Studies in Business Cycles and Macroeconomics

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Submitted in total fulfillment of the requirements of the degree of Doctor of Philosophy

May 2018

DEPARTMENT OF ECONOMICS
THE UNIVERSITY OF MELBOURNE

Produced on archival quality paper
Abstract

This thesis comprises three self-contained chapters. Each chapter is linked through the common motivation of understanding fluctuations in aggregate economic activity.

Sectors with higher separation rates have a larger response in their vacancy yield when aggregate vacancies vary. Chapter 2 constructs series of labour search models to investigate the link between separation rates and vacancy yield. The analysis shows that the separation rate does not affect the vacancy yield elasticity. In turn, productivity and vacancy creation costs, which are correlated with the separation rate, are considered. It is shown that these two variables can account for the observed relationship between the vacancy yield elasticity and separation rates.

Aggregate macroeconomic series display asymmetries in different phases of the business cycle. Peaks are sharp and quick, while troughs are protracted and relatively flat. The past literature has attributed this asymmetry to firm level frictions. Chapter 3 takes a sectoral view, investigating sectoral turning points and sectoral growth rates around aggregate and sectoral turning point dates. It is shown that more sectors are contracting around the aggregate peak date than are expanding around the aggregate trough date. Furthermore, sectors do not display asymmetry in their growth rates around their own turning points dates. These two findings go some way to explaining the observed asymmetry around aggregate turning point dates. The Chapter also shows that input-output linkages play an important role in determining the timing of an industry’s turning point dates.

Gross Domestic Product (GDP) in Australia is published two months after the end of the reference quarter. This delay presents a significant challenge for policy makers who must make decisions in real-time. Chapter 4 assesses the ability of different data-sets to now-cast Australian GDP, and anticipate discrete economic events. Particular attention is paid to business and household surveys, and how these datasets fair against a benchmark auto-regressive (AR) model and a factor augmented vector-auto-regression (FVAR) model. The results show that the FVAR model generates the most accurate point now-casts, however, the survey models are still useful when they signal GDP growth rates that are less frequent.
Declaration

This is to certify that:

i. the thesis comprises only my original work towards the PhD except where indicated in the Preface,

ii. due acknowledgment has been made in the text to all other material used,

iii. the thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Signed

Timur Behlul
Preface

This thesis consists of three solo-authored and original working papers:


Acknowledgments

While the PhD is mostly a solitary journey, its completion would not be possible without the effort and dedication of our supervisors and family. I would like to thank my supervisors Lawrence Uren, Kalvinder Shields and May Li for the time they have shared, patience they have shown and the guidance they have provided. I would like to thank my wife Emma McDonell who has been supportive, encouraging, and has always had my back.

I would also like to thank Adrian Pagan, who despite not knowing me, kindly provided comments and suggestions for one of the chapters of this thesis, the Department of Economics administrative staff who do an amazing job at looking after the PhD students, and my PhD colleagues who have accompanied me along the way. Finally, I would like to thank Chander Shekhar and Ian King for hiring me as a Research Assistant and providing financial support during my PhD.
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Chapter 1

Introduction

In almost all developed countries the path of economic growth has been punctuated by fluctuations in output and employment. While most of the fluctuations have been mild, some have been severe with disastrous consequences. It is for this reason that economists have devoted an extensive amount of time to try to understand why they happened, and whether we can anticipate them. Such an understanding can assist in devising timely policies to control the fluctuations in the future.

A number of different models have been developed to explain the nature and causes of business cycles. However, after a century of debate, there is still no definitive answer. Part of the problem has been that many models generate predictions that are consistent with much of the existing empirical regularities (for example whether we assume shocks to the aggregate production function [Kydland and Prescott, 1982] or shocks to the return to new capital [Greenwood, Hercowitz, and Huffman, 1988] both models perform equally well at explaining the variation in key macro-economic variables).

What is required is a richer understanding of the regularities of macro-economic variables as the economy moves up and down. Doing so can provide new empirical facts that can be used to evaluate the competing theories.

The first two contributions of this thesis is to gain a better understanding of the empirical regularities surrounding the fluctuations in the macro-economy. First, I present a single new empirical fact on labour market flows across the business cycle that has not been previously documented. I then assess different models' ability to match this fact. Second, I present many new facts surrounding the turning point behaviour across sectors and characterise aspects of the business cycle that have previously been overlooked.

Chapter 2 shows that sectors in the United States (US) have different elasticity of the vacancy yield (the ratio between total hires and job openings) to aggregate conditions. In particular, sectors with higher separation rates experience a larger percentage increase in their vacancy yield when aggregate vacancies (a proxy for aggregate conditions) decline. This fact has not been
previously documented or investigated; and it provides an additional statistical relationship to assess the different labour market models.

To understand the link between the vacancy yield elasticity and separation rate, a series of labour search models are constructed and differences across steady states are analysed. The first result of the Chapter shows that a standard labour search model, where workers randomly match across sectors, cannot explain this relationship. Segmenting the labour market to high- and low-separation-rate sectors, the second result reveals that the separation rate on its own also cannot explain the temporal variation in the vacancy yield.

Given this finding, the impact of different vacancy creation costs and productivity, which are shown to be correlated with separation rates, are considered. The results show that these two variables can account for the observed elasticity in the vacancy yield. The analysis sheds new light on labour flows across the business cycle, and provides a possible explanation for why sectors have dissimilar experiences when faced with similar macro-economic shocks. It also illustrates the type of market structures and firm characteristics that are required to generate the empirical patterns.

In Chapter 3 I turn my attention to understanding the observed asymmetry in total employment growth across different phases of the business cycle. The past literature has explained the asymmetry through firm level frictions (Caballero and Engel (1999), Acemoglu and Scott (1997), Chalkley and Lee (1998), Hansen and Prescott (2005), Van Nieuwerburgh and Veldkamp (2006)). Chapter 3 takes a different view by detecting and investigating turning points in sectoral employment.

I find that in the last three US recessions the typical industry did not display differences in their absolute growth rate around their own turning point dates. Furthermore, the share of industries contracting around the aggregate peak date is larger than the share expanding around the aggregate trough date. Thus, the observed asymmetry in the absolute growth rate in aggregate employment can be attributed to fact that more industries are contracting around the aggregate peak date than are expanding around aggregate trough date.

These results highlight that patterns observed at the macro level do not necessarily carry over to sub-macro level. Therefore, replicating macro patterns by generating the same behaviour at the micro level may not provide an accurate explanation for the observed patterns.

The third and final contribution of this thesis is to assess the ability of different data-sets to now-cast Australian GDP and anticipate discrete economic events. The Australian economy has not received much attention in the now-casting literature. However, the need to generate now-casts in Australia is more pressing than other parts of the world. Gross Domestic Product (GDP) is published a full two months after the end of the reference quarter, and unlike other countries, such as the US, for instance, information on industrial production, consumption, and income are all published quarterly either within
national accounts or a few days before its release. This presents a challenge for policy makers who must make decisions in real time.

Given this, Chapter 4 examines the informational content of national accounts real-time data, business survey data, household survey data, and monthly real economic indicators published by the Australian statistical agency. To assess the informational content of different data-sets I construct a framework that 1) can accommodate the revision process of GDP, and 2) incorporate a large set of variables. The now-casting performance of the different models are compared to a benchmark auto-regression (AR) model. The factor augmented vector auto-regression (FVAR) - where the factors are extracted from a set of monthly real economic indicators - is shown to generate point now-casts that are more accurate than either of the survey models, or AR model. I also find that the FVAR generates more accurate now-casts than a model that averages across all now-casts.

The survey models however, are shown to perform well at anticipating discrete economic events. This is especially true when they signal periods of less frequent growth rates, or transitions across different states. Thus they can be counted on answering questions such as will growth be above or below trend, or will growth continue to be above or below trend.

The investigation reveals which variables are relevant to understanding the current state of the economy and when; it provides a guide, both in terms of data and methodology, for practitioners and decision makers trying to anticipate short-term movements in Australian GDP.

Finally Chapter 5 concludes.
Chapter 2

Labour Flows over the Business Cycle

This paper documents the differential sectoral responses to change in aggregate conditions. In particular, sectors with relatively high separation rates are shown to experience a larger increase in their hires relative to their vacancies when aggregate conditions worsen. A general equilibrium model with frictional labour markets is constructed to account for this stylised fact. The comparative static analysis reveal that separation rates cannot account for this observation since higher separation rates have two and offsetting effects on the vacancy yield elasticity, leading to the same responses across sectors. Other factors that are correlated with higher separation rates such as lower levels productivity and vacancy creation costs are found to increase the vacancy yield elasticity, leading to larger responses to productivity shocks, and thus differential responses across sectors.

2.1 Overview

It is well known labour market flows vary across the business cycle. During expansions, voluntary separations and hires increase, and involuntary separations decline; during contractions, involuntary separations increase, and voluntary separations and hires decline. (Figure 2.1 shows the labour flows in the most recent business cycle). This pattern is also observed within sectors.

While the fluctuations of these variables over the business cycle has been extensively studied (Mortensen and Pissarides [1994], Merz [1995], Andolfatto [1996], Phelan and Trejos [2000], den Haan, Ramey, and Watson [2000a], Shimer [2005], Hall [2005], Hagedorn and Manovskii [2008], Hall and Milgrom [2008], Silva and Toledo [2009], Rogerson and Shimer [2011] and Michaillat [2012]), the temporal variation in the vacancy yield across sectors, has received less attention. The variation in the vacancy yield can shed light on the impacts of aggregate shocks on the labour market that cannot be
observed by simply looking at vacancies, hires or separations. Furthermore, the variation in the vacancy yield can help in assessing the performance of different models. For example, while many models may match the observed aggregate patterns in vacancies, hires and separations, not all may be capable of matching the observed patterns across sectors.

Past work (see for example Davis, Faberman, and Haltiwanger (2013b)) has shown that the aggregate vacancy yield fluctuates in response to changes in aggregate conditions. In their paper, Davis, Faberman, and Haltiwanger (2013b), analyse establishment level vacancy data and show as aggregate vacancies increase, the vacancy yield declines. They also show that vacancy yield exhibits a strong positive relationship to gross hires. This pattern is consistent even after accounting for several observables, which suggests that employers rely on other means of recruiting beyond opening vacant positions. The authors also document the sectoral variation in the vacancy yield. They show that government, health and education, information, finance, insurance and real estate, have low vacancy yields. Construction is an outlier in the other direction. Despite the attention given to the cross-sectional variation in the vacancy yield, the authors do not document or investigate the temporal
variation in the vacancy yield across sectors.

This paper shows the vacancy yield elasticity with respect to aggregate conditions (proxied by aggregate vacancies) varies across sectors. During downturns, sectors with typically high separation rates tend to experience a greater increase in their vacancy yield compared to sectors with lower separation rates. Utilising sectoral data from the Job Opening and Labor Turnover Survey (JOLTS), it is shown that the temporal variation in the vacancy yield varies with the separation rate.

Figure 2.2 plots the percentage deviation from the mean vacancy yield for each separation rate quartile against the aggregate vacancy-labour force ratio (which captures the state of the labour market). The figure divides 18 sectors into different groups based on their separation rate quartile. Each point in the plot represents the quarterly ratio between total hires and total vacancies for each quartile. The quartiles are determined by taking the average of each sector’s separation rate over the period 2000-2014. We can see from the plot that the slope for the 4th quartile is the steepest.

To explain these facts this paper develops a set of theoretical models that relates the separation rate to the vacancy yield over the business cycle. Previous work (Kaas and Kircher (2015) and Baydur (2017)), has investigated the cross-sectional variation in the vacancy yield that is observed in Davis, Faberman, and Haltiwanger (2013b).

Both papers introduce cross-sectional variation by assuming that firms face different initial productivity draws, which impact their hiring decisions. The two papers differ through the mechanisms in the matching process to relate firm growth, turnover and size to the rate that firms fill vacant positions. Kaas and Kircher (2015) allow firms to post wage contracts to attract workers. Since firms that grow faster can post better wage contracts they are able to attract workers at a faster rate.

In Baydur (2017) firms can vary the rate of hires by varying the number of vacancies and the time spent screening matched workers. Firms that grow quickly - since they post more vacancies - face an increasing cost of screening workers. Therefore, a growing firm to increase the rate of hires, lowers the amount of screening, increasing the rate with which it fills its vacancies. Since the firms spend less time assessing the quality of the workers, the employment

---

1 At this point the reader may be tempted to say that the observed relationship in Figure 2.2 is due to the fact that 1) high-separation rate sectors experience larger declines in their separation rates when aggregate conditions worsen, thus needing to open fewer vacancies, and 2) there are diminishing returns to vacancies. It is true that the high-separation rate sectors experience a larger decline in their separation rates, however, this does not explain the observed relationship. Running the same regression in Figure 2.2 but controlling for percent deviation from the mean number of separations, the slope between the vacancy yield and aggregate vacancy ratio is still increasing with the separation rate quartile. The respective slopes are -21.85, -29.51, -35.87, -38.13. Performing t-tests the slopes of quartiles 2, 3, 4 are still different from the slope of quartile 1 at the 1% significant level. The results can be seen in Figure 2.13 in the Appendix.
LABOUR FLOWS OVER THE BUSINESS CYCLE

Figure 2.2: Percentage deviation from mean vacancy yield vs. aggregate vacancies/labour force for four different separation rate quartiles (1, 2, 3, and 4). Each point represents the quarterly ratio between total hires and total vacancies for the quartile. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denote significance at the 10%. A t-test is used to determine whether a statistically significant difference exists between the slopes of quartiles 2, 3 and 4 and the slope of quartile 1. The slopes are estimated using OLS with Newey-West standard errors. Source: BLS - JOLTS.

Both models also generate a negative relationship between the vacancy yield and size, however, neither of the models account for the temporal variation across the different sectors - which is the focus of this paper.

To analyse the relationship between separation rates and vacancy yields a series of labour search model are constructed, and differences across steady states are analysed. First a standard Mortensen-Pissarides (MP) random search model (Mortensen and Pissarides (1994)) is extended to two sectors. The model is similar to the two-sector random search model in Acemoglu (2001), but instead of focusing on heterogeneous vacancy creation costs, this model focuses on the effects of heterogeneous separation rates. With a unified
2.2. DATA AND ESTIMATION OUTPUT

labour market, where workers are randomly matched to sectors, the standard MP model can’t account for the differential responses in vacancy yields since firms have the same job-filling rate by construction.

To allow for differences in the vacancy yield response, the labour market is segmented into two sectors: a high separation rate and low separation rate. Workers cannot move between the two sectors. In this set-up, each sector has its own vacancy yield. This model also fails to generate different responses in the vacancy yield. While the higher separation rate reduces the elasticity between the vacancy yield and productivity shocks, it also reduces the vacancy-unemployment ratio, which in turn increases the elasticity between the vacancy yield and productivity. These two effects offset each other leading to no differences in the vacancy yield response across the two sectors.

Motivated by the empirical relationship between separation rates, wages and hiring costs, this paper in turn examines the implications different productivity levels and vacancy creation costs. The results show that both productivity and vacancy creation costs are able to generate movements in the vacancy yield consistent with the data.

A higher productivity level - and vacancy creation cost - reduces the elasticity of the vacancy-unemployment ratio with respect to productivity shocks. This in turn generates smaller responses in the vacancy yield. The incentives to increase vacancies in response to positive productivity shocks decline as the level of productivity and vacancy creation costs increase.

As a final extension, the basic random search model is extended to allow a fraction of workers to direct their search efforts to a particular sector. The directed search model is able to generate variation in the vacancy yield; however this is for the same reasons as the segmented labour market under higher productivity levels and vacancy creation costs. The equilibrium outcome is that the workers who are free to move across sectors always search in the sector with the high productivity level.

While an empirical relationship is observed between separation rates and vacancy yield responses, the findings of the paper reveal that the differential response in the vacancy yield is not theoretically attributable to the separation rate. Rather it is other factors which are correlated with the separation rate. The results of the model also lend support to a segmented labour market.

2.2 Data and Estimation Output

In this section, we take a deeper and more rigorous look into the flow of hires across the different sectors. The results contained within this section are designed to highlight the correlation between aggregate vacancies and the vacancy yield, and do not identify the underlying shocks to the labour market.

\[\text{Since wages are endogenously determined, and are a function of productivity, to capture the relationship between wages and separation rates, productivity is varied across sectors.}\]
The results relating to the vacancy yield are consistent to what we observe in Figure 2.2. Sectors with the higher separation rates tend to experience a relatively large increase in their vacancy yields when aggregate conditions deteriorate.

This section also looks at hires and vacancies independently. The results show that when aggregate conditions worsen, the sectors with low and high separation rates both experience a drop in hires and vacancies, however, the high separation rate sectors experience a larger relative decline in vacancies. The change in the vacancy yield is primarily driven by the change in vacancies.

2.2.1 Data

The vacancy data comes from the Job Openings and Labor Turnover Survey (JOLTS). While JOLTS is monthly, quarterly averages are used instead. Since job openings in the current month can represent unfilled vacancies from the previous month, averages of hires and job openings will be better at measuring the vacancy yield across sectors. The data runs from the start of 2001 until the end of 2014, and there are 18 sectors.

The sectors in JOLTS are classified according to the North American Industrial Classification System (NAICS) at the 1 digit level. (Refer to Table 2.11 in the Appendix for the sectors.) The table also shows the average monthly separation rates for each quartile.

2.2.2 Reduced Form Results

To statistically analyse the vacancy yield response across separation rate quartiles, the demeaned vacancy yield growth rate of each sector is regressed against the demeaned aggregate vacancy growth rate. This term is interacted with dummies indicating the quartile the sector’s separation rate belongs to. The vacancy yield is the ratio between the number of workers a sector hires and its job openings. The basic model to be estimated is

$$\frac{\hat{H}_{i,t}}{\hat{V}_{i,t}} = \beta_0 + \beta_1 \hat{V}_t + \beta_2 Q_2 \hat{V}_t + \beta_3 Q_3 \hat{V}_t + \beta_4 Q_4 \hat{V}_t + \beta_5 \frac{H_{i,t-1}}{V_{i,t-1}} + \beta_6 \frac{H_{i,t-2}}{V_{i,t-2}} + \beta_7 S_{i,t} + \epsilon_{i,t}$$

(2.1)

where $\frac{\hat{H}_{i,t}}{\hat{V}_{i,t}}$ is the deviation from the average aggregate vacancy yield growth rate for sector $i$, $\%\Delta \frac{H_{i,t}}{V_{i,t}}$ is the growth rate of sector $i$’s vacancy yield in period $t$, and $\%\Delta \frac{H_{i,t}}{V_{i,t}}$ is the average vacancy yield growth rate of sector $i$. $\hat{V}_t = (\%\Delta V_t - \%\Delta \bar{V})$ is the deviation from the average aggregate vacancies growth rate, common across all sectors, $Q_j = 1$, $j \in \{1, 2, 3, 4\}$, if sector $i$’s separation rate belongs to quartile $j$ and 0 otherwise. During downturns in
2.2. DATA AND ESTIMATION OUTPUT

economic activity, voluntary separations tend to decline. This decline is more pronounced in sectors with high separation rates. Since lower separation rates lead to lower vacancies and thus hires, the inclusion of the separation rate in Equation (2.1) controls for the changes in the vacancy yield that are induced by this phenomena. $\hat{S}_{i,t} = (\%\Delta S_{i,t} - \%\Delta S_{i})$ is the deviation from the average separation growth rate for sector $i$.

We see in Figure 2.3 (and Table 2.12 in Appendix) that $\beta_4$ is significantly larger than the $\beta_2$ and $\beta_3$, and statistically significant at the 1% and 5% level, whereas the other two parameter estimates are not. $\beta_4$ is also different from $\beta_2$ and $\beta_3$ at the 5% statistical significance level. What is also evident in these estimates is the negative effect the growth in aggregate vacancies has on the vacancy yield of each sector. With a small number of industries, it is possible that the vacancy yield of industry $i$ is endogenous to aggregate vacancies. These estimates, however, are robust to whether the vacancies of industry $i$ are excluded from aggregate vacancies, as can be seen in Table 2.13 in the Appendix.

![Coefficient Estimates of Equation 1. Confidence intervals at 95% level. Robust standard errors.](image)

In order to understand why the vacancy yield across sectors varies with aggregate vacancies, the changes in hires and vacancies are investigated indi-

$^3$Omitting the separation rate has negligible impact on the results.
Table 2.1: Estimation results of Equation (2).

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hires</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.633***</td>
<td>1.061***</td>
</tr>
<tr>
<td></td>
<td>(3.57)</td>
<td>(6.49)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.157</td>
<td>0.159</td>
</tr>
<tr>
<td></td>
<td>(-0.84)</td>
<td>(0.72)</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-0.0766</td>
<td>0.151</td>
</tr>
<tr>
<td></td>
<td>(-0.32)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>-0.158</td>
<td>0.585*</td>
</tr>
<tr>
<td></td>
<td>(-0.73)</td>
<td>(2.10)</td>
</tr>
<tr>
<td>Vacancies</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>990</td>
<td>990</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses. Robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

vidually. The data is again from JOLTS, and sectors are broken into same four separation rate quartiles.

Let $Y_{i,t}$ denote the dependent variable belonging to sector $i$ in time $t$, where the dependent variable $Y$ can take one of:

1. Hires
2. Vacancies

All variables are once again converted into growth rates and demeaned. The model estimated is:

$$
\tilde{Y}_{i,t} = \beta_0 + \beta_1 \tilde{V}_t + \beta_2 Q_2 \tilde{V}_t + \beta_3 Q_3 \tilde{V}_t + \beta_4 Q_4 \tilde{V}_t + \sum_{k=1}^{K} \beta_{5,k} \tilde{Y}_{i,t-k} + \sum_{l=0}^{L-1} \beta_{6,l} \tilde{S}_{i,t-l},
$$

(2.2)

where $\tilde{Y}_{i,t}$ is the demeaned growth rate, $\tilde{V}_t$ is the demeaned growth rate of aggregate vacancies as above and $Q_i$ is a dummy variable that is equal to 1 if the sector belongs to quartile $i$ and zero otherwise. $K$ lags of the dependent variables are included in the regression, and the contemporaneous value plus $L - 1$ lags of the demeaned separation growth rate are included. The model’s results are shown in Table 2.1. The estimates of the lagged variables are omitted to keep the table concise.

We see in Table 2.1, controlling for changes in the separation growth rate, that as aggregate vacancies increase, the sectors with relatively high separation rates experience a relatively larger increase in vacancies than the sectors with the lower separation rates. What is also evident from these results is that as aggregate vacancies increase, there is no statistically significant difference
2.3. RANDOM SEARCH

Table 2.2: Hourly earnings of all workers, 2014 in USD. Quartiles are determined according to the assignments using JOLTS separation rates.

<table>
<thead>
<tr>
<th>Quartile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emp. Weighted-Average</td>
<td>$29</td>
<td>$26</td>
<td>$20</td>
<td>$23</td>
</tr>
</tbody>
</table>

Source: BLS - Current Employment Survey

Table 2.3: Weekly earnings of all workers, 2014 in USD. Quartiles are determined according to the assignments using JOLTS separation rates.

<table>
<thead>
<tr>
<th>Quartile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emp. Weighted-Average</td>
<td>$1201</td>
<td>$1077</td>
<td>$744</td>
<td>$922</td>
</tr>
</tbody>
</table>

Source: BLS - Quarterly Census of Wages and Employment

in the growth rates of hires. Therefore the change in the vacancy yield is primarily driven by changes in vacancies.

2.2.3 Wages and Separation Rates

This subsection investigates other characteristics associated with separation rates, and in particular the wage differentials across the different separation rate quartiles. To determine the employment weighted hourly wage for each quartile, first wage data is used from the 2014 Current Employment Survey (CES). The results are shown in Table 2.2.

A shortcoming of the CES is that it does not provide wage data for the public and education sector. Therefore, the wage estimate for quartile 1, which contains these two sectors, may be biased. Table 2.3 provides the annual average weekly wages for the different quartiles. The data is from the 2014 Quarterly Census of Wages and Employment, which has greater coverage than the Current Employment Survey. Both datasets reveal that wages of the lower quartiles tend to be higher than the wages of the upper quartile.

2.3 Random Search

Time is discrete, agents live indefinitely, and there are two sectors. There exists a continuum of individuals of total measure one, who are identical in every respect except that fraction \( u \) of them are unemployed, and fraction \( 1 - u \) are employed.

\(^4\)The average wage of quartile 4 is higher relative to quartile 3 as quartile 4 contains the professional and technical services sector, which typically pays high wages. The professional and technical services sector falls into quartile 4 since JOLTS aggregates the professional and technical services sector with the business services sector.
Labour is supplied inelastically (over the business cycle, the biggest component of the variation in hours is fluctuations in the level of employment and there is little change in the size of the labour force (Rogerson and Shimer, 2011)).

Firms open vacancies in period $t$, and fill the vacancy in period $t + 1$, to produce output in period $t + 1$. The goods market is frictionless and perfectly competitive, but each firm must search for labour, which is costly.

Firms open vacancies until the profits from an additional vacancy are zero, and the wages are determined through Nash bargaining (to be discussed below).

### 2.3.1 Unified Labour Market

In the standard multi-sector search model where workers and firms can search in a unified labour market, the job filling rate for firms is identical across the two sectors. To show this consider an economy where workers are matched with firms according to the aggregate matching function proposed by den Haan, Ramey, and Watson (2000b)

$$m = \frac{u(\mu_1 v_1 + \mu_2 v_2)}{(u^\xi + (\mu_1 v_1 + \mu_2 v_2)^\xi)^{\frac{1}{\xi}}}$$

where $u$ and $v_i$ are the number of unemployed and the number of vacancies in sector $i$, and $\mu_i \in (0, 1)$ is the matching efficiency of sector $i$. This matching function is well suited to discrete time models since it guarantees matching probabilities between 0 and 1 for all $u$ and $v_i$.

The probability of a firm in sector $i$ in period $t$ finding a worker is given by

$$q_i(\theta_t) = \frac{u_{i,t}(\mu_1 v_{1,t} + \mu_2 v_{2,t})}{v_{i,t}(u_{i,t}^\xi + (\mu_1 v_{1,t} + \mu_2 v_{2,t})^\xi)^{\frac{1}{\xi}}} \frac{\mu_{i,t} v_{i,t}}{\mu_i (1 + (\mu_1 \theta_{1,t} + \mu_2 \theta_{2,t})^\xi)^{\frac{1}{\xi}}}.$$  \hspace{1cm} (2.3)

where $\theta_{i,t} = \frac{u_{i,t}}{w}$ and $\theta_t = \{\theta_{1,t}, \theta_{2,t}\}$ is a vector of market tightness. Notice that if $\mu_1 = \mu_2$ then $q_1 = q_2$. Thus the vacancy yield is identical across sectors. Even if $\mu_1 \neq \mu_2$ this only leads to level differences in vacancy yields. There will be no differences in the elasticity of $q$ with respect to $\theta_1$ and $\theta_2$. This result is valid regardless of the nature of job creation or wage determination.

Therefore, a random search model where workers search in a unified labour market cannot account for the different responses in the vacancy yield in response to aggregate shocks.
2.3. RANDOM SEARCH

2.3.2 Segmented Labour Markets

In this subsection, we consider a similar model except that workers are now segmented into separate labour markets. We can think of the economy consisting of a low skill and a high skill sector where there is no mobility between the two markets. Let the size of the labour force in sector 1 be denoted as $LF_1$ and the size of the labour force in sector 2 be denoted as $LF_2$. Workers are matched according to sector specific matching function $m_i$,

$$m_i(v_i, u_i) = \frac{u_i(\mu_i v_i)}{(u_i^\xi + (\mu_i v_i)^\xi)^\tau};$$

The probability of a firm in sector $i$ in period $t$ finding worker is given by

$$q_i(\theta_{i,t}) = \frac{u_{i,t}(\mu_i v_{i,t})}{v_{i,t}(u_{i,t}^\xi + (\mu_i v_{i,t})^\xi)^\tau} = \frac{\mu_i}{(1 + (\mu_i \theta_{i,t})^\xi)^\tau}.$$ (2.4)

Each sector’s job-filling rate is now a function of only its own labour market tightness, $\theta$.

The probability of a worker finding a worker is given by

$$f_i(\theta_{i,t}) = \frac{u_{i,t}(\mu_i v_{i,t})}{u_{i,t}(u_{i,t}^\xi + (\mu_i v_{i,t})^\xi)^\tau} = \frac{\mu_i \theta_{i,t}}{(1 + (\mu_i \theta_{i,t})^\xi)^\tau}.$$ (2.5)

The Firm’s Problem

Employment in sector $i$ evolves according to

$$L_{i,t} = (1 - s_i)L_{i,t-1} + v_{i,t-1}q_i(\theta_{i,t-1}).$$ (2.6)

Firms hire labour in period $t$ by opening vacancies, $v_{i,t-1}$, in period $t - 1$, and find matches to those jobs in period $t$. The number of matches is given by $v_{i,t-1}q_i(\theta_{i,t-1})$. They discount the future according to the discount factor $r$.

At the end of each period a fraction of $s_i$ workers separate, and $(1 - s_i)L_{i,t-1}$ remain. Output of sector $i$ is given by

$$Y_{i,t} = A_i L_{i,t},$$ (2.7)

where $A_i$ is the labour productivity of sector $i$. For an exogenous price $p_i$, the firm chooses the optimal number of vacancies to post and labour to hire by maximising its inter-temporal profit function.
subject to (2.6). $w_i$ is the wage in sector $i$, and $\gamma_i v_{i,t}$ is the amount of labour required to open $v_i$ vacancies. Therefore, workers devoted to hiring do not produce goods. The firms therefore have a trade-off between current production and future production.

The Lagrangian for this problem is

$$\mathcal{L} = E_0 \left[ \sum_{t=0}^{\infty} r^t (p_{i,t} A_i (L_{i,t} - v_{i,t} \gamma_i) - w_{i,t} L_{i,t}) + \sum_{t=0}^{\infty} r^t \lambda_t (L_{i,t} - (1 - s_1) L_{i,t-1} - v_{i,t-1} q_i (\theta_{i,t-1}) \right], \quad (2.9)$$

from which we derive the vacancy creation curve. (see Section 2.7.4 in Appendix for the derivation)

$$r E_{t} \left( p_{i,t+1} A_{i,t+1} - w_{i,t+1} + \gamma_i p_{i,t+1} A_{i,t+1} \right) q_i (\theta_{i,t+1}) (1 - s_i) = \gamma_i p_{i,t} A_{i,t} q_i (\theta_{i,t}). \quad (2.10)$$

Before interpreting Equation (2.10) the wage equation under this environment will be derived.

**Wage Determination**

Firms and workers split the surplus generated from the match linearly. The distribution depends on the bargaining power of the workers $\beta$ and the firms $(1 - \beta)$. The cost of opening a vacancy is $\gamma_i MVPL_{i,t}$, where $\gamma_i$ is the amount of labour required to open and maintain a vacancy and $MVPL_{i,t}$ is the marginal value product of labour.

The wage for each sector is given by (refer to Section 2.7.5 in Appendix for the derivation):

$$w_{i,t} = \beta p_{i,t} A_{i,t} + (1 - \beta)z + \theta_{i,t+1} \beta \gamma_i MVPL_{i,t}. \quad (2.11)$$

We see that the worker receives a share of the marginal product of their labour, plus the rents generated from the match.

---

5This cost structure is adopted to allow the cost of a vacancy vary with labour productivity.
2.3. RANDOM SEARCH

Vacancy Determination

Substituting $MVPL_{i,t} = p_{i,t}A_{i}$ into the wage equation for sector $i$ and using the resulting wage equation in Equation (2.10), we get the job creation equation for sector $i$

$$\gamma_i p_{i,t}A_{i,t} \frac{q_i(\theta_{i,t})}{q_i(\theta_{i,t+1})} = rE_t \left[ (1 - \beta)(p_{i,t}A_{i,t} - z) \right.$$

$$\left. + (1 - s_i - f(\theta_{i,t+1})\beta) \left( \gamma_i p_{i,t+1}A_{i,t+1} \frac{q_i(\theta_{i,t+1})}{q_i(\theta_{i,t+1})} \right) \right]. \tag{2.12}$$

Equation (2.12) states that the effective cost of opening a vacancy today must equal the discounted expected return generated by the vacancy. The expected return consists of two components: the current value of a hire, and the continuation value of a hire.

Steady State

In steady state, the number of workers leaving sector $i$ must be equal to the number entering, therefore

$$s_iL_i = m_i,$$

so the amount of employment in each sector is

$$L_i = m_i = q_i(\theta_i) \frac{\theta_i u_i}{s_i}.$$

Steady state can be characterised by four equations

1. the Beveridge curve

$$u_1 = \frac{LF_1s_1}{s_1 + f(\theta_1)} \tag{2.13}$$

$$u_2 = \frac{LF_2s_2}{s_2 + f(\theta_2)} \tag{2.14}$$

2. the vacancy creation equations

$$\gamma_1 p_1 A_1 \frac{q_1(\theta_1)}{q_1(\theta_1)} = r \left[ (1 - \beta)(p_1 A_1 - z) + (1 - s_1 - f(\theta_1)\beta) \left( \gamma_1 p_1 A_1 \frac{q_1(\theta_1)}{q_1(\theta_1)} \right) \right] \tag{2.15}$$

$$\gamma_2 p_2 A_2 \frac{q_2(\theta_2)}{q_2(\theta_2)} = r \left[ (1 - \beta)(p_2 A_2 - z) + (1 - s_2 - f(\theta_2)\beta) \left( \gamma_2 p_2 A_2 \frac{q_2(\theta_2)}{q_2(\theta_2)} \right) \right] \tag{2.16}$$
LABOUR FLOWS OVER THE BUSINESS CYCLE

Calibration

A single time period represents a month. The discount factor is \( r = 0.996 \), just under five percent annually. The separation rates are set to the average separation rate for industries below the 50% quartile and the industries above the 50% quartile. These two rates, 2.5% and 4.5%, are the separation rates for sectors 1 and 2, respectively. Silva and Toledo (2009) argue that recruiting a worker uses approximately 4 percent of one worker’s quarterly wage, i.e., a recruiter can attract approximately 25 new workers in a quarter, or 8.3 in a month. Therefore, \( \gamma_1 = \gamma_2 = 1/8.3 \).

The prices in both sectors are normalised to 1, and the unemployment benefit is set equal to 70% of the marginal product of labour. As documented in Shimer (2005), a low value of \( z \) will need implausibly large productivity shocks in order to generate moderate fluctuations in vacancies. Modifications to the wage equation (Hall (2005)), or calibration (Hagedorn and Manovskii (2008)) can improve the relationship between productivity shocks and the volatility in vacancies. This paper chooses a relatively large value of \( z \) to generate large responses to aggregate shocks. \( z = 0.7 \), which is in-between what is typically used in the literature, \( z = 0.4 \), and what Hagedorn and Manovskii (2008) use, \( z = 0.955 \).

Although there are many estimates of the matching function \( m \), the choice of \( \xi \) is a bit arbitrary. \( \xi = 1.27 \), which is taken from den Haan, Ramey, and Watson (2000b), and \( \beta = 0.5 \) so workers and firms have equal bargaining power.

The full set of parameter values are shown in Table 2.4. The corresponding steady state values of the endogenous variables are shown in Table 2.5.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>Bargaining power</td>
<td>0.5</td>
</tr>
<tr>
<td>( LF_1 )</td>
<td>Labour force of ind. 1</td>
<td>0.5</td>
</tr>
<tr>
<td>( LF_2 )</td>
<td>Labour force of ind. 2</td>
<td>0.5</td>
</tr>
<tr>
<td>( s_1 )</td>
<td>Separation rate of ind. 1</td>
<td>0.025</td>
</tr>
<tr>
<td>( s_2 )</td>
<td>Separation rate of ind. 2</td>
<td>0.045</td>
</tr>
<tr>
<td>( r )</td>
<td>Discount rate</td>
<td>0.996</td>
</tr>
<tr>
<td>( \xi )</td>
<td>Matching Fn. parameter</td>
<td>1.27</td>
</tr>
<tr>
<td>( {A_1,A_2} )</td>
<td>Productivity</td>
<td>( {1,1} )</td>
</tr>
<tr>
<td>( {\mu_1,\mu_2} )</td>
<td>Matching efficiency</td>
<td>( {1,1} )</td>
</tr>
<tr>
<td>( {\gamma_1,\gamma_2} )</td>
<td>Worker-vacancy ratio</td>
<td>( {18.3,18.3} )</td>
</tr>
<tr>
<td>( z )</td>
<td>Unemployment Benefit</td>
<td>0.7</td>
</tr>
</tbody>
</table>

---

*The results are not sensitive to the choice of \( \xi \).*
Table 2.5: Steady State Values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment of Sector 1</td>
<td>0.485</td>
</tr>
<tr>
<td>Employment of Sector 2</td>
<td>0.473</td>
</tr>
<tr>
<td>Market Tightness of Sector 1</td>
<td>2.320</td>
</tr>
<tr>
<td>Market Tightness of Sector 2</td>
<td>2.213</td>
</tr>
<tr>
<td>Unemployment Rate of Sector 1</td>
<td>0.031</td>
</tr>
<tr>
<td>Unemployment Rate of Sector 2</td>
<td>0.046</td>
</tr>
<tr>
<td>Job Filling Rate of Sector 1</td>
<td>0.342</td>
</tr>
<tr>
<td>Job Filling Rate of Sector 2</td>
<td>0.354</td>
</tr>
</tbody>
</table>

From Table 2.5, we see that the sector with the higher separation rate has a higher steady state unemployment rate, and lower market tightness. The higher separation rate shifts the Beveridge curve outwards, while steepening the vacancy creation curve. The net-result is a decline in the lower market tightness. This effect is illustrated in Figure 2.4.

![Figure 2.4: Beveridge and vacancy creation curves for sectors 1 and 2.](image-url)
2.4 Results - Comparative Statics

Comparative statics involves varying $A_i$ across both sectors by the same proportion. The change in productivity can be viewed as either a demand or supply shock. We can view the shock as an aggregate demand shock where prices are fixed and output per worker varies, or a supply shock directly impacting productivity. Thus, fluctuations in productivity can represent a broad range of shocks.

We examine the effect of a 10% decline in productivity. Observing Table 2.6 and Figures 2.5 and 2.6 which show the responses relative changes to changes in productivity and aggregate vacancies, we see that for the chosen parameter values both sectors experience a decline in employment and vacancies, and both sectors experience an increase in their unemployment rates and job-filling rates. This result is consistent with the literature. A decline in productivity reduces the value of a match. Firms respond by reducing their vacancies, increasing the level of unemployment.

However, we also observe that the different separation rates play no role in generating asymmetric responses in the vacancy yields. The market tightness across the two sectors shifts by a similar magnitude, leading to quantitatively minor differences in the change in the vacancy yield.

Furthermore, contrary to the results in Table 2.1 there is no discernible difference in the change in vacancies. The conclusion from these results is that the separation rate cannot account for the asymmetric responses in the vacancy yield, which is contrary to what we observe empirically.

The absence of any difference in the vacancy yield response is discussed in the next sub-section in the context of a modified model.

Table 2.6: $\%\Delta\{L_1, L_2, u_1, u_2, \theta_1, \theta_2, v_1, v_2, q_1 \text{ and } q_2\}$ in response to a 10% decrease in $A$.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sector 1</th>
<th>Sector 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>-0.289</td>
<td>-0.545</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>9.145</td>
<td>9.467</td>
</tr>
<tr>
<td>Market Tightness</td>
<td>-26.401</td>
<td>-26.747</td>
</tr>
<tr>
<td>Vacancies</td>
<td>-19.670</td>
<td>-19.811</td>
</tr>
<tr>
<td>Job Filling Rate</td>
<td>24.127</td>
<td>24.027</td>
</tr>
</tbody>
</table>
Figure 2.5: Percentage change in $L_i$, $v_i$, $q_i$ and $u_i$ in response to percentage change in $A_i$. The changes are from initial equilibrium values to new equilibrium.
Figure 2.6: Percentage change in $L_i$, $v_i$, $q_i$ and $u_i$ in relation to percentage change in aggregate vacancies, $v$. The changes are from initial equilibrium values to new equilibrium and for proportionate productivity shocks.
2.4. RESULTS - COMPARATIVE STATICS

2.4.1 Different Levels of Productivity

The previous section highlighted that variation in the separation rate cannot explain temporal variation in the vacancy yield across sectors.

It is possible that the high separation rate is correlated with other characteristics of the job, and it is these characteristics that cause the different responses across sectors. In Tables 2.2 and 2.3 we see the employment weighted average wage for each separation rate quartile. What is evident is that the wage tends to fall as the separation rate increases.

Since wages are an endogenous outcome, to model the relationship between wages and separation rates, the sector with the lower separate rate, sector 1, will be assigned a higher labour productivity, $A_1 > A_2$. This is consistent with the theory; observing Equation (2.11) we see that wages are increasing in productivity.

All parameters from the previous model are kept the same, except for sector 1’s labour productivity, which is 20% higher than sector 2. The parameters $A_1$ and $A_2$ are set to 1.2 and 1, respectively. From Table 2.8 we see that a 20% difference in productivity leads to an approximate 20% difference in wages. This wage differential is consistent with the difference between the weighted-average wage in Quartiles 1 and 2 and Quartiles 3 and 4.

What is also evident in Table 2.8 and Figures 2.7 and 2.8 is that the elasticity of the job-filling rate with respect to productivity and aggregate vacancies in sector 2 is now significantly larger than sector 1. In Table 2.7 we see that the wage level is higher in sector 1, while the job-filling rate is higher in sector 2.

Furthermore, sector 2 now experiences a larger drop in vacancies, which is consistent with what is observed in Table 2.4.

To understand why the vacancy yield elasticity is lower in the sector with the higher level of productivity, first suppose that the economy is at a steady state, and rearrange the vacancy creation equation for sector $i$:

$$\frac{(1 - r + rs_i)\gamma_i}{q_i(\theta_i)} + r\theta_i\beta\gamma_i - (1 - \beta)(1 - \frac{z}{A_i}) = 0. \tag{2.17}$$

Implicitly differentiating Equation (2.17) with respect to $A_i$ and $\theta_i$ and multiplying the result by $A_i$ and $1/\theta_i$ we have the elasticity of $\theta_i$ with respect to $A_i$:

\footnote{As mentioned in a previous footnote, the average wage of quartile 4 is higher relative to quartile 3 as quartile 4 contains the professional and technical services sector, which typically pays high wages. The professional and technical services sector falls into quartile 4 since JOLTS aggregates the professional and technical services sector with the business services sector.}

\footnote{The elasticity of job-filling rate, $q$, with respect to market tightness, is declining in the level of $\theta$. However, for values of $\theta$ between 2 and 3, the difference in the elasticity is negligibly small. To simplify the algebra, the relationship between productivity shocks and changes in $\theta$, instead of $q$ will be analysed.}
Table 2.7: Steady state values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment of Sector 1</td>
<td>0.486</td>
</tr>
<tr>
<td>Employment of Sector 2</td>
<td>0.473</td>
</tr>
<tr>
<td>Market Tightness of Sector 1</td>
<td>3.238</td>
</tr>
<tr>
<td>Market Tightness of Sector 2</td>
<td>2.213</td>
</tr>
<tr>
<td>Unemployment Rate of Sector 1</td>
<td>0.028</td>
</tr>
<tr>
<td>Unemployment Rate of Sector 2</td>
<td>0.054</td>
</tr>
<tr>
<td>Job Filling Rate of Sector 1</td>
<td>0.263</td>
</tr>
<tr>
<td>Job Filling Rate of Sector 2</td>
<td>0.354</td>
</tr>
<tr>
<td>Job Finding Rate of Sector 1</td>
<td>0.852</td>
</tr>
<tr>
<td>Job Finding Rate of Sector 2</td>
<td>0.783</td>
</tr>
<tr>
<td>Wage of Sector 1</td>
<td>1.184</td>
</tr>
<tr>
<td>Wage of Sector 2</td>
<td>0.983</td>
</tr>
</tbody>
</table>

Table 2.8: %Δ\{L_1, L_2, u_1, u_2, \theta_1, \theta_2, v_1, v_2, q_1\text{ and } q_2\} in response to a 10% decrease in A.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Response</th>
<th>Sector 1</th>
<th>Sector 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>-0.099</td>
<td>-0.545</td>
<td></td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>3.394</td>
<td>9.467</td>
<td></td>
</tr>
<tr>
<td>Market Tightness</td>
<td>-15.743</td>
<td>-26.747</td>
<td></td>
</tr>
<tr>
<td>Vacancies</td>
<td>-12.884</td>
<td>-19.811</td>
<td></td>
</tr>
<tr>
<td>Job Filling Rate</td>
<td>14.675</td>
<td>24.027</td>
<td></td>
</tr>
</tbody>
</table>

\[
\frac{\partial \theta_i}{\partial A_i} = \frac{A_i}{\theta_i - \gamma_i(1 - r + r s_i)q''_i(\theta_i)/q_i(\theta_i)^2 + r \beta \gamma_i} > 0. \tag{2.18}
\]

Since \(q''_i(\theta_i) < 0\), then \(-\gamma_i(1 - r + r s_i)q''_i(\theta_i) > 0\). So the elasticity in Equation (2.18) is declining in the level of \(A_i\) and \(s_i\). Numerically differentiating the elasticity in Equation (2.18), with respect to \(A_1\) and \(s_1\), and evaluating the result at \(\theta_1 = 2.320\) (from Table 2.5), \(A_1 = 1\) and \(s_1 = 0.025\), yields -2.375 and -4.230, respectively.

Thus, a higher separation rate reduces the elasticity between \(\theta_i\) and \(A_i\). A higher separation rate, however, also shifts out the Beveridge curve, reducing the equilibrium level of \(\theta_i\). Numerically differentiating Equation (2.18) with respect to \(\theta_1\), and evaluating the result at \(\theta_1 = 2.320\), \(A_1 = 1\) and \(s_1 = 0.025\), yields -1.0273. Therefore, a reduction in \(\theta_i\) increases the elasticity in Equation (2.18).

Hence, a higher separation rate has two and off-setting effects on the elasticity in Equation (2.18).
Figure 2.7: Percentage change in $L_i$, $v_i$, $q_i$ and $u_i$ in response to percentage change in $A_i$. The changes are from initial equilibrium values to new equilibrium.

In Table 2.5 the difference between $\theta_1$ and $\theta_2$ is 0.107 units. So for equal levels of productivity, a separation rate that is 0.025 percentage points higher, leads to a labour market tightness that is 0.107 units lower. A decline of 0.107 units in $\theta$ implies an approximate 0.11 unit increase in the elasticity in Equation (2.18), while an increase of 0.025 percentage points in the separation rate implies an approximate 0.11 decline in the elasticity in (2.18). Thus, two effects cancel each other out and the separation rate has no effect on the elasticity. This result is robust to different parameter values.

Unlike the separation rate, a higher $A_i$ has no impact on the Beveridge curve; but it does flatten the vacancy creation curve, leading to more vacancies, and increasing $\theta_i$. Thus, there are two negative impacts on the elasticity in Equation (2.18). One is arising from the higher level of productivity itself, and the other is the higher $\theta_i$. The two impacts in this case are not off-setting each other.

To understand the intuition of this result we can think about it from the perspective of the firm. When faced with a productivity shock, the incentive to post additional vacancies depends on the percentage change in profits. The change in profits in response to productivity shocks is going to be large if the initial level of productivity, and thus profits is low (Shimer (2005), Hagedorn...
Figure 2.8: Percentage change in $L_t$, $v_t$, $q_t$ and $u_t$ in relation to percentage change in aggregate vacancies, $v$. The changes are from initial equilibrium values to new equilibrium and for proportionate productivity shocks.

Since the productivity level in sector 1 is higher, the percentage change in profits for given percentage change in productivity is smaller.

The outside option of the worker, $z$, plays an important role in the firms’s profits. The wage cost of the worker depends not just on the marginal product of the worker, but also their outside option. For a firm with a higher level of productivity, the difference between the marginal product of labour and the outside option of the worker is greater. This provides the firm greater capacity to create vacancies. But this also implies a smaller percentage change in profits, for a proportionate change in productivity. For simplicity, assume that profits from a vacancy are given by $\pi = (A - z)$. Due to the presence of $z$, the elasticity between $\pi$ and $A$ is declining in $A$.

For the sector with lower productivity, the difference between the outside option of the worker and the worker’s marginal product is lower. When productivity declines this margin declines by more than the sector with the higher productivity. The low productivity firms respond by decreasing vacancies by more, which is what we see in Figure 2.7. In equilibrium, the firms in this sector also create fewer vacancies.

When the outside option of the workers approaches zero, the differences
2.4. RESULTS - COMPARATIVE STATICS

in vacancy yield response also approach zero, which is evident in Equation (2.18).

2.4.2 Different Productivity and Vacancy Creation Costs

Apart from lower wages, past work has shown that sectors with high turnover rates tend to have lower job creation costs. Bewley (2002) noted that “secondary-sector positions have high turnover because hiring and training costs are too low to make it worthwhile for firms to pay high enough wages to reduce quitting”. Examples of secondary sector jobs include waiters and waitresses, floor crews in fast-food restaurants, sales clerks in most stores, taxi drivers, security guards, cleaners, consultants, many telemarketers and temporary, interim or contract workers. These occupations are predominately found in the industries that occupy the upper quartiles of the separation rates. Mincer (1988) and Parent (1999) also find a negative relationship between on-the-job training and turnover rates for the US.

This sub-section investigates the impact of assigning lower separation rate sectors with higher vacancy creation costs. The parameter values remain the same as in the previous example, except for the vacancy creation cost. Two values of $\gamma_1$ are considered, $\gamma_1 = 2/8.3 = 0.24$ and $\gamma_1 = 4/8.3 = 0.48$, while $\gamma_2$ remains the same.

Table 2.10 and Figures 2.9 and 2.10 display the changes in the vacancy yield and employment level in response to productivity shocks, and changes to aggregate vacancies, for different vacancy creation costs. An increase in vacancy creation costs reduces the vacancy yield response to productivity shocks. The higher vacancy creation costs also lead to a larger difference in the percentage change in vacancies across the two sectors. When $\gamma_1 = 0.24$ there is an 11% increase in sector 1’s job-filling rate in response to a 10% decrease in productivity. When $\gamma_1 = 0.48$ there is an 7% increase in sector 1’s job-filling rate in response to a 10% decrease in productivity. Sector 2’s job-filling rate on the other hand increases by 24% in response to a 10% decrease in productivity.

The impact of higher vacancy creation costs on wages is small and negative. When the vacancy creation cost of sector 1 increases from having $\gamma_1 = 0.48$ to having $\gamma_1 = 0.24$, the wage declines from 1.181 to 1.174. However, the difference between sector 1 and 2 still remains approximately 20%. Thus the wage difference in the model is primarily being driven by the productivity difference. The model implied wages are consistent with the wage differential between Quartiles 1 and 2 and Quartiles 3 and 4 in the data.

Recalling from (2.18) the elasticity of $\theta_i$ with respect to $A_i$ is

\[ \text{Consultants are an exception when it comes to wages.} \]
Table 2.9: Steady state values of $L_1, L_2, u_1, u_2, \theta_1, \theta_2, v_1, v_2, q_1$ and $q_2$.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sector 1, $\gamma_1 = 0.24$</th>
<th>Sector 1, $\gamma_1 = 0.48$</th>
<th>Sector 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>0.483</td>
<td>0.476</td>
<td>0.473</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>0.034</td>
<td>0.047</td>
<td>0.054</td>
</tr>
<tr>
<td>Market Tightness</td>
<td>1.598</td>
<td>0.775</td>
<td>2.213</td>
</tr>
<tr>
<td>Job Filling Rate</td>
<td>0.443</td>
<td>0.651</td>
<td>0.354</td>
</tr>
<tr>
<td>Vacancies</td>
<td>0.027</td>
<td>0.018</td>
<td>0.060</td>
</tr>
<tr>
<td>Wages</td>
<td>1.174</td>
<td>1.181</td>
<td>0.983</td>
</tr>
</tbody>
</table>

Table 2.10: $\%\Delta \{L_1, L_2, u_1, u_2, \theta_1, \theta_2, v_1, v_2, q_1 \text{ and } q_2\}$ in response to a 10% decrease in $A$.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sector 1, $\gamma_1 = 0.24$</th>
<th>Sector 1, $\gamma_1 = 0.48$</th>
<th>Sector 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>-0.235</td>
<td>-0.546</td>
<td>-0.545</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>6.619</td>
<td>11.015</td>
<td>9.467</td>
</tr>
<tr>
<td>Vacancies</td>
<td>-10.433</td>
<td>-7.364</td>
<td>-19.811</td>
</tr>
<tr>
<td>Job Filling Rate</td>
<td>11.386</td>
<td>7.359</td>
<td>24.027</td>
</tr>
</tbody>
</table>

\[ \frac{\partial \theta_i}{\partial A_i} A_i = \frac{r(1 - \beta)z/A_i}{\theta_i - \gamma_i (1 - r + rs_i)q_i'(\theta_i)/q_i(\theta_i)^2 + r\beta \gamma_i} > 0. \] (2.19)

Higher vacancy creation costs make it more costly to create jobs; leading to fewer vacancies in equilibrium. The lower vacancies, in turn, lead to a lower market tightness, increasing the elasticity between $\theta_1$ and $A_1$. Numerically differentiating Equation (2.19) with respect to $\theta_1$, and evaluating it at $\theta_1 = 3.238$ (from Table 2.7), $A_1 = 1.2$ and $\gamma_1 = 1/8.3$, the result is -0.439. Thus, as $\theta_1$ declines the elasticity between $\theta_1$ and $A_1$ increases.

This effect, however, is off-set by the reduction in the elasticity in Equation (2.19) induced by the higher vacancy creation cost. Numerically differentiating Equation (2.19) with respect to $\gamma_1$, and evaluating the expression at $\theta_1 = 3.238$, $A_1 = 1.2$ and $\gamma_1 = 1/8.3$, the result is -14.081. Thus, an increase in $\gamma_1$ reduces the elasticity between $\theta_1$ and $A_1$ by more than the increase that is brought upon by the decline in $\theta_1$.

What is the intuition for this result? First, when $q$ increases the effective cost of opening a vacancy declines. This means that the opportunity cost of sending - a now more productive worker - out to recruit is lower.

Second, in Equation (2.19) we observe that $\gamma_1$ appears in two terms in the denominator. The first term represents the additional costs to opening vacancies, as productivity increases the opportunity cost of sending workers
2.4. RESULTS - COMPARATIVE STATICS

Figure 2.9: Percentage change in $L_i$, $v_i$, $q_i$ and $u_i$ in response to percentage change in $A_i$. The changes are from initial equilibrium values to new equilibrium.

The second term represents the wage cost due to the rents generated from a match having to be shared with the worker. The larger these rents, $\gamma_i$, the less incentive there is to change vacancies when productivity increases, since a larger part of the productivity gain is being absorbed by the wage. Thus, the vacancy yield response in this model is also driven by the wage arrangement between firms and workers and the sharing of rents between the two parties. Equation (2.19) highlights that for the sector with low vacancy creation cost, the decision to open vacancies is weighed towards current productivity, whereas for the firm with the higher vacancy creation cost the decision is weighed towards the costs of hiring a worker.

2.4.3 A brief comment on dynamics

If the productivity shocks are permanent, because $\theta$ is a “jump” variable it will immediately take the value consistent with Equation (2.12). Thus, there is no dynamics in $\theta$, and therefore $q(\theta)$. 
If the productivity levels are mean reverting, making the shocks only temporary, then the variation in $\theta$ will be small; once again displaying no interesting dynamics. Under the set-up considered in this Chapter there is only slow dynamics in the unemployment rate.

2.5 Extension

2.5.1 Partial Mobility - Directed Search

In this section, the assumption of no worker mobility is relaxed. Workers still must search in a particular market, but unlike the previous section they have a choice in which market to search.

In such a set up, workers direct their search efforts towards the market which will yield the greatest return to unemployment. For both types of jobs to exist the benefits to being unemployed in the two sectors must be the same. However, with the productivity in sector 1 being higher there is no incentive for the unemployed to search in sector 2. To deal with this problem, a fraction of workers $LF$ are free to move across the sectors, and fractions
2.5. EXTENSION

$LF_1$ and $LF_2$ can only search in sectors 1 and 2, respectively. We can think of this arrangement as workers who are skilled and will always stay in sector 1, and workers who have very little skills and can only search in sector 2, and those in the middle who can move across sectors.

The steady state value of an unemployed worker applying to sector $i$ is

$$J^U_i = z + r(f(\theta_i))J^E_i + (1 - f(\theta_i))J^U_i..$$  \hspace{1cm} (2.20)

Rearranging

$$J^U_i = \frac{z + rf(\theta_i)J^E_i}{1 - r(1 - f(\theta_i))}..$$  \hspace{1cm} (2.21)

From Equation (2.41) in the Appendix we know that in steady state

$$J^E_i = w_i + rsJ^U_i 1 - r(1 - s_i)$$  \hspace{1cm} (2.22)

Combining (2.21) and (2.22) yields

$$J^U_i = \frac{z(1 - r(1 - s_i)) + rf(\theta_i)w_i}{(1 - r)(1 - r + rf(\theta_i) + rs_i)}..$$  \hspace{1cm} (2.23)

We can determine the unemployment rate among all sets of workers through the equilibrium conditions

$$(LF_1 - u_1)s_1 = u_1f_1(\theta_1)$$  \hspace{1cm} (2.24)

$$(LF_2 - u_2)s_2 = u_2f_2(\theta_2)$$  \hspace{1cm} (2.25)

$$\sigma(LF - u)s_1 = \eta uf_1(\theta_1)$$  \hspace{1cm} (2.26)

$$(1 - \sigma)(LF - u)s_2 = (1 - \eta)uf_2(\theta_2),$$  \hspace{1cm} (2.27)

where $\sigma$ is the share of workers who are free to move employed in sector 1, $\eta$ is the share of unemployed workers free to move searching in sector 1, $u_1$ and $u_2$ are the fraction of workers who are tied to sectors 1 and 2 and unemployed, and $u$ are the workers who are free to move and unemployed. $\eta$ will be pinned down by $J^U_1 = J^U_2$, and $\sigma$ can be determined by Equation (2.27). If $J^U_1 > J^U_2$, then $\eta = 1$.

The job filling and job finding rate equations stay the same but $\theta_1$ and $\theta_2$ are now

$$\theta_1 = \frac{v_1}{u_1 + \eta u}$$  \hspace{1cm} (2.28)

$$\theta_2 = \frac{v_2}{u_2 + (1 - \eta)u}.$$  \hspace{1cm} (2.29)

The labour force shares are set to $LF = 0.25$, $LF_1 = 0.25$, and $LF_2 = 0.5$. These values are set such that a sufficient fraction of workers can move freely across sectors. Once again productivity in sector 1 is 10% higher, and the vacancy creation costs are different across the two sectors.
Results

In Figure 2.11, we see the response of each sector to a productivity shock, and in Figure 2.12 we see the response of each sector in relation to the change in aggregate vacancies. These results are identical to the segmented labour market model in the previous section, and all the results carry over.

For workers in sector 1 to search in sector 2, the wage must be higher, as the expected duration of employment in sector 2 is lower due to the higher separation rate. However, due to the productivity differences, the wages in sector 1 is always higher, which is consistent with the empirical evidence. Thus, none of the free to move workers search in sector 2 and each sector has a labour force of 0.5, which is the same as the previous section.

Even with no differences in the level of productivity, or vacancy creation costs, there is still no asymmetry in the vacancy yield elasticity under the partial mobility model. Since the separation rate is higher in sector 2, the returns to unemployment in that sector is lower. Thus, none of the free to move workers have any incentive to search in sector 2, and the results from the segmented labour market with no productivity or vacancy creation cost differences carry over.

2.6 Conclusion

During downturns, the vacancy yield of sectors with higher separation rates increases by more than the sectors with lower separation rates.

A standard random search model where workers are free to search a unified labour market is not able to capture this stylised fact. In a standard random search model, the pool of unemployed workers randomly matches to the available vacancies. While the share of matches varies across sectors, the rate at which the unemployed workers match does not. Both sectors in the standard set-up have identical changes in their vacancy yield.

To investigate the link between the separation rate and the vacancy yield, this paper considers a model where workers are segmented, and cannot randomly match to different sectors. The results show that separation rate alone cannot account for the observed empirical patterns. The separation rate reduces the elasticity between the vacancy yield and productivity, but it also reduces vacancy-unemployment ratio, which in turn increases the elasticity between the two variables. The net effect is zero.

In light of this, the paper considers the impact of two potential variables which are correlated with the separation rate. Empirically, we observe that sectors with high separation rates have lower wages. In standard search models, this implies a relatively low level of productivity. Also, the existing empirical evidence suggest that sectors with high separation rates have low vacancy creation costs.
2.6. CONCLUSION

Figure 2.11: Percentage change in $L_i$, $v_i$, $q_i$, and $u_i$, in response to percentage change in $A_i$. The changes are from initial equilibrium values to new equilibrium.

Examining a model that contains these features, I find that sectors with high separation rates all have a higher elasticity of the vacancy yield with respect to productivity.
Figure 2.12: Percentage change in $L_i$, $v_i$, $q_i$, and $u_i$, in relation to percentage change in $v$. The changes are from initial equilibrium values to new equilibrium and for proportionate productivity shocks.
2.7 Appendix

2.7.1 Vacancy Yield Controlling for Changes in Separations

Figure 2.13: Percentage deviation from mean vacancy yield vs. aggregate vacancies/labour force controlling for the change in the number of separations. This is done by regressing vacancy yield deviation against aggregate vacancies/labour force and the percent deviation from the mean number of separations. Each point represents the quarterly ratio between total hires and total vacancies for the quartile. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denote significance at the 10%. A t-test is used to determine whether a statistically significant difference exists between the slopes of quartiles 2, 3 and 4 and the slope of quartile 1. The slopes are estimated using OLS with Newey-West standard errors. Source: BLS - JOLTS.
### 2.7.2 Sectors by Separation Quartile

Table 2.11: Sectors by quartile of average separation rate, and average monthly separation rate for quartile from JOLTS.

<table>
<thead>
<tr>
<th>Quartile</th>
<th>Separation Rate (M)</th>
<th>Sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2%</td>
<td>-Durable Goods Manufacturing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Finance &amp; Insurance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Educational Services</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Federal Public Administration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-State &amp; Local Public Administration</td>
</tr>
<tr>
<td>2</td>
<td>3%</td>
<td>-Non-durable Goods Manufacturing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Wholesale Trade</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Information</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Health Care and Social Assistance</td>
</tr>
<tr>
<td>3</td>
<td>4%</td>
<td>-Mining and Logging</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Retail Trade</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Transportation, Warehousing and Utils.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Real Estate and Rental and Leasing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Other Services</td>
</tr>
<tr>
<td>4</td>
<td>6%</td>
<td>-Construction</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Professional and Business Services</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Arts, Entertainment, and Recreation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-Accommodation and Food Services</td>
</tr>
</tbody>
</table>
### 2.7.3 Estimation Results

Table 2.12: Estimation results of Equation (2.1).

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>-0.639**</td>
</tr>
<tr>
<td></td>
<td>(-3.02)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.402</td>
</tr>
<tr>
<td></td>
<td>(-1.47)</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-0.332</td>
</tr>
<tr>
<td></td>
<td>(-1.03)</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>-1.067*</td>
</tr>
<tr>
<td></td>
<td>(-2.32)</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>-0.350***</td>
</tr>
<tr>
<td></td>
<td>(-8.18)</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>-0.106**</td>
</tr>
<tr>
<td></td>
<td>(-2.60)</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>0.292***</td>
</tr>
<tr>
<td></td>
<td>(5.86)</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>0.0651</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
</tr>
<tr>
<td>$N$</td>
<td>972</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses. Robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Table 2.13: Estimation results of Equation (2.1). Aggregate vacancies for industry $i$ excludes the vacancies of industry $i$.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>-0.549**</td>
<td>(-2.63)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.343</td>
<td>(-1.26)</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-0.240</td>
<td>(-0.76)</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>-0.953*</td>
<td>(-2.08)</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>-0.352***</td>
<td>(-8.28)</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>-0.105*</td>
<td>(-2.55)</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>0.285***</td>
<td>(5.66)</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>0.0111</td>
<td>(0.02)</td>
</tr>
<tr>
<td>$N$</td>
<td>972</td>
<td></td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses. Robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
2.7. APPENDIX

2.7.4 Derivation of Vacancy Creation Curve

The first order conditions with respect to labour and vacancies are

\[
\frac{\partial L}{\partial L_{i,t}} + \lambda_t = p_{i,t}A_{i,t} + w_{i,t} + \lambda_{t+1} - E_t^{l+1} \lambda_{t+1} (1 - s_i) = 0, \quad (2.30)
\]

for \( l \geq 1 \).

\[
\frac{\partial L}{\partial v_{i,t}} = -p_{i,t}A_{i,t} \gamma_i - rE_t^{l+1} \frac{q_i(\theta_{i,t})}{q_i(\theta_{i,t+1})}, \quad (2.31)
\]

Rearranging (2.30) and (2.31) gives

\[
\lambda_t + \lambda_{t+1} = p_{i,t}A_{i,t} + w_{i,t} + \lambda_{t+1} - E_t^{l+1} \lambda_{t+1} (1 - s_i). \quad (2.32)
\]

\[
rE_t^{l+1} = -p_{i,t}A_{i,t} \gamma_i \frac{q_i(\theta_{i,t})}{q_i(\theta_{i,t+1})}. \quad (2.33)
\]

Moving (2.33) \( l \) periods and plugging it into (2.32) yields

\[
\lambda_{t+l} = p_{i,t+l}A_{i,t+l} + \gamma_i p_{i,t+l}A_{i,t+l} + \frac{\gamma_i p_{i,t+l}A_{i,t+l}}{q_i(\theta_{i,t+l})} (1 - s_i). \quad (2.34)
\]

Letting \( l = 1 \) and substituting (2.34) into (2.33) gives

\[
rE_t \left( p_{i,t+1}A_{i,t+1} + \gamma_i p_{i,t+1}A_{i,t+1} + \frac{\gamma_i p_{i,t+1}A_{i,t+1}}{q_i(\theta_{i,t+1})} (1 - s_i) \right) = \gamma_i p_{i,t}A_{i,t} \frac{q_i(\theta_{i,t})}{q_i(\theta_{i,t+1})}. \quad (2.35)
\]

2.7.5 Wage Equation

The present value of an open vacancy for each sector is

\[
J^V_{i,t} = -\gamma_i M V P L_{i,t} + r(q_i(\theta_{i,t})E_tJ^F_{i,t+1} + (1 - q_i(\theta_{i,t})E_tJ^V_{i,t+1}). \quad (2.36)
\]

Firms create vacancies until value of an open vacancy \( J^V_{i,t} \) is driven down to zero. This implies

\[
E_tJ^F_{i,t+1} = \frac{\gamma_i M V P L_{i,t}}{r q_i(\theta_{i,t})}. \quad (2.37)
\]

The value of a filled vacancy for sector 1 and sector 2 is

\[
J^F_{i,t} = p_{i,t}A_{i,t} - w_{i,t} + r \left[ (1 - s_i)E_tJ^F_{i,t+1} + s_iE_tJ^V_{i,t+1} \right]. \quad (2.38)
\]
Equation (2.38) can also be derived by differentiating the Lagrangian in (2.9) with respect to $L_{i,t}$. Free entry together with the Bellman equation for filled jobs implies

$$J^F_{i,t} = p_{i,t} A_{i,t} - w_{i,t} + \frac{\gamma_i MVPL_{i,t}}{q_i(\theta_t)} (1 - s_i), \quad (2.39)$$

For unemployed workers, the value of being unemployed in sector $i$ is

$$J^U_{i,t} = z + r(f_i(\theta_{i,t}) E_t J^E_{i,t+1} + (1 - f_i(\theta_{i,t})) E_t J^U_{i,t+1}), \quad (2.40)$$

where $z$ is the unemployment benefit in terms of the numeraire good. The present value of being employed in sector $i$ is

$$J^E_{i,t} = w_{i,t} + r(s_i E_t J^U_{i,t+1} + (1 - s_i) E_t J^E_{i,t+1}). \quad (2.41)$$

Total surplus is given by

$$S_{i,t} = J^F_{i,t} + J^E_{i,t} - J^U_{i,t}, \quad (2.42)$$

and is distributed according to

$$\beta(J^F_{i,t} + J^E_{i,t} - J^U_{i,t}) = \beta S_{i,t}. \quad (2.43)$$

$$(1 - \beta)(J^F_{i,t} + J^E_{i,t} - J^U_{i,t}) = (1 - \beta) S_{i,t}. \quad (2.44)$$

So workers will receive $\beta$ of the total surplus, while the firm will receive $(1 - \beta)$. Using (2.38), (2.40) and (2.41) we can express the surplus as

$$S_{i,t} = p_{i,t} A_{i,t} + r(1 - s_i)(E_t J^F_{i,t+1} + E_t J^U_{i,t+1}) - z - r(f_i(\theta_{i,t}) E_t J^E_{i,t+1})$$

$$+ (1 - f_i(\theta_{i,t})) E_t J^U_{i,t+1} - s_i E_t J^F_{i,t+1} - s_i E_t J^U_{i,t+1})$$

$$= p_{i,t} A_{i,t} + r(1 - s_i)(E_t J^E_{i,t+1} + E_t J^E_{i,t+1} - E_t J^U_{i,t+1}) - z$$

$$- r f_i(\theta_{i,t})(E_t J^E_{i,t+1} - E_t J^U_{i,t+1})$$

$$= p_{i,t} A_{i,t} + r(1 - s_i)E_t S_{i,t+1} - z - r f_i(\theta_{i,t}) E_t S_{i,t+1}, \quad (2.45)$$

where we have utilised the fact that $(E_t J^E_{i,t+1} - E_t J^U_{i,t+1}) = \beta S_{i,t+1}$. We can now derive the wage equation. From (2.44) and (2.39) we get

$$(1 - \beta)S_{i,t} = p_{i,t} A_{i,t} - w_{i,t} + \frac{\gamma_i MVPL_{i,t}}{q_i(\theta_t)} (1 - s_i). \quad (2.46)$$

Using $E_t J^F_{i,t+1} = (1 - \beta) S_{i,t+1}$ and and the free entry condition (2.37), in per worker worker form, we have

$$\frac{\gamma_i MVPL_{i,t}}{r q_i(\theta_t)} = (1 - \beta) S_{i,t+1}. \quad (2.47)$$
Substituting (2.47) into (2.45) yields

\[ S_{i,t} = p_{i,t}A_{i,t} - z + \frac{\gamma_i MVPL_{i,t}}{q_i(\theta_{i,t})(1 - \beta)} (1 - s_i) - \frac{\gamma_i MVPL_{i,t}}{q_i(\theta_{i,t})(1 - \beta)} f_i(\theta_{i,t})\beta. \]

Substituting (2.46) into (2.48) and rearranging we get

\[ w_{i,t} = \beta \left( p_{i,t}A_{i,t} \right) + (1 - \beta) z + f(\theta_{i,t})\beta\frac{\gamma_i MVPL_{i,t}}{q_i(\theta_{i,t})} = \beta \left( p_{i,t}A_{i,t} \right) + (1 - \beta) z + \theta_{i,t}\beta\gamma_i MVPL_{i,t}. \]
Chapter 3

Phase-Shifts in US Sectoral Employment

This paper identifies cyclical turning points in United States sectoral employment and finds new patterns that characterise the recent business cycles. It is shown that 1) many more sectors are in the contraction phase around the aggregate employment peak date than are in expansion phase around the aggregate employment trough date, 2) sectoral growth rates don’t display asymmetry in the absolute growth rates around their own turning point dates, 3) sectoral trough dates in the last three recessions were relatively centred around the trough date of aggregate employment, compared to the National Bureau of Economic Research trough date, a pattern absent in the 1981 recession, 4) the 2008-09 recession was deep due to the extent it diffused across sectors. Finally the paper shows that input-output linkages play an important role in determining the timing of sectoral phase-shifts.

3.1 Introduction

Historically business cycles have been characterised by episodes where 1) employment in most industries of the economy jointly move up and down, and 2) the drop in employment around the aggregate peak, is sharper than the expansion around the aggregate trough. But what has received less attention is the pattern of the sectoral co-movement around aggregate turning point dates; that is, whether the peak dates across industries are more clustered around aggregate turning point dates than the trough dates. This is important, since the observed asymmetry in the absolute growth rates of macro-economic variables around peak and trough dates may be due to differences in the fraction of the industries that are contracting/expanding around aggregate peak/trough dates.

The way the past literature has typically modelled temporal asymmetries in economic fluctuations is to assume frictions at the individual level, such as
discrete choice or fixed costs (Caballero and Engel (1999), Hansen and Prescott (2005)), or a learning process to amplify shocks in the trough of a business cycle (Acemoglu and Scott (1997), Chalkley and Lee (1998), Van Nieuwerburgh and Veldkamp (2006)). These micro frictions aggregate up to generate aggregate asymmetries.

However, if asymmetries exist in the fraction of industries contracting/expanding around aggregate turning point dates, but not in the absolute growth rates around an industry’s own peak and trough dates, then this has implications for the business cycle theories that depend on asymmetries at individual level to generate aggregate asymmetries. To this end, this article explores sectoral turning points in order to better understand the aggregate turning point phenomenon, and in the process characterise the business cycle.

The National Bureau of Economic Research (NBER) - which is responsible for determining the start and end dates of recessions - defines a recession as a “significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real Gross Domestic Product (GDP), real income, employment, industrial production, and wholesale-retail sales.” The peak marks the beginning of the declining phase, and the trough marks the end of the declining phase and the start of the rising phase of the business cycle.

While the pioneering work by NBER researchers on business cycle dating (Burns and Mitchell (1946)), and the recent contributions of Stock and Watson (2010, 2014), identified turning points in many disaggregated series, their aim was to determine aggregate business cycle turning points based on the distribution of the turning points of the disaggregated series. The industry cross-sectional variation of turning points was not the subject of investigation, apart from the imprecision it created in estimating the reference periods. In addition to understanding asymmetries across the cycle, the variation across sectors can also help discern whether cycles arise from fluctuations in a few large industries, or covariation of many industries.

This article provides a descriptive study of industry-level peaks and troughs; the relative timing of these turning points; and the industry growth rates surrounding these points to characterise the business cycle. New empirical regularities surrounding the peak and trough dates of sectoral economic activity are presented and discussed. The new empirical regularities can help discern across different macro-economic models, in particular, the theories relating to the asymmetry in employment growth around aggregate peak and trough dates.

A recent study by Chang and Hwang (2015) identifies the turning points of production across industries in the manufacturing sector and finds many novel results that help characterise the business cycle. However, by focussing on industrial production, their analysis is limited to goods-producing industries. The value-added of service-providing industries is three times that of goods-producing industries, and provides more than three-fourths of total private
employment. Furthermore, the job creating abilities of service sectors vary from that of goods-producing sectors (Davis, Faberman, and Haltiwanger, 2013a). This is bound to affect the shape of recovery. For this reason, it is important to investigate the cyclical properties of service-providing industries when studying the business cycle.

Due to a lack of data on disaggregated industry output, this paper instead focuses on the cyclical behaviour of employment. Focussing on employment allows one to analyse the turning point behaviour of service-providing sectors along with goods-producing sectors.

We also know that the behaviour of employment over the business cycle has changed in the last two and a half decades, with employment growing slower following a turnaround in GDP. The changing relationship between output and employment means that a business cycle study cannot be complete without an analysis of sectoral employment. While there has been work done on the correlation of sectoral employment over the business cycle (see Quah and Sargent (1993) and Christiano and Fitzgerald (2001)), less has been done on the timing of peaks and troughs across sectors. This study attempts to fill that gap. Studying discrete turning points reveals aspects of the business cycle that correlation analysis cannot. Whether aggregate asymmetries are due to variation in durations of contraction, as opposed to the growth rates around turning point dates, for example, can only be answered by identifying the turning points.

This article performs three tasks. First, it identifies the turning points in disaggregated series and makes the sectoral variation its subject of analysis. Second, the disaggregated series extend to the whole economy, allowing a comparison between service-providing and goods-producing sectors. Lastly, it focuses on disaggregate series of employment, characterising the behaviour of employment over the business cycle. In doing so, it shows that in the last three recessions an asymmetry in sectoral turning points does exist, with sectoral peaks being more clustered around the aggregate peak date than is the case for troughs. This is true for the last three recessions.

During the recessions of 1990, 2001 and 2008, a statistically significant difference exists in the absolute sectoral growth rates around aggregate turning point dates. This statistical difference, however, disappears around an industry’s own peak and trough dates. Thus, the difference in the share of sectors expanding and contracting around aggregate turning point dates is an important, and overlooked, reason for aggregate turning point asymmetries.

What also comes out of this exercise is that during the recessions of 1990 and 2001, the fraction of service-providing sectors, which experienced a contraction at a given point in time was significantly lower than that of goods-producing sector - in fact around a 50% difference. However, this was not the case during the 2008 recession. Service-providing sectors were on average less likely to be in the same phase of the cycle as total private employment around the peak date, compared to good-producing sectors.
This raises many interesting questions, such as why the 2008 recession diffused across many more industries compared to the earlier recessions, and whether the earlier recessions were less severe due to the economy being hit by sector-specific shocks, as opposed to aggregate shocks, or whether the sector-specific shocks of 2008 were in sectors that had far reaching links to the rest of the economy. For example, the construction industry, which experienced a large decline in output during the 2008 recession, has a strong inter-connection with the rest of the economy. Boldrin, Garriga, Peralta-Alva, and Sánchez (2012) claim that the sudden drop in the output of the construction sector translated into a general reduction of demand for most other sectors. The interconnections between construction and the rest of the economy propagated and magnified the initial demand shock.

My investigation on the determinants of concurrence of phase shifts across sectors reveals that the input-output structure is an important source of co-movement. The likelihood of an industry experiencing a phase-shift increases as neighbouring industries experience a phase-shift. This lends support to the theories that stress the importance of input-output linkages in propagating industry shocks (see Long and Plosser (1983), Horvath (1998), Horvath (2000), and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)). While these papers stress the importance of supply shocks, the results indicate that the impact of demand shocks to be larger and more persistent, especially during troughs, which contrasts with Chang and Hwang (2015), who find the upstream effect to play a more important role in whether an industry reaches its trough.

These findings get to the above-mentioned point, of why aggregate cycles display asymmetries. Asymmetries at the firm level aside, the difference in the share of industries contracting around the aggregate peak, compared to the share expanding around the aggregate trough appears to be an important reason. Why sectors tend to reach their peaks at similar times, but not their trough is a question that requires investigation.

The paper is organised as follows. Section 2 discusses the data and algorithm employed. Section 3 presents the results. Section 4 provides two extensions, comparing the relative behaviour of employment and total hours, and industrial production to employment. Section 5 concludes. All figures and tables are reported in the Appendix.

3.2 Data & Dating Algorithm

This paper uses disaggregate data on employment supplied by the Bureau of Labor Statistics (BLS), as part of its Quarterly Census of Employment and Wages (QCEW) program. The QCEW provides monthly employment levels at the industry level. The program covers all establishments that report to the Unemployment Insurance (UI) programs of the United States. Employment
covered by these UI programs represents about 97% of all wage and salary civilian employment in the country. 

The QCEW counts only filled jobs, whether full or part-time, temporary or permanent, by place of work. Because the QCEW data is based on an establishment census which counts filled jobs, a multi-job holder will be counted two or more times.

The goods-producing sector consists of the following sub-sectors: natural resources and mining, construction, and manufacturing. The service-providing sectors consist of the following sub-sectors: trade, transportation and utilities, information, financial activities, real estate, rental and leasing, professional and business services, management of companies and enterprises, administration and support, waste management and remediation services, education and health services, health care and social assistance, leisure and hospitality, accommodation and food services, and other services.

While the data spans from 1975 until present, it is not continuous. Due to a major overhaul of the sectoral classification system, data from 1975-2000 are provided according to the Standard Industrial Classification (SIC) system while data from 1990-2014 are provided according to the North American Industrial Classification System (NAICS). For most of the analysis results are provided for both data sets.

Turning points in industry employment are identified using the method proposed by Bry and Boschan (1971). The implementation of the Bry and Boschan procedure is given by the six steps in Table 3.1 of the Appendix.

3.3 Results

3.3.1 Diffusion, Concordance and Cumulative Movements

This sub-section, investigates industry co-movement by viewing the extent to which the sectors are in the same cyclical phases. Like Chang and Hwang (2015), two measures of co-movement are employed, namely diffusion and concordance indices. However, this paper differs from their work by determining the indices across all sectors, and within two sectors, namely, goods-producing and service-providing. In doing so, the behaviour of services can be compared to goods.

The diffusion index measures the fraction of industries in a contraction at a given point in time, using

---

1Major exclusions from UI coverage include self-employed workers, most agricultural workers on small farms, all members of the Armed Forces, elected officials in most states, most employees of railroads, some domestic workers, most student workers at schools, and employees of certain small non-profit organisations.
where \( w_{it} \) is the weight assigned to the \( i \)th industry at time \( t \); \( S_{it} \) is a binary variable taking the value of 1 if the \( i \)th industry is in a contraction and zero otherwise; and \( N \) is the number of industries. \( S_{it} = 1 \) from the time the industry attains its peak up until the time it reaches its trough, from which point \( S_{it} = 0 \) until the industry once again reaches a peak. Two weightings are used; the first assigns each industry equal weight, and the second assigns each industry its share of total private employment in period \( t \). A difference in the two measures will be indicative of whether larger industries reach their peak at different times to smaller industries.

Figures 3.1 and 3.2 display the diffusion index using the data spanning 1975-2000 and the data spanning 1990-2014, respectively. What stands out from both figures is that during the 1991, 2001, and 2008 recessions more industries were contracting or entering into a contraction phase around the NBER reference cycle peak date, compared to the number of industries expanding or entering into an expansion phase around the NBER reference cycle trough date. There appears to be no such pattern during the earlier recessions.

It is also evident that the fraction of industries contracting - the line denoted by “Agg” - begins to increase steadily before the NBER reference cycle peak date. We also see that consistently a greater fraction of the goods-producing sector is contracting relative to the service-providing sector.

The second measure of co-movement is the concordance index, which measures the fraction of time that two cycles are in the same phase over the sample period [Harding and Pagan (2002)]. This paper modifies this measure to determine the concordance between two cycles at specific points in time. For example, while the concordance index of [Harding and Pagan (2002)] looks at the extent that two cycles are in the same phase over the entire period, this paper analyses the extent that two cycles are in the same phase around the peak and trough date of aggregate employment.

The motivation for this is to see whether the extent that the two cycles are in the same phase varies over the different phases of the business cycle. The concordance of each industry with total private employment is measured by

\[
C_{i,TP} = \frac{1}{|T|} \sum_{t \in T} [S_{it}S_{TP,t} + (1 - S_{it})(1 - S_{TP,t})],
\]

where \( S_{TP,t} \) is a binary variable indicating the phase of total private employment, and \( S_{it} \) is a binary variable indicating the phase of industry \( i \), and \( T \) is a set of dates. \( T \) includes all of the dates starting from the peak (trough) in total private employment up until 6 months after the peak (trough) date.
3.3. RESULTS

is the size of the set $T$. The idea here is to statistically capture the concordance between sectoral and aggregate employment around the peak (trough) date. This will in turn show whether sectors are more likely to be in the same phase as aggregate employment around the peak date compared to the trough date.

The concordance of phases between two industries is measured by

$$C_{ij} = \frac{1}{|T|} \sum_{t \in T} [S_{it}S_{jt} + (1 - S_{it})(1 - S_{jt})], \quad (3.3)$$

where $S_{it}$ and $S_{jt}$ are binary variables indicating contractions of industry $i$ and $j$, respectively. The set $T$ is the same as above.

The exercise is to capture any asymmetry in the clustering around aggregate cycle dates. If there is more clustering around the aggregate peak date, we expect the concordance index to be larger when we determine the index around the peak date as opposed to the trough date.

Tables 3.2, 3.3 and 3.4 present detailed summary statistics for the concordance indices. The indices are calculated according to three groupings, “Within Only”, “Within and Between”, and “Total Private”. The “Within Only” and “Within and Between” measures are calculated using Equation (3), while the measure “Total Private” is calculated using Equation (2).

Each group is in turn broken into three further groups, “Agg” which is the set of all industries, “Goods”, which is the set of goods-producing industries, and “Services”, which is the set of service-providing industries.

For “Within Only”, the first group, “Agg”, measures the concordance between industry $i$ and $j$, where both $i$ and $j$ belong to the set of all industries. The group “Goods”, measures the concordance between $i$ and $j$ where both $i$ and $j$ belong to the set of good producing industries. Finally, the group “Services” measures the concordance between industry $i$ and $j$ where both $i$ and $j$ belong to the set of service providing industries.

The group “Within and Between” once again dichotomises the industries, but this time only $i$ belongs to a particular sector (goods-producing or service-providing) and, $j$ belongs to the set of all industries. Finally, the group “Total Private” is the concordance between industry $i$ - where industry $i$ belongs to the set of all industries - and total private employment.

From Table 3.2 there appears to be no substantial difference in the concordance index between each industry and total private employment at the peak and trough dates. We see that on average 63.9% of the industries are contracting when total employment is contracting, and on average 66.6% of the industries are expanding when total private employment is expanding. The medians are identical. Focussing on “Within and Between”, we see that the average industry has an average pairwise concordance index of 57.4% around the aggregate peak date and 59.3% around the aggregate trough date.
PHASE-SHIFTS IN US SECTORAL EMPLOYMENT

Table 3.3 focuses explicitly on the 1990 recession, and Table 3.4 focuses on the 2001 and 2008 recessions. From the diffusion plots it is evident that the latter recessions are different from the earlier recessions. During the 1991 recession we see that on average 67.1% of industries are contracting when total employment is contracting and on average 48.2% of the industries are expanding when total private employment is expanding. Focussing on “Within and Between”, we see that the average industry has an average pairwise concordance index of 56% around the aggregate peak date and 50.3% around the aggregate trough date.

During the 2001 and 2008 recessions we see that on average 62.7% of the industries are contracting when total employment is contracting and on average 50.6% of the industries are expanding when total private employment is expanding. We see that the median industry has an average pairwise concordance index of 54.3% around the aggregate peak date, and 50.3% around the aggregate trough date.

It is evident that in the last three recessions, the differences in the concordance indices across periods of contraction and expansion in aggregate employment are more pronounced. That is, a greater share of industries is contracting around the peak date of total private employment, than are expanding around the trough date of total private employment.

3.3.2 Distribution of Turning Points

This sub-section looks at the concentration of industry turning points in relation to total private employment, and aggregate activity. The turning points of aggregate activity are the cycle dates as determined by the NBER. A turning point cluster is defined as a set of industry turning points whose distances from a given aggregate turning point are less than a predetermined bound. Let the \( k \)th peak of total private employment be denoted by \( P_{TP}^{k} \), and let the set of industry \( i \)'s peaks be denoted by \( \mathcal{P}^{i} \), and the \( j \)th element of \( \mathcal{P}^{i} \) be given by \( P_{ij} \). The set of industry \( i \) peaks that are close to the \( k \)th peak of total private employment, \( \psi_{i}^{k} \), is given by

\[
\psi_{i}^{k} = \{ P_{ij} | d(P_{ij} - P_{TP}^{k}) \leq \bar{d} \},
\]

where \( d(\cdot) \) is a measure of distance and \( \bar{d} \) is a predetermined cluster bound. This bound is set to 24 months. Since the 1980 and 1981 recessions overlap, the 1980 recession is ignored. Given that we are interested in the relative timing the industries peak, a single peak from \( \psi_{i}^{k} \) needs to be chosen. The single peak is determined by choosing the peak that minimises \( d(P_{ij}^{TP} - P_{ij}) \). This will guarantee a single peak. Once we have narrowed down to a single peak, we then determine the difference between the period of the industry peak and the aggregate employment peak. In figures 3.3a, 3.5a, 3.7a we see the distribution of the timing of industry peaks relative to the timing of total employment peak. The horizontal axis denotes the lead (negative) and lag
3.3. RESULTS

(positive) time over the total private employment turning point dates. In figures 3.3b, 3.5b, and 3.7b, we see the distribution of the timing of industry troughs relative to the timing of total employment trough.

The plots only consider industries that experienced peaks or troughs. Therefore, any measure of central tendency is only in relation to a subset of industries. Across all 4 recessions, however, all industries experience at least one peak and trough.

From these plots we see that more of the industries are located to the right of the trough date of total private employment when compared to the peak date. This is especially true for the 2001 and 2008 recessions. While there is clustering around the aggregate trough date, what is evident from the figures is that around the aggregate peak date many industries are already in a contraction phase or soon after entering into contraction.

Figures 3.4a, 3.4b, 3.6a, 3.6b, 3.8a, and 3.8b display the comparable plots for the NBER cycle dates. It is evident that the industry trough dates are highly skewed relative to the NBER trough date, whereas the peak dates are more centred around the NBER peak date.

Growth and Sharpness Asymmetry

Thus far this paper has focussed on the timing distribution of industry turning points. This subsection explores the difference between peak and trough clusters in the growth in employment surrounding the turning points of total private employment, the NBER cycle dates, and an industry’s own turning point date.

Previous studies, such as McQueen and Thorley (1993), have shown that at the aggregate level, output growth is larger around the NBER trough date, than NBER peak dates. Chang and Hwang (2015) find that the result not only holds at the aggregate level, but also at the disaggregated industry level.

The sharpness of employment change around a turning point date is calculated as the absolute difference between the employment growth rate from six months prior the turning point date, and from six months after the turning point date. Sharpness asymmetry is then measured by the difference in sharpness between the aggregate troughs and peaks. The results are shown in Tables 3.5, 3.6 and 3.7.

The first column indicates the different reference points from which the growth rates are determined. For example, the row “Industry” indicates the employment growth rate is determined around the industry’s own peak and trough dates. The row “NBER” reflects the fact that the industry’s employment growth rates are determined around the NBER cycle dates, and finally, the row “TPE” indicates that the industry’s employment growth rates are determined around the peak and trough dates of total private employment.

The variable $g_{P,+6}$ ($g_{T,+6}$) is the median industry growth rate of employment from the peak (trough) date to 6 months after the peak (trough) date.
The variable $g_{P,-6}$ ($g_{T,-6}$) is the growth rate of employment from 6 months before the peak (trough) date to the peak (trough) date. Finally, to capture the sharpness of the growth rate around each turning point, we have $S_P = \text{median}(|g_{P,-6} - g_{P,+6}|)$ (the measure around the trough date is similarly calculated). Note that the larger $S_P$ is, the sharper the change around the turning point.

In tables 3.5 - 3.7, we see that across all recessions there is no asymmetry in absolute growth rates for the median industry around their own turning point dates. The median industry, upon reaching its trough, expands at a similar rate to when it contracts after reaching its peak. Performing a Wilcoxon rank-sum test there is no statistical difference between the two distributions at the 10% level. In order to compare the two distributions we multiply the change around the trough date, $g_{T,+6}$, by -1. Figures 3.9a and 3.10a plot the distributions of employment growth rates for the two periods. We see considerable overlap between the two distributions.

Figures 3.9b and 3.10b, which measure the growth rates in employment from the peak/trough dates of total private employment, also display overlap. However, the histogram for the growth rates around the aggregate peak dates has greater density to the left of zero compared to the histogram for the growth rates around the aggregate trough dates, suggesting that fewer industries are expanding around the trough date than are expanding around the peak date.

The results from the Wilcoxon rank-sum test on the distributions of the growth rates around the peak/trough dates of total private employment show that the two distributions are statistically different from each other at the 1% level. Interestingly, in Tables 3.5 and 3.7 we see that the sharpness measures are higher in the earlier recessions than in the latter. Not only was employment typically growing faster before reaching its peak, but it also contracted faster once it reached its peak.

### 3.3.3 Determinants of Co-movement

This sub-section investigates whether inter-industry linkages have a significant effect on the concurrence of industry turning points, and whether the effects are symmetric between peaks and troughs. The analysis is only conducted on data ranging from 1990 to 2014.

#### Empirical Model

For the occurrence of peaks, the empirical model is

$$P_{i,t} = \mathbf{x}_{it}' \boldsymbol{\theta} + \varepsilon_{it}, \text{ for } i = 1, \ldots, N \text{ and } t = 1, \ldots, T,$$

(3.5)

where $P_{i,t}$ indicates whether industry $i$ is at a peak in period $t$; $\mathbf{x}_{it}'$ is a vector of observable covariates; $\boldsymbol{\theta}$ is a vector of corresponding coefficients; $\varepsilon_{it}$ is the
error term; and $\varepsilon_{it} \sim \text{Logistic}(0, \sigma^2)$. Given the distribution of the error term, the model becomes:

$$\Pr(P_{i,t} = 1|x_{it}') = F(x_{it}\theta), \text{ for } i = 1, \ldots, N \text{ and } t = 1, \ldots, T, \quad (3.6)$$

where $F$ is a logistic function.

The industry specific observable explanatory variables include the lags of two types of spillover effects. These are from the industries that supply goods and services, and industries that demand goods and services, $z_{k,i,t-l}, k = 1, 2$. These variables are lagged by 6, 7, 8, 9, 10, 11 and 12 months ($l = 6, 7, 8, 9, 10, 11, 12$). The lags are to avoid a potential endogeneity problem. The model for troughs can be specified in a similar way. These variables are discussed in greater detail in the next sub-section. Equation (3.6) can now be expressed as

$$\Pr(P_{i,t} = 1|x_{it}') = F(x_{it}\theta) = F(\sum_k \sum_l z_{k,i,t-l} \beta_{k,l}) \quad (3.7)$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$.

In order to deal with the issue of incidental parameters, it may be more ideal to estimate a random effects model, as opposed to a fixed effects models, which is the course Chang and Hwang (2015) follow. While the random effects model allows for differing intercepts across industries, it assumes that the industry intercepts are random and independent of the explanatory variables. If any correlation exists between the industry intercept and the explanatory variables, however, the estimates will be biased.

A solution around the incidental parameter problem is to find a minimal sufficient statistic for the industry fixed effects, which is denoted as $\alpha_i$. For a logit model Chamberlain (1980) finds that $\sum_{t=1}^{T} P_{it}$ is a minimum sufficient statistic for $\alpha_i$. This idea is the motivation for using a logit model over a probit model. The downside of the fixed effects model such as a conditional logit, however, is that one cannot calculate marginal effects. Since marginal effects depend on the fixed effect, which is conditioned out, the marginal effects cannot be determined.

Fortunately, there is a method of combining the virtues of both fixed and random effects models into one model. It is possible to obtain unbiased estimates of the effect of time-varying explanatory variables in random effects

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2See Lancaster (2000) and Baltagi (2008) for a discussion on incidental parameters. The incidental parameter problem arises whenever we are constructing non-linear models with qualitative outcomes and fixed effects.

3A linear probability model (LPM) could have been used instead, but LPMs generate incorrect test statistics, unless one can instrument for the outcome variable, see Long (1997).
models, even if unobserved heterogeneity is correlated with the explanatory variables. This can be achieved by including the unit-specific means of the explanatory variables as additional explanatory variables, and expressing the time varying co-variates as deviations from their mean.

Modelling the time-varying explanatory variables as deviations from their mean reduces the potential correlation between the random intercept and the explanatory variables. The inclusion of the average of the explanatory variables allows for between industry comparison. Such a model is called a hybrid model and is discussed in detail in [Andréß, Golsch, and Schmidt (2013)] and briefly in [Allison (2009)]. The hybrid model will take the following form:

\[
\Pr(P_{i,t} = 1|\mathbf{x}_{it}) = F(\sum_k \sum_l (z_{k,i,t-l} - \bar{z}_{k,i})\beta_{k,l} + \sum_k \bar{z}_{k,i}\lambda_k) \tag{3.8}
\]

for \(i = 1, ..., N\) and \(t = 1, ..., T\),

where \(\bar{z}_{k,i}\) is the average of the time-varying industry specific covariate. Finally, since \(P_{i,t} = 0\) for some \(t\) due to the censoring rules used for detecting turning points, zero responses at these points are discarded.

**Explanatory Variables**

The weighted average spillover effect from industry phase shifts is constructed as

\[
z_{k,i,t-l} = \sum_{j \neq i} w_{k,ij} P_{j,t-l}, \text{ for } k = 1, 2, \tag{3.9}
\]

where \(P_{j,t-l}\) is equal to 1 if industry \(j\) is at its peak at time \(t - l\) and 0 otherwise, and \(w_{k,ij}\) is the weight capturing the importance of industry \(j\) for industry \(i\). To reduce the number of parameters to estimate, only 6 lags are included.

[Shea (2002)] shows that input-output linkages are important to short run co-movement, with significant links running from both users to suppliers and suppliers to users. Let \(m_{ij}\) be the value of output produced by industry \(i\) and consumed in industry \(j\), and let \(Y_i\) be the total value of output of industry \(i\). Then the downstream spillover variable is constructed using

\[
w_{1,ij} = \frac{m_{ij}}{Y_i}. \tag{3.10}
\]

This measure is slightly different to that used in [Chang and Hwang (2015)], who consider the output of industry \(i\) heading to the other sectors in the denominator. Their measure potentially overestimates the importance of one sector.
industry to another. For example, consider a situation where 99% of industry $i$’s output is destined to consumers, while the remaining 1% heads to industry $j$. Their calculation will give industry $j$ a weight of 1, although it is not a significant user of industry $i$’s output.

Although $w_{k,ij}$ does not have a time subscript, it does vary with time. The BLS generates input-output tables running from 1993 to 2012. Each table contains use and supply information for 169 industries. Given that the sample available to compute turning points is larger than that used to generate input-output coefficients, for all points in the sample up to and including 1993, the 1993 input-output table estimates are employed. For the years 1994 to 2012, the input-output tables for those periods are used. Finally, the 2012 input-output table estimates are used for all years thereafter.

The upstream spillover variable is constructed using

$$w_{2,ij} = \frac{m_{ji}}{\sum_j m_{ji}}.$$ \hspace{1cm} (3.11)

Unlike the downstream spillover variable, the denominator here does not include total output. We are only concerned about the industries that are important intermediate good suppliers for industry $i$.

### Estimation Results

Direct interpretation of the coefficients of a logit model tells you how the log-odds ratio responds to a unit increase in the covariates. A more informative statistic is to convert the marginal response in the log-odds ratio to a probability. The non-linearity of the logit model, however, leads to differing marginal responses across different values of the explanatory variables.

There are several methods of computing the marginal effects, and two popular methods are the average marginal effect (AME), and marginal effect at the mean (MEM). The MEM is straightforward, for it is just the derivative evaluated at the average value of explanatory variables. For example, the MEM for the variable $z_{k,-l}$, $\text{MEM}_{k,-l}$ is given by

$$\text{MEM}_{k,-l} = \beta_{k,l}f(\bar{x}\theta),$$ \hspace{1cm} (3.12)

where $f(\cdot)$ is the derivative of $F(\cdot)$, with respect to $z_{k,-l}$. The AME, on the other hand, is the average of each industry’s marginal effect, and is given by

$$\text{AME}_{k,-l} = \beta_{k,l}\frac{1}{N} \sum_{i=1}^{N} \frac{1}{T} \sum_{t=1}^{T} f(x_{i,t}\theta).$$ \hspace{1cm} (3.13)

Given that the AME considers the average marginal effect - as opposed to the marginal effect of the “average” industry - it is less likely to be influenced by

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The term “important” is used quite loosely, since the importance of an input also depends on how substitutable it is.
an atypical industry, than the MEM is. For this reason the AME will be used instead of the MEM.

Since the outcome variable depends only on lagged values of the explanatory variables, we have what is called a distributed lag model. Therefore, a marginal increase in the explanatory variable will have marginal impacts that cumulate over time. The plots display the cumulative effect of an incremental increase in the explanatory variables on the probability of reaching a peak or trough. These results are displayed in Figure 3.11. Table 3.8 reports the summary statistics for the spillover indices. The coefficients estimates and average marginal effects for the spillover indices are presented in Table 3.9 in the Appendix. The coefficients on the average for each spillover index are suppressed, as these are generally not interesting.

From Figure 3.11 we see that both the upstream and downstream spillover effects are significant. The probability that an industry reaches its peak increases as both its suppliers and customers reach their peaks. The spillover from other industries during the upturn is also significant, although we see that the effect arising from downstream industries is more pronounced during troughs than it is during peaks. A one standard deviation increase in the downstream index during a trough has almost double the effect on an industry reaching its trough, than a one standard deviation increase in the downstream index has on an industry reaching its peak.

The downstream results are similar to Chang and Hwang (2015). The effect steadily increases over 6 months. For industries entering a recession the downstream effect is stronger and more persistent than the upstream effect.

Industries exiting the recession tend to be affected by both their suppliers and customers. This result is contrary to Chang and Hwang (2015), who find the downstream effect to be small, short lived, and relatively less significant than the upstream effect. Here the downstream effect is of the same magnitude, and more persistent. This result is robust to limiting the analysis to only manufacturing industries.

3.4 Extensions

3.4.1 Employment vs. Hours

The first extension looks at whether the timing of industry peaks/troughs in employment leads, coincides or lags the timing of industry peaks/troughs in total hours. The sample employed in this section is the Current Employment Statistics (CES). The employees considered in the measure of total hours and total employment is limited to production or non-supervisory employees. Production employees in the service industries include all workers who are not in management roles. The data spans from 1990 to 2014 and contains 196 industries in total. To compare the relative timing of the turning points, the
peaks of total hours for each industry are first determined. Then the peak in total employment within 12 months of either side of the peak of total hours is identified. These two dates are then compared. The relative timing for troughs is determined using the same procedure.

Figure 3.12a displays the relative timing of the peak of total hours and total employment. The industries to the left of zero reduce their level of employment before hours, while industries to the right of zero reduce their hours before employment. Most of the industries reach their peak level of employment at the same time as their peak level of total hours. As is evident from the dashed lines, this is true for the median industry and the median service industry. The median goods-producing industry appears to reduce its hours a month prior to its employment. We can see from these plots that for the median sector, the firm is adjusting along its extensive margin first.

Looking at Figure 3.12b, we see that the distribution for troughs has a smaller variance than the distribution in Figure 3.12a. The median industry, whether goods-producing or service-providing, reaches its trough in total hours at the same time as its trough in total employment.

### 3.4.2 Employment vs. Output

The second extension compares the timing of turning points of employment relative to industrial production. Given the nature of the comparison, the analysis is limited to 78 goods-producing industries, 7 of which are logging and mining, one newspaper and publishing, and the remaining 70 are manufacturing industries. For this analysis data from the QCEW from 1990 to 2014 are utilised.

It was previously argued that the results of Chang and Hwang (2015) might not extend to service-providing industries. It might be the case that output phase-shifts are fundamentally different to employment phase-shifts. In this section an attempt is made to provide a tentative answer to this question.

Figure 3.13 displays the relative timing of employment peaks and troughs. Plot 3.13a searches for employment peaks/troughs 24 months on either side of the peak/trough of output. Plot 3.13b searches for employment peaks/troughs 12 months on either side of the peak/trough of output. The motivation for including two plots is to differentiate between industries that continue contracting their employment due to reasons other than business cycle fluctuations. The industries that fall to the left of zero, reach a peak/trough in employment before the peak/trough in output. The opposite holds for the industries that fall to the right of zero.

For the median goods-producing industry, we see that it reaches a peak in output at the same time as the peak in employment, and a trough in output 3 months before the trough in employment. When the window around the peak/trough in output is narrowed to 12 months, the median industry reaches its peak in output 2 months before its peak in employment. The
median industry still reaches a trough in output 3 months before the trough in employment.

What is perhaps more informing is the empirical cumulative density function (ECDF), for it allows one to see at which points the density takes the greatest jump. The window around the peak/trough in output is 12 months. From Figure 3.14 we see that the largest discrete jump for peaks is 3 months after output has reached its peak. Whereas for troughs the largest discrete jump in the ECDF is at the time when output hits its trough. This is in accord with figures 3.12a and 3.12b, where it was shown that the median goods-producing industry reaches a peak in hours before employment, and jointly reaches its trough in employment and hours.

3.5 Conclusion

The investigation into sectoral turning points revealed that the observed growth asymmetry in aggregate employment can be explained by the difference in the number of sectors contracting and expanding around aggregate turning point dates. With more industries contracting around the aggregate peak date than are expanding around the aggregate trough date, and a lack of asymmetry in an industry’s absolute growth rate around its own turning point dates, lends support to this view.

In addition, this paper finds support for the hypothesis that shocks are propagated through the input-output linkages of the economy, showing that if neighbouring industries are contracting/expanding, the likelihood of entering the contraction/expansion phase goes up.
3.6 Appendix

Table 3.1: Bry & Boschan Procedure to Determine Turning Points.

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Determination of extremes and substitution of values. A value is considered extreme if its ratio to a 15 month preliminary unadjusted Spencer curve is 3.5 standard deviations away from the mean of this ratio. The extreme values are substituted with the Spencer curve values for the corresponding dates.</td>
</tr>
<tr>
<td>2</td>
<td>Determination of cycles in 12-month average (extremes replaced).&lt;br&gt;A. Identification of points higher (or lower) than 5 months on either side.&lt;br&gt;B. Enforcement of alternation of turns by selecting highest of multiple peaks (or lower of multiple troughs).</td>
</tr>
<tr>
<td>3</td>
<td>Determination of corresponding turns in Spencer curve (extremes replaced).&lt;br&gt;A. Identification of higher (or lowest) value with ±5 months of selected turn in 12-month moving average.&lt;br&gt;B. Enforcement of minimum cycle duration of 15 months by eliminating lower peaks and higher troughs of shorter cycles.</td>
</tr>
<tr>
<td>4</td>
<td>Determination of corresponding turns in short-term moving average of 3 to 6 months, depending on month of cyclical dominance (MCD).&lt;br&gt;A. Identification of highest (or lowest) values within ±5 months of selected turn in Spencer curve.</td>
</tr>
<tr>
<td>5</td>
<td>Determination of turning points in unsmoothed series.&lt;br&gt;A. Identification of highest (or lowest) value within ±4 months, or MCD term, whichever is larger, of selected turn in short-term moving average.&lt;br&gt;B. Elimination of turns within 6 months of beginning and end of series.&lt;br&gt;C. Elimination of peaks (or troughs) at both ends of series which are lower (or higher) than values closer to end.&lt;br&gt;D. Elimination of cycles whose duration is less than 15 months.&lt;br&gt;E. Elimination of phases whose duration is less than 5 months.</td>
</tr>
<tr>
<td>6</td>
<td>Statement of final turning points.</td>
</tr>
</tbody>
</table>

---

*a* A Spencer curve is a 15-point moving average with the following weights: -3, -6, -5, 3, 21, 46, 67, 74, 67, 46, 21, 3, -5, -6, -3.

*b* The month of cyclical dominance is the shortest span of months for which the I/C ratio is less than unity. I and C are the average month-to-month changes without regard to sign of the irregular and trend-cycle component of the series, respectively. For more details see Shiskin (1960) and Shiskin (1961).

<table>
<thead>
<tr>
<th></th>
<th>Within Only</th>
<th></th>
<th></th>
<th>Total Employment</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Agg Goods</td>
<td>Services</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
<td>Std.</td>
<td>Median</td>
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<td>0.089</td>
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<td>0.113</td>
<td>0.66</td>
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<td></td>
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<td>0.667</td>
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<td>0.113</td>
<td>0.582</td>
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<td>0.282</td>
<td>0.297</td>
<td>0.666</td>
</tr>
<tr>
<td></td>
<td>373</td>
<td>0.667</td>
<td>0.297</td>
<td>0.666</td>
</tr>
<tr>
<td></td>
<td>190</td>
<td>0.299</td>
<td>0.297</td>
<td>0.666</td>
</tr>
<tr>
<td></td>
<td>183</td>
<td>0.282</td>
<td>0.297</td>
<td>0.666</td>
</tr>
</tbody>
</table>

Notes: Trim is the trimmed mean. It involves the calculation of the mean after discarding given parts of the sample at the high and low end. The trimmed mean addresses any issues of outliers. MAD is the median absolute deviation. Within and Between calculates the concordance between industry $i$ and all other industries. The summary statistics are provided for all industries and for two sectors, goods and services. Within Only calculates the concordance between industry $i$ and $j$ where $i$ and $j$ belong to the same sector. This is once again broken down to two sectors. Total Employment determines the concordance between industry $i$ and total private employment, and it is once again broken down into two sectors.
Table 3.3: Detailed Summary Statistics of Concordance: 1990 recession only.

<table>
<thead>
<tr>
<th></th>
<th>Within Only</th>
<th>Within and Between</th>
<th>Total Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Agg</td>
<td>Goods</td>
<td>Services</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
<td>Std.</td>
</tr>
<tr>
<td>Peak</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>373</td>
<td>0.56</td>
<td>0.148</td>
</tr>
<tr>
<td>Mean</td>
<td>190</td>
<td>0.662</td>
<td>0.215</td>
</tr>
<tr>
<td>Std.</td>
<td>183</td>
<td>0.509</td>
<td>0.05</td>
</tr>
<tr>
<td>Median</td>
<td></td>
<td>0.56</td>
<td>0.148</td>
</tr>
<tr>
<td>Trim</td>
<td></td>
<td>0.503</td>
<td>0.019</td>
</tr>
<tr>
<td>MAD</td>
<td></td>
<td>0.504</td>
<td>0.019</td>
</tr>
<tr>
<td>Min</td>
<td>0.503</td>
<td>0.506</td>
<td>0.019</td>
</tr>
<tr>
<td>Max</td>
<td>0.503</td>
<td>0.506</td>
<td>0.019</td>
</tr>
<tr>
<td>Range</td>
<td>0.503</td>
<td>0.506</td>
<td>0.019</td>
</tr>
<tr>
<td>Trough</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>373</td>
<td>0.503</td>
<td>0.019</td>
</tr>
<tr>
<td>Mean</td>
<td>190</td>
<td>0.515</td>
<td>0.062</td>
</tr>
<tr>
<td>Std.</td>
<td>183</td>
<td>0.504</td>
<td>0.036</td>
</tr>
<tr>
<td>Median</td>
<td></td>
<td>0.503</td>
<td>0.019</td>
</tr>
<tr>
<td>Trim</td>
<td></td>
<td>0.503</td>
<td>0.019</td>
</tr>
<tr>
<td>MAD</td>
<td></td>
<td>0.503</td>
<td>0.019</td>
</tr>
<tr>
<td>Min</td>
<td>0.47</td>
<td>0.53</td>
<td>0.016</td>
</tr>
<tr>
<td>Max</td>
<td>0.57</td>
<td>0.53</td>
<td>0.016</td>
</tr>
<tr>
<td>Range</td>
<td>0.57</td>
<td>0.53</td>
<td>0.016</td>
</tr>
</tbody>
</table>

Notes: Trim is the trimmed mean. It involves the calculation of the mean after discarding given parts of the sample at the high and low end. The trimmed mean addresses any issues of outliers. MAD is the median absolute deviation. Within and Between calculates the concordance between industry $i$ and all other industries. The summary statistics are provided for all industries and for two sectors, goods and services. Within Only calculates the concordance between industry $i$ and $j$ where $i$ and $j$ belong to the same sector. This is once again broken down to two sectors. Total Employment determines the concordance between industry $i$ and total private employment, and it is once again broken down into two sectors.
Table 3.4: Detailed Summary Statistics of Concordance Indices: 2001 and 2008 recessions.

<table>
<thead>
<tr>
<th></th>
<th>Within Only</th>
<th>Within and Between</th>
<th>Total Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Agg Goods Services</td>
<td>Agg Goods Services</td>
<td>Agg Goods Services</td>
</tr>
<tr>
<td>Peak</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>302</td>
<td>120</td>
<td>182</td>
</tr>
<tr>
<td>Mean</td>
<td>0.543</td>
<td>0.625</td>
<td>0.524</td>
</tr>
<tr>
<td>Std.</td>
<td>0.095</td>
<td>0.162</td>
<td>0.05</td>
</tr>
<tr>
<td>Median</td>
<td>0.572</td>
<td>0.748</td>
<td>0.547</td>
</tr>
<tr>
<td>Trim</td>
<td>0.553</td>
<td>0.655</td>
<td>0.527</td>
</tr>
<tr>
<td>MAD</td>
<td>0.081</td>
<td>0.046</td>
<td>0.037</td>
</tr>
<tr>
<td>Min</td>
<td>0.373</td>
<td>0.252</td>
<td>0.373</td>
</tr>
<tr>
<td>Max</td>
<td>0.627</td>
<td>0.748</td>
<td>0.627</td>
</tr>
<tr>
<td>Range</td>
<td>0.253</td>
<td>0.495</td>
<td>0.253</td>
</tr>
<tr>
<td>Trough</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>302</td>
<td>120</td>
<td>182</td>
</tr>
<tr>
<td>Mean</td>
<td>0.508</td>
<td>0.518</td>
<td>0.514</td>
</tr>
<tr>
<td>Std.</td>
<td>0.015</td>
<td>0.044</td>
<td>0.042</td>
</tr>
<tr>
<td>Median</td>
<td>0.506</td>
<td>0.539</td>
<td>0.537</td>
</tr>
<tr>
<td>Trim</td>
<td>0.506</td>
<td>0.52</td>
<td>0.516</td>
</tr>
<tr>
<td>MAD</td>
<td>0.018</td>
<td>0.026</td>
<td>0.027</td>
</tr>
<tr>
<td>Min</td>
<td>0.468</td>
<td>0.444</td>
<td>0.432</td>
</tr>
<tr>
<td>Max</td>
<td>0.553</td>
<td>0.573</td>
<td>0.576</td>
</tr>
<tr>
<td>Range</td>
<td>0.085</td>
<td>0.129</td>
<td>0.144</td>
</tr>
</tbody>
</table>

Notes: Trim is the trimmed mean. It involves the calculation of the mean after discarding given parts of the sample at the high and low end. The trimmed mean addresses any issues of outliers. MAD is the median absolute deviation. Within and Between calculates the concordance between industry i and all other industries. The summary statistics are provided for all industries and for two sectors, goods and services. Within Only calculates the concordance between industry i and j where i and j belong to the same sector. This is once again broken down to two sectors. Total Employment determines the concordance between industry i and total private employment, and it is once again broken down into two sectors.
3.6. APPENDIX

Table 3.5: Employment growth rates surrounding the peak and trough dates of 1980 and 1981 and 1990 recessions in %.

<table>
<thead>
<tr>
<th>Relative to:</th>
<th>$g_{i,P,+6}$</th>
<th>$g_{i,T,+6}$</th>
<th>$g_{i,P,-6}$</th>
<th>$g_{i,T,-6}$</th>
<th>$SP$</th>
<th>$ST$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td>-2.613</td>
<td>2.495</td>
<td>1.591</td>
<td>-2.324</td>
<td>4.696</td>
<td>5.266</td>
</tr>
<tr>
<td>NBER</td>
<td>-.917</td>
<td>.695</td>
<td>.780</td>
<td>-1.939</td>
<td>3.328</td>
<td>3.851</td>
</tr>
<tr>
<td>TPE</td>
<td>-2.057</td>
<td>1.020</td>
<td>.0791</td>
<td>-1.026</td>
<td>3.483</td>
<td>3.532</td>
</tr>
</tbody>
</table>

Notes: Letting $g_{i,P,-6}$ and $g_{i,P,+6}$ denote, respectively, the 6-month growth rates of industry i employment before and after the benchmark peaks, $g_{i,P,-6} = \text{median}(g_{i,P,-6})$, $g_{i,P,+6} = \text{median}(g_{i,P,+6})$, and $SP = \text{median}(|g_{i,P,-6} - g_{i,P,+6}|)$. $g_{i,T,-6}$, $g_{i,T,+6}$ and $ST$ are defined in a similar way for the troughs. Sharpness asymmetry is $ST - SP$. I perform a Wilcoxon rank-sum test (the growth rates are highly skewed) on $g_{i,P,+6}$ and $-g_{i,T,+6}$ and find no statistical difference at the 10% significance level when the growth rates are evaluated around the industry’s own peak and trough dates. Performing the same test around the total employment peak and trough dates, I find a statistical difference at the 1% significance level. There is no statistical difference at the 10% level of significance between $SP$ and $ST$ when evaluated around the peak and trough dates of total private employment, however there is a statistical difference at the 5% level when evaluated around an industry’s own peak and trough dates. Turning points between the years 1978-1984 and 1988-1993 are selected to calculate the growth rates around an industry’s own peak and trough dates.

Table 3.6: Employment growth rates surrounding the peak and trough date of the 1990 recession in %.

<table>
<thead>
<tr>
<th>Relative to:</th>
<th>$g_{P,+6}$</th>
<th>$g_{T,+6}$</th>
<th>$g_{P,-6}$</th>
<th>$g_{T,-6}$</th>
<th>$SP$</th>
<th>$ST$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td>-2.007</td>
<td>1.823</td>
<td>1.114</td>
<td>-1.778</td>
<td>3.842</td>
<td>3.851</td>
</tr>
<tr>
<td>NBER</td>
<td>-1.974</td>
<td>-.252</td>
<td>.224</td>
<td>-2.405</td>
<td>2.851</td>
<td>3.081281</td>
</tr>
<tr>
<td>TPE</td>
<td>-2.405</td>
<td>.402</td>
<td>-.282</td>
<td>-.775</td>
<td>2.890</td>
<td>2.409</td>
</tr>
</tbody>
</table>

Notes: I perform a Wilcoxon rank-sum test on $g_{P,+6}$ and $-g_{T,+6}$ and find no statistical difference at the 10% significance level when the growth rates are evaluated around the industry’s own peak and trough date. Performing the same test around the total employment peak and trough dates, I find a statistical difference at the 1% significance level. There is no statistical difference at the 10% level of significance between $SP$ and $ST$ when evaluated around an industry’s own peak and trough dates, however there is a statistical difference at the 10% level when evaluated around the peak and trough dates of total private employment. Turning points between the years 1988-1993 are selected to calculate the growth rates around an industry’s own peak and trough dates.
Table 3.7: Employment growth rates surrounding the peak and trough dates of 2001 and 2008 recessions in %.

<table>
<thead>
<tr>
<th>Relative to:</th>
<th>$g_{P,+6}$</th>
<th>$g_{T,+6}$</th>
<th>$g_{P,-6}$</th>
<th>$g_{T,-6}$</th>
<th>$S_P$</th>
<th>$S_T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td>-1.553</td>
<td>1.474</td>
<td>1.135</td>
<td>-.968</td>
<td>2.922</td>
<td>2.718</td>
</tr>
<tr>
<td>NBER</td>
<td>-1.000</td>
<td>-1.100</td>
<td>-.0461</td>
<td>-2.786</td>
<td>1.769</td>
<td>3.032</td>
</tr>
<tr>
<td>TPE</td>
<td>-.936</td>
<td>.211</td>
<td>.249</td>
<td>-.836</td>
<td>1.826</td>
<td>2.100</td>
</tr>
</tbody>
</table>

Notes: I perform a Wilcoxon rank-sum test on $g_{P,+6}$ and $-g_{T,+6}$ and find no statistical difference at the 10% significance level when the growth rates are evaluated around the industry’s own peak and trough dates. Performing the same test around the total employment peak and trough dates, I find a statistical difference at the 1% significance level. There is no statistical difference at the 10% level of significance between $S_P$ and $S_T$ when evaluated around an industry’s own peak and trough dates, or the peak and trough dates of total private employment. Turning points between the years 2000-2011 are selected to calculate the growth rates around an industry’s own peak and trough dates.

Table 3.8: Summary Statistics of Spillover Indices.

<table>
<thead>
<tr>
<th></th>
<th>Peak Dowstream</th>
<th>Peak Upstream</th>
<th>Trough Dowstream</th>
<th>Trough Upstream</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.015</td>
<td>0.025</td>
<td>0.015</td>
<td>0.026</td>
</tr>
<tr>
<td>Std.</td>
<td>0.053</td>
<td>0.072</td>
<td>0.058</td>
<td>0.073</td>
</tr>
</tbody>
</table>

Notes: Downstream is the product of 1) the fraction of an industry’s total output consumed by an industry downstream, and 2) an indicator variable equal to 1 if the downstream industry reached a peak, summed across all industries. Upstream is constructed in a similar way. It is the product of 1) the fraction of intermediate inputs supplied by an upstream industry, and 2) an indicator variable equal to 1 if the upstream industry reach a peak, summed across all industries. For troughs the relevant indicator variables are not whether the downstream or upstream industries reached a trough.
### Table 3.9: Coefficient Estimates and Average Marginal Effects.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Peak</th>
<th>Trough</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>AME</td>
</tr>
<tr>
<td>Lag 6</td>
<td>2.180**</td>
<td>0.0276*</td>
</tr>
<tr>
<td></td>
<td>(0.845)</td>
<td>(0.0108)</td>
</tr>
<tr>
<td>Lag 7</td>
<td>1.488</td>
<td>0.0189</td>
</tr>
<tr>
<td></td>
<td>(1.050)</td>
<td>(0.0133)</td>
</tr>
<tr>
<td>Lag 8</td>
<td>0.708</td>
<td>0.00898</td>
</tr>
<tr>
<td></td>
<td>(1.306)</td>
<td>(0.0166)</td>
</tr>
<tr>
<td>Lag 9</td>
<td>-0.0440</td>
<td>-0.000558</td>
</tr>
<tr>
<td></td>
<td>(1.716)</td>
<td>(0.0218)</td>
</tr>
<tr>
<td>Lag 10</td>
<td>0.817</td>
<td>0.0104</td>
</tr>
<tr>
<td></td>
<td>(1.395)</td>
<td>(0.0177)</td>
</tr>
<tr>
<td>Lag 11</td>
<td>1.393</td>
<td>0.0177</td>
</tr>
<tr>
<td></td>
<td>(1.009)</td>
<td>(0.0128)</td>
</tr>
<tr>
<td>Lag 12</td>
<td>-4.630</td>
<td>-0.0587</td>
</tr>
<tr>
<td></td>
<td>(3.672)</td>
<td>(0.0467)</td>
</tr>
</tbody>
</table>

**Upstream**

| Lag 6 | 3.790*** | 0.0481*** | 1.842 | 0.0240 |
|       | (0.812) | (0.0105) | (0.997) | (0.0130) |
| Lag 7 | 0.985 | 0.0125 | 1.567 | 0.0204 |
|       | (1.356) | (0.0172) | (1.051) | (0.0137) |
| Lag 8 | 2.631** | 0.0334** | 1.077 | 0.0140 |
|       | (0.976) | (0.0125) | (1.152) | (0.0150) |
| Lag 9 | -1.566 | -0.0199 | 0.0242 | 0.000315 |
|       | (2.037) | (0.0258) | (1.444) | (0.0188) |
| Lag 10 | -4.450 | -0.0564 | 0.376 | 0.00489 |
|       | (2.646) | (0.0337) | (1.347) | (0.0175) |
| Lag 11 | 1.745 | 0.0221 | 0.917 | 0.0119 |
|       | (1.135) | (0.0144) | (1.214) | (0.0158) |
| Lag 12 | 0.833 | 0.0106 | 2.022* | 0.0263* |
PHASE-SHIFTS IN US SECTORAL EMPLOYMENT

(1.450)  (0.0184)  (0.975)  (0.0127)

Observations 34,727  34,727  34,008  34,008

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

Note: Upstream refers to shocks coming from up the stream, i.e. industries which supply to industry $i$. Downstream refers to shocks coming from down the stream, that is industries which demand from industry $i$. The lags refer to the monthly lags of the spillover variables.

Figure 3.1: Fraction of Industries Contracting: 1978-1996.

Note: The figure shows the fraction of industries experiencing a contraction at a given point in time, known as the diffusion index. The shaded region is the dates in which total employment was contracting. The region between the dashed lines is the NBER recession dates. ‘Agg’ is the set of all industries. ‘Goods’ is the set of goods-producing industries. ‘Services’ is the set of service-providing industries, and ‘AggW’ is the set of all industries, but each industry is weighted by its employment share.
Figure 3.2: Fraction of Industries Contracting: 1998-2012.

Note: The figure shows the fraction of industries experiencing a contraction at a given point in time, known as the diffusion index. The shaded region is the dates in which total employment was contracting. The region between the dashed lines is the NBER recession dates. ‘Agg’ is the set of all industries. ‘Goods’ is the set of goods-producing industries. ‘Services’ is the set of service-providing industries, and ‘AggW’ is the set of all industries, but each industry is weighted by its employment share.
Figure 3.3: Distribution of industry turning points: 1981 recession.

Note: (a) displays the histogram density plot of the difference in timing relative to total private employment that an industry reaches its peak. To the left of zero represents industries that are leading, and to the right of zero represents the industries lagging total private employment. (b) is the same as (a) but for industry troughs. ‘A’ denotes all industries, ‘G’ is the set of goods-producing industries and ‘S’ is the set of service-providing industries.

Figure 3.4: Distribution of industry turning points: 1981 recession.

Note: (a) displays the histogram of the difference in timing relative to the NBER peak date. To the left of zero represents industries that are leading, and to the right of zero represents the industries lagging the aggregate economy. (b) is the same as (a) but for industry troughs. ‘A’ denotes all industries, ‘G’ is the set of goods-producing industries and ‘S’ is the set of service-providing industries.
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Figure 3.5: Distribution of industry turning points: 1990 recession.

Note: (a) displays the histogram density plot of the difference in timing relative to total private employment that an industry reaches its peak. To the left of zero represents industries that are leading, and to the right of zero represents the industries lagging total private employment. (b) is the same as (a) but for industry troughs. ‘A’ denotes all industries, ‘G’ is the set of goods-producing industries and ‘S’ is the set of service-providing industries.

Figure 3.6: Distribution of industry turning points: 1990 recession.

Note: (a) displays the histogram of the difference in timing relative to the NBER peak date. To the left of zero represents industries that are leading, and to the right of zero represents the industries lagging the aggregate economy. (b) is the same as (a) but for industry troughs. ‘A’ denotes all industries, ’G’ is the set of goods-producing industries and ‘S’ is the set of service-providing industries.
Figure 3.7: Distribution of industry turning points: 2001 and 2008 recessions.

Note: (a) displays the histogram density plot of the difference in timing relative to total private employment that an industry reaches its peak. To the left of zero represents industries that are leading, and to the right of zero represents the industries lagging total private employment. (b) is the same as (a) but for industry troughs. ‘A’ denotes all industries, ‘G’ is the set of goods-producing industries and ‘S’ is the set of service-providing industries.

Figure 3.8: Distribution of industry turning points: 2001 and 2008 recessions.

Note: (a) displays the histogram of the difference in timing relative to the NBER peak date. To the left of zero represents industries that are leading, and to the right of zero represents the industries lagging the aggregate economy. (b) is the same as (a) but for industry troughs. ‘A’ denotes all industries, ‘G’ is the set of goods-producing industries and ‘S’ is the set of service-providing industries.
Figure 3.9: Distribution of industry growth rates around peak/trough dates: 1978-1984 & 1988-1993.

Note: (a) displays the histogram of the growth rates from an industry’s peak (trough) to six months following the peak (trough). The growth rates around the trough are multiplied by -1 in order to make the superimposed histograms comparable. (b) displays the histogram of the growth rates around the peak and trough dates of total private employment.

Figure 3.10: Distribution of industry growth rates around peak/trough dates: 2000-2011.

Note: (a) displays the histogram of the growth rates from an industry’s peak (trough) to six months following the peak (trough). The growth rates around the trough are multiplied by -1 in order to make the superimposed histograms comparable. (b) displays the histogram of the growth rates around the peak and trough dates of total private employment.
Figure 3.11: Average Marginal Effects.

Notes: The thick solid lines are the cumulative average marginal effects. The dashed lines represent the 95% confidence interval. Upstream = shocks from suppliers. Downstream = shocks from customers.
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Figure 3.12: Distribution of industry turning points.

\[ \text{(a) Peak.} \quad \text{(b) Trough.} \]

*Note:* (a) displays the kernel density plot of the difference in timing of an industry’s employment peak relative to its total hours peak. To the left of zero represents industries that first adjust employment, and to the right of zero represents industries that first adjust hours. (b) is the same as (a) but for industry troughs.

Figure 3.13: Distribution of industry turning points: Output vs. Employment.

\[ \text{(a) } \pm 24 \text{ month window.} \quad \text{(b) } \pm 12 \text{ month window.} \]

*Notes:* The solid thick line is the distribution for the peaks, while the dashed line is the distribution for the troughs. To the left of zero represents industries that first adjust employment, and to the right of zero represents industries that first adjust output. (a) compares the relative timing of employment peak to the peak of output. It looks for the closest peak in employment 24 months around the peak of output. (b) is the same as (a), but the window is narrowed to 12 months.
Figure 3.14: ECD of industry turning points: Output vs. Employment.

Notes: The solid thick line is the empirical cumulative distribution (ECD) for the peaks, while the dashed line is the ECD for troughs.
Chapter 4

What is the Informational Content of Business and Household Surveys and when should we use them?

Initial Gross Domestic Product (GDP) estimates in Australia are published 2 months after the end of the reference quarter. This is a significant delay, and creates a need to now-cast GDP. Two sets of surveys, business and household, are published in a timely manner. This paper assesses these surveys’ ability to now-cast GDP, and anticipate discrete economic developments. The performance of the models containing the surveys are compared to benchmark models not containing the surveys. The results show that while the surveys cannot outperform the benchmark models in now-casting GDP, they do a relatively good job at anticipating economic events, especially when they signal GDP growth rates that are less frequent. A factor model summarising the information within the monthly economic indicators is shown to generate substantial improvement in now-cast accuracy compared to the survey and benchmark models.

4.1 Introduction

In Australia, national accounts are published a full two months after the end of the quarter. Furthermore, the initial release of GDP is subject to revisions in subsequent quarters.

In contrast to other countries, such as the US, for instance, information on industrial production, consumption, and income are all published quarterly either within national accounts, or a few days before its release.

The delay presents a challenge for policy makers, who must make decisions on the state of the economy with information that may not be timely. Further,
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monthly economic indicators published by Australia’s statistical agency, the Australian Bureau of Statistics (ABS), may also involve significant lags and do not cover all sectors of the economy. For example, monthly statistics on retail sales, international trade, and construction approvals are published four to five weeks after the end of the reference month and ignore large parts of the service-providing sector. The lack of timely real economic indicators in Australia makes it difficult to form reliable now-casts of current quarter GDP. Given the challenges regarding official releases of national accounts data, the full use of real-time datasets, which include past vintages of national accounts, business survey data, household survey data and monthly economic indicators, can potentially fill the gap and assist with making decisions in real-time.

GDP, which is the most comprehensive measure of economic activity, is ultimately determined by decisions made by businesses and households. Business surveys typically include questions on decision variables such as output, employment and prices. The composite index constructed from the responses to these variables, may be used to provide a timely read on current economic conditions. The decisions made by businesses in turn impact the budgetary situation of the household sector, affecting their sentiment. Thus, household sentiment surveys may also provide a timely read on the current economic conditions. Finally, if decisions by economic agents display persistence or if accurate information takes time to collect, then past GDP growth rates and revisions can be used to generate more accurate now-casts.

Against this backdrop, one of the main tasks for economic forecasters is to discern which variables are relevant in understanding the current state of the economy. The aim of this paper is to provide direction in regards to the value of different datasets that are available before the release of national accounts. For example, are survey variables useful in now-casting GDP or do they only introduce noise? How do they fare against the monthly indicators published by the ABS?

This paper examines the informational content of national accounts real-time data, business survey data, household survey data, and monthly ABS indicators, by assessing their ability to now-cast the initial GDP growth rate published by the ABS and predict discrete economic events in real-time. While the surveys are constructed to provide a measure of industry and household activity, their benefits in now-casting GDP have not been rigorously assessed. In Australia the primary surveys relating to business conditions are the National Australia Bank (NAB) Quarterly/Monthly Business Survey, Australia Industry Group (AIG) Performance Indices, and the Australian Chamber of Commerce and Industry (ACCI) Industrial Trends Survey. There are two household surveys, the Westpac - Melbourne Institute Survey of Consumer Sentiment and the ANZ - Roy Morgan Consumer Confidence Rating, which are the best known measures of household sentiment in Australia. These surveys are published in a relatively timely manner, typically within 2 weeks of the end of the reference period.
Apart from their timeliness, the business surveys also provide a broader impression of economic activity than national accounts data. The survey responses are weighted by the number of firms in the sector, as opposed to the value-add of the sector. Consequently the resources sector is given a smaller weight, making the surveys less volatile than the corresponding official data. Thus, changes in the business survey represents a broad changes in economic activity and may help in discerning the underlying trends in economic activity and capturing turning points.

To assess the informational content of the different datasets, a VAR framework is employed that incorporates GDP with GDP revisions, business and household surveys, and common factors extracted from the monthly economic indicators published by the ABS. The predictive performance of these models is assessed against a bench mark auto-regressive model using statistical criteria.

In terms of point now-casts this paper finds that the business and household surveys generate now-casts that are not statistically different from the benchmark model consisting of lagged values of GDP, and the VAR model containing GDP revisions. However, when considering forecasts of discrete events, the models containing the surveys, out-perform both the AR model and VAR model containing revisions. There is evidence that the surveys are better at anticipating periods of less frequent growth rates; the business survey anticipating periods of above average growth rates, while the household survey anticipating periods of below average growth rates, and periods where GDP growth moves from being above (below) average in the current period to below (above) average in the next period.

The survey and benchmark models are out-performed by the factor model in generating point now-casts. The factor model generates significantly smaller now-cast errors than either of the models. The factor model also has greater success at anticipating some but not all of the discrete economic events considered in this paper. The factor model does not out-perform the survey models in anticipating the above mentioned events.

A short-coming of the factor model, however, is that the monthly indicators used to determine the factors suffer from publication delay, with the typical publication lag being 4 weeks. Constructing a factor model that is just as timely as the household and business surveys, leads to now-casts that are still superior to any of the models.

In conclusion, while the surveys cannot generate now-casts that can out-perform the benchmark or factor model, they can anticipate specific economic developments. In particular, the business and household surveys are a reliable source of reference in terms of signalling extreme growth rates beyond the use of the factor models.

The remainder of the paper is organised as follows. Section 2 presents the literature on real-time data used for forecasting. Sections 2-4 present the methodology and data employed in the analysis. Section 6 presents the results,
4.2 Literature

Two strands of literature are relevant to the thesis of this paper. The first relates to the modelling and use of first release and revision data to generate GDP now-casts. The second strand relates to the value of business and household survey data to forecast macroeconomic series. The existing research falls into either of the two camps, with very little research crossing over.

Many economic time series are subject to revision. Revisions to GDP are sometimes large, systematic, and may occur several quarters after the initial release. For this reason many researchers have investigated the benefits of accounting for the revision process and the pitfalls of avoiding them. Garratt, Lee, Mise, and Shields (2008) and Lee, Olekalns, Shields, and Wang (2012) illustrated the uncertainties in estimating the US and Australian output gap in real-time due to revisions. In considering Australian GDP data, Bajada (2002) found systemic patterns in the revisions. Aristidou, Lee, Shields, et al. (2018) show that incorporating past revisions to GDP in the vector-autoregression leads to statistically significant improvements in US GDP now-casts.

Diebold and Rudebusch (1991) and Swanson (1996) have noted that the use of current-vintage data can lead a researcher to include variables in their models that in real time, have little marginal predictive power. It can also lead to an exaggerated assessment of the forecasting performance of a model relative to alternative models and relative to predictions that were actually available at the time (Fair and Shiller (1990), Orphanides (2003)).

Many authors have also assessed the value of business survey data in forecasting GDP growth in other countries. Very few, however, have assessed the usefulness of business survey data in an Australia context. Aylmer, Gill, et al. (2003) examine the informational content of various Australian business surveys. They construct simple auto-regressive models of GDP with survey indices to test the ability of the business survey in explaining the variation of GDP and final demand growth. They find that business surveys provide a timely read on domestic demand as well as information about

1The more recent literature on now-casting has typically focused on evaluating the marginal impact that intra-monthly data releases have on current-quarter forecasts (see Giannone, Reichlin, and Small (2008), Aruoba, Diebold, and Scotti (2009), Banbura, Giannone, Modugno, and Reichlin (2013b) and Aastveit, Gerdrup, Jore, and Thorsrud (2014)). However, this is not the focus of this paper.

2Gruen, Robinson, and Stone (2005) showed that calculating the real-time output gap in Australia, is not due to uncertainties in the revisions of GDP but the end-point problem in many filtering techniques. The discrepancies in the two papers are due to the way potential output is determined. Lee, Olekalns, Shields, and Wang (2012) accommodate the problem with end-points.
how the economy is expected to evolve. Wang and Berger-Thomson (2015) perform similar analysis using the household sentiment surveys. They find that surveys provide timely information about economic developments (especially in household consumption), however, they also find that the strength of the relationship between the household surveys and key macroeconomic variables varies across time.

Internationally, Lahiri and Monokroussos (2013) use the responses from the business survey produced by the Institute for Supply Chain Management (ISM) to assess its ability to improve US now-casts. The ISM business survey is similar to the NAB Business Survey in that it asks questions on production, employment and inventory levels. The authors find that indices within the survey improve now-casts prior to the release of monthly economic indicators. The authors conclude that the main contribution of the survey data is their timeliness.

Angelini, Camba-Mendez, Giannone, Reichlin, and Rünstler (2011) also construct a now-casting model, but for the Euro area. Their now-casting model is based on a dynamic factor model, which incorporates both real economic indicators and survey variables. While this paper does not set out to assess ability of survey data to improve GDP forecasts, the authors do find that the survey information leads to factors which better now-cast GDP.

Matheson (2010) examines the marginal value of different New Zealand (NZ) data-set’s towards forecasting key NZ economic variables. As in this paper, he extracts the common factors from the different series, using these factors to forecast GDP and inflation. He finds that factors that incorporate business survey data provide better predictions compared to factors extracted in the absence of these surveys.

Other papers, such as Martinsen, Ravazzolo, and Wulfsberg (2014), Hansson, Jansson, and Löl (2005) and Golinelli and Parigi (2007) directly assess the contribution of business survey data towards improving GDP forecasts for several European countries. The authors all find that the survey data tends to improve forecasts compared to benchmark auto-regressive models.

While these papers are similar in nature to what this paper attempts to achieve, here we go beyond them in at least one of four aspects. First, by assessing the survey variables’ out-of-sample now-cast performance. Second, by comparing the informational content of the survey data to a composite index of monthly indicators published by the ABS, not just an auto-regressive model. Third, by taking into account the revision process, and lastly by assessing the different variables’ performance to anticipate discrete economic events.
4.3 Modelling Framework

The first challenge for the paper is to set out a modelling framework that can accommodate revisions and survey data coherently along with the first release data.

In what follows, \( y_{t-s} \) is the measure of GDP at time \( t-s \) (in log units) as released at time \( t \), while \( b_{t+s} \) and \( h_{t+s} \) is a direct measure of the business and household surveys at \( t+s \).

GDP is published with a one period delay, and the time \( t-vintage \) of the data is denoted as

\[
Y^t = \{ y_1, y_2, ..., y_{t-2}, y_{t-1}, b_2, b_3, ..., b_{t-1}, b_t, h_2, h_3, ..., h_{t-1}, h_t \},
\]

The time \(- (t+1)\) measure of GDP is simply the time \(- t\) measure plus the revision; that is, \( \exp(y_{t+1}) = \exp(y_{t-1}) + (\exp(y_{t+1}) - \exp(y_{t+1})) \). This means that the now-casted GDP growth rate includes one revision. If lagged GDP values, surveys and first revision, provide measures of the first revised measure of GDP, in making a decision at time \( t \), we can use a model that explains the following \( n=4 \) series each published in time \( t \):

\[
\begin{align*}
    g_{t}^y &= y_{t-1} - y_{t-2} : \text{growth in } y_{t-1}, \text{ which represents the first release growth rate (diagonal)} \\
    g_{t}^{r1} &= y_{t-2} - y_{t-2} : \text{first revision of } y_{t-2} \\
    g_{t+1}^b &= b_{t+1} : \text{contemporaneous value of } b_{t+1} \\
    g_{t+1}^h &= h_{t+1} : \text{contemporaneous value of } h_{t+1}.
\end{align*}
\]

The target variable is the initial release growth rate of GDP, as published by the statistical agency in period \( t+1 \):

\[
g_{t+1}^y = y_{t+1} - y_{t-1}
\]

where \( y_{t-1}^{t+1} \) has undergone one revision.

4.3.1 Basic VAR

The endogeneity of the series means that the appropriate modelling framework is a vector auto-regression (VAR). Economic decisions are made by economic agents to determine the actual values of the variables at each time, and the economic outcomes are measured reflecting the data collection and survey practices of the statistical agency. As an example, in making output and investment decisions, businesses are impacting both the business survey and the GDP measures. These decisions, through their effects on household
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budgets, feedback to household sentiment, impacting the household survey. If businesses expectations are formed on the variables by those same households, household sentiment will in turn be feeding back onto business decisions and outcomes. A simple $p$-order vector auto-regression can capture the interdependence between the series, and for this problem is given by:

$$g_t = \alpha_{10} + \sum_{k=1}^{p} \left[ \alpha_{11k} g_{t-k} + \alpha_{12k} g_{1,t-k} + \alpha_{13k} g_{t-k+1} + \alpha_{14k} g_{t-k+1} \right] + \epsilon_{1,t}$$

(4.2)

$$g_{1,t} = \alpha_{20} + \sum_{k=1}^{p} \left[ \alpha_{21k} g_{t-k} + \alpha_{22k} g_{1,t-k} + \alpha_{23k} g_{t-k+1} + \alpha_{24k} g_{t-k+1} \right] + \epsilon_{2,rt}$$

(4.3)

$$g_{t+1} = \alpha_{30} + \sum_{k=1}^{p} \left[ \alpha_{31k} g_{t-k} + \alpha_{32k} g_{1,t-k} + \alpha_{33k} g_{t-k+1} + \alpha_{34k} g_{t-k+1} \right] + \epsilon_{3,t}$$

(4.4)

$$g_{t+1} = \alpha_{40} + \sum_{k=1}^{p} \left[ \alpha_{41k} g_{t-k} + \alpha_{42k} g_{1,t-k} + \alpha_{43k} g_{t-k+1} + \alpha_{44k} g_{t-k+1} \right] + \epsilon_{4,t}$$

(4.5)

where the $\alpha$'s are coefficients and $\epsilon$'s are vectors of mean zero shocks with distribution $\epsilon_{i,t} \sim N(0, \sigma_i)$ for all $t$. The shocks represent the variation in each series that cannot be accounted for by own and cross lags of the variables. They are assumed to be independent across equations. The errors in equations (4.2) and (4.3) have another interpretation: $\epsilon_{1,t}$ is the “news” on output level in time $t - 1$ contained in the first-release data becoming available at time $t$; and $\epsilon_{2,rt}$, is the “news” on the level of output in time $t - 2$ contained in the revised data becoming available at time $t$.

4.3.2 Factor Augmented VAR

No single time series may correspond precisely to GDP. The concept of GDP, for example, may not be perfectly represented by business and household surveys. To now-cast GDP, one might wish to include multiple indicators including, say, employment and retail sales, and construction starts, which are published before national accounts.

Unfortunately, if the number of predicator variables is large, a VAR of the form specified in the previous section may not be well suited for constructing prediction models, as they would involve the estimation of a large number of coefficients, leading to degrees-of-freedom problem.

Research into factor models suggests that the information from a large number of time series can be usefully summarised by a relatively small num-
ber of estimated indexes, or factors. For example, Stock and Watson (2002) develop an approximate dynamic factor model to summarise the information in large data sets to forecast GDP. They show that forecasts based on these factors outperform univariate autoregressions, small VARs, and leading indicator models in simulated forecasting exercises.

If a small number of estimated factors effectively summarise large amounts of information about GDP, then a solution to the degrees-of-freedom problem in VAR analyses is to augment standard VAR with estimated factors. This is the approach adopted by Bernanke, Boivin, and Eliasz (2005) to map out the effect of monetary policy innovations on the economy.

In this analysis 20 monthly economic indicators are used (which are aggregated into quarterly frequencies), so to avoid parameter proliferation but at the same time capture all the relevant information in the data, this paper adopts the factor augmented VAR approach as a competing model.

To extract the common components, each series $i$ in quarter $t$, $X_{i,t}$ is modelled as the sum of two components. The first, an unobserved factors, $F_t$, captures the joint dynamics, and the second an idiosyncratic residual, $\varepsilon_{i,t}$, which is uncorrelated with the other series. In vector notation the model is

$$X_t = \Lambda F_t + \varepsilon_t, \text{ where } \varepsilon_t \sim N(0, \Sigma_\varepsilon),$$

where $\Lambda$ is a matrix of factor loadings, and $\Sigma_\varepsilon$ is a covariance matrix which is assumed to be diagonal. Each series are therefore only related through the common factors.

All series are made stationary and standardised to have mean 0 standard deviation 1. If there is a high degree of co-movement among the series, most of the dynamics can be captured by a few factors or common components. There is extensive macro-econometric literature indicating that this is in fact the case (see Stock and Watson (2011) for a recent survey).

Some of the economic indicators have different start dates. This means that in the beginning of the dataset, some variables will contain missing values. If one were to use principal component to extract the common factor, we would have to construct a complete matrix, where we drop any row that contains missing values. If we however, cast the evolution of the factors in state-space form, we can use the Kalman filter to extract the factors. The Kalman Filter can easily accommodate missing values. To apply the Kalman filtering techniques we have to further specify the structure of the model. The dynamics of the common factor are parameterised as a vector auto-regression with 1 lag\footnote{A higher order VAR can be considered, but this adds considerable computational time and the additional parameters needed to be estimated will increase the uncertainty in $\Phi$, potentially undermining the results.}, so for quarter $t$ the factor is evolving according to:

$$F_t = \Phi F_{t-1} + \nu_t, \text{ where } \nu_t \sim N(0, \Sigma_\nu).$$

(4.7)
The Expectation Maximisation (EM) algorithm as proposed by Shumway and Stoffer (1982) and Watson and Engle (1983) can be used to estimate the parameters of the model, and this is what is used in this paper. The EM tool is useful to estimate parameters with unobserved components and missing observations. In the EM algorithm two operations iterate between:

1. compute the expectation of the log-likelihood conditional on the data using the parameter estimates from the previous iteration (the expectation is computed via the Kalman Filter and Smoother)
2. re-estimate the parameters through the maximisation of the expected log-likelihood.

until convergence.

Using the EM algorithm compared to principal components has a number of advantages. First it is more efficient in small systems, and second it can deal with missing observations.

The EM algorithm needs to be initialised with initial values for the factors, $F$, and the parameters $\Phi, \Lambda, \Sigma_\epsilon$ and $\Sigma_\nu$. Principal component analysis can be used to determine the factors on the balance data-set (where rows with missing information are removed). The initial values of $F$ are set to the mean value of principal components. The rest of the parameters can be determined by either regressing the individual series against the principal components, or regressing the principal components against their lagged values. This procedure is used in other applied work (see for example Bańbura, Giannone, Modugno, and Reichlin (2013a) and Bańbura and Rünstler (2011)) and is adopted in this paper. Estimation via the EM algorithm is discussed further in the Appendix.

The factor $F_t$ enters the VAR of Section 3.1 to form a factor augmented VAR. For notational consistency $F_t$ henceforth will be denoted as $g^F_t$. The new system of equations can be written as follows:

$$g^y_t = \alpha_{10} + \sum_{k=1}^p \left[ \alpha_{11k} g^y_{t-k} + \alpha_{12k} g^v_{t-k} + \alpha_{13k} g^F_{t-k+1} + \alpha_{14k} g^h_{t-k+1} + \alpha_{15k} g^F_{t-k+1} \right] + \epsilon_{1,t} \tag{4.8}$$

$$g^r_{r,t} = \alpha_{20} + \sum_{k=1}^p \left[ \alpha_{21k} g^y_{t-k} + \alpha_{22k} g^v_{t-k} + \alpha_{23k} g^F_{t-k+1} + \alpha_{24k} g^h_{t-k+1} + \alpha_{25k} g^F_{t-k+1} \right] + \epsilon_{2,r,t} \tag{4.9}$$

$$g^h_{t+1} = \alpha_{30} + \sum_{k=1}^p \left[ \alpha_{31k} g^y_{t-k} + \alpha_{32k} g^v_{t-k} + \alpha_{33k} g^F_{t-k+1} + \alpha_{34k} g^h_{t-k+1} + \alpha_{35k} g^F_{t-k+1} \right] + \epsilon_{3,t} \tag{4.10}$$
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\[
\begin{align*}
\hat{y}_{t+1}^h &= \alpha_{40} + \sum_{k=1}^{p} \left[ \alpha_{41k} \hat{y}_{t-k}^y + \alpha_{42k} \hat{g}_{1,t-k}^r + \alpha_{43k} \hat{g}_{t-k+1}^h ight] + \epsilon_{4,t} \\
\hat{y}_{t+1}^F &= \alpha_{40} + \sum_{k=1}^{p} \left[ \alpha_{41k} \hat{y}_{t-k}^y + \alpha_{42k} \hat{g}_{1,t-k}^r + \alpha_{43k} \hat{g}_{t-k+1}^h ight] + \epsilon_{5,t}.
\end{align*}
\]

Equations (4.11)-(4.12) capture the joint dynamics of the series. They can be expressed more succinctly as

\[
g_t = \alpha_0 + \sum_{k=1}^{p} \alpha_k g_{t-k} + \epsilon_t
\]

where \( z_t = (1, g_{t-1}, ..., g_{t-k}) \), \( A = (\alpha_0, \alpha_1, ..., \alpha_k) \) and \( \epsilon_t \sim \text{MVN}(0, \Sigma) \). \( \Sigma \) is a diagonal matrix with \( \sigma_i \)'s along the diagonals. For \( t, ..., T \) (4.13) can be written as

\[
G = AZ + E,
\]

where \( \mathcal{G} \equiv [g_t, ..., g_T] \), \( \mathcal{A} \equiv [1, \alpha_1, ..., \alpha_p] \) and \( \mathcal{Z} \equiv [1', g_{t-1}, ..., g_{t-p}] \). Vectorising (4.14),

\[
\mathcal{G} = (\mathcal{Z}' \otimes I) \mathcal{A} + \mathcal{E},
\]

where \( \mathcal{A} \equiv \text{vec}(\mathcal{A}), \mathcal{G} \equiv \text{vec}(\mathcal{G}), \) and \( \mathcal{E} \equiv \text{vec}(\mathcal{E}). \)

4.4 Estimation

There are multiple methods to estimating the equations (4.8)-(4.12), each with its own costs and benefits. The two implemented here are multivariate least squares (LS) and the Bayesian VAR (BVAR).

4.4.1 Least Squares

If each equation includes the same regressors and lag lengths of the regressors, and the covariance matrix is diagonal, the estimation of the VAR simplifies to be a multivariate least squares, which is the computationally most efficient method.

The multivariate least squares estimation of \( \mathcal{A} \) in (4.15) means to choose the estimator that minimises
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\[ S(\mathcal{A}) = [G - (Z \otimes I_n)\mathcal{A}](I_T \otimes \Sigma_\epsilon^{-1})[G - (Z \otimes I_n)\mathcal{A}] \]
\[ = G(I_T \otimes \Sigma_\epsilon^{-1})G + \mathcal{A}(Z \otimes I_n)(I_t \otimes \Sigma_\epsilon^{-1})(Z \otimes I_n)\mathcal{A} \]
\[ - 2\mathcal{A}(Z \otimes I_n)(I_T \otimes \Sigma_\epsilon^{-1})G \]
\[ = G(I_T \otimes \Sigma_\epsilon^{-1})G + \mathcal{A}(ZZ' \otimes G)\mathcal{A} \]
\[ - 2\mathcal{A}(Z \otimes \Sigma_\epsilon^{-1})G, \quad (4.16) \]

where \( I_T \) is an identity matrix of size \( T \times T \), while \( I_n \) is an identity matrix of size \( n \times n \), (\( n \) is the number of variables). Differentiating \( (4.16) \) with respect to \( \mathcal{A} \) we have

\[ \frac{\partial S(\mathcal{A})}{\partial \mathcal{A}} = 2(ZZ' \otimes \Sigma_\epsilon^{-1})\mathcal{A} - 2(Z \otimes \Sigma_\epsilon^{-1})G \]
\[ \mathcal{A} = (ZZ' \otimes \Sigma_\epsilon^{-1})^{-1}(Z \otimes \Sigma_\epsilon^{-1})G, \quad (4.17) \]

where \( \mathcal{A} \) is the least squares estimator.

A short coming of the LS method, is that it does not directly quantify the uncertainty around the parameter estimates. Therefore, when generating now-cast densities, the densities will have variances that are smaller than the true variances. To address this problem there are two available solutions. One can either use boot-strapping techniques, sub-sampling from the data to generate multiple parameter estimates, or one can use a Bayesian VAR (BVAR) to generate a posterior distribution over the parameters. This paper follows the latter approach.

4.4.2 Bayesian VAR

The Bayesian approach complicates the problem of estimating the VAR in two ways; first, a prior for the model must be specified; second, estimation is no longer undertaken through optimisation\(^4\) and instead relies on simulation methods to generate a posterior distribution for the parameters, adding considerable computation time. Additionally, the Bayesian method, unlike the least squares method, requires assuming that the distribution of the data generating process (DGP) is known.

To generate a posterior over the parameters, the first step is to specify the likelihood function of data. Since we have assumed that \( \epsilon_t \sim MVN(0, \Sigma_\epsilon) \), the likelihood function is specified as a multivariate normal distribution with a diagonal covariance matrix. The second step involves choosing appropriate prior distributions for each parameter. If the goal is to capture the uncertainty

\(^4\)Penalised least squares or maximum a posteriori estimation (MAP) are Bayesian methods that involve optimisation, but neither generates a distribution over the parameters.
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in the parameters estimated in the LS method, diffuse or uninformative priors should be used. How to set diffuse priors is discussed below.

The prior for the coefficients \( \alpha_{1k}, \alpha_{2k}, \alpha_{3k}, \alpha_{4k} \) and \( \alpha_{5k} \), is an independent normal distribution. Here \( k \) denotes the lag.

\[
\alpha_{ik} \sim N(0, v_{ik}) \quad \text{for} \quad i \in \{1, 2, 3, 4, 5\},
\]

(4.18)

where

\[
v_{ik} = \begin{cases} 
\frac{s_i}{s_k} \gamma^l & \text{if } i = i \\
\frac{s_i}{s_k} \gamma^{l-1} & \text{if } i \neq 1,
\end{cases}
\]

and \( \gamma \geq 0, \theta \in [0, 1) \) and \( l \in \{0, 1, 3, \ldots\} \). The standard deviations control the extent of shrinkage in the parameters. For example to shrink all parameters, \( \gamma \) could be set to a number less than one. The traditional Minnesota prior sets \( \gamma = 0.2 \). The parameter \( \theta \) applies additional shrinkage to parameters on cross-variables, and this has varied between 0.2 and 1 in the literature. The parameter \( l \) controls the extent the higher order lags are shrunk. This parameter is typically set to 1 or 2 (see Litterman (1979), Litterman (1986), and more recently D’Agostino, Giannone, Lenza, and Modugno (2016) for BVAR model performance with different shrinkage parameters). Finally, \( s_i \) is the sample standard deviation of variable \( i \).

The uncertainty in the parameters in the VAR estimates can be captured in a straightforward way by using uninformative priors, with \( v_{ik} = \frac{s_i}{s_k} \). Furthermore, the lag length \( k \) will be the same as the VAR model. Thus, if the optimal lag length in the VAR model is 2, then the BVAR will include 2 lags.

The intercept of each equation \( \alpha_0 \) also has an uninformative prior, which is a normal distribution with mean 0 and standard deviation \( v_0 \), where \( v_0 \) is a large number.

In matrix notation, the prior distribution for the above parameters is

\[
\mathbf{\alpha} \sim MvN(\mathbf{0}, \mathbf{V}),
\]

(4.20)

or in vector notation

\[
\mathcal{A} \equiv \text{vec}(\mathbf{\alpha}) \sim N(\mathbf{0}, \text{vec}(\mathbf{V})) \equiv N(\mathbf{0}, \mathbf{V}).
\]

(4.21)

Finally, a prior distribution is required for the covariance of the error terms, \( \Sigma_e \). The original Minnesota Bayesian VAR models assumed that the covariance matrix was diagonal, and used the variance of OLS residuals along the
diagonal. With the BVAR we can generate posteriors for the variance of residuals. This is achieved by setting a prior on the standard deviation of the residuals, $\sigma_i$. An uninformative prior for the standard deviation is $\sigma_i \sim U(0, u)$, where once again $u$ is a large number.

The covariance matrix is derived through the following identity

$$\Sigma_\epsilon = \text{diag}(\sigma)I\text{diag}(\sigma),$$  \hspace{1cm} (4.22)

where $I$ is the identity matrix, and $\sigma$ is a vector of standard deviations, $\{\sigma_1, ..., \sigma_n\}$. The posterior distribution for this problem is

$$p(\mathcal{A}, \mathcal{V} | \mathcal{G}) \propto \exp \left\{ -\frac{1}{2} \left[ (\mathcal{V}^{-1/2})^T (\mathcal{V}^{-1/2}) \mathcal{A} + \{(I_T \otimes \Sigma_\epsilon^{-1/2}) \mathcal{G} - (Z' \otimes \Sigma_\epsilon^{-1/2}) \mathcal{A}) \right] \right\}. \hspace{1cm} (4.23)$$

The uniform distribution over the standard deviation $\sigma_i$ means that we can omit the prior distribution of $\Sigma_\epsilon$ in the posterior. The Hamiltonian Markov Chain Monte Carlo algorithm (Neal et al. (2011)) can be used to efficiently simulate the parameters.

### 4.5 Model Evaluation

Decision makers vary in what they value in a model. Some may just care about point now-casts, in the case of financial traders who want to know how far the consensus is from the truth, i.e. the unexpected news; others on the other-hand may care how accurately the model can anticipate periods of below - and above - trend growth, in the case of policy makers. Different decision makers care about different aspects of the now-cast distribution. Irrespective of the objective, however, a model should be able to generate now-casts that resemble the underlying distribution of the data. This section discusses the criteria to assess the different models’ now-casts.

#### 4.5.1 Point Now-casts

The first criterion for assessing the models performance will be the accuracy of their point now-casts. The accuracy of the point now-casts depend on the decision maker’s loss function. The loss function, $L(\cdot)$, describes in relative terms how costly it is to use an imperfect now-cast, $\hat{g}$, given the outcome, $g$. The loss function should reflect the actual trade-offs between different now-cast errors of different signs and magnitudes. In this paper, two popular and symmetric loss functions will be utilised. The root mean squared forecast
error (RMSE) and the mean absolute forecast error (MAE), which are given by:

\[
L_{RMSE} = \sqrt{\left( \frac{1}{T} \sum_{t=1}^{T} (\hat{g}_{t+1, \mathcal{M}_i} - g_{t+1})^2 \right)}
\]

\[ (4.24) \]

\[
L_{MAE} = \frac{1}{T} \sum_{t=1}^{T} |\hat{g}_{t+1, \mathcal{M}_i} - g_{t+1}|,
\]

\[ (4.25) \]

where \( \hat{g}_{t+1, \mathcal{M}_i} \) is model \( \mathcal{M}_i \)'s point now-cast of \( g_{t+1} \), the realised value of the initial release of GDP in period \( t + 1 \).

### 4.5.2 Log Scores/Predictive Density

An alternative to examining point forecasts is to provide a predictive density, in particular the log predictive density. Unlike the RMSE or MAE, the log-predictive density accounts for the uncertainty around the now-cast.

For example, if a model cannot account for the variation in the data, then the standard deviation of the residuals will be relatively large. If the standard deviation of one model is larger than another model, then the probability density over the outcomes is going to be flatter and wider; the probability assigned to each outcome is going to be relatively smaller.

On the other-hand if the model does a good job accounting for the variation in the data, then the standard deviation of the residuals will be relatively smaller, and the density will be more tightly packed around the mean. The probability assigned to each outcome is going to be relatively larger.

The score function that utilises the predictive density is known as the log score, and it is given by

\[
\log S = \frac{1}{T} \sum_{t=1}^{T} \sum_{k=1}^{K} d_{kt} \log(p_{kt}),
\]

where \( T \) is the number of now-casts, and \( K \) represents a finite number of mutually exclusive events. If GDP for instance, \( K \) represents the discrete bins that the variable can fall within, for example, \(-2\%\) to \(-1.95\%). \( d_{kt} \) is an indicator variable that is equal to 1 if the outcome, the realised value of GDP now-casted, falls in bin \( k \) and 0 otherwise. \( p_{kt} \) is the probability of falling in bin \( k \).

The predictive density is affected by parameter uncertainty. In models where the parameters are not estimated precisely, we expect the density to be less peaked and wider. Parameter uncertainty can be addressed by estimating a BVAR since the predictive density that takes into account parameter uncertainty naturally arises in a BVAR.
4.5. MODEL EVALUATION

4.5.3 Anticipating Economic Events

It is argued that decision-makers’ objective functions are concerned with how far GDP has deviated from its potential level. Similarly, there is an argument that policy makers are concerned with whether conditions are improving or deteriorating, with the gap between GDP and its trend rising or falling. Central bankers, for example, when setting policy, are trying to anticipate how far output will be from its potential. The Bank of England now publishes probability forecasts to “enable policy-makers to motivate and justify actions based on the forecasts, and to help a more balanced evaluation of the forecasts by the public” (Garratt, Lee, Pesaran, and Shin (2012)). In these circumstances, the decision maker requires explicit forecasts of the probability of the event of interest as opposed to a point now-cast.

This sub-section considers a series of economic events and generates the probability of the event occurring. Each model is in turn assessed to see how well they can anticipate the different events.

Due to the absence of recessions and negative growth rates in the now-casting window, less extreme events must be considered instead. The events are chosen such that they occur a sufficient number of times in the now-casting window, but capture a broad range of event frequencies.

The first set of events include GDP growth below:

- the 40th percentile,
- the 30th percentile,
- 0.5 standard deviations below the mean,
- the 5 quarter moving average,
- the previous peak value, and
- the previous trough value,

and GDP growth above:

- the 40th percentile,
- the 30th percentile,
- 0.5 standard deviations above the mean,
- the 5 quarter moving average,
- the previous peak value, and
- the previous trough value
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The peak is the value \( g^y_t \) that satisfies \( g^y_t > g^y_{t-2} \), \( g^y_t > g^y_{t-1} \), \( g^y_t > g^y_{t+1} \) and \( g^y_t > g^y_{t+2} \). The trough is the value that satisfies \( g^y_t < g^y_{t-2} \), \( g^y_t < g^y_{t-1} \), \( g^y_t < g^y_{t+1} \), \( g^y_t < g^y_{t+2} \). To ensure that the correct peak and trough is identified, a 5-quarter moving average of \( g^y_t \) is used.

The second set of events involve calculating probabilities of transitioning across states. The different states considered here are GDP growth rate below and above its long-term average. The transition probabilities will allow us to answer questions such as: if GDP growth is below its average in period \( t-1 \) what is the probability that it will be above or below average in period \( t \)? These events address the question of whether conditions are worsening or improving. The transition table looks like:

<table>
<thead>
<tr>
<th>Below average</th>
<th>Above average</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \pi_{11} )</td>
<td>( \pi_{1n} )</td>
</tr>
<tr>
<td>( \pi_{m1} )</td>
<td>( \pi_{22} )</td>
</tr>
</tbody>
</table>

where each model will assign different probabilities to \( \pi_{mn} \).

**Estimating Economic Event Probabilities**

To determine the probability of an event occurring a predictive density is constructed. While the unsystematic innovations are the main source of forecast uncertainty, as mentioned in the previous section there is another source of forecast uncertainty in finite samples: parameter uncertainty.

This concern is addressed by implementing a Bayesian VAR, where a predictive density taking into account parameter uncertainty is a natural outcome. The Bayesian predictive density is constructed through a nested Monte Carlo simulation. In the outer loop, parameters are drawn from the posterior distribution - including the standard deviation of the error terms - and the expected value of the variables is calculated. In the inner loop, using the standard deviation of the error terms drawn in the outer loop, the error terms are simulated and combined with the expected values from the outer loop.

Observing the proportion of times an event appears in the simulated data, the probability of an event can be calculated.

**Evaluating Economic Event Forecasts**

In evaluating event probabilities, it is important to penalise the models for having high false positives. So the forecast performance should concentrate on the hit rate and the false alarm rate.

A measure which does this is the Kuipers score (KS), which is obtained by taking the difference between the hit rate (\( H \)) and the false alarm rate (\( F \)), where \( H \) is the proportion of the number of times an event was forecasted to occur versus the number of times it actually occurred, and \( F \) is the proportion of the number of times the event was forecasted to occur versus the number of
4.6. DATA

4.6.1 GDP & Revisions

The GDP series, \( g_y \), revisions, \( g_r \), factors, \( g_F \), and survey variables, \( g_b \) and \( g_h \) all range from Q3 1989 to Q1 2017.

Measures of Australian GDP undergo significant revisions. Given that the policy maker is making decisions based on what he or she believes the initial release of GDP is going to be, “real-time” GDP data will be used for the now-casting exercises. The “real-time” GDP data is from a data-set created by researchers at the University of Melbourne, who have put together data vintages from past official ABS publications (Lee, Olekalns, Shields, and Wang (2012)).

The real-time GDP data changes over time for two broad reasons. These are related to definitional changes and revisions to the data. Definitional changes tend to be large once-and-for-all shifts in a series and reflect a change in the way a concept is conceived. For example, to derive real GDP measures, in the past the ABS would keep prices constant for a fixed period of time, and use these prices for subsequent years of output. However, in the recent past...
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the ABS adopted the chain-weighting methodology, which involves re-basing GDP year.

Data revisions are based on the arrival of new information that wasn’t available at the time of the first release of GDP. Some of the more reliable information is only collected annually, where as GDP is published quarterly.

These two types of changes can be distinguished from each other through the fact that the definitional changes affect the entire history of the series, where as revisions only tend to impact the more recent history of the series. To properly extract the revisions from the data, the previous periods data must be scaled by a multiplicative factor to remove the impact of definitional changes.

For example, consider the real-time GDP data in Table 4.2. Along the columns we have the different vintages of GDP and the quarter in which they are published. Along the rows we have the GDP values and the quarter to which they refer. To determine the revisions it is important to remove the definitional changes from Q3 2016 to Q4 2016. This is achieved by rebasing the series such that the two consecutive vintages are comparable.

To rebase the vintage in period \( t - 1 \) we regress the GDP values from period \( t \) against the GDP values in period \( t - 1 \).

\[
y_{t-2}^t = \mu + \beta y_{t-2}^{t-1},
\]

(4.28)

where the superscript \( t \) refers to the vintage. Following this regression we take the parameter estimates and apply them to the series in vintage \( t - 1 \). That is the new \( y_{t-2}^{t-1} \) for all \( t \) becomes

\[
y_{t-2}^{t-1} = \hat{\mu} + \hat{\beta} y_{t-2}^{t-1}.
\]

(4.29)

To continue rebasing the series such that any two consecutive vintages are comparable, we continue with the next regression, which will be

\[
y_{t-3}^{t-1} = \mu + \beta y_{t-3}^{t-2}.
\]

(4.30)

The estimates of this regression will be used to transform \( y_{t-3}^{t-2} \)

\[
y_{t-3}^{t-2} = \hat{\mu} + \hat{\beta} y_{t-3}^{t-2}.
\]

(4.31)

This process is continued until the last vintage.

After we have accounted for definitional changes, to determine the revisions we calculate the growth rates between the green and blue cells by moving across columns (this is assuming that the elements in the matrix have been transformed).
Table 4.2: Real-time GDP.

<table>
<thead>
<tr>
<th>Date</th>
<th>Q2 2016</th>
<th>Q3 2016</th>
<th>Q4 2016</th>
<th>Q1 2017</th>
<th>Q2 2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q4 2015</td>
<td>416</td>
<td>415</td>
<td>413</td>
<td>413</td>
<td>413</td>
</tr>
<tr>
<td>Q1 2016</td>
<td>420</td>
<td>420</td>
<td>417</td>
<td>417</td>
<td>417</td>
</tr>
<tr>
<td>Q2 2016</td>
<td>422</td>
<td>420</td>
<td>420</td>
<td>420</td>
<td>420</td>
</tr>
<tr>
<td>Q3 2016</td>
<td></td>
<td>418</td>
<td>419</td>
<td>420</td>
<td></td>
</tr>
<tr>
<td>Q4 2016</td>
<td></td>
<td></td>
<td>423</td>
<td>424</td>
<td></td>
</tr>
<tr>
<td>Q1 2017</td>
<td></td>
<td></td>
<td></td>
<td>425</td>
<td></td>
</tr>
</tbody>
</table>

To determine the real-time, or first release, growth rates we calculate the growth rates along the diagonal elements, moving diagonally along the green cells. The initial release growth rate published by the ABS is the growth rate along the vertical, which is the difference between the green and blue cells.

Figure 4.1: Initial Release GDP vs First Release GDP.

Notes: Initial release is the vertical growth rate determined from the latest vintage. It is the growth rate as published by the ABS. The first release is the diagonal growth rate. The initial release contains one revision.

Figure 4.1 displays the time series plot of the initial release of GDP, the vertical growth rate, against the first release, the diagonal growth rate. Table 4.28 in the Appendix shows the summary statistics for the two series. As is evident in the plot, GDP in some cases undergoes significant revision. In Table 4.28 we see that the mean value of the first release is larger than the first release. The average value of the first revision is 0.10%, which indicates a reduction in the first release growth rate by 0.10 percentage points.
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Table 4.3: Summary of surveys.

<table>
<thead>
<tr>
<th>Survey</th>
<th>Sample Size</th>
<th>Coverage</th>
<th>Commenced</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAB Business Survey</td>
<td>900</td>
<td>Non-farm sector</td>
<td>September 1989</td>
</tr>
<tr>
<td>Westpac - Melbourne Institute Consumer Survey</td>
<td>1200</td>
<td>Households</td>
<td>September 1974</td>
</tr>
</tbody>
</table>

4.6.2 Survey Data

This paper assesses information content of two surveys; namely the Quarterly NAB Business Survey and the Westpac - Melbourne Institute Consumer Survey. While several business surveys exist in Australia, apart from the NAB Business Survey, the other surveys have a relatively short history, making them unsuitable for long historical analysis. However, as was shown in [Park, 2011], these surveys do tend to move together, so we can rely on the NAB Business Survey to summarise the information in the other business surveys. Only the Westpac - Melbourne Institute Consumer Survey is included in the analysis as the Westpac - Melbourne Institute Consumer Survey and ANZ - Roy Morgan Consumer Confidence Rating are highly correlated, with the correlation coefficient equal to 0.92. Therefore, the Westpac-MI Survey is sufficient to summarise the information contained in both household surveys.

The surveys attempt to measure nationwide conditions, either using representative samples, or for the business surveys weighting the firms’ responses according to their industry, with weights based on output or the number of businesses [Park, 2011].

The business survey asks respondents whether sales, profitability, employment, capital expenditure, forward orders, capacity utilisation, inventories and prices, etc., have increased or decreased over the reference period. For each of these series a net-balance is derived. These disaggregated indices are then aggregated to derive a single index of business conditions.

The household survey consists of five core questions. Two questions ask survey participants to assess the state of their current personal finances compared with a year prior, and their expected state a year ahead. A further two questions ask participants for their expectations about broader economics conditions one year and five years ahead. A final question asks the survey participants whether they think conditions are favourable for purchase of major household items [Wang and Berger-Thomson, 2015]. The aggregate indices are an average of the responses to these five questions. This analysis utilises the aggregated indices from each survey.

Performing the augmented Dickey-Fuller test, the null that there is a unit-root is rejected at the 1% level for both the household and business surveys.
Figure 4.2: Initial Release GDP vs Surveys.

Notes: For comparison purposes, all series have been standardised to have mean 0 standard deviation 1.

Therefore, no transformation is applied to either of the surveys, and they will enter the models in levels.

Figure 4.2 displays the time series plot of the initial release of GDP against both of the surveys. Table 4.28 in the Appendix shows the summary statistics for the two variables. As can be seen in the plot the two surveys display co-movement with GDP around business cycle turning points. Unlike GDP, the surveys tend to be a lot smoother and display more persistence.

4.6.3 Official Monthly Economic Indicators

The official economic indicators are taken from the Australian Bureau of Statistics (ABS). For the purpose of this exercise, only monthly data is used as they are the most timely. The monthly data is aggregated to quarterly frequency to be consistent with the other series. The monthly indicators include statistics relating to credit lending to businesses, dwelling approvals, credit to purchase new and existing dwellings, net-exports, retail trade, employment, hours worked, and vehicle sales. The final list of variables are provided in Table 4.26 in the Appendix.

The monthly indicators are all taken from the latest vintages, and therefore include revisions. While Koenig, Dolmas, and Piger (2003) showed that substantial improvements in out-of-sample forecasts can be achieved by using both un-revised dependent and independent variables, the lack of such data for most of the monthly indicators, makes it difficult to do so. However, if the revisions across different series are un-correlated, then the common factor
from the series should be similar to using un-revised series. Therefore, the factors that are extracted from the monthly indicators will be using the latest vintages of data.

Three factors are extracted and included in the analysis. During preliminary analysis, it was found that only 3 factors have a statistical significant correlation, and partial correlation, with GDP. Figure 4.3 plots the factors against the initial release GDP growth rate. It is evident that the factors co-move with GDP, capturing the turning points around the business cycle dates, and the short term movements during other times. The summary statistics of the factors can also be found in Table 4.28 in the Appendix.
4.7 Empirical Results

All now-casts are produced out-of-sample to simulate the real-time experience of practitioner. An initial sample using data from $t = 1, ..., T$ is used to estimate the models, and 1-step ahead now-casts are produced starting at date $T$. The sample is increased by one, the models are re-estimated, and 1-step ahead now-casts are produced starting at $T + 1$. This process is repeated for 30 quarters from Q4 2009 to Q1 2017.

4.7.1 Point Estimates and Log Scores

Tables 4.4 and 4.5 display the results from Granger causality tests, and the RMSE, MAE and log scores for the different models. The models are considered in the following order:

1. Model 1: AR(2) model: GDP,
2. Model 2: VAR(2) model: GDP and first revision,
3. Model 3: VAR(2) model: GDP, first revision and second revision
4. Model 4: VAR(1) model: GDP and factors
5. Model 5: VAR(2) model: GDP and NAB Business Survey Index

Notes: For comparison purposes, all series have been standardised to have mean 0 standard deviation 1. Factor 2 is multiplied by -1 to have the same sign as the other factors.
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7. Model 7: VAR(1) model: GDP, factors and 1st revision

8. Model 8: VAR(2) model: GDP, NAB Business Survey index and 1st revision


The lag order for the AR and VAR models is determined using the Akaike Information Criterion. The results are presented as a ratio of the benchmark AR(2) GDP model. Smaller values indicate a reduction in now-cast errors.

In Table 4.4 we see that business and household surveys and the factors Granger cause the first release of GDP at the 1% level. The revisions, on the other-hand, do not Granger cause the first release of GDP.

The results in Table 4.5 indicate that factor augmented VAR is the best model in terms of now-casting performance. Relative to the benchmark AR(2) model the MAE, RMSE and log scores are between 16 and 28% smaller when now-casting the initial release of GDP.

Following the factor model, the next best model is the model containing the first revision. The model generates now-cast errors that are statistically smaller than the AR(2) model using the MAE criterion and log score, though the statistical difference in the log scores disappears once we take parameter uncertainty into account. The models containing the survey variables do not outperform the benchmark AR(2) model. Neither the RMSE, MAE or log-scores are statistically different from the AR(2) model.

The results in Table 4.5 indicate that the inclusion of the first revision leads to more accurate first-release GDP now-casts. It is also evident that failing to take into account the parameter uncertainty in the model, could exaggerate the forecast performance. The factor model, which contains the most variables, experiences the largest drop in the log score when parameter uncertainty is taken into account - moving from being 20% smaller than the benchmark AR(2) model to being 12% smaller.

\footnote{Using the latest vintage as opposed to the first release of GDP increases the now-cast error between 15-20\% across the different models. This further highlights the importance of taking into account the revision process when now-casting the first release of GDP.}
### Table 4.4: Granger Causality Tests.

<table>
<thead>
<tr>
<th>Model</th>
<th>Dependent Variable</th>
<th>Regressors</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 - 1st Rev.</td>
<td>GDP</td>
<td>First Revision</td>
<td>0.121</td>
</tr>
<tr>
<td>3 - 1st &amp; 2nd Rev.</td>
<td>GDP</td>
<td>First &amp; Second Revision</td>
<td>0.223</td>
</tr>
<tr>
<td>4 - Factor</td>
<td>GDP</td>
<td>Factors</td>
<td>0.000</td>
</tr>
<tr>
<td>5 - Bus. Survey</td>
<td>GDP</td>
<td>NAB Business Survey</td>
<td>0.000</td>
</tr>
<tr>
<td>6 - HH Survey</td>
<td>GDP</td>
<td>Westpac/MI Household Survey</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*Notes: The elements in the table show the p-values for F-tests where the null hypothesis is that the variable in the column ‘Regressors’ Granger causes GDP.*
Table 4.5: Forecast Evaluation. Smaller values indicate better performance relative to AR(2) model.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>Log-Score</th>
<th>Log-Score (w. param. uncer-tainty)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - AR</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2 - 1st Rev.</td>
<td>0.93*</td>
<td>0.97</td>
<td>0.97*</td>
<td>1.02</td>
</tr>
<tr>
<td>3 - 1st &amp; 2nd Rev.</td>
<td>0.99</td>
<td>1.01</td>
<td>0.99</td>
<td>1.07**</td>
</tr>
<tr>
<td>4 - Factor</td>
<td>0.73***</td>
<td>0.87**</td>
<td>0.84***</td>
<td>0.94*</td>
</tr>
<tr>
<td>5 - Bus. Survey</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.99</td>
</tr>
<tr>
<td>6 - HH Survey</td>
<td>1.04</td>
<td>1.04</td>
<td>1.03</td>
<td>1.00</td>
</tr>
<tr>
<td>7 - Factor w. 1st Rev.</td>
<td>0.72***</td>
<td>0.84**</td>
<td>0.80***</td>
<td>0.88***</td>
</tr>
<tr>
<td>8 - Bus. Survey w. 1st Rev.</td>
<td>0.93</td>
<td>0.97</td>
<td>0.96</td>
<td>0.94*</td>
</tr>
<tr>
<td>9 - HH Survey w. 1st Rev.</td>
<td>0.99</td>
<td>1.02</td>
<td>1.00</td>
<td>1.04</td>
</tr>
</tbody>
</table>

Notes: A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The small sample adjusted Diebold and Mariano test is used to determine whether the MAE and RMSE are significantly smaller than the benchmark AR(2) GDP model. The Wilcoxon Signed Rank test is used for the log scores to determine whether the sample locations are statistically different. The displayed log scores are ratios of the mean log score of each model relative to mean of the benchmark AR(2) model.
4.7. EMPIRICAL RESULTS

4.7.2 Evaluating Economic Events

This sub-section analyses the different models’ ability to anticipate discrete economic events. Tables 4.6, 4.7, 4.8, and 4.9 display the hit and false alarm rates along with the Kuiper scores, for growth below the 30th and 40th percentile and above the 60th and 70th percentile. The hit and false alarm rates are shown for different probability thresholds. Tables 4.10 and 4.11 perform the same analysis but for growth rates 0.5 standard deviations below and above the mean growth rate.

The results show that the factor model has the greatest success at anticipating periods of low-growth. The factor model most accurately anticipates growth rates that are below the 30th percentile, 40th percentile and 0.5 standard deviations below the mean. Using a probability cut-off threshold of 0.5 for all events the factor model correctly anticipates the events 57%, 71% and 16.7% of times, and incorrectly anticipates the non-events 13%, 6.2% and 0% of the times. The differences between the hit and false alarm rates are statistically greater than zero at the 5% level.

Interestingly, the business survey outperforms the factor model at anticipating the events on the opposite side of the distribution, i.e. growth that is above the 70th percentile, 60th percentile and 0.5 standard deviations above the mean. Using a probability cut-off threshold of 0.5, 0.6, and 0.5, respectively, the business survey model correctly anticipates the events 33%, 27% and 33% of the times, and incorrectly anticipates the non-events 8.3%, 0% and 8.3% of the times. The differences between the hit and false alarm rates are statistically greater than zero at the 10% level. The remaining models do a relatively poor job at anticipating either of the events. The difference between the hit and false alarm rate is statistically greater than zero at the 10% level.

The associated probabilities for each model are displayed in Figures 4.7, 4.8, 4.9, 4.10, 4.11 and 4.12 in the Appendix. The figures reveal that the factor model consistently assigns a higher probability to low growth rates, whereas the other models consistently assign a higher probability to periods of high-growth. The factor model therefore has a higher miss-rate at anticipating low-growth rates, whereas the business survey model has a higher miss-rate at anticipating high-growth rates. The household survey model does a relatively poor job at anticipating any of these events.
Table 4.6: Event - Growth less than the 40th percentile.

<table>
<thead>
<tr>
<th>q</th>
<th>M1 AM</th>
<th>M2 1st Rev.</th>
<th>M3 1st &amp; 2nd Rev.</th>
<th>M4 Factor</th>
<th>M5 Bus. Survey</th>
<th>M6 HH Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
</tr>
<tr>
<td>0.6</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>21.4 0.0 21.4***</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0 12.5 -12.5</td>
<td>7.1 6.2 0.9</td>
<td>21.4 18.8 -2.7</td>
<td>71.4 6.2 65.2**</td>
<td>7.1 18.8 -11.6</td>
<td>14.3 12.5 -1.8</td>
</tr>
<tr>
<td>0.4</td>
<td>28.6 56.2 -27.7</td>
<td>42.9 43.8 -6.9</td>
<td>50.0 43.8 6.2</td>
<td>100.0 62.5 37.5***</td>
<td>28.6 25.0 -1.6</td>
<td>50.0 50.0 0.0</td>
</tr>
<tr>
<td>0.3</td>
<td>100.0 100.0 0.0</td>
<td>92.9 100.0 -7.1</td>
<td>100.0 91.2 18.8**</td>
<td>100.0 93.9 0.2</td>
<td>71.4 62.5 8.9</td>
<td>92.9 87.5 5.4</td>
</tr>
</tbody>
</table>

Notes: H=Hit Rate, F=False Alarm Rate, KS=Kuiper Score. \( q \) represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.7: Event - Growth more than the 60th percentile.

<table>
<thead>
<tr>
<th>q</th>
<th>M1 AM</th>
<th>M2 1st Rev.</th>
<th>M3 1st &amp; 2nd Rev.</th>
<th>M4 Factor</th>
<th>M5 Bus. Survey</th>
<th>M6 HH Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
</tr>
<tr>
<td>0.6</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>9.1 10.5 -1.4</td>
<td>0.0 0.0 0.0</td>
<td>27.3 0.0 27.3***</td>
<td>9.1 5.3 3.8</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0 36.8 -36.8</td>
<td>36.4 36.8 -5.5</td>
<td>43.3 47.4 -1.9</td>
<td>9.1 0.0 9.1</td>
<td>34.5 42.1 12.4</td>
<td>45.3 26.3 19.1</td>
</tr>
<tr>
<td>0.4</td>
<td>72.7 100.0 -27.3</td>
<td>81.8 79.9 2.9</td>
<td>72.7 68.4 -4.3</td>
<td>63.6 21.1 42.6**</td>
<td>90.9 68.4 22.5*</td>
<td>81.8 68.4 13.4</td>
</tr>
<tr>
<td>0.3</td>
<td>100.0 100.0 0.0</td>
<td>90.9 100.0 -9.1</td>
<td>90.9 100.0 -9.1</td>
<td>100.0 68.4 31.6**</td>
<td>90.9 94.7 -3.8</td>
<td>90.9 100.0 -0.1</td>
</tr>
</tbody>
</table>

Notes: H=Hit Rate, F=False Alarm Rate, KS=Kuiper Score. \( q \) represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.8: Event - Growth less than the 30th percentile.

<table>
<thead>
<tr>
<th>q</th>
<th>M1 AM</th>
<th>M2 1st Rev.</th>
<th>M3 1st &amp; 2nd Rev.</th>
<th>M4 Factor</th>
<th>M5 Bus. Survey</th>
<th>M6 HH Survey</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
<td>H F KS</td>
</tr>
<tr>
<td>0.6</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
<td>0.0 0.0 0.0</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0 4.3 -4.3</td>
<td>0.0 4.3 -4.3</td>
<td>0.0 4.3 -4.3</td>
<td>57.1 13.0 44.1***</td>
<td>0.0 4.3 -4.3</td>
<td>0.0 4.3 -4.3</td>
</tr>
<tr>
<td>0.4</td>
<td>14.3 21.7 -7.5</td>
<td>14.3 21.7 -7.5</td>
<td>14.3 21.7 -7.5</td>
<td>85.7 34.8 50.9***</td>
<td>0.0 21.7 -21.7</td>
<td>28.6 21.7 6.8</td>
</tr>
<tr>
<td>0.3</td>
<td>85.7 91.3 -5.6</td>
<td>71.4 73.9 -2.5</td>
<td>71.4 65.2 6.2</td>
<td>100.0 91.3 8.7</td>
<td>42.9 47.8 -5.0</td>
<td>85.7 69.6 16.1</td>
</tr>
</tbody>
</table>

Notes: H=Hit Rate, F=False Alarm Rate, KS=Kuiper Score. \( q \) represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.
4.7. EMPIRICAL RESULTS

Table 4.9: Event - Growth more than the 70th percentile.

<table>
<thead>
<tr>
<th>q</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
</tr>
</thead>
<tbody>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>8.3</td>
<td>-8.3</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>12.5</td>
<td>-12.5</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>33.3</td>
<td>8.3</td>
<td>25.0*</td>
</tr>
<tr>
<td>0.4</td>
<td>33.3</td>
<td>33.3</td>
<td>0.0</td>
<td>33.3</td>
<td>37.5</td>
<td>-4.2</td>
<td>50.0</td>
<td>45.8</td>
<td>4.2</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>83.3</td>
<td>45.8</td>
<td>37.5**</td>
</tr>
<tr>
<td>0.3</td>
<td>83.3</td>
<td>95.8</td>
<td>-12.5</td>
<td>100.0</td>
<td>83.3</td>
<td>16.7</td>
<td>100.0</td>
<td>75.0</td>
<td>25.0*</td>
<td>83.3</td>
<td>45.8</td>
<td>37.5**</td>
<td>100.0</td>
<td>75.0</td>
<td>25.0*</td>
</tr>
</tbody>
</table>

Notes: $H$=Hit Rate, $F$=False Alarm Rate, $KS$=Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.10: Event - Growth less than 0.5 standard deviation below the mean. Frequency in data is 24%.

<table>
<thead>
<tr>
<th>q</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
</tr>
<tr>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>16.7</td>
<td>0.0</td>
<td>16.7**</td>
</tr>
<tr>
<td>0.4</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>16.7</td>
<td>4.2</td>
<td>12.5</td>
<td>0.0</td>
<td>16.7</td>
<td>-16.7</td>
<td>16.7</td>
<td>0.0</td>
<td>16.7**</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
</tr>
<tr>
<td>0.3</td>
<td>16.7</td>
<td>29.2</td>
<td>-12.5</td>
<td>33.3</td>
<td>37.5</td>
<td>-4.2</td>
<td>50.0</td>
<td>41.7</td>
<td>8.3</td>
<td>100.0</td>
<td>66.7</td>
<td>33.3**</td>
<td>16.7</td>
<td>20.8</td>
<td>-4.2</td>
</tr>
</tbody>
</table>

Notes: $H$=Hit Rate, $F$=False Alarm Rate, $KS$=Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.11: Event - Growth more than 0.5 standard deviation above the mean. Frequency of event=32%.

<table>
<thead>
<tr>
<th>q</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>8.3</td>
<td>-8.3</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>12.5</td>
<td>-12.5</td>
<td>0.0</td>
<td>4.2</td>
<td>-4.2</td>
<td>33.3</td>
<td>8.3</td>
<td>25.0*</td>
</tr>
<tr>
<td>0.4</td>
<td>33.3</td>
<td>41.7</td>
<td>-8.3</td>
<td>50.0</td>
<td>37.5</td>
<td>12.5</td>
<td>50.0</td>
<td>45.8</td>
<td>4.2</td>
<td>0.0</td>
<td>12.5</td>
<td>-12.5</td>
<td>83.3</td>
<td>45.8</td>
<td>37.5**</td>
</tr>
<tr>
<td>0.3</td>
<td>83.3</td>
<td>95.8</td>
<td>-12.5</td>
<td>100.0</td>
<td>83.3</td>
<td>16.7</td>
<td>100.0</td>
<td>70.8</td>
<td>25.0*</td>
<td>83.3</td>
<td>50.0</td>
<td>33.3**</td>
<td>100.0</td>
<td>79.2</td>
<td>20.8</td>
</tr>
</tbody>
</table>

Notes: $H$=Hit Rate, $F$=False Alarm Rate, $KS$=Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.
WHAT IS THE INFORMATIONAL CONTENT OF BUSINESS AND HOUSEHOLD SURVEYS AND WHEN SHOULD WE USE THEM?

Tables 4.12, 4.13, 4.14, 4.15, 4.16, and 4.17 show the results for growth below and above the 5 quarter moving average, the previous peak, and the previous trough. The associated probabilities for each model and event are displayed in figures 4.13, 4.14, 4.15, 4.16, 4.17, and 4.18.

The factor model once again performs better at anticipating periods of low growth, capturing when the growth rate is going to be below the previous trough with more accuracy than either of the models. Using a probability cut-off threshold of 0.5, the factor model correctly anticipates 75% of the events, incorrectly predicting 9.1% of the non-events. The difference in the hit and false alarm rate is statistically greater than zero at the 5% level.

The factor model also outperforms the other models at anticipating when growth is going to be below the 5-quarter moving average. Using a probability cut-off threshold of 0.5 it correctly predicts 88% of events, incorrectly predicting 39% of the non-events. This difference between these two measures is statistically greater than zero a the 5% level.

The business and household survey model does better than the factor model at capturing growth above the previous peak, and 5-quarter moving average.

Using a probability cut-off threshold of 0.5, the business survey model correctly predicts 78% and 92% of events, incorrectly predicting 48% and 47% of non-events, whereas the household survey model correctly predicts 55.6% and 92% of the events and incorrectly predicts 28.6% and 35% of non-events. These difference between the hit and false alarm rates are statistically greater than zero at the 10% level. We also see that the household survey model performs better than the benchmark, and business survey model at anticipating periods of growth below the previous trough.

Table 4.12: Event - Growth less than the 5 quarter moving average. Frequency in data is 50%.

<table>
<thead>
<tr>
<th>q</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>11.8</td>
<td>0.0</td>
<td>11.8</td>
<td>11.8</td>
<td>7.7</td>
<td>11.8</td>
<td>11.8</td>
<td>7.7</td>
<td>4.1</td>
<td>56.8</td>
<td>0.0</td>
<td>58.8***</td>
</tr>
<tr>
<td>0.5</td>
<td>52.9</td>
<td>15.4</td>
<td>37.6**</td>
<td>56.8</td>
<td>15.4</td>
<td>41.4***</td>
<td>52.9</td>
<td>21.1</td>
<td>29.9***</td>
<td>66.2</td>
<td>36.5</td>
<td>49.8***</td>
</tr>
<tr>
<td>0.4</td>
<td>94.1</td>
<td>61.5</td>
<td>26.7***</td>
<td>94.1</td>
<td>61.5</td>
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<td>94.1</td>
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<td>26.7***</td>
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<td>92.3</td>
<td>1.8</td>
<td>94.1</td>
<td>92.3</td>
<td>1.8</td>
<td>100.0</td>
<td>92.3</td>
<td>7.7</td>
</tr>
</tbody>
</table>

Notes: H=Hit Rate, F=False Alarm Rate, KS=Kuiper Score. q represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.
Table 4.13: Event - Growth more than 5 quarter moving average. Frequency of event=50%.

<table>
<thead>
<tr>
<th>q</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
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</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>36.5</td>
<td>31.8</td>
<td>26.7**</td>
<td>36.5</td>
<td>5.9</td>
<td>32.0***</td>
<td>46.2</td>
<td>17.6</td>
<td>28.5**</td>
<td>38.5</td>
<td>0.0</td>
<td>38.5***</td>
<td>76.0</td>
<td>23.5</td>
<td>55.4***</td>
<td>30.8</td>
<td>17.6</td>
<td>13.1</td>
</tr>
<tr>
<td>0.5</td>
<td>84.8</td>
<td>73.5</td>
<td>37.8**</td>
<td>84.8</td>
<td>41.2</td>
<td>43.4***</td>
<td>70.9</td>
<td>41.2</td>
<td>29.9**</td>
<td>62.5</td>
<td>11.8</td>
<td>49.5***</td>
<td>92.1</td>
<td>47.1</td>
<td>41.2***</td>
<td>92.3</td>
<td>31.3</td>
<td>37.0***</td>
</tr>
<tr>
<td>0.4</td>
<td>100.0</td>
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<td>11.8</td>
<td>92.3</td>
<td>94.1</td>
<td>11.8</td>
<td>92.3</td>
<td>88.2</td>
<td>4.1</td>
<td>100.0</td>
<td>41.2</td>
<td>58.8***</td>
<td>92.3</td>
<td>70.6</td>
<td>21.7*</td>
<td>92.3</td>
<td>76.5</td>
<td>15.8</td>
</tr>
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<td>100.0</td>
<td>0.0</td>
<td>100.0</td>
<td>100.0</td>
<td>0.0</td>
<td>100.0</td>
<td>94.1</td>
<td>5.9</td>
<td>100.0</td>
<td>76.5</td>
<td>23.5**</td>
<td>100.0</td>
<td>94.1</td>
<td>5.9</td>
<td>92.3</td>
<td>100.0</td>
<td>-7.7</td>
</tr>
</tbody>
</table>

Notes: *H* = Hit Rate, *F* = False Alarm Rate, *KS* = Kuiper Score. *q* represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.14: Event - Growth below the previous peak value. Frequency in data is 70%.

<table>
<thead>
<tr>
<th>q</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
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<td>22.2**</td>
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<td>22.2</td>
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<td>44.4</td>
<td>27.6*</td>
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<tr>
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<td>89.9</td>
<td>6.3</td>
<td>95.2</td>
<td>66.7</td>
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<td>100.0</td>
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<td>0.0</td>
</tr>
</tbody>
</table>

Notes: *H* = Hit Rate, *F* = False Alarm Rate, *KS* = Kuiper Score. *q* represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.15: Event - Growth above the previous peak value. Frequency in data is 30%.

<table>
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<th>F</th>
<th>KS</th>
<th>H</th>
<th>F</th>
<th>KS</th>
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<td>6.3</td>
<td>31.3</td>
<td>4.8</td>
<td>28.6**</td>
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<td>0.0</td>
<td>0.0</td>
<td>44.4</td>
<td>19.0</td>
<td>25.4*</td>
<td>0.0</td>
<td>4.8</td>
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<td>0.0</td>
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<td>-4.8</td>
<td>44.4</td>
<td>42.9</td>
<td>1.6</td>
<td>22.2</td>
<td>0.0</td>
<td>22.2**</td>
<td>77.8</td>
<td>67.6</td>
<td>30.2*</td>
<td>55.6</td>
<td>28.6</td>
<td>27.6*</td>
</tr>
<tr>
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<td>-4.8</td>
<td>100.0</td>
<td>90.0</td>
<td>-4.8</td>
<td>77.8</td>
<td>91.4</td>
<td>6.3</td>
<td>100.0</td>
<td>28.6</td>
<td>39.1**</td>
<td>77.8</td>
<td>66.7</td>
<td>11.1*</td>
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<td>88.9</td>
<td>85.7</td>
<td>3.2</td>
<td>100.0</td>
<td>76.2</td>
<td>23.8*</td>
<td>88.9</td>
<td>90.5</td>
<td>-1.6</td>
<td>88.9</td>
<td>100.0</td>
<td>-1.1</td>
</tr>
</tbody>
</table>

Notes: *H* = Hit Rate, *F* = False Alarm Rate, *KS* = Kuiper Score. *q* represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.
WHAT IS THE INFORMATIONAL CONTENT OF BUSINESS AND
106 HOUSEHOLD SURVEYS AND WHEN SHOULD WE USE THEM?

Table 4.16: Event - Growth below the previous trough value. Frequency in data is 32%.

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( H )</td>
<td>( F )</td>
<td>( KS )</td>
<td>( H )</td>
<td>( F )</td>
<td>( KS )</td>
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<td>0.0</td>
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<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>0.5</td>
<td>12.5</td>
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<td>8.0</td>
<td>25.0</td>
<td>4.5</td>
<td>20.5**</td>
</tr>
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<td>50.0</td>
<td>18.2</td>
<td>31.8**</td>
</tr>
<tr>
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<td>42.0**</td>
<td>77.5</td>
<td>45.5</td>
<td>42.0**</td>
</tr>
</tbody>
</table>

Notes: \( H \)=Hit Rate, \( F \)=False Alarm Rate, \( KS \)=Kuiper Score. \( q \) represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.17: Event - Growth above the previous trough value. Frequency in data is 68%.

<table>
<thead>
<tr>
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<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( H )</td>
<td>( F )</td>
<td>( KS )</td>
<td>( H )</td>
<td>( F )</td>
<td>( KS )</td>
</tr>
<tr>
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<td>77.3</td>
<td>50.0</td>
<td>31.8**</td>
<td>77.3</td>
<td>62.5</td>
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<td>8.0</td>
<td>95.5</td>
<td>75.0</td>
<td>20.5**</td>
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</tr>
<tr>
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<td>100.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Notes: \( H \)=Hit Rate, \( F \)=False Alarm Rate, \( KS \)=Kuiper Score. \( q \) represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.
The final set of results for this subsection relate to the probabilities capturing the movements across states. Table 4.18 shows that the business survey model is better at anticipating when GDP growth will remain below average in period $t$ conditional on being below average in period $t-1$. At a probability cut-off threshold of 0.5, it correctly anticipates the events 38% of the time, and incorrectly anticipates the non-events 9% of the time. The difference in the hit and false alarm rate is statistically greater than zero at the 5% level.

From Table 4.19 we see that the household survey has the highest hit rate at 100% for events of below average growth in period $t-1$ and above average growth in period $t$. However, the false alarm rate is quite high at 60%. The difference between the hit and false alarm rate is statistically greater than zero at the 1% level. The performance between the factor model and business survey model is comparable. The factor model, however, has a lower false alarm rate. The outcomes across both models are statistically greater than zero at the 5% level.

Table 4.20 shows that the household survey model out-performs the other models in capturing the change from above average growth to below average growth. Using a probability cut-off threshold of 0.5, the household survey model correctly anticipates 60% of the events and incorrectly anticipates 10% of the non-events. The difference between the hit and false alarm rates is statistically greater than zero at the 1% level.

From Table 4.21 we see that neither of the models can anticipate periods where GDP growth remains in the above average state across two periods. Overall, however, the survey models capture the transitions across states better than the factor and the benchmark model. Perhaps one reason why this is the case is that survey respondents choose not to update their responses until their experience has changed significantly. Alternatively, what constitutes a “change” for a firm or household could vary. As noted in Cunningham (1997), firms most likely have some ‘indifference band’, where small changes in the response variable are recorded as no change. Therefore, the surveys pick up changes when they are sufficiently large, such as moving from above average to below average.

Furthermore, the business survey responses are weighted according to the number of firms within the sector, rather than the value-add of the sector. This results in the resources sector being given less weight in the business survey than in national accounts. The business survey consequently is less volatile than the official data, and captures fluctuations that are more aggregate in nature; a less frequent event than the fluctuations of the resources sector (which is affected by the weather, shifts in global demand and discoveries of foreign deposits).

Figures 4.19, 4.20, 4.21 and 4.22 show the associated probabilities of each event and model.
Table 4.18: Event - Below average growth in period $t-1$ and below average growth in period $t$. Frequency of event=23%.

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<td>31.8</td>
<td>-6.8</td>
<td>62.5</td>
<td>63.6</td>
<td>-1.1</td>
<td>37.5</td>
<td>9.1</td>
<td>28.4**</td>
<td>12.5</td>
<td>31.8</td>
<td>-29.3</td>
</tr>
<tr>
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<td>-3.4</td>
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<td>62.5</td>
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<td>0.0</td>
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<td>90.9</td>
<td>9.1</td>
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</tbody>
</table>

Notes: $H=$Hit Rate, $F=$False Alarm Rate, $KS=$Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.19: Event: Below average growth in period $t-1$ and above average growth in period $t$. Frequency of event=26%.

<table>
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<th>$F$</th>
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<td>10.0</td>
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<td>10.0*</td>
<td>70.0</td>
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<td>80.0</td>
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<td>75.0</td>
<td>25.0**</td>
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Notes: $H=$Hit Rate, $F=$False Alarm Rate, $KS=$Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

4.8 Extensions

4.8.1 Model Combination

In this sub-section we compare the point now-casts of different models over time, and the relative performance of a model that combines forecasts across models 1, 2, 3, 7, 8 and 9. The models are weighted according to the MAE, RMSE and log-score from the previous 5 periods. Three different combination schemes are considered, which includes a weighted combination of all models, a weighted combination of the top 3 models and finally weighted combination of the top 2 models. The top models refer to the models with the lowest now-cast error.

Comparing Table 4.22 to Table 4.5 we see that model combination yields more accurate now-casts than either of the survey models. However, it does not lead to better now-casts than the factor model. It is also evident that weighting the different models according to their log-scores yields the best
### 4.8. EXTENSIONS

Table 4.20: Event: Above average growth in period $t - 1$ and below average growth in period $t$. Frequency of event=27%.

<table>
<thead>
<tr>
<th>$q$</th>
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<th>$F$</th>
<th>$KS$</th>
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<td>15.0</td>
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<td>70.0</td>
<td>20.0</td>
<td>90.0</td>
<td>55.0</td>
<td>25.0</td>
<td>**100.0</td>
<td>95.0</td>
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<td>70.0</td>
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<td>85.0</td>
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<td>85.0</td>
<td>15.0*</td>
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</tbody>
</table>

**Notes:** $H$=Hit Rate, $F$=False Alarm Rate, $KS$=Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Table 4.21: Event: Above average growth in period $t - 1$ and above average growth in period $t$. Frequency of event=24%.

<table>
<thead>
<tr>
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<th>$F$</th>
<th>$KS$</th>
<th>$H$</th>
<th>$F$</th>
<th>$KS$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>0.0</td>
<td>10.7</td>
<td>-10.7</td>
<td>0.0</td>
<td>25.0</td>
<td>-25.0</td>
<td>50.0</td>
<td>32.1</td>
<td>17.9</td>
<td>0.0</td>
<td>3.6</td>
<td>-3.6</td>
<td>50.0</td>
<td>46.4</td>
<td>3.6</td>
</tr>
<tr>
<td>0.5</td>
<td>50.0</td>
<td>85.7</td>
<td>-35.7</td>
<td>50.0</td>
<td>82.1</td>
<td>-32.1</td>
<td>50.0</td>
<td>71.4</td>
<td>-21.4</td>
<td>50.0</td>
<td>35.7</td>
<td>14.3</td>
<td>50.0</td>
<td>85.7</td>
<td>-35.7</td>
</tr>
<tr>
<td>0.4</td>
<td>100.0</td>
<td>100.0</td>
<td>0.0</td>
<td>50.0</td>
<td>100.0</td>
<td>-50.0</td>
<td>50.0</td>
<td>100.0</td>
<td>-50.0</td>
<td>100.0</td>
<td>75.0</td>
<td>25.0</td>
<td>50.0</td>
<td>96.4</td>
<td>-46.4</td>
</tr>
<tr>
<td>0.3</td>
<td>100.0</td>
<td>100.0</td>
<td>0.0</td>
<td>100.0</td>
<td>100.0</td>
<td>0.0</td>
<td>50.0</td>
<td>100.0</td>
<td>-50.0</td>
<td>100.0</td>
<td>96.4</td>
<td>3.6</td>
<td>50.0</td>
<td>100.0</td>
<td>-50.0</td>
</tr>
</tbody>
</table>

**Notes:** $H$=Hit Rate, $F$=False Alarm Rate, $KS$=Kuiper Score. $q$ represents the threshold probability, above which the event is predicted to occur. The event probabilities take into account sampling and parameter uncertainty. A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The Pesaran and Timmermann (1992) test is used to determine whether the Kuiper Score is greater than zero.

Figure 4.4 displays the evolution of the log scores from the different models against the evolution of GDP growth. What is evident is that the factor model tends to perform worse in times of below-average growth. As GDP growth begins to rise towards its long-term level (the horizontal line), the weight assigned to the factor model increases. The weight assigned to the business survey increases as the growth rate rises above its historical average. The VAR model containing the first revision does better in times of lower growth.
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Table 4.22: Forecast Evaluation - Combination of Models 1, 2, 3, 7, 8, and 9: Based on Weights calculated from scores from previous 5 periods.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Factor Model w. 1st Rev.</td>
<td>0.76***</td>
<td>0.86***</td>
</tr>
<tr>
<td>Bus. Survey w. 1st Rev.</td>
<td>0.92</td>
<td>0.97</td>
</tr>
<tr>
<td>HH Survey w. 1st Rev.</td>
<td>0.90*</td>
<td>0.97</td>
</tr>
</tbody>
</table>

**Weights: Log**

<table>
<thead>
<tr>
<th>Scores</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>All weights</td>
<td>0.79***</td>
<td>0.90***</td>
</tr>
<tr>
<td>Top 3</td>
<td>0.78***</td>
<td>0.89***</td>
</tr>
<tr>
<td>Top 2</td>
<td>0.79***</td>
<td>0.89***</td>
</tr>
</tbody>
</table>

**Weights: RMSE**

<table>
<thead>
<tr>
<th>All weights</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 3</td>
<td>0.84***</td>
<td>0.93***</td>
</tr>
<tr>
<td>Top 2</td>
<td>0.85***</td>
<td>0.93***</td>
</tr>
</tbody>
</table>

**Weights: MAE**

<table>
<thead>
<tr>
<th>All weights</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 3</td>
<td>0.84***</td>
<td>0.93***</td>
</tr>
<tr>
<td>Top 2</td>
<td>0.85***</td>
<td>0.93***</td>
</tr>
</tbody>
</table>

Notes: A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The small sample adjusted Diebold and Mariano test is used to determine whether the MAE and RMSE are significantly smaller than the AR(2) model. The performance of the factor model has changed due to the 5 less observations in the sample.
Figure 4.4: 10 Quarter Moving-Average GDP and 5 Quarter Moving-Average Log Score.

Notes: The log scores do not take into account parameter uncertainty.
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4.8.2 Is the benefit of the surveys their timeliness?

In this sub-section, we look at the performance of the factor model when the factors are generated 2 weeks after the reference quarter. This equates to the publication date of the surveys. In doing so we will answer the question of whether the surveys’ primary benefit is their timeliness.

Table 4.26 provides a list of the variables that enter into the factor model and the publication delay of each variable. The delay represents the weeks after the end of the reference month. The labour force variables are published 2 weeks after the reference month. The rest of the variables are published in excess of 2 weeks of the reference month. Therefore, to generate factors 2 weeks after the reference quarter these particular variables must have their third and final month forecasted. To determine the factors and account for the publication delay, a two-step method will be used. The first step will use an ARIMA model to predict the third and missing month of the quarter for the variables that are yet to be published. These forecasts will be aggregated with the previous two months (which have been published). The second step will generate the factors as outlined in sub-section 3.2.

In Table 4.26 we see that the factor model with the factors determined via the two-step approach yield just as accurate now-casts as the original factor model. A factor model that is just as timely as the surveys can be constructed to yield point now-casts that are more accurate than the business and household surveys.

4.8.3 Do the surveys provide better now-casts of revised GDP?

The previous sections assessed the different variables’ ability to now-cast the initial release of GDP. In this section we look at the different models’ performance to now-cast the second and third release of GDP.

The model specification and data remain the same but instead of using the initial release, $y_{t+1}$, as the target variable, the second, $y_{t+1+1}$, and third release, $y_{t+1+2}$, are used.

The motivation for this section is to see whether the survey variables are better at anticipating revised GDP estimates compared to the benchmark models. Since the ABS releases preliminary GDP estimates to provide a more timely measure on the state of the economy, it is possible that the survey variables are capturing the underlying “true” GDP measure instead of the preliminary release.

---

*It should be noted that this two-step approach is model dependent, and therefore introduces an additional source of uncertainty. For example, during times of “normal” GDP growth, the ARIMA model may generate forecasts that are accurate, thus leading factors that resemble the full data case. However, during periods where GDP is volatile, the ARIMA model may perform badly, leading to factors that generate poor now-casts.*
Table 4.23: Forecast Evaluation: Comparing factor models, with factors extracted 2 weeks after reference quarter and 6 weeks after reference quarter.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>Log-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor w. 1st Rev. (6 weeks after reference quarter)</td>
<td>0.72***</td>
<td>0.84**</td>
<td>0.80***</td>
</tr>
<tr>
<td>Factor w. 1st Rev. (2 weeks after reference quarter)</td>
<td>0.71***</td>
<td>0.83***</td>
<td>0.79***</td>
</tr>
<tr>
<td>Bus. Survey w. 1st Rev.</td>
<td>0.93</td>
<td>0.97</td>
<td>0.96</td>
</tr>
</tbody>
</table>

Notes: A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The small sample adjusted Diebold and Mariano test is used to determine whether the MAE and RMSE of the third release now-cast is statistically smaller than the first release now-cast. The Wilcoxon Signed Rank test is used for the log scores to determine whether the sample locations are statistically different. The displayed log-scores are ratios of the mean log-score of each model's third release now-cast relative to mean of the first release now-cast.

To assess the different models performance, this section looks at the RMSE, MAE and log scores (ignoring parameter uncertainty) of each model. The different performance measures are calculated for the 1st release (as above), 2nd release and 3rd release. The relative performance is then determined by calculating the reduction in the forecast error within models and across GDP releases. In Table 4.24 the column MAE displays the ratio between the MAE when the 2nd release is used as a target against the MAE when the 1st is used as a target. A smaller value indicates that the model on average predicts the second release more accurately than first.

In Table 4.24 we see that the business and household survey models do a better job at now-casting the 2nd release than the 1st. Using the Diebold and Mariano test, the forecast error on the 2nd release is statistically smaller than the forecast error of the 1st release. This applies both to the MAE and RMSE for the business survey model and the MAE for the household survey model. The log scores of the 2nd release now-cast are statistically different at the 1% level from the log scores of the 1st release now-cast for both the business and household surveys.

7One possible reason why the business survey is better at now-casting the second release over the initial release is the use of incomplete data to generate preliminary estimates of capital formation in Australia. In the subsequent quarter, as additional data...
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In Figure 4.5, we see that the business survey model on average has the same weight assigned to it as the factor model. This is in contrast to the result in Figure 4.4, where the factor model is assigned more weight than the business survey model.

In Table 4.25, we see that the models have less success at now-casting the 3rd release of GDP. While the log scores of the 3rd release are statistically smaller than the log scores of the 1st release, the RMSE and MAE are not statistically different from each other.

Table 4.24: Forecast Evaluation: Second Release vs First Release. Smaller values indicate that the forecast error is smaller around the second release than the first.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>Log-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - AR</td>
<td>0.94</td>
<td>0.93</td>
<td>0.94*</td>
</tr>
<tr>
<td>2 - 1st Rev.</td>
<td>0.96</td>
<td>0.92</td>
<td>0.93*</td>
</tr>
<tr>
<td>3 - 1st &amp; 2nd Rev.</td>
<td>0.93</td>
<td>0.92</td>
<td>0.92**</td>
</tr>
<tr>
<td>4 - Factor w. 1st Rev.</td>
<td>0.94</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>5 - Bus. Survey w. 1st Rev.</td>
<td>0.87**</td>
<td>0.88*</td>
<td>0.88***</td>
</tr>
<tr>
<td>6 - HH Survey w. 1st Rev.</td>
<td>0.9**</td>
<td>0.92</td>
<td>0.9***</td>
</tr>
</tbody>
</table>

Notes: A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The small sample-adjusted Diebold and Mariano test is used to determine whether the MAE and RMSE of the 2nd release now-cast is statistically smaller than the 1st release now-cast. The Wilcoxon Signed Rank test is used for the log scores to determine whether the sample locations are statistically different. The displayed log scores are ratios of the mean log score of each model’s second release now-cast relative to mean of the first release now-cast.

is comes in, a more comprehensive and updated estimate of capital formation is derived. This plays an important role in revising capital formation, and therefore GDP. The NAB Business Survey may be capturing the “true” level of capital formation, as opposed to the preliminary estimate that enters the initial release of GDP. See the explanatory notes in http://www.abs.gov.au/ausstats/abs@.nsf/mf/8755.0.
4.8. EXTENSIONS

Table 4.25: Forecast Evaluation: Third Release vs First Release. Smaller values indicate that the forecast error is smaller around the third release than the first.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>Log-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - AR</td>
<td>0.89</td>
<td>0.89</td>
<td>0.92*</td>
</tr>
<tr>
<td>2 - 1st Rev.</td>
<td>0.91</td>
<td>0.89</td>
<td>0.92</td>
</tr>
<tr>
<td>3 - 1st &amp; 2nd Rev.</td>
<td>0.89</td>
<td>0.89</td>
<td>0.92</td>
</tr>
<tr>
<td>4 - Factor w. 1st Rev.</td>
<td>0.94</td>
<td>0.87</td>
<td>0.9</td>
</tr>
<tr>
<td>5 - Bus. Survey w. 1st Rev.</td>
<td>0.9</td>
<td>0.86</td>
<td>0.88*</td>
</tr>
<tr>
<td>6 - HH Survey w. 1st Rev.</td>
<td>0.9</td>
<td>0.89</td>
<td>0.89**</td>
</tr>
</tbody>
</table>

Notes: A * denotes significance at the 10% level, ** denotes significance at 5% level and *** significance at the 1% level. The small sample-adjusted Diebold and Mariano test is used to determine whether the MAE and RMSE of the 3rd release now-cast is statistically smaller than the 1st release now-cast. The Wilcoxon Signed Rank test is used for the log scores to determine whether the sample locations are statistically different. The displayed log-scores are ratios of the mean log score of each model’s third release now-cast relative to mean of the first release now-cast.

Figure 4.5: 10 Quarter Moving-Average 2nd Release GDP and 5 Quarter Moving-Average Log Score. Factor and survey models with only first revision.

Notes: The log scores do not take into account parameter uncertainty.
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Figure 4.6: 10 Quarter Moving-Average 3rd Release GDP and 5 Quarter Moving-Average Log Score. Factor and survey models with only first revision.

Notes: The log scores do not take into account parameter uncertainty.
4.9 Conclusion

This paper assesses the business and household surveys’ ability to now-cast GDP growth and anticipate discrete economic events in real-time.

While the model incorporating the business and household survey generates now-cast that are not statistically different from the benchmark model incorporating lagged values of GDP and the VAR model incorporating GDP revisions, they are more reliable than either model at anticipating discrete economic events, such as below and above the average growth rates. The results also show that the model incorporating the business survey is better at now-casting the second release of GDP than the first. Therefore the business survey is a better indicator of revised GDP, then the initial release.

The monthly indicators published by the ABS, which typically are published two to three weeks after the business survey, can be effectively summarised through a factor model to produce more accurate now-casts than either of the survey and benchmark model. The factor model also outperforms the benchmark and survey and benchmark models in anticipating the economic events not mentioned above. The paper also showed that factors extracted two weeks after the end of the reference quarter (making them as timely as the surveys) are capable of generating now-casts that are more accurate than either of the survey or benchmark models.

The conclusion from this study is that a model consisting of factors derived from monthly ABS indicators are the best option for now-casting GDP and understanding many economic developments. However, the surveys should still be referred to if they are signalling extreme or less frequent economic events, especially since these are often the most important events of interest to policy makers.
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4.10 Appendix

4.10.1 Estimation by the EM algorithm

The linear state-space model is described by the following two equations:

\[ X_t = \Lambda F_t + \varepsilon_t, \quad \text{where} \quad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \]  \hfill (4.32)
\[ F_t = \Phi_1 F_{t-1} + \nu_t, \quad \text{where} \quad \nu_t \sim N(0, \Sigma_\nu). \]  \hfill (4.33)

The outputs \( X_t \) are a linear function of the factors \( F_t \), and the factors at one time step depends linearly on the previous state. Based on (4.32) and (4.33) we can write the conditional density for the outputs and factors as

\[ P(X_t | F_t) = \exp \left( -\frac{1}{2} (X_t - \Lambda F_t)' \Sigma_\varepsilon (X_t - \Lambda F_t) \right) \left( 2\pi \right)^{-p/2} |\Sigma_\varepsilon|^{-1/2} \]  \hfill (4.34)
\[ P(F_t | F_{t-1}) = \exp \left( -\frac{1}{2} (F_t - \Phi_1 F_{t-1})' \Sigma_\nu (F_t - \Phi_1 F_{t-1}) \right) \left( 2\pi \right)^{-k/2} |\Sigma_\nu|^{-1/2}. \]  \hfill (4.35)

A sequence of \( T \) outputs \((X_1, X_2, ..., X_T)\) and factors \((F_1, F_2, ..., F_T)\) is denoted by \( \{ X \} \) and \( \{ F \} \). Using the assumption that the shocks are independent across outputs and factors we have

\[ P(\{ X \} | \{ F \}) = P(F_1) \prod_{t=2}^{T} P(F_t | F_{t-1}) \prod_{t=1}^{T} P(X_t | F_t). \]  \hfill (4.36)

Assuming normal initial density

\[ P(F_1) = \exp \left( -\frac{1}{2} (F_1 - F_0)' E_1 (F_1 - F_0) \right) \left( 2\pi \right)^{-k/2} |E|^{-1/2}, \]  \hfill (4.37)

where \( F_0 \) is the stationary value of the factors. The joint log probability is:

\[
\log P(\{ X \} | \{ F \}) = -\sum_{t=1}^{T} \left( \frac{1}{2} (X_t - \Lambda F_t)' \Sigma_\varepsilon^{-1} (X_t - \Lambda F_t) \right) - \frac{T}{2} \log |\Sigma_\varepsilon| \\
- \sum_{t=2}^{T} \left( \frac{1}{2} (F_t - \Phi_1 F_{t-1})' \Sigma_\nu^{-1} (F_t - \Phi_1 F_{t-1}) \right) - \frac{T-1}{2} \log |\Sigma_\nu| \\
- \frac{1}{2} (F_1 - F_0)' E_1^{-1} (F_1 - F_0) - \frac{1}{2} \log |E_1| - \frac{T(p+k)}{2} \log 2\pi.
\]  \hfill (4.38)
In the case where there are missing values, we replace all missing values with zeroes and (4.34) becomes

\[
P(X_t|F_t) = \exp\left(-\frac{1}{2} (X_t - S_t\Lambda F_t)' S_t \Sigma^{-1}_\epsilon S_t' (X_t - S_t\Lambda F_t)\right)
\times (2\pi)^{-p/2}|S_t\Sigma S_t'|^{-1/2},
\] (4.39)

where \(S_t\) is a selection matrix, i.e. it is a diagonal matrix with ones corresponding to the non-missing observations in \(X_t\) and zeros otherwise. The rest of the equations remain the same.

The EM algorithm

Since the factors are unobservable, we require computing the expected likelihood, hence the E in EM,

\[
Q = E[\log P(\{X\}\{F\}; \theta(j))|X_t].
\] (4.40)

This quantity depends on three expectations, \(E[F_t|\{X\}], E[F_tF_t'|\{X\}]\) and \(E[F_tF_t-1|\{X\}]\) and the initial parameter set \(\theta(j)\). These expectations can be estimated using the Kalman Filter and Smoother algorithm. The estimation of the initial parameters is discussed in subsection 3.2.

The M step involves estimating \(\theta(j + 1)\), which is the updated parameters. It is achieved by taking the partial derivative of the expected log-likelihood with respect to the parameters in \(\theta\), setting it to zero and solving. The new parameter estimates are:

\[
\frac{\partial Q}{\partial \Lambda} = -\sum_{t=1}^{T} \Sigma^{-1}_\epsilon X_t E[F_t|\{X\}]' + \sum_{t=1}^{T} \Sigma^{-1}_\epsilon E[F_tF_t'|\{X\}] = 0
\]

\[
\Lambda(j + 1) = \left(\sum_{t=1}^{T} X_t E[F_t|\{X\}]\right) \left(\sum_{t=1}^{T} E[F_tF_t'|\{X\}]\right)^{-1}.
\] (4.41)

\[
\frac{\partial Q}{\partial \Sigma^{-1}_\epsilon} = \frac{T}{2} \Sigma^{-1}_\epsilon - \sum_{t=1}^{T} \left(\frac{1}{2} X_tX_t' - \Lambda E[F_t|\{X\}]X_t' + \frac{1}{2} \Lambda E[F_tF_t'|\{X\}]\Lambda'\right) = 0
\]

\[
\Sigma^{-1}_\epsilon(j + 1) = \frac{1}{T} \sum_{t=1}^{T} \left(X_tX_t' - \Lambda(j + 1)E[F_t|\{X\}]X_t'\right).
\] (4.42)
\[
\frac{\partial Q}{\partial \Phi} = - \sum_{t=2}^{T} \Sigma_{\nu} E[F_t F'_t|\{X\}] + \sum_{t=2}^{T} \Sigma_{\nu}^{-1} \Phi E[F_{t-1} F'_{t-1}|\{X\}] = 0
\]
\[
\Phi(j + 1) = \left( \sum_{t=2}^{T} E[F_t F'_t|\{X\}] \right) \left( \sum_{t=2}^{T} E[F_{t-1} F'_{t-1}|\{X\}] \right)^{-1}.
\tag{4.43}
\]
\[
\frac{\partial Q}{\partial \Sigma_{\nu}^{-1}} = \frac{T-1}{2} \Sigma_{\nu} - \frac{1}{2} \sum_{t=2}^{T} \left( E[F_t F'_t|\{X\}] - \Phi E[F_{t-1} F'_t|\{X\}] - E[F_t F'_{t-1}|\{X\}]\Phi' \right)
+ \Phi E[F_t F'_{t-1}|\{X\}]\Phi') = 0
\]
\[
= \frac{T-1}{2} \Sigma_{\nu} - \frac{1}{2} \left( \sum_{t=2}^{T} E[F_t F'_t|\{X\}] - \Phi(j + 1) \sum_{t=2}^{T} E[F_{t-1} F'_t|\{X\}] \right)
\]
\[
\Sigma_{\nu}(j + 1) = \frac{1}{T-1} \left( \sum_{t=2}^{T} E[F_t F'_t|\{X\}] - \Phi(j + 1) \sum_{t=2}^{T} E[F_{t-1} F'_t|\{X\}] \right).
\tag{4.44}
\]
\[
\frac{Q}{F_0} = E[F_1 - F_0] E_1^{-1} = 0
\]
\[
F_0(j + 1) = E[F_1].
\tag{4.45}
\]
\[
\frac{Q}{E_1} = \frac{1}{2} E_1 - \frac{1}{2} \left( E[F_1 F'_1] - E[F_1] F'_0 - F_0 E[F'_1] + F_0 F'_0 \right)
\]
\[
E_1 = E[F_1 F'_1] - E[F_1] E[F'_1].
\tag{4.46}
\]

With missing observations (4.41) and (4.42) become:
\[
\Lambda(j + 1) = \left( \sum_{t=1}^{T} S_t X_t E[F_t|\{X\}] \right)' \left( \sum_{t=1}^{T} E[F_t F'_t|\{X\}] \otimes S_t \right)^{-1}.
\tag{4.47}
\]
\[
\Sigma_{e}(j + 1) = \frac{1}{T} \sum_{t=1}^{T} \left( S X_t X'_t S' - S X_t E[F'_t|\{X\}] \Lambda(j + 1)' S 
- S \Lambda(j + 1) E[F'_t|\{X\}] X'_t S - S E[F_t F'_t|\{X\}] \Lambda(j + 1)' S 
+ (I_m - S_t) \Sigma_{e}(j)(I_m - S_t) \right),
\tag{4.48}
\]

where \( I_m \) is an identity matrix of size \( m \times m \), where \( m \) is the number of variables in the factor model.
4.10.2 Variable List for Factor Model

Table 4.26: Variable list. All series are sourced from the Australian Bureau of Statistics.

<table>
<thead>
<tr>
<th>Variable Names</th>
<th>Transformation</th>
<th>Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Credit Extended to Business</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>2 Housing Finance Commitments - Construction of dwellings - Number</td>
<td>Log Difference</td>
<td>6 weeks</td>
</tr>
<tr>
<td>3 Credit Extended to Investor Housing</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>4 Credit Extended to Owner-Occupier Housing</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>5 Nominal Exports</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>6 Nominal Imports</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>7 Total Employment</td>
<td>Log Difference</td>
<td>2 weeks</td>
</tr>
<tr>
<td>8 Lending Commitments - Commercial</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>9 Lending Commitments - Total investment housing</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>10 Lending Commitments - Construction of investment housing</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>11 Lending Commitments - Construction of owner-occupier housing</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>12 Lending Commitments - Total owner-occupier housing</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>13 Lending Commitments - Personal</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>14 Monthly Hours Worked in All Jobs</td>
<td>Log Difference</td>
<td>2 weeks</td>
</tr>
<tr>
<td>15 Purchase of Established Housing - No.</td>
<td>Log Difference</td>
<td>6 weeks</td>
</tr>
<tr>
<td>16 Purchase of Established Housing - Value</td>
<td>Log Difference</td>
<td>6 weeks</td>
</tr>
<tr>
<td>17 Nominal Retail Sales</td>
<td>Log Difference</td>
<td>5 weeks</td>
</tr>
<tr>
<td>18 Total Number of Housing Approvals</td>
<td>Log Difference</td>
<td>4 weeks</td>
</tr>
<tr>
<td>19 Total Passenger Vehicles Sold</td>
<td>Log Difference</td>
<td>3 weeks</td>
</tr>
<tr>
<td>20 Unemployment Rate</td>
<td>Difference</td>
<td>2 weeks</td>
</tr>
</tbody>
</table>
### 4.10.3 Summary Statistics of Variables

Table 4.28: Summary Statistics of First and Initial Release GDP, Business and Household Surveys, Factors and Revisions.

<table>
<thead>
<tr>
<th></th>
<th>First Release GDP, %Δ</th>
<th>Initial Release GDP, %Δ</th>
<th>HH Survey, Index</th>
<th>Bus. Survey, Index</th>
<th>Factor 1, Index</th>
<th>Factor 2, Index</th>
<th>Factor 3, Index</th>
<th>1st Rev., %Δ</th>
<th>2nd Rev., %Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.74</td>
<td>0.64</td>
<td>102.11</td>
<td>1.46</td>
<td>-0.43</td>
<td>0.78</td>
<td>-0.28</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Std.</td>
<td>0.68</td>
<td>0.60</td>
<td>10.99</td>
<td>13.18</td>
<td>2.36</td>
<td>2.33</td>
<td>1.70</td>
<td>0.31</td>
<td>0.25</td>
</tr>
<tr>
<td>Min</td>
<td>-1.40</td>
<td>-1.66</td>
<td>68.37</td>
<td>-39.66</td>
<td>-6.75</td>
<td>-4.20</td>
<td>-4.55</td>
<td>-0.97</td>
<td>-0.59</td>
</tr>
<tr>
<td>25%</td>
<td>0.46</td>
<td>0.39</td>
<td>96.88</td>
<td>-4.61</td>
<td>-1.69</td>
<td>-1.17</td>
<td>-1.51</td>
<td>-0.05</td>
<td>-0.09</td>
</tr>
<tr>
<td>50%</td>
<td>0.82</td>
<td>0.64</td>
<td>103.86</td>
<td>2.79</td>
<td>-0.42</td>
<td>0.08</td>
<td>-0.12</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>75%</td>
<td>1.15</td>
<td>1.04</td>
<td>110.43</td>
<td>10.86</td>
<td>0.97</td>
<td>2.79</td>
<td>0.78</td>
<td>0.29</td>
<td>0.15</td>
</tr>
<tr>
<td>Max</td>
<td>2.27</td>
<td>1.84</td>
<td>120.97</td>
<td>21.21</td>
<td>5.68</td>
<td>5.53</td>
<td>4.10</td>
<td>1.25</td>
<td>1.14</td>
</tr>
</tbody>
</table>

**Notes:** First Release GDP growth rate represents the unrevised first release GDP growth rate, or the growth rate along the diagonal of the real-time GDP table. The Initial Release GDP Growth Rate is the growth rate as published by the statistical agency and it represents the growth rate along the vertical of the latest vintage of GDP.
4.10.4 Figures for Event Probabilities

Figure 4.7: Probability of growth rates less than the 40th percentile.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN($0$, $\Sigma$).
WHAT IS THE INFORMATIONAL CONTENT OF BUSINESS AND HOUSEHOLD SURVEYS AND WHEN SHOULD WE USE THEM?

Figure 4.8: Probability of growth rates greater than the 60th percentile.

![Figure 4.8: Probability of growth rates greater than the 60th percentile.](image)

*Notes:* The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted valued. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).

Figure 4.9: Probability of growth rates less than the 30th percentile.

![Figure 4.9: Probability of growth rates less than the 30th percentile.](image)

*Notes:* The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted valued. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).
Figure 4.10: Probability of growth rates greater than the 70th percentile.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a $\text{MVN}(0, \Sigma)$.

Figure 4.11: Probability of growth rates less than 0.5 standard deviations below the mean.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a $\text{MVN}(0, \Sigma)$. 
Figure 4.12: Probability of growth rates greater than 0.5 standard deviations above the mean.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted valued. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).
4.10. APPENDIX

Figure 4.13: Growth below 5 quarter moving average.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).
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Figure 4.14: Growth above 5 quarter moving average.

![Graph showing growth above 5 quarter moving average with dates and probability y-axis.](image)

**Notes:** The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).

Figure 4.15: Growth below previous peak value.

![Graph showing growth below previous peak value with dates and probability y-axis.](image)

**Notes:** The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).
Figure 4.16: Growth above previous peak value.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a $\text{MVN}(\theta, \Sigma)$.

Figure 4.17: Growth below previous trough value.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a $\text{MVN}(\theta, \Sigma)$. 
Figure 4.18: Growth above previous trough value.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).

Figure 4.19: Below average growth in period \( t - 1 \) and in period \( t \); low-low growth state.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, Σ).
Figure 4.20: Below average growth in period $t - 1$ and above average growth period $t$; low-high growth state.

**Notes**: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN(0, $\Sigma$).
WHAT IS THE INFORMATIONAL CONTENT OF BUSINESS AND HOUSEHOLD SURVEYS AND WHEN SHOULD WE USE THEM?

Figure 4.21: Above average growth in period $t - 1$ and below average growth period $t$; high-low growth state.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted valued. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a $\text{MVN}(0, \Sigma)$.
Figure 4.22: Above average growth in period $t - 1$ and period $t$; high-high growth state.

Notes: The vertical bars represent the actual event dates. The observed probability is calculated from an empirical distribution of the predicted values. The empirical distribution is constructed by drawing parameter estimates from the posterior distribution and errors from a MVN$(0, \Sigma)$. 
Chapter 5

Conclusion

This thesis has looked at different aspects of business cycles and fluctuations in economic activity. New empirical regularities that can be used to evaluate macro-economic models were presented in Chapter 2 and 3. While Chapter 4 assessed the ability of a variety of data-sets to generate now-casts and anticipate discrete economic events in Australia.

Chapter 2 investigated the empirical link between separation rates and the temporal variation in vacancy yields. The Chapter begins by showing that sectors with higher separation rate tend to experience a larger increase in their vacancy yield when aggregate vacancies decline.

Extending a labour search model to two sectors, the analysis showed that differences in separation rates alone cannot generate the observed variation in the vacancy yield elasticity. Given this result, differences in productivity and vacancy creation costs, which are correlated with the separation rate, were considered. The results showed that these variables can account for the observed temporal variation in the vacancy yield. A future path of research is to investigate the out-of-steady-state properties of the model.

Chapter 3 presented new findings on sectoral turning points around aggregate turning point dates. It was shown that sectors are more likely to be in the same phase as aggregate employment around the aggregate peak date than the aggregate trough date. Furthermore, the typical sector does not display any asymmetries in their absolute growth rates around their own turning point dates.

These two findings show that the observed asymmetry around aggregate turning point dates is due to the lack of industries expanding around the aggregate trough date. This phenomena requires further investigation. In addition, the results should be compared to the predictions of business cycle models.

Finally Chapter 4 considered the utility of different data-sets to now-cast Australian GDP and anticipate discrete economic events. It was shown that a factor augmented VAR can generate point now-casts that are superior to a benchmark AR model, or a VAR containing business and household surveys. The business and household surveys, however, are shown to be useful when they signal periods of less frequent growth rates.
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