among others, Lack (2006), Mertens (2016), Mertens and Nason (2020), and Trehan (2015).

When comparing the three bivariate models ($Model_{NC}^{BG}$, $Model_{NC}^{M}$, and $Model_{NC}^{W}$), we find that the model including inflation expectations of men performs more accurate forecasts. This finding is in line with NIER (2014), which uses expectations data from ETS and finds that men have a higher forecast precision than women. However, when comparing the fourvariate models ($Model_{C}^{BG}$, $Model_{C}^{M}$, and $Model_{C}^{W}$), our results show that the RMSE of the models are close to each other, with the model including inflation expectations of women estimating a marginally lower RMSE. Nevertheless, since none of these models outperform those excluding inflation expectations, these results imply that none of the aggregated inflation expectations series contribute to more accurate inflation forecasts. The implications of these findings are discussed further in the next coming subsections.

7.1 Limitations

It is important to point out that our results are impacted by several choices and limitations made in this study. One limitation is the relatively short forecasting period, with comparisons made between forecasts performed for 8 quarters (12 quarters in the sensitivity analysis). As stated before, there is evidence to suggest that the predictive power of inflation expectations with regard to inflation trends may be influenced by different regimes or undergo alterations over time. The short forecasting period could therefore be considered a possible partial justification for why we do not detect any evidence that inflation expectations Granger cause inflation. Even though our forecasting period is short, our results imply that the forecast performance of models with inflation expectations indeed changes over time and that the benefits from including expectations are significant in some periods for some models. However, the dimension of this result may be underpredicted since the forecast horizon of 12 quarters covers the Covid-19 pandemic which reasonably in general generates greater AFE estimates than in periods with lower economic uncertainty. Hence, in a setting outside of the pandemic, this effect may be larger.

Our results are valid in the inflation environment during the forecasting period, with a low and stable inflation level. As discussed in Lack (2006), low and stable inflation may have the potential to weaken the formation of rational expectations and critical analysis. Further, both models of central banks and other financial institutes, and the formation of individuals' expectations tend to adapt to an RW-like behavior during these low and stable inflation times. This reasoning may partially explain the poor contribution of the inflation expectations variables in our result. Additionally, Ang et al. (2007) and Gil-Alana et al. (2012) discuss that one possible explanation for their finding that survey-based forecasts outperform a wide variety of time series models, is the expectations' ability to quickly react and adapt to major changes and shocks in the economic environment and data generating process for inflation. Since our estimated period does not include such changes and shocks, using inflation expectations in forecasts is likely not as beneficial as it was for them.

We could also see from Figure 1 that the inflation expectations series of men and women follow each other, as well as the inflation series, very closely. This is especially true for the end of our sample. This empirical finding is likely also an explanation for the inflation expectations series' failure to contribute to higher accuracy in our forecasts: In addition to the inflation series, the inflation expectations series do not provide enough variation in the data to improve the forecast precision. This reasoning may imply that the importance of inflation expectations is greater in an environment of high and volatile inflation than in our forecasting period. As can be seen in the figure, all inflation expectations series are in general further from the actual CPI series in these periods.

We find that $Model_{NC}^{M}$ performs more accurate forecasts than the other models including inflation expectations and excluding macro-financial indicators. However, when including macro-financial indicators, we do not find any distinct differences in forecast accuracy between the models including inflation expectations. As stated earlier, there are generally no significant differences between the inflation expectations of men and women in our sample. Our finding that the contribution to more accurate inflation forecasts is not different between the inflation expectations series in the models including macro-financial indicators is therefore rather expected. However, small differences do exist in certain periods of our sample, with men having slightly lower expectations than women and being closer to the actual CPI. These differences appear in periods where the actual CPI is more volatile, for instance during the financial crisis. This implies that the forecasting contribution of the various inflation expectations series could differ distinctly between the series in more uncertain periods with volatile inflation.

7.2 Policy Implications

Our results imply that forecasters of Swedish inflation would not benefit from including data on individuals' inflation expectations from ETS in the models used to forecast inflation in the studied period. However, as pointed out earlier in this section, our results are valid for a period with a low and stable inflation level where inflation expectations are conjectured to have low predictive power on future inflation. Following this reasoning, it is important that inflation forecasting institutions, such as the Riksbank, NIER, and the Ministry of Finance, keep evaluating whether inflation expectations should be incorporated in inflation forecasts. This is especially important in times like these, with higher economic uncertainty and a rising inflation rate as well as policy rate.

Another finding in our results is that the four models including macro-financial indicators generally have a lower RMSE (0.2850 : 0.7420) than the four models excluding them (0.3613 : 1.1398). In other words, the models including macro-financial indicators generally outperform the models excluding them, with $Model_C^{NE}$ estimating the lowest RMSE of all models. As pointed out by Dellas et al. (2018), large forecast errors may result in suboptimal policies that cause inefficient fluctuations in aggregate economic activity and inflation, meaning that it is important to keep the forecast errors small. Hence, our results indicate that it is more important for the forecast accuracy to include the macro-financial indicators than the inflation expectations variables.

Although inflation expectations may not be particularly valuable to the model-based forecasts of this thesis, collecting them is not entirely futile. From a policy standpoint, survey-based inflation expectations can still offer relevant insights into issues such as the credibility of the inflation target or other obstacles that central banks may encounter while implementing monetary policy. It is of high value for the Riksbank to keep closely monitoring these expectations when considering adjustments to the policy rate. For instance, the Riksbank considers the survey-based inflation expectations as implications of future economic activity (Riksbank, 2023). Since the Riksbank's adjustments of the policy rate are affected by the inflation expectations, the Riksbank at times is likely to adjust the policy rate to impact the inflation rate in a way that differs from the expectations. For example, when the inflation rate and the inflation expectations are high, the Riksbank can raise the policy rate to create a dampening effect on the economy via inflation expectations. This can be thought of as a kind of 'feedback' where increasing inflation expectations makes the Riksbank raise the policy rate, which in turn decreases the inflation rate. This feedback possibly reduces the inflation expectations' ability to forecast inflation, since they change in opposite directions. In addition, even though the Swedish inflation forecasting institutions do not explicitly include data on households' inflation expectations in their forecasts, one can presume that these expectations still have an impact on their judgmental predictions of inflation.

8 Conclusions

Being able to perform accurate predictions of future inflation is crucial for a wide range of actors in the economy, as well as for the effectiveness of monetary policy decisions. This thesis intends to build on the understanding of how individuals' inflation expectations in Sweden relate to future inflation, and further investigate whether they contribute to more accurate inflation forecasts. In addition, the analysis is extended by using data on individuals' inflation expectations disaggregated by gender to assess their respective potential impacts on inflation. The study is done by conducting inflation forecasts using quarterly data between 2002Q1-2018Q1. Forecasts are performed with a forecast horizon of 8 quarters, over the period 2018Q2-2020Q1. We make use of two benchmark models without inflation expectations - an ARIMA model including data on CPI ($Model_{NC}^{NE}$) and a VAR model including CPI, the unemployment rate, and the 3-month treasury bill rate ($Model_{C}^{NE}$). These models are compared to three VEC models each, where inflation expectations series of both genders, men, and women are respectively added as predictors. The forecasts of all eight models are also compared to the forecasts of an RW model to see whether it can be outperformed by these models.

We find that the models including inflation expectations are all outperformed by the benchmark models, implying that none of the expectations series contribute to more accurate inflation forecasts in Sweden. Hence, inflation expectations are not found to Granger cause inflation. Furthermore, we find that the forecast accuracy only marginally differs between the models including the inflation expectations series of men and women respectively when including macro-financial indicators. Another finding is that the models including inflation expectations series generally perform more accurate forecasts at a longer forecast horizon, while the opposite is true for those excluding expectations. This finding suggests that the performance of models that include inflation expectations varies over time and that there are distinct benefits to incorporating inflation expectations into particular models during certain periods. This is particularly evident for models that do not include macro-financial indicators.

It is important to note that our results are valid for a relatively short forecasting period, with a low and stable inflation rate. While inflation expectations may not hold significant value for the model-based predictions in this study, gathering such information is not in vain. From a policy perspective, survey-based inflation expectations can still provide relevant insights into matters such as the credibility of the inflation target or any obstacles that central banks may face while implementing monetary policy.

Taking into account the findings and limitations of this thesis, the following potential directions for future research are suggested. We consider a promising avenue for future research to be analyzing a longer forecasting period and looking at later data including periods with higher economic uncertainty and a more volatile inflation rate. For instance, we suggest assessing the incorporation of individuals' inflation expectations in inflation forecasts in a period covering the recent Covid-19 pandemic and the Russian invasion of Ukraine. We further suggest evaluating the ability of inflation expectations to enhance inflation forecast accuracy using expectations aggregated on age groups and education levels. In addition, including cross-group data on inflation expectations, i.e., observations from men aged 24-35 years old with post-secondary education, could be a way to assess whether these inflation expectations series can contribute to more accurate inflation forecasts.

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A Data

A.1 Data Series

Table A.1: Correlation Between CPI and the Other Selected Variables

Variable	Correlation
CPI	1
Exp. CPI, BG	0.7394
Exp. CPI, M	0.7156
Exp. CPI, W	0.7276
Unemployment	-0.6516
T-bill	0.5748

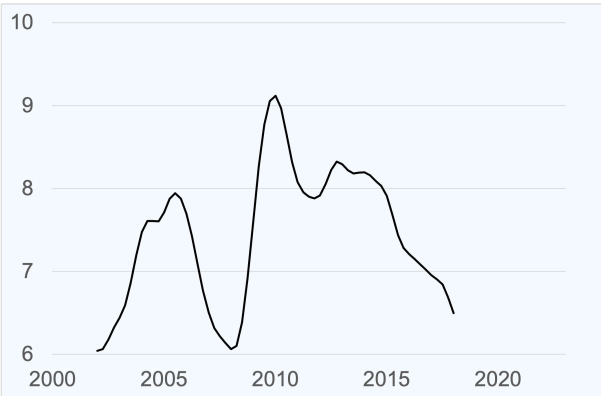
Notes: The table displays the correlation between CPI and the other selected variables in our sample on quarterly data. The correlations are rounded to four decimals. In the presented order, the abbreviations for variable names refer to: CPI - Consumer Price Index, Exp. CPI, BG - Expected CPI of both genders, Exp. CPI, M - Expected CPI of men, Exp. CPI W - Expected CPI of women, Unemployment - Unemployment rate, T-bill - 3-month treasury bill rate.

(a) CPI

(b) Exp. CPI, BG

(c) Exp. CPI, M

(d) Exp. CPI, W



(e) Unemployment rate

(f) T-bill

Figure A.1: Plots of Selected Variables in the Data Set

Notes: The figure displays monthly data on the year-on-year Swedish headline CPI series (panel a), the inflation expectations series of both genders (panel b), men (panel c) and women (panel d) respectively from ETS, quarterly data on the unemployment rate (panel e), and monthly data on the 3-month treasury bill rate (panel f). The CPI series are shown for 2002M1-2020M3, the unemployment rate series 2002Q1-2018Q1 and the other series 2002M1-2018M3.
Sources: Statistics Sweden, NIER.

A.2 Collection of Data

The CPI described in Section 3.2 is constructed by Statistics Sweden using price notations for a selection of goods and services, so called 'representative products'. Prices are collected from a variety of categories, such as food, clothes, education, medical care and transportation. The report of CPI in Sweden is constructed in accordance with Classification of Individual Consumption by Purpose (COICOP), an international classification of households' private consumption. The relative meaning of different 'representative products' are specified by weighting numbers, which show how large value share the goods and services represent of the total private domestic consumption. The prices are partly collected directly from stores through store visits or calls from interviewers from Statistics Sweden. In addition, the prices are partly collected through a central price collection by officials at the Price Division at Statistics Sweden via internet, e-mail, or paper form. The prices are collected during three measuring weeks every month. The first measuring week each month is the week before the week in which the 15^{th} occurs. The second measuring week is the week in which the 15^{th} occurs, and the third is the week after the 15^{th} occurs. The centrally collected prices are collected as of the 15^{th} of the month or during the week in which the 15^{th} occurs. CPI is published monthly, usually around 10–14 days after the end of the reported month (Statistics Sweden, 2023).

The survey-based inflation expectations described in Section 3.3 are obtained from ETS by NIER. The target population of ETS is the Swedish public in the age from 18 to 84 years and the target object is households, while the object of observation is individual. The selection of households is random and is monthly drawn from a consumer database, containing almost 7 million individuals, allocated over around 4.3 million households. The data is generally collected between the 1^{th} and the 15^{th} each month. Before November 2020, the answers from the households were collected over telephone interviews. The results from the survey are reported at the end of the month, around a week after the data collection is finished. The results are reported in total for all household, but also distributed by gender, age, and region of residence (NIER, 2023).

The unemployment rate is, as described in Section 3.4.1, measured from seasonally adjusted quarterly data for people aged 16-74 years. This data is obtained from the Labour Force Surveys by Statistics Sweden and has been adjusted for a time series break caused by adjustments in the surveys in January 2021. The surveys are conducted every month, with approximately 18,200 individuals being contacted for a telephone interview. The sample selection is drawn randomly from the population register. The results are reported at the end of each month of January, April, July and October (Statistics Sweden, n.d. b).

Treasury bills are interest-bearing bonds that the state uses to borrow money, as mentioned in Section 3.4.2. Monthly data of the 3-month treasury bill rate is obtained from Statistics Sweden, where the rates are calculated as a monthly average over the daily rates. In Sweden, the Swedish National Debt Office borrows on behalf of the Swedish central government to finance budget deficits and refinance maturing loans. This is mainly done by issuing government securities in SEK, such as nominal government bonds, inflation-linked bonds, and treasury bills. Treasury bills enable the Debt Office to conduct short-term borrowing and are primarily issued to compensate for short-term fluctuations in the borrowing requirement. The planning of their borrowing is based on predictions regarding the Swedish economy and balance of payments. New treasury bills are given out every second Wednesday through an auction by the Debt Office with maturities of 3 or 12 months. The terms of each auction are published a week in advance (Swedish National Debt Office, 2019).

A.3 Data Transformation and Pre-Testing

The following form of the ADF test, including a drift, is used to test the transformed variable y_t:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=1}^{4} \Delta y_{t-4} + \epsilon_t \tag{10}$$

where Δy_t is the first difference of y_t, a_0 is the drift term, and ϵ_t is the white noise error term (Stock and Watson, 2020). The null hypothesis that $\gamma = 0$ is tested against the alternative hypothesis that $\gamma < 0$. Since the aggregation level of the data is quarterly, we test the first four lags in the ADF tests.

The results are shown in Table A.2. As seen in the table, we are able to reject the null of a unit root for each of the transformed series at the 5% significance level and can proceed with our analysis with the variables being integratied of order one, $I(1)$.

Table A.2: Unit Root Testing Results

Variable	Transformation	ADF test p-value
CPI	1^{st} diff	0.010
Exp. CPI, BG	1^{st} diff	0.016
Exp. CPI, M	1^{st} diff	0.014
Exp. CPI, W	1^{st} diff	0.010
Unemployment	1^{st} diff	0.010
T-bill	1^{st} diff	0.019

Notes: The table presents the test result of the ADF test for each series. The p-values of the ADF test are rounded to three decimals and the confidence level is 5%. In the presented order, the abbreviations for variable names refer to: CPI - Consumer Price Index, Exp. CPI, BG - Expected CPI of both genders, Exp. CPI, M - Expected CPI of men, Exp. CPI W - Expected CPI of women, Unemployment - Unemployment rate, T-bill - 3-month treasury bill rate.

B Reported Results

Table B.1: Predicted CPI From All Estimated Models and Actual CPI, 2018Q2-2020Q1

Quarter	Actual outcome	$Model^{RW}$	$Model_{NC}^{NE}$	$Model_{NC}^{BG}$	$Model_{NC}^{M}$	$Model_{NC}^{W}$	$Model_{C}^{NE}$	$Model_{C}^{BG}$	$Model_{C}^{M}$	$Model_{C}^{W}$
2018Q2	1.9000	1.7000	1.7919	1.4410	1.5152	1.3648	1.9959	1.6419	1.6027	1.6430
2018Q3	2.1333	1.7000	1.7919	1.0277	1.1608	0.9441	1.9982	1.3275	1.2107	1.3738
2018Q4	2.1000	1.7000	1.7919	0.8243	0.9796	0.7390	1.9273	1.0959	0.9626	1.1040
2019Q1	1.9000	1.7000	1.7919	0.6439	0.8212	0.5423	1.8665	1.1012	0.9790	1.0377
2019Q2	2.0333	1.7000	1.7919	0.5115	0.6777	0.4404	1.6760	1.3019	1.1815	1.1862
2019Q3	1.5333	1.7000	1.7919	0.5628	0.7089	0.4948	1.7062	1.7502	1.6239	1.5757
2019Q4	1.7333	1.7000	1.7919	0.6464	0.7781	0.5867	1.7888	1.9961	1.8569	1.8269
2020Q1	0.9667	1.7000	1.7919	0.7527	0.8575	0.7115	1.6231	1.8615	1.7242	1.7316

Notes: Reported predicted values of CPI from the models respectively and actual CPI for each quarter over the period 2018Q2-2020Q1. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.

Table B.2: AFE From All Estimated Models, 2018Q2-2020Q1

Quarter	$Model^{RW}$	$Model_{NC}^{NE}$	$Model_{NC}^{BG}$	$Model_{NC}^{M}$	$Model_{NC}^{W}$	$Model_{C}^{NE}$	$Model_{C}^{BG}$	$Model_{C}^{M}$	$Model_{C}^{W}$
2018Q2	0.2000	0.1081	0.4590	0.3848	0.5352	0.0959	0.2581	0.2973	0.2570
2018Q3	0.4333	0.3414	1.1056	0.9726	1.1892	0.1352	0.8058	0.9227	0.7596
2018Q4	0.4000	0.3081	1.2757	1.1204	1.3610	0.1727	1.0041	1.1374	0.9960
2019Q1	0.2000	0.1081	1.2561	1.0788	1.3577	0.0335	0.7988	0.9210	0.8623
2019Q2	0.3333	0.2414	1.5219	1.3556	1.5930	0.3573	0.7315	0.8519	0.8471
2019Q3	0.1667	0.2586	0.9705	0.8244	1.0385	0.1728	0.2168	0.0906	0.0424
2019Q4	0.0333	0.0586	1.0869	0.9553	1.1466	0.0555	0.2628	0.1236	0.0936
2020Q1	0.7333	0.8253	0.2139	0.1092	0.2552	0.6564	0.8948	0.7575	0.7649

Notes: AFE for each quarter over the period 2018Q2-2020Q1 from estimating the models respectively. The AFE is the absolute difference between the predicted forecast value for each model each quarter subtracted from the actual CPI. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.

C Results From the Sensitivity Analysis

Table C.1: AFE From All Estimated Models, 2020Q2-2021Q1

Quarter	$Model^{RW}$	$Model^{NE}_{NC}$	$Model^{BG}_{NC}$	$Model^{M}_{NC}$	$Model^{W}_{NC}$	$Model^{NE}_{C}$	$Model^{BG}_{C}$	$Model^{M}_{C}$	$Model^{W}_{C}$
2020Q2	1.6000	1.6919	0.7837	0.8674	0.7508	1.3796	1.5212	1.4322	1.4052
2020Q3	1.1333	1.2253	0.4060	0.4833	0.3747	0.8689	0.8482	0.7949	0.7572
2020Q4	1.3667	1.4586	0.6876	0.7626	0.6543	1.07422	0.9499	0.8838	0.8908
2021Q1	0.1333	0.2253	0.5249	0.4422	0.5729	0.1016	0.3110	0.4204	0.3695

Notes: AFE for each quarter over the period 2020Q2-2021Q1 from estimating the models respectively, with extended forecast horizons. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.

Table C.2: Predicted CPI From All Estimated Models and Actual CPI With U.S. Data, 2018Q2-2020Q1

Quarter	Actual outcome	$Model^{RW}$	$Model^{NE}_{NC}$	$Model^{BG}_{NC}$	$Model^{M}_{NC}$	$Model^{W}_{NC}$	$Model^{NE}_{C}$	$Model^{BG}_{C}$	$Model^{M}_{C}$	$Model^{W}_{C}$
2018Q2	1.2333	2.2667	2.3120	2.4632	2.4949	2.5151	2.2000	2.1907	2.2192	2.1958
2018Q3	1.3000	2.2667	2.1112	2.3941	2.4048	2.4517	1.8824	1.8884	1.9138	1.8846
2018Q4	1.5667	2.2667	2.1112	2.2670	2.2544	2.3602	1.9205	1.9969	2.0113	2.0174
2019Q1	2.2667	2.2667	2.1112	2.1000	2.1423	2.1468	2.0968	2.1915	2.2325	2.1981
2019Q2	2.9667	2.2667	2.1112	1.9101	1.9568	1.9436	2.2427	2.3600	2.4211	2.3180
2019Q3	2.000	2.2667	2.1112	1.9101	1.9393	1.9528	2.5039	2.7352	2.7779	2.6947
2019Q4	2.2333	2.2667	2.1112	1.9740	2.0070	2.0105	2.7131	2.9264	2.9173	2.9190
2020Q1	1.9667	2.2667	2.1112	2.0067	2.0405	2.0618	2.8067	2.9071	2.8682	2.9173

Notes: Reported predicted values of CPI from the models respectively and actual CPI for each quarter over the period 2018Q2-2020Q1, using U.S. data. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.

Table C.3: AFE From All Estimated Models With U.S. Data, 2018Q2-2020Q1

Quarter	$Model^{RW}$	$Model^{NE}_{NC}$	$Model^{BG}_{NC}$	$Model^{M}_{NC}$	$Model^{W}_{NC}$	$Model^{NE}_{C}$	$Model^{BG}_{C}$	$Model^{M}_{C}$	$Model^{W}_{C}$
2018Q2	1.0333	1.0787	1.2299	1.2616	1.2818	0.9667	0.9574	0.9859	0.9624
2018Q3	0.9667	0.8112	1.0941	1.1048	1.1517	0.5824	0.5884	0.6138	0.5846
2018Q4	0.7000	0.5445	0.7003	0.6877	0.7936	0.3539	0.4303	0.4446	0.4508
2019Q1	0.0000	0.1555	0.1667	0.1244	0.1199	0.1699	0.0751	0.0342	0.0686
2019Q2	0.7000	0.8555	1.0565	1.0099	1.0231	0.7240	0.6067	0.5455	0.6486
2019Q3	0.2667	0.1112	0.0899	0.0607	0.0473	0.5039	0.7352	0.7779	0.6947
2019Q4	0.0333	0.1221	0.2594	0.2263	0.2228	0.4798	0.6931	0.6840	0.6857
2020Q1	0.3000	0.1445	0.0400	0.0738	0.0952	0.8400	0.9405	0.9015	0.9506

Notes: AFE for each quarter over the period 2018Q2-2020Q1 from estimating the models respectively, using U.S. data. The abbreviations in the subscripts and superscripts in the model names refer to the inclusion of respectively variable: NE - No Expectations, BG - Inflation Expectations of Both Genders, M - Inflation Expectations of Men, W - Inflation Expectations of Women, NC - No Macro-Financial Indicators, C - Macro-Financial Indicators, and RW - Random Walk.