Economics Working Paper Series

2013/001

A New Look at Variation in Employment Growth in Canada: The Role of Industry, Provincial, National and External Factors.

Michele Campolieti, Deborah Gefang and Gary Koop

The Department of Economics
Lancaster University Management School
Lancaster LA1 4YX
UK

A New Look at Variation in Employment Growth in Canada: The Role of Industry, Provincial, National and External Factors

Michele Campolieti*

Department of Management, University of Toronto Scarborough

Centre for Industrial Relations, University of Toronto

Deborah Gefang

Department of Economics, Lancaster University

Gary Koop

Department of Economics, University of Strathclyde

February 5, 2013

Abstract

We examine fluctuations in employment growth using Canadian data from 1976 to 2010. We consider a wide range of models and examine the sensitivity of our findings to modeling assumptions. The results from our most preferred model, which we selected using the Bayesian Information Criteria, indicate that most of the variance in employment growth that

*Campolieti gratefully acknowledges the financial support of the Social Sciences and Humanities Research Council of Canada (SSHRC). Please address correspondence to Michele Campolieti, Centre for Industrial Relations, University of Toronto, 121 St. George Street, Toronto, Ontario, M5S 2E8, Canada; email: campolie@chass.utoronto.ca.

is not due to the idiosyncratic error comes from domestic sources, with most of this coming from industry and provincial factors. Overall, we find external and national factors play a much smaller role in employment fluctuations than earlier research. We provide some possible explanations for these differences.

1 Introduction

Fluctuations in the labor market can have a number of different sources. They might be driven by broad business cycle trends for the economy as a whole. Or they might be specific to a region (e.g. due to policies pursued by regional governments or regional differences in economic growth rates). Alternatively, they might be specific to an industry, e.g. due to changes in productivity or changes in demand for an industry's output, or they might even be due to external forces in the world economy. Understanding the roles played by these various sources of shocks to the labor market should lead to better policy-making because the appropriate policy may differ depending on the source of fluctuations. For example, if fluctuations are due to regional-specific factors, then a centralized response at the national level may not be appropriate for stabilizing employment fluctuations.

There are many papers which examine the sources of economic fluctuations and the empirical literature breaks into two main streams. One stream of research examines the sources of shocks and their relative contribution to economic fluctuations in industrial production and GDP. The other stream focusses directly on the labor market and investigates shocks and fluctuations in unemployment and/or employment. This paper relates to this second stream. In particular, we investigate the sources of fluctuations in employment growth in Canada using data disaggregated by industry and province.

We focus on the labor market since data is available at a disaggregated level such as province-industry. In contrast, industrial production and GDP data series are limited by aggregation issues. That is, they are sometimes not presented at very disaggregated levels. We consider employment (as opposed to unemployment) so as to avoid the definitional issues associated with unemployment measured at the industry level. Also, Riddell (1999) noted that some of the differences in unemployment rates across countries, e.g., Canada and the US as well as Europe versus the US, arise from differences in the definition of unemployment. For example, some persons that are considered unemployed in the US would be considered out of the labor force in Canada. Consequently, employment is more likely to be consistently measured at the industry level and comparable across countries.

While there are differences across the two streams of research in terms of the focus of their investigation, both streams have used dynamic factor models (DFMs) in their empirical specifications. Our econometric methods will also use DFMs. DFMs have become an increasingly common way of quantifying the extent of co-movements in macroeconomic variables (e.g., among others, Otrok and Whiteman, 1998; Kose, Otrok and Whiteman, 2003; Crucini, Kose and Otork, 2011; Mumtaz, Simonelli and Surico, 2011) and financial time series (e.g., among others, Aguilar and West, 2000; Gourieroux and Jasiak, 2001; Diebold, Rudebusch and Aruoba, 2006; and, Koopman, Lucas and Schwaab, 2012). In our setting, DFMs can quantify the degree of co-movement in employment growth across industries and regions and allow us to determine the sources of fluctuations in employment growth, i.e., how much of the fluctuations in employment growth can be attributed to industry factors, regional factors, national factors or external factors.

The existing literature has largely focussed on the US, although there have been several studies of Canada as well as some European countries.[1] Canada is an instructive country to study for a number of reasons. First, it is a large country with a great deal of variation in industrial composition across its regions. Second, its political structure is a federal system, with both a national government along with provincial governments. Third, it is an open economy and international factors (primarily the US) are thought to have a large effect on its economy. Consequently, Canada provides an ideal setting to study the contributions of different sorts of shocks to employment fluctuations.

In this paper we use an updated Canadian data set of annual data through 2010 to thoroughly investigate the sensitivity of decompositions of fluctuations in employment growth to modelling assumptions. We consider both DFMs as well as VAR models augmented with dynamic factor structures. DFMs are driven by unobserved latent factors, so the results can be quite sensitive to identifying assumptions or assumptions about the dynamics of the factors. We consider a wide range of models, some that have been considered before in the literature, as well as some alternative specifications that have not been considered before. These models differ in terms of how they allow for persistence in employment fluctuations. With VARs and factor models, Bayesian methods are enjoying an increasing popularity and we follow this trend. In addition to standard arguments in favor of Bayesian methods in such high-dimensional models (see, e.g., Koop and Korobilis, 2009), there are some advantages particular to this literature. First, assessing model fit is much more straightforward with Bayesian methods and does not encounter the problems with determining the degrees of freedom for goodness-of-fit tests with minimum distance estimators (e.g., Altonji and Ham, 1990; Clark, 1998). This makes it possible for us to determine the most appropriate model, which we also compare to some other

[1] Some of the literature has also looked at cities, e.g., among others, Kuttner and Sbordone (1997) and Carlino, DeFina and Sill (2001).

models commonly used in the literature to determine the sensitivity of our findings to model specification choices. Second, our MCMC methods provides us with draws of the factors which can be used to produce estimates of them or measures of uncertainty associated with them in a manner not considered before in the previous literature. Our paper also updates the literature and provides more timely and relevant information about the sources of labor market fluctuations in Canada. Earlier papers (Altonji and Ham, 1990; Prasad and Thomas, 1998) have only considered data until the early-1980s or early-1990s, so their results may not capture the effects of the North American Free Trade agreement or outsourcing on the Canadian labor market (Trefler, 2004).

In the next section we present the models that we consider in our analysis. Section 3 presents a brief review of the previous literature considering the sources of employment fluctuations. Section 4 describes our data sources as well as some patterns in the summary statistics. Section 5 presents our empirical results and a comparison to the earlier literature. Section 6 concludes the paper with a summary of our findings and their implications.

2 Dynamic Factor Models for Employment Growth

Before surveying the literature on employment growth decompositions, it is useful to specify our modelling framework so as to make clear the relationship of our model to previous work. Let y_{ipt} be the employment growth rate of industry i (for $i = 1, 2, ..., I$) in province p (for $p = 1, 2, ..., P$) in year t (for $t = 1, 2, ..., T$).

Employment growth is assumed to be driven by various latent factors and current and lagged US GDP growth. We assume that there is an idiosyncratic error term and three types of factors: I industry specific factors (f_{it}^{I}, one per industry), P province specific factors (f_{pt}^{P}, one per province), and a single national factor (f_t^N). Thus, the model can be written as:

$$Y_t = \lambda + \beta_0 DGDP_t^{US} + \beta_1 DGDP_{t-1}^{US} + \gamma^I f_t^I + \gamma^P f_t^P + \gamma^N f_t^N + \varepsilon_t, \tag{1}$$

where $DGDP_t^{US}$ is the annual percentage change in US GDP, $f_t^I = \left(f_{1t}^I, .., f_{It}^I\right)'$ is the $I \times 1$ vector of industry factors, f_t^P is the $P \times 1$ vector of provincial factors, f_t^N is the (scalar) national factor and ε_t is the idiosyncratic error. As for the factor loadings: γ^I is a $PI \times I$ matrix, γ^P is a $PI \times P$ matrix and γ^N is a $PI \times 1$ vector. The dependent variable, Y_t is a $PI \times 1$ vector which stacks all the employment growth rates for each industry and province.

Factor models require identification restrictions to ensure that each term on the right hand side of (1) has the desired interpretation. In this paper we adopt standard identifying assumptions. In particular, the covariance matrix for ε_t is assumed to be diagonal so that each element, ε_{ipt}, is a purely idiosyncratic shock which is specific to industry i in province p at time t. γ^P has zero restrictions which impose that the factor for province p only loads on employment growth in industries in province p, γ^I is restricted to ensure the factor for industry i only loads on employment growth in that industry. Employment growth rates in all industries in all provinces load onto the national factor.

From an economic perspective the decomposition in (1) is an interesting one. But it is relatively silent about the dynamic properties of the various components in the model. If we assume the factors and ε_t are independent over time, then we obtain a static factor model (apart from the dynamics accounted for by $DGDP_{t-1}^{US}$). In our empirical work, we do consider such a static factor model. However, time series data such as that used in this paper typically exhibits persistence and it is potentially important for a statistical model to account for it. Different approaches exist in the literature for incorporating this persistence. Given that we have a short annual data set, we will work with

AR(1) or VAR(1) dynamics in this paper. However, such processes can be used in various ways on Y_t, f_t and/or ε_t.

With regards to the factors, a common version of the DFM (e.g. Otrok and Whiteman, 1998 or Kose, Otrok and Whiteman, 2003) assumes the factors follow independent AR(1) processes (for $s = i, p, n$ and $S = I, P, N$)

$$f_{st}^S = f_{s(t-1)}^S \phi_{s,1} + v_{st}^S \tag{2}$$

where v_{st}^S are i.i.d. $N(0,1)$ or, in matrix notation,

$$f_t = \Phi f_{t-1} + v_t \tag{3}$$

where Φ is a diagonal matrix and v_t is i.i.d. $N(0, I)$. Setting the error covariance matrix in the factor equation to I is a standard identification assumption. A final standard identification assumption (see Kose, Otrok and Whiteman, 2003) is that appropriate elements of the factor loading matrices are assumed to be non-negative (or zero as noted above). Note that (2) or (3) builds in the property that, e.g., the dynamics of the manufacturing sector factor are specific to the manufacturing sector. There are no spillovers from one sector to another. However, the specification does allow for persistence in the dynamics of each individual factor.

Dynamics are also conventionally built into the DFM by assuming that the idiosyncratic errors have an AR(1) structure. For instance, in Otrok and Whiteman (1998) the error terms, ε_{ipt}, are assumed to follow AR(1) processes:

$$\varepsilon_{ipt} = \rho_{ip} \varepsilon_{ip(t-1)} + u_{ipt} \tag{4}$$

where u_{ipt} are assumed to be i.i.d. $N(0, \sigma_{ip}^2)$ or in matrix notation as a VAR(1) process for the vector ε_t

$$\varepsilon_t = \Upsilon \varepsilon_{t-1} + u_t \tag{5}$$

where Υ is a diagonal $PI \times PI$ matrix and u_t is i.i.d. $N(0, D)$ and D is a diagonal matrix. Crucially, the AR(1) processes for the different industries/provinces are assumed to be independent of one another.

In this paper, we do consider models which restrict Φ and Υ in (3) and (5) to be diagonal matrices and the static factor model sets $\Phi = \Upsilon = 0$. However, we see no underlying economic justification for doing so. A model where Φ and/or Υ is left unrestricted allows for spillovers across industries or provinces with a one year time lag. So, for instance, if Φ is unrestricted the factor for industry i could have an impact on industry j with a one year time lag.

It is worth stressing that an AR structure allows for persistence in employment growth, which is an important feature of the data. For example, Fujita (2011) and Campolieti, Gefang and Koop (2012) show that the process of labor market adjustment in the US and Canada (as well as Spain, France and the UK) exhibits persistence (to varying degrees) since shocks to labor market flows and vacancies take time to dissipate. This suggests that DFMs of employment growth with richer dynamics on the errors and factors may better reflect the process of labor market adjustment in many countries.

While applications of DFMs in finance and macroeconomics often include an AR structure directly on the factors or the residuals (see, e.g., Stock and Watson, 2011), the literature examining the labor market does not (e.g., Norrbin and Schlagenhauf, 1988; Altonji and Ham, 1990; Clark, 1990). What this literature does is use a VAR structure directly on Y_t and, typically, the factors are assumed to be independent over time. In essence, dynamics are removed via this VAR structure rather than through the factors. To be explicit, papers such as Norrbin and Schlagenhauf (1988), Altonji and Ham (1990) and Clark (1998) use a socalled VAR-factor approach and model the dynamics by including lags of the PI dependent variables as follows:

$$Y_t = \lambda + \Lambda Y_{t-1} + \beta_0 DGDP_t^{US} + \beta_1 DGDP_{t-1}^{US} + \gamma^I f_t^I + \gamma^P f_t^P + \gamma^N f_t^N + \varepsilon_t. \quad (6)$$

Note that Λ will contain a large number of parameters. Accordingly, some papers in the literature restrict Λ to obtain a more parsimonious specification that is easier to estimate. An alternative approach could make use of parsimonious Bayesian VAR techniques (e.g. through use of the Minnesota prior), so there is no need to impose such restrictions (unless they are empirically warranted). In our empirical work, we investigate both these approaches.[2]

One set of restrictions on Λ that has been used in the literature is to include lagged aggregate employment growth, average (across industries) provincial employment growth and average (across provinces) industrial employment growth in (6). Such a specification implies a set of restrictions on Λ which we refer to as: Λ restricted*. This sort of restriction is equivalent to the specification in equation (6b) of Altonji and Ham (1990), which is also used in Norrbin and Schlagenhauf (1988) with US data. To be precise, this version of the model restricts Λ so that the lagged dependent variables enter as: the national aggregate growth rate at time t; the aggregate growth rate in province p at time t; and the aggregate growth rate in industry i at time t. The aggregates are constructed as fixed-weight averages of the province-industry variable, with weights corresponding to employment shares as described in Altonji and Ham (1990), p. 207.

Another set of restrictions on Λ that could be used in (6) is to allow only the own lag coefficients in Λ to be non-zero and the off diagonal elements to be zero. That is, each equation just has AR(1) dynamics (i.e. the equation for Y_{ipt}

[2]We also use the Minnesota prior on Υ or Φ when they are unrestricted matrices.

contains $Y_{ip,t-1}$ as an explanatory variable, but not $Y_{lr,t-1}$ for $l \neq i$ and $r \neq p$). We consider this model in our empirical work and refer to it as: Λ restricted**.

The discussion above relates to the modelling of persistence and spillovers in DFMs and shows how there are several possible treatments of these issues. The economics of the problem offers little guidance in how exactly to model the persistence in each component.[3] Should lags of the dependent variable be used or should the idiosyncratic errors have AR processes? Should the AR processes be independent of one another or not? In the absence of definitive theoretical answers to these questions, it is best to use a statistical approach (when possible) to choose an appropriate specification. This is what we do in this paper. Persistence can appear through the factors, ε_t and Y_t and we investigate which in our empirical work. For the dynamics on ε_t and Y_t, we restrict consideration to models which either have lagged dependent variables or have autocorrelated idiosyncratic errors (but not both). This reduces the number of potential models somewhat. The existing literature typically makes a specific choice on how persistence and spillovers enter the model. However, empirical results may be sensitive to this choices. For instance, the VAR-factor model in (6) has the property that lags of employment growth in every industry (or province) can influence employment growth in any particular industry (or province). So, for instance, in (6) the financial industry in Ontario can affect the resources industry in Alberta (with a lag of one year). In contrast, in the DFM in (1) with i.i.d. errors or the autocorrelated errors as specified in (4), the only way that the financial sector in Ontario can influence the resources industry in Alberta is through the national factor. Such differences can potentially have a big impact on empirical results. It is also potentially important to have AR process in both the factors and the idiosyncratic component (although this is not

[3] Norrbin and Schlagenhauf (1988) present an economic model of fluctuations that shows the a role for industry and region specific factors and also includes the possibility of dynamics and spillovers.

always done in the literature). If not, there will be a tendency to bias results in favour of the component containing the AR process. For instance, if the factors are assumed to be i.i.d. but ε_{ipt} has an AR process, then all persistence in the employment growth data (even that which is common to an industry or a province) would be allocated to ε_{ipt} and the idiosyncratic component would receive a disproportionate weight in a variance decomposition.

In summary, we argue that there is a wide range of factor models which could be sensibly used to carry out a variance decomposition on the employment growth data. In the absence of a compelling economic reason to prefer some over others, our empirical work considers all the models and uses econometric methods to shed light on which are to be preferred. We summarize the models we consider in Table 1.

Table 1: List of Models			
Name	Lagged Y	Lagged ε_t	Lagged factors
Static Factor Model	No	No	No
VAR-factor1	Λ unrest.	No	No
VAR-factor2	Λ restricted*	No	No
VAR-factor3	Λ unrest.	No	Φ unrest.
VAR-factor4	Λ restricted*	No	Φ unrest.
VAR-factor5	Λ unrest.	No	Φ diagonal
VAR-factor6	Λ restricted*	No	Φ diagonal
VAR-factor7	Λ restricted**	No	No
VAR-factor8	Λ restricted**	No	Φ unrest.
VAR-factor9	Λ restricted**	No	Φ diagonal
DFM1	No	Υ unrest.	No
DFM2	No	Υ diagonal	No
DFM3	No	Υ unrest.	Φ unrest.
DFM4	No	Υ diagonal	Φ unrest.
DFM5	No	Υ unrest.	Φ diagonal
DFM6	No	Υ diagonal	Φ diagonal
DFM7	No	No	Φ unrest.
DFM8	No	No	Φ diagonal
Note 1: Λ restricted* = lagged weighted averaged aggregate growth, lagged weighted averaged provincial growth rates, and lagged weighted averaged industrial growth rates enter each equation in lieu of the lagged Ys			
Note 2: Λ restricted** = only own lag coefficients are non-zero.			

We estimate these models using a Bayesian approach, employing MCMC methods. As we noted earlier, one advantage of the Bayesian approach is that assessing model fit is straight forward compared to the minimum distance estimator used in the earlier literature.[4] Since Bayesian MCMC methods for DFMs and VARs are well-established in the literature (see, e.g., Koop and Korobilis, 2009) we will not provide them here. The reader is referred to the online appendix associated with this paper which is available at http://personal.strath.ac.uk/gary.koop/research.htm. This appendix also describes our priors. We make priors as similar as possible for different models so that meaningful comparisons can be made between models.

To assess the relative contribution of the different sources of fluctuations in employment growth we compute variance decompositions. We compute two

[4] Altonji and Ham (1990) noted that with the minimum distance approach the sample moment matrix is of dimension of PI, but is only of rank T. This makes it difficult to determine the degrees of freedom for the χ^2 goodness of fit tests.

variance decompositions, a one-period ahead and a long-run steady state decomposition,[5] which we refer to as the short- and long-horizon variance decompositions. The variance decompositions attribute shares of the forecast error variances to the sources we consider: the US (i.e., external); national; provincial; industry; and idiosyncratic. The online appendix provides exact formulae for the variance decompositions.

3 Literature Review

This section describes in more detail the existing literature and how it relates to the factor models described in the preceding section.

Altonji and Ham (1990) used a VAR-factor model (i.e., VAR-factor 2 in Table 1) to look at sources of employment fluctuations in Canada using annual level employment data disaggregated by 1-digit SIC and region from 1961 to 1982.[6] In order to incorporate the effects of international or US shocks in their analysis, Altonji and Ham (1990) also included US GDP in their specification. Altonji and Ham (1990) found that the US shock accounts for the bulk of the employment fluctuations in Canada. Their results also indicated that the national shock accounts for about a third of the fluctuations in employment growth. Provincial shocks played a smaller role and industry-specific shocks tended to account for very little of the fluctuations in employment.

Prasad and Thomas (1998) also examined Canadian employment data, but used data from 1975 to 1993. Prasad and Thomas (1998) did not use a DFM, but instead used regressions with dummy variables to capture the effects of the national, provincial and industry-specific shocks. Unlike Altonji and Ham (1990), Prasad and Thomas (1998) found that there was a much bigger role for

[5] Following Clark and Shin (1999) this is based on the 251-step ahead forecast errors.

[6] Altonji and Ham (1990) combined a few provinces in their analysis and also excluded Newfoundland and Prince Edward Island, so the number of regions they considered is less than the 10 provinces in Canada.

industry-specific shocks in their analysis. In fact, industry-specific shocks accounted for the largest fraction of fluctuations in employment growth, although they also found that regional/provincial and aggregated shocks had a significant contribution to employment fluctuations. However, Prasad and Thomas (1998) also found that a sizable fraction of the fluctuations in employment growth could be attributed to growth in US GDP. Prasad and Thomas (1998) noted that their findings could differ from those in Altonji and Ham (1990) because their sample period includes more recent data that could show more of the effects of globalization on the Canadian economy.

Rosenbloom and Sundstrom (1997) also used the dummy variable approach, similar to Prasad and Thomas (1998), but applied it to biennial employment data from the US for manufacturing industries by state for years during the Great Depression. Rosenbloom and Sundstrom (1997) found that common shocks accounted for about 11 percent and industry shocks explained 16 percent of region-industry variation. Rosenbloom and Sundstrom (1997) concluded that the effect of the Great Depression did not differ a great deal across regions once trends and industry structure are accounted for.

Rissman (1999) found in her study of regional employment growth in US Census regions (1961Q1 to 1998Q2) that a common aggregate factor was an important contributor to regional employment growth. However, she also found that local shocks also played an important role, accounting for as much as 60 percent of steady state variance in some regions. She concluded that regional policies could be an important component of economic stabilization policy.

Clark (1998) used a VAR-factor model to look at the contribution of national, regional and industry shocks in US employment fluctuations with quarterly data from 1947 to 1990, where regions are the Census Bureau aggregate regions not individual states.[7] Clark's model differs from Altonji and Ham (1990) since it

[7] Clark (1998) also conducted some analyses with alternative defintions of aggregated re-

is more aggregated. Clark's VAR specification includes lags of growth in real oil prices and the US exchange rate as well as lagged employment growth. Clark (1998) found that regional shocks account for about 41 percent of the innovation variance, while common and industry shocks accounted for about 40 and 20 percent of the innovation variance. Clark (1998) also found that regional shocks propagate across regions. The disadvantage of highly aggregated regional data is that many shocks originate at a state level or even county level, which may not be properly reflected in a more broadly defined region. Clark and Shin (1999) found that using state level data lowered the estimates of the effects of national and industry specific shocks and increased the importance of idiosyncratic shocks. However, as noted by Clark and Shin (1999), the aggregated VAR model used by Clark (1998) imposes fewer coefficient restrictions than the disaggregated model, so it allows for richer feedback effects between regions.

Norrbin and Schlagenhauf (1988) estimated a VAR-factor model using quarterly employment data from the US for 1954 to 1984 disaggregated by 1-digit industries and region (Census Bureau aggregate regions). Norrbin and Schlagenhauf (1988) included factors for national, region-specific and industry-specific factors as well as lagged values of employment. The results of Norrbin and Schlagenhauf (1988) indicate that the common shock accounts for about 50 percent of the variation in the employment growth. Norrbin and Schlagenhauf (1988) also found that industry-specific shocks are a fairly large component (28 percent of the variance) and region specific shocks account for about 11 percent of the variance. Clark and Shin (1999) noted that the discrepancy between some of Norrbin and Schlagenhauf (1988) results and Clark (1998) are likely the result of their model specification (lag length) and the period they consider.

Clark and Shin (1999) used a VAR-factor model to examine the fluctuations in employment in the US using an aggregated model like Clark (1998) and data

gions and found that it did not have an effect on his conclusions.

from 1948Q2 to 1997Q4.[8] Clark and Shin (1999) found that region specific shocks account for about 52 percent of the innovation variance, while common shocks account for about 23 percent and industry-specific shocks account for about 24.5 percent of the innovation variance. Clark and Shin (1999) also estimated a disaggregated model, like that in Altonji and Ham (1990), for the US. For this latter model, they found that idiosyncratic shocks account for a large share of innovation variance representing about 49 percent when the analysis was done at the region-industry level. They also found that region-specific shocks account for about 13 percent of the innovation variance, but industry specific shocks accounted 25 percent of the variance. National shocks accounted for about 13 percent of the innovation variance. When the analysis is undertaken at the region level, the idiosyncratic share of the innovation variance falls to 23 percent on average. The common and region-specific shocks each account for about 32 percent of the innovation variance on average, while industry-specific shocks represent about 12.5 percent of the innovation variance.

Clark and Shin (1999) noted in their review of the earlier literature that studies using data for countries other than the US tended to find that common shocks play a smaller role relative to findings from studies that use US data. In addition, Clark and Shin (1999) also concluded that region-specific shocks matter more outside the US, but industry-specific shocks play a larger role in the US data.

Our discussion indicates that there is a great range in the relative importance of these factors in the earlier studies of fluctuations in employment. Some

[8] Clark and Shin (1999) also consider some European countries, but use industrial production instead of employment. Their results for the European countries indicate that region-specific shocks (on average) account for the bulk of innovation or steady-state variance (76 and 66 percent). Common shocks account for 21 percent of innovation variance and 14 percent of steady state variance on average. While industry-specific shocks account for very little of the innovation variance (3.5 percent), they do acount for about 20.5 percent of steady state variance. Overall, it seems that region-specific shocks play a larger role in output fluctuations in Europe.

of these differences are due to methodology, while some can be attributed to differences in the country or periods being covered. Our analysis will explore the sensitivity of the results to different model specifications using Canadian data.

4 Data

We use annual data between 1976 and 2010 to estimate our models. The US (annual) GDP growth rates we use in our models are calculated based on data we obtain from the FRED at the St. Louis Federal Reserve Bank. The employment growth rate data are obtained from the Statistics Canada's CANSIM database. The industry level data in the CANSIM database are NAICS groupings, but the earlier literature used 1-digit SIC codes. In order to maintain comparability with the earlier literature we mapped the most aggregated level of the NAICS codes to the most similar grouping in the earlier 1-digit SIC definitions. We use 9 groupings (with the NAICS 1-digit in parentheses when several sectors were combined): Agriculture, denoted AG; Resources (Forestry, Fishing, Oil and Gas), denoted RES; Transportation Communication and Utilities (transportation, warehousing, information culture and recreation and utilities), denoted TCU; Construction, denoted CON; Manufacturing, denoted MFG; Trade (wholesale and retail trade), denoted TRAD; Finance and Real Estate (finance and insurance, real estate and leasing), denoted FIN; Services (professional scientific and technical services, business building and other support services, educational services, healthcare and social assistance, accommodation and food services, other services), denoted SERV; Public Administration, denoted ADM. There are 10 provinces in Canada, but we exclude Newfoundland and Prince Edward since they are quite small in terms of population and some of the industry groupings have very small employment levels. Earlier papers have also noted this problem and have also excluded them from their samples. We group Nova Scotia and New Brunswick (NS/NB) as well as Saskatchewan and Manitoba (SASK/MAN), both of these grouped province pairs share a common border and similar industry mixes. We consider the remaining provinces, i.e., British Columbia (BC), Alberta (ALB), Ontario (ONT) and Quebec (QUE), as individual provinces since they have large labor markets. This means that we have 6 province/regions in our analysis along with the 9 industry groupings. We present a breakdown of employment by region and industry in Table 2. As can be seen in Table 2, most of employment in Canada is in Ontario and Quebec. From an industry perspective, the service sector is the largest employer in Canada, followed by trade and manufacturing. While the service sector tends to be the leading industry in most regions, there is some regional variation in employment in the other industries.

Tables 3 and 4 present the correlation in employment growth rates across different provinces/regions and industries. In both tables the numbers above the main diagonals are simple correlations, while those below the main diagonals are partial correlations that control for the effects of growth in US GDP. The correlations in Table 2 suggest that the regional correlations are much stronger in the Central and the Eastern parts of Canada. Alberta and British Columbia, while they have a fairly large strong correlations with each other have weaker correlations with the rest of the country, although the correlations with Ontario and Quebec tend to be somewhat larger. The partial correlations below the main diagonal tend to be smaller than those above the main diagonal, which suggests that external factors could play a role in employment fluctuations in Canada. However, some of the differences between the correlations and partial correlations are not very large so it is not clear how large these effects would be. The correlations by industry in Table 4 are much smaller than those by region.

In fact, about 30 of 36 correlations in Table 4 are less than 0.5.[9] Like Table 3, there are differences between the correlations and the partial correlations, which suggests that external factors could be playing a role in the fluctuations in employment across industries. However, there is a large range in these differences, which also suggests some variation across industries. The correlations and partial correlations in Tables 3 and 4 show some evidence of the potential co-movements in employment growth across regions and industries, but it is difficult to determine the strengths of these effects based on a comparison of correlations and partial correlations. Our VAR-factor and dynamic factor models will allow us to quantify these co-movements more directly.

Table 2: Average Percentage Shares in Employment

	NS/NB	QUE	ONT	MAN/SASK	ALB	BC	Totals
AG	0.10	0.49	0.81	0.83	0.60	0.22	3.05
RES	0.20	0.33	0.36	0.17	0.69	0.38	2.13
TCU	0.51	2.36	4.03	0.79	1.12	1.45	10.27
CON	0.33	1.18	2.29	0.40	0.89	0.91	6.00
MFG	0.59	4.38	7.34	0.66	0.84	1.36	15.16
TRAD	0.89	3.91	6.09	1.17	1.68	2.06	15.80
FIN	0.25	1.40	2.76	0.40	0.59	0.82	6.23
SERV	1.91	8.59	13.84	2.55	3.80	4.80	35.48
ADM	0.39	1.54	2.23	0.48	0.57	0.67	5.88
Totals	5.18	24.19	39.75	7.46	10.77	12.66	100

Table 3

A. Means, Standard Deviations (SD), and Correlations for Provincial Employment Growth

	NS/NB	QUE	ONT	MAN/SASK	ALB	BC
Mean	1.25	1.27	1.67	0.99	2.52	2.22
SD	1.56	1.78	1.87	1.05	2.39	2.19
B. Simple Correlations above the Diagonal/Partial Correlations below the Diagonal						
NS/NB	1.00	0.84	0.83	0.59	0.42	0.48
QUE	*0.77*	1.00	0.83	0.71	0.42	0.56
ONT	*0.73*	*0.72*	1.00	0.62	0.51	0.47
MAN/SASK	*0.49*	*0.65*	*0.54*	1.00	0.45	0.34
ALB	*0.33*	*0.28*	*0.43*	*0.45*	1.00	0.61
BC	*0.31*	*0.38*	*0.24*	*0.28*	*0.60*	1.00

Note: We control for the current and lagged US GDP growth when calculate the partial correlations.

[9]By comparison, Altonji and Ham (1990) reported 23 out of 36 correlations by industry were less than 0.5.

Table 4									
A. Means, Standard Deviations (SD), and Correlations for Industrial Employment Growth									
	AG	RES	TCU	CON	MFG	TRAD	FIN	SERV	ADM
Mean	-1.28	0.76	1.56	1.74	-0.18	1.58	2.16	2.79	1.14
SD	3.69	5.79	2.33	4.72	4.12	1.69	2.47	1.22	2.35
B. Simple Correlations above the Diagonal/Partial Correlations below the Diagonal									
AG	1.00	-0.14	-0.28	-0.09	-0.09	-0.09	-0.11	0.21	-0.13
RES	*-0.09*	1.00	0.34	0.35	0.38	0.37	0.40	0.41	0.28
TCU	*-0.30*	*0.12*	1.00	0.51	0.68	0.53	0.10	0.54	-0.22
CON	*-0.04*	*0.08*	*0.33*	1.00	0.41	0.49	0.14	0.47	0.12
MFG	*0.03*	*0.14*	*0.40*	*0.05*	1.00	0.60	0.11	0.62	-0.23
TRAD	*-0.11*	*0.11*	*0.39*	*0.27*	*0.13*	1.00	0.12	0.45	-0.04
FIN	*-0.18*	*0.39*	*0.15*	*0.18*	*-0.13*	*0.16*	1.00	0.25	0.31
SERV	*0.03*	*0.17*	*0.48*	*0.36*	*-0.07*	*0.33*	*0.40*	1.00	0.09
ADM	*-0.16*	*0.23*	*-0.20*	*0.07*	*-0.42*	*0.06*	*0.45*	*0.40*	1.00
Note: We control for the current and lagged US GDP growth when calculate the partial correlations.									

5 Empirical Findings

5.1 Model Comparison Results

We use the Bayes Information Criterion (BIC) to compare the models listed in Table 1. This is defined as:

$$BIC = -2\hat{l} + log(T)d \tag{7}$$

where $\hat{l}$ is the maximum of the likelihood function and d is the number of parameters. This method is particularly appealing as it does not involve integration and does not depend on the priors (Wasserman, 2000).

Table 5 presents the BIC measures for the competing models. In general, restricted VAR-factor models and restricted dynamic factor models are more favoured. The most preferred model chosen by the BIC is the VAR-factor 9 model. As shown in Kass and Raftery (1995), the Bayes factor can be approximated by the exponential of $-\frac{1}{2}$ times the differences between two models' BIC

measures calculated by equation (7). Thus, if we assume uniform prior model probabilities, the most preferred model will receive almost 100% of the posterior probability.

The findings in Table 5 are clear and striking in relation to persistence and spillovers. It is important to account for persistence (since the static factor model performs poorly), but it is not as important to account for spillovers. In particular, parsimonious models which do not allow spillovers between provinces/industries with a one year time lag are preferred by the data. That is, models which allow for Λ, Φ and/or Υ to be unrestricted perform worst. We stress that, for these models, we are using conventional, informative, Minnesota priors which should help shrink the many coefficients in these parameters so as to avoid over-fitting. But clearly the Minnesota prior shrinkage is not enough. Models where off-diagonal elements of Λ, Φ and/or Υ are set to zero are preferred by the data. This result is reassuring to much of the existing literature which did not allow for such spillovers. However, some aspects are less assuring for the existing literature. In particular, the restrictions in the models we label Λ restricted*, where lagged average aggregate, provincial and industrial growth rates are included as regressors, are not supported by the data. These (or similar) restrictions are used in several papers such as Altonji and Ham (1990), Norrbin and Schlagenhauf (1988) and Clark and Shin (1999). Models which assume purely AR(1) behavior for each Y_{ipt} or involve the idiosyncratic errors having independent AR(1) processes as in (4) score better when measured by the BIC.

Furthermore, Table 5 emphasizes the importance of also allowing the factors to be dynamic (a feature not included in much of the existing literature). However, allowing for spillovers (with a lag) across the factors is not supported by the data. Instead, the simple specification of (2) where each factor follows an independent AR(1) process is supported by the data.

Table 5: Model Comparison Results				
Name	Lagged Y	Lagged ε_t	Lagged factors	BIC
VAR-factor 9	Λ restricted**	No	Φ diagonal	8961.99
DFM 2	No	Υ diagonal	No	9011.20
VAR-factor 7	Λ restricted**	No	No	9017.80
DFM 6	No	Υ diagonal	Φ diagonal	9086.36
VAR-factor 2	Λ restricted*	No	No	9269.07
VAR-factor 6	Λ restricted*	No	Φ diagonal	9380.83
Static Factor Model	No	No	No	9405.46
DFM 8	No	No	Φ diagonal	9513.98
DFM 7	No	No	Φ unrest.	9516.66
DFM 4	No	Υ diagonal	Φ unrest.	9833.10
VAR-factor 8	Λ restricted**	No	Φ unrest.	9900.96
VAR-factor 1	Λ unrest.	No	No	10091.79
VAR-factor 5	Λ unrest.	No	Φ diagonal	10120.34
VAR-factor 4	Λ restricted*	No	Φ unrest.	10196.35
VAR-factor 3	Λ unrest.	No	Φ unrest.	10975.35
DFM 1	No	Υ unrest.	No	12816.87
DFM 5	No	Υ unrest.	Φ diagonal	13012.23
DFM 3	No	Υ unrest.	Φ unrest.	13747.47
Note 1: Λ restricted* = lagged weighted averaged aggregate growth, lagged weighted averaged provincial growth rates, and lagged weighted averaged industrial growth rates enter each equation in lieu of the lagged Ys				
Note 2: Λ restricted** = only own lag coefficients are non-zero.				

5.2 Correlation Between Factors

If Φ is restricted to be a diagonal matrix (or the factors are static), then the factors should theoretically be uncorrelated with one another and the interpretation of the variance decomposition as reflecting the individual roles of orthogonal factors is clear and straightforward. In the preceding section, we found strong evidence in favor of a model where Φ is restricted to be a diagonal matrix. However, to present additional support for this specification, and to confirm that the estimated factors are consistent with their theoretical properties it is useful to look into this aspect more deeply. In particular, following Brooks and Del Negro (2005), we check the correlations between the national, province and industry factors to see if the orthogonality assumption is violated. Table 6 reports the correlations between the national, province and industry factors for each of the eighteen models. These correlations use the posterior mean of each factor and calculate a simple correlation with each other factor. Since there are many industrial and provincial factors, Table 6 presents the median (taken across provinces or industries as appropriate). We use N./-N. to denote the median of the correlations between the national factor and the rest of the factors. Similarly, we use N./P., N./I., P./P., I./I., and P./I. to denote the median of the correlations between the national factor and the provincial factors, the national factor and the industry factors, a province factor and the rest of the province factors, an industry factor and the rest of the industry factors, and a province factor and the industry factors, respectively.

Table 6 presents strong evidence that all of the models are estimating factors which are roughly uncorrelated with one another. Even models which do not necessarily imply factors are orthogonal (e.g. VAR-factor 3, 4 and 8), the estimated factors are found to be roughly orthogonal.

Table 6: Correlations Between Factors (Median)						
Model	N./-N.	N./P.	N./I.	P./P.	I./I.	P./I.
Static Factor Model	0.03	-0.22	0.08	0.04	0.09	0.04
VAR-factor 1	0.04	0.05	0.04	0.17	0.06	0.03
VAR-factor 2	0.04	0.03	0.04	-0.11	0.02	-0.07
VAR-factor 3	0.00	-0.03	0.00	0.27	0.14	0.06
VAR-factor 4	0.00	0.06	0.00	-0.10	0.05	-0.03
VAR-factor 5	0.02	0.07	0.02	0.08	0.09	0.01
VAR-factor 6	0.02	-0.06	0.04	-0.04	-0.01	-0.02
VAR-factor 7	-0.05	-0.02	-0.07	0.11	-0.06	-0.05
VAR-factor 8	0.01	-0.07	0.15	0.04	-0.08	-0.02
VAR-factor 9	0.07	0.12	0.02	0.14	0.05	0.03
DFM 1	-0.06	-0.03	-0.06	0.16	0.03	0.17
DFM 2	0.04	0.13	-0.04	-0.05	0.08	0.01
DFM 3	0.24	0.28	0.22	0.12	0.14	0.13
DFM 4	0.00	-0.17	0.01	0.06	0.07	-0.03
DFM 5	0.27	0.27	0.23	0.17	0.13	0.12
DFM 6	-0.02	-0.03	-0.02	-0.11	-0.04	0.01
DFM 7	-0.14	-0.22	-0.08	0.07	0.08	-0.01
DFM 8	-0.11	-0.22	-0.10	0.08	0.06	-0.02

5.3 Variance Decompositions for the Preferred Model

This section presents results from the model selected by the BIC. Recall that this is a VAR-factor model where the factors evolved according to independent AR(1) processes and the VAR process is restricted so that Λ is diagonal. Since we have multiple provincial and industrial factors, for the sake of brevity, Table 7 presents short-run variance decompositions averaged over all industries within a province. Table 8 averages over all provinces within an industry. Tables 9 and 10 are of the same format but are for long-run variance decompositions.

One general finding is that the idiosyncratic error tends to play a large role at both short and long horizons, accounting for roughly half of the forecast error variance in most provinces and industries. However, there are some exceptions to this. In particular, the idiosyncratic component plays a smaller role in Alberta and in the resource industry. Our detailed discussion in the following paragraphs will focus on the other factors as being of more economic interest, but the key role of the idiosyncratic factors should not be forgotten.

Consider first Table 7. In this short-run variance decomposition, the industrial factors play a particularly important role, followed by the provincial factors. Interestingly, the national and US factors tend to be the smallest, rarely account for much more than 10% of the one-period forecast error variance and typically being around 5%. This suggests that most of the variance not due to the idiosyncratic component is due to domestic sources, with the industry factors accounting for the largest share of the variance decomposition in all provinces.

Next consider Table 8 which presents the short-run results for each industry. These results are similar to those in Table 7, but some differences do emerge. The predominance of the idiosyncratic error again emerges (except for the resource industry) and the industry factors tend to be the next most important. However, the resource sector is an exception to this, since the provincial factors account for 50.7 percent of the variance. The US factor also tends to be more prominent in the variance decompositions for the construction and trade sectors, although for the other industry groups the share of US factor is much smaller than that for the industry factor. The national factor tends to account for the smallest share of the variance in employment for all industries in this table.

Table 9 presents the long-horizon variance decompositions for the provinces. Results are similar to Table 7, but again there are some difference. It is interesting to note that, at the long horizon, the US factor plays a larger role, particularly in Nova Scotia/New Brunswick, Ontario and British Columbia. However, the industry factor plays a bigger role in Quebec, Manitoba/Saskatchewan and Alberta. The provincial factor accounts for about 10 to 14.7 percent of the variance, while the national factor ranges from 3.2 to 8.4 percent of the variance.

The long-horizon variance decompositions for industries are presented in Table 10. These tend to be much more variable than their counterparts with the one-period ahead variance decomposition. Apart from the idiosyncratic term, the US factor is the largest contributor of the variance in employment in manufacturing, the provincial factor is the largest component in the resource sector and the industry factor accounts the for the largest share of the variance in agriculture. In general, the industry factor also accounts for very large shares of the variance in most of the industries, being the second largest (after idiosyncratic) component in five industries (resource, trade communication and utilities, finance and real estate, services and public administration). However, the US factor does play a prominent role in some industries (e.g., construction and trade). The provincial and national factors play a relatively small role in the long-horizon variance decompositions in most industries, with most of the shares of the variance decomposition taking values less than 10 percent. The exceptions would be the agriculture and resource sectors, where the provincial factors account for 21 and 48 percent of the variance. In addition, the share of the variance accounted for by the provincial factor is larger than the share due to the national factor in eight of the nine industries, the only exception being the public administration sector.

Table 7: Average One-Period Ahead Variance Decompositions For Provinces (VAR-factor 9)					
Province	US	National	Province	Industry	Idiosyn.
NS/NB	0.0994	0.0322	0.1445	0.1638	0.5601
	0.1350	*0.0371*	*0.2186*	*0.2054*	*0.2563*
Quebec	0.0477	0.0335	0.1555	0.2678	0.4955
	0.0411	*0.0261*	*0.1794*	*0.1592*	*0.2875*
Ontario	0.0882	0.0587	0.1038	0.1627	0.5865
	0.0847	*0.0475*	*0.1780*	*0.1469*	*0.2749*
MAN/SASK	0.0523	0.0427	0.1158	0.1792	0.6100
	0.0558	*0.0247*	*0.1737*	*0.1674*	*0.2684*
Alberta	0.1079	0.0720	0.1420	0.3886	0.2895
	0.1125	*0.1138*	*0.1439*	*0.2192*	*0.2154*
BC	0.1299	0.0372	0.1538	0.2004	0.4786
	0.1206	*0.0342*	*0.2565*	*0.1910*	*0.3186*
Note: Standard errors are in italics.					

Table 8: Average One-Period Ahead Variance Decompositions For Industries (VAR-factor 9)					
Industry	US	National	Province	Industry	Idiosyn.
AG	0.0486	0.1096	0.2247	0.3260	0.2911
	0.0565	*0.1268*	*0.2465*	*0.2242*	*0.1651*
RES	0.0675	0.0514	0.5071	0.2357	0.1383
	0.0539	*0.0483*	*0.2063*	*0.1434*	*0.2320*
TCU	0.0908	0.0302	0.0709	0.2037	0.6044
	0.0841	*0.0175*	*0.0690*	*0.2146*	*0.2476*
CON	0.1669	0.0610	0.0973	0.1735	0.5012
	0.1470	*0.0401*	*0.1114*	*0.1292*	*0.2399*
MFG	0.0725	0.0167	0.0525	0.2560	0.6023
	0.0754	*0.0047*	*0.0516*	*0.1849*	*0.2281*
TRAD	0.1561	0.0264	0.0650	0.1596	0.5929
	0.1711	*0.0213*	*0.1165*	*0.1841*	*0.2999*
FIN	0.0343	0.0366	0.1090	0.1463	0.6738
	0.0424	*0.0281*	*0.1266*	*0.2089*	*0.3287*
SERV	0.0637	0.0251	0.0456	0.3346	0.5309
	0.0651	*0.0089*	*0.0202*	*0.2188*	*0.1993*
ADM	0.0879	0.0572	0.0511	0.2082	0.5956
	0.0744	*0.0581*	*0.0285*	*0.2344*	*0.2218*
Note: Standard errors are in italics.					

Table 9: Average Long Run Variance Decompositions For Regions (VAR-factor 9)					
Province	US	National	Province	Industry	Idiosyn.
NS/NB	0.2089	0.0321	0.1360	0.1405	0.4826
	0.1869	*0.0404*	*0.1993*	*0.1770*	*0.2543*
Quebec	0.1288	0.0354	0.1471	0.2513	0.4373
	0.0803	*0.0298*	*0.1642*	*0.1527*	*0.2506*
Ontario	0.2416	0.0597	0.1004	0.1366	0.4617
	0.2081	*0.0516*	*0.1747*	*0.1395*	*0.2564*
MAN/SASK	0.1064	0.0469	0.1133	0.1767	0.5566
	0.1492	*0.0275*	*0.1715*	*0.1709*	*0.2644*
Alberta	0.1742	0.0839	0.1370	0.3543	0.2505
	0.1320	*0.1343*	*0.1442*	*0.1952*	*0.1864*
BC	0.2145	0.0402	0.1404	0.1939	0.4110
	0.1684	*0.0365*	*0.2356*	*0.1977*	*0.2895*
Note: Standard errors are in italics.					

Table 10: Average Long Run Variance Decompositions For Industries (VAR-factor 9)					
Industry	US	National	Province	Industry	Idiosyn.
AG	0.0664	0.1227	0.2133	0.3281	0.2695
	0.0550	*0.1489*	*0.2228*	*0.2304*	*0.1569*
RES	0.1066	0.0528	0.4809	0.2280	0.1318
	0.0748	*0.0502*	*0.1839*	*0.1377*	*0.2279*
TCU	0.1456	0.0335	0.0678	0.1942	0.5589
	0.0839	*0.0240*	*0.0644*	*0.1969*	*0.2397*
CON	0.2202	0.0720	0.0985	0.1617	0.4475
	0.1601	*0.0520*	*0.1116*	*0.1237*	*0.2064*
MFG	0.4578	0.0115	0.0358	0.1661	0.3288
	0.1390	*0.0026*	*0.0405*	*0.1393*	*0.1537*
TRAD	0.2586	0.0264	0.0632	0.1510	0.5008
	0.1944	*0.0214*	*0.1155*	*0.1785*	*0.2647*
FIN	0.0630	0.0405	0.1097	0.1461	0.6407
	0.0834	*0.0307*	*0.1274*	*0.2065*	*0.3175*
SERV	0.1300	0.0284	0.0451	0.3216	0.4750
	0.1089	*0.0108*	*0.0225*	*0.2178*	*0.1787*
ADM	0.1634	0.0595	0.0472	0.1833	0.5466
	0.0839	*0.0627*	*0.0240*	*0.1881*	*0.2316*
Note: Standard errors are in italics.					

For the sake of space, we do not provide plots of the factors themselves. These can be seen in the online appendix associated with this paper. But it is worthwhile to summarize the general patterns they illustrate. The variability in the national factor tends to be somewhat larger in the 1970s and 1980s, with this variability moderating in the last decade or so of our study period. It tends to be procyclical, decreasing around recession dates and economic downturns. In contrast, the provincial factors tend to be more countercyclical, so that the troughs in the national factor proceed troughs in the provincial factor. However, the provincial factors tend to be more aligned with the national factor towards the end of our study period in most provinces. The industry factors present some differences relative to the national and provincial factors. The factors for most industries tend to be countercyclical, but some are more procyclical although they might not be entirely aligned with the national factor. The patterns in the industry factors also differ quite a bit from industry to industry, as does the extent of the variability. Moreover, there are some changes in the extent of this variability in the industry factors across time.

5.4 Sensitivity Analysis

The preceding results were for our single preferred model. In this sub-section, we present a smaller selection of results for all of our models. In particular, Table 11 (12) reports short-run (long-run) variance decompositions averaged over both provinces and industries for each of the models listed in Table 1.

Overall, there is a fair degree of robustness and results from our preferred VAR-factor 9 model are similar to those provided by other models. However, there are two important exceptions to this and these relate to the treatment of spillovers and persistence. The first is that the static factor model is producing results which tend to be quite different from our preferred model. This indicates the importance of appropriately modelling persistence. The second is that any model with the high-dimensional matrices Λ and Υ left unrestricted over-fits (even when using strong Minnesota priors) and, thus, the role of the idiosyncratic component becomes much smaller. The poor performance of unrestricted VARs of such high-dimension may seem unsurprising. However, in the macroeconomics literature, papers such as Banbura, Giannone and Reichlin (2010) have documented successful forecasting performance of very large VARs (e.g. involving more than 100 dependent variables). Hence, large VARs can be implemented successfully in some empirical contexts, but not in the one under study in this paper. It is interesting to note, however, that the same variance decomposition properties are not observed when the factors have an unrestricted VAR form.

Table 11: Average One-Period Ahead Variance Decompositions					
Model	US	National	Province	Industry	Idiosyn.
Static Factor Model	0.0590	0.1005	0.1378	0.3072	0.3955
	0.0786	*0.1174*	*0.1781*	*0.1806*	*0.2675*
VAR-factor 1	0.2004	0.1457	0.2391	0.4053	0.0096
	0.2055	*0.1720*	*0.1980*	*0.2476*	*0.0151*
VAR-factor 2	0.0657	0.0332	0.0873	0.1791	0.6347
	0.0798	*0.0410*	*0.1186*	*0.1324*	*0.1746*
VAR-factor 3	0.1868	0.1377	0.2767	0.3899	0.0089
	0.1830	*0.1549*	*0.2300*	*0.2158*	*0.0125*
VAR-factor 4	0.0669	0.0323	0.0934	0.1801	0.6273
	0.0803	*0.0403*	*0.1323*	*0.1253*	*0.1758*
VAR-factor 5	0.1871	0.1403	0.2688	0.3951	0.0088
	0.1856	*0.1642*	*0.2149*	*0.2219*	*0.0120*
VAR-factor 6	0.0770	0.0291	0.0821	0.1512	0.6605
	0.0873	*0.0311*	*0.1182*	*0.1154*	*0.1697*
VAR-factor 7	0.0905	0.0482	0.1333	0.2416	0.4863
	0.0987	*0.0620*	*0.1845*	*0.1865*	*0.2682*
VAR-factor 8	0.0829	0.0667	0.1325	0.2617	0.4561
	0.0939	*0.0733*	*0.1780*	*0.1980*	*0.2672*
VAR-factor 9	0.0876	0.0460	0.1359	0.2271	0.5034
	0.0977	*0.0556*	*0.1867*	*0.1925*	*0.2802*
DFM 1	0.5010	0.2393	0.0392	0.0906	0.1299
	0.2929	*0.2324*	*0.0387*	*0.1359*	*0.1215*
DFM 2	0.0815	0.1758	0.1255	0.2023	0.4149
	0.0904	*0.0844*	*0.1544*	*0.1461*	*0.2369*
DFM 3	0.3438	0.2294	0.1662	0.1763	0.0843
	0.2617	*0.1370*	*0.1284*	*0.1523*	*0.0843*
DFM 4	0.0879	0.1028	0.1417	0.2155	0.4520
	0.0947	*0.0591*	*0.1703*	*0.1618*	*0.2519*
DFM 5	0.3515	0.2157	0.1661	0.1823	0.0844
	0.2659	*0.1366*	*0.1348*	*0.1601*	*0.0849*
DFM 6	0.0889	0.1149	0.1314	0.2116	0.4533
	0.0951	*0.0843*	*0.1673*	*0.1586*	*0.2560*
DFM 7	0.0590	0.1005	0.1512	0.2789	0.4104
	0.0768	*0.1123*	*0.1867*	*0.1756*	*0.2595*
DFM 8	0.0590	0.0999	0.1513	0.2761	0.4137
	0.0775	*0.1165*	*0.1872*	*0.1755*	*0.2610*
Note: Standard errors are in italics.					

Table 12: Average Long Run Variance Decompositions					
Model	US	National	Province	Industry	Idiosyn.
Static Factor Model	0.1514	0.0923	0.1307	0.2784	0.3472
	0.1525	*0.1142*	*0.1737*	*0.1670*	*0.2432*
VAR-factor 1	0.2322	0.0922	0.2678	0.4008	0.0070
	0.1117	*0.0578*	*0.0810*	*0.0941*	*0.0035*
VAR-factor 2	0.1638	0.0302	0.0828	0.1653	0.5579
	0.1484	*0.0376*	*0.1154*	*0.1260*	*0.1613*
VAR-factor 3	0.2149	0.0788	0.2967	0.4026	0.0070
	0.1081	*0.0541*	*0.0940*	*0.0814*	*0.0036*
VAR-factor 4	0.1511	0.0315	0.0961	0.1770	0.5444
	0.1445	*0.0377*	*0.1279*	*0.1215*	*0.1684*
VAR-factor 5	0.1981	0.0756	0.2937	0.4260	0.0065
	0.1058	*0.0534*	*0.0895*	*0.0893*	*0.0032*
VAR-factor 6	0.1706	0.0296	0.0813	0.1423	0.5763
	0.1494	*0.0329*	*0.1171*	*0.1111*	*0.1705*
VAR-factor 7	0.1865	0.0449	0.1247	0.2189	0.4249
	0.1619	*0.0626*	*0.1760*	*0.1778*	*0.2458*
VAR-factor 8	0.1687	0.0634	0.1316	0.2494	0.3868
	0.1575	*0.0718*	*0.1660*	*0.1886*	*0.2398*
VAR-factor 9	0.1791	0.0497	0.1290	0.2089	0.4333
	0.1594	*0.0644*	*0.1758*	*0.1818*	*0.2579*
DFM 1	0.1040	0.0114	0.0017	0.0044	0.8785
	0.1073	*0.0145*	*0.0026*	*0.0091*	*0.1069*
DFM 2	0.1890	0.1595	0.1161	0.1795	0.3558
	0.1716	*0.0880*	*0.1475*	*0.1405*	*0.2114*
DFM 3	0.4348	0.1402	0.0968	0.1106	0.2175
	0.2524	*0.1208*	*0.0949*	*0.1179*	*0.1626*
DFM 4	0.1925	0.0961	0.1345	0.1996	0.3773
	0.1702	*0.0604*	*0.1649*	*0.1576*	*0.2248*
DFM 5	0.4396	0.1294	0.0940	0.1153	0.2217
	0.2539	*0.1188*	*0.0960*	*0.1182*	*0.1664*
DFM 6	0.1959	0.1026	0.1238	0.1977	0.3801
	0.1733	*0.0825*	*0.1596*	*0.1567*	*0.2264*
DFM 7	0.1448	0.0901	0.1437	0.2553	0.3662
	0.1395	*0.1010*	*0.1819*	*0.1637*	*0.2399*
DFM 8	0.1380	0.0930	0.1471	0.2652	0.3567
	0.1352	*0.1072*	*0.1846*	*0.1678*	*0.2380*
Note: Standard errors are in italics.					

5.5 Comparison with Related Literature

Our findings in the short-horizon variance decompositions indicate that the industry factors play a much larger role in the variance decompositions by region than those in Altonji and Ham (1990), who found that the US and national factor accounted for most of the variance. In addition, we find that, in the short-horizon variance decompositions by industry, the national factor accounts for much less of the variance than in Altonji and Ham (1990). While we do find a larger role for the US factor in our long-horizon variance decompositions, the shares allocated to the US factor and national factor are generally much smaller than those in Altonji and Ham (1990). However, we have both more recent data and our preferred model is not the same as the one used in Altonji and Ham (1990) which could account for the differences in the findings we observe. In order to investigate this issue, in this sub-section we present results for our VAR-factor 2 model which is the same as that used in Altonji and Ham (1990). Remember that the VAR-factor 2 model does not have any dynamics on the factors and includes lagged weighted averages of aggregate, provincial and industry growth rates in employment, while the VAR-factor 9 (our most preferred model based on the BIC) has a restricted VAR coefficient matrix (only own lag coefficients are non-zero) and independent AR(1) dynamics on the factors. Tables 13 through 16 present the same variance decompositions as in Tables 7 through 10 for the VAR-factor 2 model.

Table 13 presents the one-period ahead variance decomposition for regions based on the VAR-factor 2 model. The idiosyncratic error tends to account for larger shares of the variance in the VAR-factor 2 model than in the VAR-factor 9 model. While the industry factors are still the most prominent of the factors the proportions of the variance they account for are smaller than their counterparts based on the VAR-factor 9. The shares of the variance due to the provincial factors also tend to be slightly smaller with the VAR-factor 2 model. The shares of the variance due to the US and the national factor do not differ a great deal between the VAR-factor 2 and VAR-factor 9 models. The one-period ahead variance decompositions for industries in Table 14 also show similar patterns, i.e., the idiosyncratic component tends to account for a larger share of the variance decompositions in most industries. In addition, the shares due to the industry and provincial factors in the VAR-factor 2 model tend to be lower than their counterparts in the VAR-factor 9 model. For example, using the VAR-factor 2 model the provincial factors account for 27.4 percent of the variance and the industry factors account for the 26.9 percent of the variance in the resource sector. In the VAR-factor 9 model the comparable figures are 50.7 and 23.6 percent. While the shares of the national and US factors vary somewhat across industries, they are generally much lower than the shares of the industry and provincial factors.

For the long-horizon variance decomposition by province (Table 15) the idiosyncratic error accounts for 50 percent or more of the variance in all the provinces. The US factor tends to be the next largest source of variance in Nova Scotia/New Brunswick and Ontario, while in the other regions the industry factor is. The national factor tends to have the smallest share, with the shares for the provincial factor being larger in all the provinces. Overall, while the US factor is more prominent, most of the variance not due to the idiosyncratic term is due to domestic sources. For the long-horizon variance decomposition by industry (Table 16), the idiosyncratic error is still the largest share of the variance. Like the variance decompositions by province in Table 15, the US factor is more prominent in the longer-horizon decomposition. However, the shares of the US and national factor tend to be much smaller than their counterparts in Altonji and Ham (1990). Our estimates of the VAR-factor 2 model also show that a lower share of the variance of employment growth is due to the national and US factor than in the VAR-factor 9 model.

These findings indicate that, although differences in specification account for some of difference between our results and those of Altonji and Ham (1990), most of the difference is likely due to our having a very different data span.

With relation to other key papers in the literature, our estimates suggest that the industry and provincial factors account for a larger share of the variance in employment growth, although we tend to find a larger component due to the idiosyncratic error as well. Prasad and Thomas (1998) also found that industry specific shocks played a bigger role in their analysis of employment fluctuations. However, Prasad and Thomas (1998) did not estimate a model with a factor structure and were unable to compute variance decompositions, which makes it difficult to make comparisons to their results. However, Prasad and Thomas (1998) also noted that differences in the data, their study period included data up until the early-1990s, could explain some of the differences in their findings from those in Altonji and Ham (1990).

The rise in the importance of industry factors suggests a shift in the sources of employment fluctuations in Canada. Clark and Shin (1999) noted that industry specific factors play a larger role in US employment fluctuations than in other countries. One interpretation of our results is that Canada may becoming more similar to the US in terms of the factors driving the fluctuations in employment as the role of external factors become less prominent as a source of fluctuations.

A smaller role for external factors has also been observed in the literature examining global business cycles. For example, Kose, Otrok and Prasad (2012) found that there was a decline in the importance of global business factors after 1985 in their analysis of the co-movements in output, consumption and investment, which is similar to our findings. Mumtaz, Simonelli and Surico (2011) and Kose, Otrok and Prasad (2012) also noted that increased trade linkages lead to increased specialization and this could lessen the effects of external business cycle factors if industry specific factors are driving the business cycle. The decline in the importance of the US, i.e., external, factor as a source of fluctuations in employment growth might also reflect the looser alignment of the business cycles in Canada and the US during the last few decades. For example, Cross (2001) highlights that Canada did not enter a recession in the early-2000s, unlike the US. Similarly, Campolieti (2012) noted that there were more quarters of recessions in the US than Canada after the mid-1990s and that the timing of recessions in Canada and the US were much more similar before the mid-1990s.

Table 13: Average Short-run Variance Decompositions By Province (VAR-factor 2)

Province	US	National	Province	Industry	Idiosyn.
NS/NB	0.0905	0.0199	0.0839	0.1403	0.6655
	0.1197	*0.0121*	*0.1292*	*0.1539*	*0.1578*
Quebec	0.0445	0.0386	0.1034	0.1710	0.6425
	0.0547	*0.0479*	*0.1215*	*0.1070*	*0.1774*
Ontario	0.0535	0.0396	0.0755	0.1528	0.6785
	0.0590	*0.0405*	*0.1222*	*0.1022*	*0.2024*
MAN/SASK	0.0426	0.0321	0.0834	0.1587	0.6831
	0.0448	*0.0414*	*0.1025*	*0.1321*	*0.1936*
Alberta	0.0752	0.0408	0.0954	0.2279	0.5607
	0.0817	*0.0653*	*0.1263*	*0.1451*	*0.0999*
BC	0.0876	0.0281	0.0822	0.2239	0.5781
	0.1003	*0.0262*	*0.1405*	*0.1555*	*0.2034*

Note: Standard errors are in italics.

Table 14: Average Short-run Variance Decompositions By Industry (VAR-factor 2)					
Industry	US	National	Province	Industry	Idiosyn.
AG	0.0276	0.0283	0.2207	0.2166	0.5067
	0.0398	*0.0241*	*0.1698*	*0.1642*	*0.0881*
RES	0.0343	0.0154	0.2737	0.2691	0.4075
	0.0149	*0.0115*	*0.1407*	*0.1095*	*0.2182*
TCU	0.0672	0.0254	0.0332	0.1358	0.7385
	0.0700	*0.0308*	*0.0360*	*0.1194*	*0.1255*
CON	0.1292	0.0962	0.0749	0.1343	0.5654
	0.1101	*0.0791*	*0.1086*	*0.0650*	*0.1359*
MFG	0.0596	0.0114	0.0208	0.1987	0.7095
	0.0669	*0.0046*	*0.0188*	*0.1119*	*0.1238*
TRAD	0.1195	0.0163	0.0286	0.1216	0.7141
	0.1436	*0.0071*	*0.0278*	*0.1644*	*0.1925*
FIN	0.0196	0.0572	0.0488	0.1447	0.7297
	0.0244	*0.0490*	*0.0450*	*0.1742*	*0.1884*
SERV	0.0522	0.0253	0.0297	0.2375	0.6552
	0.0547	*0.0129*	*0.0116*	*0.1251*	*0.0760*
ADM	0.0818	0.0232	0.0554	0.1536	0.6861
	0.0749	*0.0142*	*0.0292*	*0.1273*	*0.1035*
Note: Standard errors are in italics.					

Table 15: Average Long-run Variance Decompositions by Province (VAR-factor 2)					
Province	US	National	Province	Industry	Idiosyn.
NS/NB	0.2058	0.0174	0.0798	0.1272	0.5697
	0.1845	*0.0112*	*0.1248*	*0.1439*	*0.1587*
Quebec	0.1257	0.0370	0.0962	0.1603	0.5808
	0.0858	*0.0468*	*0.1138*	*0.1002*	*0.1398*
Ontario	0.2213	0.0339	0.0727	0.1294	0.5427
	0.1855	*0.0323*	*0.1222*	*0.0951*	*0.1849*
MAN/SASK	0.0993	0.0302	0.0803	0.1534	0.6367
	0.1314	*0.0392*	*0.1001*	*0.1314*	*0.1945*
Alberta	0.1625	0.0364	0.0911	0.2086	0.5015
	0.1117	*0.0594*	*0.1248*	*0.1238*	*0.0763*
BC	0.1682	0.0261	0.0768	0.2130	0.5159
	0.1683	*0.0254*	*0.1366*	*0.1579*	*0.1901*
Note: Standard errors are in italics.					

Table 16: Average Long-run Variance Decompositions By Industry (VAR-factor 2)					
Industry	US	National	Province	Industry	Idiosyn.
AG	0.0367	0.0282	0.2167	0.2174	0.5010
	0.0376	*0.0241*	*0.1647*	*0.1624*	*0.0864*
RES	0.0733	0.0147	0.2627	0.2619	0.3874
	0.0300	*0.0107*	*0.1350*	*0.1058*	*0.2003*
TCU	0.1547	0.0238	0.0302	0.1253	0.6660
	0.0761	*0.0292*	*0.0320*	*0.1033*	*0.1216*
CON	0.2020	0.0865	0.0715	0.1292	0.5108
	0.1292	*0.0726*	*0.1056*	*0.0658*	*0.1045*
MFG	0.4187	0.0071	0.0132	0.1275	0.4335
	0.1298	*0.0030*	*0.0112*	*0.0899*	*0.1127*
TRAD	0.2418	0.0136	0.0258	0.1158	0.6030
	0.2002	*0.0054*	*0.0264*	*0.1576*	*0.1869*
FIN	0.0754	0.0524	0.0476	0.1463	0.6783
	0.0894	*0.0444*	*0.0453*	*0.1716*	*0.1721*
SERV	0.1203	0.0234	0.0275	0.2251	0.6037
	0.0972	*0.0115*	*0.0106*	*0.1175*	*0.0746*
ADM	0.1512	0.0220	0.0500	0.1395	0.6372
	0.0786	*0.0142*	*0.0246*	*0.1074*	*0.1248*
Note: Standard errors are in italics.					

6 Conclusion

In this paper, we have examined the sources of growth in employment using data disaggregated by industry and province. We consider a range of models, which include VARs augmented with factor structures as well as DFMs. We compare the results from these alternative specifications and provide a detailed analysis for our most preferred model, which we selected using the BIC.

The results from the most preferred model, a VAR-factor model with a restricted coefficient matrix (i.e., only own lag coefficients are non-zero) and an independent AR(1) structure on the factors indicates the idiosyncratic component accounts for a large share of the forecast error variances. For the variance not due to the idiosyncratic term, we find that industry and provincial factors tend to account for the largest shares of employment growth in the variance decompositions. We find a much smaller role for the national factor in most of the variance decompositions we compute, while the US factor does play a large role in the variance decompositions for some industries. The longer-horizon variance decompositions do show that the external factor accounts for a larger share of the variance in some regions and industries, but these shares are much smaller than those in the earlier literature. Overall, we find a much smaller role for the national and US factor than did Altonji and Ham (1990). As noted earlier, the business cycles in Canada and the US have been less closely aligned for the last decade or so and this might be reflected in lower share of fluctuations in employment attributed to the US factor.

From the perspective of policy makers, our results suggest that external shocks play a much smaller role in employment fluctuations than previously thought. Most of the fluctuations in employment not due to the idiosyncratic error are also coming from more disaggregrated sources (i.e., industry and province factors). While the US factor does play a larger role in some industries, it seems that a larger share of fluctuations in employment are due to domestic sources that are more disaggregated in nature.

References

Aguilar, O., West, M., 2000. Bayesian Dynamic Factor Models and Portfolio Allocation. Business of Business & Economic Statistics 18, 338-357.

Altonji, J.G., Ham, J.C., 1990. Variation in Employment Growth in Canada: The Role of External, National, Regional and Industrial Factors. Journal of Labor Economics 8, S198-S236.

Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models.

Econometrica 70, 191-221.

Banbura, M, Giannone D., Reichlin L., 2010. Large Bayesian vector auto regressions. Journal of Applied Econometrics 25, 71-92.

Brooks, R., Del Negro, M., 2005. A Latent Factor Model with Global, Country, and Industry Shocks for International Stock Returns. IMF Working Paper, WP/05/52.

Campolieti, M., 2012. The Canada-US Unemployment Rate Gap: A New Look with a New Decomposition for Cross-Country Differences in Unemployment Rates. Canadian Public Policy 38, 411-425.

Campolieti, M., Gefang, D., Koop, G., 2012. Time Variation in the Dynamics of Worker Flows: Evidence from North America and Europe. Journal of Applied Econometrics, forthcoming.

Carlino, G., DeFina, R., Sill, K., 2001. Sectoral Shocks and Metropolitan Employment Growth. Journal of Urban Economics 50, 396-417.

Clark, T.E., 1998. Employment Fluctuations in U.S. Regions and Industries: The Roles of National, Region-Specific and Industry-Specific Shocks. Journal of Labor Economics 16, 202-229.

Clark, T.E., Shin, K., 1999. The Sources of Fluctuations Within and Across Countries. In: Intranational Macroeconomics, G.D. Hess and E. van Wincoop (eds.). Cambridge University Press: Cambridge.

Cross, P., 2001. Tracking the Business Cycle: Monthly Analysis of the Economy at Statistics Canada, 1926-2001. Canadian Economic Observer (January).

Crucini, M.J., Kose, M.A., Otrok, C., 2011. What are the Driving Forces of International Business Cycles. Review of Economic Dynamics 14, 156-175.

Diebold, F.X., Rudebusch, G.D., Aruoba, S.B., 2006. The Macroeconomy and the

Yield Curve: A Dynamic Latent Factor Approach. Journal of Econometrics 131, 309-338.

Fujita, S., 2011. Dynamics of Worker Flows and Vacancies: Evidence from the Sign Restriction Approach. Journal of Applied Econometrics 26, 89-121.

Gourieroux, C., Jasiak, J., 2001. Dynamic Factor Models. Econometric Reviews 20, 385-424.

Kass, R.E. Raftery, A.E., 1995. Bayes Factors. Journal of the American Statistical Association 90, 773-795.

Koop, G., Korobilis, D., 2009. Bayesian Multivariate Time Series Methods for Empirical Macroeconomics. Foundations and Trends in Econometrics 3, 267-358.

Koopman, S.J., Lucas, A., Schwaab, B., 2012. Dynamic Factor Models with Macro, Frailty, and Industry Effects for U.S. Default Counts: The Credit Crisis of 2008. Journal of Business & Economic Statistics 30, 521-532.

Kose, M.A., Otrok, C., Whiteman, C., 2003. International Business Cycles: World, Region and Country-Specific Factors. American Economic Review 93, 1216-1239.

Kose, M.A., Otrok, C., Prasad, E., 2012. Global Business Cycles: Convergence or Decoupling. International Economic Review 53, 511-538.

Kuttner, K.N., Sbordone, A.M., 1997. Source of New York Employment Fluctuations. Federal Reserve Bank of New York Economic Policy Review 3, 21-35.

Lopes, H.F., West, M., 2004. Bayesian model assessment in factor analysis. Statistica Sinica 14, 41-67.

Mumtaz, H., Simonelli, S., Surico, P., 2011. International Comovements, Business Cycles and Inflation: A Historical Perspective. Review of Economic Dynamics 14, 176-198.

Norrbin, S.C., Schlagenhaufand, D.E., 1988. An Inquiry into the Sources of Macroeconomic Fluctuations. Journal of Monetary Economics 22, 43-70.

Otrok, C., Whiteman, C., 1998. Bayesian Leading Indicators: Measuring and Predicting Economic Conditions in Iowa. International Economic Review 39, 997-1014.

Prasad, E., Thomas, A., 1998. A Disaggregated Analysis of Employment Growth Fluctuations in Canada. Atlantic Economic Journal 26, 274-287

Riddell, W.C., 1999. Canadian Labour Market Performance in International Perspective. Canadian Journal of Economics 32, 1097-1134.

Rissman, E.R., 1999. Regional Employment Growth and the Business Cycle. Federal Reserve Bank of Chicago Economic Perspectives 23, 21-39.

Rosenbloom, J. L., Sundstrom, W.A., 1999. The Sources Of Regional Variation In The Severity Of The Great Depression: Evidence From U.S. Manufacturing, 1919-1937. Journal of Economic History 59, 714-747.

Stock, J., Watson, M., 2011. Dynamic Factor Models. In: Oxford Handbook of Forecasting, Michael P. Clements and David F. Hendry (eds), Oxford: Oxford University Press.

Trefler, D., 2004. The Long and Short of the Canada-U.S. Free Trade Agreement. American Economic Review 94, 870-895.

Wasserman, L., 2000. Bayesian Model Selection and Model Averaging. Journal of Mathematical Psychology 44, 92-107.