“State-level wage Phillips curves”

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State-level wage Phillips curves

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Abstract
We examine reduced form versions of New Keynesian wage Phillips curves using monthly US state-level data for the period 1982-2016, taking account of the endogeneity of unemployment by instrumentation and the presence of common correlated effects (CCE). We find that theoretically coherent specifications taking account of the aggregate dynamics of unemployment may be estimated by the CCE estimator, whereas less efficient and potentially inconsistent methods differ and are problematic.

JEL Codes: E24, E31, E32.

Keywords: Wage Phillips curves, state-level data, panel estimation, CCE, endogeneity.

1 Introduction

In this paper we estimate reduced form versions of New Keynesian wage Phillips curves using state-level data and appropriate techniques allowing for heterogeneity and common correlated effects, an exercise which has not been previously undertaken.

The original Phillips curve (Phillips (1958)) explained wage inflation. The Phillips curve in its modern New Keynesian configuration (the NKPC) is the forward looking relationship between price inflation and marginal costs, the latter often proxied by real unit labour costs or a capacity measure such as the output gap or unemployment, presumed to be correlated with marginal costs. The specification exploits the recursive nature of the dynamic problem to generate a specification that looks similar to a traditional Phillips curve, although the interpretation is quite different. Woodford (2003) is a common citation for an exposition. Interest has been maintained by policymakers as the relationship between activity and wages is a key part of the inflationary process. The wage Phillips curve in macro models is typically also modelled as a forward looking process with staggered wage setting or other rigidities. As Galí (2011) notes, there has been less empirical attention to the wage setting process than to prices, which he hoped to partially rectify by specifying and estimating a New Keynesian Wage Phillips Curve (NKWPC).

What may be missing, however, is a recognition that labour markets are local. In general, aggregation has a large impact on the dynamics of aggregate relationships. Imbs et al. (2007) explores the implication of ignoring heterogeneity on aggregate dynamics in the context of French industry level data. In this paper we

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1In its ‘expectations augmented’ form, eg Phelps (1967).
2See Robertson and Symons (1992) and Imbs et al. (2005) for an application to the real exchange rate.
seek to address this issue in the context of a theoretically well-motivated model, an augmented New Keynesian wage Phillips curve (ANKWPC) due to Galí (2011). We use US state-level data to estimate an average wage Phillips curve which delivers an estimate of the average dynamic process, more relevant in structural models than estimates derived from aggregate data. We take account of the existence of common correlated effects, which are known to be important empirically in dynamic panels of the type we examine, and allow for endogeneity among the regressors.

Previous panel and sectoral estimates exist, but this specific exercise has not been conducted before on any set of panel data. M J Luengo-Prado and Sheremirov (2017) examine US sectoral inflation. Leduc and Wilson (2017) examine city-level relationships. Smith (2014) examines the effect of labour market slack on wages at state level. More closely related, the model in Kumar and Orrenius (2014) is based on the traditional Phillips curve approach, with an emphasis on non-linearity, and focuses on pooled estimates. A rare example of a panel approach to the NKPC (not the NKWPC) is Byrne et al. (2013). They use a MG panel approach to the NKPC using data for 14 geographically and economically dispersed countries accounting for cross-sectional heterogeneity to a limited extent, but not endogeneity. They look at a group of countries whose aggregate has no well-defined meaning and are not part of a federal or common currency area, although some of the countries are in the eurozone, trade with each other and to varying degrees have freedom of movement. By contrast, US states are in a federation and connected via frictionless trade, free movement of labour, geographical contiguity, culture and a common monetary and fiscal framework.

2 The New Keynesian Wage Phillips Curve

The standard New Keynesian Phillips Curve (NKPC) is a forward looking approach to price setting that exploits the recursive nature of the dynamic problem to generate a specification that looks similar to a traditional Phillips curve, although the interpretation is quite different. Similarly, there are forward-looking models of staggered wage setting that have similar properties. Galí (2011) set out an analytical structure for what he termed a New Keynesian Wage Phillips Curve. Using his notation, his Equation 13 is

\[
\Delta w_t = \beta E^t_t \{\Delta w_{t+1}\} - \lambda_w \varphi \hat{u}_t + \varepsilon_t
\]  

(2.1)

where \(w_t\) is the (log) nominal wage, \(u_t\) is unemployment, \(u_n\) the natural rate and \(\hat{u}_t = u_t - u_n\) is the deviation from the natural rate. \(\varphi\) determines the marginal disutility of work and \(\beta\) is the rate of time discount. With wage indexation the augmented NKWPC is

\[
\Delta w_t = \alpha + \gamma \Delta p_{t-1} + \beta E^t_t \{\Delta w_{t+1} - \gamma \Delta p_t\} - \lambda_w \varphi u_t + \varepsilon_t
\]  

(2.2)

(his Equation 14) where \(p_t\) is a measure used for price indexation. \(\lambda_w = \frac{(1-\theta_w)(1-\beta \lambda_w)}{\theta_w} > 0\) where \(\epsilon_w\) is the wage elasticity of demand for labour (that determines the wage mark-up) and \((1 - \theta_w)\) is the Calvo-style probability that wages are reset each period. \(\alpha = (1 - \beta)\left((1 - \gamma) \pi^P + g\right)\) where \(\pi^P\) is steady state inflation, \(g\) is the steady state rate of growth of productivity and \(\gamma\) is the weight of steady state inflation in the indexation formula. Not all of these structural parameters can be recovered from the NKWPC or ANKWPC alone but their plausibility can be assessed using calibration. \(\beta\) and \(\gamma\) are identified.

\(^3\)Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, The Netherlands, Portugal, Spain, Sweden, the UK and the USA.

\(^4\)Here and in the empirical work we assume that \(u_n\) is constant and set it to 0, as we note in Section 4.1.
2.1 Backward specifications

Gali (2011) shows that if we assume (the deviation of) unemployment (from the natural rate) follows an AR(2)
such that

$$ u_t = \phi_1 u_{t-1} + \phi_2 u_{t-2} + \epsilon_t $$  \hspace{1cm} (2.3)

then the reduced form wage equation corresponding to (2.2) is

$$ \Delta w_t = \alpha + \gamma \Delta p_{t-1} + \psi_0 u_t + \psi_1 u_{t-1} + \epsilon_t. $$  \hspace{1cm} (2.4)

The underlying parameters are not all uniquely identified but

$$ \psi_0 \equiv -\frac{\lambda \varphi}{1 - \beta(\phi_1 + \phi_2)}, $$  \hspace{1cm} (2.5)

$$ \psi_0 \equiv -\frac{\lambda \varphi \beta \phi_2}{1 - \beta(\phi_1 + \phi_2)}. $$  \hspace{1cm} (2.6)

Orlandi et al. (2017) have a related model with real wage rigidities (RNKWC). Here

$$ \Delta w_{pg,t} = \alpha + \beta \gamma \Delta w_{pg,t-1} + (1 - \gamma)\Delta w_{pg,t-1} - \lambda_{wpg} u_t + \epsilon_t $$  \hspace{1cm} (2.7)

where $\Delta w_{pg,t} = \Delta w_t - \Delta p_t - g_t$ and $g_t$ is the growth in trend productivity. The backward version is similar to Gali’s:

$$ \Delta w_{pg,t} = \alpha + \beta \Delta w_{pg,t-1} + \psi_0 u_t + \psi_1 u_{t-1} + \epsilon_t $$  \hspace{1cm} (2.8).

3 Estimation methodology

The common correlated effect (CCE) methodology for the estimation of large-$N$ panels was introduced by Pesaran (2006). We consider the general model

$$ y_{it} = \beta_0 + \beta_1 y_{i,t-1} + \beta_2 x_{it} + \beta_3 z_{it} + u_{it} $$  \hspace{1cm} (3.1)

$$ u_{it} = X_i'f_t + \epsilon_t $$

$$ x_{it} = \pi_i + \Pi z_{it} + A_i f_t + v_{it} $$

where the $y_{it}$ are endogenous variables to be explained, $x_{it}$ are other potentially endogenous explanatory variables, $z_{it}$ are exogenous and $f_t$ are unobserved interactive effect variables.

We assume that $\epsilon_{it}$ and $v_{it}$ are correlated for given $i$, but uncorrelated across $i$, and are martingale difference processes over time as is $u_{it}$. Chudik and Pesaran (2015) discuss the use of cross sectional average proxies to augment (3.1) and estimate its coefficients. In particular, due to the presence of the lagged dependent variable in (3.1), they suggest that $\bar{y}_t$, $\bar{z}_t$ and $\bar{x}_t$ and their lags be used to augment (3.1), and then either pooled or mean group panel estimation be carried out. If $\epsilon_{it}$ and $v_{it}$ are correlated one needs further to instrument $x_{it}$ by some appropriate instrument $w_{it}$ as discussed in Harding and Lamarche (2011). Note that since $\epsilon_{it}$ and $v_{it}$ are uncorrelated across $i$ the endogeneity does not affect the cross sectional average proxies. In particular, letting $R_i = (y_i, X_i, Z_i)$, $W_i = (y_{i,-1}, W_i, Z_i)$, $y_t = (y_t, ..., y_{t-T})'$, $y_{i,-1} = (y_{i,-1}, ..., y_{i,-T-1})'$, $X_i = (x_1, ..., x_m)$', $x_i = (x_{i2}, ..., x_{iT})'$, $Z_i = (z_1, ..., z_m)'$, $z_t = (z_{t2}, ..., z_{tT})'$, $W_i = (w_{i1}, ..., w_{in})'$, $w_1 = (w_{12}, ..., w_{1T})'$ and $M = I - P(P'P)^{-1}P'$ where $P$ contains the cross sectional proxies and a constant, the pooled estimator is
given by

\[
\begin{pmatrix}
\hat{\beta}_{1i} \\
\hat{\beta}_{2i} \\
\hat{\beta}_{3i}
\end{pmatrix} = \left[ \sum_{i=1}^{N} R'_i M W_i (W'_i M W_i)^{-1} W'_i M R_i \right]^{-1} \left[ \sum_{i=1}^{N} R'_i M W_i (W'_i M W_i)^{-1} W'_i M y_i \right].
\]

4 Results

4.1 Aggregate data

Gali (2011) reports that on aggregate quarterly US data an AR(2) of

\[u_t = 0.22^{**} + 1.66^{**} u_{t-1} - 0.70^{**} u_{t-2} + \varepsilon_t\]

where ** indicates 5% significance is a good model for the period from 1948Q1 to 2009Q3. Our data are monthly and cover 1982M1 to 2016M12. Figure 1 shows the aggregate monthly data over the sample we use, together with the average of our state-level data. In contrast to (eg) the European data, it is more plausible that the data are stationary. Following Gali, we assume the natural rate is constant and work with the level.

Figure 1: Average and aggregate unemployment: 1982 - 2016

Corresponding to Gali’s specification, over these two periods a monthly AR(6) exhibit some autocorrelation at annual frequencies but have similar properties. A simplified version for our 1982 to 2016 sample is

\[u_t = 0.02^{***} + 1.097^{***} u_{t-1} - 0.111^{***} u_{t-6} + \varepsilon_t\]

where *** indicates 1% significance. As in Gali (2011), this process is persistent but stationary. The impulse responses to a shock are similar to Gali’s when adjusted for the frequency. Gali used two alternative definitions for the indexation variable, quarterly inflation and year-on-year inflation, which in our monthly case is \(p_t - p_{t-12} (\Delta^{12} p_t)\), lagged one month. For reference, his quarterly specification (2.4) estimated over 1964Q1 to 2007Q4 for average hourly earnings of production and non-supervisory employees with the level of unemployment and the former inflation series returned estimates of \(\Delta w_t = \alpha + 0.503^{**} \Delta p_{t-1} - 0.33^{**} u_t + 0.294^{**} u_{t-1}\). Gali also obtains \(\Delta w_t = \alpha + 0.687^{**} \Delta p_{t-1} - 0.552^{**} u_t + 0.453^{**} u_{t-1}\) using year-on-year annual price inflation. With the aggregate monthly data over our sample with the lags on unemployment implied by the simplified AR, however, we do not find a significant relationship as the unemployment terms are very small and insignificant. No US reference estimate for the real-wage specification is available, but when we estimate it the unemployment terms are again insignificant.

4.2 Panel results

We now report results using our disaggregated data. In contrast to the aggregate data, we find well-determined results in line with the theory.

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5 Defined as in Gali (2011): earnings-based measure.
6 The unweighted state-level data average to a lower value than the aggregate and are smoother, but follow a similar trend.
7 The natural rate could be modeled by a bandpass filter, a state-space model as in Orlandi et al. (2017) or by a structural model using natural rate drivers. All present problems and moreover in each case are impracticable to construct at state level.
8 We also adopt this specification for the disaggregated data.
Figures 2, 3 and 4 show the average of the state level price inflation, the log-level of the wage and the productivity-adjusted ‘real wage’ inflation rates together with the aggregate data for comparison. The price inflation data differ but are closely aligned. The wage data however are much more volatile at the average state-level than the aggregate, as can be seen in the chart of the level. There is also an average level difference (scaled away in the chart) and an average growth difference for the period up to 1990. The real wage is constructed using aggregate productivity data as state-level data on output (or productivity) are unavailable and may also be taken to more closely represent the underlying trend. These data are reported as inflation rates, which emphasises the volatility relative to the aggregate following from the wage measure.

![Figure 2: Average and aggregate inflation rate: 1982 - 2016](image1)

![Figure 3: Average wage inflation rate: 1982 - 2016](image2)

![Figure 4: Average real wage inflation rate: 1982 - 2016](image3)

We estimate monthly versions of (2.1) and (2.1) imposing the lag structure for unemployment that is implied by our parsimonious AR reported in the previous subsection. We use year-on-year inflation for the indexation series, which is both intuitively attractive and removes seasonality in the price indices. We estimate four models, instrumenting $u_t$ with four instruments sets where applicable, using up to four lags. For reference we report results using simple pooled OLS, a standard fixed effects model (FE) and a standard mean-group specification (MG), as well as the preferred efficient CCE estimator. As there is no lagged dependent variable the OLS and

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FE estimates do not suffer from the bias identified by Pesaran and Smith (1995), but suffer from misleading inference and are potentially inconsistent.\textsuperscript{10} We instrument the endogenous variables with a prior regression as in Harding and Lamarche (2011). The results are reported in Table 4.1 (* indicates significance at 10%).

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>FE</th>
<th>MG</th>
<th>CCE</th>
<th>OLS</th>
<th>FE</th>
<th>MG</th>
<th>CCE</th>
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<td>-0.076***</td>
<td>-0.084***</td>
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<td>-0.156***</td>
<td>-0.075***</td>
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<td>$u_{t-5}$</td>
<td>0.049***</td>
<td>0.044***</td>
<td>0.043***</td>
<td>0.063***</td>
<td>0.048***</td>
<td>0.043***</td>
<td>0.054***</td>
<td>0.064***</td>
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<td>$\Delta_{12}P_{t-1}$</td>
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<td>0.3288***</td>
<td>0.3132***</td>
<td>0.5604*</td>
<td>0.3492***</td>
<td>0.3288***</td>
<td>0.3096***</td>
<td>0.5604*</td>
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<td>OLS</td>
<td>FE</td>
<td>MG</td>
<td>CCE</td>
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<tr>
<td>$u_t$</td>
<td>-0.073***</td>
<td>-0.081***</td>
<td>-0.094***</td>
<td>-0.166***</td>
<td>-0.072***</td>
<td>-0.080***</td>
<td>-0.092***</td>
<td>-0.164***</td>
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<tr>
<td>$u_{t-5}$</td>
<td>0.046***</td>
<td>0.042***</td>
<td>0.051*</td>
<td>0.072**</td>
<td>0.045*</td>
<td>0.040*</td>
<td>0.050*</td>
<td>0.071**</td>
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<tr>
<td>$\Delta_{12}P_{t-1}$</td>
<td>0.3492***</td>
<td>0.3288***</td>
<td>0.3132***</td>
<td>0.5286</td>
<td>0.3492***</td>
<td>0.3288***</td>
<td>0.3132***</td>
<td>0.5352*</td>
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<td>CCE</td>
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<tr>
<td>$u_t$</td>
<td>-0.130***</td>
<td>-0.138***</td>
<td>-0.152***</td>
<td>-0.162***</td>
<td>-0.128***</td>
<td>-0.136***</td>
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<tr>
<td>$u_{t-5}$</td>
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<td>0.094***</td>
<td>0.099***</td>
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<td>-0.496***</td>
<td>-0.492***</td>
<td>1.002***</td>
<td>-0.496***</td>
<td>-0.496***</td>
<td>-0.492***</td>
<td>1.002***</td>
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<td>CCE</td>
<td>OLS</td>
<td>FE</td>
<td>MG</td>
<td>CCE</td>
</tr>
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</table>

Table 4.1: A backward looking specification for nominal ANKWPC

The results are largely invariant to the instrument set. The OLS, FE and MG estimates are similar to each other. However, the preferred CCE estimates differ, with a larger impact from unemployment and a price indexation term that is around two thirds higher than the less efficient results, albeit only marginally significant in two cases. The data are scaled to make them comparable to those in Galí. Although estimated with a different data set, frequency and sample, the CCE results are broadly comparable to Galí’s. The main difference to Galí’s results are that the net impact of unemployment is larger using the disaggregated data, while the inflation indexation term is very similar.

Table 4.2 reports the results from the Orlandi et al. (2017) real wage rigidity specification using actual (aggregate) productivity.\textsuperscript{11} In this case (following their notation) the coefficient on the lagged productivity adjusted real wage growth term is given by $\beta_0 = \frac{\gamma \theta}{\theta - 1}$ where $\beta$ is the discount factor (assumed close to and less than one), $\theta$ is the elasticity of substitution of labour, $\gamma$ is a wage adjustment parameter and $\phi$ is the degree of real wage inertia that lies between 0 and 1. If $\phi = 0$ implying no real wage rigidity then $\beta_0$ will be close to but less than one. In this case the dynamic bias due to Pesaran and Smith (1995) does hold, in addition to any issues flowing from common correlated errors. As above, the results are largely invariant to the instrument set. The results for OLS, FE and MG (the latter not subject to dynamic bias) are similar but the estimate of the coefficient on the lagged dependent variable are very different from the CCE estimates. Crucially, the OLS, FE and MG results are each inconsistent with the theory as $\hat{\beta}_0 < 0$. By contrast, in the CCE case, the coefficient is close to unity. We cannot reject a plausible value such as 0.98 on a two-sided test, so the results are consistent with even quite substantial values of the discount factor and no real wage rigidity.

<table>
<thead>
<tr>
<th></th>
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<th>FE</th>
<th>MG</th>
<th>CCE</th>
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<tbody>
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<td>-0.134***</td>
<td>-0.151***</td>
<td>-0.169***</td>
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<tr>
<td>$u_{t-5}$</td>
<td>0.088***</td>
<td>0.080***</td>
<td>0.094***</td>
<td>0.105***</td>
<td>0.086***</td>
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<td>$wpg_{t-1}$</td>
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<td>-0.496***</td>
<td>-0.492***</td>
<td>1.002***</td>
<td>-0.496***</td>
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<td>MG</td>
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<tr>
<td>$u_t$</td>
<td>-0.126***</td>
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<td>$u_{t-5}$</td>
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<td>$wpg_{t-1}$</td>
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<td>FE</td>
<td>MG</td>
<td>CCE</td>
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</table>

Table 4.2: A backward looking specification for a real NKWPC (actual productivity)

\textsuperscript{10}Pesaran (2006).

\textsuperscript{11}The results using HP filtered productivity are very similar.
Thus we find that two alternative specifications for a NKPC may be estimated. The standard inefficient and potentially inconsistent methods produce similar results that are economically different from those produced by the CCE method. Somewhat remarkably, the CCE results are close to those produced by Gali (2011) using entirely different data sets and samples. In the case of the real wage rigidity specification only the CCE estimates are theoretically admissible. The CCE specification does however point to the absence of real wage rigidity.

5 Conclusions

We examine reduced form versions of a New Keynesian wage Phillips curve using monthly US state-level data for the period 1982-2016, taking account of the endogeneity of unemployment by instrumentation and the presence of common correlated effects, an exercise that has not previously been undertaken. One is augmented by inflation and another operates with real wage rigidity. We find specifications taking account of the aggregate dynamics of unemployment may be estimated, and the results are consistent with the theory. Although not all the parameters can be identified, the real wage rigidity version suggests there is in fact no real wage rigidity, lending support to the NKWPC augmented with partial wage indexation. Arguably, these average estimates of wage inflation dynamics capture structural dynamics more accurately than those obtainable with aggregate data.
A Appendix: data

<table>
<thead>
<tr>
<th>Description</th>
<th>Source</th>
<th>Notes</th>
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<tr>
<td>$w$</td>
<td>Average hourly nominal wage rates</td>
<td>Usual hourly earnings for hourly and non-hourly workers. We have constructed those variables manually. Monthly state data.</td>
</tr>
<tr>
<td>$u$</td>
<td>The state unemployment rates / Unemployment levels / Employment levels</td>
<td>CPS</td>
</tr>
<tr>
<td>$p$</td>
<td>CPI-U</td>
<td>We use the 4 Census regions as described in BLS and mapped all states to these Census regions accordingly. Monthly data.</td>
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<td>$\Delta wpg$</td>
<td>$\Delta wpg_{i,t} = \Delta w_{i,t} - \Delta p_{i,t} - g_t$</td>
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Table A.1: Data notes

References


