A Bayesian dynamic factor model of New Zealand's core inflation*

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DRAFT — NOT FOR CITATION
June 17, 2010

Abstract

I estimate a measure of core CPI inflation for New Zealand using a Bayesian dynamic factor model with Gibbs sampling. Within the model, I identify one factor as a tradable inflation factor, and the other as a non-tradable inflation factor.

I examine the properties of both the model's core CPI inflation estimate as well as the tradable and non-tradable factors driving it. My results show core CPI inflation is heavily influenced by non-tradable prices. As an application, I use a simple Taylor-type rule to examine how monetary policy has responded to the persistent (core) component of inflation.

*The views expressed in this paper are those of the author and do not necessarily represent those of the Reserve Bank of New Zealand. The author would like to thank Özer Karagedikli and Haroon Mumtaz for their helpful comments and suggestions.

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1 Introduction

The headline measure of the Consumer Price Index (CPI) can potentially provide policymakers with a misleading picture of the true underlying inflation pressures in an economy. Temporary shocks and other measurement issues introduce noise into the CPI measure of inflation. As a result, central banks often also look at various measures of core inflation when formulating policy decisions in an attempt to abstract from these temporary fluctuations.

As discussed by Holden (2006) and Wynne (2008), among others, despite the widespread use of the concept of core inflation, there is no consensus on either the exact definition of core inflation, or the most appropriate approach to measuring it. As an example of this uncertainty, the Reserve Bank of New Zealand regularly publishes five different measures of core inflation alongside the official CPI measure of inflation in their quarterly *Monetary Policy Statement*.[1]

Similar to Kapetanios (2004), I take an a-theoretical view on the definition of core inflation. Using a Bayesian dynamic factor model and a panel of disaggregated CPI category data, I derive a measure of core inflation that is driven by the common co-movement in tradable and non-tradable prices. Dynamic factor models provide a useful method for reducing the dimensionality of a large panel of data. This approach has be used in Amstad and Fischer (2004), Cristadoro et al (2005), and Giannone and Matheson (2007) to derive measures of core inflation for various countries and the Euro area.

Two main features distinguish the core inflation measure derived in this paper from the typical dynamic factor model estimate of core inflation. First, unlike most dynamic factor model estimates of core inflation, this model is estimated using Bayesian estimation with Gibbs sampling.[2] This approach allows for the characterisation of parameter uncertainty around the estimate of core inflation. And second, it employs an identification scheme to identify one factor as a tradable factor, and the other as a non-tradable factor. As a result, it is possible to tell a pseudo structural story of the main drivers of core inflation.

The motivation for identifying a separate tradable and non-tradable factor comes from New Zealand's experiences as a small open economy. According the to official Statistics New Zealand CPI basket, the weighting between tradable and non-tradable prices is split almost equally. Both

[1] These measures are: (1) Factor model estimate of core CPI inflation, (2) CPI trimmed mean, (3) CPI weighted median, (4) CPI ex food, petrol and government charges, and (5) CPI ex food and energy.

[2] However, Bayesian estimation techniques have been used on dynamic factor models for other purposes. See Tekatli (2007) and Karagedikli et al (2010) as examples.

New Zealand's experiences as well as economic theory suggest that international factors are important drivers for tradable prices (see Mumtaz and Surico 2008 for an investigation on the common co-movement of prices across countries). Non-tradable prices on the other hand, are likely to have very different drivers from tradable prices — being influenced more heavily by domestic economic conditions than international factors.

In addition, the Reserve Bank has a long history of focusing not only on headline CPI inflation, but also the tradable/non-tradable inflation split. Both the Reserve Bank's current policy model, KITT (Beneš et al 2009), and its previous model, FPS (Black et al 1997), featured a tradable/non-tradable inflation split. Forecasts for tradable and non-tradable inflation are also published in *Monetary Policy Statement* releases.

From this new approach to estimating core inflation for New Zealand, I find that there is significantly more co-movement in non-tradable prices than in tradable prices. In addition, I find that the core inflation measure derived in this paper is predominately driven by the non-tradable factor. Also since 2000Q1, the Bayesian dynamic factor model produces a real-time estimate of core inflation that is similar to the final vintage estimate.

The remainder of this paper is organised as follows. Section 2 outlines the panel of inflation data used in the model. Section 3 gives details on the estimation method. Section 4 discusses the results from the estimation of the model. Section 6 provides a brief conclusion.

2 Data

For my analysis, I consider the sample period 1991Q1 to 2010Q1. Below, the data series used for the dynamic factor model are discussed in more detail.

2.1 Inflation data

The Dynamic factor model is estimated using a panel of 105 components of the CPI basket as measured by Statistics New Zealand.[3] To this panel I also add the official headline CPI, tradable CPI, and non-tradable CPI indices.

From this panel of data, I remove nine individual series that do not span

[3] For more details on the inflation data used see appendix A.

the entire length of the sample.[4] As a result, we are left with a panel of 99 series (headline CPI, tradable CPI, non-tradable CPI, and 96 CPI component series). The individual indices of each remaining series are then transformed into a quarterly percentage change, and standardised to have a mean of zero and standard deviation of unity.[5]

3 The Dynamic Factor Model

To construct a measure of core CPI inflation, I assume that quarterly CPI inflation (π_t) can can be decomposed into two orthogonal components; a 'core inflation' component (π_t^{core}) and a non-core or noise component (π_t^{nc}):

$$\pi_t = \pi_t^{core} + \pi_t^{nc} \tag{1}$$

Such a decomposition of inflation lends itself naturally to the dynamic factor model framework. Below I discuss in more detail the Bayesian dynamic factor model and how it relates to equation 1, the estimation process, and how to construct a measure of core headline inflation from the estimated dynamic factor model.

3.1 Methodology

Let the panel of inflation data be denoted as $\Pi_t = (\pi_{1,t}, \pi_{2,t}, \ldots \pi_{n,t})'$, where for convenience $\pi_{1,t}$ denotes headline inflation, and $\pi_{i,t}$ for $i = (2, \ldots, n)$ denotes the other inflation rates in the panel.

For our panel of data, the general form of a dynamic factor model can be denoted as:

$$\pi_{i,t} = \boldsymbol{\beta}_{\mathbf{i}}'\mathbf{F_t} + \nu_{i,t} \tag{2}$$

Where $\mathbf{F_t}$ is a vector of (orthogonal) common factors that capture the co-movement across the entire panel, $\boldsymbol{\beta}_{\mathbf{i}}$ denotes the vector of factor loadings between series $\pi_{i,t}$ and the common factors, and $\nu_{i,t}$ denotes the idiosyncratic term associated with series $\pi_{i,t}$.

[4] The series removed are: Water supply, Refuse disposal and recycling, Therapeutic appliances and equipment, Rail passenger transport, Road passenger transport, Sea passenger transport, Telecommunication equipment, Package holidays, and Electrical appliances for personal care.

[5] The estimate of core inflation is robust to outliers in the individual category series. In addition to removing series not spanning the entire sample length, I also estimated the model using a panel of data that had been cleaned of outliers using the algorithm proposed by Giannone and Matheson (2007). The results did not alter significantly.

Equating equation 1 with equation 2 for headline inflation ($i = 1$ in our panel), we can see that core inflation can be expressed as the factor loadings for headline inflation times the common factors ($\pi_t^{core} = \boldsymbol{\beta_1}\mathbf{F_t}$), and non-core inflation can be expressed as the idiosyncratic term ($\pi_t^{nc} = \nu_{1,t}$).

For the analysis in this paper, I choose to use a dynamic factor model with two factors. One factor will be the tradable factor that captures the co-movement in tradable prices, and the other will be the non-tradable factor that captures the co-movement in non-tradable prices.

Therefore, for the i^{th} inflation series in the panel of CPI data ($\pi_{i,t}$), I use the following structure for the dynamic factor model:

$$\pi_{i,t} = \beta_i^{tr} F_t^{tr} + \beta_i^{nt} F_t^{nt} + \nu_{i,t} \tag{3}$$

where F_t^{tr} denotes the tradable inflation factor, and F_t^{nt} denotes the non-tradable inflation factor. β_i^{tr} and β_i^{nt} represent the tradable and non-tradable factor loadings respectively. And $\nu_{i,t}$ denotes the idiosyncratic error term.

Both the tradable and non-tradable inflation factors are assumed to follow an autoregressive process of order two [REFERENCE]:

$$F_t^k = c^k + \sum_{j=1}^{2} \rho_j^k F_{t-j}^k + \varepsilon_t^k \tag{4}$$

where k denotes either tradable or non-tradable ($k = \{tr, nt\}$), and ε_t^k is a white noise i.i.d. shock.

I also allow for the possibility of serial correlation in the idiosyncratic error term of the dynamic factor model (equation 3) by assuming $\nu_{i,t}$ follows an autoregressive process of order one:

$$\nu_{i,t} = \alpha_i \nu_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

where $\varepsilon_{i,t}$ is a white noise i.i.d. shock.

3.2 Identification

To identify the two factors in the Bayesian dynamic factor model as a tradable and non-tradable factor, I impose a sign restriction scheme on the factor loadings. Specifically, inflation series $\pi_{i,t}$ is loaded onto factor F_t^k ($k = \{tr, nt\}$), if and only if, inflation series i is classified by Statistics New Zealand as a tradable or non-tradable good respectively.

According to the classification of tradable and non-tradable goods by Statistics New Zealand, 47 inflations component series appear only in the headline tradable basket, 37 inflation component series appear only in the headline non-tradable basket, and 10 series appear in both baskets.[6] In the case of headline CPI inflation, the series is loaded onto both the tradable and non-tradable factor. The headline tradable inflation series is only loaded onto the tradable factor, and the headline non-tradable series is loaded only onto the non-tradable factor.[7]

It is known that dynamic factor models suffer from an indeterminacy of the factor rotation — where we are unable to uniquely identify the factor and factor loadings without imposing some further identification restrictions.[8] To uniquely identify the factors and factor loadings in equation 3, I employ the use of informative priors on the factor loadings (follow the approaches given by Geweke and Zhou 1996). I base the priors on the factor loadings implied by principle components.

3.3 Estimation

The dynamic factor model consisting of equations 3 to 5, is estimated using Bayesian methods. The posterior distribution is approximated by a Gibbs sampling algorithm. All priors and initial values required to initiate the Gibbs sampling algorithm are found using principle components. The steps of the Gibbs sampling algorithm are outlined below:

1. Sample the factor loadings β_i^{tr} and β_i^{nt} for each i^{th} series:
    - Using equations 3 and 5, transform the dynamic factor model by the Cochrane-Orcutt estimation procedure to remove any serial correlation in the error term.
    - Sample the factor loadings via OLS.
    - Sample the distribution variance of each factor loading.
2. Sample the serial correlation coefficients α_i:
    - Using the updated factor loadings and current draws for the factors, calculate the idiosyncratic error terms ($\nu_{i,t}$) from equation 3.

[6]See appendixA for a detailed list of inflation category in the tradable and non-tradable classifications.

[7]A similar identification approach is used by Mumtaz and Surico (2008) to identify a world inflation factor and an idiosyncratic country factor in a cross country panel of headline inflation data.

[8]The indeterminacy of factor rotation can be summarised as being unable to distinguish between the factor model $r_t = \alpha + \boldsymbol{\beta}\mathbf{F_t} + \varepsilon_t$, and the equivalent factor model $r_t = \alpha + \boldsymbol{\beta}^*\mathbf{F_t^*} + \varepsilon_t$ (where $\mathbf{F_t^*} = \mathbf{P}\mathbf{F_t}$ is a rotation of the original factor, and $\boldsymbol{\beta}^* = \mathbf{P}\beta^*$ is a rotation of the original factor loadings), for any orthogonal matrix $\mathbf{P}$.

- Use the new estimates of the idiosyncratic error term to update the estimates of α_i via equation 5.

3. Sample R_i, the variance of the white noise shocks $\varepsilon_{i,t}$ (from equation 5) from the Inverse Gamma distribution.

4. Sample the coefficients of the transition equation 4 for both the tradable and non-tradable factors:

   - For identification purposes the variance of $\varepsilon_{i,t}^{k}$ is assumed to be unity.

   - Sample the coefficients from equation 4 via OLS.

5. Conditional on the updated parameter estimates, simulate the factors F_t^{tr} and F_t^{nt}:

   - This step is completed following the procedure described in Kim and Nelson (1999) and employs the Carter-Kohn algorithm (Carter and Kohn 1994).

6. Repeat steps one to five N times, and burn the first Z draws.

I use 50,000 draws of the Gibbs sampling algorithm, and discard the first 45,000 draws as the burn-in period. Plotting the moments of the estimated parameters from the remaining 5,000 draws reveals the moments are relatively constant, suggesting the estimation process has converged.

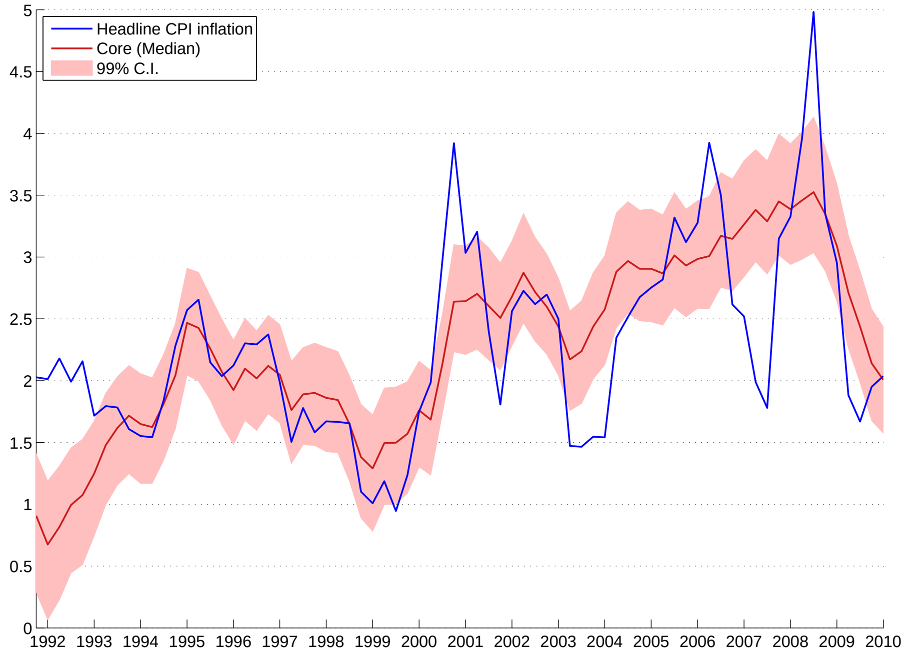
3.4 Construction of the core headline CPI inflation measure

Once the Bayesian dynamic factor model in equations 3 to 5 has been successfully esimated, we can compute the estimate of core headline inflation by taking the two factors and multiplying them by the factor loadings for headline inflation ($\pi_{1,t}^{core} = \beta_1^{tr} F_t^{tr} + \beta_1^{nt} F_t^{nt}$). And because the data has been standardised in order to compute the Bayesian dynamic factor model, we need to multiply core inflation by the standard deviation of headline CPI inflation, and add back the sample mean of headline CPI inflation to transform the estimate of core inflation into the same scale as headline CPI inflation.

4 Results

In this section, I present the results of the estimated core inflation measure and the properties of the tradable and non-tradable factors. Unless otherwise stated, the re-scaled core inflation is reported.

Figure 1: Estimated core headline CPI inflation measure



4.1 Core inflation

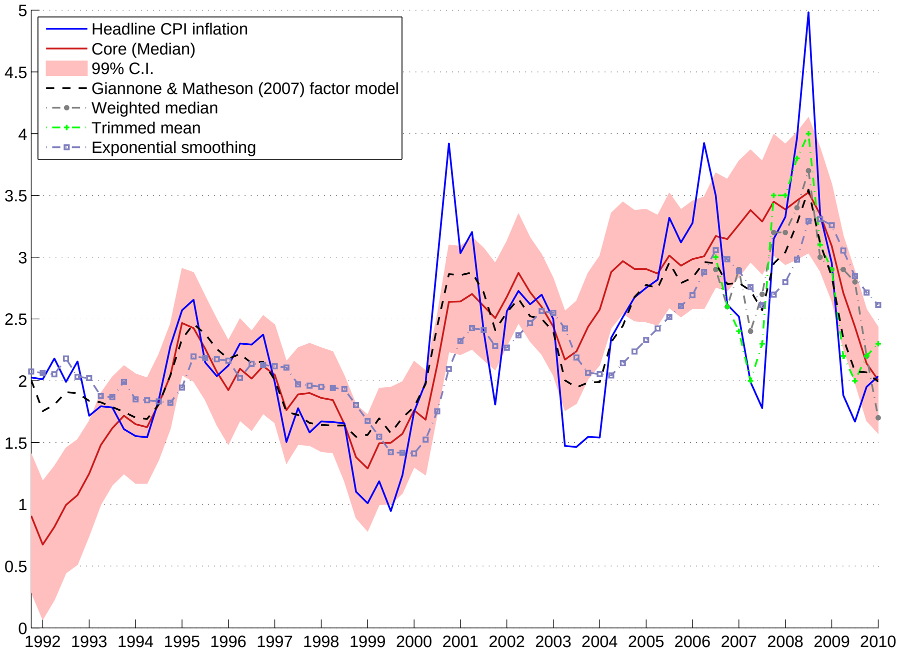
The estimate of core inflation based on data up to 2010Q1 is plotted against headline CPI inflation in figure 1. For convenience, the quarterly rates have been converted to annual rates.

The estimate of core inflation shows a starting-point problem, with the estimate being much lower than headline inflation for the first year and a half.[9] However, after this initial period, the core inflation measure does provide a track that smooths out much of the volatility in headline CPI inflation. Most notably, the inflation spikes in 2000Q4 and 2009 are interpreted by the model as temporary/non-core inflation. Also of interest is that the estimate of core inflation shows a persistent increase from around 2004 up until 2008, and the onset of the global financial crisis.

As a check of the plausibility of this new core inflation estimate, I plot it against a number of other common measures of core inflation in figure 2. Despite the exact definition of core inflation differing between the various core estimates, one would still expect the Bayesian dynamic factor model's estimate to be broadly consistent with the other measures. Specifically I compare my estimate of core inflation to the measure found by Giannone and Matheson (2007) in their dynamic factor model,

[9]This problem is exasperated in part by the use of annual percentage changes.

Figure 2: Various core inflation measures



a weighted median, a trimmed mean, and an exponentially smoothed measure.[10]

Figure 2 reveals that my measure of core inflation is broadly similar to that of Giannone and Matheson (2007) over most of the sample period. This is despite the differences in the number of factors employed in each model, and different estimation techniques.[11] In addition, it is also broadly similar to the other core inflation measures.

4.2 The dynamic factors

One of the major advantages of this proposed approach to estimating core inflation is the pseudo-structural story that comes from the estimated tradable and non-tradable factors. Figure 3 shows the (unscaled) profiles of the tradable and non-tradable factors of the final vintage (2010Q1) estimate of core inflation.[12]

[10]The official weighted median and trimmed mean series published by Statistics New Zealand are only available from 2006Q3 onwards.

[11]In addition, the dynamic factor model of Giannone and Matheson (2007) is designed to predict the two-year moving average of headline CPI inflation in real time. While my dynamic factor model is not designed to match any preconceived definition of core inflation.

[12]As a robustness check, I estimated a simple 2 factor Bayesian dynamic factor model without the sign restrictions to identify the factors as tradable and non-tradable

Figure 3: Two dynamic factors

(a) Tradable factor (b) Non-tradable factor

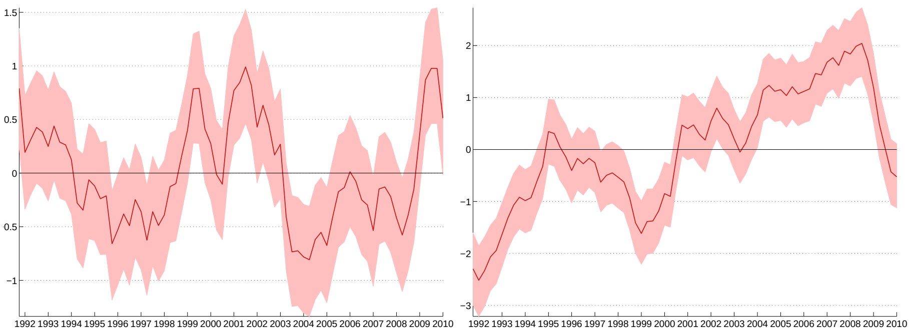


Figure 3 reveals that the non-tradable factor is much more persistent than the tradable factor (a characteristic also found in the headline data). In addition, it appears that the starting-point problem seen in the core inflation estimate is driven by a starting-point problem in the non-tradable factor.

Figure 4 shows the mean relative contribution of each factor to core inflation. That is, each factor multiplied by the appropriate factor loadings for headline CPI inflation ($\beta_1^k F_t^k$), and scaled up by the standard deviation of headline CPI inflation. The plot of the contributions reveals that core headline inflation is driven primarily by the non-tradable factor (shown in blue).[13]

This finding suggests that if the Reserve Bank was interested in targeting the persistent part of inflation, it should focus on non-tradable prices as opposed to tradable prices. This finding is likely a result of the number of large and temporary tradable inflation shocks in our sample period that the model is interpreting as non-core inflation.

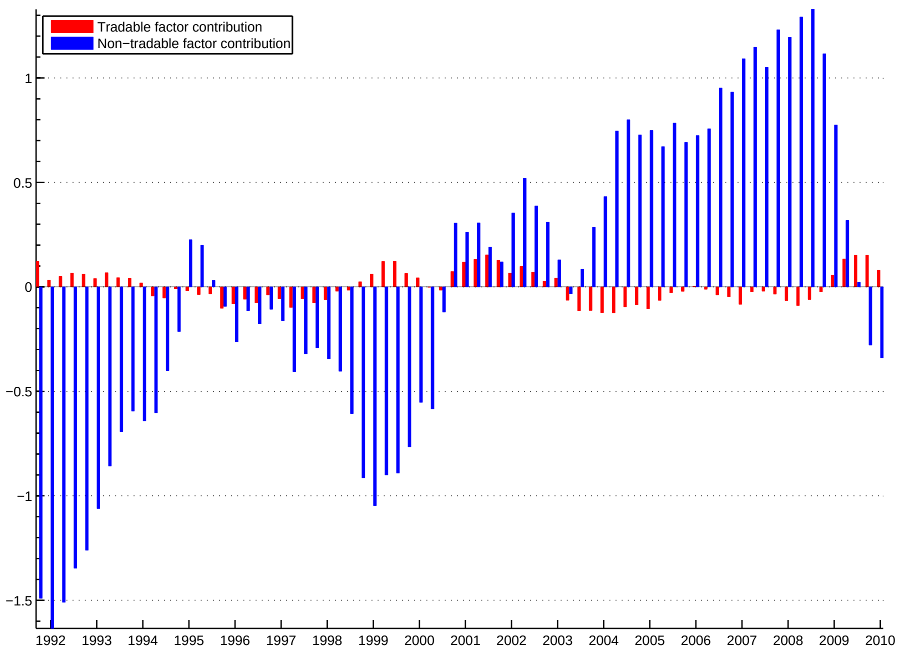
4.3 Variance decomposition

Because each factor of the dynamic factor model is orthogonal by design, the variance of inflation series $\pi_{i,t}$ can be expressed as:

factors. The first factor from this model was visually similar to the non-tradable factor shown in figure 3b, and the second was similar to the tradable factor shown in figure 3a. The estimate of core headline CPI inflation from this model did not differ significantly from the identified model's estimate.

[13]The factor loadings for headline CPI inflation are both positive, but the average loading onto the non-tradable factor (1.68) is larger than the loading onto the tradable factor (0.40).

Figure 4: Factor contribution to core CPI inflation measure



$$var(\pi_{i,t}) = \left(\beta_i^{tr}\right)^2 var\left(F_t^{tr}\right) + \left(\beta_i^{nt}\right)^2 var\left(F_t^{nt}\right) + var\left(\nu_{i,t}\right) \qquad (6)$$

Using equation 6, we are able to decompose the variance of each inflation series into the shares due to each factor, and the share due to the idiosyncratic component. The variance of inflation series $\pi_{i,t}$ explained by the tradable and non-tradable factors is given by $\frac{(\beta_i^k)^2 var(F_t^k)}{var(\pi_{i,t})}$, where $k = \{tr, nt\}$, and the variance explained by the idiosyncratic component is given by $\frac{var(\nu_{i,t})}{var(\pi_{i,t})}$.

However, despite the dynamic factor model being orthogonal by design, sampling error in the computation of the Markov chain results in the factors being weakly correlated. Therefore, to ensure the add up of equation 6, I follow the approach of Kose et al (2003) and orthogonalise the sampled factors at each iteration before computing the variance decomposition.

The results of decomposing the variance of quarterly headline CPI inflation are present in table 1. In addition to the variance decomposition of headline CPI inflation, I also show the variance decomposition of tradable and non-tradable inflation.

Around one third of the variance in quarterly headline CPI inflation can be explained by the the variance of the non-tradable factor (median

Table 1: Variance decomposition of different (quarterly) inflation measures

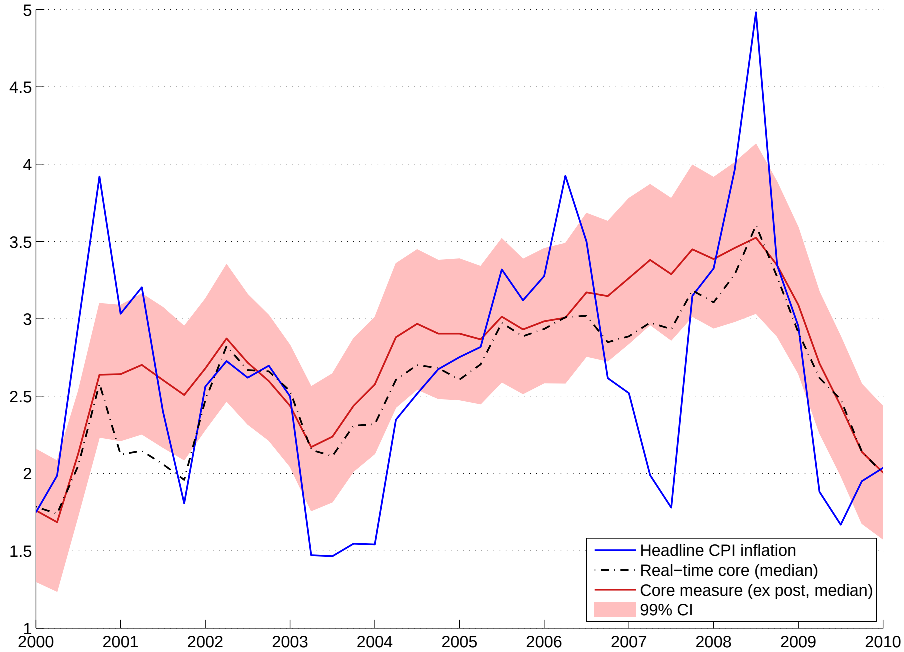
	Variance explained by each factor		
	10th percentile	**Median**	**90th percentile**
	CPI inflation		
Tradable factor	0.36	1.94	4.83
Non-tradable factor	26.91	33.51	40.02
Idiosyncratic	57.64	64.14	70.69
	Tradable inflation		
Tradable factor	8.75	14.30	20.58
Non-tradable factor	0.00	0.00	0.00
Idiosyncratic	79.42	85.70	91.25
	Non-tradable inflation		
Tradable factor	0.00	0.00	0.00
Non-tradable factor	16.79	23.02	29.54
Idiosyncratic	70.46	76.98	83.21

variance explained = 33.51%). While the tradable factor explains very little of the quarterly variance in headline CPI inflation (1.94%). Only around 14% of the variance of quarterly tradable inflation is explained by the tradable factor, suggesting there is not a high degree of co-movement in the various tradable inflation components.

Including more tradable factors into the dynamic factor model may increase the variance of tradable inflation explained by the dynamic factor model. However, there are two main draw backs from doing so. First, it will become difficult to distinguish between the drivers of multiple orthogonal tradable factors. *A priori*, one might expect that the tradable factors are closely related to the exchange rate and/or oil prices. However, beyond these two common drivers of tradable prices, it is difficult to distinguish what could be driving the third or more factor. And second, we would need to have a target amount of the variance of tradable inflation we wish the core measure to explain. This will implicitly force a target definition of core inflation onto the model — taking us away from the a-theoretical approach (i.e. core inflation would be defined as the co-movement in the variables needed to explain X% of the total variance).

For the quarterly non-tradable inflation measure, nearly half of the variance can be explained by the non-tradable factor.

Figure 5: real-time vs. ex post core inflation measures



4.4 Real-time core inflation

The estimation of core inflation from the Bayesian dynamic factor model employees the Kalman smoother, and uses all the data available at any point in time to estimate the historical level of core inflation. As a result, the estimate of core inflation is subject to historical revisions when more data becomes available.

I compute a real-time estimate of core inflation by estimating the model at each point in time over the sample range 2000Q1 to 2010Q1 (allowing for the period 1992Q1 to 199Q4 to initiate the real-time estimation, and to minimise the impact of any starting-point/small-sample bias). At each point in time, the estimate of core inflation for the latest quarter is saved, and the results are plotted in figure 5 against the final ex-post core inflation estimate.[14]

The real-time estimate of core inflation in figure 5 shows a track broadly similar to the final ex-post estimate. However, there are two notable deviations. Between 2001-2002 and 2007-2008, the real-time core estimate is noticeably lower than the ex-post estimate.

One approach to quantifying the size of the historical revisions to core inflation over time is to compare the mean revisions and/or mean abso-

[14]Because I am only saving down the current quarter's estimate of core inflation, I am not accounting for the historical revisions of core inflation that will take place.

Table 2: Revision to the real-time annual core estimate (2000q1-2010q1)

	t	**t+1**	**t+2**	**t+3**	**t+4**
Mean revision	0.164	0.149	0.136	0.126	0.114
Mean absolute revision	0.183	0.172	0.166	0.157	0.145

lute revisions between the historical vintage estimates of core inflation and the final full sample (ex-post) estimate. Formally, for each quarter (t) between 2000Q1 and 2009Q4, I take the core inflation estimate using data up to t, and for periods $t, t-1, t-2, t-3, \ldots, 1$ compute the difference between the estimated level of core inflation from that vintage and the ex-post estimate of core inflation. These results are then averaged across all the results from 2000Q1 to 2009Q4. The results for the contemporaneous quarter and first four lags are presented in table 2.[15]

Table 2 reveals that on average, the estimated historical level of core inflation made at any point between 2000Q1 to 2009Q4 is around 0.16 percentage points lower than the full-sample estimate of the historical core level. And as would be expected, the size of these revisions decline for longer lags. A part of this revision could be due to the change in the mean inflation rate over our sample range.[16] The Bayesian dynamic factor model assumes a constant mean over the entire sample, thus a rising sample mean will bias the real-time estimate downwards. However, the results are dependant upon the sample period used.[17]

5 Monetary policy's response to core inflation

[TBC]

6 Conclusion

In this paper I construct and estimate an a-theoretical estimate of core inflation using a Bayesian dynamic factor model on a panel of disaggregated CPI data. The main contribution from this paper is to use two factors in the model and identify, through the use of sign restrictions, one as a tradable factor and the other as a non-tradable factor. This allows for a pseudo-structural story of the factors driving core inflation in New

[15] A positive number indicates that the real-time estimate is revised upwards over time.

[16] One potential source for this change is the change in the inflation target of the Reserve Bank which has twice been revised upwards over our sample range.

[17] In general, a much smaller real-time sample period will produce smaller revisions as the data difference between the first and ex-post estimates will be much smaller.

Zealand. The use of Bayesian estimation with Gibbs sampling on the model also makes it possible to characterise the parameter uncertainty surrounding the estimate of core inflation

A decomposition of the core inflation estimate into the contributions for the tradable and non-tradable factors reveals that core inflation is driven more by the non-tradable factor. The non-tradable factor also explains significantly more of the variance in quarterly headline CPI inflation relative to the tradable factor explains. Finally an analysis of the real-time estimates of the core show that they are broadly consistent with the ex-post estimate.

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A Inflation Data

Table 3: CPI weightings for the series used in our panel

ID code	Description	Contribution to inflation basket CPI	Tradable	Non-tradable
pssf	Fruit	0.87	0.87	
psfv	Vegetables	1.33	1.33	
psmp	Meat and poultry	2.48	1.92	0.56
psfish	Fish and other seafood	0.34	0.34	
psbc	Bread and cereals	2.01	1.13	0.87
psmce	Milk, cheese and eggs	1.57	1.41	0.16
psof	Oils and fats	0.31	0.31	
psfac	Food additives and condiments	0.46	0.46	
psscn	Confectionery, nuts and snacks	1.65	1.65	
psogf	Other grocery food	0.70	0.70	
psbev	Coffee, tea and other hot drinks	0.32	0.32	
pssfd	Soft drinks, waters and juices	1.30	1.13	0.17
psrest	Restaurant meals	1.79		1.79
psrtef	Ready-to-eat food	2.24		2.24
psbeer	Beer	2.18		2.18
pswine	Wine	1.51	1.05	0.46
psspli	Spirits and liqueurs	1.28	0.71	0.57
psct	Cigarettes and tobacco	2.23		2.23
psmcl	Men's clothing	1.08	1.08	
pswcl	Women's clothing	2.00	2.00	
psccl	Children's and infants' clothing	0.73	0.73	
psskm	Knitting and sewing supplies	0.07	0.07	
pscs	Clothing services	0.07		0.07
psmfo	Men's footwear	0.24	0.24	
pswfo	Women's footwear	0.43	0.43	
pscfo	Children's and infants' footwear	0.12	0.12	
psar	Actual rentals for housing	6.87		6.87
psphsg	Purchase of housing	4.66		4.66
pspmm	Property maintenance materials	0.63	0.63	
pspms	Property maintenance services	1.61		1.61
psws	Water supply	0.16		0.16
psrdr	Refuse disposal and recycling	0.12		0.12
pslarp	Local authority rates and payments	2.16		2.16
pse	Electricity	3.29		3.29
psg	Gas	0.40		0.40
pssfuel	Solid fuels	0.13	0.13	
psfurn	Furniture and furnishings	1.59	1.59	
psfcov	Carpets and other floor coverings	0.49	0.49	
pshht	Household textiles	0.53	0.53	
psmha	Major household appliances	0.89	0.89	
psseha	Small electrical household appliances	0.15	0.15	
psrhha	Repair and hire of household appliances	0.13		0.13
psdk	Glassware, tableware and household utensils	0.35	0.35	
psmthg	Major tools and equipment for the house and garden	0.18	0.15	0.03
pssthg	Small tools and accessories for the house and garden	0.27	0.27	
pscphs	Cleaning products and other household supplies	0.77	0.77	
pshhse	Other household services	0.16		0.16
pspp	Pharmaceutical products	0.77	0.43	0.33
psomp	Other medical products	0.04	0.04	
pstae	Therapeutic appliances and equipment	0.33	0.33	
psmeds	Medical services	2.09		2.09

continued on next page

Table 3: *continued*

ID code	Description	Contribution to inflation basket CPI	Tradable	Non-tradable
psds	Dental services	0.86		0.86
psparas	Paramedical services	0.47		0.47
pshosps	Hospital services	0.68		0.68
pspnmv	Purchase of new motor cars	1.69	1.69	
pspshmv	Purchase of second-hand motor cars	3.30	3.30	
pspmc	Purchase of motorcycles	0.19	0.19	
pspbic	Purchase of bicycles	0.05	0.05	
psvpm	Vehicle parts and accessories	0.72	0.72	
pspet	Petrol	5.38	5.38	
psovfl	Other vehicle fuels and lubricants	0.44	0.44	
psmvrm	Vehicle servicing and repairs	1.48		1.48
psots	Other private transport services	1.27		1.27
psrail	Rail passenger transport	0.08		0.08
psroad	Road passenger transport	0.46		0.46
psdoma	Domestic air transport	0.73		0.73
psinta	International air transport	1.36	1.36	
pssea	Sea passenger transport	0.10		0.10
pspost	Postal services	0.16		0.16
pstele	Telecommunication equipment	0.15	0.15	
pstels	Telecommunication services	2.96		2.96
psave	Audio-visual equipment	0.94	0.94	
pscompe	Computing equipment	0.49	0.49	
psrecm	Recording media	0.40	0.40	
psmrecce	Major recreational and cultural equipment	0.42	0.42	
psgth	Games, toys and hobbies	0.37	0.37	
pseoutd	Equipment for sport, camping and outdoor recreation	0.47	0.47	
pspfgs	Plants, flowers and gardening supplies	0.57	0.57	
pspetp	Pet-related products	0.59	0.59	
psrecss	Recreational and sporting services	1.01		1.01
pscults	Cultural services	1.63	0.18	1.45
psvets	Veterinary services	0.24		0.24
psbook	Books	0.45	0.45	
psnews	Newspapers and magazines	0.87	0.39	0.48
psstdm	Stationery and drawing materials	0.26	0.26	
psacc	Accommodation services	0.66		0.66
psph	Package holidays	0.84	0.76	0.08
pseced	Early childhood education	0.35		0.35
pspsed	Primary and secondary education	0.70		0.70
pstpsed	Tertiary and other post-school education	1.03		1.03
pshpgs	Hairdressing and personal grooming services	0.67		0.67
pseapc	Electrical appliances for personal care	0.02	0.02	
psoaapc	Other appliances, articles and products for personal care	1.44	1.44	
psjewel	Jewellery and watches	0.37	0.33	0.04
psope	Other personal effects	0.22	0.22	
pslife	Life insurance	0.69		0.69
psdwel	Dwelling insurance	0.19		0.19
pscont	Contents insurance	0.25		0.25
psheal	Health insurance	0.18		0.18
psvehins	Vehicle insurance	0.38		0.38
psdcsc	Direct credit service charges	0.76		0.76
psvocs	Vocational services	0.30		0.30
psprofs	Professional services	0.35		0.35
psres	Real estate services	1.11		1.11
psoms	Other miscellaneous services nec	0.19		0.19