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# Aviation activity as a leading indicator of economic activity[1]

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## Abstract

Changes in economic trends can often be well underway by the time economic data is published, giving policy makers little time to respond. A leading indicator of economic activity is useful to policy makers as it allows more time to respond to anticipated changes in the economy. This study investigates whether data on domestic aviation activity in Australia could be used as an indicator of Australian economic activity – with the view of developing an indicator of regional economic activity should initial tests be successful. Graphical analysis was the predominant method used to test the predictive power of aviation data, which is collected on a monthly basis by the Bureau of Infrastructure, Transport and Regional Economics (BITRE), against Gross Domestic Product (GDP) and employment. The study found that load factor data on the Melbourne-Sydney air route best predicted variations in GDP. However, even the best performing variable did not sufficiently predict fluctuations in economic data to be a useful leading indicator for policy makers.

## Introduction

Economic data is often published on a quarterly basis, making it difficult for policy makers to predict, let alone react, to fluctuations in economic performance. Changes in trends can often be well underway by the time data is published, giving policy makers little time to respond. Further, real Gross Domestic Product (GDP) data is one of the most often revised data series published by the Australian Bureau of Statistics (ABS), adding to uncertainty around economic performance (Connolly et al., 2014). A leading indicator of economic activity would predict turning points in deviations from trend of measures of economic activity, and would be useful to policy makers by allowing more time to respond to changes in the economy.

This study investigates whether data on domestic aviation activity could be used as a leading or contemporaneous indicator of domestic economic activity - with the view of developing an indicator of regional economic activity. The study first tested the relationship between aviation data and economic indicators of the national economy. Time series data on passenger numbers, aircraft movements and passenger load factors, which are all published on a monthly basis by the Bureau of Infrastructure, Transport and Regional Economics (BITRE), were tested against time series data on GDP and

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employment published by the ABS. These tests were conducted on the basis that aviation data would need to clearly lead data on the national economy (the aggregate of Australia's regions) if it were to consistently lead economic data on individual regions. Aviation data on the Melbourne to Sydney air route was also tested against aggregated economic data due to its status as the busiest air route in Australia, and also due to recent claims that data on the Melbourne-Sydney air route can be used as a leading indicator of business activity (James, 2016 and 2017).

For aviation data to be a leading indicator of economic data, it must move before the economic data, after taking into account seasonal factors and trend. There are two steps in testing whether aviation data can be used for this purpose. Firstly, the smoothed aviation and economic series are compared graphically. Secondly, if the series of aviation data are found to graphically lead economic data, they are further tested using regression analysis. The graphical tests found that overall, aviation data had little power to predict fluctuations in economic activity. Of the variables tested, passenger load factors on the Melbourne-Sydney air route had the highest ability to predict economic activity. However, even the best performing variable did not predict fluctuations in economic data well enough to be a useful leading indicator – the variable's lead times were generally too short to be of use to policy makers. Thus, regression analysis on the series was not pursued.

While the study suggests that aviation data cannot be used as a leading indicator of economic activity on the national scale or consistently across regions, this study did not examine its relevance to specific regions with high reliance on industries that are closely linked to aviation - such as tourism or mining. Further, whether aviation data could be used as part of a composite indicator was beyond the scope of this paper.

# Background

The aviation industry has long been associated with economic growth, and is thought to have direct and indirect economic benefits reaching from the local economy of an airport to the national economy. Commonly cited benefits include job generation within the aviation sector and supportive industries, boosts to tourism and trade in an airport's local economy, and increases in expenditure in the broader economy as a result of increased employment in aviation (multiplier effect).

The economic impact of the aviation industry is difficult to measure, and estimates vary. Further, studies which examine the economic impact of the aviation industry are often commissioned by transport or aviation associations. For example, the Air Transport Action Group (ATAG) estimated that in 2014 aviation contributed US$2.7 trillion to the global economy (ATAG, 2016). A study undertaken by Deloitte Access Economics and which was commissioned by the Australian Airport Association estimated that Australia's airports contributed around $17.3 billion, or 1.2 per cent of the Australian economy in 2011 (Deloitte Access Economics, 2012).

Studies also examine the impacts of airports through assessing the contribution of airports to employment, however estimates for this also vary. ATAG estimated that the aviation industry supported the employment of 62.7 million people worldwide in 2014 (ATAG, 2016). In the Australian context, BITRE estimated that for every million annual passengers 580 people were employed on-site at ten selected major Australian airports in 2011 (BITRE, 2013). On the other hand, a number of European studies including Robertson (1995), ACI Europe (1998) Hakfoort et al. (2001) and York Aviation (2004) suggest that for every million annual passengers, 1000 direct on-site positions are generated (cited in BITRE, 2013). Breukner (2003) shows that a 10 per cent increase in passenger numbers in metropolitan areas of the United States leads to approximately a one per cent increase in employment in service-related industries. Percoco (2010) also investigates the impact of airports on employment across provinces in Italy, and concludes that a one per cent increase in the number of airport passengers results in a 0.45 per cent increase in local service sector employment.

While the broad consensus in the literature is that aviation activity and economic growth are correlated, there is little agreement on the direction of causality between aviation activity and economic growth (Lee et al., 2017). Literature on the direction of causality between air transport and economic growth remains relatively undeveloped, and conclusions vary. Some studies conclude that a bi-directional relationship exists between the two variables. However, some also argue that there is a uni-directional causal relationship, and some conclude that the causal relationship differs depending on whether a short or long-run approach is adopted.

Existing studies predominately examine the broad relationship between two variables that represent growth in passenger numbers and growth in GDP, and test the causality of the relationship. One body of literature examines the relationship between these two variables in specific countries using domestic time series data (Marazzo et al., 2010; Chi and Baek, 2013; Mehmood et al., 2014; Brida et al., 2016; Alshammary, 2017). For example, Brida et al. (2016) examine the long-run relationship between economic growth and air transport in Mexico, and conclude that there is bi-directional causality between the two variables. Marazzo et al. (2010) examine this relationship in Brazil, and report that while GDP causes passenger movements, passenger movements do not cause GDP. Mehmood et al. (2014) examine the link between aviation demand and economic growth in the Czech Republic, and conclude that while the variables are co-integrated in the long run and the short run, causality only runs from GDP to passenger numbers. Alshammary (2017) tests the hypothesis that aviation leads economic growth in Saudi Arabia, controlling for population, banking credit to the private sector and jet fuel production, and concludes that aviation does cause economic development in the Saudi Arabian context.

Another body of work examines the relationship across regions using cross sectional or panel data (Mukkala et al., 2013; Baker et al., 2015; Hu et al., 2015; Hakim et al., 2016). For example, Hakim et al. (2016) examine panel data on GDP, air passenger traffic and freight volumes across eight South Asian countries, and conclude that while there is no causal relationship in the short run, economic growth causes growth in passenger numbers in the long run. Hu et al. (2015) examine panel data on Gross Regional Product (GRP) and air traffic data across 29 provinces in China, and conclude that there is strong bi-directional causality between passenger numbers and economic growth in the long run, but that the causality only runs from passenger numbers to economic growth in the short run.

Some studies have a narrower focus. For example, Baker et al. (2015) examine the impact of regional, remote and rural (RRR) airports on local economies in Australia through analysing panel data on income and passenger numbers, by region. Mukkala et al. (2013) also consider how air traffic affects economic growth across remote and core regions, using panel data on 86 European regions. Baker et al. (2015) conclude that bi-directional causality exists between regional aviation and economic growth, and Mukkala et al. (2013) conclude that while regional growth causes airport activity in core regions, the causality is bi-directional in remote regions.

More recently, the question as to whether data on aviation activity could be used as a leading indicator of economic activity has been posed by CommSec Chief Economist Craig James, who used activity on the Melbourne-Sydney air route as a proxy measure for business activity (James, 2016; James, 2017). Tests on this specific relationship have not been made public, and there is very little literature on the prospect of using data on aviation activity as a leading (or contemporaneous) indicator of economic growth. The most prominent study in this space is Green (2007), who sets out to examine whether activity at a metropolitan airport can help predict population and employment growth, using panel data on boardings at airports in the US as well as other control variables. Green

(2007) concludes that passenger boardings per capita (with respect to an airport's local population) is a predictor of population and employment growth. However, Green's (2007) conclusions are based on his regression analysis, and more rigorous work is required in this space to thoroughly consider the use of aviation activity as a predictor of economic variables. The use of aviation data as a predictor or indicator of economic activity is an area which remains significantly underexplored.

The literature on aviation activity and economic growth remains very high level, with very few studies incorporating additional variables that may impact the aviation industry or economic growth (such as exchange rates, interest rates and productivity) into their models. Some studies, including Percoco (2009), Green (2007) and Alshamarry (2017) develop a more robust model by controlling for other exogenous variables that affect economic growth. However, the lack of additional variables in existing analyses remains a gap in the literature, and more work is required to control for other influencing variables.

Another limitation with the current literature is that many studies do not account for seasonal, irregular and cyclical components of the data used in models, and it is often unclear whether original, or smoothed data has been used. Removing these components is necessary to reveal long-term trends in time series data, and is a vital process to properly examine the relationship between different time series variables. For example, seasonal effects on air traffic data may include heightened activity during the Christmas or Easter holiday seasons. Similarly, economic activity is likely to be heightened during holiday seasons as consumer spending rises during these periods. The noise that these seasonal patterns create can obscure other movements in the data as well as the underlying trend (ABS, 2012). Using data that has not been adjusted for such noise may lead to inaccurate conclusions about the relationship between two data series.

Further, the data used in the studies discussed above are often non-stationary. That is, the mean and variance of the data series are variable over time, and do not revert to a constant long-run mean or variance. For example, aviation traffic data has an overall upward trend, and therefore the mean and variance of aviation traffic data grows over time. This is to be expected, as demand for air transportation will grow as the population of a region grows over time. Similarly, economic activity is also likely to grow as the population grows. Therefore, both aviation data and economic activity are likely to be non-stationary and are driven by the same underlying population growth over time. These characteristics in a time series can often hide other important patterns and trends in the data. This means that what may appear to be a close relationship between the two variables at first glance, or even after running regression analysis, may in fact simply be that the same exogenous factor is increasing the two series together. Making conclusions about the relationship between two variables without first converting the data into a stationary series may lead to spurious results. Many studies in the current literature do take into account stationarity issues, for example by transforming non-stationary data into stationary data. However, some do not, and future work in this area should ensure that data is adjusted as required.

As is evident from the discussions above, the relationship between aviation activity and economic growth within Australia has not been thoroughly examined. As discussed, Baker et al. (2015) examine the impact of airports in regional, rural and remote areas of Australia, and Deloitte Access Economics (2012) has also conducted a study examining the social and economic impacts of Australian Airports. In addition to these studies, BITRE (2012) maintains a forecasting model of airport passengers. Three groups of air passenger movements are modelled (per capita international movements of Australian residents, per capita international movements of overseas visitors and per capita domestic movements of all passengers), controlling for per capita GDP, airfares, the exchange rate and shocks such as the Sydney Olympic Games, terrorism incidents and the Global Financial Crisis. Stationarity issues are controlled for in the model, by converting passenger movements and GDP to a per capita basis. The inclusion of GDP as an independent variable in the forecasting model suggests that economic growth does drive movements in aviation activity.

As mentioned, the use of aviation data as a predictor or leading indicator of economic activity is an area which remains significantly underexplored, and there is scope to test the relationship between economic activity and aviation activity in the Australian context. This study sought to create value in this space, by examining whether monthly aviation data published by BITRE could be used to predict economic growth. The study initially tested the use of aggregated national aviation data as a predictor of economic activity. It then tested the use of data on the Melbourne-Sydney air route against data on the national economy. The Melbourne-Sydney air route was selected due to its status as the busiest air route in Australia, as well as to test past claims by James (2016 and 2017) that the Melbourne-Sydney air route is a leading indicator of national business activity. The initial intention for the study was to test the predictive power of aviation data at the national scale, and further test the use of aviation data at a state or regional scale should a strong relationship be initially observed at higher scales. This is because it is unlikely that any useful relationship will be discovered at a regional scale if a strong relationship is not first observed at higher levels.

## Box 1: Leading indicators

Individual and composite leading indicators are correlated to future movements in the economy, and can provide information on when a change in the economy is likely to occur (Mongardini et al., 2003; Connolly et al., 2008). For a leading indicator to be useful, it should typically be an accurate measure of an important economic variable, bear a consistent relationship with business cycle movements over time, should not be dominated by irregular and non-cyclical movements, and should be reported frequently and with little time lag. These characteristics ensure that the indicator will provide regular and timely information on the state of the economy and its business cycles (Ratti, 1985).

Leading indicators were first explored in the U.S. in the 1920's and 1930's, initially by the Harvard Economic Service and later by the National Bureau of Economic Research (NBER) where researchers examined whether a group of economic variables consistently led, coincided with, or lagged behind turning points in the U.S. business cycle (Gorton, 1985; Mongardini et al., 2003; Friedman, 2013). Composite indicators consisting of the best leading variables were subsequently developed, and through the work of Moore and Shishkin (1967) weights were eventually applied to those composite variables (cited in Mongardini et al., 2003). The first composite leading indicators were subjective, in regards to both the selection of their component variables and the weights that were applied to them. However, leading indicators are now often developed using econometric methods (Mongardini et al., 2003).

Two commonly used methods used to develop composite leading indicators are the NBER and Stock and Watson (1989, 1991) procedures (cited in Cotrie et al., 2009). Both methods seek to use a range of variables to estimate the “state of the economy”, and calculate the indicator using a weighted average of the component series (Cotrie et al., 2009).

However, the two approaches differ in how these component series and weights are determined. The NBER method is based on the work by Moore and Shishkin (1967), and uses a scoring system to select the component series and their weights (cited in Simone, 2001). The system assigns scores to the component series based on how well they align with the desirable characteristics of a leading variable. The Stock and Watson method on the other hand adopts a more rigorous econometric approach, using regression techniques and causality analysis to select the component series and the weights applied to them (Simone, 2001).

There are two approaches in which leading indicators can be used to forecast future movements in economic activity, and the variable selected will be determined based on which approach is preferred. The first is known as the turning point approach, where the indicator is used to predict turning points in economic activity (Gorton, 1982; Simone, 2001). The second is known as the period-by-period approach, where the indicator predicts movements in economic activity across all points of the business cycle, and not just turning points (Gorton, 1982; Simone, 2001). One issue with the turning point approach is the need to decide what constitutes a “turning point”, as forecasts do change depending on how a turning point is defined. The common approach is to predict a turning point when the indicator has consistently moved higher or lower for a specified number of months. However, defining the correct number of months can become an issue (Gorton, 1982). The period-by-period approach on the other hand compares the forecast value from the observed value, and creates challenges in defining such deviations (Simone, 2001).

A local example of a composite leading indicator is the Commonwealth Department of Jobs and Small Business’ (DJSB) Monthly Leading Indicator of Employment, which is a composite leading indicator of employment consisting of five equally-weighted component series and an average lead time of just over one year (DJSB, 2018a). A fall or rise in the indicator implies that the growth rate of employment will fall or rise above its long term trend rate in the future, and a turning point is defined as six movements in the same direction following a turn in direction (Connolly et al., 2008).

The methodology used to develop the DJSB Monthly Leading Indicator of Employment is described in Connolly et al. (2008), and is provided below:

1. The component series and the employment series are smoothed using 13-term Henderson weights to remove their irregular elements. This gives the one-year trend employment level.
2. The resulting series are then exponentially extrapolated both forwards (and backwards where necessary), using an average compound growth rate for the preceding five years, for 36 monthly observations and the trend elements are calculated as 73-term centred moving averages. This allows us to obtain the six-year trend employment level.
3. The cyclical elements of the series are obtained by subtracting the six-year trend level from the one-year trend level of each series.
4. The cyclical elements are then obtained by subtracting the mean from each series and then dividing by each series’ standard deviation to normalise (or standardise) the series.
5. The partial forward indicators’ components are combined linearly, applying equal weights of 20 per cent to each of the five components.
6. The Indicator is then obtained by dividing the combined set of components by its standard deviation to restandardise it.

# Data

There are several reasons for examining aviation data as a possible leading indicator of economic activity. Aviation has multiple links to different facets of the economy, and deviations from trend in aviation activity could provide information on how the economy will perform in the future. For example, as James (2016 and 2017) suggests, flights related to business could be an indicator of business activity in the overall economy. Likewise, air travel for leisure is likely tied to tourism activity, and therefore will also be tied to broader economic conditions.

BITRE releases a range of aviation data on a monthly basis. It is the most appropriate data on aviation to test in the Australian context, because it is released frequently (monthly), has a minimal lag time, is obtained from a reliable source and is publicly and easily accessible. The following aviation data published by BITRE were examined:

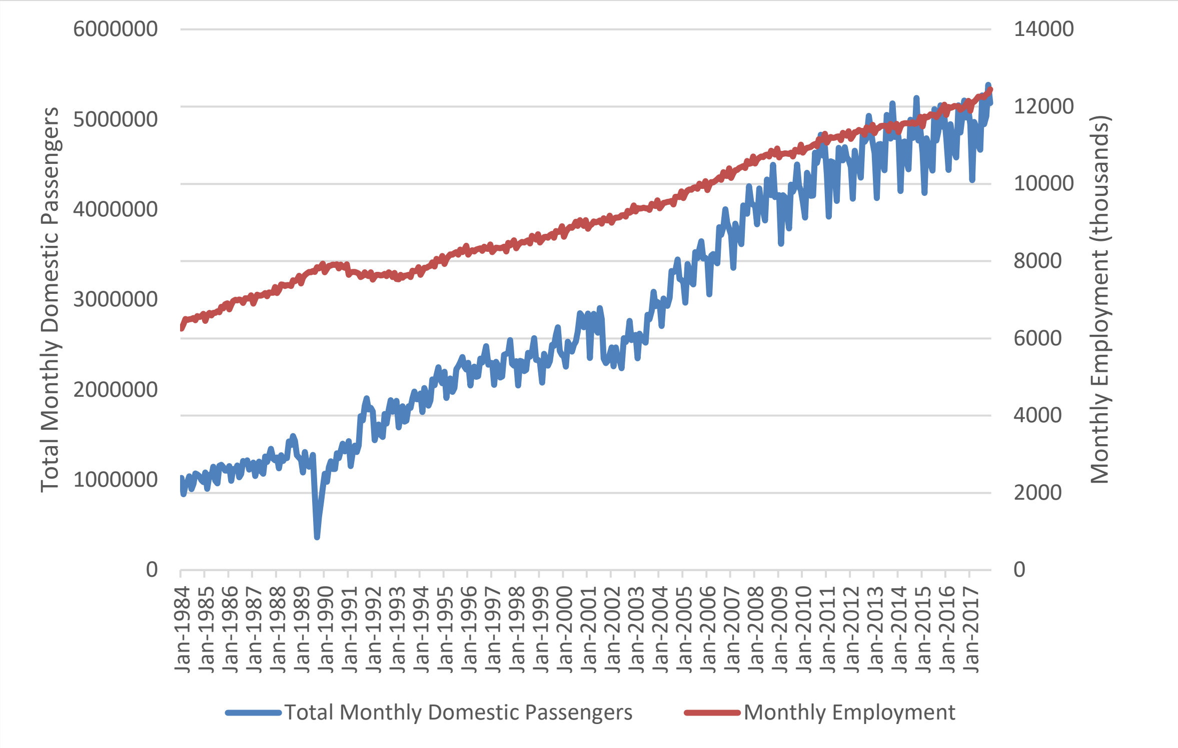
- Domestic Airline Monthly Total Revenue passengers U/D (Uplift/Discharge)
- Total Domestic Monthly Aircraft Departures
- Total Domestic Monthly Passenger Load Factor
- Melbourne-Sydney Monthly Revenue Passengers
- Melbourne-Sydney Monthly Aircraft Trips
- Melbourne-Sydney Monthly Revenue Passenger Load Factor

The above aviation data was examined against the economic data published by other Commonwealth departments and agencies:

- Employment (ABS cat. no. 6202.0, published monthly)
- GDP, chain volume measures (ABS cat. no. 5206.001, published quarterly)

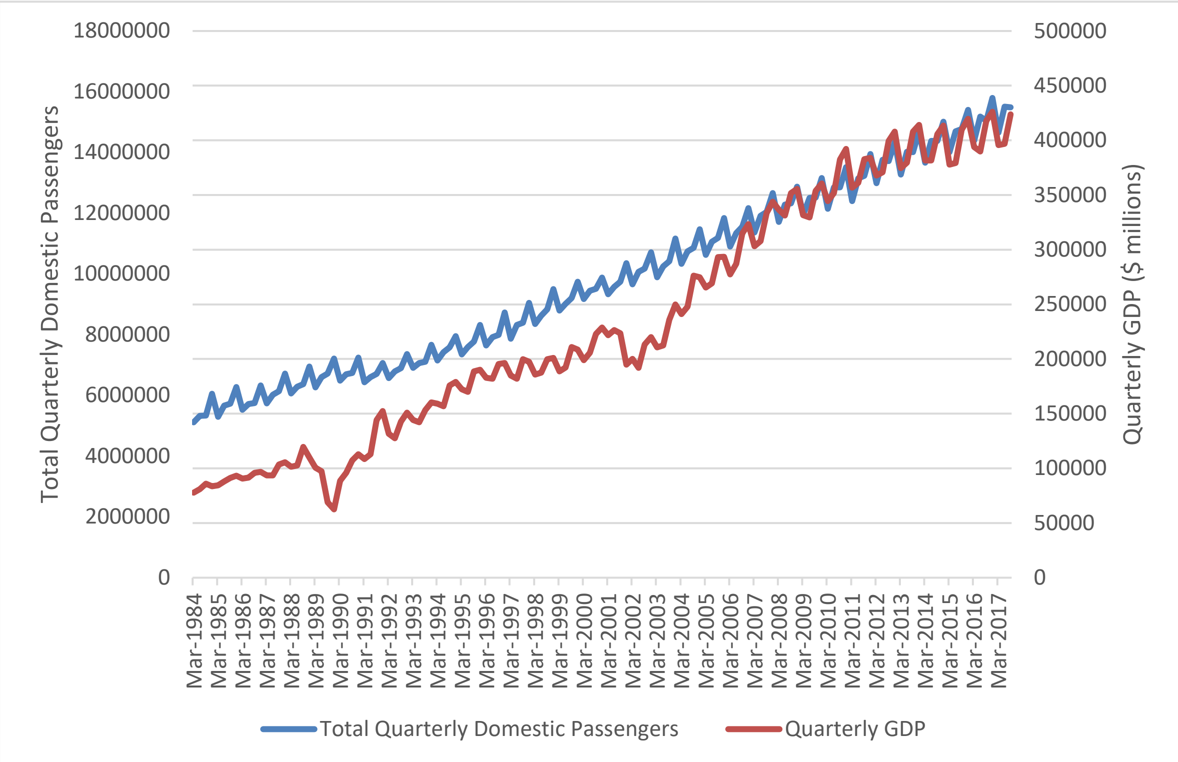
As discussed previously, the employment data, GDP data and aviation data used in this study are non-stationary, and may even be highly influenced by the same external factors – possibly, for example, population growth. This is clearly illustrated in the charts below, where the economic data are plotted with data on passenger numbers. All series have an obvious upward trend, and increase with time.

**Figure 1: Original data: Monthly Employment and Total Monthly Domestic Passengers**



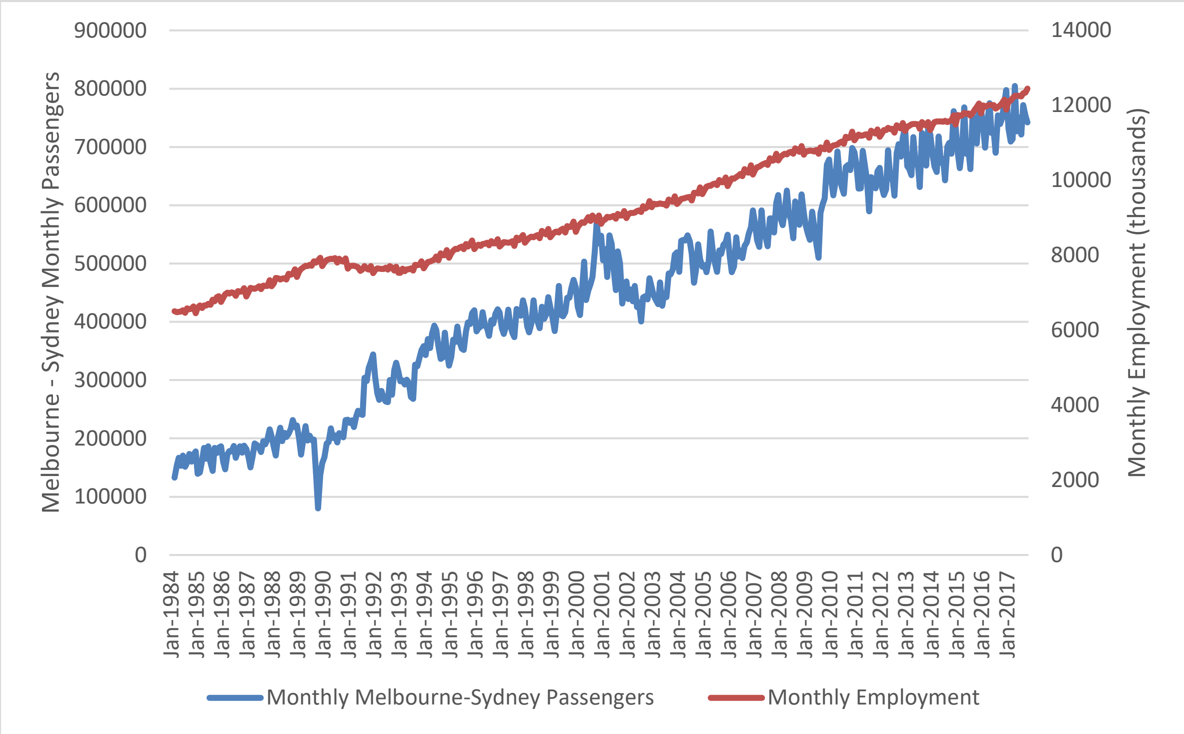

Source: ABS (2018a) and BITRE (2018a).

**Figure 2: Original data: Quarterly Gross Domestic Product and Total Quarterly Domestic Passengers**



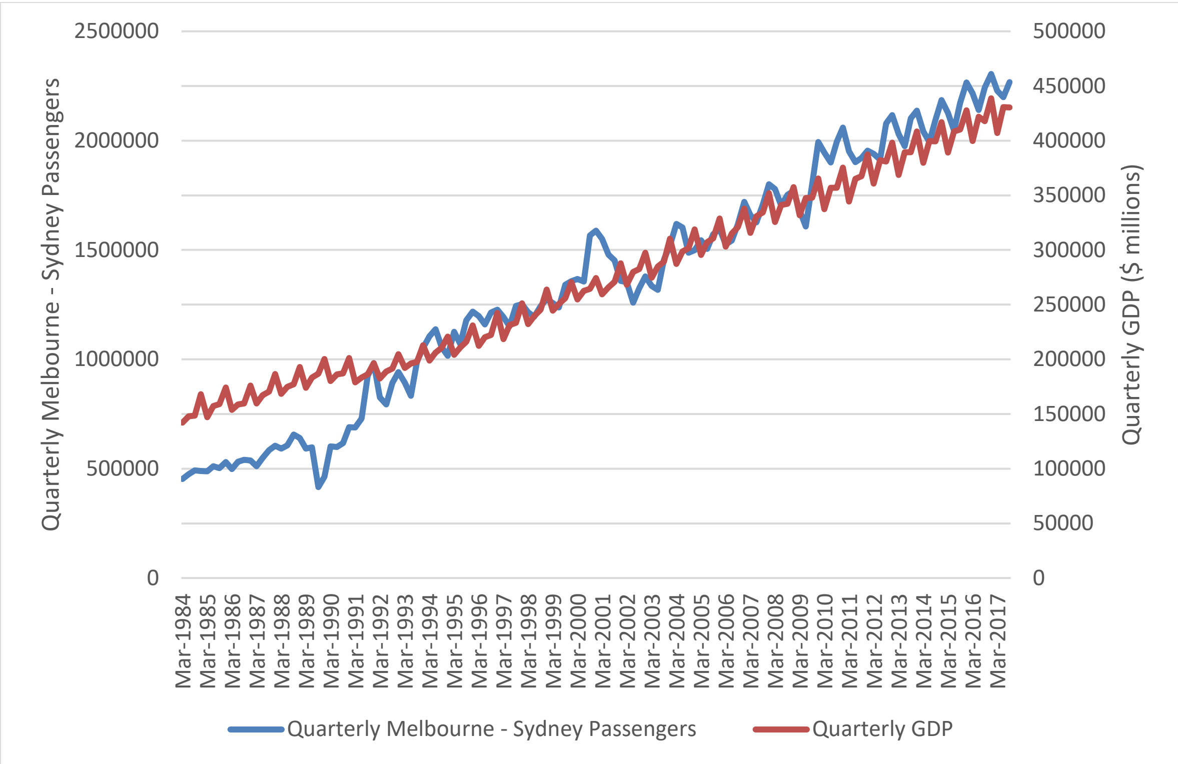

Source: ABS (2018b) and BITRE (2018a).

**Figure 3: Original data: Monthly Employment and Monthly Melbourne - Sydney Passengers**




Source: ABS (2018a) and BITRE (2018b).

**Figure 4: Original data: Quarterly Gross Domestic Product and Quarterly Melbourne - Sydney Passengers**




Source: ABS (2018b) and BITRE (2018b).

While the series all move together in the same direction, the deviations in this upward trend may differ from series to series. From historic data, it is expected that all series will continue to grow over time, however, it will be useful for policy makers to know when large deviations from this upward trend will occur. To isolate these deviations, the upward trend must be removed from the raw data. This will assist in testing whether the deviations from trend move together across the series. The methods used to test this are discussed in the Method section.

In addition to non-stationarity, it is evident from the charts above that all series of data are highly seasonal. The employment data for example, consistently displays troughs in the months of January and August. The monthly domestic passenger data consistently displays troughs in February, and both the quarterly GDP data and quarterly passenger data display troughs in the March quarter. While the seasonality of the quarterly series move together, this does not help predict shocks or deviations from regular movements.

# Method

This study scoped whether aviation data can be used as a leading indicator of aggregated economic activity – with a view to developing a model to predict regional economic activity should initial tests be successful. The tests involved two key steps – comparing deviations from trend in the aviation data and economic data graphically, with the view to conducting regression analysis should graphic analysis suggest the series have a clear relationship.

To conduct these tests, the series were first smoothed into long-term trends and short-term trends, which were used to isolate the deviations from trend. The methods of Connolly et al. (2008) discussed in Box 1 provide a framework to accomplish this – particularly in terms of obtaining the cyclical elements of the data series by subtracting six-year trend levels from the one-year level. The 'turning point' method was adopted to predict future movements in economic activity. The methods undertaken are summarised below:

1. Raw data was smoothed into one-year and six-year trend levels. The methods used to smooth data differed by data series, as is discussed in detail in the next section:
    a. 13-term moving average with a Henderson filter and 73-term centred moving average for monthly employment data
    b. 12-term centred moving average and 72-term centred moving average for monthly aviation data
    c. 4-term centred moving average and 24-term centred moving average for quarterly aviation and GDP data
2. The six-year trend level was subtracted from the one-year trend level to obtain the cyclical elements of that series.
3. Deviations from the series' long term trend was standardised by subtracting the mean of the series and dividing by the series' standard deviation.
4. Graphical analysis was conducted to determine if turning points in aviation data predict turning points in economic data.
5. Regression analysis was to be undertaken to determine the statistical significance of the relationship, should graphical analysis first suggest that aviation data does lead economic data. This step was not completed due to the findings of the graphical analysis.

Detail on the techniques used, as well as the findings, are discussed in the following sections.

## Data smoothing

There are multiple approaches to smoothing time series data, and all vary in how they remove noise from the series. Moving averages were used to smooth data in this study.

The data series used in this study have different characteristics. It soon became evident that each required a different approach to smoothing to retain the optimal amount of information while reducing unnecessary noise in the data. For example, while both the aviation data and employment data are released on a monthly basis, the aviation data displays significantly more seasonality (this can be seen in Figures 1 to 4). Using the same moving average to smooth the two series either removed too much information from one series, or left too much seasonality in the other. Similarly, GDP data, which is published as a quarterly time series, required a slightly different approach to the monthly time series to adjust for the frequency of data collection.

A range of smoothing methods were tested on the aviation, employment and GDP time series data used for the study, to determine which method best smoothed each data series. The use of different smoothing methods implies that calculations of deviations from trend are internally inconsistent within this exercise. In simply testing whether aviation data leads other economic variables, the use of differing methods should not obscure whether aviation data leads, is concurrent with, or lags the economic variable being tested, as long as the filters do not result in a phase shift. The smoothing methods tested for the study are listed below:

### Monthly data:

1. 13-term symmetric Henderson moving average and 73-term centred moving average
2. 13-term centred moving average and 73-term centred moving average
3. 12-term centred moving average and 72-term centred moving average

### Quarterly data:

1. Five-term weighted moving average and 25-term weighted moving average
2. Four-term centred moving average and 24-term centred moving average

For the purposes of this study, seasonal adjustment methods such as the X11 and X12ARIMA procedures or the SEASABS package (SEASonal Analysis, ABS Standards) developed by the ABS were not tested. While these methods would apply a high-quality seasonal adjustment to the time series, the use of such techniques are unlikely to change the results of this exercise. For example, trading day effects and month-to-month changes are unlikely to have any significant impact on the one-year and six-year trend levels which are used to assess the predictive power of aviation data. Thus, such seasonal adjustment methods were not tested in this study in light of the increased complexity using such methods would induce, and the unlikely improvement they will make in the quality of results.

## Monthly data

Ultimately, two different methods were used to smooth the monthly time series data. The employment data was smoothed using a 13-term Henderson filter to determine the one year trend, and 73-term centred moving average to determine the six-year trend. Conversely, the aviation data was smoothed using a 12-term centred moving average and 72-term centred moving average. As discussed above, while the two smoothing methods do differ, there is minimal shift in phase between the two methods, and the smoothed data display the necessary information to determine whether aviation data consistently leads employment data. Thus, for the purposes of testing whether aviation data leads employment data, the use of the two different methods suffice.

### 13-term symmetric Henderson moving average and 73-term centred moving average:

Building on the framework developed by Connolly et al. (2008), the one-year trends of monthly employment and aviation time series data were initially computed using a 13-term symmetric Henderson moving average, and the six-year trends were computed using a 73-term centred moving average. While the use of Henderson weights smoothed employment data well, it did not sufficiently remove seasonality from the aviation data. Thus, while this method was suitable for the employment data, the aviation data required a separate method of smoothing.

### 12-term centred moving average and 72-term centred moving average:

Using a 12-term centred moving average and 72-term centred moving average with equal weights also removed too much information from the employment data, but sufficiently smoothed the aviation data. Thus, while this method was not appropriate for use on the employment data, it was the best fit for the aviation data.

Table 2 below illustrates the method used to calculate the 12-term centred moving average. The 72-term centred moving average is calculated similarly, but uses 72 periods rather than 12 as for the one-year trend.

**Table 1: Method for 12-term centred moving average calculation**

| Month and Year | Monthly Domestic Airlines Load Factor | 12 Term Average | 12 Term Centred Moving Average |
|---|---|---|---|
| Jan-1984 | 73.77682055 | | |
| Feb-1984 | 68.55576602 | | |
| Mar-1984 | 68.9398137 | | |
| Apr-1984 | 72.60659247 | | |
| May-1984 | 69.63616569 | | |
| Jun-1984 | 70.54741336 | 71.5912 | 71.61497 |
| Jul-1984 | 71.02227077 | 71.63874 | |
| Aug-1984 | 73.5276819 | 71.52785 | 71.5833 |
| Sep-1984 | 73.77803321 | 71.55081 | 71.53933 |
| Oct-1984 | 72.2226235 | 71.58987 | 71.57034 |
| Nov-1984 | 71.6406476 | 71.85029 | 71.72008 |
| Dec-1984 | 72.8405431 | 71.89238 | 71.87133 |
| Jan-1985 | 74.34733317 | 71.85929 | 71.87583 |
| Feb-1985 | 67.22508846 | 71.79211 | 71.8257 |
| Mar-1985 | 69.21534168 | 71.76754 | 71.77982 |

Source: Authors' calculations

## Quarterly data

The aviation data, which is released as a monthly time series, was converted into quarterly data to be compared to the quarterly GDP data. For data on aircraft load factors, which is published as a rate on a monthly basis, the middle month was used as a reference month for the corresponding quarter. Two methods of smoothing were tested for the quarterly data, which produced very similar results. Since both methods tested produced similar results, the simpler of the two – the four-term and 24-term centred moving averages – were selected to smooth the quarterly data.

### Four-term centred moving average and 24-term centred moving average:

The second method tested on the quarterly data was the application of a four-term centred moving average for the one-year trend and a 24-term centred moving average for the six-year trend. This method was similar to the 12-term centred moving average and 72-term centred moving average, which was applied to the monthly aviation data. The results for this method were positive, and very similar to the results of the weighted moving average discussed above.

Table 5 below illustrates the method used to calculate the four-term centred moving average, which represents the one-year trend level. The 24-term centred moving average, which calculates the six-year trend level is calculated similarly, but uses 24 periods rather than four as for the one-year trend.

**Table 4: Method for four-term centred moving average calculation**

| Month and Year | Total rev PAX U/D | 4 Term Average | 4 Term Centred Moving Average |
|---|---|---|---|
| Mar-1984 | 2802518 | | |
| Jun-1984 | 2916234 | 2955616 | |
| Sep-1984 | 3089687 | 3014993 | 2985305 |
| Dec-1984 | 3014026 | 3079362 | 3047178 |
| Mar-1985 | 3040026 | 3128589 | 3103975 |
| Jun-1985 | 3173708 | 3213466 | 3171027 |

Source: Authors' calculations

## Deviations from trend

Deviations from long term trends were calculated by subtracting the six-year trend level of each series from the one-year trend level. These figures were then standardised for each series using the average and standard deviation of these figures.

While the time series used provide data until 2017, the use of moving averages to smooth the series shortened the time series to 2014. However, the data series were not extrapolated (to avoid the reduction in time series length) for the purposes of this study, as the shortened time series was sufficient to make conclusions about the power of aviation data in predicting economic activity.

## Turning points

The study again builds on the framework developed by Connolly et al. (2008) in defining what constitutes a turning point. For this study, a strong turning point in monthly data was defined as six consecutive monthly movements in deviations from trend in one direction, followed by six consecutive movements in deviations from trend in the opposite direction. A weak turning point was defined as three consecutive monthly movements in the one direction followed by three movements in the opposite direction. Connolly et al. took a more liberal approach in defining a weak turning point; weak turning points have at least six consecutive movements in one direction on one side of the turning point, and three consecutive movements in the other direction on the other side (Department of Small Jobs and Business, 2018).

These definitions were slightly altered for the quarterly data. This is because, for example, simply adopting the monthly definition of a 'weak' turning point (three consecutive monthly movements) would result in every quarter being defined as a weak turning point. Thus, for the quarterly data a 'strong' turning point was defined as four consecutive quarterly movements in one direction followed by four consecutive movements in the opposite direction. A 'weak' turning point was defined as two consecutive quarterly movements in one direction followed by two consecutive movements in the opposite direction.

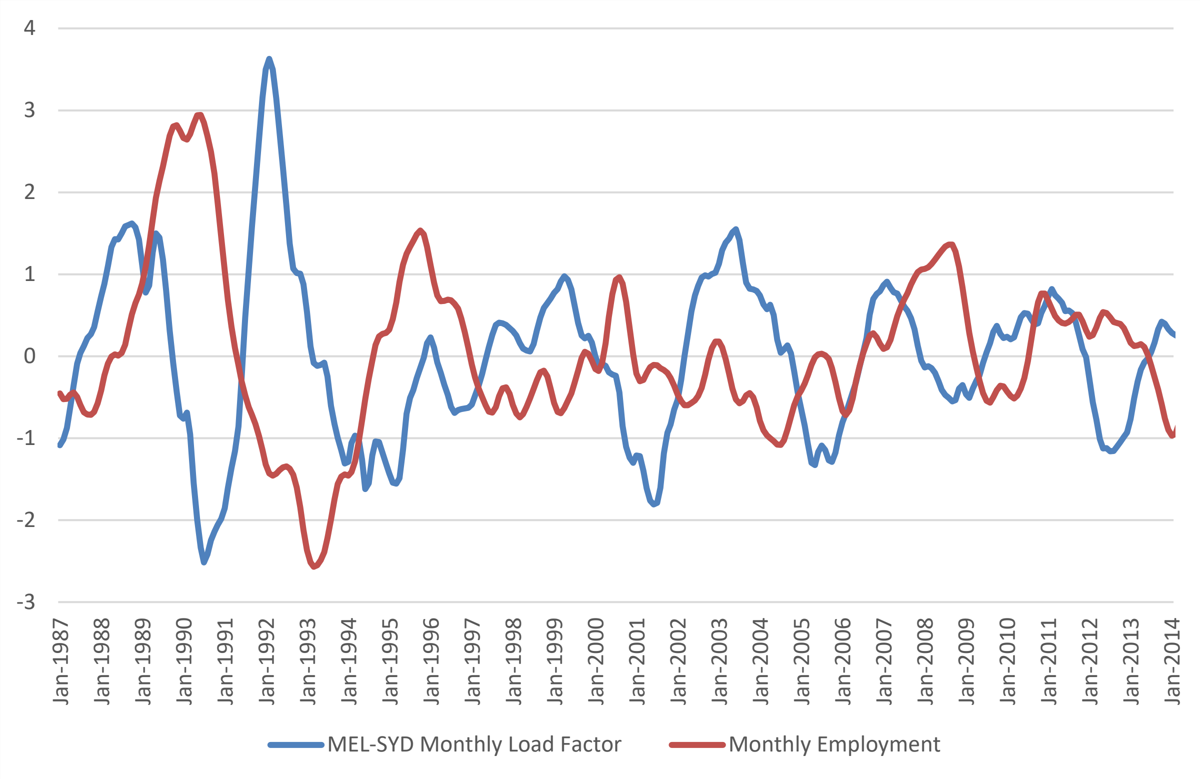
For a leading indicator to be useful it must allow enough time for the turning point to be first confirmed, and then allow additional time for policy makers to respond to the anticipated change in the economy. For the purpose of this study, a strong turning point in the aviation data was considered to be a lead if it was followed by a strong turning point in the economic data within six to 36 months for monthly data, or within three to 12 quarters for quarterly data.

## Graphical analysis

The graphical analysis undertaken comprised two stages. Firstly, the deviations from trend in employment and GDP were simply plotted against deviations from trend in the aviation data. While this first set of charts was useful in identifying whether movements in the series followed one another, other movements in the data obscured turning points, making it difficult to make robust conclusions about predictability. The second stage of graphical analysis reduced this noise, by isolating and only graphing turning points. The second set of charts clearly illustrates whether turning points in aviation data lead turning points in economic data.

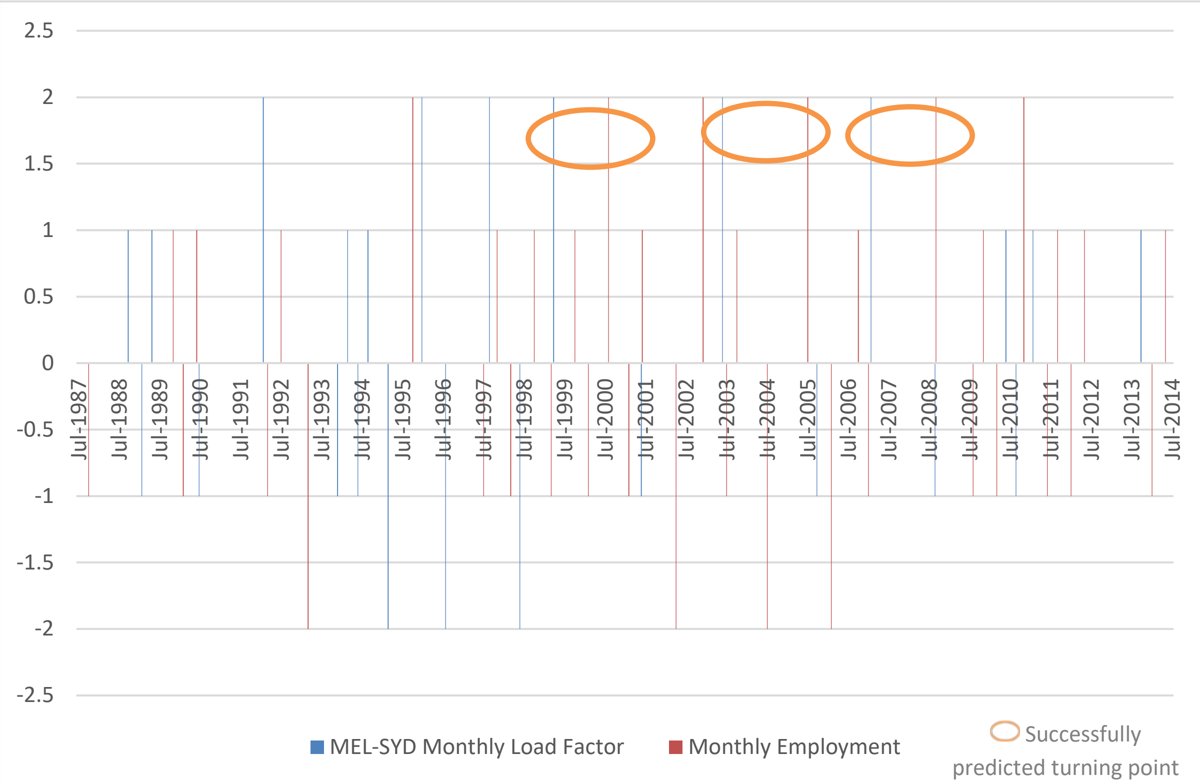
For example, the load factors of aircraft traveling on the Melbourne-Sydney air route (Figure 5) visibly appeared to have power to predict employment data. Figure 5 suggests the load factors of aircraft on the Melbourne-Sydney air route led employment data during the period from 1987 to approximately 2005. However, there seems to be very little relationship between the two variables beyond 2005. While there appeared to be a strong visual lead between 1987 to 2005 in Figure 5, Figure 6 confirms that many of these signals are 'weak', and that strong turning points in employment cannot be predicted using the data on MEL-SYD load factors. In fact, the load factors of aircraft on the Melbourne-Sydney air route predicted just three turning points, failed to predict eight turning points, and implied a further five false turning points (non-existent turning points). Further examples of both sets of charts are provided below and in the discussion, and the full set of charts analysed in this study can be found in the Appendix. Successfully predicted turning points have been circled in orange on the charts discussed in this paper.

**Figure 5: Deviations from Trend: Monthly Employment and MEL-SYD Monthly Load Factor**



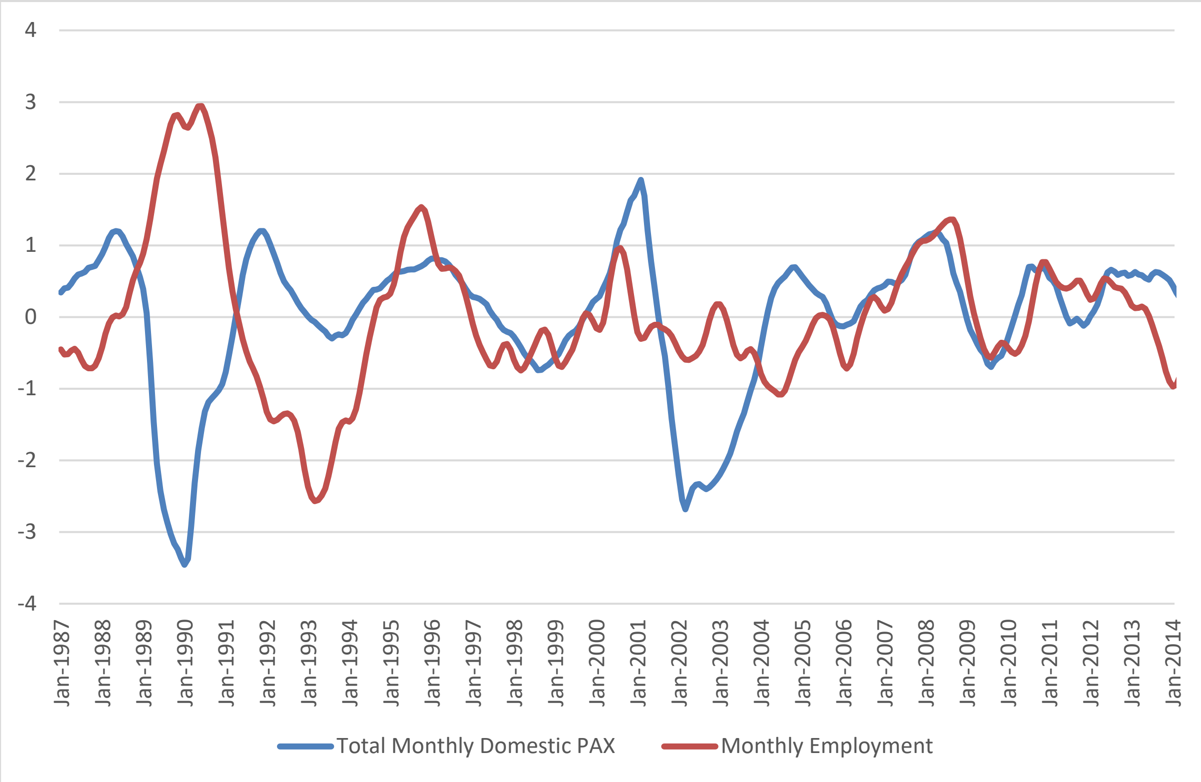

Source: ABS (2018a) and BITRE (2018b).

**Figure 6: Turning Points: Monthly Employment and MEL-SYD Monthly Load Factor**



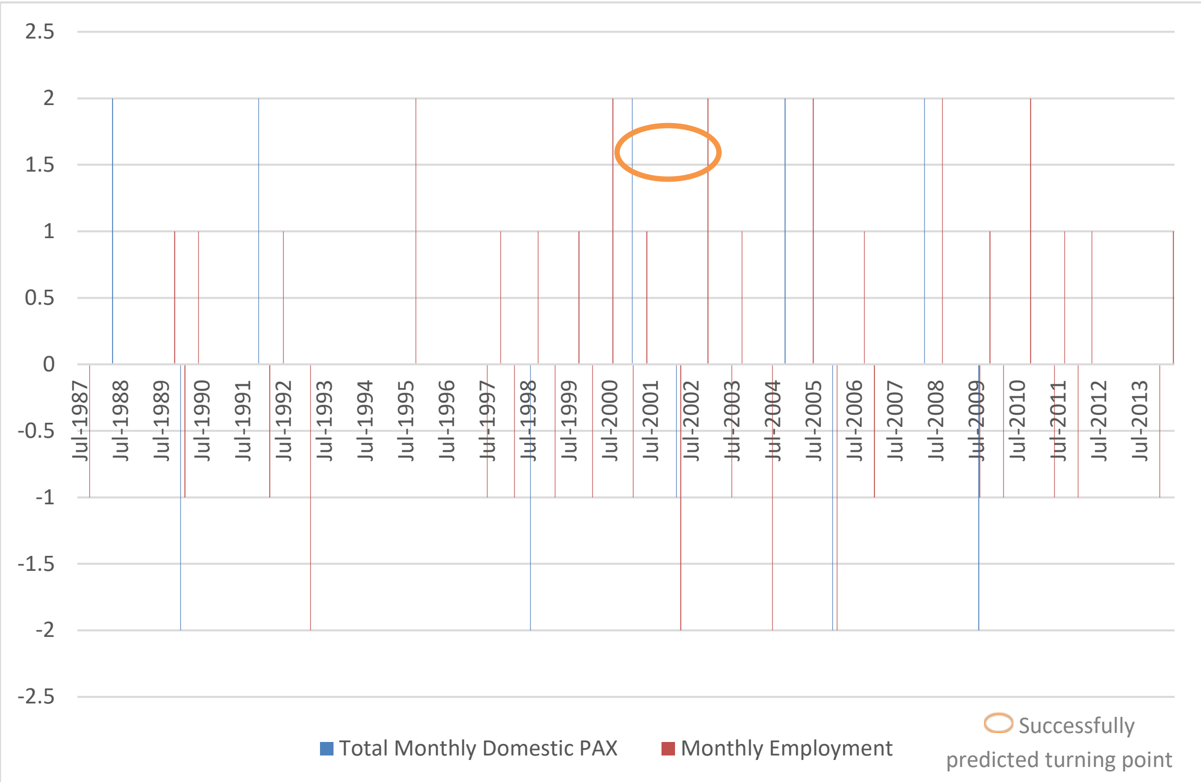

Source: ABS (2018a) and BITRE (2018b).

**Figure 7: Deviations from Trend: Employment and Total Monthly Domestic Passengers**




Source: ABS (2018a) and BITRE (2018a)

**Figure 8: Turning Points: Employment and Total Monthly Domestic PAX**

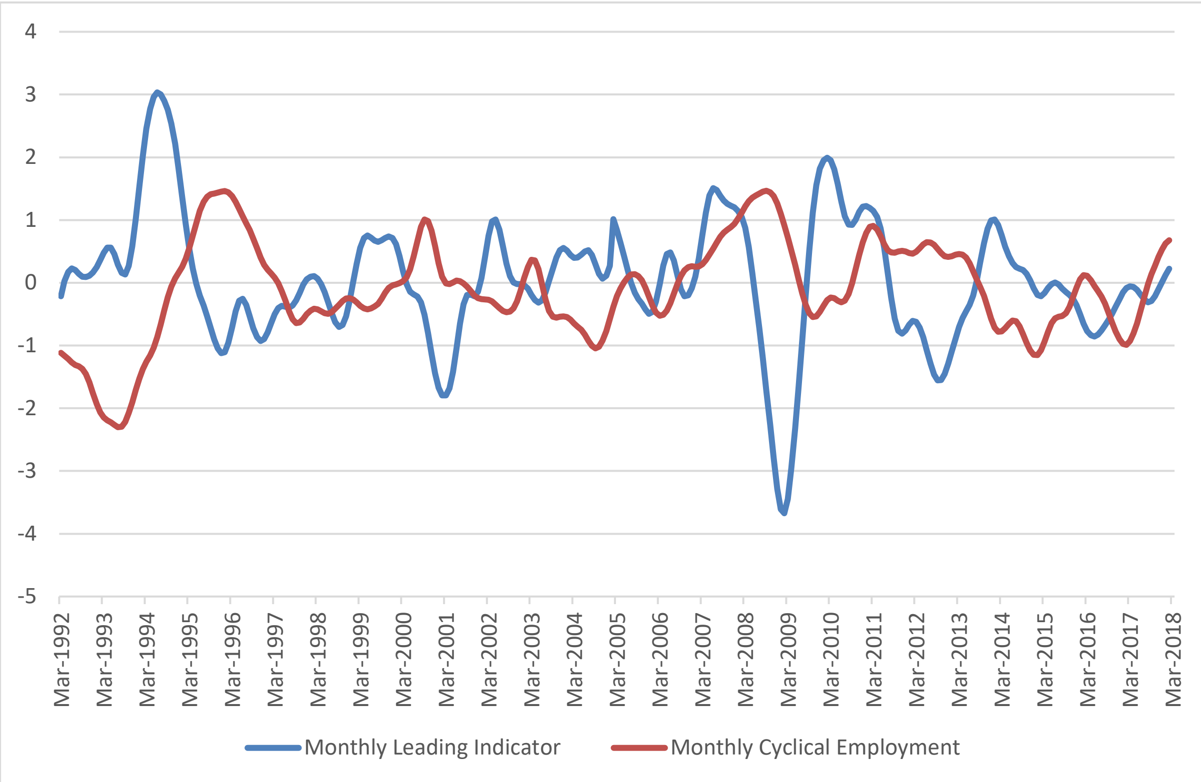



Source: ABS (2018a) and BITRE (2018a)

# Discussion:

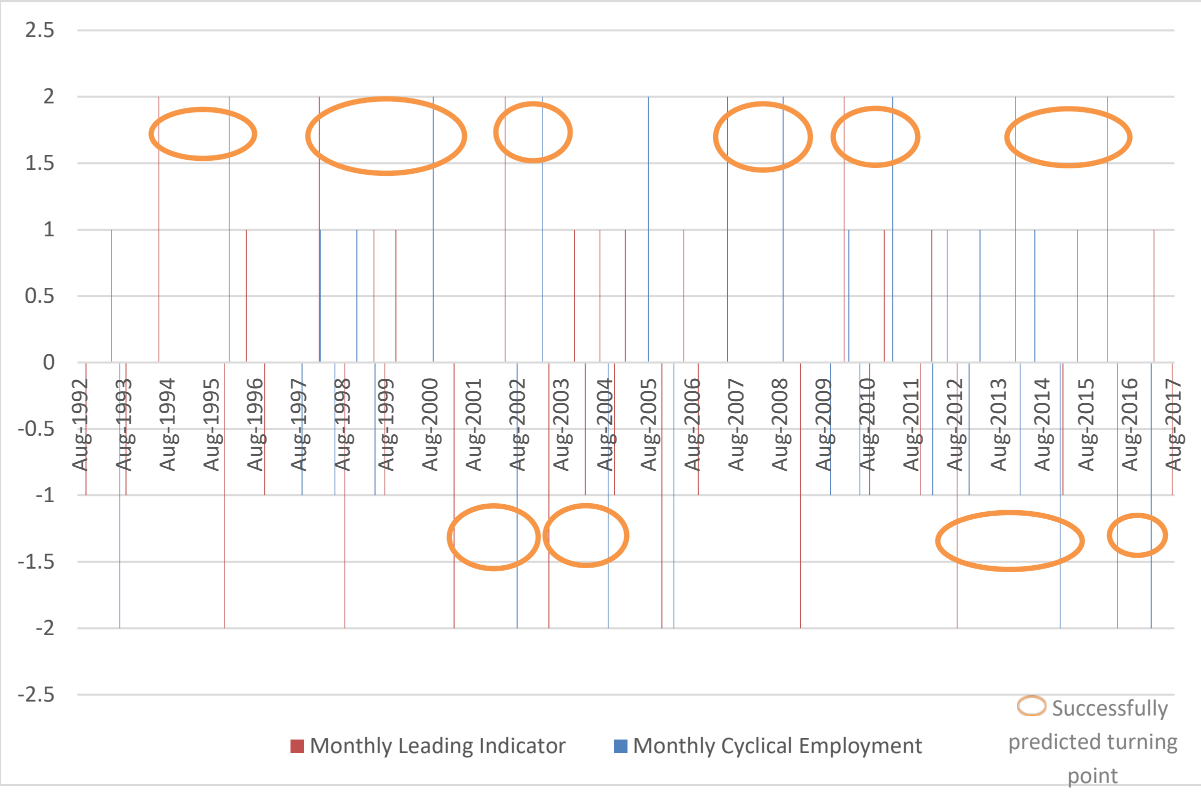
Figures 7 and 8 provide a sample of the charts analysed, and the full set of charts analysed can be found in the Appendix. Similar charts illustrating the DJSB's existing Leading Indicator of Cyclical Employment are also provided below at Figures 9 and 10 for comparison, and provide a useful benchmark for the graphical analysis conducted.

**Figure 9: Deviations from Trend: Cyclical Employment and Leading Indicator of Cyclical Employment**




Source: DJSB (2018b).

**Figure 10: Turning Points: Cyclical Employment and Leading Indicator of Cyclical Employment**




Source: DJSB (2018b).

According to the definition of a leading turning point used in this paper, the existing Leading Indicator of Cyclical Employment predicts 10 turning points during the period between August 1992 and August 2017. It missed three turning points in employment (1993, 2005 and 2006) and also returned four false turning points. The indicator delivers an average lead time of 18 months, with a maximum lead period of 30 months and minimum of nine months. The full list of lead times for the indicator is provided in the table below:

**Table 5: Lead Times for Leading Indicator of Cyclical Employment**

| **Predicted turning point** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Lead time (quarters)** | 18 | 30 | 16 | 9 | 13 | 14 | 12 | 27 | 24 | 8 |

Source: Authors' calculations

In comparison, on average aviation data predicted between four and five turning points in the economic data between July 1987 and May 2014. The results from the full analysis are provided at Table 6 below:

**Table 6: Number of turning points predicted by variable**

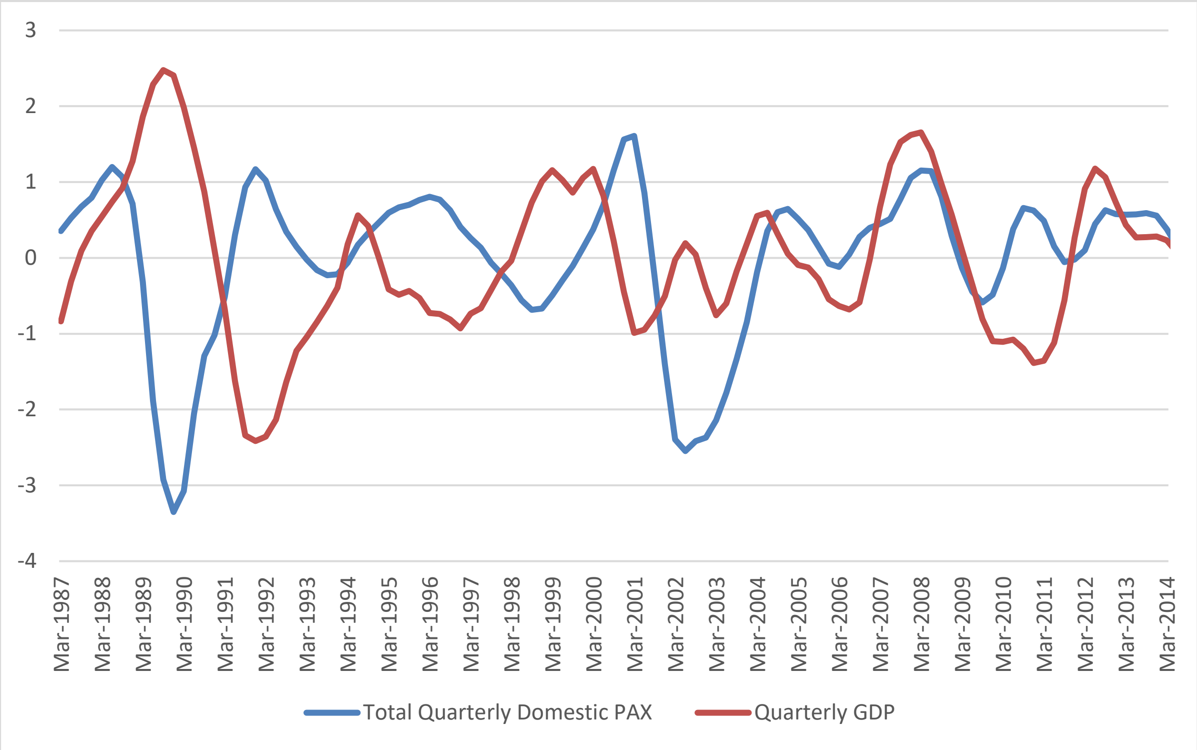
| Employment | Predicted turning points | Missed turning points | False turning points | Average Lead time (months) | Maximum lead time (months) | Minimum lead time (months) |
|---|---|---|---|---|---|---|
| **Total Monthly Domestic Passengers** | 1 | 9 | 8 | 21 | 21 | 21 |
| **Monthly Domestic Load Factor** | 5 | 5 | 3 | 19.4 | 27 | 11 |
| **Monthly Domestic Trips** | 2 | 8 | 8 | 25 | 27 | 23 |
| **MEL-SYD Monthly Passengers** | 4 | 6 | 8 | 17.3 | 24 | 6 |
| **MEL-SYD Monthly Load Factor** | 3 | 7 | 6 | 19 | 24 | 15 |
| **MEL-SYD Monthly Trips** | 3 | 7 | 6 | 16 | 23 | 12 |
| | | | | | | |
| **GDP** | **Predicted turning points** | **Missed turning points** | **False turning points** | **Average Lead time (quarters)** | **Maximum lead time (quarters)** | **Minimum lead time (quarters)** |
| **Total Domestic Passengers** | 8 | 1 | 6 | 8.9 | 12 | 4 |
| **Domestic Airline Load Factor** | 5 | 4 | 5 | 4.8 | 10 | 3 |
| **Total Domestic Air Trips** | 7 | 2 | 8 | 8.7 | 12 | 4 |
| **MEL-SYD Passengers** | 6 | 3 | 10 | 7 | 9 | 4 |
| **MEL-SYD Load Factor** | 6 | 3 | 3 | 4 | 8 | 3 |
| **MEL-SYD Trips** | 4 | 5 | 4 | 6.5 | 8 | 4 |

Source: Authors' calculations

Overall, the aviation data does appear to lead the employment or GDP data over certain periods. However, the leads are generally not reliable enough to be useful as a leading indicator; the lead times are inconsistent, many turning points in the economic variables are not predicted by the aviation data, and there are also many false turning points.

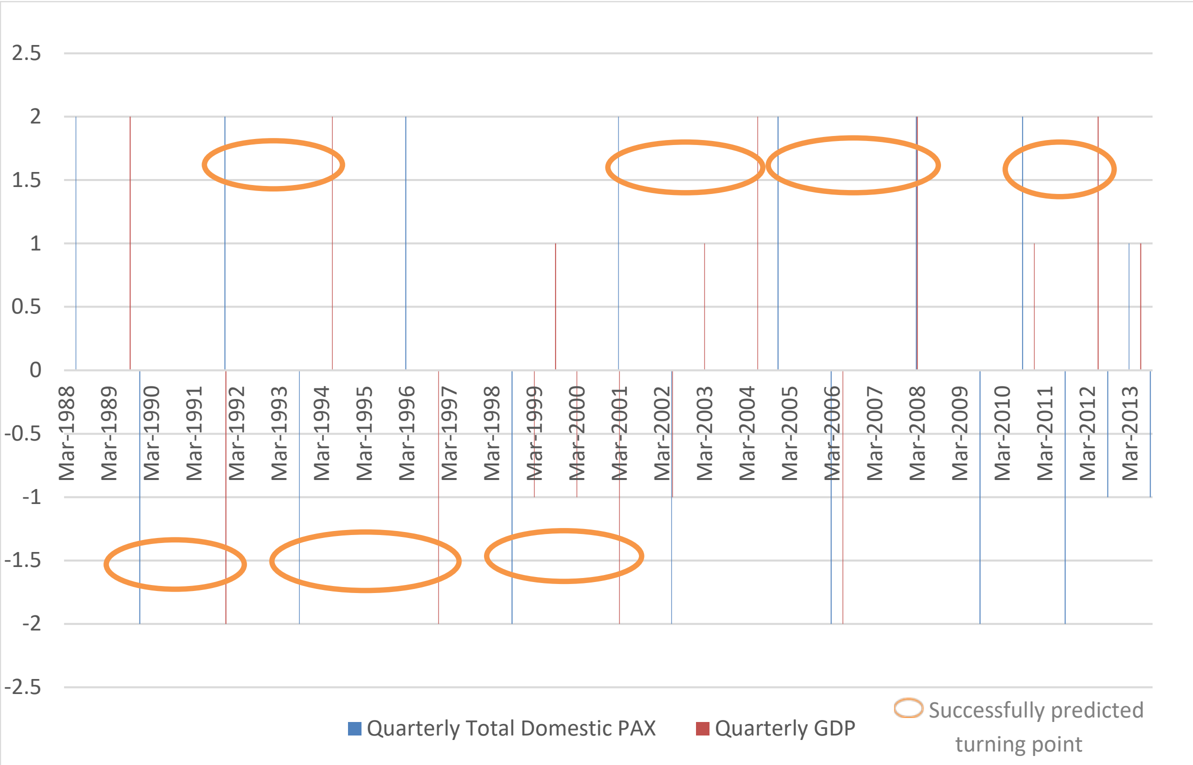
The variable which returned the highest number of predicted turning points was Total Domestic Passengers, when it was compared with quarterly GDP figures. However, while it predicted eight turning points in GDP and only missed one, it also returned six false turning points. The large number of false turning points may be attributed to aviation industry specific shocks, such as the Australian pilot's dispute in 1989, and the collapse of Ansett and the 9/11 terrorist attack in 2001. Its lead times were also relatively variable, ranging from 4 quarters to 12 quarters. While the variable predicted the highest number of turning points, its variable lead time and high number of false turning points suggests the variable would not be robust or useful in predicting trends in GDP growth.

**Figure 11: Deviations from Trend: Quarterly GDP and Total Quarterly Domestic Passengers**




Source: ABS (2018b) and BITRE (2018a).

**Figure 12: Turning Points: Quarterly GDP and Total Quarterly Domestic Passengers**




Source: ABS (2018b) and BITRE (2018a).

Taking into consideration lead times, the number of missed turning points and number of false turning points, the best performing series overall was the data on load factors on the Melbourne-Sydney air route, when compared to GDP figures (Figures 13 and 14). The variable predicted six of nine turning points in GDP and returned three false turning points. Its lead times ranged from three quarters (nine months) to eight quarters (two years), and its average lead time was four quarters. The full list of lead times is provided in the table below.

***Table 7: Lead Times for Melbourne-Sydney Airline Load Factor***

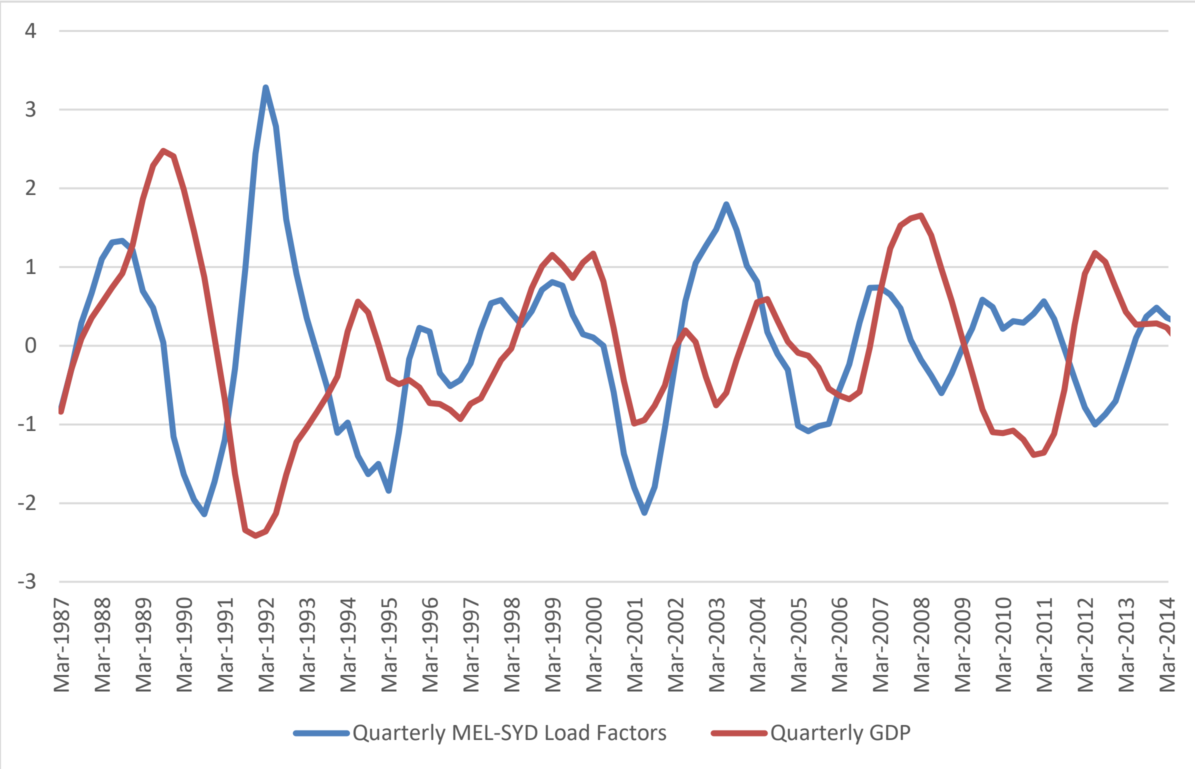
| **Predicted turning point** | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **Lead time (quarters)** | 3 | 4 | 8 | 3 | 3 | 3 |

Source: Authors' calculations

The lead times for the predicted turning points were fairly consistent - four of the six predicted turning points were predicted with a lead time of three quarters. A lead time of three quarters is not optimal. A greater lead time would allow for more time to first confirm the turning point, as well as time for policy makers to respond to pre-empted changes in the economy. While an occasional lead time of three quarters may be sufficient, this variable consistently leads turning points by three quarters and thus is not a high performing leading indicator. Further, the range in lead times (three quarters to eight quarters) further reduces the reliability of the variable's predictions.

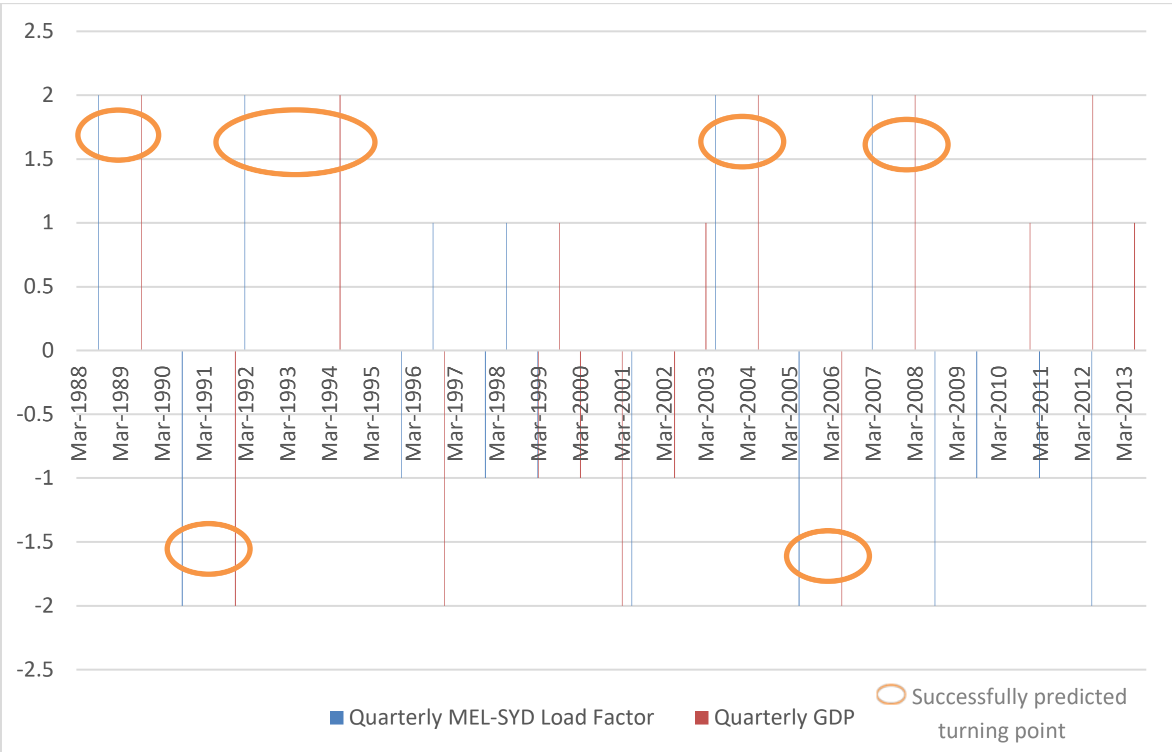
While the variable manages to predict turning points in GDP with minimal false and missed turning points, it is unlikely to be useful in practice. Further work to assess the variable more thoroughly may include extrapolating the data series to assess its performance beyond 2014, or assessing the power of Melbourne-Sydney load factor data in predicting economic performance at a local level. However, with the consistent shortness in lead times, the current analysis alone suggests that the variable is unlikely to be useful regardless of further analysis.

**Figure 13: Deviations from Trend: Quarterly GDP and Quarterly Melbourne-Sydney Load Factor**




Source: ABS (2018b) and BITRE (2018b).

**Figure 14: Turning Points: Quarterly GDP and Quarterly MEL-SYD Load Factor**




Source: ABS (2018b) and BITRE (2018b).

# Conclusions and future directions

Through this study, six variables on aviation activity were tested for their ability to predict turning points in employment and GDP data. The study developed a method to smooth the time series data and reveal deviations from their long term trends. Turning points in these deviations were then graphically illustrated and the variables were assessed for their ability to predict turning points in economic data. Most of the variables tested did not sufficiently predict turning points in the economic data, or delivered too many false turning points and missed too many turning points for the variables to be a useful leading indicator.

Of the variables assessed, the best performing data series was the Melbourne-Sydney load factor when compared to quarterly GDP data. It predicted seven of nine turning points in GDP and returned three false turning points. However, its lead time ranged between 3 quarters and 8 quarters, and most of the lead times were three quarters. The variable is unlikely to be a reliable predictor of economic activity – particularly to policy makers who require time to confirm the turning point, and as much additional time and certainty as possible to respond to pre-empted changes in the economy. Further work could be conducted to thoroughly assess the variable. However, the evidence from this exercise suggests that the variable’s predictive power is not reliable or useful enough for any further work to be pursued.

As discussed earlier, there is a relatively undeveloped literature examining the causal relationship between aviation activity and economic development, and an even smaller literature on whether aviation activity can be used to predict economic activity. Green (2007) and James (2016 and 2017) both argue that aviation data can be used as predictors of economic activity. The findings of this study however, are contrary to those of previous works. While the study discovered that data on load factors on the Melbourne-Sydney air route has the greatest ability to predict economic activity of all the aviation data series tested, there is little evidence to suggest that aviation data can be used to usefully predict fluctuations in economic activity. Thus, there is insufficient evidence for this research to be pursued any further.

There are three possible extensions of this study for the future. Firstly, there is scope to test the causal relationship between the aviation data and economic data used in this study, through conducting a multi-variate Granger Causality Test. BITRE is currently developing a multi-variate model to forecast aviation passenger numbers, incorporating per capita GDP, the price of domestic travel and accommodation, the exchange rate for the Australian dollar and dummy variables which capture shocks to the aviation industry, as independent variables. The development of this model will create opportunities to extend this research through conducting robust multi-variate Granger Causality Tests in the future. Secondly, there is scope to test the predictive power of aviation data in relation to specific regions which are heavily reliant on industries closely linked to aviation, such as mining or tourism.  Finally, there may also be further scope to test the use of aviation data as part of a composite leading indicator of economic activity. However, given the results of this study, there is currently no intention to extend this research.

# References:


Air Transport Action Group 2016, Benefits Beyond Borders, Switzerland.

Alshammary, M. 2017, Study of causality between civil aviation sector and economic development in Saudi Arabia. *Journal of Governance and Regulation*, 6(2), pp.22-31.

Australian Bureau of Statistics (ABS) 2012, *Interpreting Time Series: Are you being misled by the Seasons, 2012* (cat. no. 1346.0.55.003), viewed 21 February 2018, http://www.abs.gov.au/ausstats/abs@.nsf/mf/1346.0.55.003

ABS 2018a, *6202.0 Labour Force, Dec 2017*, viewed 02 February 2018, www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6202.0Dec%202017?OpenDocument

ABS 2018b, *5206.0 Australian National Accounts: National Income, Expenditure and Product, Dec 2017*, viewed 02 February 2018, www.abs.gov.au/AUSSTATS/abs@.nsf/allprimarymainfeatures/403EA140D4D3C932CA258248000BBE1F?opendocument

Baker D., Merkert, R. and Kamruzzaman, M. 2015. Regional aviation and economic growth: cointegration and causality analysis in Australia. *Journal of Transport Geography*, *43*, pp.140-150.

Bureau of Infrastructure, Transport and Regional Economics (BITRE) 2012, *Air passenger movements through capital and non-capital city airports to 2030-31*. Report 133, Canberra ACT.

BITRE 2013, *Employment Generation and Airports*, Information Sheet 46, BITRE. Canberra ACT.

BITRE 2018a, *Monthly Airline Performance*, viewed 02 February 2018, bitre.gov.au/publications/ongoing/domestic_airline_activity-time_series.aspx

BITRE 2018b, *Domestic Totals and Top Routes*, viewed 02 February 2018, bitre.gov.au/publications/ongoing/domestic_airline_activity-time_series.aspx

Brida, J.G., Rodriguez-Brindis, M.A., Lanzilotta, B. and Rodriguez-Collazo, S. 2016, Testing Linearity in the Long-Run Relationship between Economic Growth and Passenger Air Transport in Mexico. *International Journal of Transport Economics= Rivista Internazionale de Economia dei Trasporti*, *43*(4).

Brueckner, J.K. 2003, Airline traffic and urban economic development. *Urban Studies*, *40*(8), pp.1455-1469.

Chi, J. and Baek, J. 2013, Dynamic relationship between air transport demand and economic growth in the United States: A new look. *Transport Policy*, 29, pp.257-260.

Connolly, G. and Stevens, L. 2008, *Information on calculating the DEEWR Monthly Leading Indicator of Employment*, Canberra.

Connolly, G., and Ryland, B. 2014, *Results of the Review of the Leading Indicator of Employment,* Canberra.

Cotrie, G., Craigwell, R.C. and Maurin, A. 2009, Estimating Indexes of Coincident and Leading Indicators for Barbados. *Applied Econometrics and International Development*, *9*(2), pp.1-33.

Deloitte Access Economics 2012. *Connecting Australia: The Economic Social Contribution of Australia's Airports*, Deloitte Access Economics Pty Ltd, Barton ACT.

Department of Jobs and Small Business (DJSB) 2018a, *Department of Jobs and Small Business' Leading Indicator of Employment latest release,* viewed 03 September 2018, https://www.jobs.gov.au/department-employment-s-leading-indicator-employment-latest-release

DJSB 2018b, *Leading Indicator of Employment Data – Feb 2018*, viewed 02 March 2018, www.jobs.gov.au/historical-data-department-employment-s-leading-indicator-employment

Friedman, W. 2013, *Fortune tellers: The story of America's first economic forecasters*. Princeton University Press.

Gorton, G. 1982, Forecasting With the Index of Leading Indicators. *Business Review*, (Nov/Dec), pp.15-27.

Green, R.K. 2007, Airports and economic development. *Real estate economics*, *35*(1), pp.91-112.

Hakim, M.M. and Merkert, R. 2016, The causal relationship between air transport and economic growth: Empirical evidence from South Asia. *Journal of Transport Geography*, *56*, pp.120-127.

Hu, Y., Xiao, J., Deng, Y., Xiao, Y. and Wang, S. 2015, Domestic air passenger traffic and economic growth in China: Evidence from heterogeneous panel models. *Journal of Air Transport Management*, *42*, pp.95-100.

James, C. 2016, Record passengers on Sydney-Melbourne route. *Economic Insights*, CommSec, Sydney.

James, C. 2017, Record number take to the air. *Economic Insights*, CommSec, Sydney.

Percoco, M. 2010, Airport activity and local development: evidence from Italy. *Urban Studies*, *47*(11), pp.2427-2443.

Lee, E. Jain, V. and McKellar, D. 2017, Economic growth and air traffic: A look ahead. In: *Connectivity and growth: the Brexit issue*, PwC UK, pp.13-19.

Marazzo, M., Scherre, R. and Fernandes, E. 2010, Air transport demand and economic growth in Brazil: A time series analysis. *Transportation Research Part E: Logistics and Transportation Review*, *46*(2), pp.261-269.

Mehmood, B. and Shahid, A. 2014, Aviation Demand and Economic Growth in the Czech Republic&58; Cointegration Estimation and Causality Analysis. *Statistika: Statistics and Economy Journal*, *94*(1), pp.54-63.

Mongardini, M.J. and Saadi-Sedik, T. 2003, *Estimating Indexes of coincident and leading indicators: An application to Jordan* (No. 3-170). International Monetary Fund.

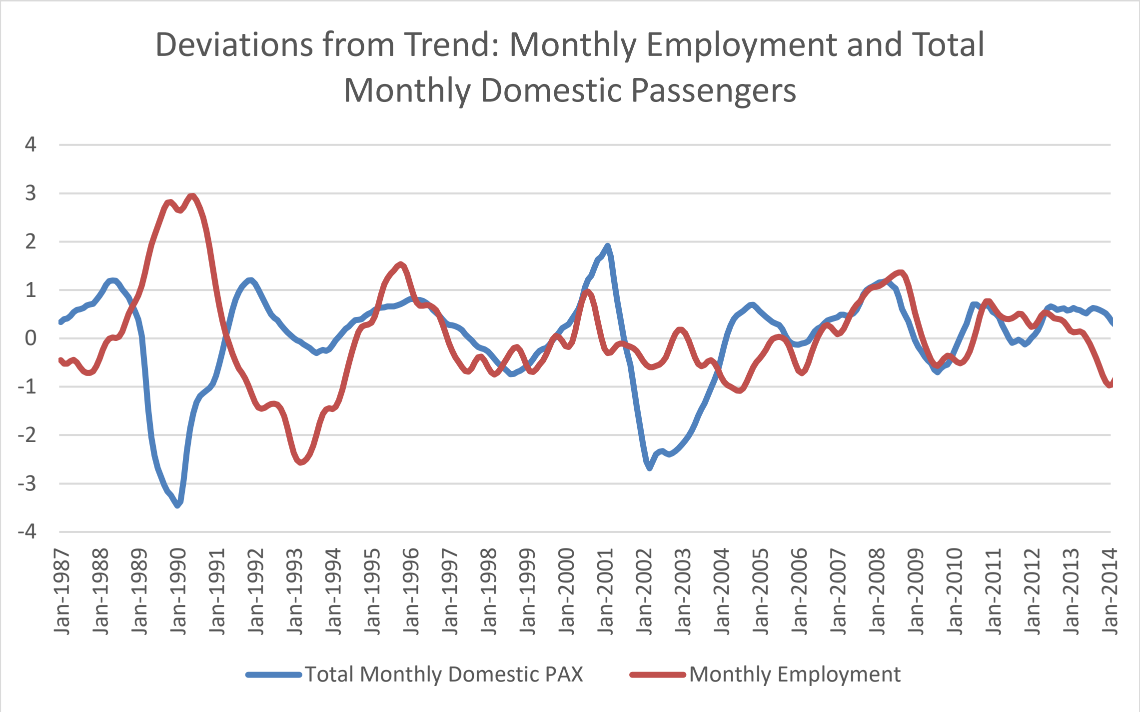
Mukkala, K. and Tervo, H. 2013, Air transportation and regional growth: which way does the causality run?. *Environment and Planning A*, *45*(6), pp.1508-1520.

Ratti, R.A. 1985, A descriptive analysis of economic indicators. *Federal Reserve Bank of St. Louis Review*, (Jan), pp.14-23.

Simone, M.A. 2001, *In search of Coincident and leading Indicators of Economic Activity in Argentina* (No. 1-30). International Monetary Fund.

# Appendix:

## Deviations from Trend: Employment

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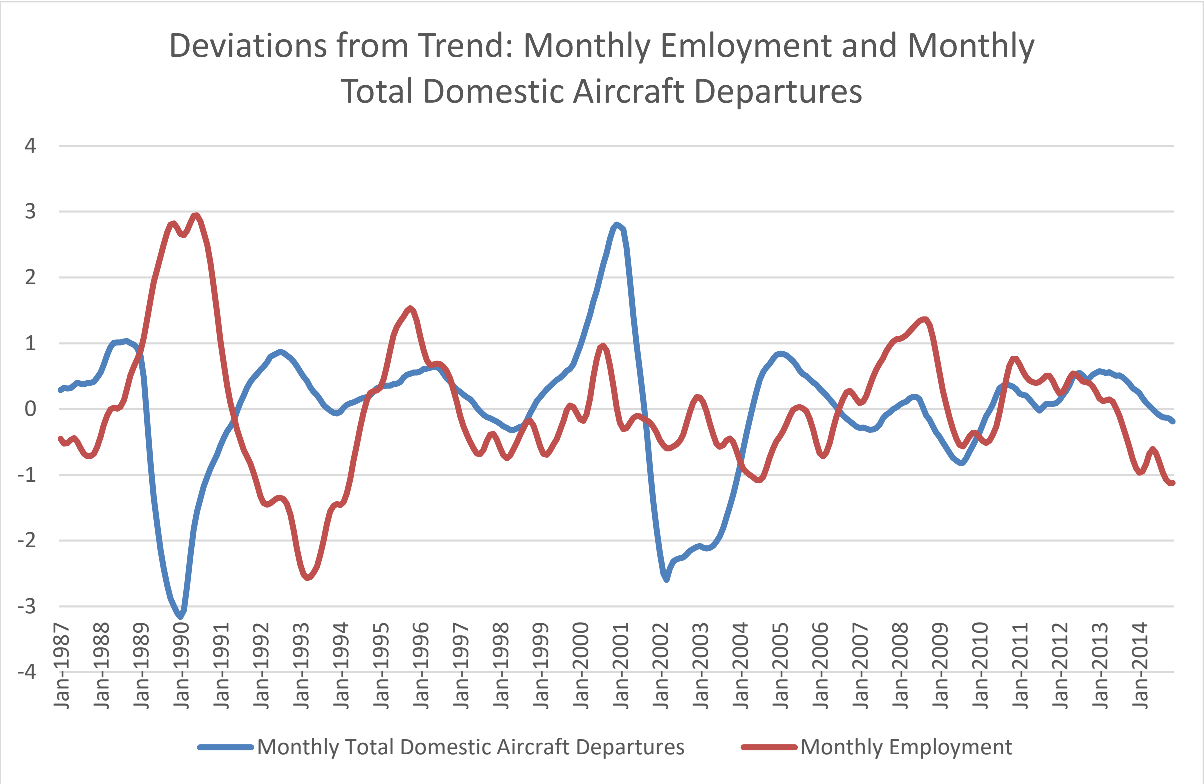


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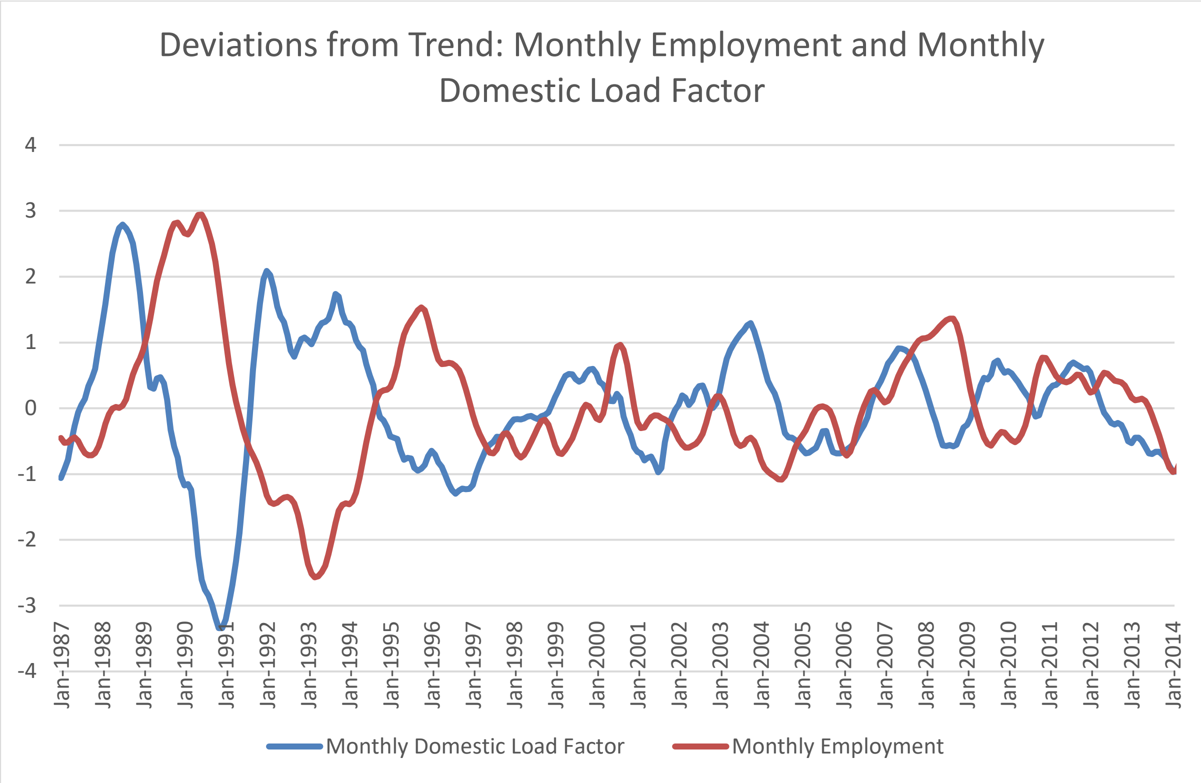


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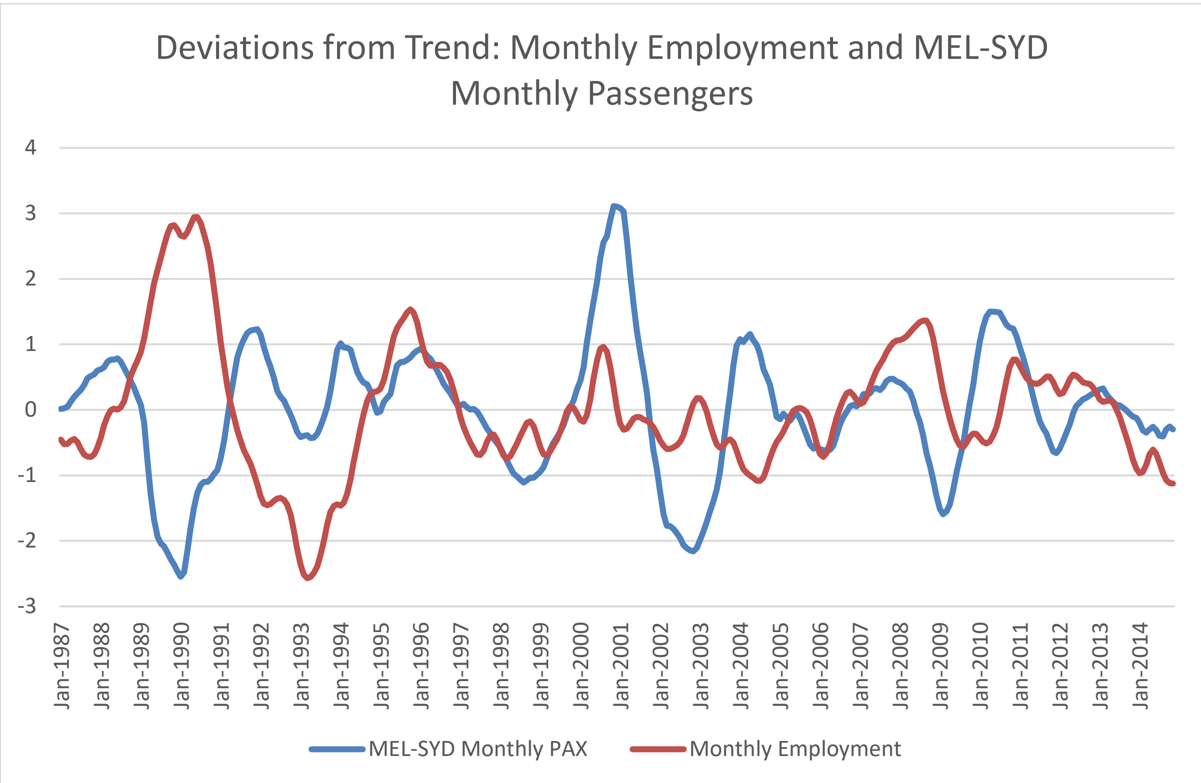


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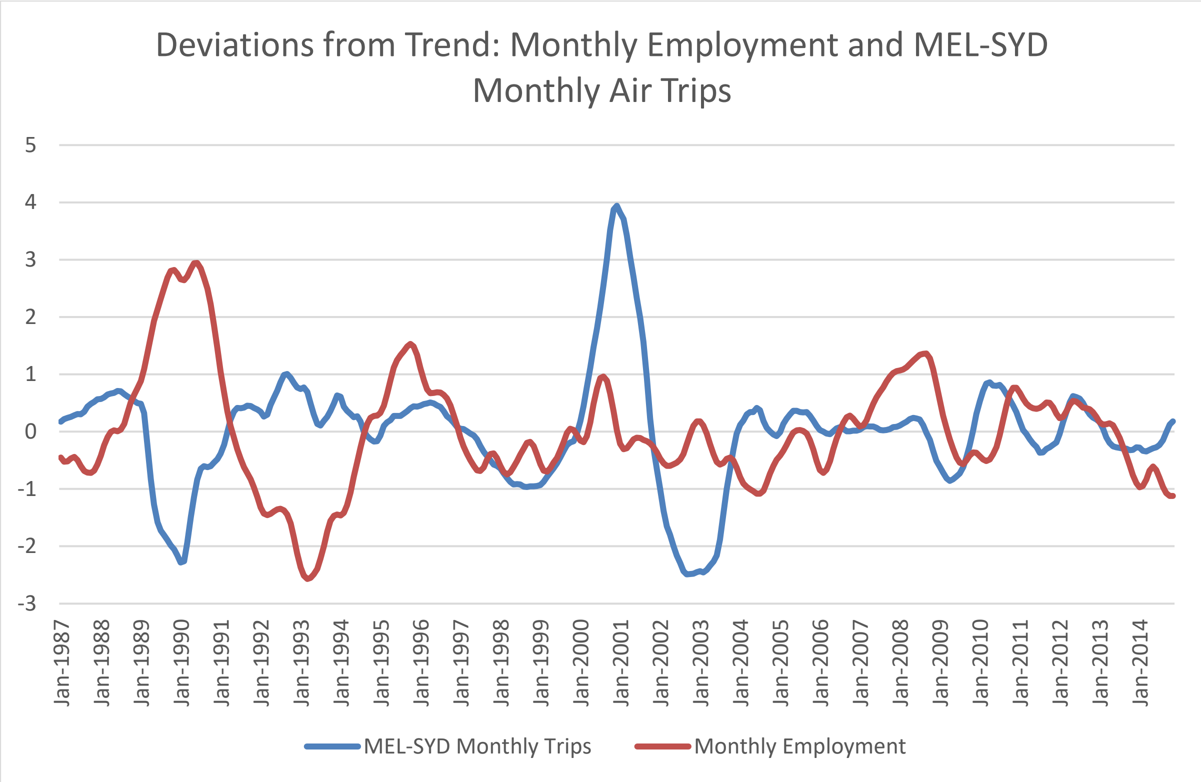


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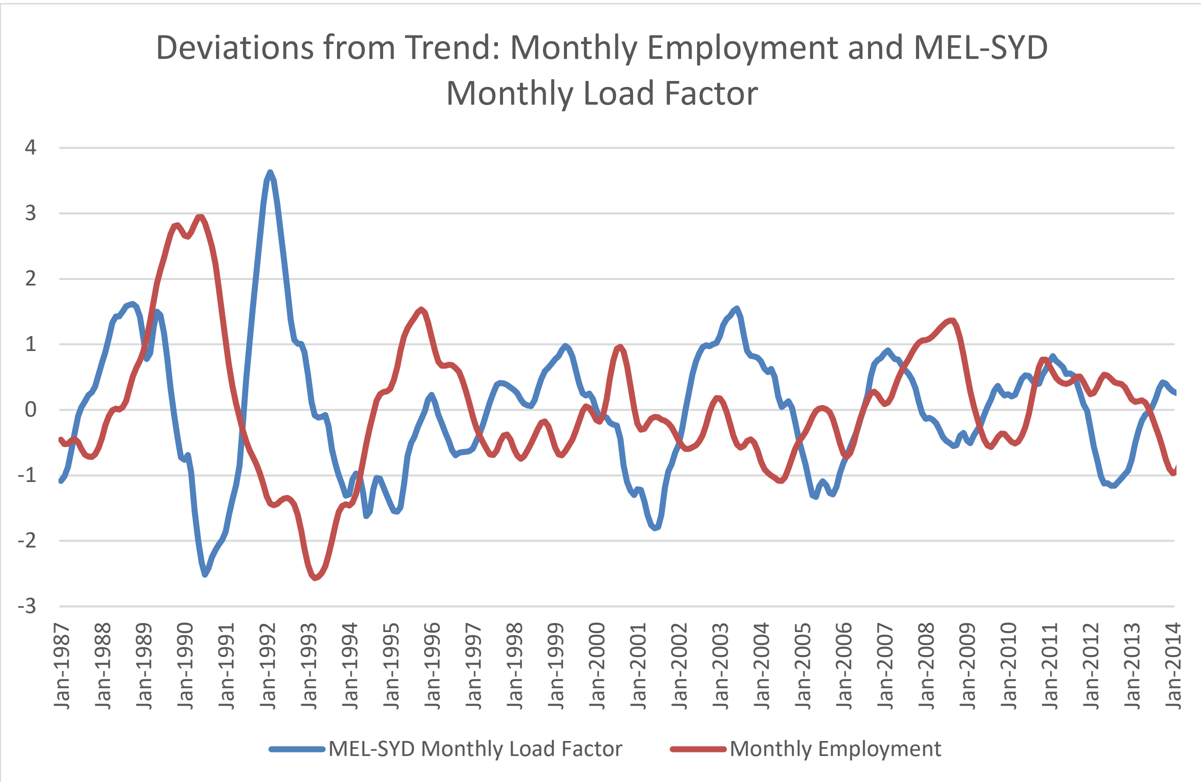


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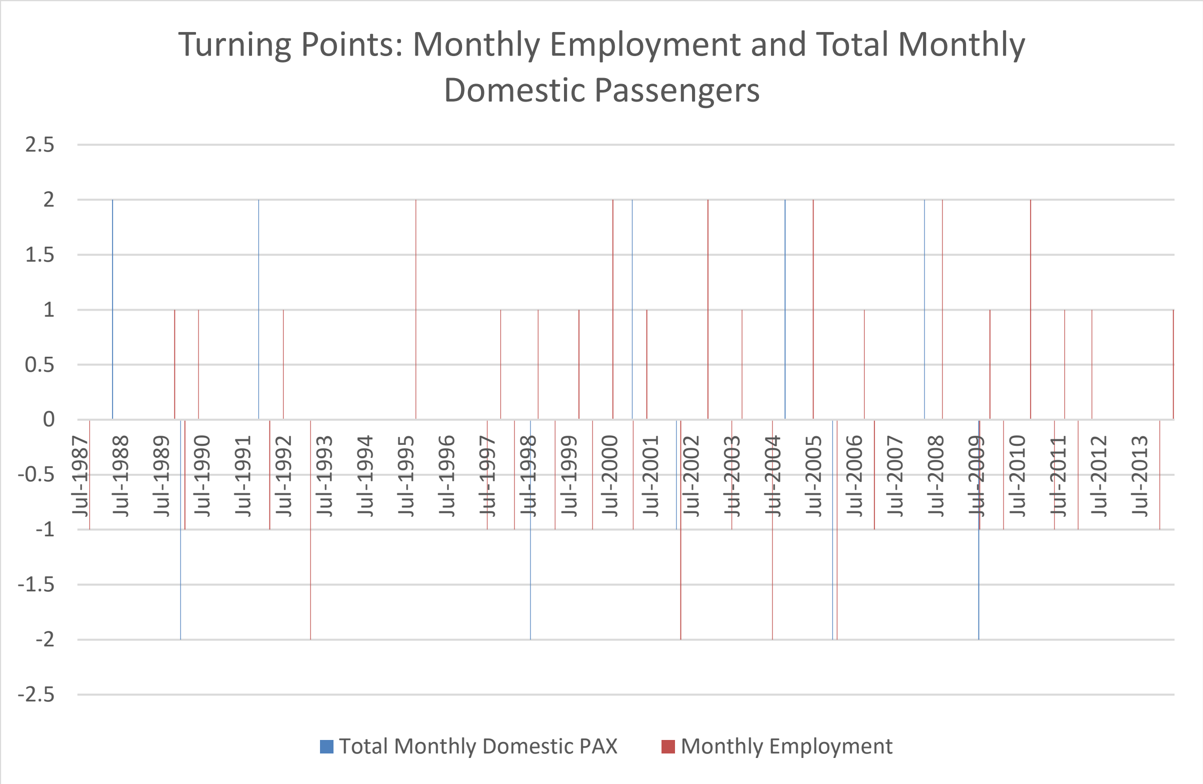
## Turning Points: Employment

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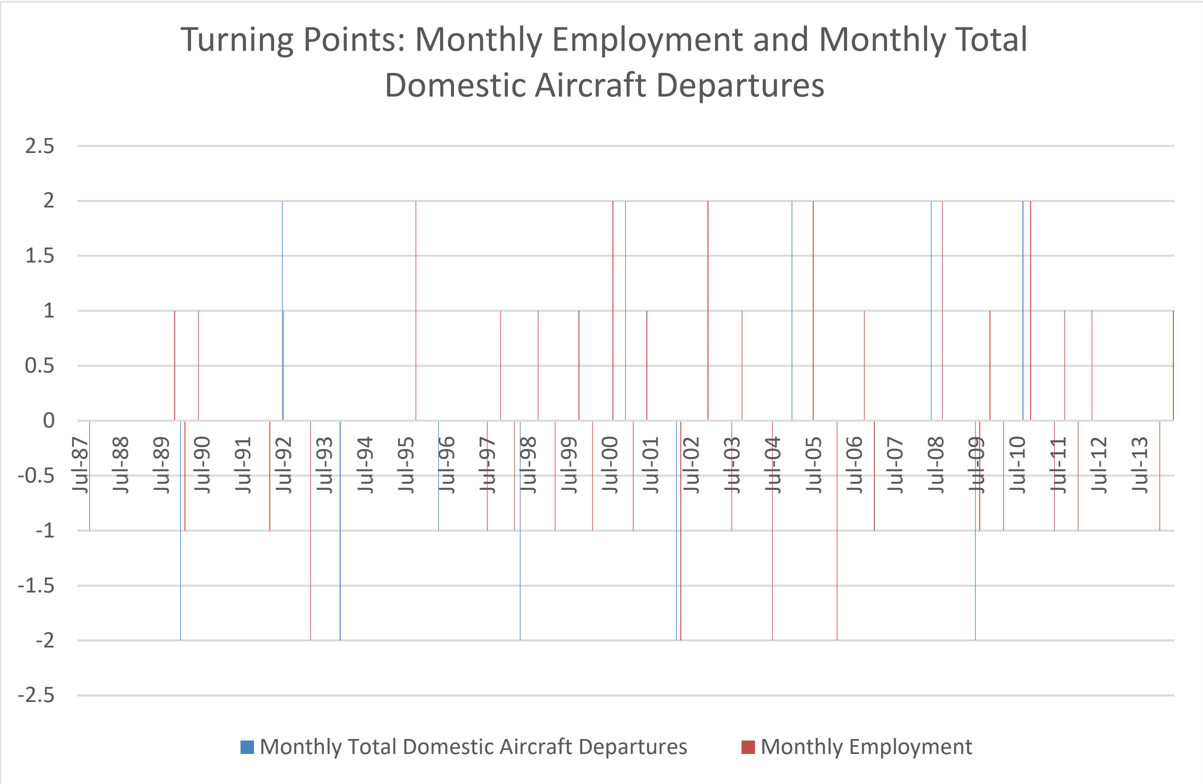


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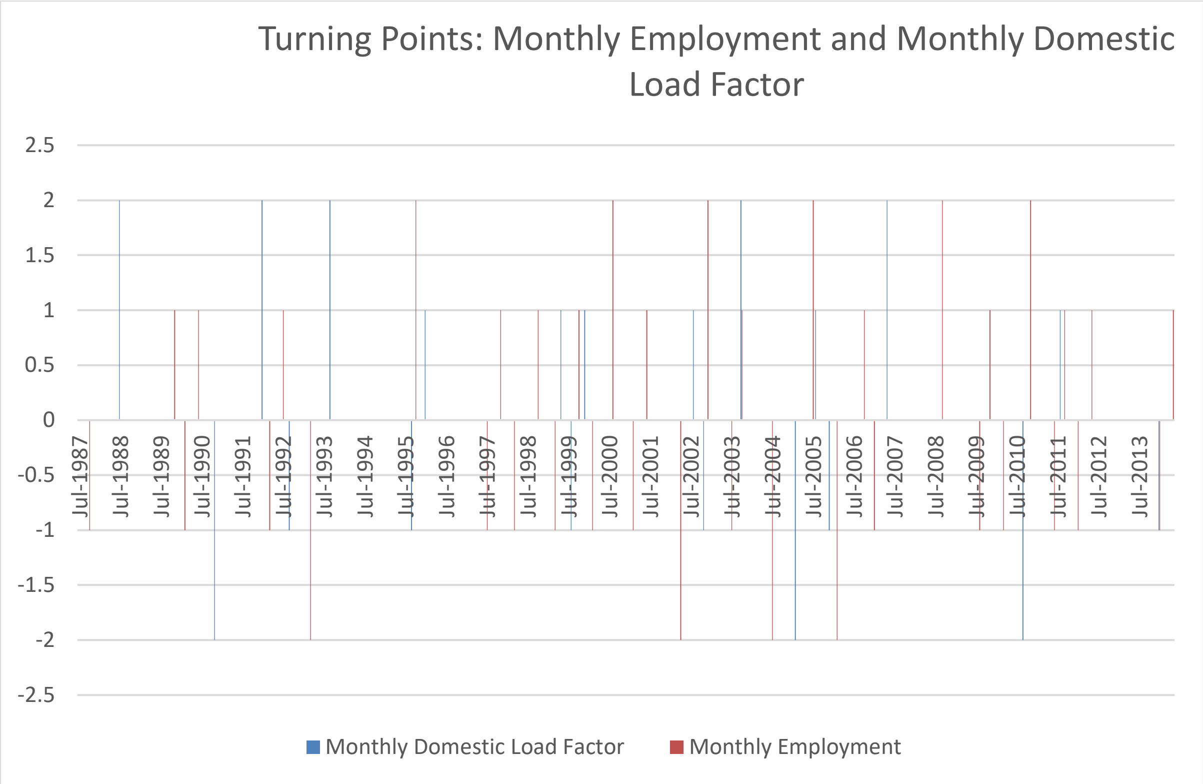


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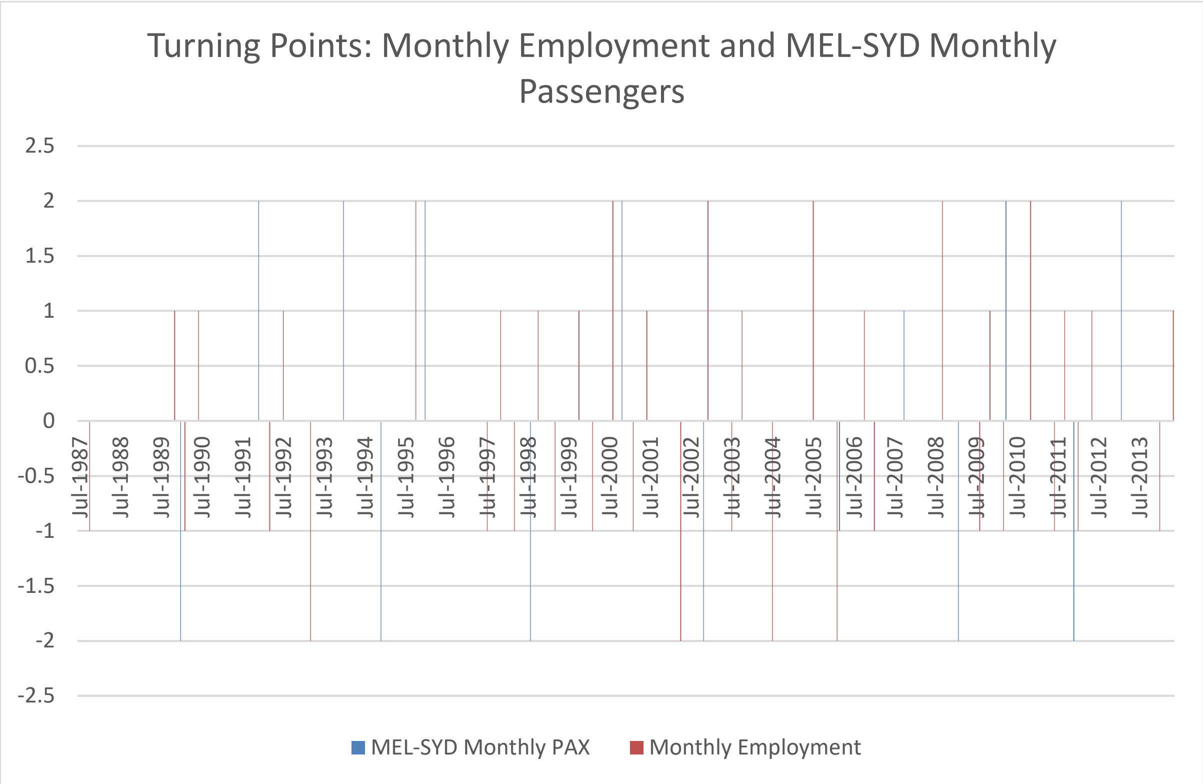


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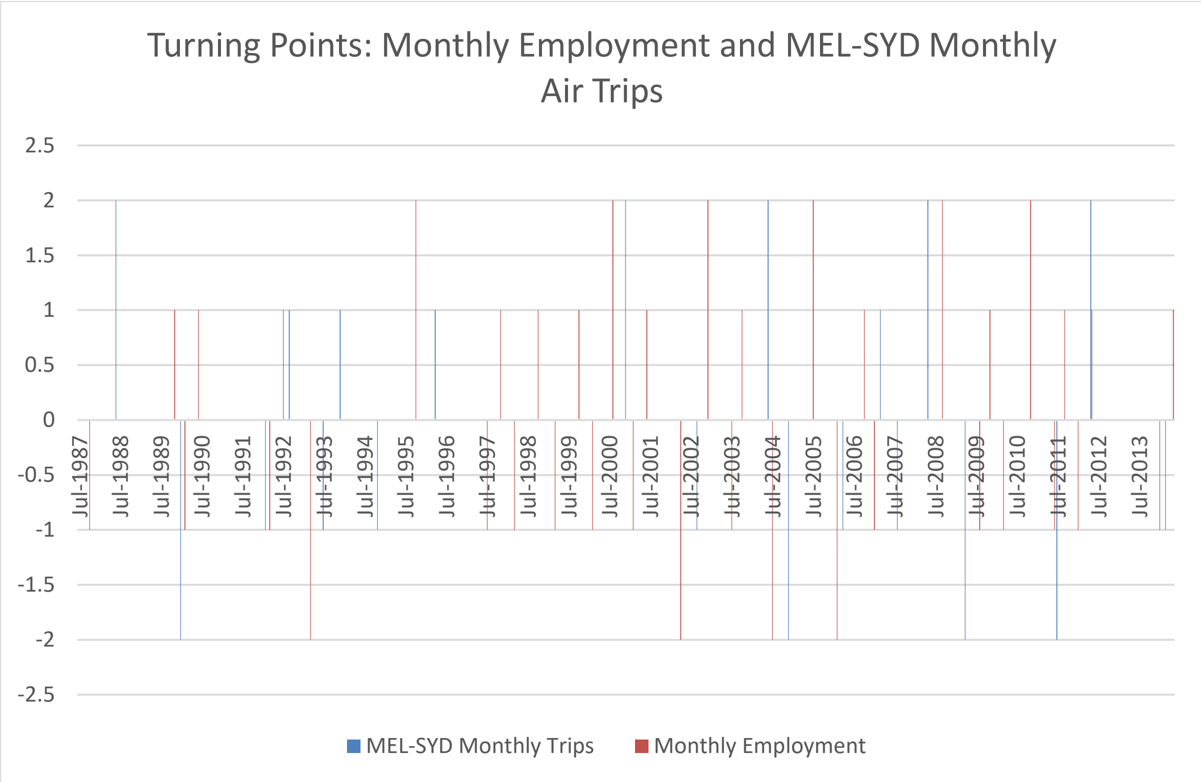


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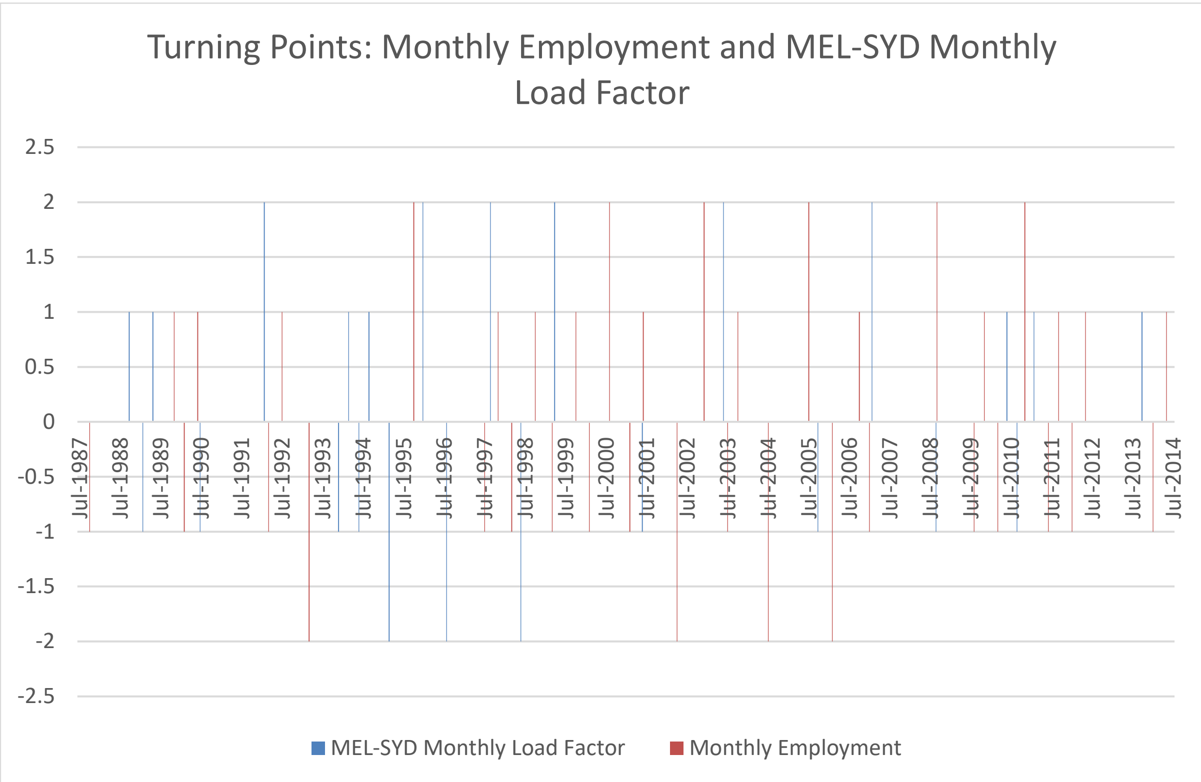
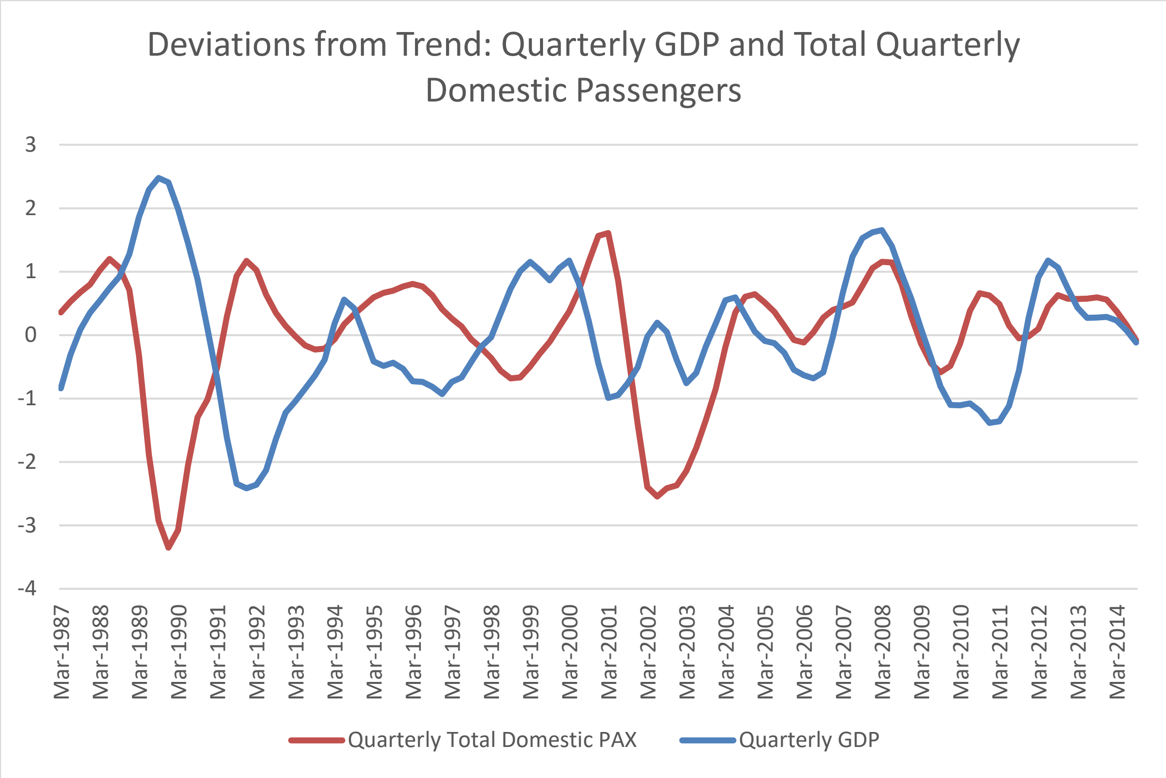



Source: ABS (2018a) and BITRE (2018b)

## Deviations from Trend: GDP

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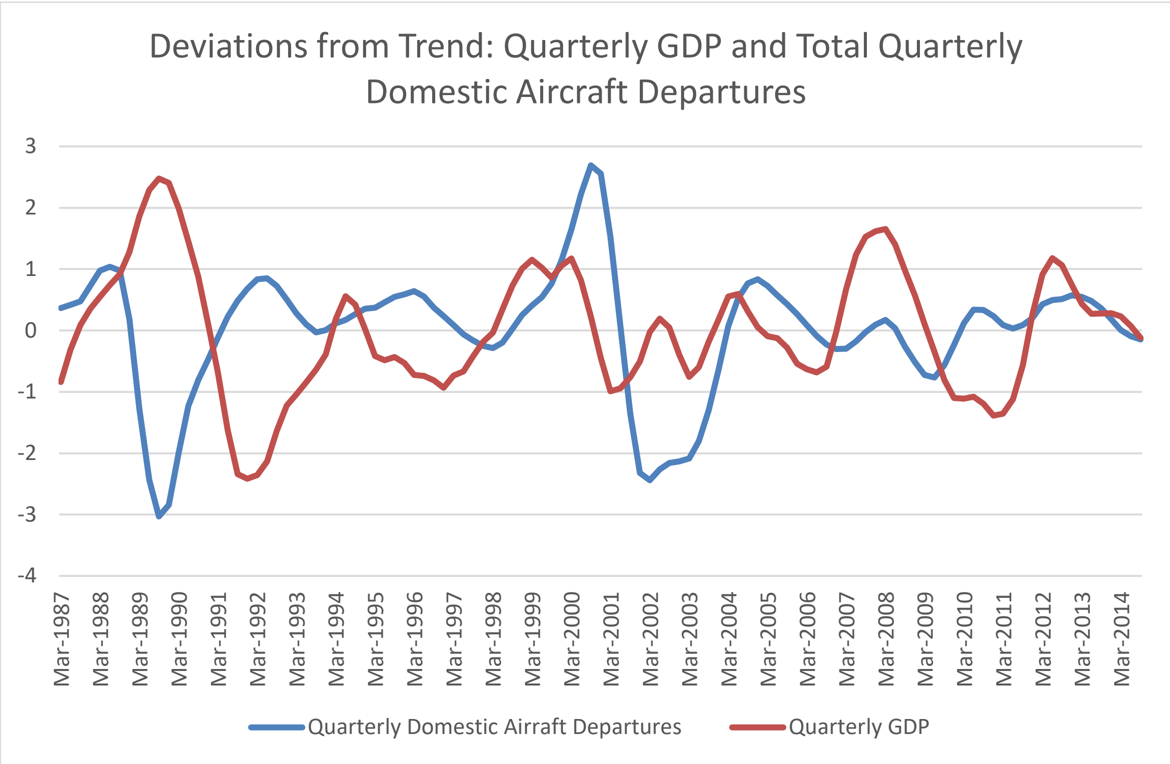


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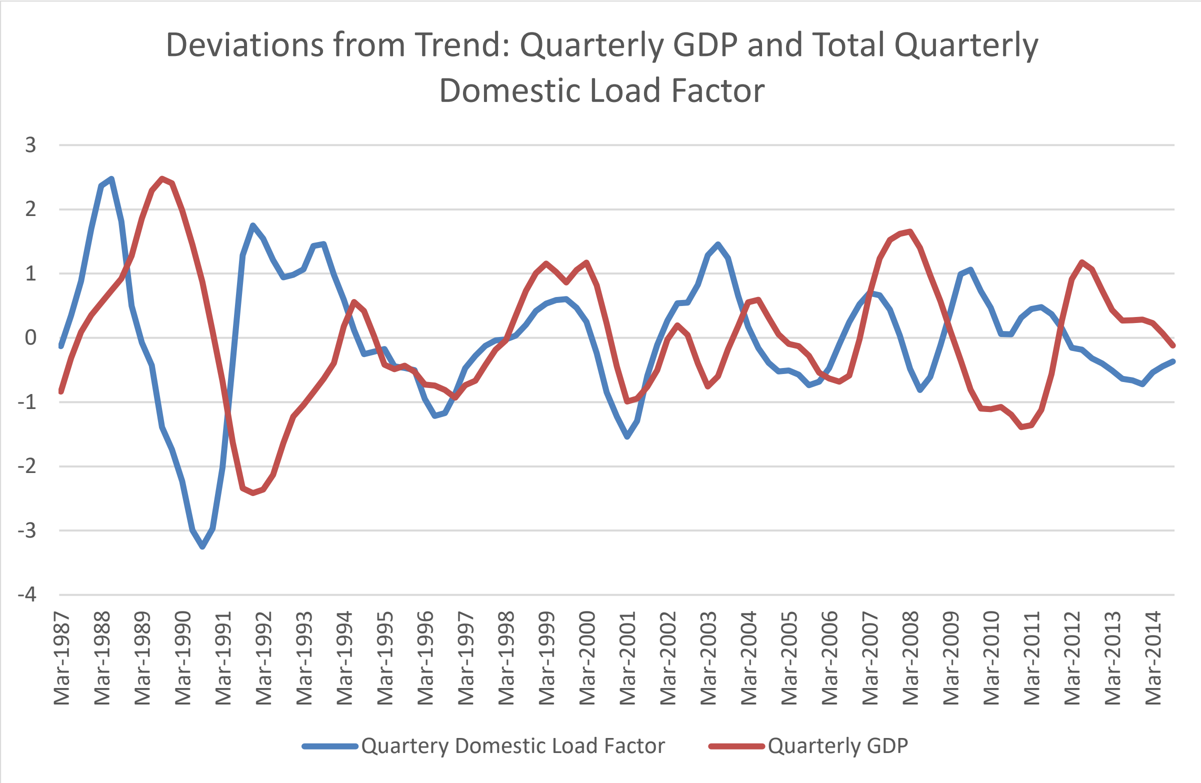


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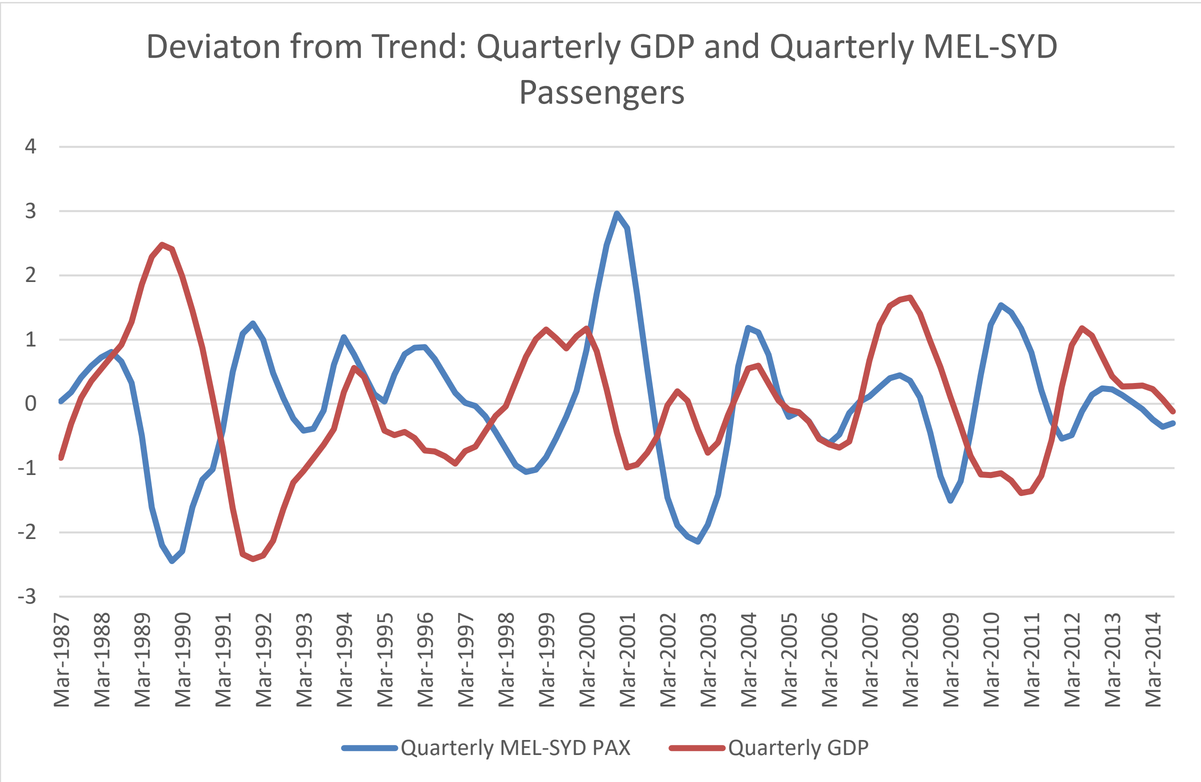


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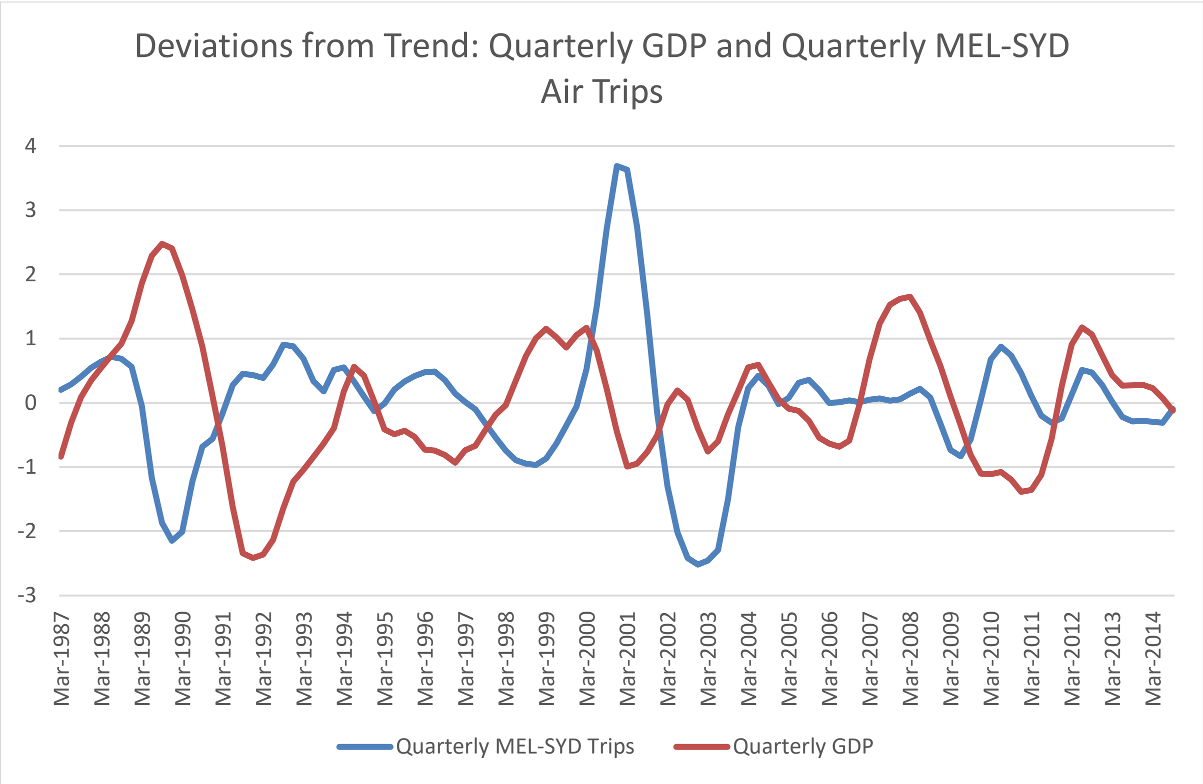


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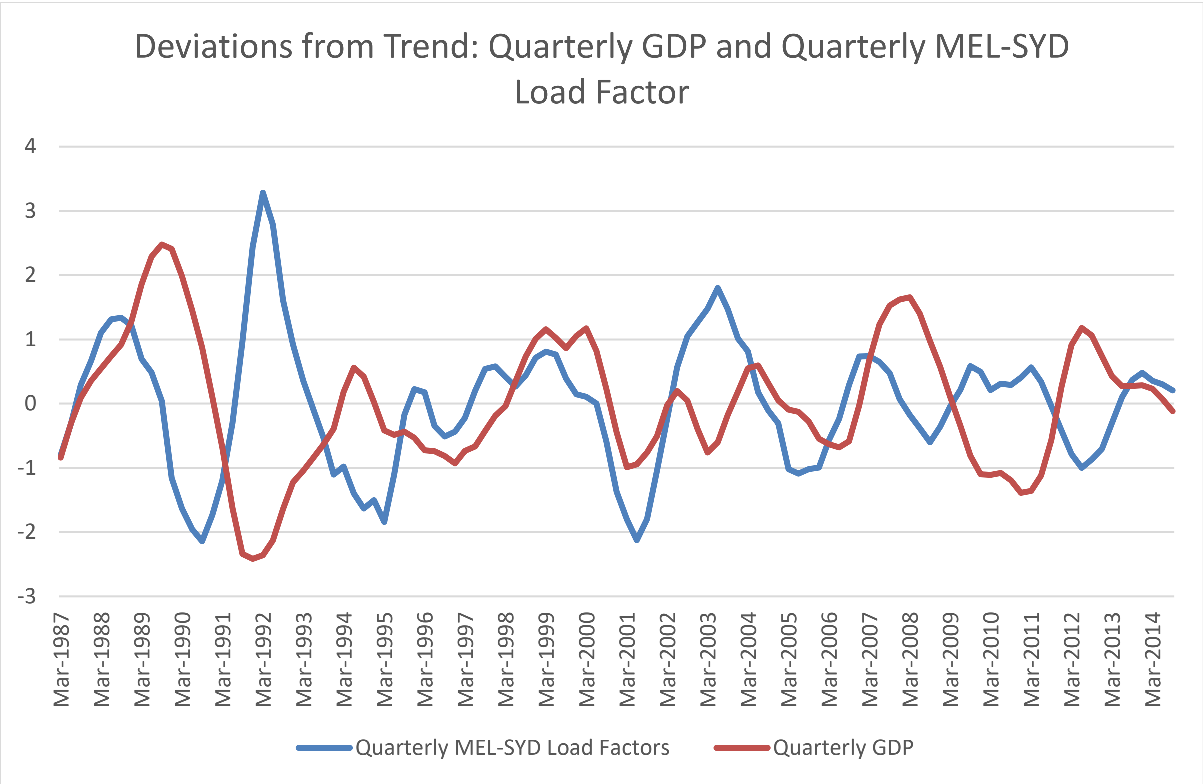
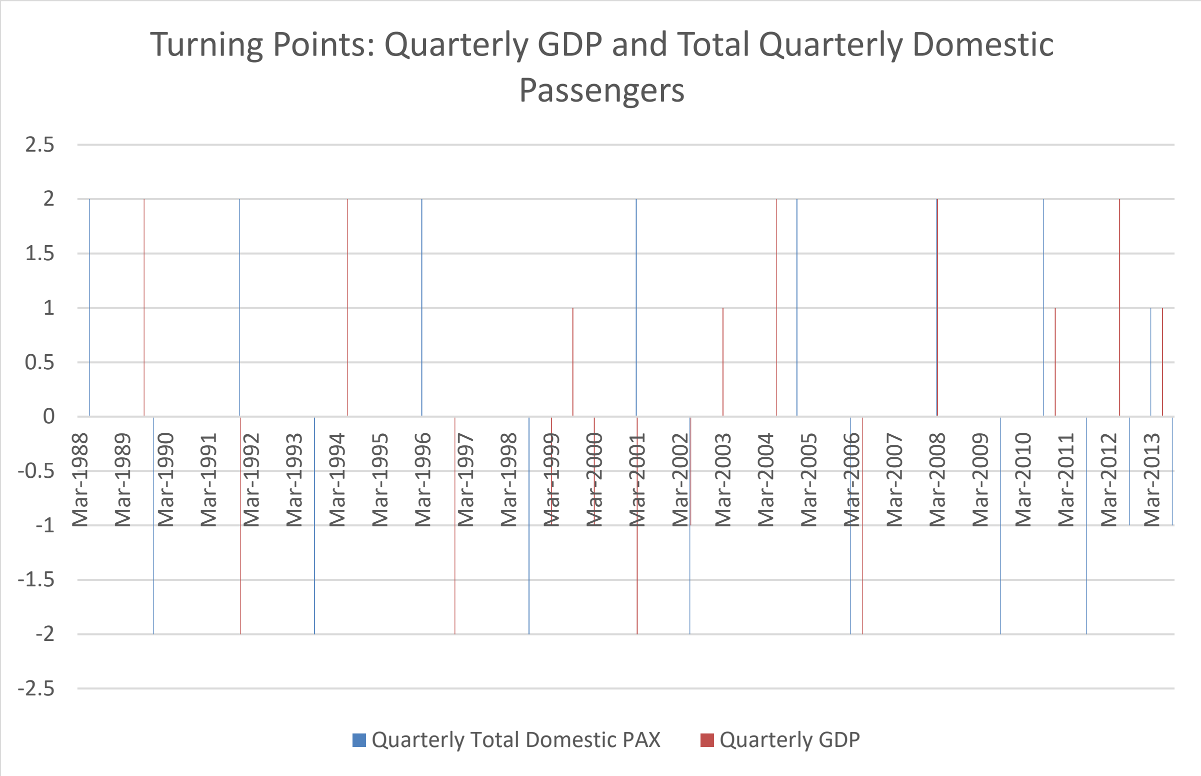
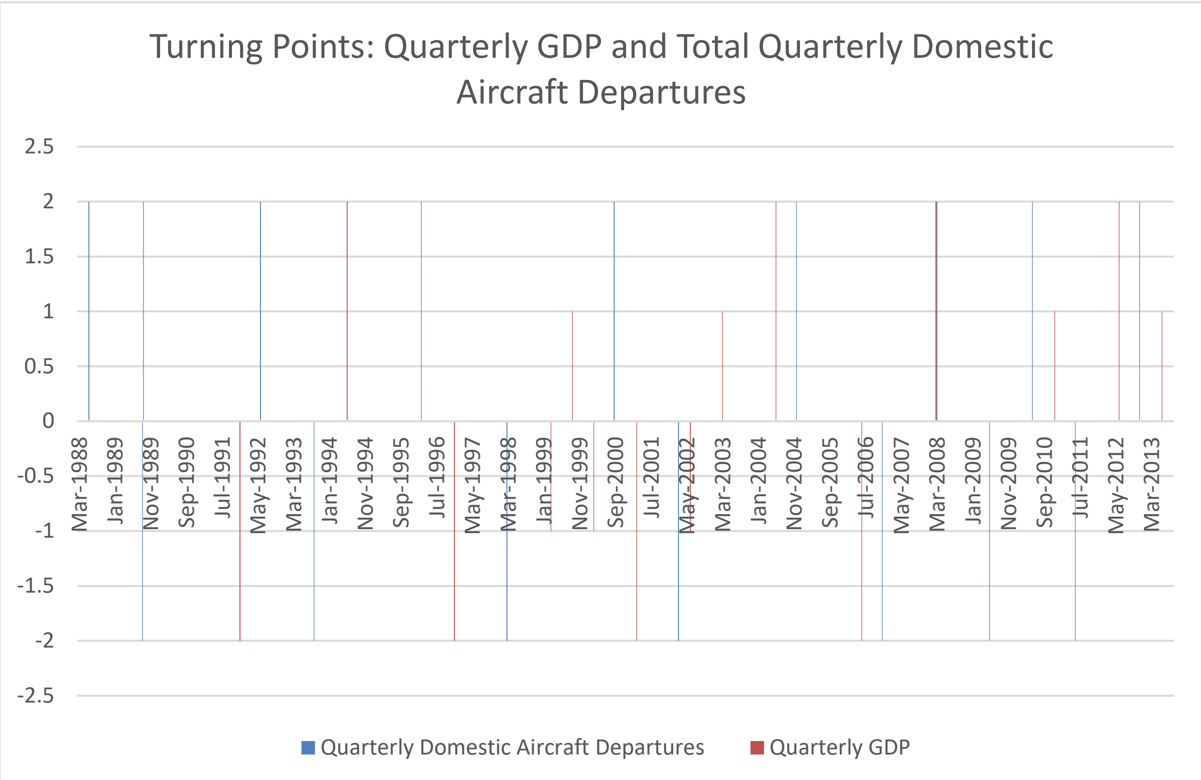



Source: ABS (2018b) and BITRE (2018b)

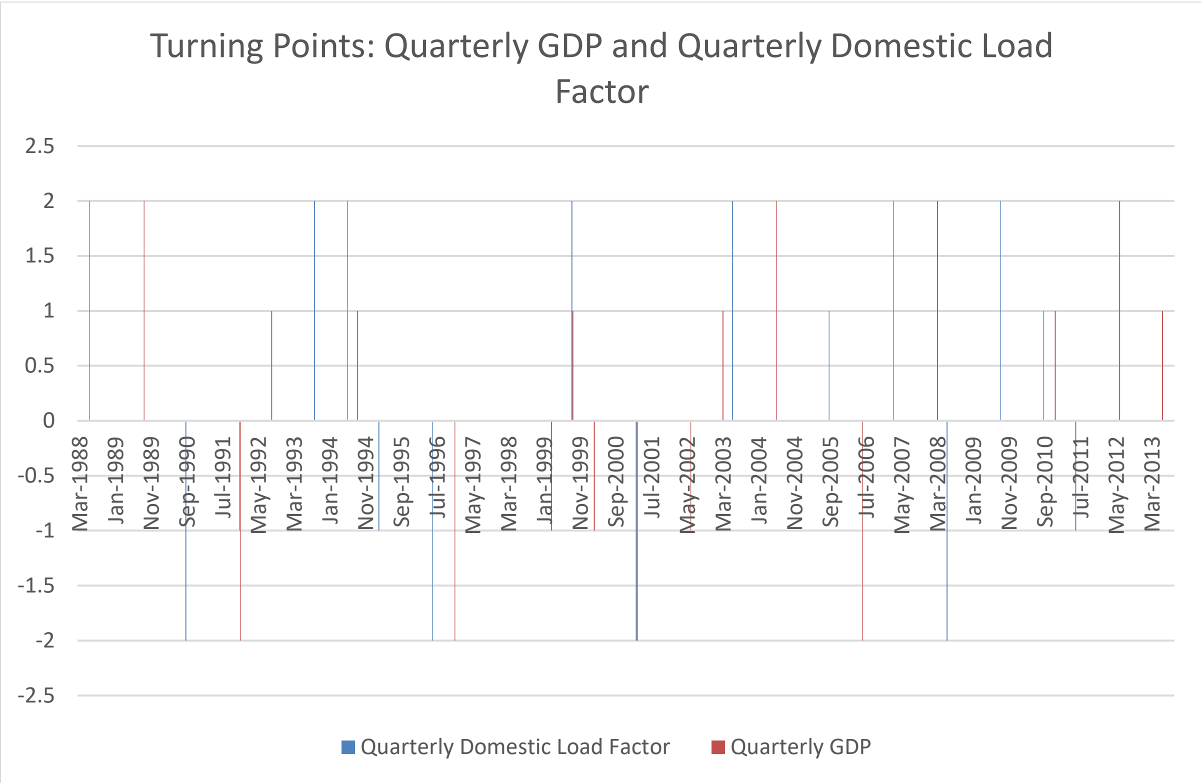
## Turning Points: GDP



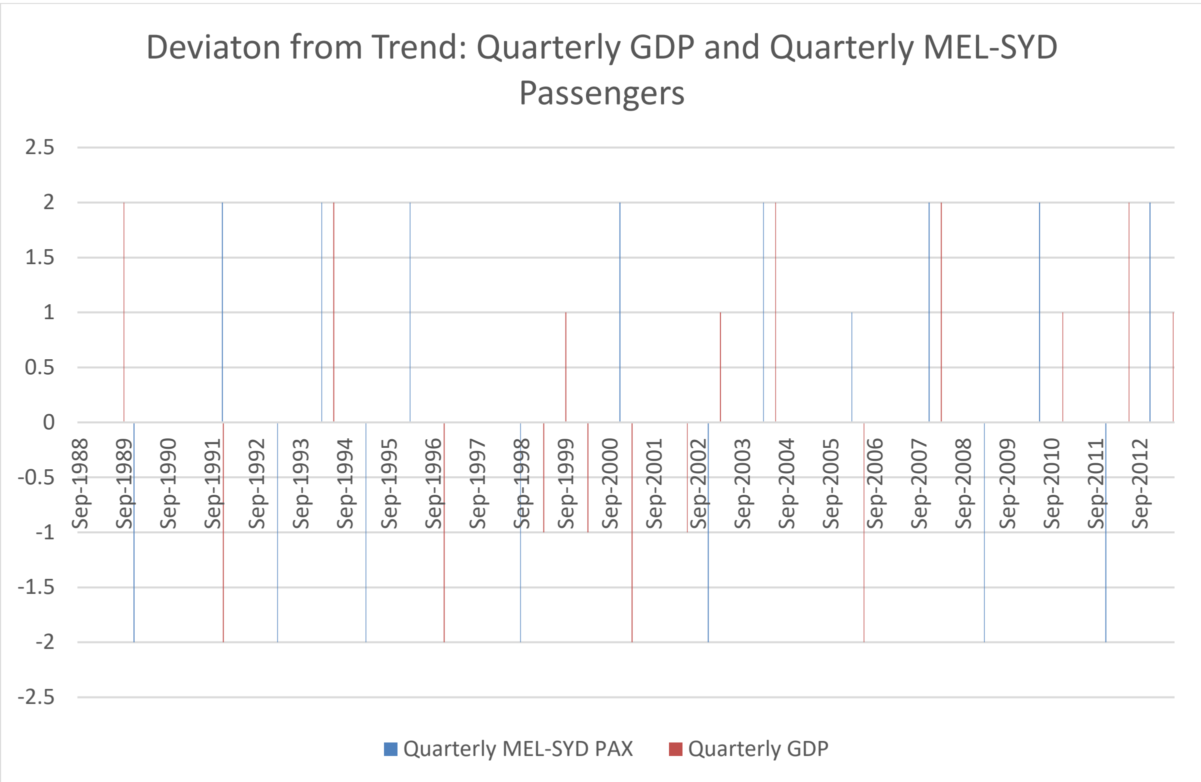

Source: ABS (2018b) and BITRE (2018a)



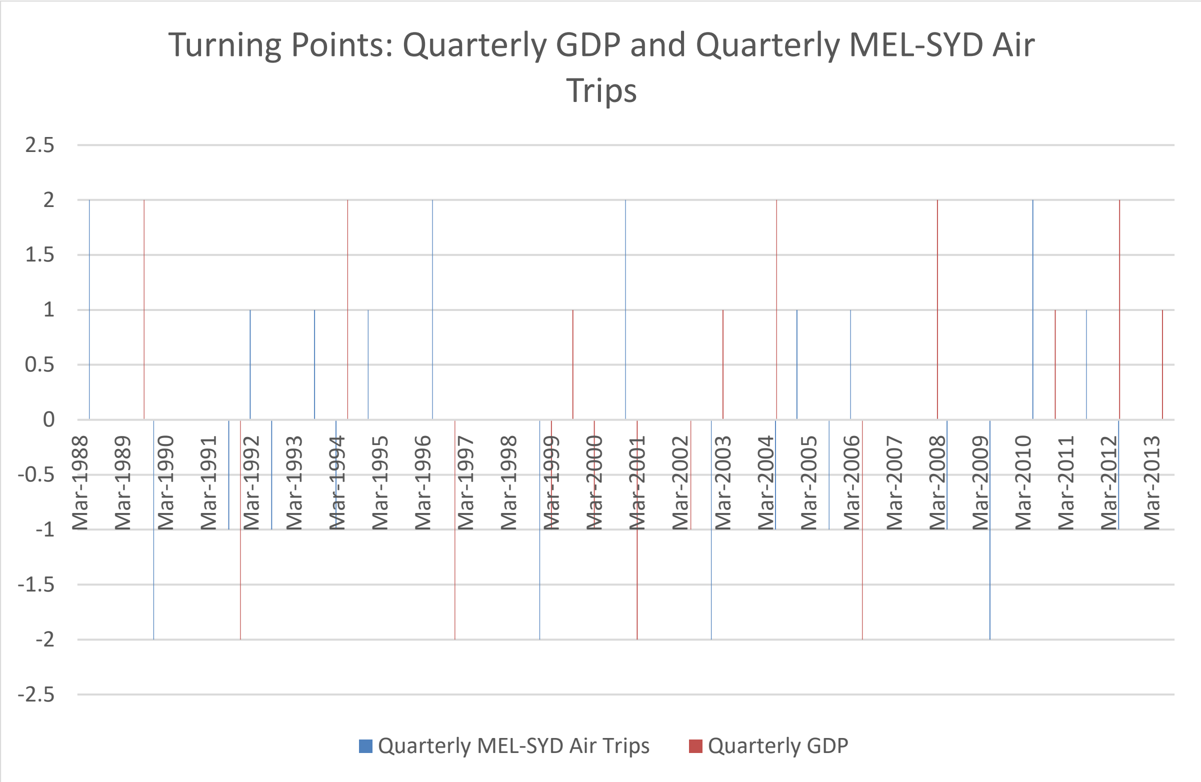

Source: ABS (2018b) and BITRE (2018a)



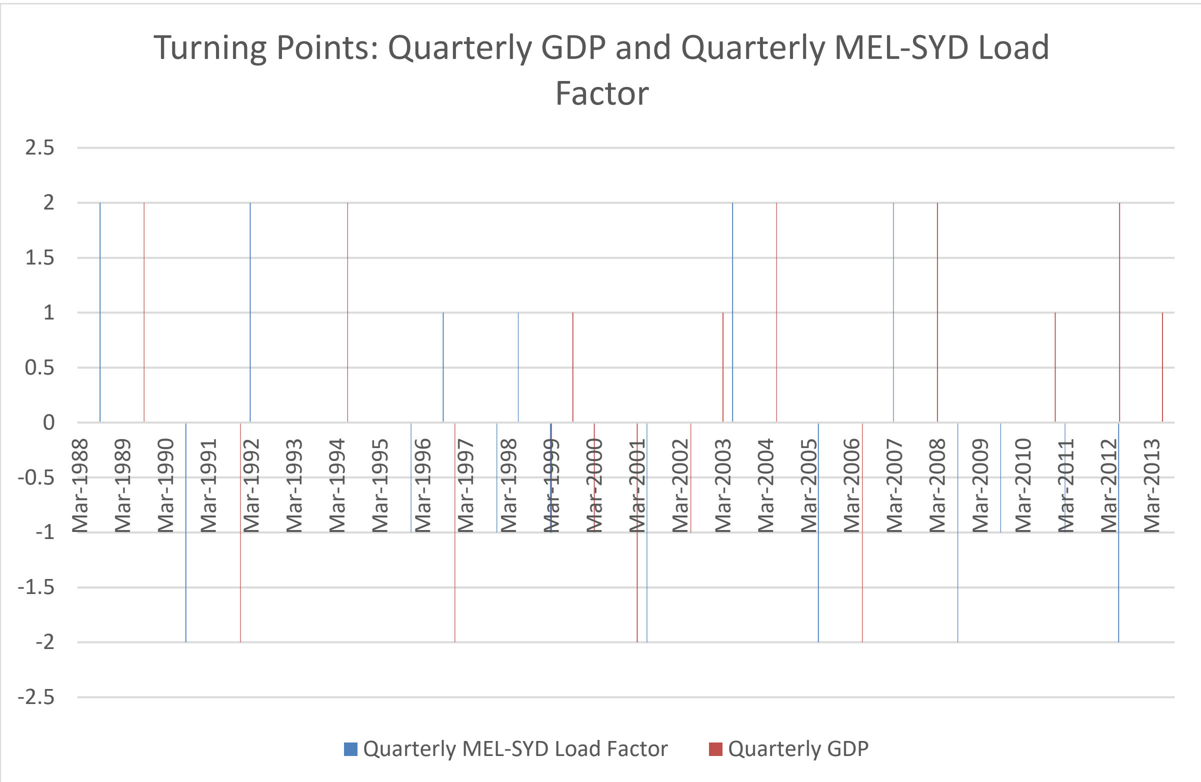

Source: ABS (2018b) and BITRE (2018a)




Source: ABS (2018b) and BITRE (2018b)




Source: ABS (2018b) and BITRE (2018b)




Source: ABS (2018b) and BITRE (2018b)

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## Use of the Coat of Arms



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