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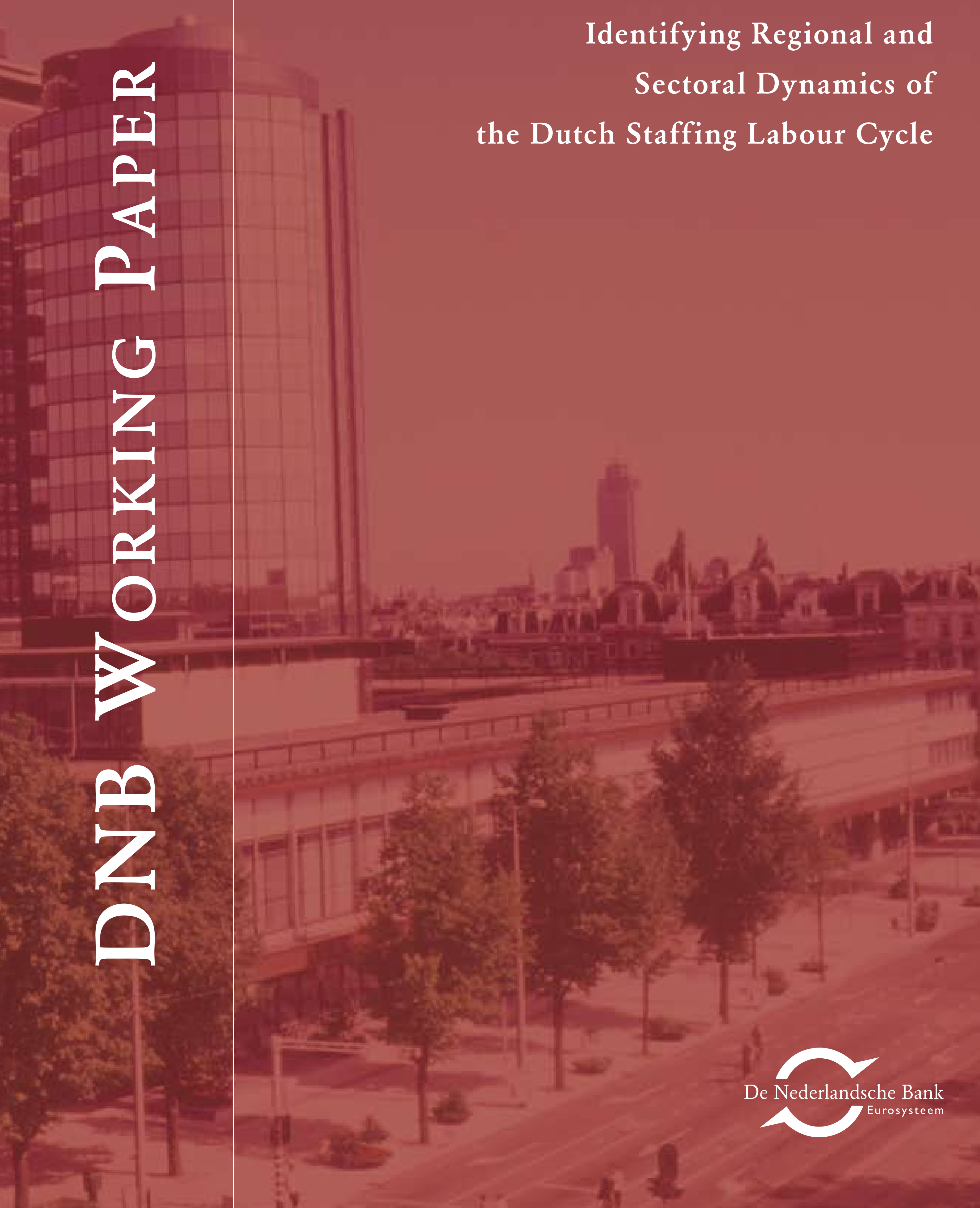

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Identifying Regional and Sector Dynamics of the Dutch Staffing Labour Cycle

Ard den Reijer *

* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Identifying Regional and Sectoral Dynamics of the Dutch Staffing Labour Cycle.*

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Abstract

This study analyses the dynamic characteristics of staffing employment across different business sectors and across different geographical regions in the Netherlands. We analyse a micro data set of the market leader of the Dutch staffing employment market, i.e. Randstad. We apply the dynamic factor model to extract common information out of a large data set and to isolate business cycle frequencies with the aim of forecasting economic activity. We identify regions and sectors whose cyclical developments lead the staffing labour cycle at the country level. The second question is then which model specification can best exploit the identified leading indicators at the disaggregate level to forecast the country aggregate? The dynamic factor model turns out to outperform univariate benchmark forecasting models by exploiting the substantial temporal variation of the staffing labour market at the disaggregate level.

keywords: staffing labour, dynamic factor model, disaggregate forecasting

JEL-code: C31, C53, J44, J63

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1 Introduction

Flexible staffing agency work is characterized by a triangular relationship between the user firm, the employee and the private labour market intermediary. The staffing agency is a private matchmaker that acts as an intermediary between temporary labour supply and demand. Staffing agencies derive their income from fees charged to user firms for the temporary employment of workers registered with the agency. Staffing agencies perform the recruitment of personnel and provide a ready source of labour for their business clients. Kvasnicka's (2003) empirical analysis of the German staffing labour market shows that more than one third of the employees work in multiple client engagements, enabling the temporary staffing agency to spread the recruitment and dismissal costs per employee effectively across different clients. According to Houseman (2001), the most cited reason for user firms to use all types of flexible staffing arrangements are the needs to adjust for workload fluctuations and staff absences. Many employers also use staffing temporaries to screen workers for regular positions. The flexible staffing industry effectively creates a spot market for labour, so user firms can replace absent employees or adjust the labour force to short-term changes and fluctuations in market demand without incurring the usual hiring and firing costs (cf. Katz and Krueger, 1999). From the perspective of the client firm, flexible staffing labour constitutes a mere variable factor of production.

Peck and Theodore (2007) and Theodore and Peck (2002) show that the American flexible staffing industry is not just a purveyor of flexibility at the micro level of meeting the needs of individual enterprises, but also at the macro level of mediating macroeconomic pressures and socioeconomic risks across the labour market as a whole. During the last 30 years, temporary employment expanded rapidly prior to macroeconomic upturns, while sharp declines in temporary employment preceded recessions (cf. Segal and Sullivan, 1997; Theodore and Peck, 2002). Hence, fluctuations in staffing employment are timely indicators of broader business cycle motions. Concerning the Netherlands, Goldschmeding (2003), Franses and de Groot (2005b) and Den Reijer (2006) analyse flexible staffing labour market developments to monitor and forecast macroeconomic business cycles. Berkhout and Van Leeuwen's (2004) international comparison shows a mature Dutch flexible staffing industry that serves a relatively large part of total employment. Randstad Nederland (hereafter Randstad) is the market leader in the Dutch staffing services market. In this study, we analyse staffing turnover data that are directly obtained from the administrative source of the company. The data are nearly real-time available at a sectoral and geographical disaggregate level. Kvasnicka's (2003) German data set obtained from a private staffing agency is to our knowledge so far the only other analysed data set, which consists of direct observations from a market participant instead of survey based observations. Kvasnicka's (2003) German data set is less detailed sectorally and geographically, but contains additional information on the characteristics of the workers, the conditions of the work assignments, as well as the terms of their employment contract with the agency.

The primary objective of this paper is to document the cyclical developments of staffing employment in the Netherlands at the disaggregate level and to identify the regions and sectors that show leading properties. The second question is then how the disaggregate information, particularly the identified leading indicators at the sectoral and geographical level, can be exploited to forecast the country aggregate of staffing employment, (cf. Hendry and Hubrich, 2006). The paper is structured as follows. Section 2 describes the staffing labour market. Section 3 provides a detailed explanation of the available data set. Section 4 introduces the factor model and extracts the staffing labour cycle from the data. Section 5 classifies the staffing labour cycle at the disaggregate level and identifies the most pronounced leading and lagging regions and sectors. Finally, section 6 compares different model specifications that exploit the information at the disaggregate level to forecast the staffing labour developments at the country level.

2 Staffing agency work

Flexible labour can come in many different forms and can broadly be defined as all employment relationships apart from permanent jobs. Berkhout and Van Leeuwen (2004) distinguish five types of categories that describe the relationship between the employer and employee: full-time permanent work, part-time permanent work, self-employment, temporary work, which can both be part- or full-time and staffing agency work. The essential feature of self-employment is the absence of a formal employer-employee relationship. Part-time work refers to employees working on a permanent contract, but less hours than specified in a full-time contract. The formal employer-employee relationship for temporary and staffing employment can either be part-time or full-time, but is based on a limited duration contract. The difference between temporary employment and staffing agency employment is that the latter one is mediated by private labour market organizations. The employer's own recruitment of personnel for a limited duration contract is then temporary employment. Fixed term contracts are often used as a preface screening device for a tenured position. The most important characteristic of the staffing industry is the triangular relationship (cf Gottfried, 1992) between the user firm, the staffing agency worker and the private labour market agency. Following Ecorys-NEI's (2002) terminology, an agency worker concludes a contract with a private employment agency to be assigned to a user firm, in order to undertake work under the supervision of the latter. The private employment agency is often referred to as staffing services organization[1]. In addition to getting a salary, the agency worker becomes acquainted with various employers, gains working experience and increases his employability in pursuit of a permanent contract. The staffing agency offers flexibility to the user firm, which can replace absent employees or adjust the labour force to changes and fluctuations in market demand without incurring the usual hiring and firing costs. Staffing agencies transform labour from a quasi-fixed into a variable factor of production and therefore effectively create an efficient spot market for labour (cf Katz and Krueger, 1999). This flexibility makes the staffing employment market the segment of the labour market that is most sensitive to business cycle motions.

The structure of the labour market and the importance of temporary and agency work differ between countries because of the legislative framework, see Berkhout and Van Leeuwen (2004) for an international comparison and Dunnewijk (2001) for a brief history in the Netherlands. The Dutch staffing services market grew from its inception as a percentage of the labour force from 0% in 1960 to 5% in 2004. Randstad is the market leader and covers a stable market share of 40% over this entire period (cf. Franses and de Groot, 2005a). Randstad Nederland is the country branch of the Randstad Holding, which is one of the largest temporary and contract staffing organizations in the world.

[1] The terminology of "agency work", "agency worker" and "employment agency" is practiced by the *International Confederation of Temporary Work Businesses* (CIETT). The alternative terminology of "staffing work", "staffing employee" and "staffing company" is used by the *American Staffing Association* (ASA).

2.1 Data

The data set is directly obtained from the administrative source of Randstad and consists of 1.276.393 observations on the number of contracted staffing hours. The data run from 1998 until 2005 and each year is divided into 13 subsequent administrative periods of a four week duration. Every observation consists of four dimensions; the number of staffing hours for each time period is sectorally and geographically disaggregated. The sectoral classification occurs along the four digit SBI-code and the geographical classification along the four digit system of postal codes, see appendix A for details.

At this level of disaggregation, each observation almost always corresponds to a single user firm. By nature of staffing employment, a single user firm does not make use of staffing services continuously during the entire sample period. In order to create a balanced data set, we aggregate the individual observations to the level of 15 regions and 58 sectors. The regions consist of the 12 provinces from which the agglomerations of the three largest cities are separated out. The sectors correspond to the two digit SBI-code. Now, $X_{ij,t}$ represents the total number of hours of staffing employment in region $i = 1, ..., 15$ and sector $j = 1, ..., 58$ during period t, running from the first period in 1998 until the second period in 2005 consisting of 92 four-weeks periods. Moreover, we create a balanced data set by deleting the combination of region i and sector j if the time series shows missing observations, that is delete X_{ij} if $\exists t$ such that $X_{ij,t} = 0$. Out of the 15*58=870 possible combinations, the balanced data set consists of N=536 different time series. Some combinations are not feasible as the type of economic activity is hardly performed in the particular region, e.g. the activity Fishing in the province Drenthe, or not present at all in the

Netherlands, e.g. the activity Mining of uranium and thorium ores. The resulting balanced data set covers 97.3% of the total data set in terms of the number of observations and 98.2% in terms of the number of staffing hours. Seven sectors disappear for the balanced data set and, on the other hand, 22 sectors do not lose observations at all as a result of balancing the data set. The overall loss of roughly 2% of observations is not concentrated within a specific remaining sector, region or time period.

We calculate the aggregates of each sector i, each region j and the country total as $X_{i*,t} = \sum_j X_{ij,t}$, $X_{*j,t} = \sum_i X_{ij,t}$ and $X_t = \sum_i \sum_j X_{ij,t}$ respectively. In order to aply the dynamic factor model, all series are transformed to remove non-stationarity and corrected for outliers (cf. Altissimo et al., 2006). The stationarity inducing transformation amounts to calculating the period-on-period growth rates, so we analyse $x_{ij,t} = \Delta \ln (X_{ij,t})$, where Δ is the difference operator in the time dimension. The time series of growth rates are corrected for outliers by replacing those observed growth rates that are more than three sample standard deviations away from the sample mean with average of the remaining observed growth rates. In order to apply the factor method as outlined below, we construct standardized growth rates $x^s_{ij,t}$ by subtracting the sample average from the for outliers corrected growth rates and dividing by the sample standard deviation.

3 Dynamic factor model

In order to extract the cyclical developments of staffing employment in the Netherlands at the disaggregate level and to identify the regions and sectors that show leading properties for the staffing cycle at the aggregate level, we fit a dynamic factor model to the balanced stationary data set. Breitung and Eickmeier (2006) provide an overview of dynamic factor models and their applications to economic indicators, forecasting and business cycle analysis. Factor models are developed as a tool to cope with many variables without running into problems with too little degrees of freedom often faced in regression based analysis. Firstly, factor models summarize large data sets in few underlying forces. The extracted low-dimensional common information is then used to discern the "common signal" χ from the "idiosyncratic noise" ξ for each of the underlying variables, so $x^s_{ij,t} = \chi_{ij,t} + \xi_{ij,t}$. The idiosyncratic motion of a variable includes the effects of local shocks that are typically sector or region specific, while the common signal affects all sectors and regions. The common component $\chi_{ij,t}$ is driven by the impact of $k = 1, ..., q$ unobserved "dynamic factors" u_{kt} that are common to all the variables in the data set. Secondly, the dynamic factor model allows for dynamic factor loadings $\alpha_{ijk}(L)$, $k = 1, ..., q$, which describe the dynamic impact of the common dynamic factors u_{kt} on the common component: $\chi_{ij,t} = \alpha_{ij1}(L) u_{1t} + ... + \alpha_{ijq}(L) u_{qt}$, where L is the lag operator. The common driving forces u_k can affect the individual variables with different leads and lags, which enables to classify the variables, regions and sectors as leading, coincident and lagging. Thirdly, we further decompose the common component χ_{ijt} into a cyclical medium- and long-run component ϕ_{ijt} and a non-cyclical seasonal and irregular part ψ_{ijt}, that is $x^s_{ijt} = \phi_{ijt} + \psi_{ijt} + \xi_{ijt}$. This decomposition is based on a two-sided, symmetric, square summable bandpass filter $\beta(L)$, which separates waves of periodicity larger than a given critical number of periods $\tau : \phi_{ij,t} = \sum\limits_{k=-\infty}^{\infty} \beta_k \chi_{ij,t-k}$, $\beta_k = \begin{cases} \frac{1}{k\pi} \sin(2k\pi/\tau) \text{ for } k \neq 0, \\ 1/\tau \text{ for } k = 0. \end{cases}$. The cyclical medium- and long-run component $\phi_{ij,t}$ is filtered for short-run seasonal and erratic fluctuations and therefore signals more smoothly the underlying development of the staffing employment growth[2].

We set $\tau = 13$, so all cyclicality with a duration shorter than 13 periods, or one year, is filtered out. The medium- and long-run component then describes the cyclicality of duration longer than one year and, given the length of the sample of observations of $T = 92$ periods, shorter than seven years. Like Altissimo et al. (2006), the finite sample approximation of $\beta(L)$ consists of truncating the tails of the band-pass filter that involve unavailable data observations $\beta_k = 0$, $k > M$.

We apply the generalized dynamic factor model outlined in Forni et al. (2000), Forni et al. (2004) and Forni and Lippi (2001), which exploits the dynamic structure of the data by estimating the factors as the dynamic principal components of the spectral density matrix. In order to estimate the generalized dynamic factor model, we need to specify the number of dynamic factors q, the parameter M that determines the maximum lag of auto-covariance. The identifying factor model assumption requires that the q largest dynamic eigenvalues diverge, whereas the remaining $N - q$ eigenvalues remain bounded as the number of time series variables N increases. We follow Forni et al.'s (2000) heuristic approach and select $q = 3$ in the finite-sample, because the marginal explained variance of the q^{th} dynamic eigenvalue is larger than 10% and the $(q+1)^{th}$ one is smaller than 10%. The corresponding q dynamic eigenvectors are the estimators for the common dynamic factors u_k, $k = 1, ..., q$ and the dynamic factor loadings $\alpha_{ijk}(L)$ describe the dynamic impact of the k-th common factor u_k on the time series variable x_{ijt}. We follow Forni et al. (2000) and set the maximum lead and lag of M periods, that is $\alpha_{ijk,\pm n} L^{\pm n} u_{kt} = 0$ for $n > M$, at $M(T) = round\left(2T^{(1/2)}\right) = 19$ for the data set with $T = 92$ observations in

[2]CEPR´s coincident indicator of the euro area (€urocoin) reposes on a similarly composed measure behind short-lived oscillations.

the time dimension.

Figure 1 plots the year-on-year growth rates of the total employment in the Netherlands as reported by Statistics Netherlands together with the aggregate common signal $\widehat{\phi}_t$. We refer to appendix A.3 for details on the estimation procedure. The figure illustrates that $\widehat{\phi}_t$ tracks the pattern of total employment, which is shifted backwards in time by 10 quarters.

Figure 1 around here

3.1 Aggregate and aggregated staffing employment

The aggregate signal at the country level ϕ_t, at the sectoral level $\phi_{i*,t}$, at the regional level $\phi_{*j,t}$ and at the disaggregate level $\phi_{ij,t}$ can be determined by projecting the corresponding aggregates x_t^s, $x_{i*,t}^s$, $x_{*j,t}^s$ and $x_{ij,t}^s$ respectively on the dynamic factors u_{kt}, which can be estimated by dynamic principal components. The linear projection of the data on the dynamic principal components provides the parameter estimates, or factor loadings $\widehat{\alpha}_k(L), \widehat{\alpha}_{i*,k}(L), \widehat{\alpha}_{*j,k}(L)$ and $\widehat{\alpha}_{ijk}(L)$, $k = 1, ..., q$ respectively.

Alternatively, the aggregated signal of the country, of each sector i and each region j can be constructed as the weighted aggregate of the individual signals $\phi_{ij,t}$, that is $\overline{\phi}_{i*,t} = \sum_j a_{*j,t-1}\phi_{ijt}$, $\overline{\phi}_{*j,t} = \sum_i a_{i*,t-1}\phi_{ijt}$ and $\overline{\phi}_t = \sum_i \sum_j a_{ij,t-1}\phi_{ijt}$ respectively. The time-varying weights α_{ijt} consist of the shares of the individual variables in the aggregate multiplied by the ratio of the standard deviations of x_t and $x_{ij,t}$: $a_{ij,t} = \frac{\sigma_{x_{ij}}}{\sigma_x} b_{ij,t}$ with $b_{ij,t} = \frac{X_{ij,t}}{\sum_i \sum_j X_{ij,t}}$ the share of variable $X_{ij,t}$, which belongs to sector i and region j, in the total staffing turnover X_t at time t. Appendix A.2 shows that calculating the standardized growth rates x_t^s from the aggregate X_t is mathematically equivalent to aggregating the standardized growth rates of the disaggregates

$x^s_{ij,t}$ using the delayed weights $a_{ij,t-1}$. However, projecting the aggregate x^s_t on the dynamic principal components is only mathematically equivalent to aggregating the projected disaggregates $x^s_{ij,t}$ if the weights are constant $\alpha_{ij,t} = \alpha_{ij}$. So, the mathematical equivalence between the aggregate signal and the aggregated signal, $\phi_t = \overline{\phi}_t$, does not hold because of time varying weights.

Figure 2 shows the aggregate growth rate x_t, its aggregate common component $\widehat{\chi}_t$, the time-varying aggregated signal $\widehat{\overline{\phi}}_t$ and the aggregate signal $\widehat{\phi}_t$. The figure suggests that the aggregated signal is empirically equivalent to the aggregate signal even though time varying aggregation weights are employed.

Figure 2 around here

The correlation structure of the panel of observations across both the regional and sectoral dimensions characterizes the staffing labour cycle in the Netherlands at a disaggregate level. The correlation is calculated using a sample period of seven years of available observations and is therefore only based on at most one complete business cycle. The correlation structure is summarized by the cross-correlation ρ of each individual variable's cyclical medium- and long-run component $\phi_{ij,t}$ with the aggregate cycle ϕ_t. The corresponding lead l^* is determined as $l^*_{ij} = \arg\max_l |\rho_{ij}(\phi_t, \phi_{ij,t-l})|$ and $\rho^*_{ij} = \rho_{ij}\left(y_t, y_{ij,t-l^*_{ij}}\right)$. The optimal aggregate correlation and lead measures (ρ^*_{i*}, l^*_{i*}) and $\left(\rho^*_{*j}, l^*_{*j}\right)$ are likewise obtained by employing the regional aggregate $\phi_{i*,t}$ and the sectoral aggregate $\phi_{*j,t}$ respectively.

The optimal aggregated correlation and lead measures $\left(\overline{\rho}^*_{i*}, \overline{l}^*_{i*}\right)$ and $\left(\overline{\rho}^*_{*j}, \overline{l}^*_{*j}\right)$ at the regional and sectoral level, respectively, are alternatively obtained as the weighted average of the optimal disaggregate measures, i.e. $\overline{l}^*_{i*} = \sum_j b_{*j|T}\, l^*_{ij}$ and $\overline{l}^*_{*j} = \sum_i b_{i*|T}\, l^*_{ij}$, respectively, where the weights $b_{ij|T}$

represents the variable´s share in the total staffing turnover that is constant over time: $b_{ij|T} = \frac{1}{T}\sum_{t=1}^{T} b_{ij,t}$. The empirical measures $\overline{\rho}^*$ are likewise obtained.

The following stylized example illustrates the difference between the optimal aggregate measures (ρ^*, l^*) and the aggregated optimal measures $\left(\overline{\rho}^*, \overline{l}^*\right)$. Consider a data set of three series y_{ij}, $i = 1, 2, 3$ with weights $b_{ij} = \frac{1}{6}, \frac{1}{6}, \frac{2}{3}$ respectively. Let the correlation coefficient be $\rho_{ij}\left(y_t, y_{ij,t-l_{ij}}\right)=\frac{1}{2}$ and zero otherwise with the corresponding leads $l_{ij} = -1, 0, 1$ respectively. The weighted average correlation is $\overline{\rho}^*_{*j} = \frac{1}{2}$ and $\overline{l}^*_{*j} = -\frac{1}{6} + \frac{2}{3} = \frac{1}{2}$. The aggregated series reads as $y_{*j} = \frac{1}{6}y_{1j} + \frac{1}{6}y_{2j} + \frac{2}{3}y_{3j}$ and its optimal measures are $\rho^*_{*j} = \frac{1}{2}$ and $l^*_{*j} = 1$. The stylized example shows that the optimal aggregate measures capture the characteristics of the underlying time series variable that is most dominant in terms of weight and cross-correlation. Given equal weights and positive correlation coefficients, the underlying time series variable that shows the highest cross-correlation will be selected: $\rho^* \geq \overline{\rho}^* \, (\geq 0)$.

3.2 The empirics of staffing employment

We summarize the correlation structure across both the regional and sectoral dimensions of the staffing labour cycle as represented by the medium- and long-run signal $\widehat{\phi}$ and the year-on-year growth rate of X_{ijt}, i.e. $x^{13}_{ijt} = \Delta_{13}\ln(X_{ijt})$. Christiano and Fitzgerald's (2003) band-pass filter is applied to the latter growth rates to smooth away the irregularities and remaining seasonalities with periodicity smaller than one year. The year-on-year growth rates relate to the period-on-period growth rates as follows[3]: $x^{13}_{it} = \left(1 + L + ... + L^{12}\right)(\phi_{it} + \psi_{it} + \xi_{it})$. So, the cross-correlation of x^{13}_{it} with another variable, say x^{13}_{kt}, involves, apart from the cross-correlation

[3]Note that $\Delta_{13} = 1 - L^{13} = (1 - L)\left(1 + L + ... + L^{12}\right)$. Then, $x^{13}_{it} = \left(1 + L + ... + L^{12}\right)x_{it} = \left(1 + L + ... + L^{12}\right)(\phi_{it} + \psi_{it} + \xi_{it})$.

$\rho(\phi_{it}, \phi_{kt})$, the auto-correlations $\rho(\phi_{it}, \phi_{kt\pm j})$, $j = 1, ..., 12$ and the correlations between the seasonal components $\rho(\psi_{it}, \psi_{kt\pm j})$ and the idiosyncratic components $\rho(\xi_{it}, \xi_{kt\pm j})$, $j = 0, ..., 12$.

For $y = \left\{\widehat{\phi}, x^{13}\right\}$ the reference cycle is the aggregate series y_t and each of the series $y_{ij,t}$, $y_{i*,t}$ and $y_{*j,t}$ can be classified as pro- or counter-cyclical according to the phase angle with the reference cycle at the zero frequency[4]. Tables 1 and 2 show at the regional respectively sectoral level both the optimal aggregate results $\{l^*_{i*}, \rho^*_{i*}\}$ and the aggregated optimal results $\left\{\overline{l}^*_{i*}, \overline{\rho}^*_{i*}\right\}$ for both $\left\{\widehat{\phi}, x^{13}\right\}$. The first column of both tables reports the number of time series variables present in the corresponding region respectively sector. The subsequent two columns of both tables show respectively the weighted average of the variance of the common components $\overline{var}(\widehat{\chi})$ and the variance of the aggregate common component $var(\widehat{\chi})$. Both measures report the fraction of the variance explained by the static factor model. The difference between both measures shows that the static factor model explains the covariation at the aggregate level much better than at the disaggregate level. The idiosyncratic motions of the variables die out in the aggregation as they are only weakly cross-correlated. The common factors explain on average 75% respectively 60% of the variation of the aggregate at the regional and sectoral level.

Table 1 reports the empirical results of the staffing labour cycle at the regional level. The four different measures for the lead almost always indicate the number of lead periods of $-6 < l < 6$. The regions that show a robust, but modest lead across the four different measures are Gelderland and Over-

[4] We recall that the cross-spectral density between two variables h and j can be expressed, in its 'polar form' as $S_{hj}(\theta) = A_{hj}(\theta)\, e^{-i\phi_{hj}(\theta)}$ where $\phi_{hj}(\theta)$ is the 'phase'. The phase measures the angular shift between the cosine waves of h and j at frequency θ, $-\pi < \theta \leq \pi$. At frequency zero, the phase may be either 0 or π depending on whether the long-run correlation is positive or negative, respectively.

ijssel. The leading characteristics correspond with the relatively dominant presence of leading sectors like Wholesale and Manufacture of motor vehicles. The region of Zeeland is dominated by the sector Manufacture of food products and beverages.

Table 2 reports the empirical results of the staffing labour cycle at the sectoral level. The differences across the sectors are more pronounced than across the regions according to the different statistical measures. The five sectors for which the variation is best explained by the common dynamics are: Manufacture of food products and beverages, Construction, Financial intermediation, Health and social work, and Wholesale trade and commission trade. Some sectors are more driven by idiosyncratic dynamics instead of by the common dynamics of the staffing labour cycle. Due to the hub function of the Netherlands for international freight flows in Europe, sectors like Air transport and Water transport are likely more reactive to world trade developments than to the national business cycle. The sectors Manufacture of tobacco products and Financial Intermediation show anti-cyclicality with respect to the aggregate staffing labour cycle. The four different measures of the lead period almost always indicate a number of lead periods of $-26 < l < 17$. The variation in leading and lagging patterns is more pronounced across sectors than across regions. The two most leading sectors according to the four different measures are in addition to some Manufacturing sectors are Supporting and auxiliary transport activities, and Sale, maintenance and repair of motor vehicles and motorcycles. Retail trade shows a modest lead of less than half a year. The latter two mentioned sectors' leading properties are confirmed by business cycle analysts. The variable of issued motor vehicle permits is incorporated in OECD's (2002) composite leading indexes for many countries. Moreover, the retail sales are part of the total sales series, which is a key indicator in The Conference Board Index, (cf. The Conference Board, 2000). The five manufacturing sectors of Electrical machinery and apparatus, Machinery and equipment and Wearing appeal, Wood and products of wood and Radio, television and communication also show a modest lead of less than half a year. The three sectors that show lagging characteristics across the four different measures are Public administration, defence and compulsory social security, Insurance and pension funding and Water transport.

3.3 Forecasting aggregate staffing employment

The natural question is how the identified leading indicators at the disaggregate level can be exploited to forecast the country aggregate of the staffing employment. This variable is closely monitored to discern patterns of the macroeconomic Dutch business cycle, cf.Goldschmeding (2003), Franses and de Groot (2005b) and Den Reijer (2006). As the data set is closed in the sense that the country aggregate is by definition the sum of the disaggregates, we can moreover analyse the forecasting performance from a different perspective: does forecasting the aggregate improve upon aggregating the forecasts?

We refer to the h-period ahead forecast of the growth rate of the country aggregate based on observations until time t as $x_{t+h|t}$ and to the aggregated forecast as $\overline{x}_{t+h|t} = \sum_i b_{ij|t} x_{ij,t+h|t}$ Moreover, the different forecasts are labelled as $x^{m,fe}_{ij,t+h|t}$, where the different model specifications $m = \{SF, DF, DFC, AR, \mu\}$ employ static factors (SF), one-sided dynamic factors (DF), one-sided cyclical dynamic factors (DFC), a second order autoregressive model (AR) and the first moment of the time series (μ), respectively. The latter two model specifications are purely univariate and act as a benchmark for multivariate factor specifications. Appendix A.3 shows how to estimate the one-sided cyclical dynamic factors $\widehat{f}_t^{DFC}$, the one-sided dynamic factors $\widehat{f}_t^{DF}$ as a special case with $\tau = 0$ and the static factors $\widehat{f}_t^{SF}$ as a special case with both $\tau = 0$ and $M = 0$. If the forecast equation $fe = \{u, fm\}$ admits the factor model structure $fe = fm$, the h-step ahead common components $\widehat{\chi}_{ij,t+h}^m$ are projected on the t-dated estimated factors $\widehat{f}_t^m$ and so, the autocorrelation structures of the common and idiosyncratic components are exploited separately. The factor forecasts of the common components $\widehat{\chi}_{ij,T+h|T}^m$ are transformed to forecasts of the target variable by the inverse standardization, i.e. $\widehat{x}_{ij,T+h|T}^m = \widehat{\sigma}_T \widehat{\chi}_{ij,T+h|T}^m + \widehat{\mu}_T$, where $\widehat{\mu}_T$ and $\widehat{\sigma}_T$ are the sample mean and, respectively, the standard deviation. If the forecast equation $fe = \{u, fm\}$ is unrestricted $fe = u$, the h-step ahead data $x_{ij,t+h}$ are projected on the t-dated estimated factors $\widehat{f}_t^m$ and a constant. Both approaches $fe = \{u, fm\}$ deliver identical forecasts only if the data adheres to the factor model assumptions and the model parameters are known. Boivin and Ng (2005) propose full flexibility for the forecasting equation to adapt to the data, i.e. $fe = u$.

In order to determine the dynamic structure of the data, Forni et al.'s (2000) factor model applies two-sided filters to measure the temporal variation of the time series. This two-sidedness makes the model less suitable for forecasting purposes, since no signal can be extracted at the end of the sample. To solve this problem, Forni et al. (2005) propose a two-step procedure. The second forecasting step then exploits the contemporaneous covariance of the common component, see appendix $A.3$ for details. The one-sided dynamic factors f_t^{DF} are the contemporaneous weighted cross-sectional averages of the times series variables for which the weights depend on the common-to-idiosyncratic variance ratios. These ratios are already determined in the first step based on the temporal variation of the data. Bai and Ng's (2002) information criteria (BNIC) determine the number of $r = 2$ factors as a trade-off between the goodness-of-fit and overfitting, see appendix A.3 for details. Stock and Watson's (2002) static factors f_t^{SF} do not exploit the dynamic structure of the data and can evidently be obtained as a special case of the dynamic approach by setting the discretization parameter $M = 0$. If the data do not exhibit too much temporal variation, the dynamic method could induce an efficiency loss since it requires the estimation of the spectral density matrices. The recent macroeconomic literature that compares factor model forecasting using large data sets, i.e. Boivin and Ng (2005), Eickmeier and Ziegler (2007), Schumacher (2006) and Stock and Watson (2006) reports mixed results on the performance of various factor model specifications for different data sets.

The out-of-sample forecasting exercise starts in 2002.9 and produces 32 forecasts for each horizon[5]. We perform the forecasting exercise using both a recursive estimation window and a rolling window of a size of 61 periods. Eickmeier and Ziegler's (2007) meta-analytic review of the empirical factor forecasting literature shows that a rolling estimation window improves the factor forecasting performance as the estimated coefficients adapt to potentially available non-linearities and structural breaks in the data. The forecasting performance of the different models is measured by the forecast error, i.e. the difference between the forecasts and the realizations. The summary statistics are the mean squared forecast error (mse) and the variance of the forecast error (var). The difference between these two statistics is the squared mean forecast error, i.e. the bias. Tables 3 and 4 report the forecasting performance for the different specifications $\{m, fe\}$ for the

[5] All forecasts are incorporated in the evaluation since the country aggregate data are available until 2006.11

forecasting exercises employing a recursive respectively a rolling estimation window. The first column reports for each forecast horizon $h = 1, ..., 13$ the forecasting performance of the AR-model. The upper part of the column reports the *mse* and the lower part the *var* of the forecast errors. The other columns report the forecasting performance of the respective models as a ratio to the performance of the benchmark AR-model.

The difference between table 3 and table 4 reveals the effects of applying a rolling versus a recursive window. The recursive window method performs slightly better for the aggregate forecasts, while the rolling window method performs on average much better for the aggregated forecasts. The latter result originates from the smaller bias of the rolling window method. Apparently, the data at the disaggregate level, which show a high temporal variation, are better described by a short window size that allows the model specification to adapt more flexibly to the data.

The difference between the forecasts of x and $\overline{x}$ reveals the performance of forecasting the aggregate versus aggregating the forecasts. For the recursive window method, forecasting the aggregate performs on average better than aggregating the forecasts. The rolling window method shows no distinctive differences between forecasting the aggregate versus aggregating the forecasts. Note that forecasting the aggregate employing the factor models $m = \{SF, DF, DFC\}$ incorporates the disaggregate information as contained by the factors. So, these results confirm Hendry and Hubrich's (2006) theoretical result on predictability that forecasting the aggregate using disaggregate information outperforms aggregating the forecasted disaggregates.

The difference between SF, DF and DFC on the one hand and $AR(2)$ and μ on the other reveals the value added of forecasting based on a large cross-section of data. The forecasts of the $AR(2)$ and μ models perform on average equally well. The general conclusions that are robust across window specification and aggregation are threefold. Firstly, the SF model performs worse than the $AR(2)$ benchmark model with an efficiency loss in mse terms of about 10%. Secondly, the DF model performs better than the $AR(2)$ benchmark model with an efficiency gain in mse terms of about 10%. The outperformance by the DF model implies that the underlying data exhibit substantial dynamics. Thirdly, the DFC model performs equally well as the $AR(2)$ benchmark model. As the observed aggregate staffing employment series exhibits a substantial seasonal pattern, exploiting only the cyclical common dynamics results in a loss of information. Finally, the differences between the specifications of $fe = \{u, fm\}$ show that the unrestricted forecast equation performs better for the DF and DFC models and equally well for the SF model.

4 Conclusion

This paper analyses the developments of the staffing labour cycle in the Netherlands at a disaggregate level using the data set from Randstad. We create a balanced data set that describes the number of hours of staffing employment for 15 different regions and 58 different sectors. We apply factor models to extract low-dimensional common information from the data set and show that the extracted signal resembles the year-on-year growth rate of aggregate staffing employment. The common signal, which excludes the effects of sector or region specific shocks, is also extracted at the disaggregate level. We analyse the correlation structure and classify the disaggregate cycles as leading and lagging according to eight empirical measures. Almost all regions lead or lag the staffing labour cycle by less than half a year. The regions, whose modest leading characteristics are robust across four different empirical measures, are Gelderland and Overijssel.

Almost all regions show a lead that lies between -2 years and +1.5 years. The differences across the sectors are more pronounced than across the regions. Three leading sectors, whose leading characteristics are robust across four different empirical measures, are Supporting and auxiliary transport activities, Sale, maintenance and repair of motor vehicles and motorcycles, and Retail trade. The turnover in the latter two sectors are known to be stylized business cycle leading indicators.

We then explored how the identified leading indicators at the disaggregate level can be exploited to forecast the country aggregate of the staffing employment. The final section compares different model specifications that employ static factors, dynamic factors, cyclical dynamic factors, a second order autoregressive model and the first moment of the time series. The performance is measured by the forecast bias and the mean squared forecast error. Detailed information does not necessarily improve the forecasting performance as the static factor model does not outperform the benchmark autoregressive model. Due to substantial temporal variation within the disaggregate staffing labour market developments, the dynamic factor model manages to outperform the univariate benchmark forecasting models.

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A Appendix

A.1 Data

The data set consists of 1.276.393 observations on the number of contracted staffing hours employed by Randstad. The observation consists of the number of paid hours of contracted staffing agency work. The number of paid hours is larger than the number of invoiced hours since for instance holiday hours and sickness leave are included in addition to worked hours. Every observation consists of four dimensions; the number of paid hours of contracted staffing agency work, the time dimension denoted by the year and the period, the sector to which the user company belongs and the geographical area where the user firm is located. So, the sector and location refers to the company at which the staffing agency worker is employed. The user firm that hires a staffing employee is located in a geographical area that is classified according to the 4-digit postal code. The data consists of 2882 different postal codes that can be aggregated to 466 different municipalities and 15 different regions. The time dimension of the data is divided into years and periods. Every year consists of 13 subsequent administrative periods of 4 weeks. Observations are available from the first period of 1998 until and including the first period of 2005.

Statistics Netherlands (*Centraal Bureau voor de Statistiek,* CBS) employs a systematic hierarchical classification system for economic activities called the *Standaard Bedrijfsindeling* (SBI). The currently operational SBI ´93 was settled in 1993 and consists of five levels. On the highest 2-digits level of compartments, the classification consists of 58 different sectors, which are not all present in the Netherlands[6]. The SBI-code equals for

[6] Compartments describing activities that are not present in the Netherlands are for instance the "mining of uranium and thorium ores" and the "mining of metal ores".

the highest 4-digits level Eurostat´s *Nomenclature statistique des activités économiques dans la Communauté Européenne* (NACE, in particular Rev. 1). On the highest 2-digits level, the SBI´93 and NACE Rev.1 are compatible with the International Standard Industrial Classification of All Economic Activities (ISIC, in particular Rev 3.1), which is the recommended classification of economic activities as established in March 2002 by the statistics commission of the United Nations.

Statistics Netherlands employs a systematic hierarchical classification system for regional units called the *Nomenclatuur van Territoriale eenheden voor de Statistiek* (NUTS). The system provides a non-overlapping country-wide division of the Netherlands in 40 regional units (NUTS3), which can be aggregated to 12 provinces (NUTS2). In this study, we employ 15 regions that correspond to the 12 provinces from which the agglomerations of the three largest cities are separated out. The three NUTS3 regional units *Groot-Amsterdam, Groot-Rijmond* and *Agglomeratie ´s Gravenhage* correspond with the agglomerations of the three biggest cities Amsterdam, Rotterdam and the Hague, respectively.

A.2 On aggregation

The balanced data set consists of the series $X_{ij,t}$, which are the total number of hours of staffing employment in region $i = 1, ..., 15$ and sector $j = 1, ..., 58$ during period t, running from 1998.1 until 2005.1 consisting of 92 four-weeks periods. The time series of aggregate staffing employment at the regional level consists of $X_{i*,t} = \sum_j X_{ij,t}$, the sectoral level equivalent $X_{*j,t} = \sum_i X_{ij,t}$ and the time series of total staffing employment in the Netherlands equals $X_t = \sum_i \sum_j X_{ij,t}$. Let the time-varying shares of the individual variables in the aggregate be defined as: $\alpha_{ij,t} = \frac{X_{ij,t}}{\sum_i \sum_j X_{ij,t}}$. Lemma (1) shows that calculating the growth rates x_t of the aggregate X_t is equivalent to aggregating the growth rates of the disaggregates $x_{ij,t}$ using the delayed weights $\alpha_{ij,t-1}$.

Lemma 1 *Let $X_t = X_{1,t} + X_{2,t}$ be a time series variable. Let x_t be the growth rate of X_t and let $b_{i,t} = \frac{X_{i,t}}{X_t}$. Then $x_t = b_{1,t-1}x_{1,t} + b_{2,t-1}x_{2,t}$*

Proof. $\Delta \ln (X_t) \approx x_t = \frac{\Delta X_t}{X_{t-1}} = \frac{\Delta X_{1,t}+\Delta X_{2,t}}{X_{1,t-1}+X_{2,t-1}} = \frac{\Delta X_{1,t}}{X_{1,t-1}} \frac{X_{1,t-1}}{X_{1,t-1}+X_{2,t-1}}$ $+ \frac{\Delta X_{2,t}}{X_{2,t-1}} \frac{X_{2,t-1}}{X_{1,t-1}+X_{2,t-1}} = x_{1,t} \left(\frac{X_{1,t-1}}{X_{1,t-1}+X_{2,t-1}} \right) + x_{2,t} \left(\frac{X_{2,t-1}}{X_{1,t-1}+X_{2,t-1}} \right) = b_{1,t-1}x_{1,t} +$ $b_{2,t-1}x_{2,t}$. ■

The dynamic factor model decomposition is only defined for data sets that consist of a panel of stationary time series.

Lemma 2 *Let $X_t = X_{1,t} + X_{2,t}$ be a first-order integrated, $I(1)$, time series variable. For $i = 1, 2$ let x_t and $x_{i,t}$ be the corresponding growth rates, x_t^s and $x_{i,t}^s$ the standardized growth rates with means μ_x and μ_{x_i} and standard deviations σ_x and σ_{x_i} respectively. Let the time-varying weights be $b_{i,t} = \frac{X_{i,t}}{X_t}$. Then $x_t^s = a_{1,t-1}x_{1,t}^s + a_{2,t-1}x_{2,t}^s$ with $a_{i,t} = b_{i,t}\frac{\sigma_{x_i}}{\sigma_x}$.*

Proof. *Lemma (1) shows that $\sigma_x x_t^s + \mu_x = b_{1,t-1} \left(\sigma_{x_1} x_{1,t}^s + \mu_{x_1} \right)$ $+ b_{2,t-1} \left(\sigma_{x_2} x_{2,t}^s + \mu_{x_2} \right)$. Rewriting this equation leads to $x_t^s = b_{1,t-1}\frac{\sigma_{x_1}}{\sigma_x} x_{1,t}^s +$*

$b_{2,t-1}\frac{\sigma_{x_2}}{\sigma_x}x^s_{2,t}$ *and* $\mu_x = b_{1,t-1}\mu_{x_1} + b_{2,t-1}\mu_{x_2}$. ■

Projecting the aggregate x^s_t on the estimated factors is only mathematically equivalent to aggregating the projected disaggregates $x^s_{ij,t}$ if the weights are constant $a_{ij,t} = a_{ij}$. Let x^s_{it} denote a vector of T observations for $i = 1, 2$ and u a $(T \times q)-$matrix of q common components u_{it}. Say, you have $x^s_t = a_1 x^s_{1t} + a_2 x^s_{2t}$, then $\chi^{'}_t = \left(u^{'}_t u_t\right)^{-1} u^{'}_t x^s_t u^{'}_t = \left(u^{'}_t u_t\right)^{-1} u^{'}_t \left(a_1 x^s_{1t} + a_2 x^s_{2t}\right) u^{'}_t = a_1 \left(u^{'}_t u_t\right)^{-1} u^{'}_t x^s_1 u^{'}_t + a_2 \left(u^{'}_t u_t\right)^{-1} u^{'}_t x^s_{2t} u^{'}_t = a_1 \chi^{'}_{1t} + a_2 \chi^{'}_{2t}$.

The assumptions needed for this mathematical equivalence are not necessarily met in practice. Firstly, the weights a_i are time varying. Secondly, lemma (1) does not hold precisely since the disaggregate growth rates $x_{i,t}$ and the aggregate growth rate x_t are separately corrected for outliers.

A.3 Estimation

The dynamic method as outlined in Forni et al. (2000), Forni et al. (2004), Forni and Lippi (2001) and Forni et al. (2005) (FHLR) consists of the frequency-domain counterpart of the static method. The dynamic factors $\mathbf{u}_t = (u_{1t}...u_{qt})^{'}$ are estimated by the dynamic principal components, which are the static principal components of the spectral density matrix as outlined by Brillinger (1981). Denote by $\mathbf{X}^{nT} = (x_{it})_{i=1...n,t=1...T}$ an $n \times T$ rectangular of observations, which are realisations of real-valued stationary stochastic processes $\left\{\mathbf{x}_t = (x_{1t}...x_{nt})^{'}\right\}$. Let $\widehat{\mathbf{\Gamma}}^{nT}_{\mathbf{X}}(k) = \frac{1}{T-k}\sum_{t=k+1}^{T}\mathbf{x}^{nT}_t \mathbf{x}^{nT'}_{t-k}$ be the k-lag sample covariance of $\mathbf{x}^{nT}_t$. FHLR suggest the following stepwise procedure. (i) estimate the spectral density matrix of $\mathbf{X}^{nT}$ as $\sum^{nT}_{\mathbf{X}}(\theta_h) = \sum\limits_{k=-M}^{M} \widehat{\Gamma}^{nT}_{\mathbf{X}}(k)\,\omega_k e^{-ik\theta_h}$, $\theta_h = 2\pi h/(2M+1)$, $h = 0, ..., 2M$, where $\omega_k = 1 - |k|/(M+1)$ is the Bartlett window of size M. Like Forni et al. (2000), we set $M(T)$=

$round\left(2T^{(1/2)}\right)$ such that the convergence rate is $M(T)/T = O\left(T^{(1/2)}\right)$; (ii) calculate from $\sum_{\mathbf{X}}^{nT}(\theta_h)$ the q largest eigenvalues $\lambda_j^{nT}(\theta_h)$ and the corresponding eigenvectors $\mathbf{p}_j^{nT}(\theta_h)$, $j = 1,...,q$.for $h = 0,...,2M$. We follow Forni et al.'s (2000) heuristic approach and select $q = 3$ in a finite-sample such that the marginal explained variance of the q^{th} dynamic eigenvalue is larger than 10% and the $(q+1)^{th}$ equivalent is smaller than 10%; (iii) let $\underline{\mathbf{p}}_q^{nT}(\theta_h) = \left(\mathbf{p}_1^{nT'}(\theta_h)...\mathbf{p}_q^{nT'}(\theta_h)\right)'$ the $(q\times n)-$matrix of dynamic eigenvectors and $\underline{\lambda}_q^{nT}(\theta_h)$ a diagonal matrix with the q largest eigenvalues on the diagonal. Inverse Fourier transform $\widehat{\sum}_{\chi}^{nT}(\theta_h) = \underline{\mathbf{p}}_q^{nT'*}(\theta_h)\underline{\lambda}_q^{nT}(\theta_h)\,\underline{\mathbf{p}}_q^{nT}(\theta_h)$ ($*$ denotes complex conjugate) to obtain $\widehat{\Gamma}_{\chi}^{nT}(k) = \frac{1}{(2M+1)}\sum_{k=-M}^{M}\widehat{\sum}_{\chi}^{nT}(\theta_h)\,\omega_k e^{ik\theta_h}$ for $h = 0,...,2M$. Moreover, the estimated common dynamic factors are $\widehat{\boldsymbol{u}}_t^{nT} = \frac{1}{(2M+1)}\sum_{k=-M}^{M}\sum_{h=0}^{2M}\underline{\mathbf{p}}_q^{nT}(\theta_h)\,e^{ik\theta_h}\mathbf{x}_{t-k}^{nT}$ and the estimated common component is $\widehat{\boldsymbol{\chi}}_{nt}^{nT} = \frac{1}{(2M+1)}$ $\sum_{k=-M}^{M}\sum_{h=0}^{2M}\underline{\mathbf{p}}_q^{nT'*}(\theta_h)\,\underline{\mathbf{p}}_q^{nT}(\theta_h)\,e^{ik\theta_h}\mathbf{x}_{t-k}^{nT}$; (iv) repeat step (iii) using the $(q+1)$ to n ordered eigenvalues to obtain $\widehat{\Gamma}_{\xi}^{nT}(k)$; (v) let $\widehat{\mathbf{S}}^{nT} = \left(\widehat{S}_1^{nT'}...\widehat{S}_r^{nT'}\right)'$ the $(r\times n)$-matrix containing the r generalized eigenvectors of the couple of matrices $\left(\widehat{\Gamma}_{\chi}^{nT}(0), \widehat{\Gamma}_{\xi}^{nT}(0)\right)$ with the normalization that $\widehat{S}_i^{nT'}diag\left(\widehat{\Gamma}_{\xi}^{nT}(0)\right)\widehat{S}_j^{nT'} = 1$ if $i = j$ and zero otherwise. We use Bai and Ng's (2002) information criteria (BNIC) to determine the r generalized static factors as a trade-off between the goodness-of-fit and overfitting.

Let $\widetilde{\chi}_{i,T+h|T}^{nT}$ be the h-step ahead factor forecasts of the common component of the i-th variable given T observations of n time series variables. The estimated factors and the forecast of the common component with the dynamic method read as:

$$\widehat{\mathbf{F}}^{nT}=\widehat{\mathbf{S}}^{nT}\mathbf{X}^{nT},\ \widetilde{\chi}^{nT}_{i,T+h|T}=\left[\widehat{\Gamma}^{nT}_{\chi}(h)\right]\widehat{\mathbf{S}}^{nT\prime}\left(\widehat{\mathbf{S}}^{nT}\widehat{\Gamma}^{nT}_{\mathbf{X}}(0)\,\widehat{\mathbf{S}}^{nT\prime}\right)^{-1}\widehat{\mathbf{S}}^{nT}\mathbf{X}^{nT} \tag{1}$$

where $\widehat{\mathbf{F}}^{nT}=\left(\widehat{\mathbf{f}}_1^{nT}...\widehat{\mathbf{f}}_T^{nT}\right)$ the $(r\times T)$ −matrix of the stacked estimated generalized static factors. Evidently, Stock and Watson's (2002) static factors $\widehat{\widehat{\mathbf{F}}}^{nT}$ obtain as a special case of $\widehat{\mathbf{F}}^{nT}$ with $M=0$ and assuming in step (v) that $diag\left(\widehat{\Gamma}^{nT}_{\xi}(0)\right)=I_N$, i.e. the identity matrix. Step (i) until step (iii) allow to estimate the dynamic factor model. The estimated common component $\widehat{\boldsymbol{\chi}}_{nt}$ is calculated by applying time filters to the x´s before averaging along the cross-section. The dynamic estimation method consists of two-sided filters and cannot be applied at the end of the sample, which is the most important part for forecasting. By truncating the time filters, the performance of the estimator of χ_{it} deteriorates as t approaches T. Therefore in step (v), FHLR construct generalized principal components $\mathbf{F}^{nT}$, which are contemporaneous averages of $\mathbf{X}^{nT}$ that minimize the ratio of the variance of the idiosyncratic to common component. Computing the generalized principal components of $\mathbf{x}_{nt}$ is equivalent to computing the standard principal components of $\mathbf{y}_{nt}=H\mathbf{x}_{nt}$ with $\det(H)\neq 0$ and H such that $H\xi_{nt}\xi_{nt}^{\prime}H^{\prime}$ is the $n\times n$-identity matrix. When the idiosyncratic variance-covariance matrix is diagonal, the normalization amounts to dividing each of the x´s by the standard deviation of its idiosyncratic component. The estimated in-sample common component $\widetilde{\chi}^{nT}_{i,T|T}$ is the artificial projection of the (unobserved) χ on $\widehat{\mathbf{F}}^{nT}$.

The factor model forecasting approach distinguishes in two main respects. First, dynamic factors $\widehat{\mathbf{F}}^{nT}$ and static factors $\widehat{\widehat{\mathbf{F}}}^{nT}$ can be employed in (1). Second, the factor model restrictions can be imposed on the forecasting equation. Boivin and Ng (2005) point out that Stock and Watson (2002) do not impose restrictions on the forecasting equation and their forecast reads as $\widehat{\widehat{\chi}}^{nT}_{i,T+h|T} = \left[\widehat{\Gamma}^{nT}_{\mathbf{X}}(h)\right] \widehat{\widehat{\mathbf{S}}}^{nT\prime} \left(\widehat{\widehat{\mathbf{S}}}^{nT\prime} \widehat{\Gamma}^{nT}_{\mathbf{X}}(0) \widehat{\widehat{\mathbf{S}}}^{nT\prime}\right)^{-1} \widehat{\widehat{\mathbf{S}}}^{nT\prime} \mathbf{X}^{nT}$. So, this equation differs from (1) in that the data are directly projected on the estimated factors, i.e. $\widehat{\Gamma}^{nT}_{\mathbf{X}}(h)$ instead of projecting only the common component $\widehat{\Gamma}^{nT}_{\chi}(h)$. The autocorrelation structure of the data is fully employed in the forecasting equation instead of cultivating only the autocorrelation structures of the common and idiosyncratic components separately. If the data adheres to the factor model assumptions and the model parameters are known, then both approaches deliver identical forecasts.

Table 1: The empirical results of the staffing labour cycle at the regional level.

	$\overline{var}_{i*}\left(\widehat{\chi}\right)$	$var_{i*}\left(\widehat{\chi}\right)$	$\overline{\rho}^*_{i*}\left(\widehat{\phi}\right)$	$\overline{\rho}^*_{i*}\left(x^{13}\right)$	$\rho^*_{i*}\left(\widehat{\phi}\right)$	$\rho^*_{i*}\left(x^{13}\right)$	$\overline{l}^*_{i*}\left(\widehat{\phi}\right)$	$\overline{l}^*_{i*}\left(x^{13}\right)$	$l^*_{i*}\left(\widehat{\phi}\right)$	$l^*_{i*}\left(x^{13}\right)$
Drenthe	0.38	0.80	0.11	0.16	0.60	0.65	-0.31	-2.62	0.00	0.00
Noord-Brabant	0.49	0.84	0.05	0.16	0.89	0.76	-3.43	-0.71	6.00	3.00
Noord-Holland	0.46	0.79	0.26	0.07	0.96	0.78	-0.75	0.85	-2.00	-4.00
Gelderland	0.54	0.96	0.51	0.38	0.77	0.85	0.04	1.11	4.00	1.00
Zuid-Holland	0.49	0.90	0.36	0.10	0.68	0.68	-2.54	2.49	0.00	-7.00
Zeeland	0.29	0.53	0.03	-0.14	-0.73	-0.45	0.12	3.03	17.00	7.00
Friesland	0.38	0.82	0.16	0.10	0.86	0.37	-5.90	-0.73	0.00	0.00
Overijssel	0.47	0.80	0.10	0.16	0.70	0.85	2.00	1.89	2.00	0.00
Flevoland	0.31	0.60	0.34	0.25	0.81	0.63	-0.35	2.42	0.00	0.00
Limburg	0.40	0.74	0.16	0.11	0.98	0.90	5.31	2.02	0.00	-2.00
Utrecht	0.51	0.77	0.11	0.31	0.95	0.74	0.66	1.59	0.00	0.00
Groningen	0.36	0.81	0.06	0.02	0.52	0.59	3.22	-1.06	0.00	-2.00
Groot-Amsterdam	0.39	0.69	0.44	0.43	0.84	0.78	2.81	1.01	1.00	-1.00
Groot-Rijnmond	0.40	0.89	0.44	0.15	0.81	0.68	0.59	1.49	5.00	-1.00
Ag.'s-Gravenhage	0.24	0.74	-0.34	-0.01	-0.86	0.53	-0.12	3.24	11.00	3.00

The variance (var) of the common component reports the fraction of the total variance that is explained by the static factor model. The correlation ρ and the time shift l are calculated for the cycle of the corresponding region with respect to the aggregate cycle at the country level. The table reports the result for both the signal ϕ, which is extracted with the factor model, and the growth rates x^{13}. The aggregate measures without a bar summarize the results for the aggregate variables at the regional level. The aggregated measures with a bar summarize the results for the disaggregate variables. The disaggregate results are aggregated to the regional level using as aggregation weights $b_{*j|T}$.

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Table 2: The empirical results of the staffing labour cycle at the sectoral level.

	$\overline{var}_{*j}\,(\widehat{\chi})$	$var_{*j}\,(\widehat{\chi})$	$\overline{\rho}^*_{*j}\left(\widehat{\phi}\right)$	$\overline{\rho}^*_{*j}\left(x^{13}\right)$	$\rho^*_{*j}\left(\widehat{\phi}\right)$	$\rho^*_{*j}\left(x^{13}\right)$	$\overline{l}^*_{*j}\left(\widehat{\phi}\right)$	$\overline{l}^*_{*j}\left(x^{13}\right)$	$l^*_{*j}\left(\widehat{\phi}\right)$	$l^*_{*j}\left(x^{13}\right)$
Agriculture, hunting and related service activities	0.29	0.70	0.19	0.10	0.87	0.88	3.22	-1.75	21.00	16.00
Manufacture of food products and beverages	0.56	0.81	-0.02	-0.05	0.71	-0.05	6.36	0.39	0.00	1.00
Manufacture of tobacco products	0.18	0.26	-0.69	-0.60	-0.74	-0.64	6.04	0.00	7.00	1.00
Manufacture of textiles	0.31	0.48	0.39	0.52	0.87	0.84	4.47	-0.54	3.00	-2.00
Manufacture of wearing apparel; dressing and dyeing of fur	0.23	0.31	0.29	0.57	0.51	0.79	4.48	4.54	8.00	7.00
Tanning and dressing of leather	0.45	0.48	-0.72	0.40	-0.72	0.40	14.00	0.00	14.00	0.00
Manufacture of wood and of products of wood and cork, except furniture	0.42	0.80	0.45	0.31	0.74	0.83	4.63	3.21	8.00	7.00
Manufacture of paper and paper products	0.32	0.69	-0.17	0.18	0.67	0.37	0.78	-0.80	5.00	3.00
Publishing, printing and reproduction of recorded media	0.35	0.73	-0.06	0.13	0.64	0.59	1.38	5.40	17.00	-1.00
Manufacture of coke, refined petroleum products and nuclear fuel	0.25	0.54	0.07	0.31	0.76	0.66	2.11	-0.80	11.00	6.00
Manufacture of chemicals and chemical products	0.44	0.84	0.28	0.09	0.68	0.54	-0.43	0.04	-1.00	-8.00
Manufacture of rubber and plastics products	0.44	0.79	0.51	0.47	0.68	0.61	4.77	1.82	8.00	0.00
Manufacture of other non-metallic mineral products	0.43	0.86	0.45	0.41	0.95	0.78	-3.13	1.75	4.00	2.00
Manufacture of basic metals	0.39	0.72	0.21	0.46	0.51	0.77	7.47	-1.06	7.00	3.00
Manufacture of fabricated metal products, except machinery and equipment	0.50	0.88	0.13	0.47	0.72	0.67	-5.31	2.77	7.00	4.00
Manufacture of machinery and equipment n.e.c.	0.42	0.84	0.29	0.49	0.45	0.73	2.67	3.36	6.00	2.00
Manufacture of office, accounting and computing machinery	0.10	0.39	0.05	0.03	-0.17	-0.04	2.94	1.03	0.00	0.00
Manufacture of electrical machinery and apparatus n.e.c.	0.34	0.66	0.50	0.36	0.67	0.66	3.65	3.10	9.00	2.00
Manufacture of radio, television and communication eq.	0.29	0.47	0.60	0.47	0.74	0.71	7.54	2.90	9.00	4.00
Manufacture of medical, precision and optical instruments	0.30	0.74	0.33	0.32	0.87	0.82	-2.94	-1.93	0.00	-6.00
Manufacture of motor vehicles, trailers and semi-trailers	0.39	0.74	0.63	0.65	0.83	0.91	0.56	-7.15	0.00	-4.00
Manufacture of other transport equipment	0.27	0.64	0.03	0.37	0.84	0.87	-1.21	3.03	8.00	2.00
Manufacture of furniture; manufacturing n.e.c.	0.29	0.62	-0.22	-0.13	0.66	-0.62	5.53	2.84	-15.00	6.00
Recycling	0.02	0.02	0.51	0.09	0.58	0.49	-2.73	-1.48	0.00	-6.00
Electricity, gas, steam and hot water supply	0.22	0.74	0.25	-0.07	-0.81	0.55	-10.61	3.70	12.00	-17.00
Collection, purification and distribution of water	0.12	0.19	0.02	0.21	-0.23	0.20	7.51	10.51	0.00	4.00
Construction	0.63	0.90	0.14	0.35	0.34	0.54	3.27	-0.52	1.00	-2.00
Sale, maintenance and repair of motor vehicles and motorcycles;	0.19	0.26	0.21	0.34	0.57	0.77	6.54	5.64	9.00	11.00
Wholesale trade and commission trade	0.59	0.90	0.35	0.20	0.85	0.68	-1.86	1.53	5.00	0.00
Retail trade, except of motor vehicles and motorcycles;	0.33	0.61	0.38	0.56	0.92	0.87	1.86	0.88	6.00	5.00
Hotels and restaurants	0.43	0.75	0.59	0.55	0.88	0.82	5.45	-1.12	2.00	3.00
Land transport; transport via pipelines	0.38	0.61	0.56	0.34	0.95	0.80	0.03	-0.81	-2.00	-12.00
Water transport	0.16	0.17	0.73	0.56	0.73	0.56	-8.00	-11.00	-8.00	-11.00
Air transport	0.18	0.15	0.78	0.48	0.79	0.49	18.90	0.11	19.00	0.00
Supporting and auxiliary transport activities	0.27	0.70	0.58	0.51	0.86	0.91	5.77	2.66	9.00	9.00
Post and telecommunications	0.25	0.33	0.55	0.29	0.87	0.55	3.63	-0.16	14.00	-2.00
Financial intermediation, except insurance and pension funding	0.61	0.88	-0.14	-0.11	-0.68	-0.26	1.73	3.11	9.00	6.00
Insurance and pension funding, except compulsory social security	0.29	0.47	0.32	0.23	0.68	0.52	-8.00	-1.44	-12.00	0.00
Activities auxiliary to financial intermediation	0.10	0.20	-0.09	0.06	-0.92	0.67	-2.29	-4.31	-25.00	2.00
Real estate activities	0.26	0.74	0.43	0.31	0.75	0.70	1.87	-1.73	8.00	1.00
Renting of machinery and equipment without operator	0.23	0.54	0.26	0.43	0.69	0.69	-0.54	0.27	4.00	0.00
Computer and related activities	0.21	0.45	0.21	0.63	0.93	0.94	-0.43	-1.35	1.00	-3.00
Research and development	0.26	0.69	0.20	0.32	0.28	0.51	3.52	1.53	3.00	0.00
Other business activities	0.39	0.67	0.00	0.16	0.78	0.56	3.76	3.26	-1.00	0.00
Public administration and defence; compulsory social security	0.55	0.80	0.31	0.24	0.93	0.69	-3.71	-2.49	-20.00	-9.00
Education	0.45	0.68	0.08	0.18	0.89	0.48	2.45	0.29	-26.00	-1.00
Health and social work	0.59	0.85	0.00	-0.52	-0.92	-0.91	-0.55	6.21	13.00	10.00
Sewage and refuse disposal, sanitation and similar activities	0.45	0.78	0.53	0.30	0.70	0.37	4.39	-0.84	6.00	-4.00
Activities of membership organizations n.e.c.	0.16	0.46	0.09	0.11	0.16	0.24	1.03	0.92	0.00	-4.00
Recreational, cultural and sporting activities	0.19	0.42	0.47	0.35	0.75	0.47	2.40	-0.68	8.00	-3.00
Other service activities	0.37	0.66	0.25	0.15	0.62	0.73	5.85	-0.64	1.00	14.00

The variance (var) of the common component reports the fraction of the total variance that is explained by the static factor model. The correlation ρ and the time shift l are calculated for the cycle of the corresponding sector with respect to the aggregate cycle at the country level. The table reports the result for both the signal ϕ, which is extracted with the factor model, and the growth rates x^{13}. The aggregate measures without a $\overline{\text{bar}}$ summarize the results for the aggregate variables at the sectoral level. The aggregated measures with a $\overline{\text{bar}}$ summarize the results for the disaggregate variables. The disaggregate results are aggregated to the sectoral level using as aggregation weights $b_{i*|T}$.

Table 3: Forecasting performance of different models using recursive windows

h	$x^{AR,u}_{t+h\|t}$ mse	$x^{\mu,u}_{t+h\|t}$ ratio	$x^{SF,u}_{t+h\|t}$ ratio	$x^{SF,fm}_{t+h\|t}$ ratio	$x^{DF,u}_{t+h\|t}$ ratio	$x^{DF,fm}_{t+h\|t}$ ratio	$x^{DFC,u}_{t+h\|t}$ ratio	$x^{DFC,fm}_{t+h\|t}$ ratio	$\bar{x}^{AR,u}_{t+h\|t}$ ratio	$\bar{x}^{\mu,u}_{t+h\|t}$ ratio	$\bar{x}^{SF,u}_{t+h\|t}$ ratio	$\bar{x}^{SF,fm}_{t+h\|t}$ ratio	$\bar{x}^{DF,u}_{t+h\|t}$ ratio	$\bar{x}^{DF,fm}_{t+h\|t}$ ratio	$\bar{x}^{DFC,u}_{t+h\|t}$ ratio	$\bar{x}^{DFC,fm}_{t+h\|t}$ ratio
1	0.75	1.04	1.39	1.36	1.09	1.08	1.13	1.07	1.04	1.04	1.36	1.37	1.05	1.04	1.09	1.06
2	0.75	1.03	1.09	1.08	0.92	0.92	1.05	1.05	1.01	1.03	1.08	1.08	0.91	0.91	1.04	1.04
3	0.75	1.02	1.07	1.06	0.98	0.98	1.04	1.04	1.01	1.02	1.06	1.06	0.98	0.98	1.04	1.04
4	0.75	1.01	1.20	1.20	0.97	0.97	1.07	1.02	0.98	1.01	1.19	1.20	0.95	0.95	1.08	1.02
5	0.80	0.98	1.00	0.98	0.89	0.89	0.97	0.98	0.97	0.99	0.99	0.99	0.90	0.90	0.98	0.99
6	0.80	0.97	1.35	1.30	0.77	0.79	0.95	0.99	0.88	0.98	1.32	1.32	0.77	0.79	0.96	0.99
7	0.75	1.00	0.98	1.03	0.63	0.68	0.80	1.02	0.93	1.00	1.07	1.04	0.64	0.69	0.82	1.03
8	0.75	0.99	1.06	1.05	0.90	0.92	1.01	1.00	1.01	1.00	1.06	1.07	0.90	0.92	1.02	1.01
9	0.77	0.99	1.01	1.02	0.86	0.89	0.99	0.99	0.98	0.99	1.04	1.04	0.85	0.89	0.99	1.00
10	0.74	1.03	1.05	1.06	0.98	0.98	1.05	1.04	1.05	1.04	1.06	1.07	0.98	0.99	1.06	1.05
11	0.78	0.97	1.00	1.00	0.97	0.96	1.10	0.98	0.96	0.98	1.01	1.01	0.98	0.97	1.09	0.99
12	0.74	0.96	1.07	1.10	0.82	0.83	0.90	0.97	0.65	0.97	1.09	1.09	0.79	0.84	0.86	0.98
13	0.79	1.00	0.55	0.56	0.52	0.74	0.60	0.99	0.61	1.00	0.54	0.54	0.52	0.75	0.60	0.99
h	mse	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio
1	0.75	1.04	1.39	1.36	1.09	1.08	1.13	1.06	1.04	1.04	1.36	1.37	1.05	1.04	1.09	1.06
2	0.75	1.03	1.09	1.08	0.92	0.92	1.05	1.04	1.01	1.03	1.08	1.08	0.91	0.90	1.04	1.04
3	0.75	1.02	1.07	1.06	0.98	0.98	1.04	1.04	1.01	1.02	1.06	1.06	0.98	0.97	1.04	1.04
4	0.75	1.01	1.21	1.20	0.97	0.97	1.07	1.02	0.98	1.01	1.19	1.20	0.95	0.95	1.08	1.02
5	0.79	0.99	1.00	0.98	0.89	0.89	0.98	0.99	0.96	0.99	0.99	0.99	0.91	0.90	0.98	0.99
6	0.78	0.97	1.37	1.32	0.79	0.80	0.97	0.99	0.85	0.97	1.33	1.32	0.78	0.79	0.97	0.99
7	0.73	1.01	1.00	1.04	0.63	0.69	0.82	1.03	0.91	1.01	1.08	1.05	0.64	0.69	0.83	1.03
8	0.73	1.01	1.08	1.06	0.92	0.93	1.01	1.02	0.99	1.01	1.06	1.07	0.92	0.93	1.02	1.02
9	0.76	1.00	1.02	1.03	0.87	0.90	1.00	1.00	0.97	1.00	1.04	1.04	0.86	0.90	1.00	1.00
10	0.73	1.04	1.06	1.07	0.99	0.99	1.07	1.04	1.04	1.04	1.07	1.07	0.99	0.99	1.07	1.04
11	0.76	0.99	1.01	1.01	0.98	0.97	1.11	0.99	0.95	0.99	1.02	1.02	0.98	0.97	1.10	0.99
12	0.73	0.97	1.08	1.11	0.81	0.84	0.88	0.98	0.64	0.97	1.10	1.10	0.78	0.83	0.84	0.98
13	0.79	1.00	0.54	0.55	0.51	0.74	0.56	0.99	0.60	1.00	0.54	0.54	0.51	0.75	0.56	0.99

$x^{m,fe}_{t+h|t}$, represents the h-step ahead forecast with the different model specifications $m = \{SF, DF, DFC, AR, \mu\}$. The specifications employ respectively static factors, dynamic factors, cyclical dynamic factors, 2^{nd} order autoregressive model and the first moment of the time series. Moreover, the forecast equation $fe = \{u, fm\}$ is unrestricted such that the time series variables are forecasted directly, or, respectively, admits the factor model structure such that the common component is forecast. The first column reports for each forecast horizon h the forecast performance of the AR-model. The upper part of the column reports the Mean Squared Error (mse) and the lower part the Variance (var) of the forecast errors. The other columns report the forecasting performance of the respective models as a ratio to the performance of the benchmark AR-model. The forecasting exercise starts in 2002.9 and produces 32 forecasts for each horizon. All forecasts are evaluated since the aggregate data at the country level are available until 2006.4. The forecasts are generated using a recursive estimation window.

Table 4: Forecasting performance of different models using rolling windows

h	$x^{AR,u}_{t+h\|t}$ mse	$x^{\mu,u}_{t+h\|t}$ ratio	$x^{SF,u}_{t+h\|t}$ ratio	$x^{SF,fm}_{t+h\|t}$ ratio	$x^{DF,u}_{t+h\|t}$ ratio	$x^{DF,fm}_{t+h\|t}$ ratio	$x^{DFC,u}_{t+h\|t}$ ratio	$x^{DFC,fm}_{t+h\|t}$ ratio	$\overline{x}^{AR,u}_{t+h\|t}$ ratio	$\overline{x}^{\mu,u}_{t+h\|t}$ ratio	$\overline{x}^{SF,u}_{t+h\|t}$ ratio	$\overline{x}^{SF,fm}_{t+h\|t}$ ratio	$\overline{x}^{DF,u}_{t+h\|t}$ ratio	$\overline{x}^{DF,fm}_{t+h\|t}$ ratio	$\overline{x}^{DFC,u}_{t+h\|t}$ ratio	$\overline{x}^{DFC,fm}_{t+h\|t}$ ratio
1	0.76	1.01	1.35	1.35	1.03	1.03	1.16	1.07	1.01	1.02	1.32	1.34	1.00	1.01	1.13	1.06
2	0.75	1.02	1.12	1.11	1.03	1.02	1.01	1.04	1.02	1.02	1.10	1.09	1.01	1.00	1.00	1.04
3	0.79	0.97	1.03	1.02	0.94	0.94	0.99	0.98	0.96	0.96	1.02	1.02	0.93	0.93	0.99	0.98
4	0.77	0.99	1.19	1.19	0.94	0.95	1.11	1.02	0.98	1.00	1.16	1.17	0.94	0.94	1.11	1.02
5	0.70	1.14	1.14	1.14	1.12	1.10	1.16	1.16	1.11	1.16	1.15	1.15	1.13	1.11	1.16	1.16
6	0.81	0.98	1.41	1.36	0.76	0.77	0.94	0.98	0.94	0.97	1.35	1.33	0.77	0.78	0.96	0.98
7	0.73	1.02	1.05	1.05	0.69	0.73	1.03	1.04	1.00	1.02	1.09	1.06	0.70	0.74	1.00	1.04
8	0.74	1.02	1.11	1.10	0.93	0.95	1.02	1.04	1.03	1.02	1.10	1.11	0.93	0.96	1.01	1.04
9	0.80	0.96	1.04	1.03	0.89	0.90	0.95	0.97	0.97	0.97	1.03	1.03	0.88	0.90	0.94	0.97
10	0.76	1.01	1.05	1.05	0.97	0.97	1.11	1.01	1.01	1.02	1.04	1.05	0.96	0.97	1.10	1.02
11	0.82	0.95	0.96	0.96	0.95	0.92	1.07	0.94	0.97	0.93	0.96	0.96	0.95	0.92	1.02	0.94
12	0.72	0.97	1.12	1.12	0.83	0.87	0.79	1.00	0.82	0.98	1.10	1.10	0.83	0.87	0.78	1.00
13	0.76	1.06	0.57	0.57	0.53	0.76	0.81	1.05	0.90	1.06	0.56	0.55	0.52	0.76	0.79	1.05
h	mse	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio	ratio
1	0.76	1.02	1.36	1.35	1.04	1.03	1.16	1.07	1.01	1.03	1.33	1.34	1.01	1.01	1.13	1.07
2	0.75	1.02	1.12	1.11	1.02	1.01	1.01	1.04	1.02	1.02	1.10	1.09	1.00	1.00	1.00	1.04
3	0.79	0.97	1.03	1.02	0.94	0.93	0.99	0.98	0.96	0.96	1.02	1.02	0.92	0.93	0.99	0.98
4	0.77	0.99	1.18	1.18	0.94	0.95	1.11	1.02	0.98	1.00	1.16	1.16	0.93	0.94	1.10	1.01
5	0.70	1.13	1.12	1.11	1.11	1.09	1.13	1.14	1.10	1.14	1.12	1.12	1.12	1.10	1.12	1.14
6	0.80	0.97	1.38	1.34	0.74	0.75	0.92	0.96	0.93	0.96	1.32	1.30	0.75	0.76	0.93	0.95
7	0.70	1.04	1.08	1.07	0.69	0.74	1.05	1.05	1.02	1.04	1.11	1.08	0.71	0.75	1.02	1.05
8	0.72	1.02	1.10	1.10	0.92	0.95	1.01	1.03	1.02	1.01	1.09	1.10	0.93	0.95	1.00	1.02
9	0.79	0.95	1.01	1.01	0.88	0.89	0.92	0.94	0.96	0.95	1.01	1.01	0.86	0.88	0.91	0.94
10	0.75	1.01	1.04	1.04	0.96	0.96	1.11	1.00	1.01	1.02	1.03	1.04	0.95	0.96	1.09	1.00
11	0.80	0.96	0.97	0.97	0.94	0.91	1.07	0.93	0.97	0.93	0.96	0.96	0.93	0.91	1.03	0.93
12	0.71	0.96	1.11	1.11	0.79	0.84	0.75	0.99	0.79	0.98	1.08	1.08	0.79	0.85	0.75	0.98
13	0.76	1.06	0.56	0.57	0.52	0.75	0.79	1.04	0.89	1.05	0.54	0.54	0.50	0.76	0.76	1.04

$x^{m,fe}_{t+h|t}$, represents the h-step ahead forecast with the different model specifications $m = \{SF, DF, DFC, AR, \mu\}$. The specifications employ respectively static factors, dynamic factors, cyclical dynamic factors, 2$^{\text{nd}}$ order autoregressive model and the first moment of the time series. Moreover, the forecast equation fe $= \{u, fm\}$ is unrestricted such that the time series variables are forecasted directly, or, respectively, admits the factor model structure such that the common component is forecast. The firs column reports for each forecast horizon h the forecast performance of the AR-model. The upper part of the column reports the Mean Squared Error (mse) and the lower part the Variance (var) of the forecast errors. The other columns report the forecasting performance of the respective models as a ratio to the performance of the benchmark AR-model. The forecasting exercise starts in 2002.9 and produces 32 forecasts for each horizon. All forecasts are evaluated since the aggregate data at the country level are available until 2006.4. The forecasts are generated using a rolling estimation window of 61 periods.

Figure 1: Year-on-year growth rate of total employment and cyclical component of staffing turnover

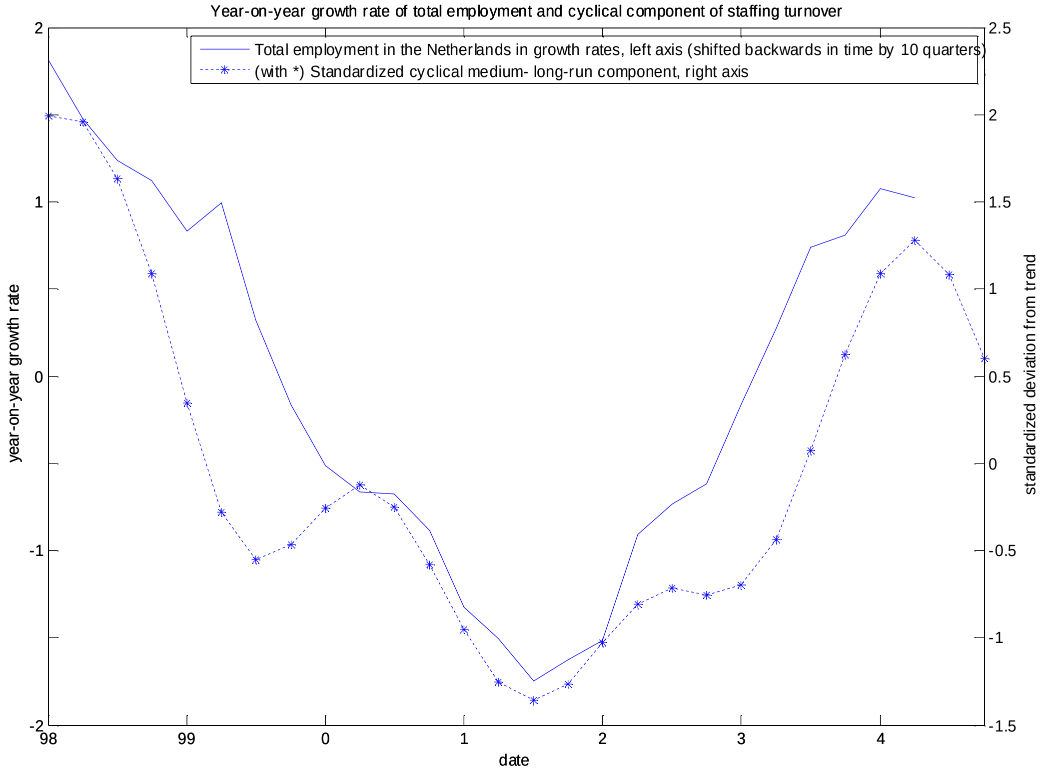
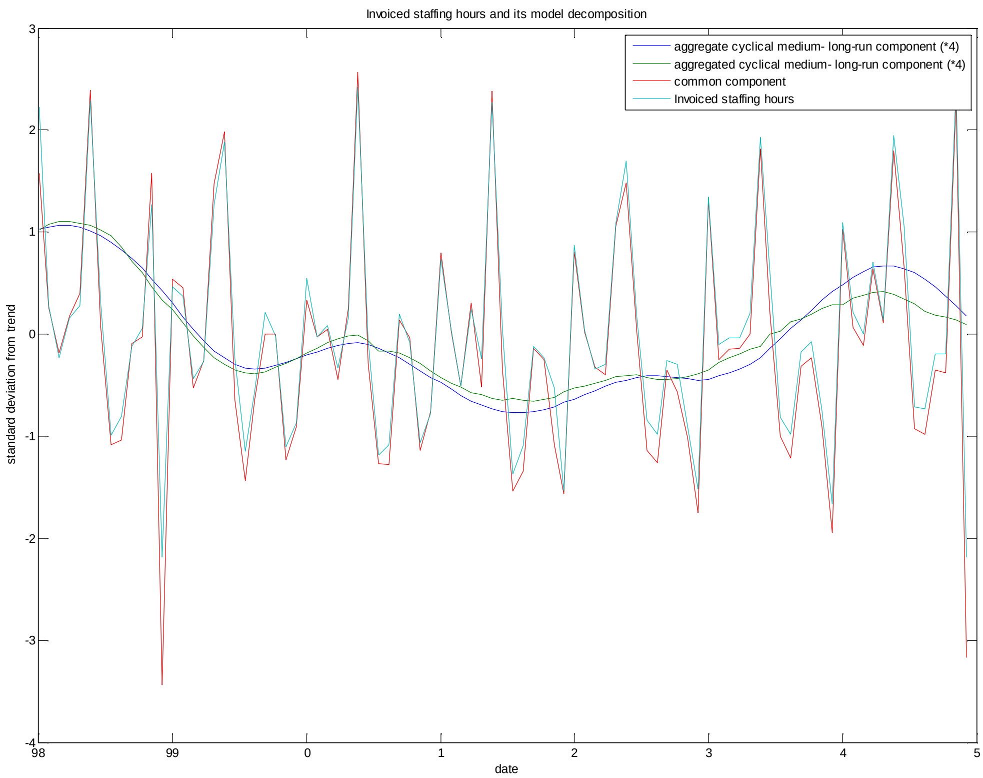


Figure 2: Invoiced staffing hours and its model decomposition



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