Can inflation expectations in business or consumer surveys improve inflation forecasts ?

by Raïsa Basselier, David de Antonio Liedo,
Jana Jonckheere and Geert Langenus

October 2018 **No 348**

NationalBank OF BELGIUM
Eurosystem

Can inflation expectations in business or consumer surveys improve inflation forecasts?

Raïsa Basselier[*], David de Antonio Liedo[†], Jana Jonckheere[‡], Geert Langenus[§]

Abstract

In this paper we develop a new model that incorporates inflation expectations and can be used for the structural analysis of inflation, as well as for forecasting. In this latter connection, we specifically look into the usefulness of real-time survey data for inflation projections. We contribute to the literature in two ways. First, our model extracts the inflation trend and its cycle, which is linked to real economic activity, by exploiting a much larger information set than typically seen in this class of models and without the need to resort to Bayesian techniques. The reason is that we use variables reflecting inflation expectations from consumers and firms under the assumption that they are consistent with the expectations derived from the model. Thus, our approach represents an alternative way to shrink the model parameters and to restrict the future evolution of the factors. Second, the inflation expectations that we use are derived from the qualitative questions on expected price developments in both the consumer and the business surveys. This latter source, in particular, is mostly neglected in the empirical literature. Our empirical results suggest that overall, inflation expectations in surveys provide useful information for inflation forecasts. In particular for the most recent period, models that include survey expectations on prices tend to outperform similar models that do not, both for Belgium and the euro area. Furthermore, we find that the business survey, i.e. the survey replies by the price-setters themselves, contributes most to these forecast improvements.

Key words: inflation forecasts, monthly consumer and producer surveys, qualitative survey information, model-consistent expectations, JDemetra+ SSF library[1]
JEL Classification: E31, E37.

[*]National Bank of Belgium, Economics and Research Department, e-mail: raisa.basselier@nbb.be.
[†]National Bank of Belgium, R&D Statistics, e-mail: david.deantonioliedo@nbb.be.
[‡]National Bank of Belgium, Economics and Research Department, e-mail: jana.jonckheere@nbb.be.
[§]National Bank of Belgium, Economics and Research Department, e-mail: geert.langenus@nbb.be.

[1]The model presented in this paper has been developed and estimated with the software JDemetra+, which is well known for seasonal adjustment, but it also contains very efficient algorithms for the estimation of state-space models like the ones used here. We would like to thank Jean Palate for having developed the R interface (publicly available in GitHub) that has allowed us to specify our models in R and estimate them in JDemetra+.

Contents

1 Introduction **3**

2 Motivation: recent inflation projections for Belgium and the euro area **6**

3 Data description **9**
3.1 Survey data on price expectations 9
3.2 Other variables 12

4 Unobserved component models with expectational variables **14**
4.1 Model set-up 14
4.2 Small model 15
4.3 Small X 17
4.4 Large X 20
4.5 Estimation 23

5 Results **25**
5.1 Set-up of the forecasting evaluation 25
5.2 A first look: one-step-ahead forecasts 26
5.3 Quantifying forecasting accuracy 33
5.4 Adding noise: AR(1) measurement errors in the two survey equations . . . 34

6 Focus on the recent period and interpretation **37**
6.1 A change in the forecast evaluation sample 37
6.2 Businesses or consumers? 39

7 Conclusion **42**

8 Annexes **47**

1 Introduction

This paper aims to assess whether the accuracy of Belgian and euro area inflation projections can be improved by explicitly incorporating information on expected price developments, drawn from the EC consumer and business surveys, into a structural model. In recent years, inflation has generally been remarkably low in advanced countries. Conventional models have, in particular, mostly failed to predict and explain the very slow pick-up of price growth after the great recession. The "missing inflation" puzzle has fuelled the debate in the literature on the slope of the Phillips curve. In addition, the possibility of changes in the trend or the persistence of inflation has been discussed. Different strands of the literature have focused on the pass-through of costs or exchange rate movements to final prices, as well as on the role of inflation expectations and a possible deanchoring of those expectations. However, as shown by Mankiw *et al.* (2003), different measures of inflation expectations can diverge strongly. In the empirical literature, the question of the usefulness of inflation expectations is mostly addressed by looking at *implied* expectations that are derived from financial market indicators and the term structure of interest rates, as well as at (point or range) forecasts of economist experts and, to a lesser extent, consumers. In this connection, Carroll (2003) finds that surveys regarding forecasts by economic experts are more informative for inflation projections than price expectations of consumer surveys. Ang et al. (2007) show that projection models for US inflation that include expectations of professional forecasters can outperform structural Phillips curve models. The same is true for consumer expectations in the University of Michigan consumer survey but the accuracy gains are smaller. Literature on *qualitative* inflation expectations is somewhat scarcer. Scheufele (2011) finds that qualitative inflation expectations in the ZEW survey can improve inflation forecasts for Germany. Similarly, Forsells and Kenny (2004) show that the qualitative data on price expectations in the EC consumer surveys can provide a reasonably accurate predictor of actual inflation. Within this strand of literature, research on the usefulness of qualitative information provided by producers is not strongly represented. Yet, as suggested by Bernanke (2007), the latter can be an even more important source of information for forecasts, as the survey respondents are the actual price-setters. Hence, we will investigate the role of (qualitative) survey information on both consumers' and producers' inflation expectations that

we take from the EC consumers and business surveys. To the best of our knowledge only a few papers have specifically used these survey data for inflation projections. One example is Stockhammar and Österholm (2016) who find that the inflation expectations in the Swedish National Institute of Economic Research's Business Tendency Survey (that, however, also includes consumers as respondents, in addition to firms) improve model forecast precision for Swedish inflation in a meaningful way, in particular for the shorter horizons. Remarkably, this is much less the case for the TNS Sifo Prospera's inflation survey – which is conducted on behalf of the Sveriges Riksbank – that is restricted to businesses and does not include consumers. The Federal Reserve Bank of Atlanta on the other hand routinely uses price expectations from its business surveys to shape its views on future inflation developments.[2]

This paper contributes to the literature in multiple ways. First of all, we follow the path traced by Coibion and Gorodnichenko (2015) and Coibion *et al.* (2018) and add to the scarce literature on the role of *qualitative* real-time survey data on inflation forecasting. More specifically, we incorporate information from *both* consumers and firms and look into their information content for both headline and core inflation. To the best of our knowledge, no similar exercise was ever performed for Belgium or the euro area. We also investigate which of the two surveys offers the most added value in terms of forecasting accuracy. Furthermore, by assuming that the survey information is consistent with the expectations derived from our proposed model, we offer a method to impose cross-equation restrictions on the model parameters and the future evolution of the factors.

The model used is inspired by Stella and Stock (2013) and belongs to the class of unobserved components models (UCM). Our dataset contains up to ten variables that range from (core and total) inflation to oil prices, the import deflator, real GDP, the unemployment rate, the mark-up, a global sentiment indicator and two variables reflecting inflation expectations from consumers and businesses. Fluctuations of headline and core inflation are given by a trend and a cyclical component. The latter could co-move with the cyclical component of real activity, which is the common factor for all variables, providing a linkage between real and nominal economic activity. This way, our model is larger than others belonging to the same class, with the advantage that due to the assumed model-consistency of the survey information, we do not need to specify priors

[2]Please refer to: https://www.frbatlanta.org/research/inflationproject/bie

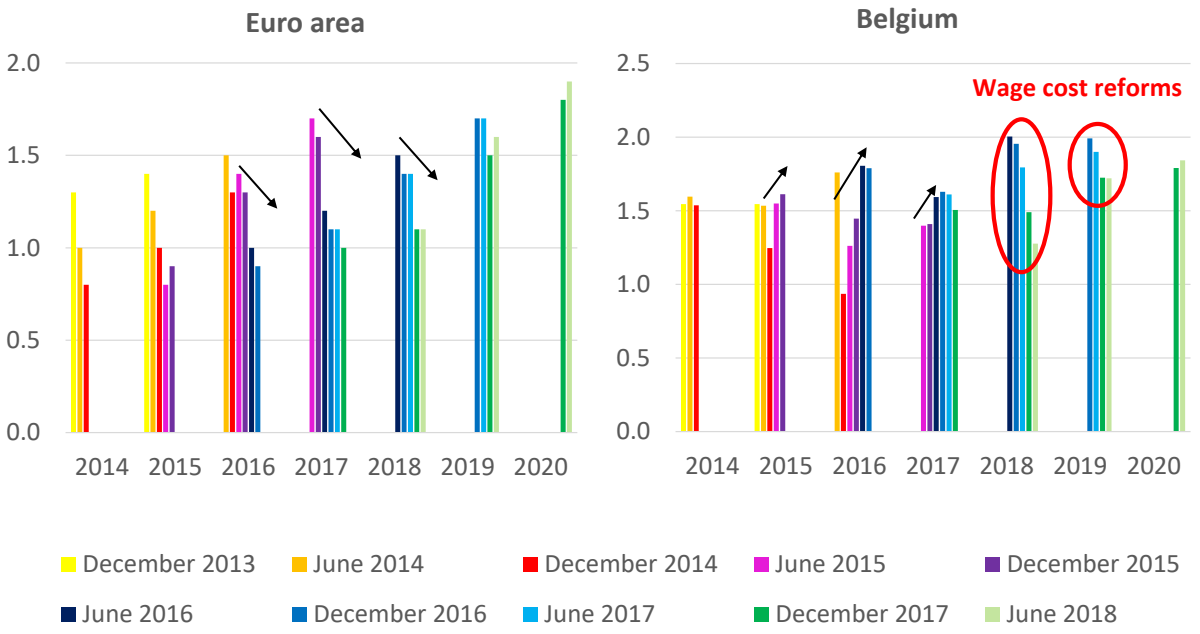
for the multiple parameters, as done for example in Chan *et al.* (2016), who use bounds to improve estimation of the trend, or in Hasenzagl *et al.* (2018), who propose a model of the same class as ours.

The remainder of the paper is organised as follows. Following a description of the motivation and context of this paper, the data that are used in the model will be described, focusing in particular on the survey data that we incorporate. In Section 4, the unobserved components model will be described. First, a basic version of the model is considered, which is then extended to also include the oil price and the mark-up, among others. In both cases, it is verified whether adding the price expectations from both the relevant business surveys and the consumer survey in a model-consistent manner improves forecast accuracy. Results are presented in Section 5, where forecasting accuracy of the different models is evaluated. We compare the Root Mean Squared Errors of the models that do not include surveys, with the ones that do. It turns out that survey information generally improves the accuracy, at least for Belgium. However, Section 6 shows that survey information may matter for euro area inflation projections as well, if only the more recent period would be considered. We also investigate whether this result is mostly due to information coming from businesses or consumers. The last section concludes.

2 Motivation: recent inflation projections for Belgium and the euro area

We explicitly chose to juxtapose Belgium and the euro area, as both seem to be polar cases of the recent difficulties faced by inflation projection models. While the projections made for the euro area by the ECB tended to overestimate inflation, the opposite holds for those for Belgium, that were typically too low. In the latter case the pass-through of the Belgian policies to significantly curb unit labour costs to final prices may have been different than predicted by benchmark macro models. In this connection, survey data from firms (i.e. price-setters) on expected price developments could inform inflation projections, as respondents are likely to take into account envisaged changes in mark-ups.

Figure 1: Macroeconomic projections of core inflation over time: from the December 2013 to the June 2018 exercise

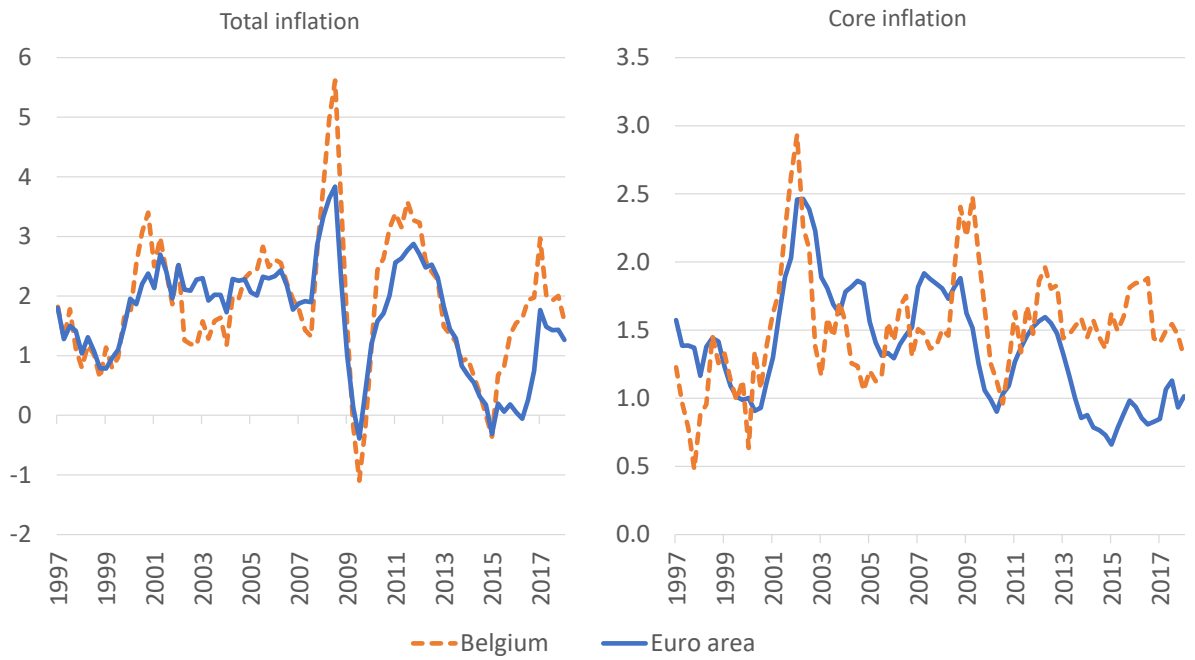


Source: ECB, NBB.

Not only the forecast (errors), also the actual inflation rates in Belgium and in the euro area have recently diverged significantly. While the euro area was burdened by (the risk of) deflation, the overall inflation rate according to the Harmonised Consumer Price Index (HICP) in Belgium has been almost consistently rising from 2015 to 2017. The left-hand side of figure 2 shows how the Belgian total inflation rate has been diverging away from the euro area average since early 2015, and has only recently come closer to

the euro area average again.

Figure 2: YoY total and core inflation rate in Belgium and the euro area, based on the HICP (quarterly data, seasonally adjusted, in %)



Source: EC.

The difference can be partly explained by diverging evolutions in the energy component, which was partly related to government interventions.[3] However, part of the higher overall price increases can be traced back to the level of core inflation, which represents the total inflation excluding energy and food items. Ever since 2013, Belgian core inflation has consistently hovered around 1.5 % - between 2015 and 2016 it was even between 1.5 % and 2 % - while the euro area average has been on a downward trend since 2012 (cf. right-hand side of figure 2).

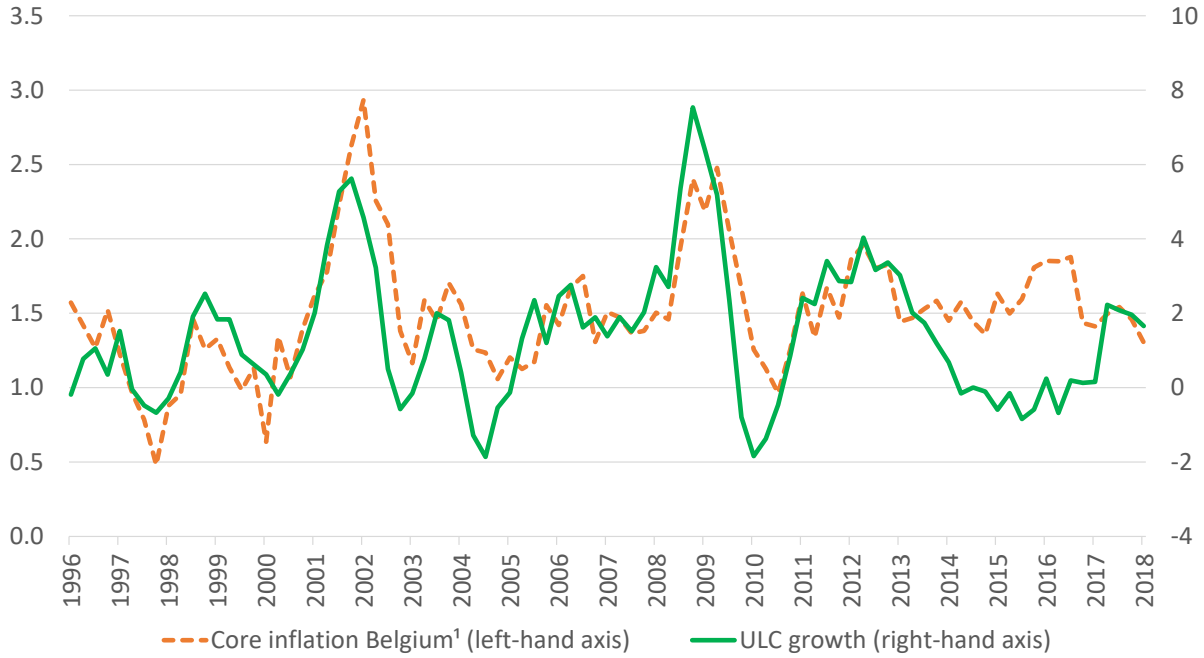
The recent persistence in Belgian core inflation is all the more remarkable given the very moderate growth in unit labour costs (ULC)[4] (see figure 3). Persistent core inflation in Belgium can largely be attributed to the service and retail sector, where firms have more possibilities to maintain or even raise prices, due to lack of (international) competition.

[3]In 2015, the Belgian government reversed the reduction of the VAT rate on electricity. In March 2016, the Flemish regional government decided to pass on to final consumers the sizeable debt overhang from supporting renewable energy. This was reversed again in January 2018.

[4]This is the result of specific government policies to improve cost competitiveness. These policies included constraints on centralised real wage bargaining, a temporary suspension of the indexation mechanisms that link wage growth to inflation, as well as various cuts in employers' social security contributions in the context of the pluriannual taxshift.

Thum-Thysen and Canton (2015) found the Belgian retail trade sector to have one of the largest mark-ups among EU countries in 2013. A key feature in this regard is the lower-than-expected pass-through of changes in costs by firms, as witnessed by changes in firms' mark-ups and profit margins. As business leaders dispose of more information on their costs and hence on their future price setting, this motivated the choice to incorporate survey data, in particular for businesses.

Figure 3: YoY core inflation rate in Belgium (SA) and YoY growth of ULC (quarterly data, in %)



Source: EC, NAI, NBB.
[1] This series is seasonally adjusted.

3 Data description

3.1 Survey data on price expectations

Measures of consumers' and producers' inflation perceptions can be derived from surveys. In some cases, that are referred to as quantitative survey data, respondents are asked to put an exact figure on the expected change or on their expected level of inflation. Besides these exact measures, surveys may also ask for a general tendency only, allowing respondents to reply by using more general, *qualitative* statements, for example on whether they expect prices to rise or drop. This is the case in the monthly consumer and producer survey used in this paper. These surveys are harmonised across EU countries and data are available via the website of the European Commission. For Belgium, the surveys are conducted by the National Bank of Belgium among a fixed panel of about 6000 firms and a sample of 1850 households.

As regards the business survey, respondents from four different sectors (manufacturing, services, trade, construction) indicate each month how they expect their selling prices to change over the next three months (increase, remain unchanged or decrease). An analysis of qualitative survey responses can be conducted by synthesizing the survey information using balances. The balance is calculated per sector by subtracting the share of negative replies (decrease) from the fraction of positive replies (increase). For Belgium, survey responses for all four industries are only available as of 2000. Before that date, there are no survey data available for the construction industry. However, as the construction industry is not directly represented in the basket of goods that is used to compose the HICP index, the survey replies from this industry were deemed irrelevant as a predictor of HICP headline and core inflation. Hence, we continue with a simple average[5] of the results of three industries, available as of 1995. At the euro area level, data for all three industries are only available as of mid-2003. In order to have sufficiently long series, the series was prolonged using only data from the manufacturing industry between 1995 and 2003.

On the consumer side, one of the questions pertains to the inflation outlook, and consumers need to indicate how they expect consumer prices to evolve over the next

[5]Other weighting schemes (that aim to capture the industry's weight for the consumption basket) were considered but turned out not to deviate much from the simple average.

twelve months, in comparison with the past twelve months. Consumers may indicate that prices are increasing more rapidly, increasing at the same rate, increasing at a slower rate, stay about the same or fall. The net balance is calculated by giving the full weight to the extreme cases (i.e. increase more rapidly or fall) and half the weight to the less extreme case (i.e. increasing at the same rate and stay about the same). Consumer survey results on inflation are available since 1985 for Belgium and the euro area.

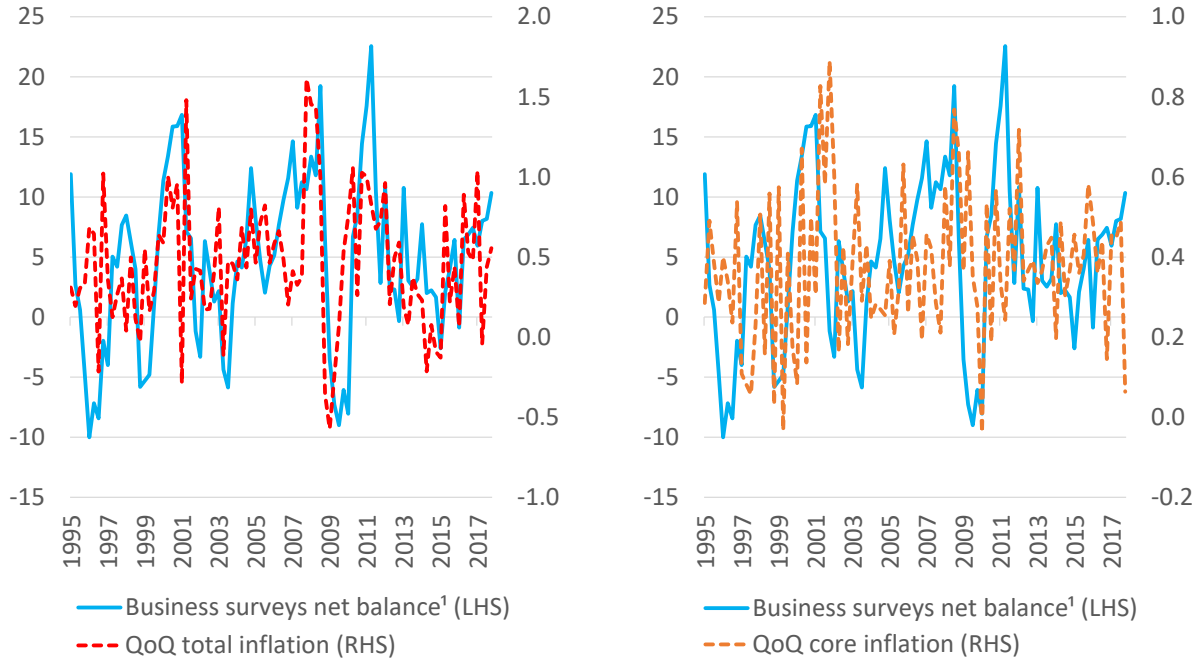
It should be stressed that the relevant horizon for the price questions in each survey is different: while consumers are being asked about their inflation perspectives for the coming year, business owners are requested to comment on the expected evolution in the next three months. It may be considered a specific advantage of this survey dataset that replies pertain to a fixed time period (i.e. the next three/twelve months), which is not the case in, for example, the Consensus Forecast, where respondents provide their expected inflation rate for a certain year (but hence, with a varying forecasting horizon, depending on the moment at which the forecast is conducted). The business and consumer surveys are available on a monthly basis, but are converted to a quarterly frequency. In order to exploit their information as early as possible, the value for any specific quarter is proxied by using the value of the first month of that quarter.

Although no point forecast of the expected rate of inflation can be directly obtained from the survey data, there is some literature that suggests that the aggregate difference between the fraction of experts that expect an increase in the inflation rate and those that expect a decrease (i.e. the balance that was constructed earlier) can still be used to construct an aggregate measure of inflation expectations (Scheufele, 2011; Carlson and Parkin, 1975).

In this paper, the approach is to use the seasonally adjusted series of the balance, to be linked with the seasonally adjusted quarter-on-quarter inflation rates. In line with the time period of the question asked in the survey, in our model, the consumer survey is linked to the factors underlying year-on-year (YoY) inflation (a cumulated sum of the factors underlying quarter-on-quarter (QoQ) inflation), whereas the business survey is linked to the factors underlying QoQ inflation. Figure 4 displays the balance of net replies to the question in the business survey, combined with, respectively, quarterly total and core inflation rates. Figure 5 shows the net balance of replies in the consumer survey, plotted against year-on-year total and core inflation rates. These figures already show

that the movements of the balance of survey replies and the headline inflation seem to be correlated, to some extent.

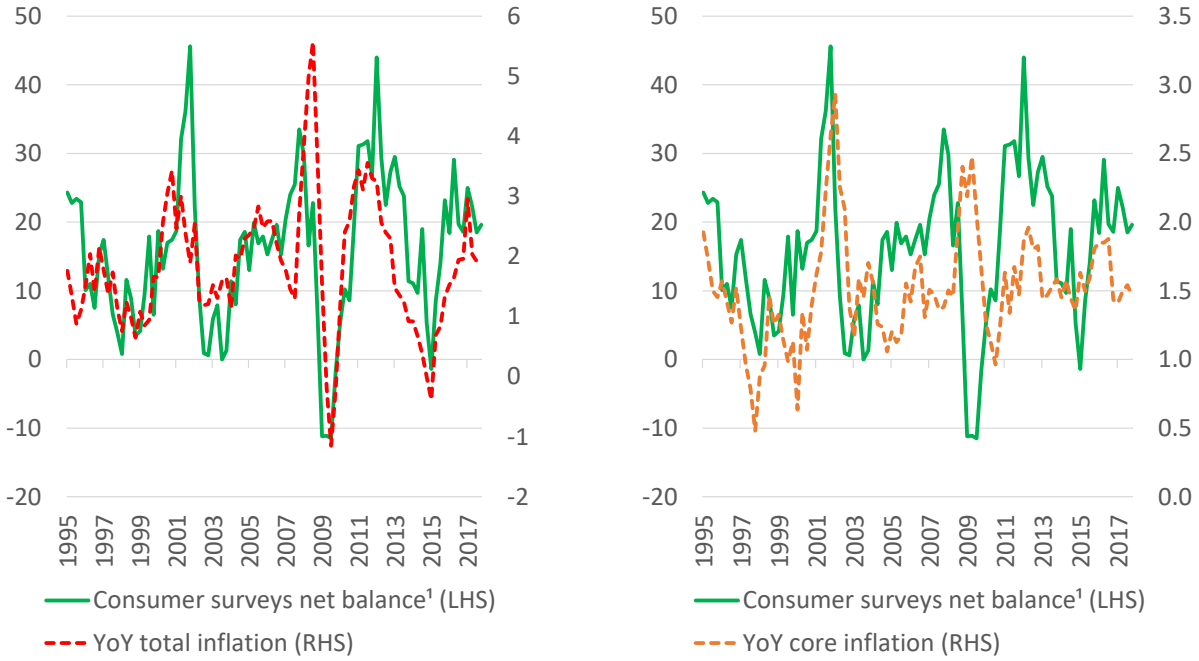
Figure 4: QoQ total and core inflation rate in Belgium and the business survey on inflation (quarterly data)



Source: EC, NBB.
[1] The value of the first month of the quarter is taken as a proxy for the quarterly average.

It should be acknowledged that it is definitely not guaranteed that respondents have the HICP in mind when making their assessment of the future price evaluation. More specifically, producers are inquired about "selling" prices, while consumers are expected to think in terms of "consumer prices". Furthermore, the average survey respondent can never be expected to take into account the same (amount of) information as is being incorporated in the HICP (ECB, 2007). More specifically, the literature suggests that consumer inflation expectations, for example, can be quite sensitive to media reporting on rising prices (Carroll, 2003), which, in turn, is mostly related to gasoline prices (Ehrmann, Pfajfar and Santoro, 2017). According to Souleles (2004), consumer expectations are known to be biased and inefficient, while forecast errors are found to be systematically correlated with demographic characteristics.

Figure 5: YoY total and core inflation rate in Belgium and the consumer survey on inflation
(quarterly data)



Source: EC, NBB.
[1] The value of the first month of the quarter is taken as a proxy for the quarterly average.

3.2 Other variables

Besides the inflation variables and survey measures on price expectations, some macroeconomic variables will be added to our unobserved components model. They are listed in table 1. Even though some variables are available on a monthly basis, those will be converted to a quarterly frequency in order to have a consistent database.

Table 1: Specification of the variables that are used in the model

Name	Description	Source
Total inflation (π_t)	Total Harmonised Index of Consumer Prices (HICP), all items, seasonally adjusted (quarterly average)	Eurostat
Core inflation (π_t^{core})	Harmonised Index of Consumer Prices, all items excluding energy and food, seasonally adjusted (quarterly average)	Eurostat
Import deflator (π_t^M)	QoQ growth rate of the import deflator (quarterly)	Eurostat
Oil (in euros) (π_t^{Oil})	Average of the daily price of a barrel of Brent oil in dollars, divided by the euro/dollar exchange rate (quarterly)	ECB
Real GDP (y_t)	Gross Domestic Product at market prices (quarterly)	Eurostat
Unemployment rate (u_t)	Unemployment rate as a % of the labour force (quarterly)	Eurostat
Mark-up (μ_t)	YoY growth of GDP deflator minus YoY growth of unit labour costs (quarterly)	Eurostat
BS Global; Belgium (S_t^y)	Overall business sentiment indicator using a panel of about 6000 business leaders in Belgium. The survey is harmonised at the European level. Monthly indicator, last month of the quarter taken	NBB
ESI; Euro area (S_t^y)	Economic sentiment indicator. The monthly survey is harmonised at the European level (last month of the quarter is taken)	DG ECFIN
Inflation Surveys (S_t^B, S_t^C)	Business and consumers surveys harmonised at the European level. As regards the price survey variable, we use the businesses' and consumers' assessment on future price developments, seasonally adjusted, monthly available but first month of the quarter taken	DG ECFIN

4 Unobserved component models with expectational variables

4.1 Model set-up

Our model aims to capture the inter-linkages among ten variables that are very different in nature. One the one hand, we have observables directly related to inflation: headline inflation, core inflation, oil prices and the import deflator. On the other hand, we have two variables related to economic activity apart from the unemployment rate that is traditionally used to model price-activity relationships (in e.g. the Phillips curve): real output and an economic sentiment indicator. We aim to extract the relevant cyclical component of economic activity by aggregating information from those three macro variables. Additionally, we exploit data on price mark-ups, which is a measure of the degree of competition in the market, and ultimately, a determinant of output and unemployment deviations from their potential level.

The building blocks of our approach are based on the structural time series models of Harvey (1985). Our application is inspired by Stella and Stock (2013), who propose an unobserved components model for unemployment and inflation. Apart from our proposal to extract the unobserved components from a larger information set, a key innovation with regard to the existing literature lies in the particular way we filter the informative content of data reflecting inflation expectations. We use business and consumer surveys regarding inflation expectations one and four quarters ahead, respectively. The extent to which these variables can help to improve our estimates of the inflation trend and its cyclical component in our model depends on the compatibility of those surveys with the expectations derived from the model. Although we focus on qualitative surveys, our approach can be applied to both quantitative and qualitative surveys, as well as to financial variables that contain information regarding inflation expectations.

This section will make a distinction between unobserved components models that exploit either a limited or a broad information set (see table 2). In the smallest version, only four 'basic' variables are included. In the next step, the Small model is expanded with two additional (survey) variables on expectations and will be labelled as Small X. These survey variables could potentially help to improve the identification of the trend and the

cyclical component of inflation, which was so far only determined by the output gap. The Large model contains four additional variables, including imports and oil prices. We will show that in this larger model, the cyclical component of inflation is determined by both the output gap and a factor that is also present in oil prices. Thus, when the inflation surveys are added to this model (Large X), we can potentially improve the identification of both (i) the output gap and (ii) the oil prices component.

The *fully* model consistent approach, which will be described below, is labelled as X. It imposes cross-equation restrictions that help us to deal with the curse of dimensionality. In turn, the X2 approach has the same reduced form, but the parameters that link the surveys to the unobserved components are not restricted, so parameter uncertainty is higher. Such distinction will be clarified below.

Table 2: Six UCMs estimated for the euro area and for Belgium

	Limited Information Set	Broad Information Set
No inflation surveys	Small	Large
Surveys (model consistent: exact)	Small X	Large X
Surveys (model consistent: reduced form)	Small X2	Large X2

4.2 Small model

In the most simple version of the model, four variables are included: total inflation (π_t), core inflation (π_t^{core}), the unemployment rate (u_t) and real GDP (y_t). Inflation is represented as the sum of a trend, a cyclical component that is common to the real activity variables, and a measurement error. As opposed to Stella and Stock (2013), we consider both core and headline inflation (i.e. total HICP inflation). In particular, we link core inflation to the fourth lag of the cyclical component, acknowledging the predictive value of the business cycle on inflation in the medium term. Thus, the cyclical component of inflation (δ_t) is in our case an unobserved factor that is common to unemployment and output. The equations describing the small model follow:

$$\pi_t = \tau_t^{\pi} + \lambda_{\pi}\delta_t + \eta_t^{\pi} \quad (1)$$

$$\pi_t^{core} = \tau_t^{\pi} + \lambda_{core}\delta_{t-4} + \eta_t^{core} \quad (2)$$

$$u_t = \tau_t^{u} + \kappa_u\delta_t + \eta_t^{u} \quad (3)$$

$$y_t = \tau_t^{y} + \kappa_y\delta_t + \eta_t^{y} \quad (4)$$

where the measurement errors η_t^i are $i.i.d.N(0, r_i)$ and uncorrelated with each other and the common trend for the inflation series follows a random walk without drift:

$$\tau_t^{\pi} = \tau_{t-1}^{\pi} + \epsilon_t^{\pi} \quad (5)$$

The trend in inflation is therefore assumed to be driven by shocks that are $i.i.d.N(0, \sigma_{\epsilon^{\pi}})$ and uncorrelated with the cyclical component. Thus, the factors affecting inflation will have a permanent effect only if they stem from the innovations underlying the trend component, ϵ_t^{π}. Those innovations are also independent from the trends for output and unemployment:

$$\tau_t^{u}(1-L)^2 = \epsilon_t^{u} \quad (6)$$

$$\tau_t^{y}(1-L)^2 = \epsilon_t^{y} \quad (7)$$

where we impose the presence of two unit roots with the only purpose of obtaining a smooth trend. Note that the widely used Hodrick and Prescott (HP) filter yields a trend that minimizes the variance of its second differences, so in a sense, we are emulating the HP filter. However, our approach is more flexible than the HP filter not only because we do not impose any restriction on the variance of the innovations, but also because of our multivariate approach. The assumption that all trends are independent, i.e. each innovation is $i.i.d.N(0, \sigma_{\epsilon^i})$ and uncorrelated with each other, ensures that the dynamic correlation patterns between inflation and economic activity are driven by the cyclical component, which is specified as an autoregressive process of order two:

$$\delta_t = \alpha_1\delta_{t-1} + \alpha_2\delta_{t-2} + \zeta_t \quad (8)$$

where ζ_t is $i.i.d.N(0, \sigma_\zeta)$ and σ_ζ has been normalized to one.

Our model, even in its simplest form, aims to obtain an estimate of the economic cycle δ_t, which is the common factor among all series. Dynamic factor models were introduced in macroeconomics by Sargent and Sims (1977) and Geweke (1977), and in our current framework, increasing the number of variables may help to obtain sharper estimates of the unobserved factors. Chan *et al.* (2016) use a similar model with Bayesian restrictions for the estimation of the trend components and time-varying parameters to investigate whether there are periods of time where the ECB has been more tolerant of inflation or less. However, our paper is very different to theirs because we consider the use of variables reflecting expectations, which could absorb part of the time-variation, and because our focus on recent data. The next subsection describes how we incorporate inflation surveys.

4.3 Small X

The model presented above contains the key elements of a New-Keynesian Philips Curve (NKPC) if one interprets the trend as long term inflation expectations and the cyclical component as a measure of activity that is correlated with the unemployment rate. In this framework, we raise the question of how the survey variables should be introduced in the model. As these survey questions are supposed to reflect both short and long-term inflation expectations, they are added in a model consistent way. That implies that the variables are included in separate measurement equations, allowing for their informative content to improve the estimation of the underlying factors and thereby, the overall forecasting accuracy of the model.

Surveys as rational expectations forecasts

Given that the business survey asks respondents about inflation expectations for the next quarter and the consumer survey refers to one year ahead expected change in prices, the business (S_t^B) and consumer (S_t^C) survey information could be represented as follows:

$$S_t^B \propto E[\pi_{t+1}^{total}|\Omega_t] \tag{9}$$

$$S_t^C \propto E[\pi_{t+1}^{total} + \pi_{t+2}^{total} + \pi_{t+3}^{total} + \pi_{t+4}^{total}|\Omega_t] \tag{10}$$

Those surveys are qualitative, so respondents are asked whether they believe prices

will increase or decrease and, as a result, a sum of balances is obtained. Thus, we assume that the surveys reflect inflation expectations up to a multiplicative constant, α_B for the business survey and α_C for the consumer survey. The possibility that surveys represent an imperfect measure of those inflation forecasts is represented by the additive *i.i.d.* measurement error components η_t^B and η_t^C.

Equations (9) and (10) represent surveys as variables that are proportional to a rational expectations forecast, although they are contaminated with measurement errors. Those errors could capture deficiencies in the way information is communicated and processed. As suggested by Coibion *et al.* (2018), firms may update their beliefs in a Bayesian manner when presented with new information about the economy, but inflation expectations are not always a key determinant of their business decisions, so there may be a *rational inattention* motive affecting the quality of their replies. This would imply that the variance of the survey data compiled by the statistical agency may be smaller than what we would expect from a rational expectations forecast and as a result, their correlation with the expectations derived from the model would be smaller than one.

Introducing surveys in a model-consistent way

The trend of inflation follows a random walk, so $E[\tau_{t+1}^{\pi}|\Omega_t] = \tau_t^{\pi}$. As the cyclical component is assumed to follow an AR(2), the one-step-ahead prediction of the cycle can be formalized as $E[\delta_{t+1}|\Omega_t] = \alpha_1\delta_t + \alpha_2\delta_{t-1}$. By taking into account the forecasts for both the trend and the cycle, it turns out that the one-step-ahead forecast for inflation can be written as $E[\pi_{t+1}|\Omega_t] = \tau_t^{\pi} + \lambda_\pi\alpha_1\delta_t + \lambda_\pi\alpha_2\delta_{t-1}$. The arguments above regarding the rationality of the surveys lead to specify them in the measurement equation in terms of the expected value of the factors and (white noise) measurement components η_t^B and η_t^C:

$$S_t^B = \alpha_B\tau_t^{\pi} + \alpha_B\lambda_\pi\alpha_1\delta_t + \alpha_B\lambda_\pi\alpha_2\delta_{t-1} + \eta_t^B \Longleftrightarrow S_t^B = \alpha_B\tau_t^{\pi} + \phi_1\delta_t + \phi_2\delta_{t-1} + \eta_t^B \quad (11)$$

$$S_t^C = \alpha_C\tau_t^{\pi} + \alpha_C\lambda_\pi\alpha_1^*\delta_t + \alpha_C\lambda_\pi\alpha_2^*\delta_{t-1} + \eta_t^C \Longleftrightarrow S_t^C = \alpha_C\tau_t^{\pi} + \phi_1^*\delta_t + \phi_2^*\delta_{t-1} + \eta_t^C \quad (12)$$

where α_1^* and α_2^* that appear in the left-hand side of expression (12) are a non-linear combination of the parameters α_1 and α_2. Thus, the measurement equation for both surveys is partially determined by parameters that also appear in the so-called transition

equation. The right-hand side of expression (12) represents what will be referred to as the reduced form of the measurement equations. When the parameters ϕ_1, ϕ_2, ϕ_1^* and ϕ_2^* are estimated directly, i.e. without taking into account their dependence on α_1, α_2 and δ_π, we refer to this case as the *reduced form* of our model with consistent expectations (i.e. the X2-model in table 2). This formulation would not allow the surveys to impose the kind of cross equation restrictions implied by the formulation in equation (12). Hasenzagl *et al.* (2018) use this approach to integrate quantitative consumer surveys and professional forecasts. Although they use a model of the same class as ours, they do not impose the same cross equation restrictions implied by our definition of model consistency. Instead, they shrink the parameter space through the use of Bayesian priors.

Note that α_B and α_C are scaling factors that multiply all the factors, including the trend. Survey respondents do not decompose their forecasts in terms of trend and cycle. They simply answer whether they believe inflation will increase, stay the same, or increase. Hence, it is not obvious that the balance of responses could be informative about the trend, i.e. long-term expectations, as is nonetheless implied by equation (12). If, for example, inflation would be expected to follow a very clear decreasing path with small cyclical fluctuations around that path, the fact that all respondents will respond systematically according to their belief that inflation will keep on decreasing will never yield a decreasing pattern for the survey. The reason is that the number of respondents is finite and therefore the surveys have a clear lower (and upper) bound. This fact makes the surveys unsuitable to help us to quantify a measure of the trend in inflation. For this reason, and given the fact that they represent short- and medium-run inflation expectations, respectively, we assume that those surveys will only be linked to the cyclical component of inflation, which is going to drive short- and medium-term inflation expectations. Thus, the trend will disappear from the equations above.[6]

Coibion and Gorodnichenko (2015) defend the use of consumer surveys because consumers are very sensitive to changes in oil prices, which is a variable missing in the Small model. The Large model described in the next section contains additional variables, including oil prices. Thus, the cyclical component of inflation will be given by both the output gap, and oil prices. We will show that surveys can affect inflation forecasts via

[6]It can be shown that introducing the trend in the measurement equation for the surveys does not yield any improvements in forecasting accuracy.

two separate channels: (i) the economic slack expectations, (ii) the oil price expectations.

4.4 Large X

The Small model is extended in a straightforward manner by adding four more variables: two variables are directly related to inflation (oil prices and the import deflator) and two variables are tied to the real side of the economy (the mark-up and global business survey). First, oil prices and the import deflator are assumed to have their own trend and are driven by the common cyclical component (δ_t), as well as by a new factor (ϑ_t), that is common across the inflation variables. This factor may be considered to represent the oil cycle. The resulting equations related to inflation become:

$$\pi_t = \tau_t^{\pi} + \lambda_{\pi}\delta_t + \zeta_{\pi}\vartheta_t + \eta_t^{\pi} \tag{13}$$

$$\pi_t^{core} = \tau_t^{\pi} + \lambda_{core}\delta_{t-4} + \eta_t^{core} \tag{14}$$

$$\pi_t^{M} = \tau_t^{M} + \lambda_{M}\delta_t + \zeta_{M}\vartheta_t + \eta_t^{M} \tag{15}$$

$$P_t^{oil} = \tau_t^{Oil} + \lambda_{Oil}\delta_t + \zeta_{Oil}\vartheta_t + \eta_t^{Oil} \tag{16}$$

where the measurement errors η_t^i are $i.i.d.N(0, r_i)$ and uncorrelated with each other and the trends are specified as follows:

$$\tau_t^{\pi} = \tau_{t-1}^{\pi} + \epsilon_t^{\pi} \tag{17}$$

$$\tau_t^{M} = \tau_{t-1}^{M} + \epsilon_t^{M} \tag{18}$$

$$\tau_t^{Oil} = c_{Oil} + \tau_{t-1}^{Oil} + \epsilon_t^{Oil} \tag{19}$$

and the cyclical components of output (δ_t) and of oil prices (ϑ_t) follow a stationary AR(2) process:

$$\delta_t = \alpha_1\delta_{t-1} + \alpha_2\delta_{t-2} + \zeta_t^{\delta} \tag{20}$$

$$\vartheta_t = \rho_1\delta_{t-1} + \rho_2\delta_{t-2} + \zeta_t^{\vartheta} \tag{21}$$

where ζ_t is $i.i.d.N(0, \sigma_{\zeta})$.

Note that the import deflator π_t^M is allowed to have its own independent trend τ_t^M.

Oil prices enter the model in logarithms, and their trend is given by a random walk with drift. As opposed to Hasenzagl *et al.* (2018), we allow for the possibility that the cyclical component (δ_t) informs oil prices, recognizing that their evolution depends strongly on the business cycle. The main difference with respect to the smaller model is that the new oil component, ζ_{Mt}, which is independent from the output gap, loads on headline inflation. Thus, the measurement equations of headline inflation, import deflator and oil prices have a similar structure.

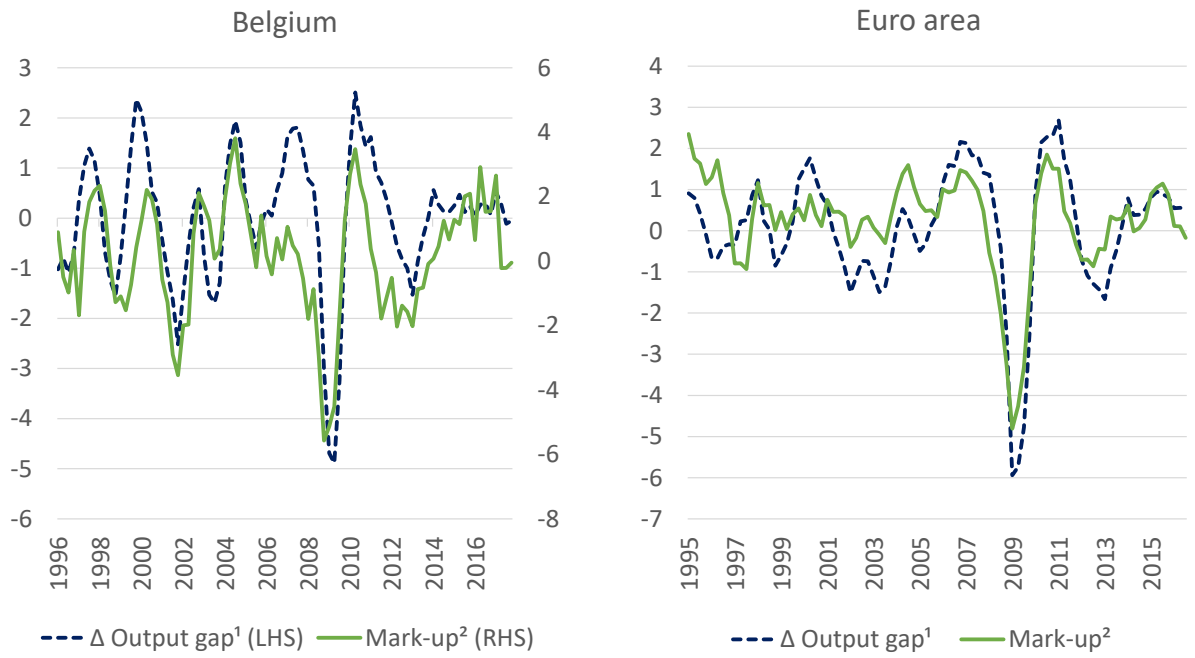
While the import deflator and oil prices should help with the identification of imported inflation, the two other new variables (the overall business confidence indicator and the mark-up) are likely to improve the identification of the economic cycle, represented by δ_t. The advantage of the business confidence indicator is that it is published before the end of each month, and as shown by de Antonio Liedo (2015) and Basselier *et al.* (2018), it has a relevant contribution at nowcasting GDP growth in Belgium and the euro area. Thus, the inclusion of this synthetic variable can help to improve the estimation of GDP's cyclical component in real time.[7]

Although much less timely than the business surveys, the mark-up is a widely monitored variable for economists following inflation developments as it relates to the GDP deflator and the so-called unit labour cost, which measures the wages per capita and turns out to be a proxy for labour productivity. In practice, the mark-up variable measures the extent to which aggregate price levels in the economy are higher or lower than labour productivity, leading to inflationary and deflationary pressures. In this paper, this variable will be directly linked to the changes in the economic cycle, which is a key unobserved component of our model. By doing so, we assume that when the economy grows beyond potential, there will be an equivalent increase in the mark-up. Figure 6 reveals that the mark-up observed for Belgium and the euro area seems to be highly correlated with the changes in the output gap. Intuitively, this suggests that by including the mark-up variable, it will be possible to obtain a more precise estimate of the economic cycle.

The equations for the business survey and the mark-up do not require additional trend

[7]We assume these data are linked to the year-on-year growth rate of real GDP, as suggested by de Antonio Liedo (2015) and Basselier *et al.* (2018). Although this survey aggregates questions regarding expectations for economic activity two quarters ahead, we could not link them to the expected factors derived from the model because such kind of specifications turned out to be at odds with the data. In other words, this variable cannot be introduced in a model consistent way, as we do for the inflation surveys.

Figure 6: Mark-up and change in the output gap



Sources: EC, NAI, NBB.
[1] This output gap was obtained by HP-filtering the real GDP series as a proxy for potential output.
[2] The mark-up is defined by the YoY growth of unit labour cost growth – YoY growth of GDP deflator.

components. They are both informed by the economic cycle δ_t:

$$\begin{aligned} S_t^Y &= m_S + \kappa_S(\delta_t - \delta_{t-4}) + \eta_t^S \\ \mu_t &= m_\mu + \kappa_\mu(\delta_t - \delta_{t-4}) + \eta_t^\mu \end{aligned} \tag{22}$$

In addition to the four variables mentioned above, our Large X-model will be characterized by the *model-consistent* introduction of the business and consumer survey question on price expectations in the measurement equation. In other words, the surveys will be linked to the expectation of the factors derived from the model. For the business survey, which we assume to be linked to inflation expectations one quarter ahead, we have:

$$\begin{aligned} S_t^B &= \alpha_B \tau_t^\pi + \alpha_B \lambda_\pi \alpha_1 \delta_t + \alpha_B \lambda_\pi \alpha_2 \delta_{t-1} + \alpha_B \zeta_\pi \rho_1 \vartheta_t + \alpha_B \zeta_\pi \rho_2 \vartheta_{t-1} + \eta_t^B \\ &\Longleftrightarrow \\ S_t^B &= \alpha_B \tau_t^\pi + \phi_1 \delta_t + \phi_2 \delta_{t-1} + \omega_1 \delta_t + \omega_2 \delta_{t-1} + \eta_t^B \end{aligned} \tag{23}$$

The surveys should now help us to obtain a sharper estimate of the cyclical component

of inflation, which is given by both the economic slack δ_t and oil developments ϑ_t. The consumer survey, which is assumed to represent one year ahead inflation projections, is introduced into the measurement equation as follows :

$$
\begin{aligned}
S_t^C &= \alpha_C \tau_t^\pi + \alpha_C \lambda_\pi \alpha_1^* \delta_t + \alpha_C \lambda_\pi \alpha_2^* \delta_{t-1} + \alpha_C \zeta_\pi \rho_1^* \vartheta_t + \alpha_C \zeta_\pi \rho_2^* \vartheta_{t-1} + \eta_t^C \\
&\Longleftrightarrow \\
S_t^C &= \alpha_C \tau_t^\pi + \phi_1^* \delta_t + \phi_2^* \delta_{t-1} + \omega_1^* \delta_t + \omega_2^* \delta_{t-1} + \eta_t^C \qquad (24)
\end{aligned}
$$

where $\phi_1^* = \alpha_C \lambda_\pi \alpha_1^*$. Note that α_1^* is a non-linear combination of coefficients $\alpha_1, \alpha_2, \lambda_\pi$ resulting from cumulating the forecasts for $\delta_{t+1}, \delta_{t+2}, \delta_{t+3}$ and δ_{t+4}. Equivalently, $\omega_1^* = \alpha_C \zeta_\pi \rho_1^*$, where ρ_1^* is also a non-linear combination of coefficients $\rho_1, \rho_2, \lambda_\pi$. Hence, adding this variables has a very small cost in terms of new parameters to estimate. On the contrary, they help to better identify the Philips curve coefficient λ_π and the cyclical component parameters $\rho_1, \rho_2, \alpha_1, \alpha_2$.

Please refer to the Annex for the complete state-space representation of the Large X-model, which encompasses the Simple X-model described before (see expressions A.1 and A.2).

4.5 Estimation

All models are written in state-space form. For didactic purposes, we have used the representation of the expectations-augmented UCM in expressions A.1 and A.2. This expression highlights that the factor loadings in the measurement equation of the surveys depend on the parameters of the transition equation. It is important to underline that the incorporation of surveys imposes cross-equation restrictions that can potentially improve the estimation of the parameters and the factors.

From a computational point of view, however, we use a very different (but equivalent) state-space representation, inspired by the traditional recursions used for the estimation of ARIMA models (see for example Brockwell and David, 1987). Instead of deriving the expectation of the factors in terms of the transition equation matrices and the current and lagged factors, as suggested in the annex, we incorporate those forecasted factors directly in the state vector. Thus, the state vector contains both forecasts of the factors, current

and lagged factors.

Estimation is conducted maximizing the *marginal likelihood* with optimization methods (Levenberg–Marquardt algorithm) after normalizing all the series. The marginal likelihood definition by Francke *et al.* (2010) is used instead of the more usual *diffuse likelihood* because the latter could potentially lead to invalid inference in a model like ours, where the parameters of the measurement equation cannot be made independent from the non-stationary factors. In our expectations-augmented model, however, we have assumed that the cyclical component is stationary and the inflation trend does not appear in the measurement equation of the surveys, so the diffuse and the marginal likelihood turn out to yield equivalent results. The R code required to specify our model and estimate it through the state-space framework developed in Java for *J*Demetra+ can be accessed via GitHub.

5 Results

5.1 Set-up of the forecasting evaluation

We perform a pseudo real-time forecasting exercise, during which we take into account the publication lags of the different series, but not the presence of data revisions.[8] Table 3 represents our dataset, as it would look like at the time when the first out-of-sample forecast is made. It features a ragged edge because we assume that at the time of calculating the forecasts, we are at the end of the first month of a given quarter. At this point, an out-of-sample forecast will be performed for inflation in the current quarter and up to four more quarters ahead. The evaluation period for the out-of-sample forecasting exercise was chosen in order to include the great recession, so we start at the end of October 2007. At this point, inflation data until September 2007 are already published and data from 1995 up to the third quarter of 2007 can be considered as known. The same holds for GDP and the unemployment rate, where data for 2007Q3 would be published 30 days after the end of that quarter. As regards the mark-up and the import deflator, however, they are available with a delay of two months and data for Q3 would only be published at the end of November. Hence, in our specific set-up, where we consider the forecast to be made already at the end of October, this implies that we have two unknown quarters for these variables. For oil, we always take the average of the full quarter except for the current quarter (which is, in our example case, 2007Q4). That is, at the end of October, we only dispose of data of that first month. For the global sentiment indicator, the set-up is similar for the current quarter. For the previous quarters, however, we take the last month of the quarter instead of the average of the quarter, since the correlation of the last month's datapoint with GDP growth is slightly higher. As regards the surveys on inflation, we always take the first month of each quarter.

Coefficients are estimated based on an expanding dataset, that starts in 1995Q1 and runs – at least – until 2007Q4.

[8] Inflation data, our inflation expectations data, and the global business survey, which is important to determine the output gap, are not revised after the initial release, so the issue of data revisions may be less relevant in our context than in nowcasting applications focusing on real economic activity.

Table 3: Dataset used for the first out-of-sample forecast

	Total inflation	Core inflation	Business and consumer survey on price expectations	GDP	Unemployment rate	Mark-up	Import deflator	Oil prices	Global survey on economic sentiment
1995 Q1								Average of Q	Last M of Q
...								Average of Q	Last M of Q
2007 Q2								Average of Q	Last M of Q
2007 Q3								Average of Q	Last M of Q
2007 Q4								First M of Q	First M of Q

Note: This table shows how our (ragged) dataset looks like at the end of October 2007 (i.e. the first month of the quarter).

5.2 A first look: one-step-ahead forecasts

This section shows the one-step-ahead forecasts that have been generated by the models in this paper, against the true outcome. In the next section, results will be discussed more formally, by means of Root Mean Squared Errors (RMSE).

Belgium

Figure 7 shows the QoQ-rates for Belgian **total inflation** and the 1-step ahead forecasts produced by three different models depicted in table 2 . The left-hand side of the graph already allows us to state that the Small and Large model can yield quite different forecasts. Furthermore, we see that the forecast produced by the Large model is generally a bit closer to the true outcome than the Small, especially in the periods of 2008-2009 and 2013-2015. Figure 8 allows for a decomposition of the difference between the two forecasts, into oil, the cycle and the inflation trend. The left-hand side of this figure confirms that, since 2011, the Large forecast has generally been lower than the Small. The decomposition shows that this difference was largely due to a different cycle in both models. Indeed, the inclusion of survey information may have an impact on the estimation of the unobserved components and the estimate of δ_t, the economic cycle, may change between different models.[9]

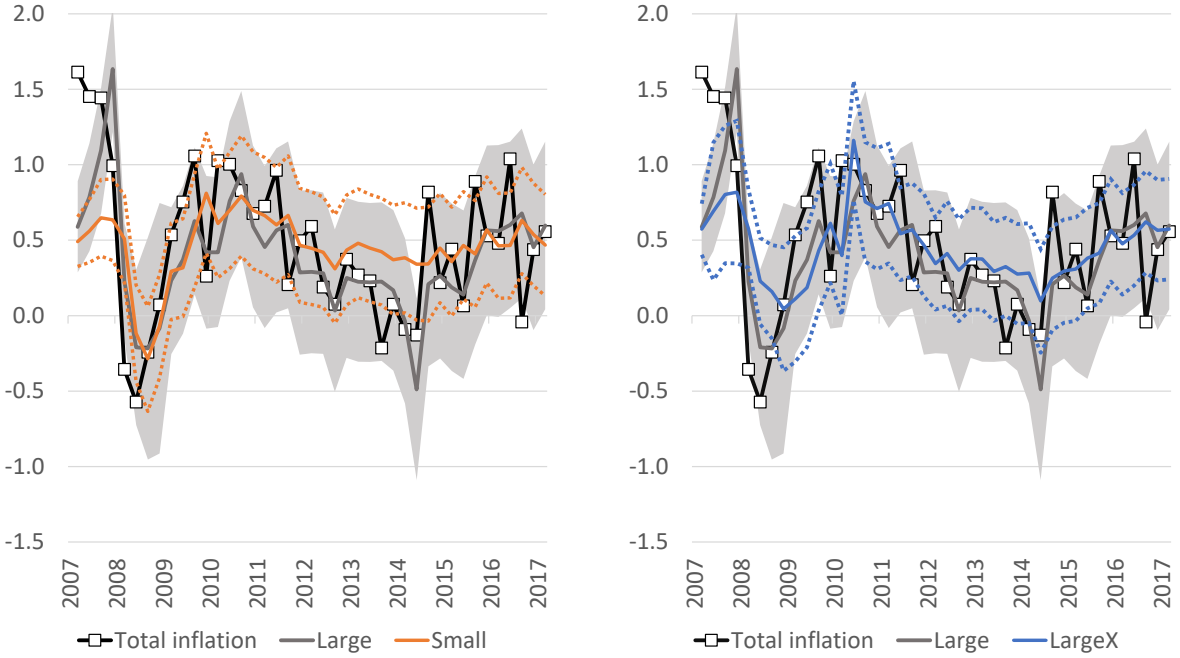
To assess the difference between forecasts for total inflation made by the Large and Large X-model, we refer to the right-hand-sides of figures 7 and 8. These forecasts lie closer together and more detailed calculations are required to verify which one fits the actual inflation best (cf. Section 5.3). If anything, it is possible to deduct that the Large X-model tends to yield a smoother forecast as it does not reach the same peaks and dips

[9]This is demonstrated by the recursive estimation of the output gaps (i.e. filtered output gaps) that are available in figure A.1). The smoothed output gaps estimated by all six models are also available in Annex (figure A.2).

as the Large model. More specifically, one noticeable dip in the Large forecast, which is not produced by Large X (nor by Small), is situated in the first quarter of 2015. Figure 8 demonstrates that the forecast difference at this point is clearly driven by oil. At this specific point, oil prices dropped by almost 40% on a quarterly basis; the strongest drop observed since the great recession. Obviously, this oil price movement will not be captured by the Small model, as it does not include oil among its dependent variables. What is more remarkable, however, is that the Large X-model incorporates a less negative impact from oil on the forecast, causing it to remain more stable than the Large. Hence, it seems that, due to the inclusion of survey information, the short-term forecasts for total inflation would become less sensitive to oil.

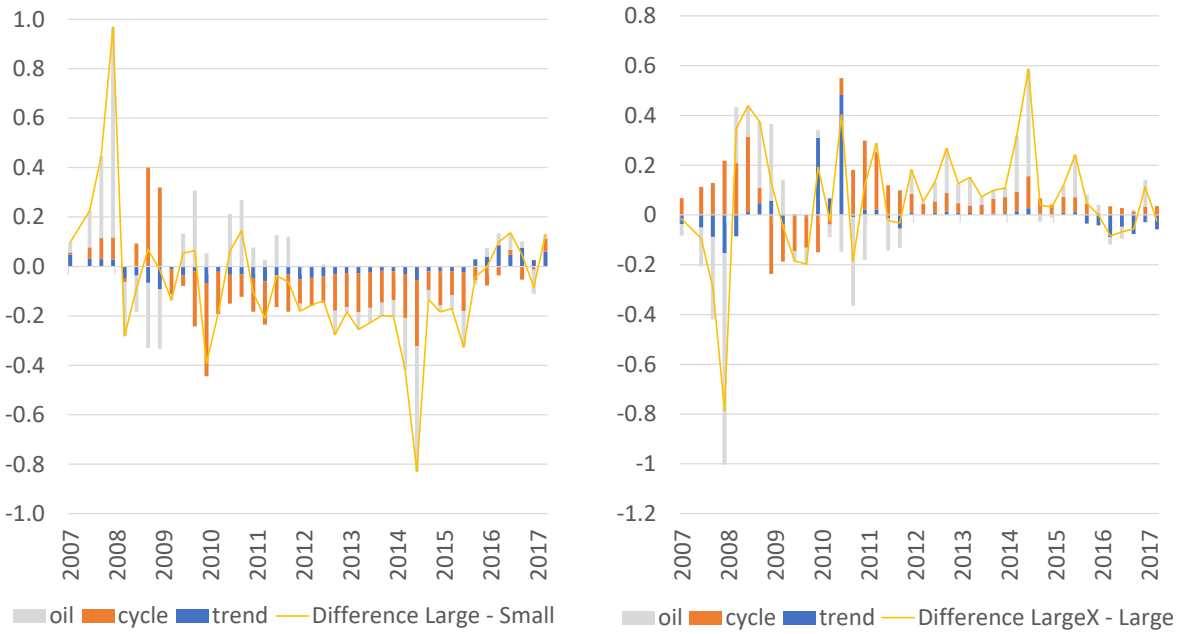
Turning to Belgian **core inflation**, the left-hand side of figure 9 immediately shows some interesting results. From 2011 to 2013, the Small forecast lies at the upper confidence bound of the Large forecast. It is thus consistently higher during this period and, as it would seem, also closer to the actual outcome for core inflation. The decomposition of the difference between the forecasts can be found in figure 10. It shows that the Large forecast has a more negative contribution from the cycle, as well as from the trend, from 2011 onwards. The part of oil prices that is independent from the business cycle does not have a direct influence on core inflation by construction (cf. equation (14)), which explains why oil does not appear in the decomposition of the forecast (difference). From the right-hand side of these figures, we deduct that the forecasts produced by the Large and the Large X-model are quite similar as of 2012. From 2010 to 2012, however, the forecast made by Large X demonstrates some more volatility, which relates better to the actual core inflation.

Figure 7: Belgium: 1-step ahead forecast for total inflation



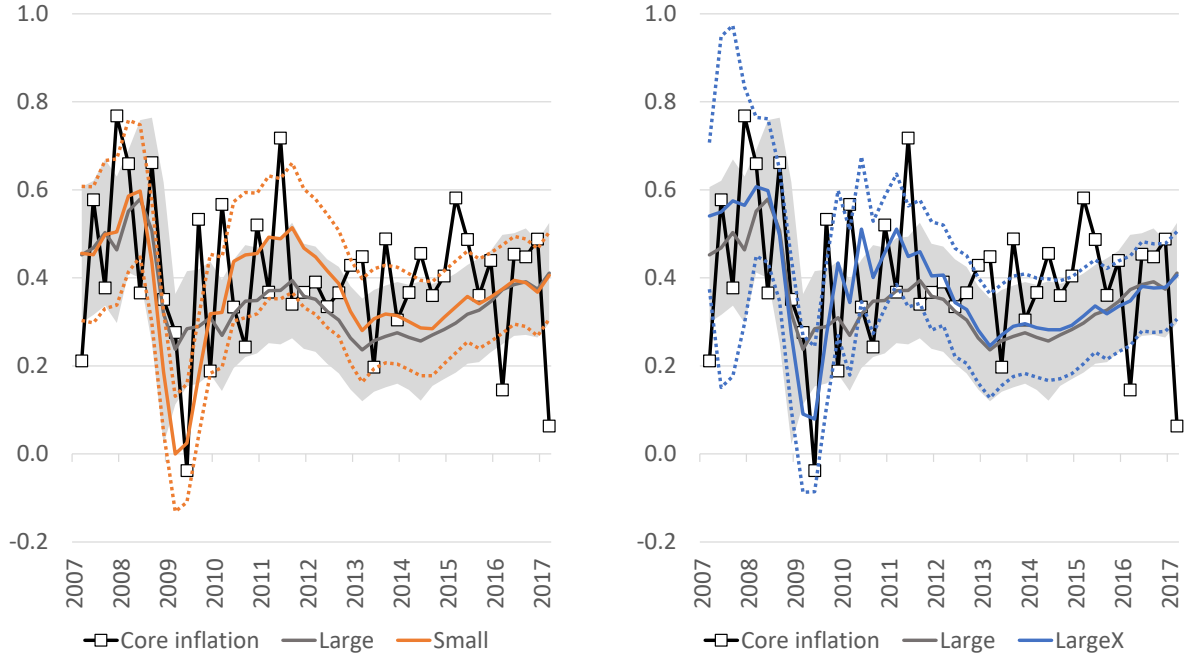
Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large model. The dotted lines show the upper and lower confidence bounds for, respectively, the Small model on the left side and the Large X-model on the right side.

Figure 8: Belgium: decomposition of difference between forecasts for total inflation



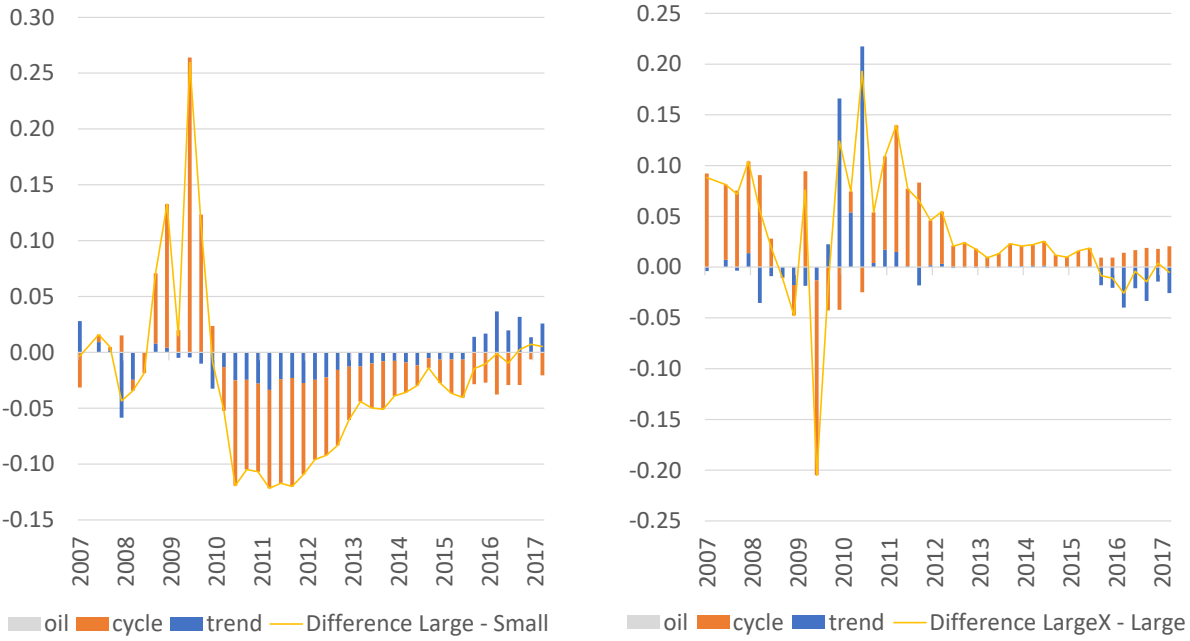
Source: NBB.

Figure 9: Belgium: 1-step ahead forecast for core inflation



Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large model. The dotted lines show the upper and lower confidence bounds for, respectively, the Small model on the left side and the Large X-model on the right side.

Figure 10: Belgium: decomposition of difference between forecasts for core inflation

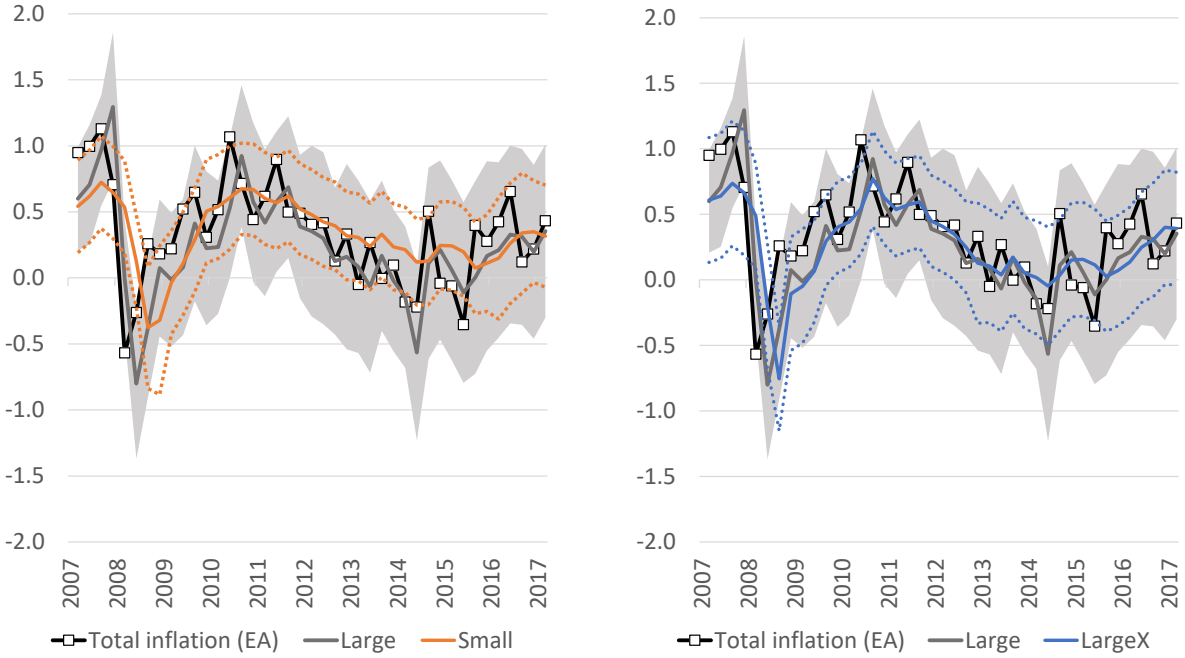


Source: NBB.

Euro area

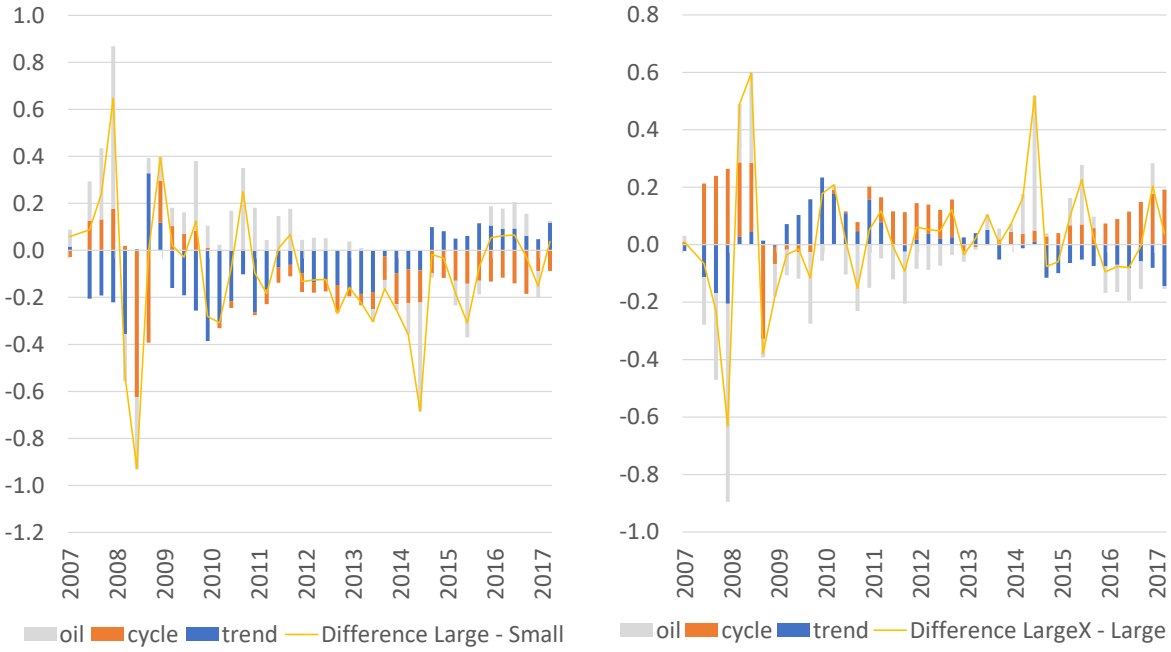
As regards the 1-step-ahead forecasts for **total inflation** in the euro area, figure 11 indicates that the Large forecast lies closer to the actual series than the Small forecast. Remarkably, figure 12 reveals that the difference between these two forecasts is to a large extent driven by a different estimate for trend inflation, which would have been generally lower according to the Large model. The forecasts produced by the Large and Large X-models lie quite close together, although the confidence band around the survey-augmented model is clearly more moderate. The main differences between the two point forecasts occur in 2008, 2014 and 2015. For the latter two periods it holds that the Large forecast incorporates a more negative impact from oil prices. The conclusion is therefore the same as for Belgium: including survey information appears to temper the weight of oil changes on the short-term inflation forecast. Turning to **core inflation**, it is immediately clear that the forecast made by the Large model is difficult to beat (cf. figure 13). While the forecasts produced by the Small, the Large and the Large X differ very little in the recent period, there is a wide gap during the great recession. In the course of 2009-2010, both the Small and Large X-model predicted euro area core inflation to be very low, while this wasn't actually the case. According to the decomposition (figure 14), this large difference is mainly due to a different assessment of the cyclical component.

Figure 11: Euro area: 1-step ahead forecast for total inflation



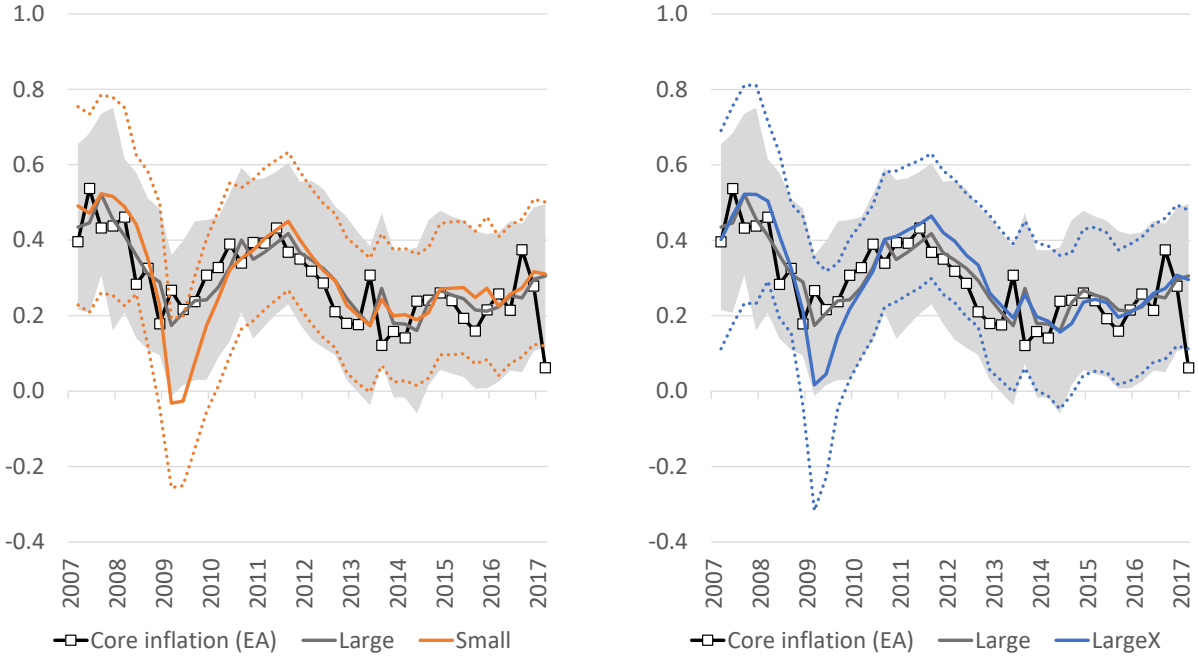
Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large model. The dotted lines show the upper and lower confidence bounds for, respectively, the Small model on the left side and the Large X-model on the right side.

Figure 12: Euro area: decomposition of difference between forecasts for total inflation



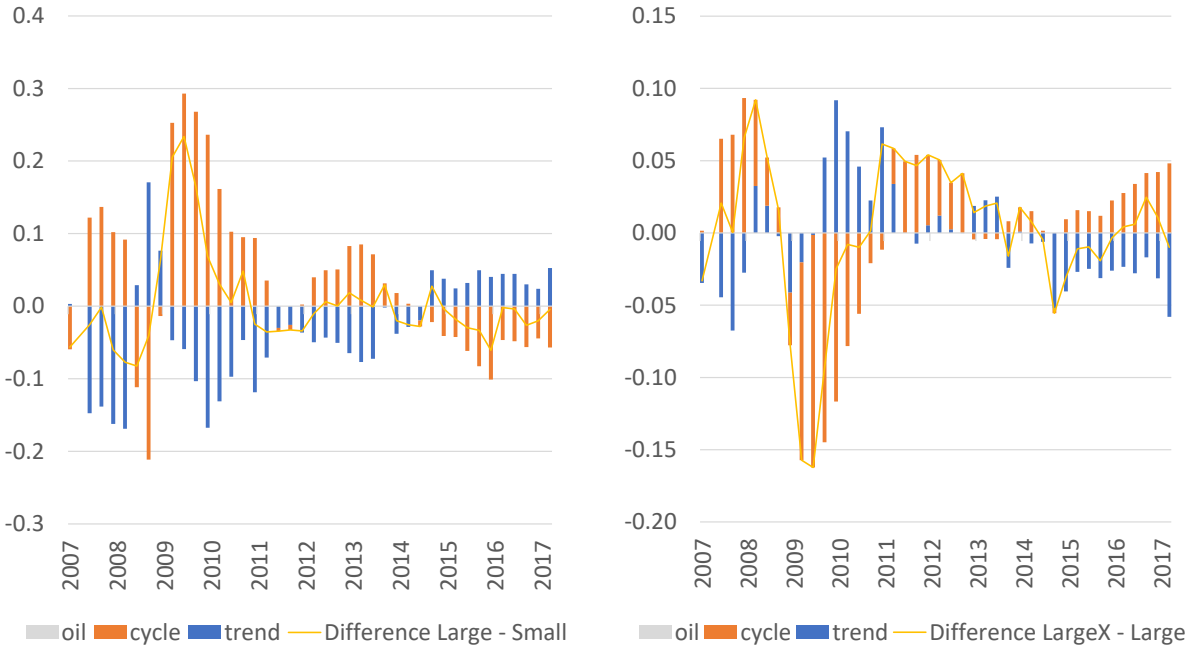
Source: NBB.

Figure 13: Euro area: 1-step ahead forecast for core inflation



Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large model. The dotted lines show the upper and lower confidence bounds for, respectively, the Small model on the left side and the Large X-model on the right side.

Figure 14: Euro area: decomposition of difference between forecasts for core inflation



Source: NBB.

5.3 Quantifying forecasting accuracy

The Root Mean Squared Errors (RMSE) can be calculated for the forecast outcomes of all the models. As a benchmark, the RMSE is calculated for a naïve forecast, similar to the one put forward by Atkeson and Ohanian (2001), where the expected rate of inflation equals the sum of observations over the past h quarters. Results will be shown relative to the naïve RMSE. Ideally, all lines should lie below '1', which would indicate that they perform relatively better than the naïve. It is interesting to note that even if the corresponding RMSE sometimes lie very close together and their differences are unlikely to be statistically significant. the previous section has demonstrated some qualitative differences in the forecasts produced by the models (for example, between the Large and Small model in figure 9). This may imply that *combining* certain forecasts may yield additional information and could further lower the RMSE.

Belgium

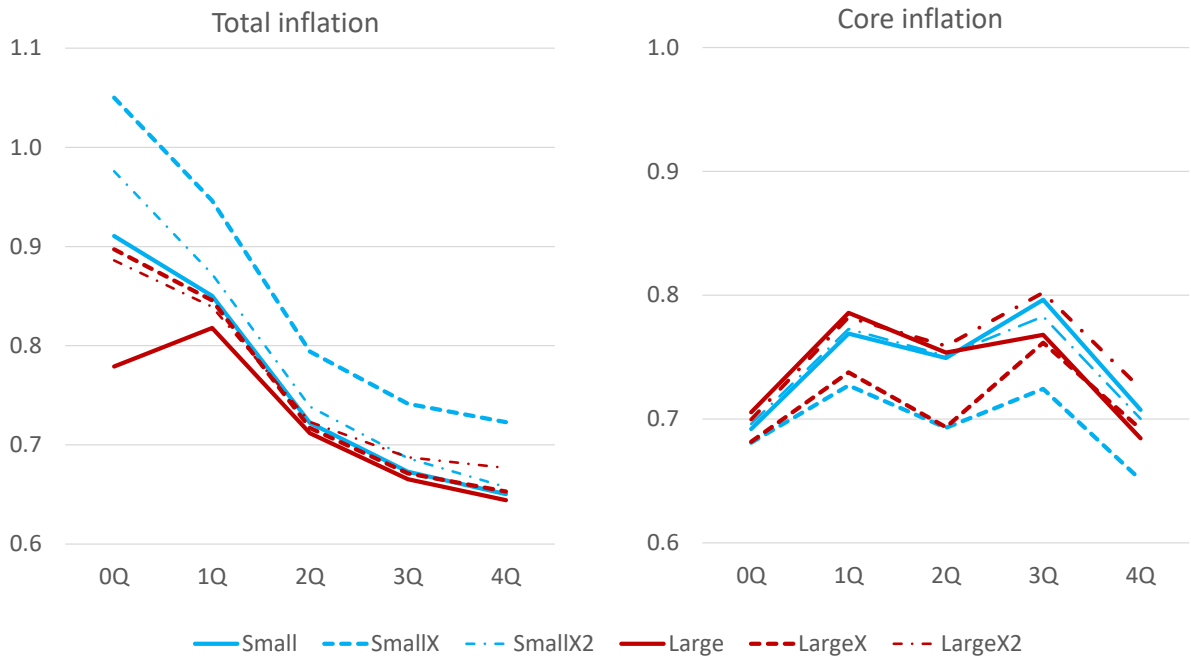
Results for Belgium are shown in figure 15, relative against the naïve benchmark for different horizons, so values smaller than one imply that our model is more accurate than the benchmark. When it comes to total inflation, the gain from including survey information in the forecasting model seems limited at first sight, as the most accurate forecasts are produced by the large model without survey expectations. However, keep in mind that the graph displays expected inflation *cumulated* over the forecasting horizon and the accuracy of the Large and Large X-models mainly (or only) differs at the shortest horizon. This suggests that the two-steps-ahead forecast from Large X is actually more accurate than the one coming from Large.

Forecasts for core inflation, on the other hand, could benefit more clearly from the inclusion of survey information, as the dotted lines (expectations-augmented models) lie beneath the full lines (models that include no surveys).

Euro area

Figure 16 shows the relative forecasting accuracy of the models for the euro area inflation rates. For both total and core inflation, Large delivers the most accurate forecasts over the evaluation period. The usefulness of survey information seems less clear than in the Belgian case: models augmented with expectations (X or X2) are generally unable to further improve the forecasting accuracy. Also, as indicated by the right-hand side of

Figure 15: Belgium: relative RMSE for six models for total and core inflation



Source: NBB.

Note: the forecast evaluation period runs from 2007Q4 to 2017Q4.

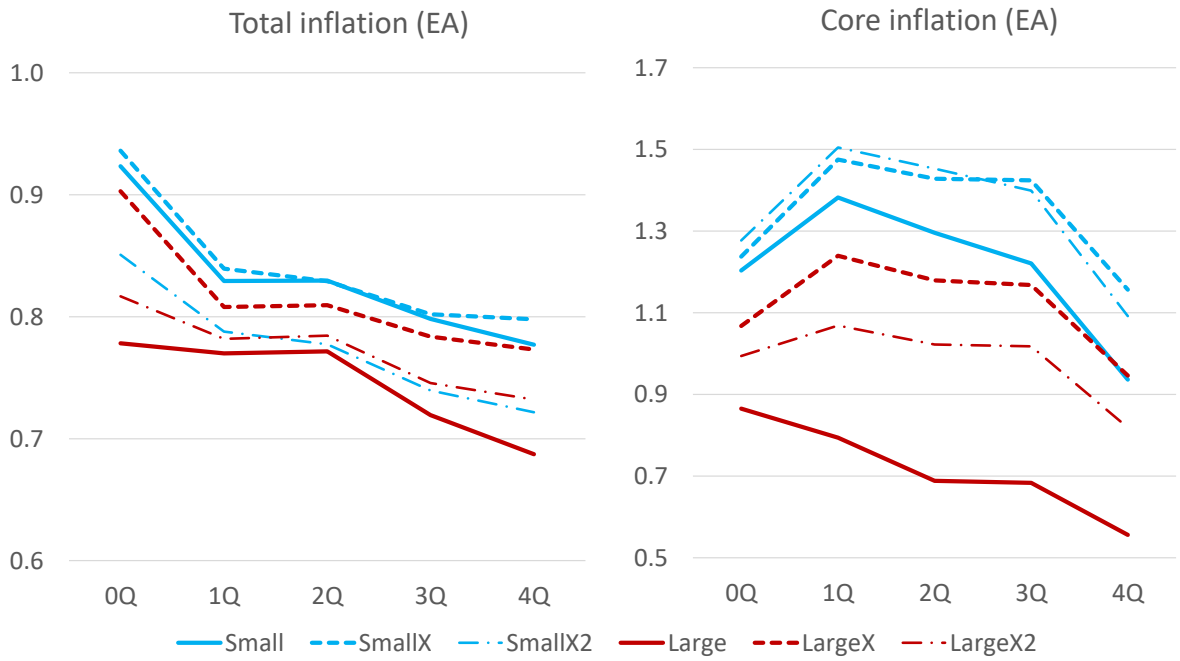
the graph, only the Large model manages to outperform the naïve benchmark for core inflation.

5.4 Adding noise: AR(1) measurement errors in the two survey equations

Model consistency may impose a very strict restriction on the way survey data is exploited. First, in the presence of model misspecification, it may not be a good idea to link the surveys with forecasts coming from the (possibly misspecified) model. Second, even if model misspecification would be small, our qualitative measures of inflation expectations are a sum of balances where the respondents are simply asked to produce a binary output, i.e. "prices will go up" vs "prices will go down". In this context, it may be too much to expect that the balance of responses will exactly match a quantitative measure of inflation expectations that can be made consistent with the model.

By including autocorrelated measurement errors that are orthogonal to all factors, we aim to re-interpret the fluctuations in the surveys according to their correlation with the model factors. This way, less weight would be attributed to fitting the surveys in a

Figure 16: Euro area: relative RMSE for six models for total and core inflation



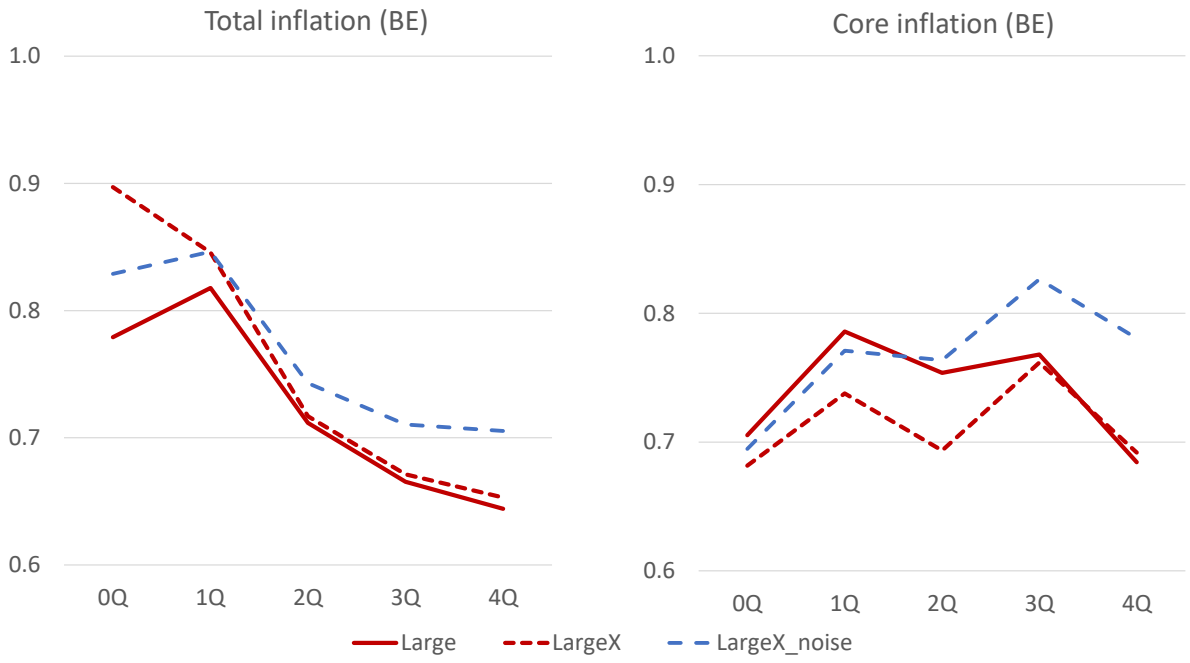
Source: NBB.
Note: the forecast evaluation period runs from 2007Q4 to 2017Q4.

model-consistent way.

As shown by the blue line in figure 17, for Belgium, this new specification (called "X noise") does typically not improve the accuracy of the Large X-model, with the exception of the current period forecast for total inflation. It is likely that, in the alternative model, by allowing for more noise in the measurement equation of the surveys, the role of the surveys decreases in favour of the hard data on oil prices, which in Belgium is highly correlated with headline inflation. This would explain why the current-quarter forecast of the model with noise is more accurate for total inflation, where we found earlier that surveys tend to diminish the weight given to oil price changes (cf. Section 5.2).

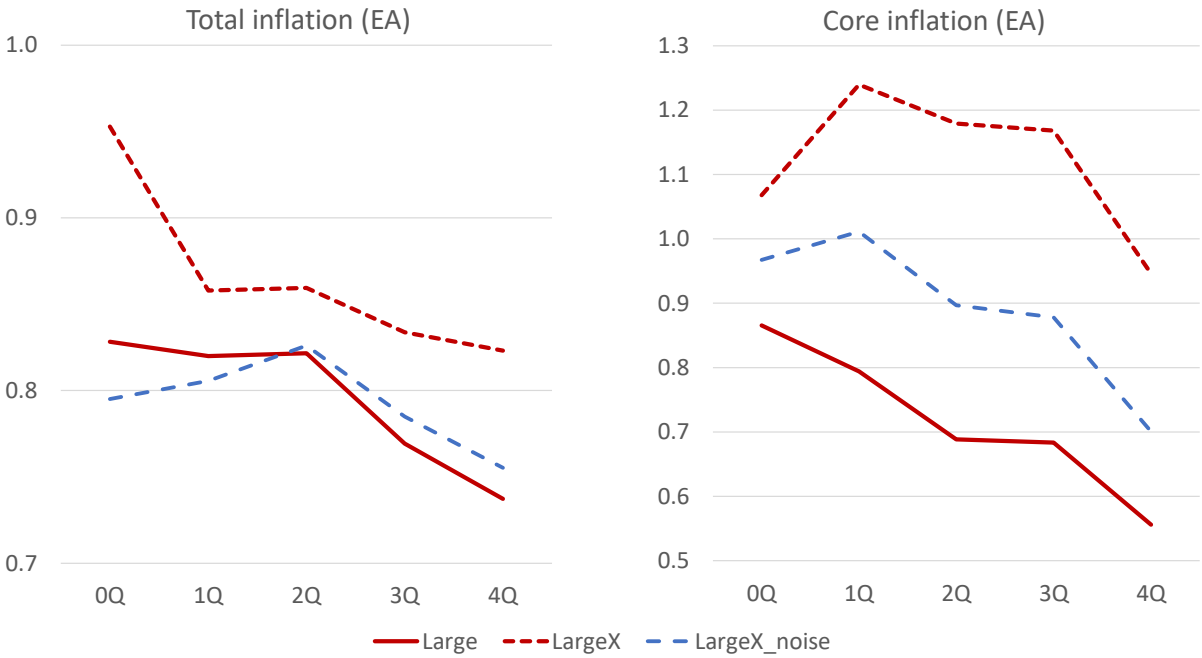
For the euro area, the alternative model allowing for persistent measurement errors consistently outperforms the Large X-model, while it only manages to outperform the Large model without any survey information at the horizons 0 and 1 (figure 18).

Figure 17: Belgium: sensitivity analysis of large models



Source: NBB.

Figure 18: Euro area: sensitivity analysis of large models



Source: NBB.

6 Focus on the recent period and interpretation

6.1 A change in the forecast evaluation sample

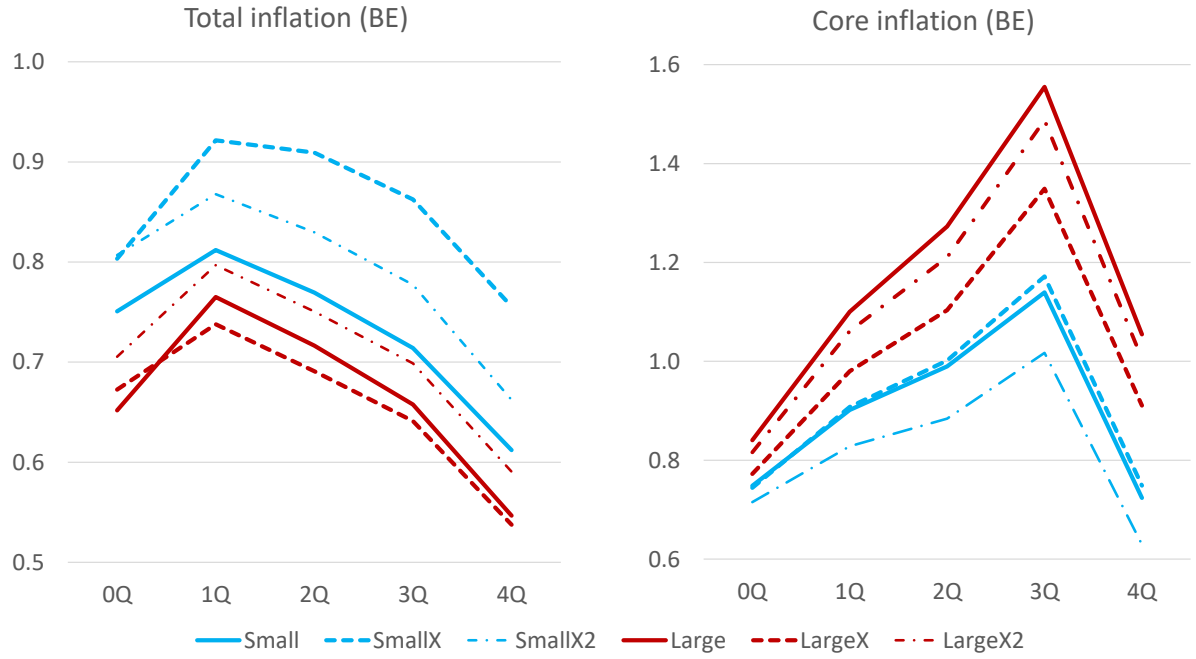
Our pseudo out-of-sample evaluation suggests that the reported differences in accuracy are related to a few outliers during the great recession period. Figure 13, in particular, illustrated the large differences in performance over three consecutive quarters alone. This section evaluates how our results (and conclusions) may change if we focus on the most recent period only and start evaluating the forecasts as of 2012. After all, this is the period that is of most interest to us: due to the appearance of inflation (forecast) puzzles, we wanted to investigate the usefulness of surveys. Results are shown in figures 19 and 20.

For Belgian core inflation, the conclusion remains that the survey-augmented models are more accurate. However, while before the Large and Small models were found to be equally accurate, the Small model prevails when focusing on the shorter evaluation sample. For Belgian total inflation, the shorter evaluation sample could lead us to conclude that adding surveys could be beneficial (in case of the Large model).

Turning to the euro area, the survey-augmented X2-models for total inflation seem to beat the Large model, when the forecasting horizon reaches at least 1 quarter ahead. Also for core inflation, the Large X2-model is found to be somewhat more accurate than the Large over this specific evaluation sample.

As the differences in RMSE's can be very little, it is worth looking at the actual forecasts. More specifically, we investigate 4-steps-ahead forecasts for total and core inflation, for Belgium and the euro area respectively. Inflation rates and forecasts are cumulated over 4 periods, in order to make the differences clear on a graph. Figure 21 is mainly interesting from the perspective of core inflation (on the right-hand side of the graph). It is visually immediately clear that the Large model performs best during the great recession. However, in the most recent period, say as of early 2013, the Large X2-model is actually consistently (much) closer to the actual core inflation in Belgium. This figure thereby also illustrates the "missing low inflation puzzle" for Belgium, because all forecasts were significantly below the actual outcome in the recent period. One would have expected (core) inflation to be much lower than it turned out. While the puzzle

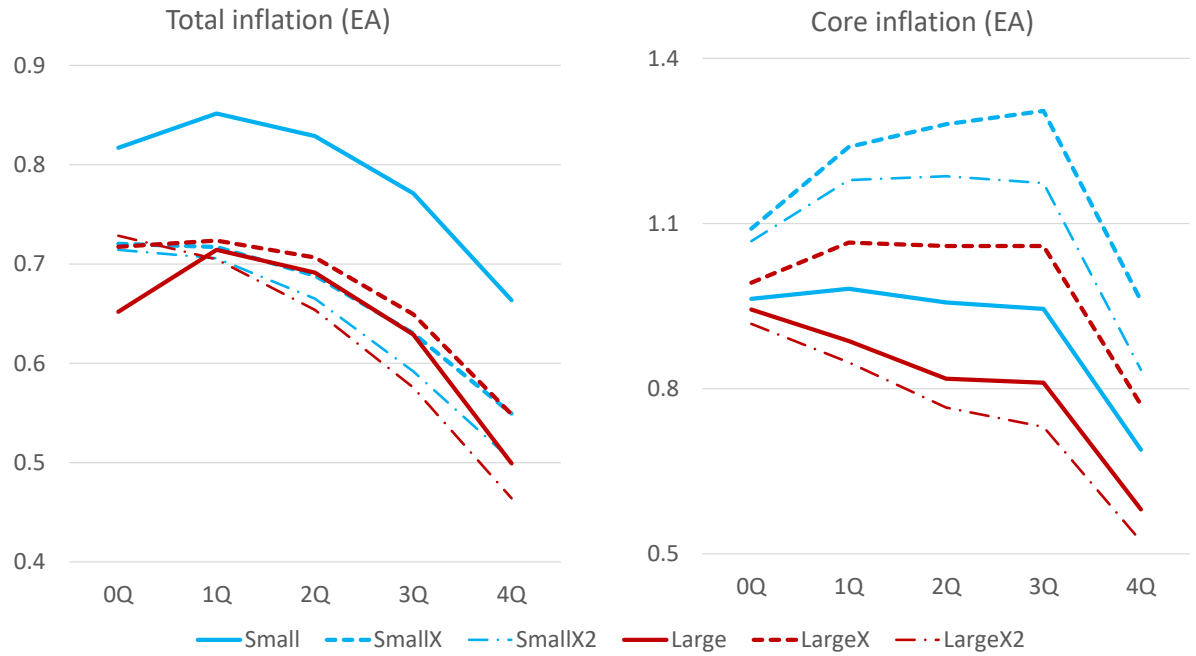
Figure 19: Belgium: relative RMSE for six models for total and core inflation (robustness)



Source: NBB.

Note: the forecast evaluation period for the robustness exercise runs from 2012Q1 to 2017Q4.

Figure 20: Euro area: relative RMSE for six models for total and core inflation (robustness)



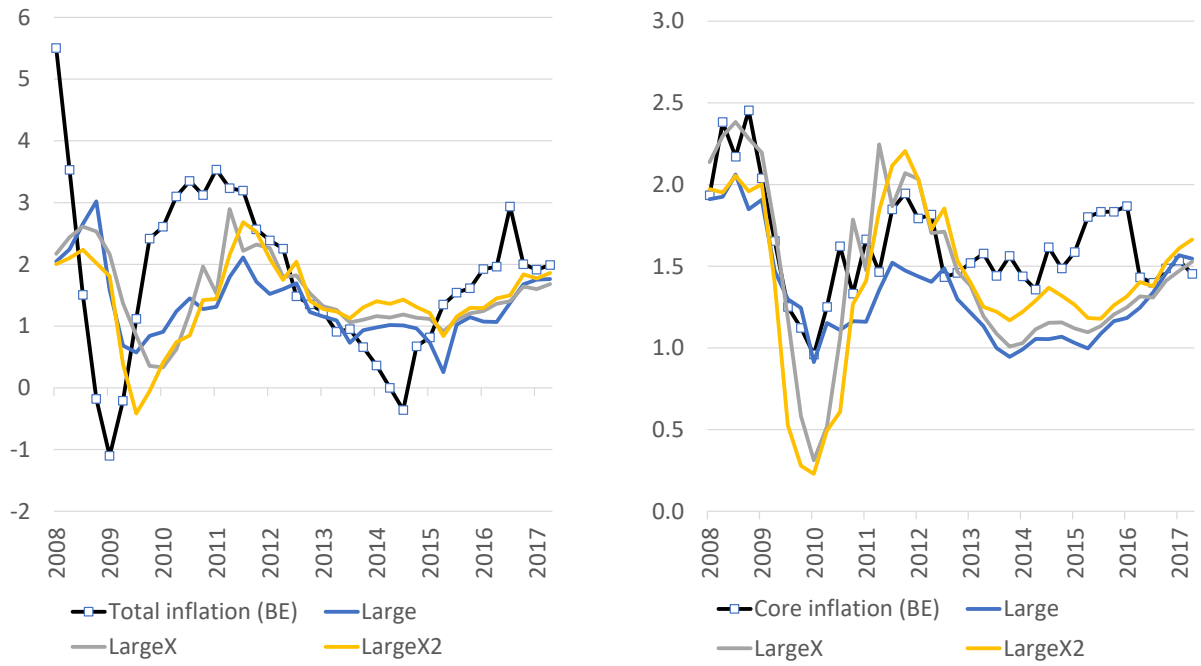
Source: NBB.

Note: the forecast evaluation period for the robustness exercise runs from 2012Q1 to 2017Q4.

cannot be completely solved using survey information, adding this source of information does help. For Belgian total inflation, the forecasts incorporating survey information only clearly prevail as of 2015.

For the euro area, total inflation as of 2011 is best approximated by models containing surveys; either in a model-consistent way (X) or in a looser way (X2). The forecasting puzzle here is different than for Belgian core inflation: forecasts for euro area inflation were generally too positive during 2013-2016 and inflation surprised on the downside. For euro area core inflation, there is no obvious forecasting puzzle, yet forecasts made by the Large X2-model seem to end up closest to the actual inflation rates between 2012 and 2015 (figure 22).

Figure 21: Belgium: 4-steps ahead inflation forecasts (cumulated figures)

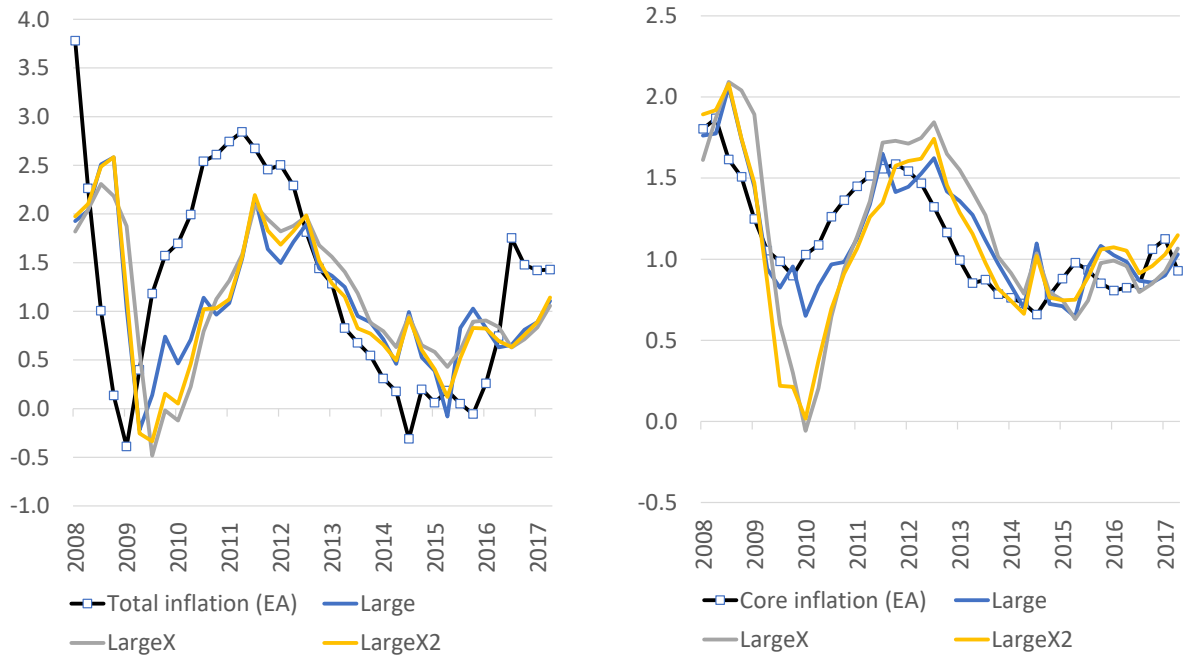


Source: NBB.

6.2 Businesses or consumers?

Now that the previous sections have established that, at least for certain periods, survey information may be useful for the purpose of inflation forecasting, one may wonder which of the two surveys is yielding the most relevant information: is it the business or the consumer survey?

Figure 22: Euro area: 4-steps ahead inflation forecasts (cumulated figures)



Source: NBB.

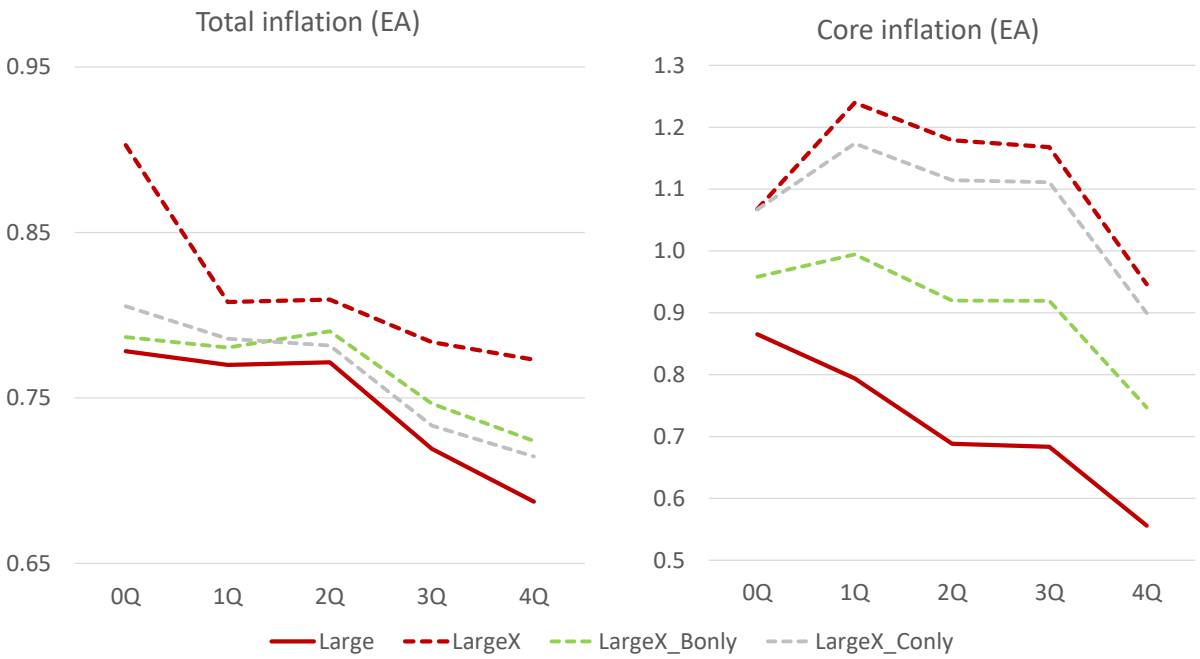
Figure 23: Belgium: relative RMSE of survey-augmented models (business versus consumer surveys)

Source: NBB.
Note: The forecast evaluation period runs from 2007Q4 to 2017Q4. Bonly and Conly represent the case in which the model is augmented with survey information from businesses, respectively consumers, only.

For Belgian core inflation, accuracy gains realized by Large X mostly come from the short-term price expectations in the business surveys. The model that includes business expectations only ("Bonly" in figure 23) is about as accurate as the normal Large X-model, while the model that includes consumer expectations only ("Conly") clearly delivers a less accurate forecast. This suggests that disregarding the readily available survey information from price-setters leads to sub-optimal inflation projections.

While for the euro area, the added value from surveys is less clear than for Belgium, figure 24 yields the same conclusion as in the Belgian case. If anything, survey information from businesses ("Bonly") tends to improve the forecasting accuracy most.

Figure 24: Euro area: relative RMSE of survey-augmented models (business versus consumer surveys)



Source: NBB.
Note: The forecast evaluation period runs from 2007Q4 to 2017Q4. Bonly and Conly represent the case in which the model is augmented with survey information from businesses, respectively consumers, only.

7 Conclusion

The motivation for this paper can be traced back to the recent difficulties in correctly forecasting inflation developments, in particular using models based on the Phillips Curve. In this connection, the euro area and Belgium are interesting cases as inflation typically turned out lower than expected in the euro area, while the opposite was true for Belgium.

Several studies have tried to gauge the usefulness of including measures of inflation expectations in forecasting models and have found mixed results. However, the literature has mostly focused on indicators derived from financial markets, inflation estimates of professional forecasters and, to a lesser extent, expectations in consumer surveys. In this paper we use qualitative information from both consumer and business surveys that are harmonised at the EU level. Consumers are asked about the development of consumer prices over the next twelve months while respondents to the business survey have to indicate whether or not they expect increases in selling prices over the next quarter. We argue that, in both cases, the balance of replies can provide useful information, on a monthly basis, regarding inflation expectations.

With a view to formally testing the information content of these survey indicators for inflation projections, we develop a suite of unobserved component models for both the euro area and Belgium. In some models, surveys are linked to the expectations derived from the model, while in others, they are simply added to the information set while imposing weaker forms of model consistency. We specifically include headline as well as core inflation and assess whether adding the survey information on expected price changes leads to accuracy gains. Results are mixed if one considers the whole evaluation period covering the last ten years. For Belgium, surveys do not help to explain total inflation: the larger models that also explicitly take into account the oil price and the price mark-up, but not the survey information on prices are the most accurate. As regards core inflation estimates, surveys do seem to matter and we specifically show that it is the business survey that is driving this result. However, for the euro area, adding price expectations from surveys to the models does not improve their accuracy. All in all, we do not find convincing evidence that shows that survey information can always inform inflation projections.

However, a focus on the most recent period alters the conclusion. If the evaluation sample is restricted to the period starting in 2012 only, models that include the survey

expectations on prices tend to outperform similar models that don't, both for Belgium and the euro area. This may suggest that, specifically in periods where structural models fail to account for actual developments, such as in the recent ones, price expectations from business surveys in particular could provide information that can be used to improve the forecasts. Our paper just presents one modelling approach that allows to combine structural drivers of inflation with survey information. Further research is definitely necessary to assess the best manner to include survey information in actual forecasting models (the design and structure of which may depend on the horizon considered). Our results suggest that it may be worthwhile to explore that option.

Another avenue for further research relates to the more formal identification of the periods for which survey information could improve the accuracy of the projections, or – to put it differently – for which the accuracy of the traditional models is particularly low. One tentative interpretation of the recent episode is that this may pertain to significant changes in underlying cost drivers and the misspecification of the pass-through to final prices. At least for the Belgian case, a slower pass-through of the policy-driven moderation in labour costs (as also evidenced by very dynamic profit margins around that time) has definitely contributed to keeping inflation high. To the extent that the business survey measures the expectations of the actual price-setters, they could specifically inform about the planned pass-through of changes in costs that may be different from the one included in the structural models that are routinely used for forecasting.

References

[1] Atkeson, A. and L.E. Ohanian (2001), Are Phillips curves useful for forecasting inflation?, *Federal Reserve Bank of Minneapolis Quarterly Review*, **Win**, 2-11.

[2] Ang, A., G. Bekaert and M. Wei (2007), Do macro variables, asset markets, or surveys forecast inflation better?, *Journal of Monetary Economics*, **4**, 1163-1212.

[3] Basselier, R., D. de Antonio Liedo and G. Langenus (2018), Nowcasting real economic activity in the euro area : Assessing the impact of qualitative surveys, *Journal of Business Cycle Research*,**14**, 1-46

[4] Bernanke, B.S. (2007), Inflation expectations and inflation forecasting, speech given at the Monetary Economics Workshop of the National Bureau of Economic Research Summer Institute, Cambridge, Massachusetts, July 10, 2007.

[5] Brockwell, P.J. and R.A. Davis (1987), Time Series: Theory and Models, *New York: Springer-Verlag* .

[6] Carlson, J.A. and M. Parkin (1975), Inflation Expectations, *Economica*, **42 (166)**, 123-138.

[7] Carroll, C. (2003), Macroeconomic expectations of households and professional forecasters, *The Quarterly Journal of Economics*, **118 (1)**, 269-298.

[8] Chan, J., G. Koop and S. Potter (2016), A Bounded Model of Time Variation in Trend Inflation, Nairu and the Phillips Curve, *Journal of Applied Econometrics*, **31 (3)**, 551-565.

[9] Coibion, O. and Y. Gorodnichenko (2015), Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation, *American Economic Journal: Macroeconomics*, **7 (1)**, 197-232.

[10] Coibion, O., Y. Gorodnichenko and R. Kamdar (2018), How Do Firms Form Their Expectations? New Survey Evidence, *Forthcoming in American Economic Review*

[11] de Antonio Liedo, D. (2015), Nowcasting Belgium, National Bank of Belgium, *Eurostat Review of National Accounts and Macroeconomic Indicator*, Special Issue on New Techniques and Technologies for Statistics **2**, 7-41.

[12] ECB (2007), Recent developments in consumers' inflation perceptions and expectations in the euro area, ECB Monthly Bulletin, November 2007, 38-41.

[13] Ehrmann, M., D. Pfajfar and E. Santoro (2017), Consumers' Attitudes and Their Inflation Expectations, *International Journal of Central Banking*, **13 (1)**, 225-259.

[14] Forsells, M. and G. Kenny (2004), Survey expectations, rationality and the dynamics of euro area inflation, *Journal of Business cycle measurement and analysis*, **1**, 13-41.

[15] Francke, M.K., S.J. Koopman, and A.F. de Vos (2010), Likelihood functions for state space models with diffuse initial conditions, *Journal of Time Series Analysis*, **31**, 407-414.

[16] Geweke, J. (1977), The Dynamic Factor Analysis of Economic Time Series. In: Aigner, D.J. and Goldberger, A.S., Eds., Latent Variables in Socio-Economic Models 1, North-Holland, Amsterdam.

[17] Harvey, A. (1985), Trends and Cycles in Macroeconomic Time Series, *Journal of Business and Economic Statistics*, **3 (3)**, 216-227.

[18] Hasenzagl, T., F. Pellegrino, L. Reichlin and G. Ricco (2018), A model of the FED's view on inflation, *Sciences PO OFCE Working Paper*, **03**.

[19] Mankiw, NG., R. Reis and J. Wolfers (2004), Disagreement about inflation expectations, *NBER Macroeconomics Annual 2003*, **18**, 209-270.
autoregressive-moving average process, *Biometrika*, **67**, 232-233.

[20] Sargent, T.J. and C.A. Sims (1977), Business cycle modeling without pretending to have too much a priori economic theory, Federal Reserve Bank of Minneapolis, Working Paper 55.

[21] Scheufele, R. (2011), Are qualitative inflation expectations useful to predict inflation?, *Journal of Business Cycle Measurement and Analysis*, **2**, 29-53.

[22] Souleles, N.S. (2004), Expectations, Heterogeneous Forecast Errors and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys, *Inflation Expectations*, **36 (1)**, 39-72.

[23] Stella, A. and J.H. Stock (2013), A State-Dependent Model for Inflation Forecasting, *FRB International Finance Discussion Paper*, **1062**.

[24] Stockhammer, P. and P. Österholm (2016), Do inflation expectations Granger cause inflation?, *National institute of economic research working paper*, **145**.

[25] Thum-Thysen, A. and E. Canton (2015), Estimation of service sector mark-ups determined by structural reform indicators, European Commission, Economic Papers 547.

8 Annexes

Equation (A.1): State-Space form of the Large X-UCM: measurement equation 48
Equation (A.2): State-Space form of the Large X-UCM: transition equation 49
Figure A.1: Belgium: output gaps produced by different models - filtered result 50
Figure A.2: Belgium: output gaps produced by different models - smoothed result ... 51
Figure A.3: Euro area: output gaps produced by different models - filtered result 52

State-Space form of the Large X-UCM: measurement equation

$$
\begin{pmatrix} U_t \\ Y_t \\ \pi_t \\ \pi_t^{core} \\ \pi_t^{M} \\ P_t^{oil} \\ \mu_t^{YoY} \\ S_t^{y} \\ S_t^{B} \\ S_t^{C} \end{pmatrix}
=
\begin{pmatrix} m_u \\ m_y \\ m_\pi \\ m_{core} \\ m_m \\ m_{oil} \\ m_\mu \\ m_s \\ m_b \\ m_c \end{pmatrix}
+
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \kappa & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \lambda_\pi & 0 & 0 & 0 & 0 & \zeta_\pi & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_{core} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \lambda_M & 0 & 0 & 0 & 0 & \zeta_M & 0 & \phi_M \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & \lambda_{Oil} & 0 & 0 & 0 & 0 & \zeta_{Oil} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_\mu & 0 & 0 & 0 & -\lambda_\mu & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \kappa_S & 0 & 0 & 0 & -\kappa_S & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_1 & \Lambda_2 & 0 & 0 & 0 & Z_1 & Z_2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_1^* & \Lambda_2^* & 0 & 0 & 0 & Z_1^* & Z_2^* & 0
\end{pmatrix}
\begin{pmatrix} \tau_t^U \\ \tau_{t-1}^U \\ \tau_t^Y \\ \tau_{t-1}^Y \\ \tau_t^\pi \\ \tau_t^{core} \\ \tau_t^M \\ \tau_t^{Oil} \\ \tau_{t-1}^{Oil} \\ \delta_t \\ \delta_{t-1} \\ \delta_{t-2} \\ \delta_{t-3} \\ \delta_{t-4} \\ \vartheta_t \\ \vartheta_{t-1} \\ \xi_t^M \end{pmatrix}
+
\begin{pmatrix} \eta_t^U \\ \eta_t^Y \\ \eta_t^\pi \\ \eta_t^{core} \\ \eta_t^M \\ \eta_t^{oil} \\ \eta_t^\mu \\ \eta_{S,t}^{BC} \\ \eta_{S,t}^{B} \\ \eta_{S,t}^{C} \end{pmatrix}
\tag{A.1}
$$

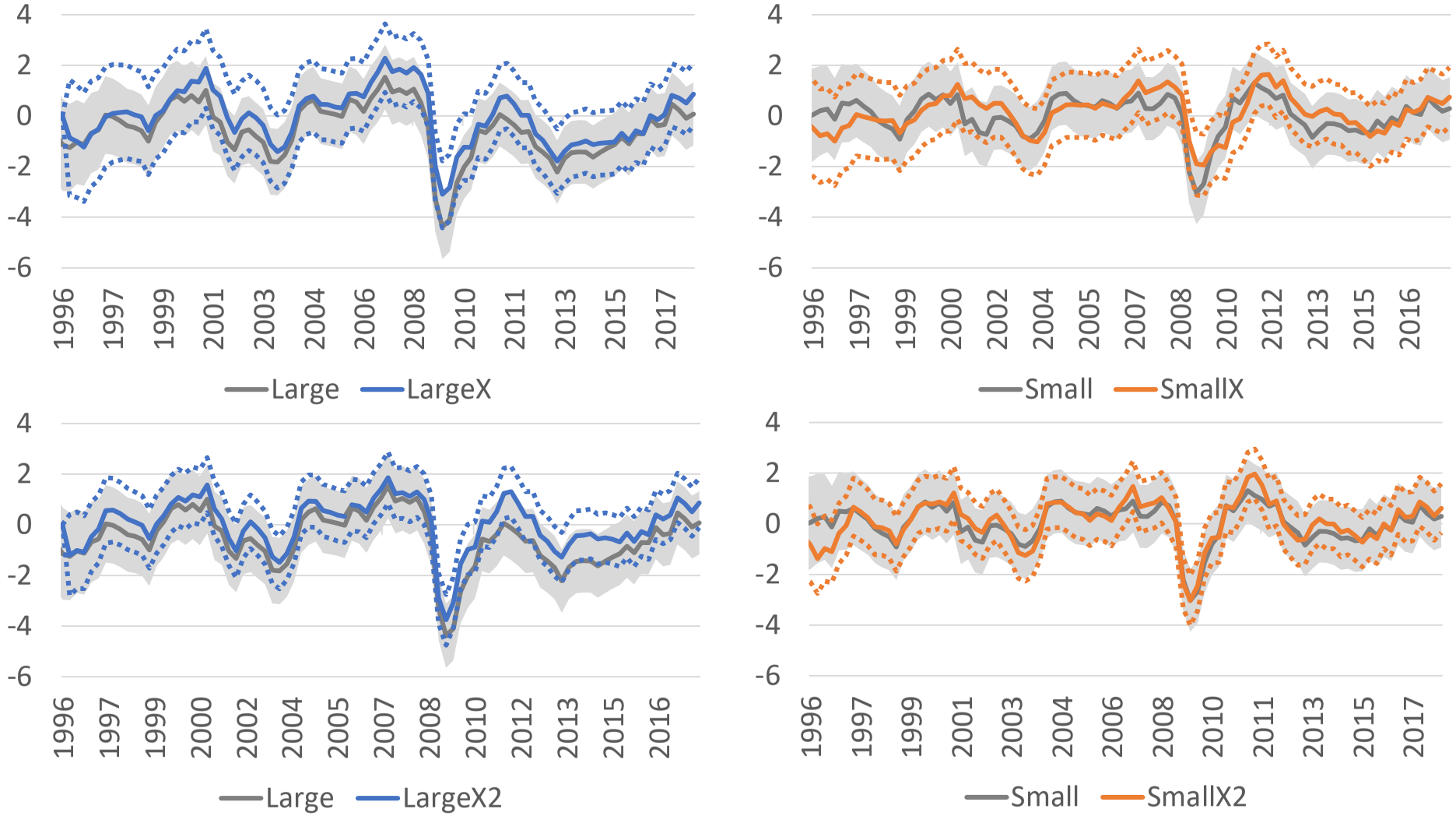
State-Space form of the Large X-UCM: transition equation

$$
\begin{pmatrix}
\tau_t^U \\ \tau_{t-1}^U \\ \tau_t^Y \\ \tau_{t-1}^Y \\ \tau_t^\pi \\ \tau_t^{core} \\ \tau_t^M \\ \tau_t^{Oil} \\ \tau_{t-1}^{Oil} \\ \delta_t \\ \delta_{t-1} \\ \delta_{t-2} \\ \delta_{t-3} \\ \delta_{t-4} \\ \vartheta_t \\ \vartheta_{t-1} \\ \xi_t^M
\end{pmatrix}
=
\begin{pmatrix}
0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ c_{oil} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0
\end{pmatrix}
+
\begin{pmatrix}
2 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 2 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha_1 & \alpha_2 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_1 & \rho_2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_M
\end{pmatrix}
\begin{pmatrix}
\tau_{t-1}^U \\ \tau_{t-2}^U \\ \tau_{t-1}^Y \\ \tau_{t-2}^Y \\ \tau_{t-1}^\pi \\ \tau_{t-2}^{core} \\ \tau_{t-1}^M \\ \tau_{t-1}^{Oil} \\ \delta_{t-1} \\ \delta_{t-2} \\ \delta_{t-3} \\ \delta_{t-4} \\ \delta_{t-5} \\ \vartheta_{t-1} \\ \vartheta_{t-2} \\ \xi_{t-1}^M
\end{pmatrix}
+
\begin{pmatrix}
\varepsilon_t^U \\ 0 \\ \varepsilon_t^Y \\ 0 \\ \varepsilon_t^\pi \\ \varepsilon_t^{core} \\ \varepsilon_t^M \\ \epsilon_t^{Oil} \\ \zeta_t^\vartheta \\ 0 \\ 0 \\ 0 \\ 0 \\ \zeta_t^\vartheta \\ 0 \\ e_t^M
\end{pmatrix}
\tag{A.2}
$$

Model consistency (X) implies:

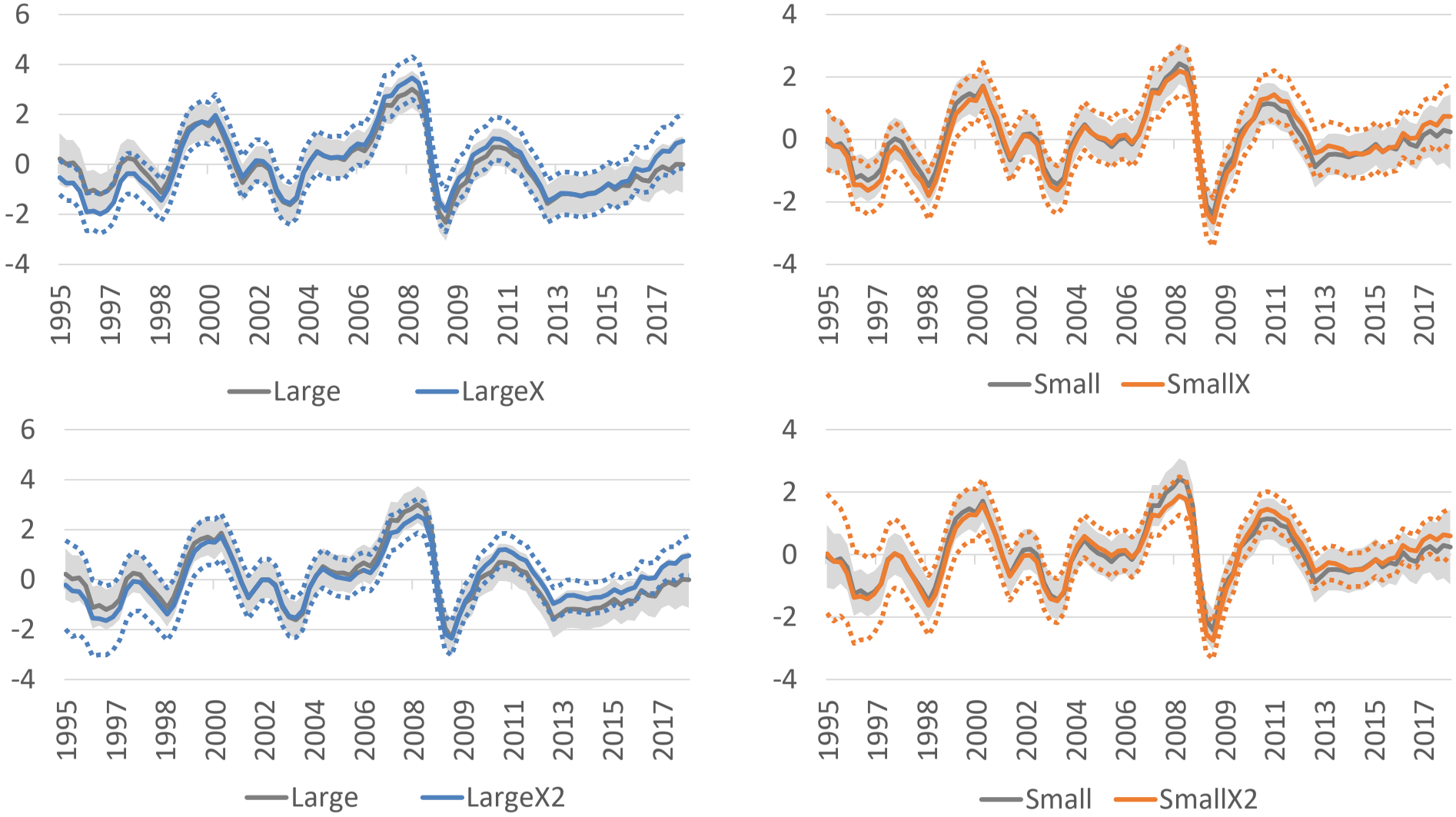
$$
\begin{aligned}
\Lambda_1 = f(\alpha_B \lambda_\pi, \alpha_1), \Lambda_2 = f(\alpha_B \lambda_\pi, \alpha_2) \\
Z_1 = f(\alpha_B \zeta_{pi}, \rho_1), Z_2 = f(\alpha_B \zeta_{pi}, \rho_2) \\
\Lambda_1^* = f(\alpha_B \lambda_\pi, \alpha_1, \alpha_2), \Lambda_2^* = f(\alpha_B \lambda_\pi, \alpha_1, \alpha_2) \\
Z_1^* = f(\alpha_B \zeta_{pi}, \rho_1, \rho_2), Z_2^* = f(\alpha_B \zeta_{pi}, \rho_1, \rho_2)
\end{aligned}
$$

Figure A.1: Belgium: output gaps produced by different models - filtered result



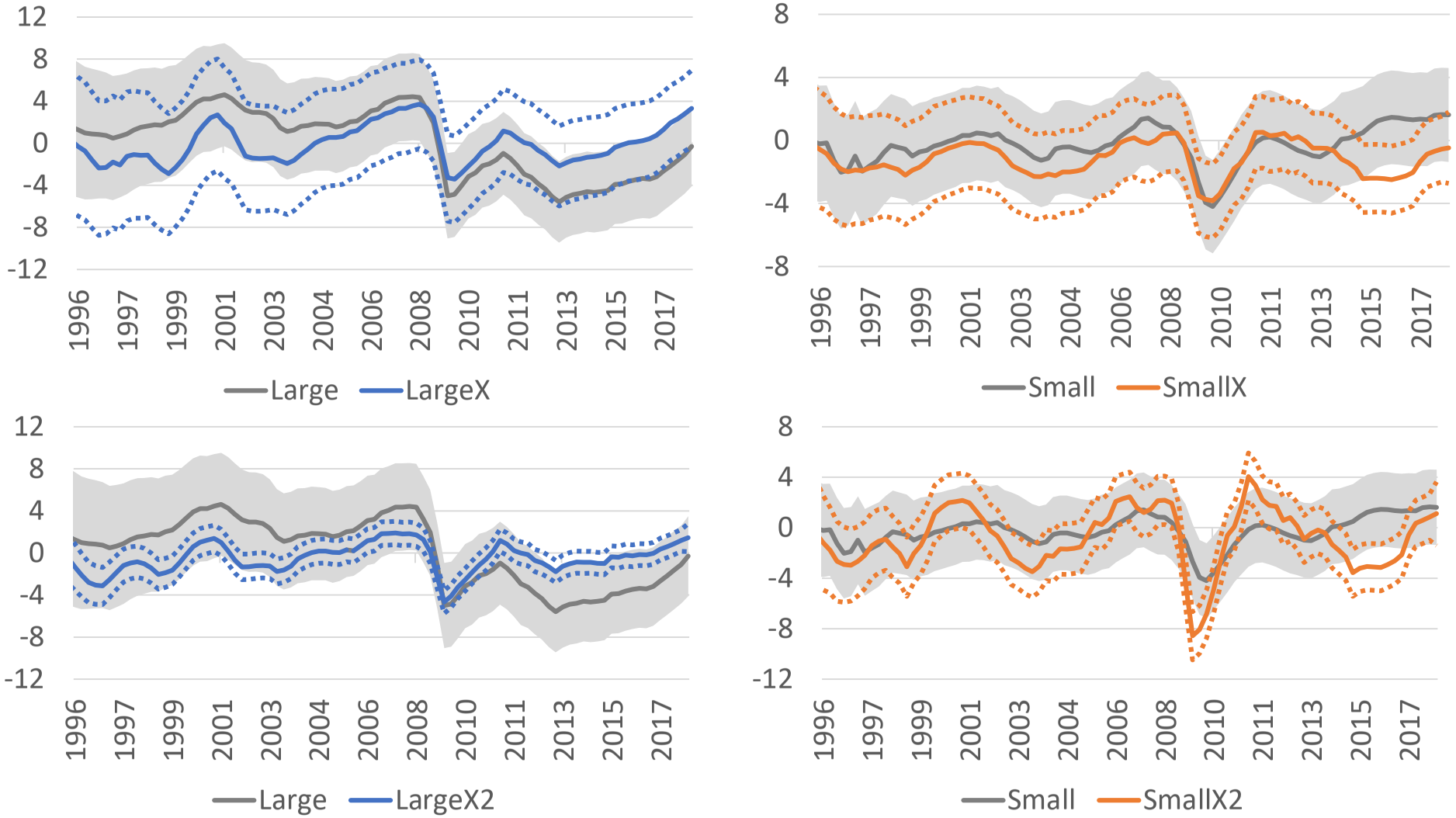
Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large and the Small model. The dotted lines show the upper and lower confidence bounds for, respectively, the X or X2 variant.

Figure A.2: Belgium: output gaps produced by different models - smoothed result



Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large and the Small model. The dotted lines show the upper and lower confidence bounds for, respectively, the X or X2 variant.

Figure A.3: Euro area: output gaps produced by different models - filtered result



Source: NBB.
Note: the gray, shaded area shows the 95% confidence band for the Large and the Small model. The dotted lines show the upper and lower confidence bounds for, respectively, the X or X2 variant.

NATIONAL BANK OF BELGIUM - WORKING PAPERS SERIES

The Working Papers are available on the website of the Bank: http://www.nbb.be.

302. "The transmission mechanism of credit support policies in the Euro Area", by J. Boeckx, M. de Sola Perea and G. Peersman, *Research series*, October 2016.
303. "Bank capital (requirements) and credit supply: Evidence from pillar 2 decisions", by O. De Jonghe, H. Dewachter and S. Ongena, *Research series*, October 2016.
304. "Monetary and macroprudential policy games in a monetary union", by R. Dennis and P. Ilbas, *Research series*, October 2016.
305. "Forward guidance, quantitative easing, or both?, by F. De Graeve and K. Theodoridis, *Research series*, October 2016.
306. "The impact of sectoral macroprudential capital requirements on mortgage loan pricing: Evidence from the Belgian risk weight add-on", by S. Ferrari, M. Pirovano and P. Rovira Kaltwasser, *Research series*, October 2016.
307. "Assessing the role of interbank network structure in business and financial cycle analysis", by J-Y Gnabo and N.K. Scholtes, *Research series*, October 2016.
308. "The trade-off between monetary policy and bank stability", by M. Lamers, F. Mergaerts, E. Meuleman and R. Vander Vennet, *Research series,* October 2016.
309. "The response of euro area sovereign spreads to the ECB unconventional monetary policies", by H. Dewachter, L. Iania and J-C. Wijnandts, *Research series*, October 2016.
310. "The interdependence of monetary and macroprudential policy under the zero lower bound", by V. Lewis and S. Villa, *Research series*, October 2016.
311. "The impact of exporting on SME capital structure and debt maturity choices", by E. Maes, N. Dewaelheynes, C. Fuss and C. Van Hulle, *Research series*, October 2016.
312. "Heterogeneous firms and the micro origins of aggregate fluctuations", by G. Magerman, K. De Bruyne, E. Dhyne and J. Van Hove, *Research series*, October 2016.
313. "A dynamic factor model for forecasting house prices in Belgium", by M. Emiris, *Research series*, November 2016.
314. "La Belgique et l'Europe dans la tourmente monétaire des années 1970 – Entretiens avec Jacques van Ypersele", by I. Maes and S. Péters, *Research series*, December 2016.
315. "Creating associations to substitute banks' direct credit. Evidence from Belgium", by M. Bedayo, *Research series*, December 2016.
316. "The impact of export promotion on export market entry", by A. Schminke and J. Van Biesebroeck, *Research series*, December 2016.
317. "An estimated two-country EA-US model with limited exchange rate pass-through", by G. de Walque, Ph. Jeanfils, T. Lejeune, Y. Rychalovska and R. Wouters, *Research series,* March 2017.
318. Using bank loans as collateral in Europe: The role of liquidity and funding purposes", by F. Koulischer and P. Van Roy, *Research series*, April 2017.
319. "The impact of service and goods offshoring on employment: Firm-level evidence", by C. Ornaghi, I. Van Beveren and S. Vanormelingen, *Research series*, May 2017.
320. "On the estimation of panel fiscal reaction functions: Heterogeneity or fiscal fatigue?", by G. Everaert and S. Jansen, *Research series*, June 2017.
321. "Economic importance of the Belgian ports: Flemish maritime ports, Liège port complex and the port of Brussels - Report 2015", by C. Mathys, *Document series*, June 2017.
322. "Foreign banks as shock absorbers in the financial crisis?", by G. Barboni, *Research series*, June 2017.
323. "The IMF and precautionary lending: An empirical evaluation of the selectivity and effectiveness of the flexible credit line", by D. Essers and S. Ide, *Research series*, June 2017.
324. "Economic importance of air transport and airport activities in Belgium – Report 2015", by S. Vennix, *Document series*, July 2017.
325. "Economic importance of the logistics sector in Belgium", by H. De Doncker, *Document series*, July 2017.
326. "Identifying the provisioning policies of Belgian banks", by E. Arbak, *Research series*, July 2017.
327. "The impact of the mortgage interest and capital deduction scheme on the Belgian mortgage market", by A. Hoebeeck and K. Inghelbrecht, *Research series,* September 2017.
328. "Firm heterogeneity and aggregate business services exports: Micro evidence from Belgium, France, Germany and Spain", by A. Ariu, E. Biewen, S. Blank, G. Gaulier, M.J. González, Ph. Meinen, D. Mirza, C. Martín and P. Tello, *Research series*, September 2017.
329. "The interconnections between services and goods trade at the firm-level", by A. Ariu, H. Breinlichz, G. Corcosx, G. Mion, *Research series,* October 2017.

330. “Why do manufacturing firms produce services? Evidence for the servitization paradox in Belgium”, by P. Blanchard, C. Fuss and C. Mathieu, *Research series,* November 2017.
331. “Nowcasting real economic activity in the euro area: Assessing the impact of qualitative surveys”, by R. Basselier, D. de Antonio Liedo and G. Langenus, *Research series,* December 2017.
332. “Pockets of risk in the Belgian mortgage market: Evidence from the Household Finance and Consumption Survey (HFCS)”, by Ph. Du Caju, *Research series,* December 2017.
333. “The employment consequences of SMEs’ credit constraints in the wake of the great recession” by D. Cornille, F. Rycx and I. Tojerow, *Research series*, December 2017.
334. “Exchange rate movements, firm-level exports and heterogeneity”, by A. Berthou and E. Dhyne, *Research series*, January 2018.
335 “Nonparametric identification of unobserved technological heterogeneity in production”, by L. Cherchye, T. Demuynck, B. De Rock and M. Verschelde, *Research series*, February 2018.
336 “Compositional changes in aggregate productivity in an era of globalisation and financial crisis”, by C. Fuss and A. Theodorakopoulos, *Research series*, February 2018.
337. “Decomposing firm-product appeal: How important is consumer taste?”, by B. Y. Aw, Y. Lee and H. Vandenbussche, *Research series*, March 2018.
338 “Sensitivity of credit risk stress test results: Modelling issues with an application to Belgium”, by P. Van Roy, S. Ferrari and C. Vespro, *Research series*, March 2018.
339. “Paul van Zeeland and the first decade of the US Federal Reserve System: The analysis from a European central banker who was a student of Kemmerer”, by I. Maes and R. Gomez Betancourt, *Research series*, March 2018.
340. “One way to the top: How services boost the demand for goods”, by A. Ariu, F. Mayneris and M. Parenti, *Research series*, March 2018.
341 “Alexandre Lamfalussy and the monetary policy debates among central bankers during the Great Inflation”, by I. Maes and P. Clement, *Research series*, April 2018.
342. “The economic importance of the Belgian ports: Flemish maritime ports, Liège port complex and the port of Brussels – Report 2016”, by F. Coppens, C. Mathys, J.-P. Merckx, P. Ringoot and M. Van Kerckhoven, *Document series*, April 2018.
343. “The unemployment impact of product and labour market regulation: Evidence from European countries”, by C. Piton, *Research series,* June 2018.
344. “Trade and domestic production networks”, by F. Tintelnot, A. Ken Kikkawa, M. Mogstad, E. Dhyne, *Research series*, September 2018.
345. “Review essay: Central banking through the centuries”, by I. Maes, *Research series,* October 2018.
346 “IT and productivity: A firm level analysis”, by E. Dhyne, J. Konings, J. Van den Bosch, S. Vanormelingen, *Research series*, October 2018.
347 “Identifying credit supply shocks with bank-firm data: methods and applications”, by H. Degryse, O. De Jonghe, S. Jakovljević, Klaas Mulier, Glenn Schepens, *Research series*, October 2018.
348 “Can inflation expectations in business or consumer surveys improve inflation forecasts?”, by R. Basselier, D. de Antonio Liedo, J. Jonckheere and G. Langenus, *Research series*, October 2018.

National Bank of Belgium
Limited liability company
RLP Brussels – Company's number: 0203.201.340
Registered office: boulevard de Berlaimont 14 – BE-1000 Brussels
www.nbb.be

Editor

Jan Smets
Governor of the National Bank of Belgium

© Illustrations: National Bank of Belgium

Layout: Analysis and Research Group
Cover: NBB AG – Prepress & Image

Published in October 2018