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Aviation activity as a leading indicator of economic activity

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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 scopes 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 flight path best predicted variations in GDP. However, even the highest performing variable did not sufficiently predict fluctuations in economic data to be a useful leading indicator for policy makers.

1. Introduction

Economic data is often published on a quarterly basis, and changes in the economy can be well under way by the time data is published. This creates difficulties for policy makers in predicting, let alone reacting, to fluctuations in economic performance. A leading indicator of economic activity would predict peaks and troughs in measures of economic activity, and would be useful to policy makers by allowing more time to respond to anticipated changes in the economy.

This study scopes 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 tested the relationship between aviation data and economic indicators of the national economy, 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 for individual regions. 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 Gross Domestic Product (GDP) and employment published by the Australian Bureau of Statistics (ABS). Aviation data on the Melbourne to Sydney flight path were also tested against aggregated economic data due to its status as the busiest flight path in Australia, as well as recent claims that data on the Melbourne-Sydney flight path can be used as a leading indicator of business activity (James, 2016 and 2017).

For the aviation data to be a leading indicator of economic data, it must move before the economic data, after removing seasonal and trend elements. 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 flight path had the highest ability to predict economic activity. However, even the highest performing variable did not sufficiently predict fluctuations in economic data 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 is beyond the scope of this paper.

2. 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. However, the economic impact of the aviation industry is difficult to measure, and estimates vary. The Air Transport Action Group (ATAG) has estimated that aviation contributed US$2.7 trillion to the global economy in 2014 (ATAG 2016), while a study undertaken by Deloitte Access Economics 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 assess the contribution of airports to employment. 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 onsite at ten selected major Australian airports in 2011 (BITRE 2013). On the other hand, a number of European studies including Robertson (1995), Hakfoort, Root and Rietveld (2001) and York Aviation (2004) suggest that for every million annual passengers, 1000 direct on-site positions are generated (cited in BITRE 2013, p. 2). Breukner (2003) shows that a 10 per cent increase in passengers in metropolitan areas of the United States leads to approximately a one per cent increase in employment in service-related industries, and Percoco (2010) concludes that a one per cent increase in passengers results in a 0.45 per cent increase in local service sector employment across provinces in Italy.

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, Jain & McKellar 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, while others 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 through methods such as the Granger Causality Test. One body of literature examines the relationship between these variables in specific countries using domestic time series data (Marazzo, Scherre & Fernandes 2010; Chi & Baek 2013; Mehmood & Shahid 2014; Brida, Rodriguez-Brandis, Lanzolita & Rodriguez-Collazo 2016; Alshammary 2017). For example, Rodriguez-Brandis, Lanzolita and Rodriguez-Collazo (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, Scherre and Fernandes (2010) examine this relationship in Brazil, and report that while GDP causes passenger movements, passenger movements do not cause GDP. Mehmood and Shahid (2014) examine the link between aviation demand and economic growth in the Czech Republic, and conclude that causality only runs from GDP to passenger numbers. Alshammary (2017) concludes that aviation does cause economic development in the Saudi Arabian context, controlling for population, banking credit to the private sector and jet fuel production.

Another body examines the relationship across regions using cross sectional or panel data (Mukkala & Tervo 2013; Baker, Merkert & Kamruzzaman 2015; Hu, Xiao, Deng, Xiao & Wang 2015; Hakim & Merkert 2016). Hakim and Merkert (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, Xiao, Deng, Xiao and Wang (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. Baker, Merkert and Kamruzzaman (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 and Tervo (2013) also consider how air traffic affects economic growth across remote and core regions, using panel data on 86 European regions. Baker, Merkert and Kamruzzaman (2015) conclude that bi-directional causality exists between regional aviation and economic growth, and Mukkala and Tervo (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 flight path as a proxy measure for business activity (James 2016; James 2017). 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 an extrapolation from 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 literature on aviation activity and economic growth remains very high level, with 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. For example, some studies in the literature make conclusions about the causal relationship

between aviation activity and economic activity, through conducting Granger Causality Tests on bi-variate models comprising only of these two variables. However, failure to incorporate other relevant variables into the models, may lead to spurious conclusions about the causal relationship between the variables tested (Granger 1969). Some studies, including Percoco (2009), Green (2007) and Alshamarry (2017) develop a more robust model by controlling for exogenous variables that affect economic growth. Nevertheless, the lack of additional variables in existing analyses remains a gap in the literature.

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. 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. 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 boosted 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. 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, however, some do not, and future work in this area should ensure that data is adjusted as required.

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 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 found at the national scale.

2.1 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 & Saadi-Sedik 2003; Connolly & Stevens 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 lag time (Ratti 1985).

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).

A local example of a composite leading indicator is the Commonwealth Department of Jobs and Small Business' Monthly Leading Indicator of Employment, which consists of five equally-weighted component series and has an average lead time of just over one year (Department of Jobs and Small business, 2018). 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 & Stevens 2008).The methodology used to develop the Department of Jobs and Small Business' Monthly Leading Indicator of Employment is described in detail on their Departmental website.

3. Data

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. It is possible however, that shocks that specifically affect the aviation sector, such as terrorist attacks or pilot strikes, may not have as significant an effect on the broader economy.

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 series were examined in this study:

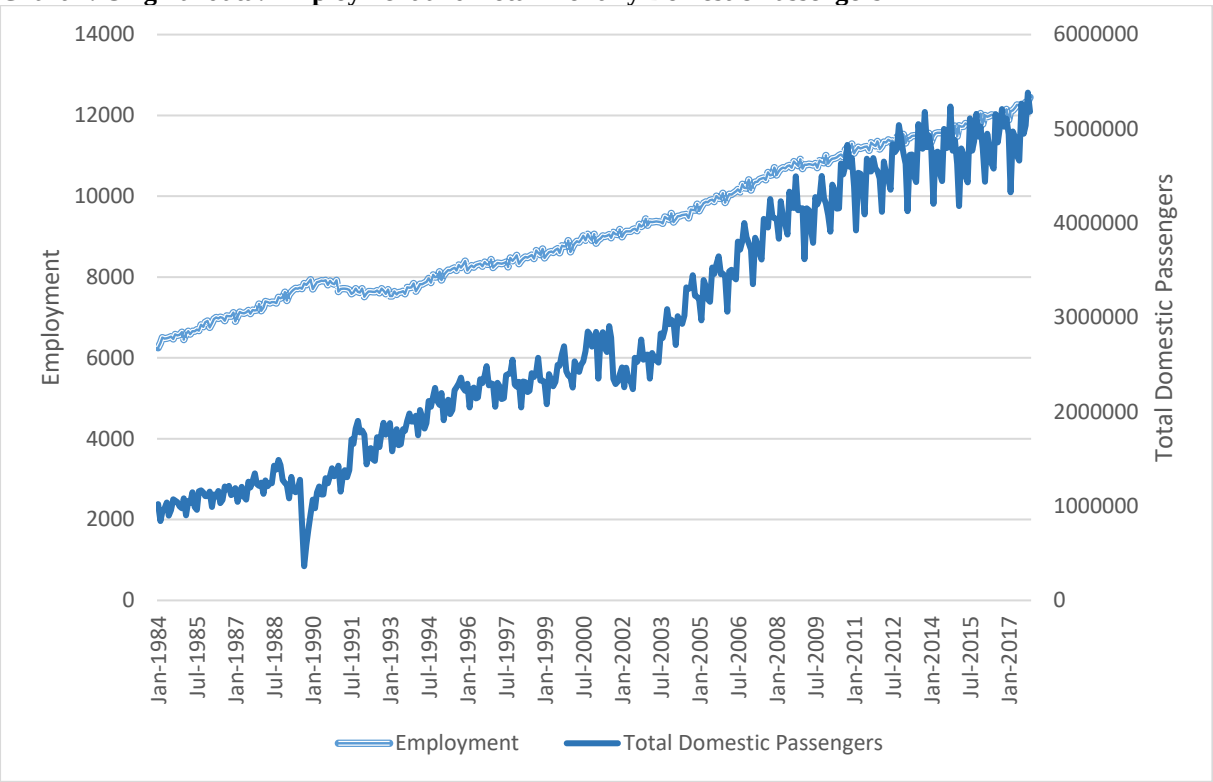
- Domestic Airline Monthly Total Revenue passengers U/D (Uplift/Discharge)
- Total Domestic Monthly Aircraft Departures
- Total Domestic Monthly Passenger Load Factor
- Melbourne-Sydney Monthly Revenue Passengers
- Melbourne-Sydney Monthly Air Trips
- Melbourne-Sydney Monthly Passenger Load Factor

The above aviation data was examined against the following economic data published by the ABS:

- Employment (published monthly by the ABS, CAT 6202.0,)
- GDP, chain volume measures (published quarterly by the ABS, CAT 5206.001)

As discussed previously, the employment, GDP 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 chart below, where raw employment data plotted with raw data on passenger numbers.

Chart 1: Original data: Employment and Total Monthly Domestic Passengers



Source: ABS 2018, 6202.0 Labour Force, Dec 2017 and BITRE 2018, Monthly Airline Performance

Both series have an obvious upward trend, and increase with time. While the series move together in the same direction, 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 original series. 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.

4. Method

Two key tests were used to scope whether aviation data can be used as a leading indicator of aggregated economic activity – deviations from trend in the aviation data and economic data were compared graphically, with a view to conduct 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 & Stevens (2008) provide a framework to accomplish this. 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.

4.1. 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 in this study. However, as the data series used in this study have different characteristics, and 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 CHART 1). Using the same moving average to smooth the two series either removed too much information from one series, or retained too much seasonality in the other. Similarly, the 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.

4.2. Monthly data

Ultimately, two different methods were used to smooth the monthly time series data. Building on the framework developed by Connolly & Stevens (2008), 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. 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.

4.3. 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 proportion on a monthly basis, the middle month was used as a reference month for the corresponding quarter.

A four-term centred moving average was applied to all quarterly series to determine the one-year trend, and a 24-term centred moving average was applied to determine 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.

4.4. 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 series.

While the time series used provide data until 2017, the use of moving averages to smooth the series shortened the time series to 2014. 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.

4.5. Turning points

The study again builds on the framework developed by Connolly & Stevens (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 & Stevens 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).

The definitions used for the study 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 potentially 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.

4.6. 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. Overall, the first set of charts showed that there was little connection between the aviation data and economic data, and any relationship that did exist was obscured heavily by noise in

the data. The second stage of graphical analysis reduced this noise, by isolating and only graphing turning points, and clearly illustrate whether turning points in aviation data lead turning points in economic data.

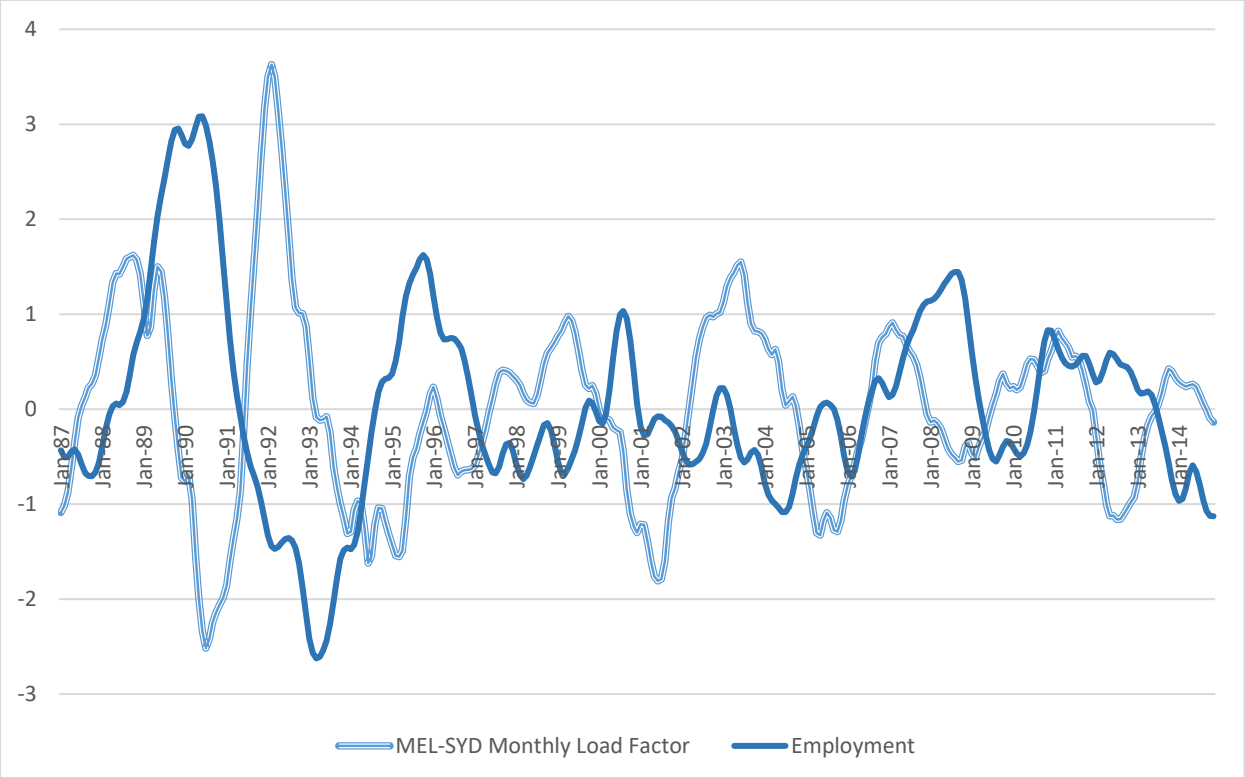
For example, the load factors of aircraft traveling on the Melbourne-Sydney flight path (CHART 2) visibly appeared to have power to predict employment data. CHART 2 suggests the load factors of aircraft on the Melbourne-Sydney flight path led employment data during the period from 1987 to approximately 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 CHART 2, CHART 3 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. As TABLE 1 indicates, the load factors of aircraft on the Melbourne-Sydney flight path predicted just three turning points, failed to predict seven turning points, and implied a further six false turning points (non-existent turning points).

Further examples of both sets of charts are provided 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 on the charts discussed in this paper, and missed turning points and false turning points have been annotated with crosses and triangles respectively.

Table 1: Results of Employment and MEL-SYD Load Factor

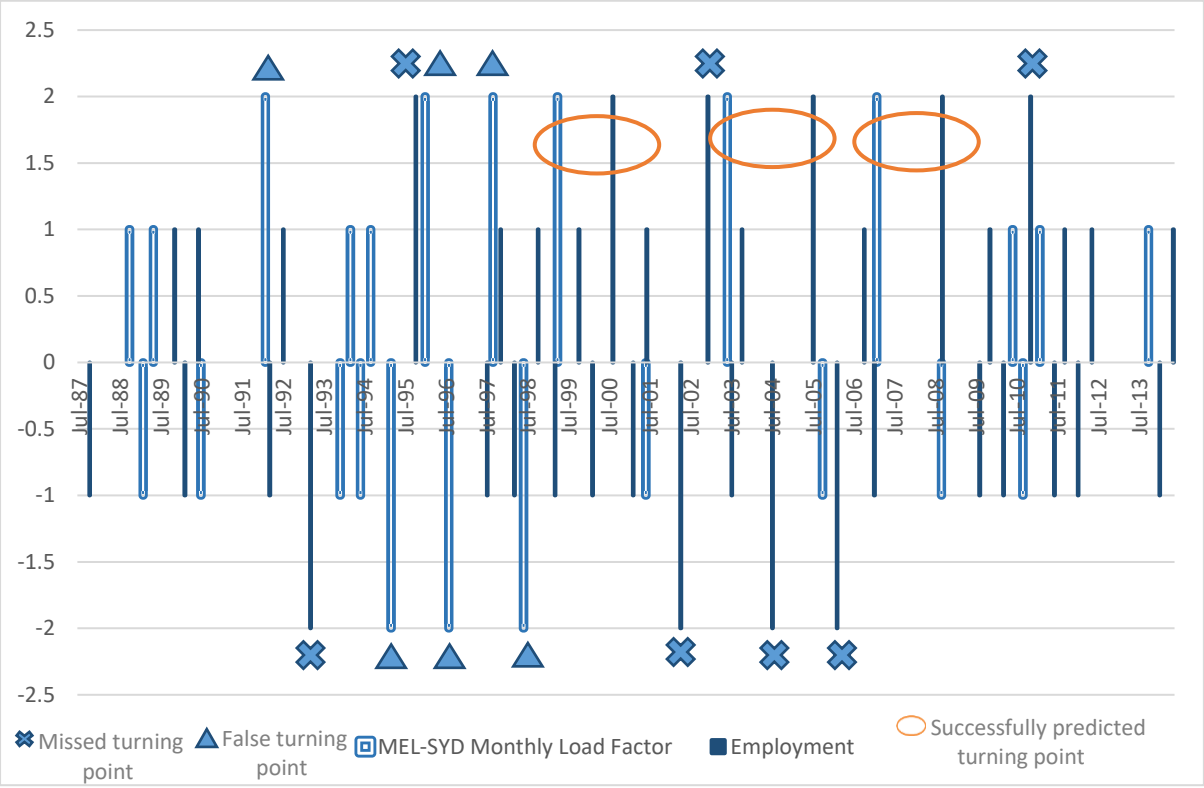
Employment and MEL-SYD Load Factor	
Predicted turning points	3
Missed turning points	7
False turning points	6

Chart 2: Deviations from Trend: Employment and MEL-SYD Monthly Load Factor



Source: ABS 2018, 6202.0 Labour Force, Dec 2017 and BITRE 2018, Monthly Airline Performance

Chart 3: Turning Points: Employment and MEL-SYD Monthly Load Factor

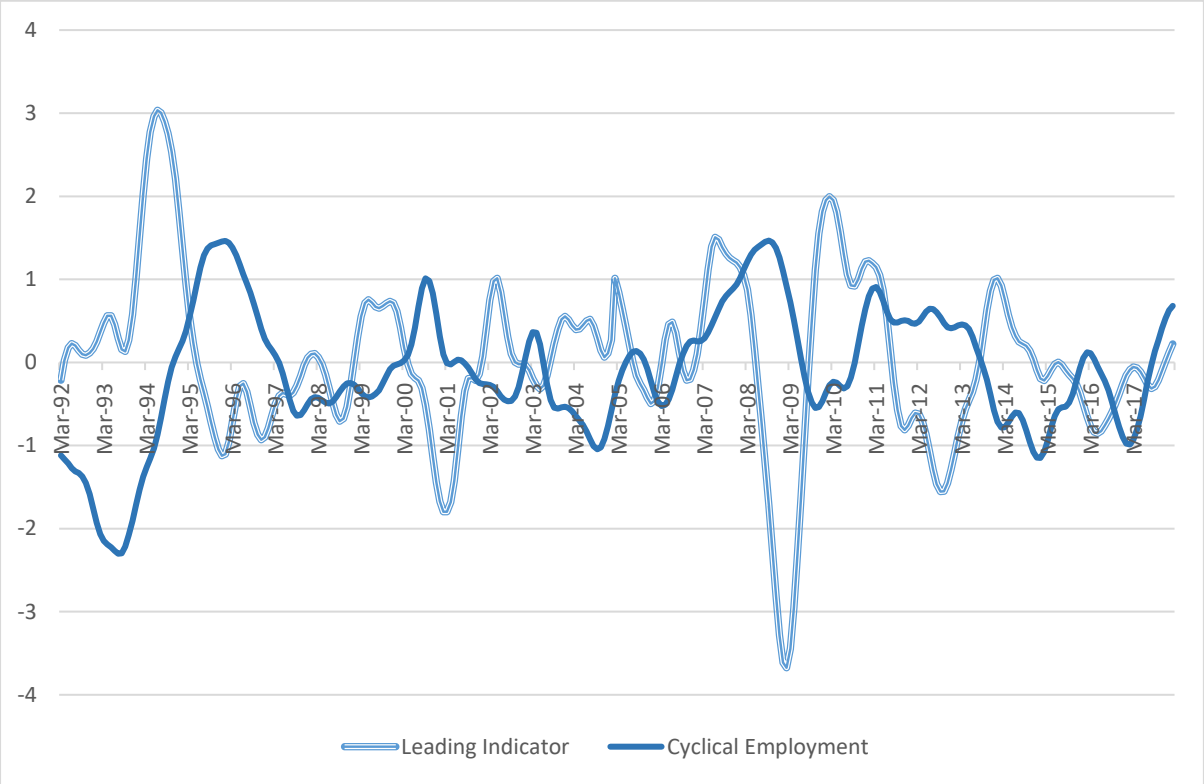


Source: ABS 2018, 6202.0 Labour Force, Dec 2017 and BITRE 2018, Domestic Totals & Top Routes

5. Discussion

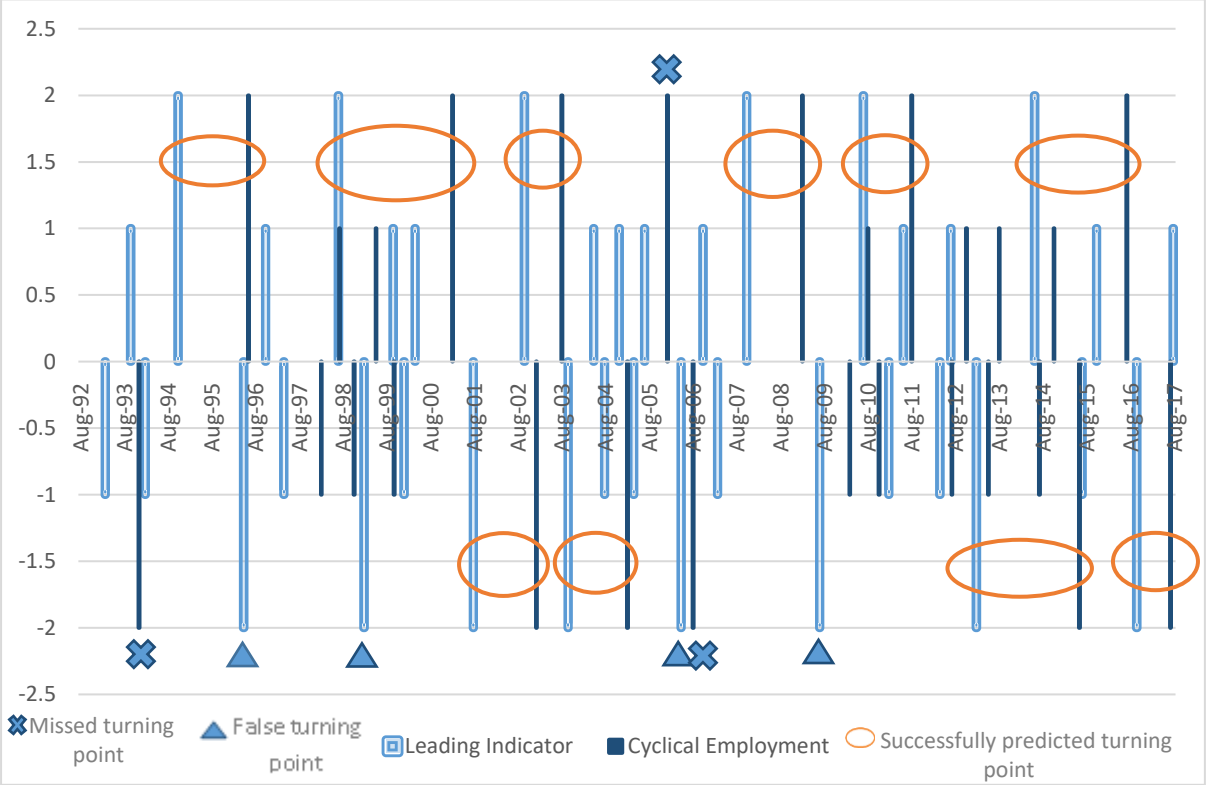
CHARTS 4 and 5 provide a sample of the charts analysed. Similar charts illustrating the Department of Jobs and Small Business' existing Leading Indicator of Cyclical Employment are also provided below in CHARTS 6 and 7 for comparison, and provide a useful benchmark for the graphical analysis conducted.

Chart 6: Deviations from Trend: Cyclical Employment and Leading Indicator of Cyclical Employment



Source: Department of Jobs and Small Business 2018, Leading Indicator of Employment Data – Feb 2018

Chart 7: Turning Points: Cyclical Employment and Leading Indicator of Cyclical Employment



Source: Department of Jobs and Small Business 2018, Leading Indicator of Employment Data – Feb 2018

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 TABLE 2 below:

Table 2: 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

Table 3: Results of Leading Indicator of Cyclical Employment

Leading Indicator of Cyclical Employment	
Predicted turning points	10
Missed turning points	3
False turning points	4

In comparison, on average aviation data predicted approximately four turning points in the economic data between July 1987 and May 2014. The results from the full analysis are provided at TABLE 4 below:

Table 4: Number of turning points predicted by variable

Employment	**Predicted turning points**	**Missed turning points**	**False turning points**	**Average Lead time (months)**	**Maxiumum 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)**	**Maxiumum 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

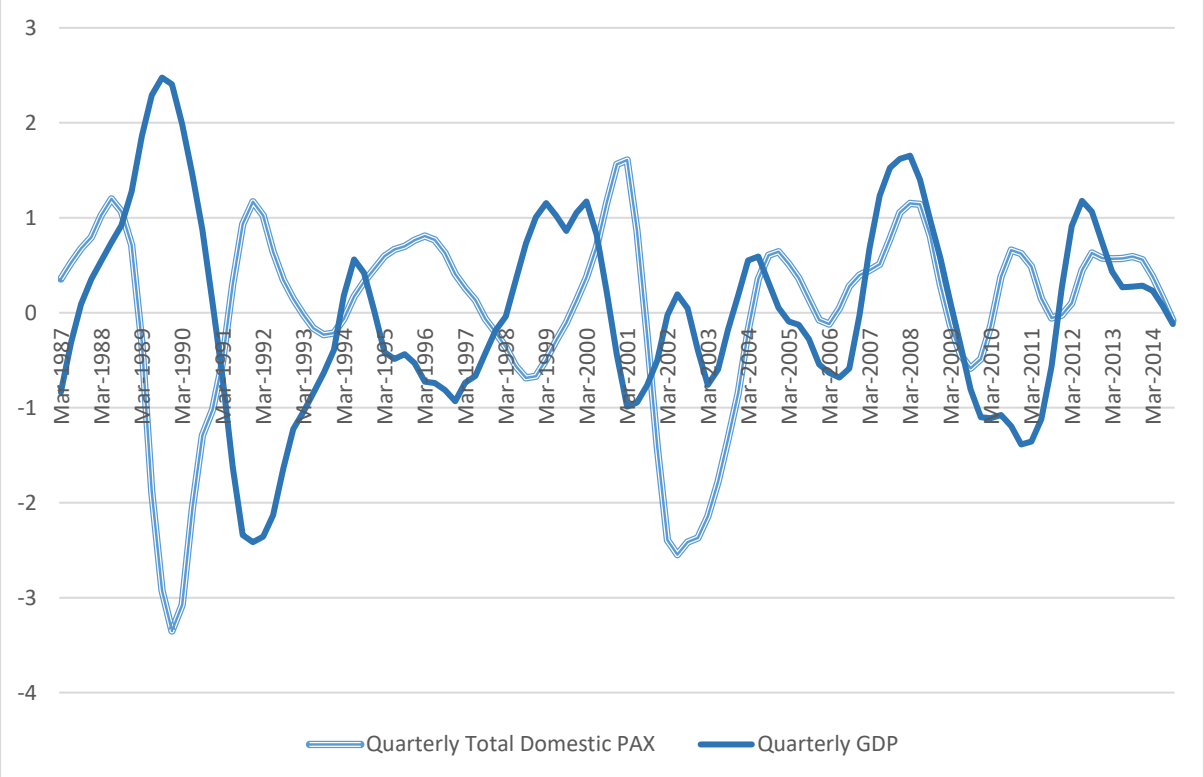
Overall, the aviation data does appear to lead the employment or GDP data over certain periods. However, the leads are generally not reliable enough to be useful as a leading indicator; the lead times are inconsistent, many turning points in the economic variables are not predicted by the aviation data,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

Table 5: Results of GDP and Total Domestic Passengers

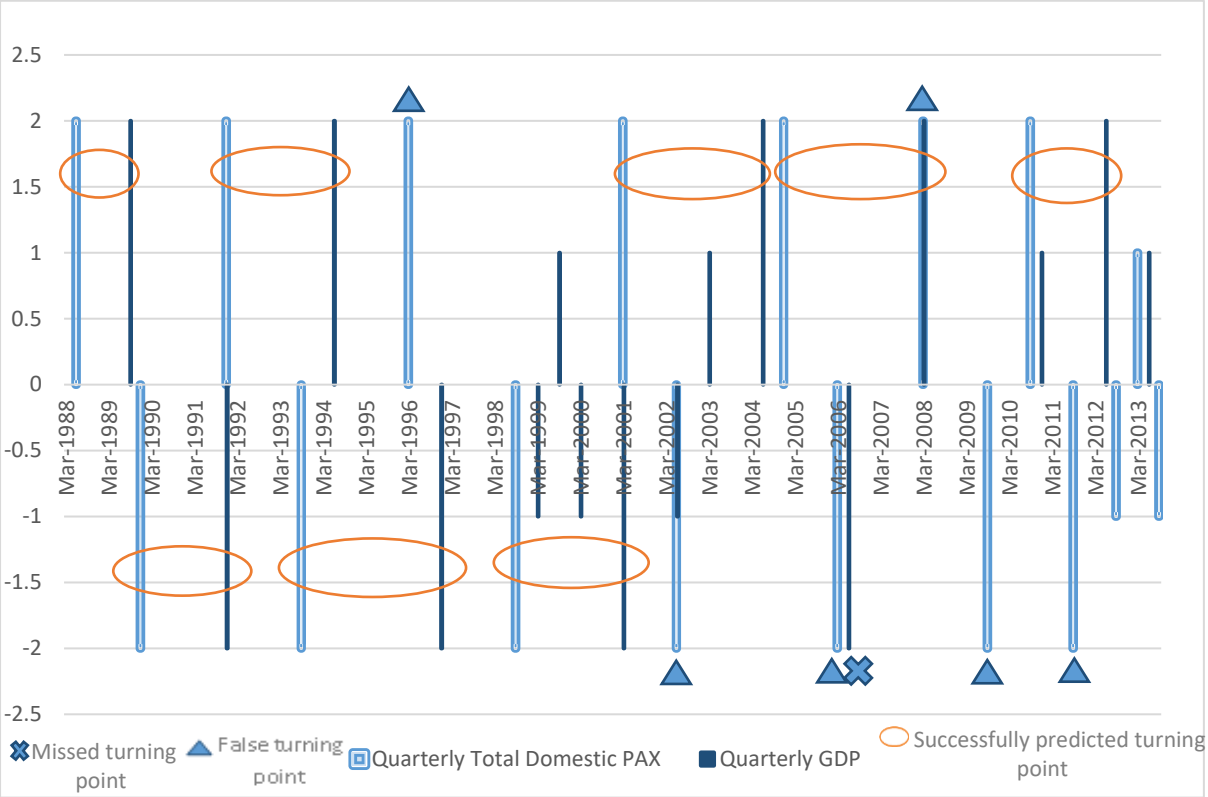
GDP and Total Domestic Passengers	
Predicted turning points	8
Missed turning points	1
False turning points	6

Chart 8: Deviations from Trend: GDP and Total Domestic Passengers



Source: ABS 2018, 5206.0 Australian National Accounts: National Income, Expenditure and Product, Dec 2017 and BITRE 2018, Monthly Airline Performance

Chart 9: Turning Points: GDP and Total Domestic Passengers



Source: ABS 2018, 5206.0 Australian National Accounts: National Income, Expenditure and Product, Dec 2017 and BITRE 2018, Monthly Airline Performance

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 flight path, when compared to GDP figures (CHARTS 10 and 11). The variable predicted six of nine turning points in GDP and returned three false and missed 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 6: 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

Table 7: Results of GDP and MEL-SYD Load Factor

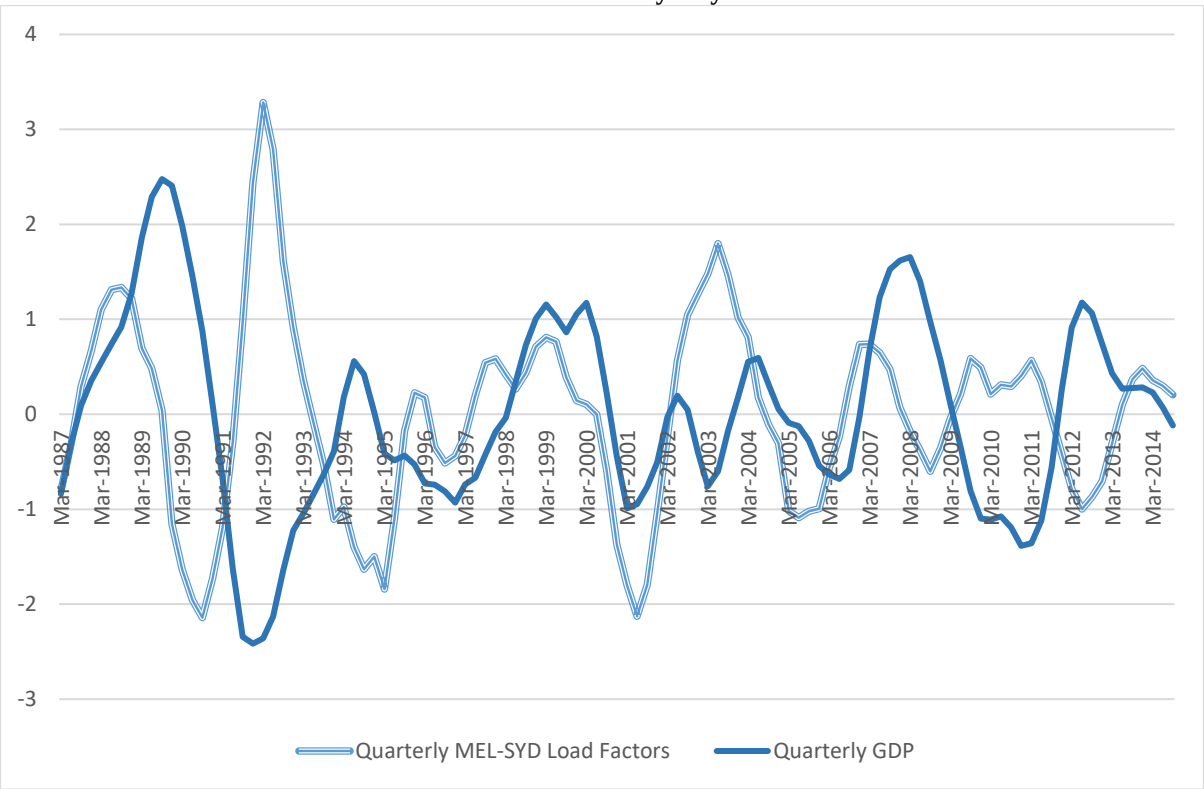
GDP and MEL-SYD Load Factor	
Predicted turning points	6
Missed turning points	3
False turning points	3

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. However, 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 anticipated 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.

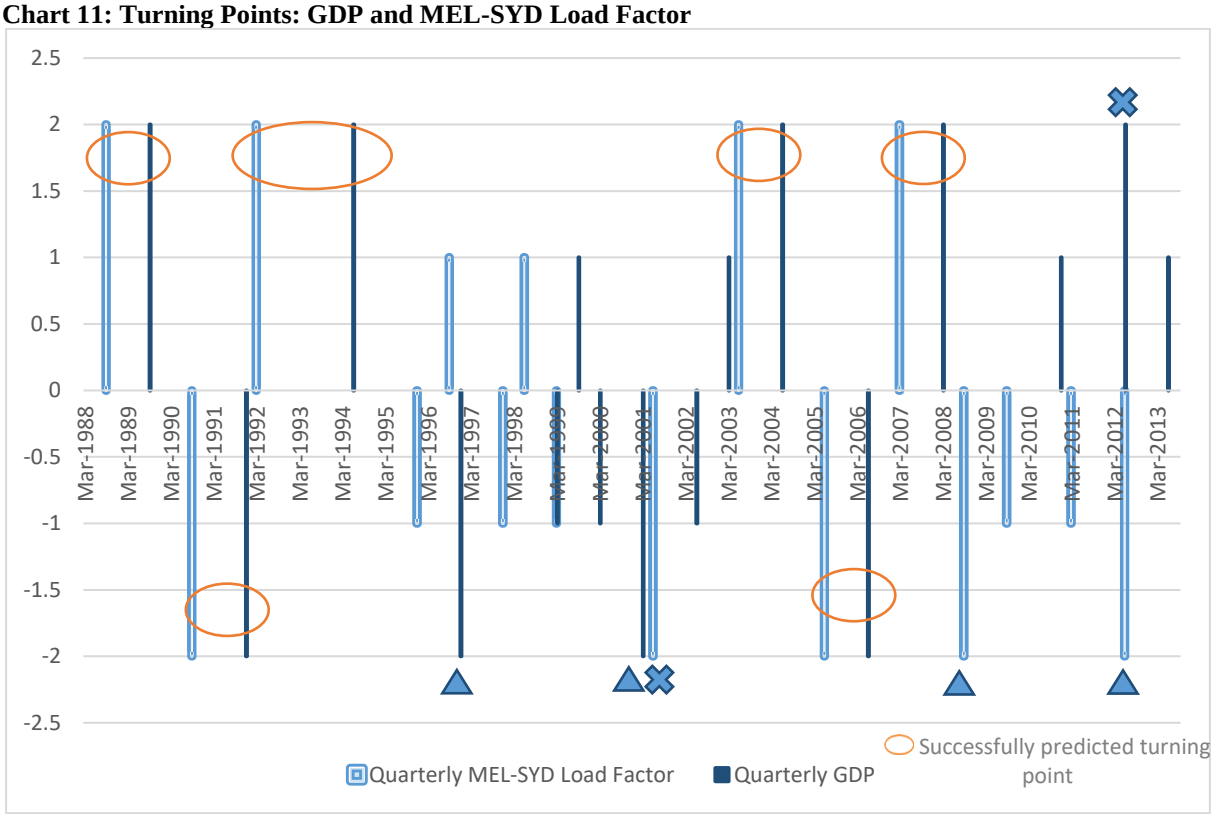
While the variable manages to predict turning points in GDP with minimal false and missed turning points, it is unlikely to be useful in practice. Further work to assess the variable more thoroughly may include extrapolating the data series to assess its performance beyond 2014, or assessing the power 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.

Chart 10: Deviations from Trend: GDP and Melbourne-Sydney Load Factor



Source: ABS 2018, 5206.0 Australian National Accounts: National Income, Expenditure and Product, Dec 2017 and BITRE 2018, Domestic Airline Activity Top Routes

Chart 11: Turning Points: GDP and MEL-SYD Load Factor



Source: ABS 2018, 5206.0 Australian National Accounts: National Income, Expenditure and Product, Dec 2017 and BITRE 2018, Domestic Airline Activity Top Routes

6. Conclusions and future directions

Through this study, six variables on aviation activity were tested for their ability to predict turning points in national 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 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 time and certainty as possible to respond to anticipated 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, do not illustrate aviation data as having a strong predictive capacity. 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 on the national scale, or across individual regions.

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.

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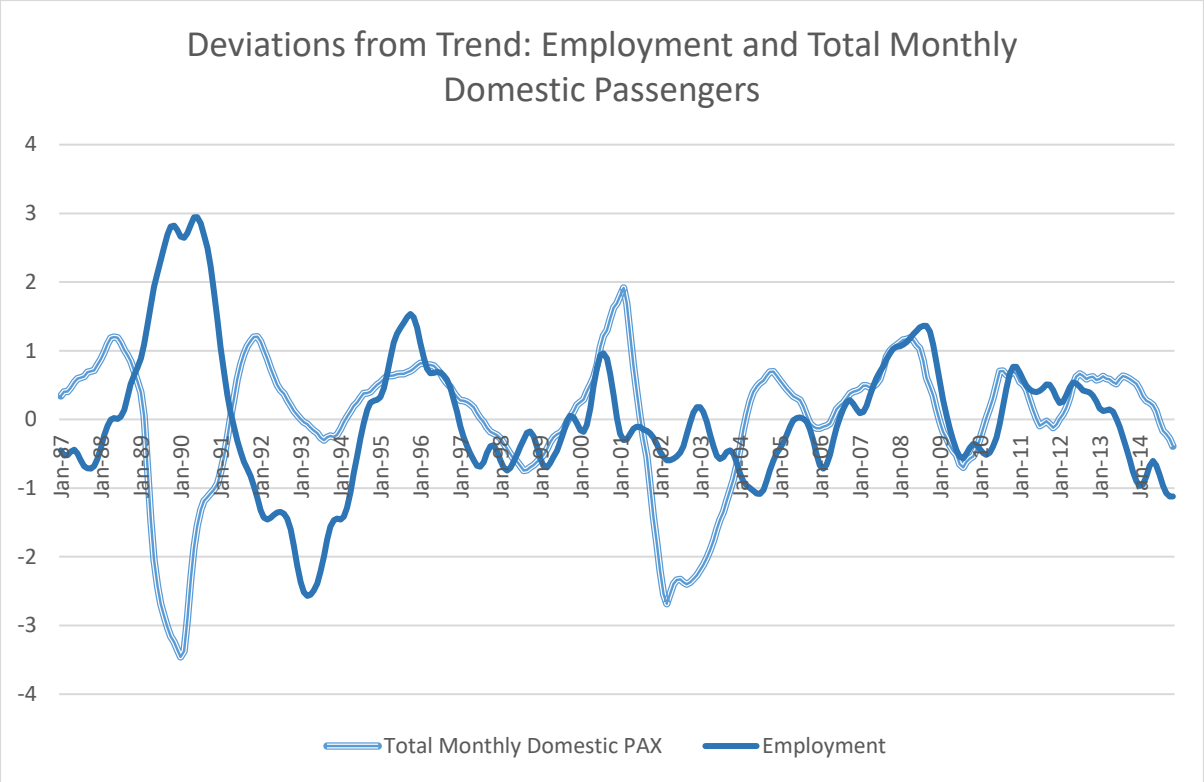
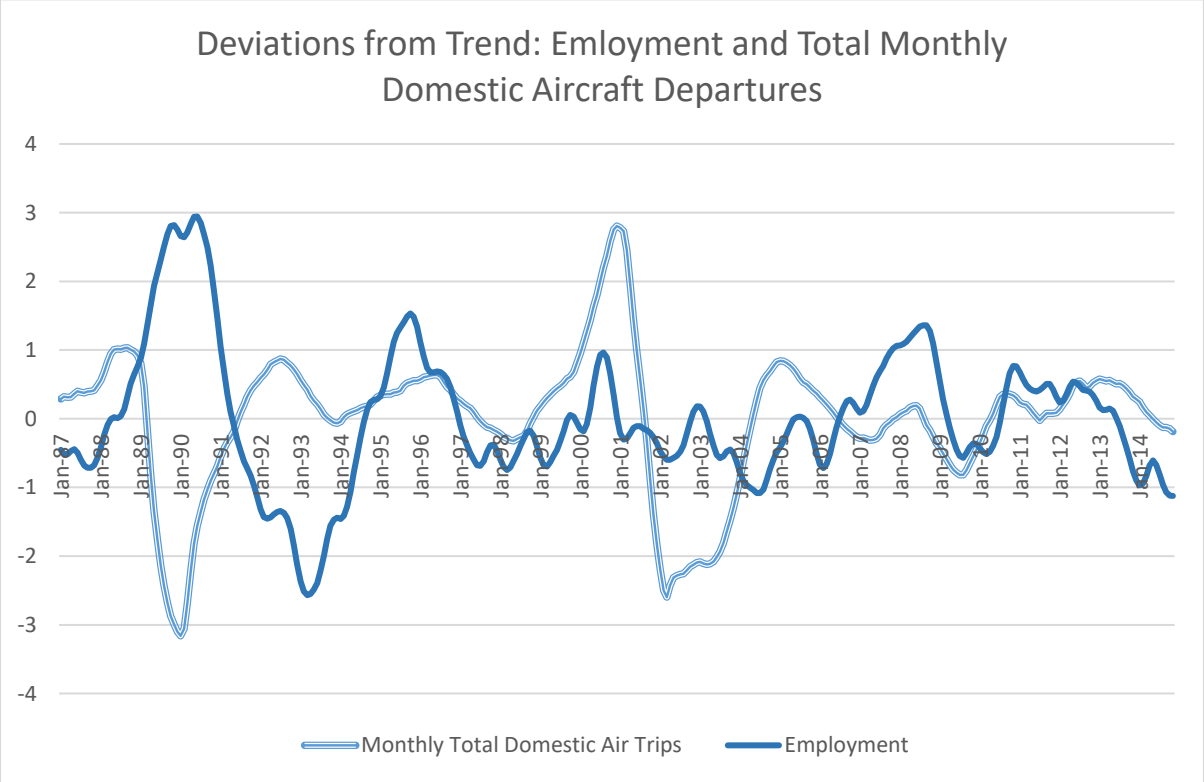
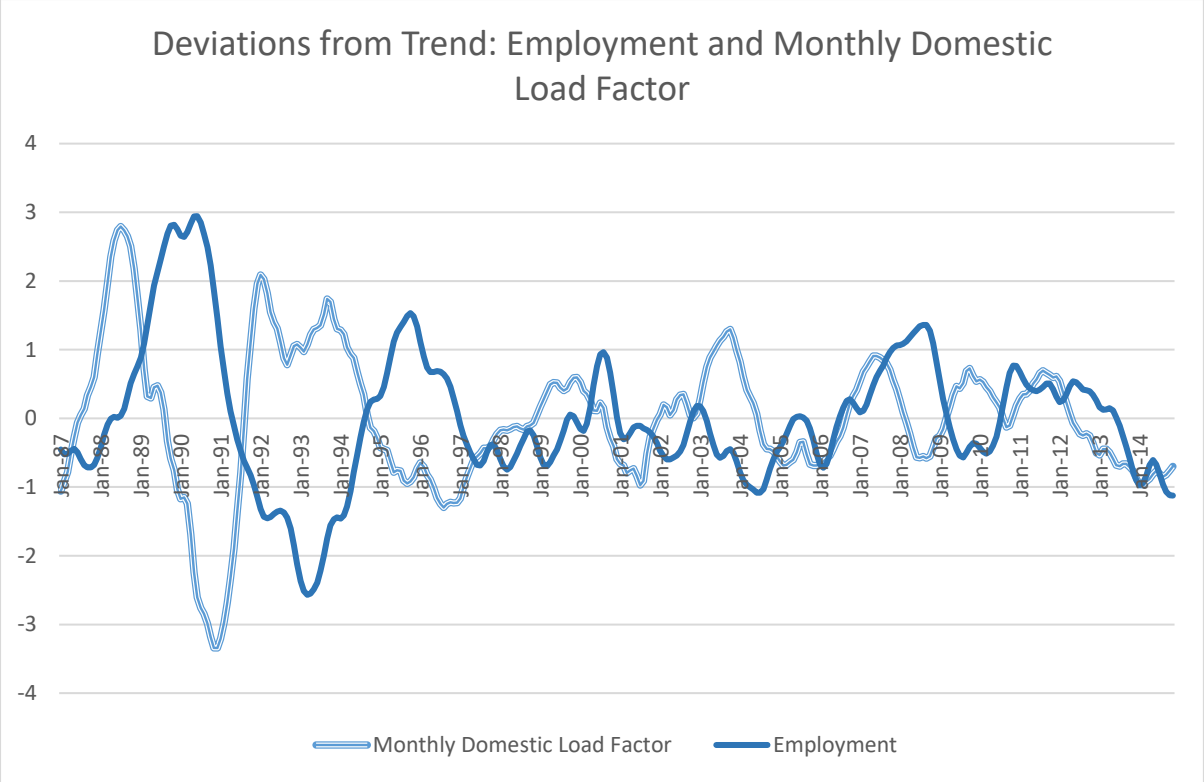
Appendix:

Deviations from Trend: Employment



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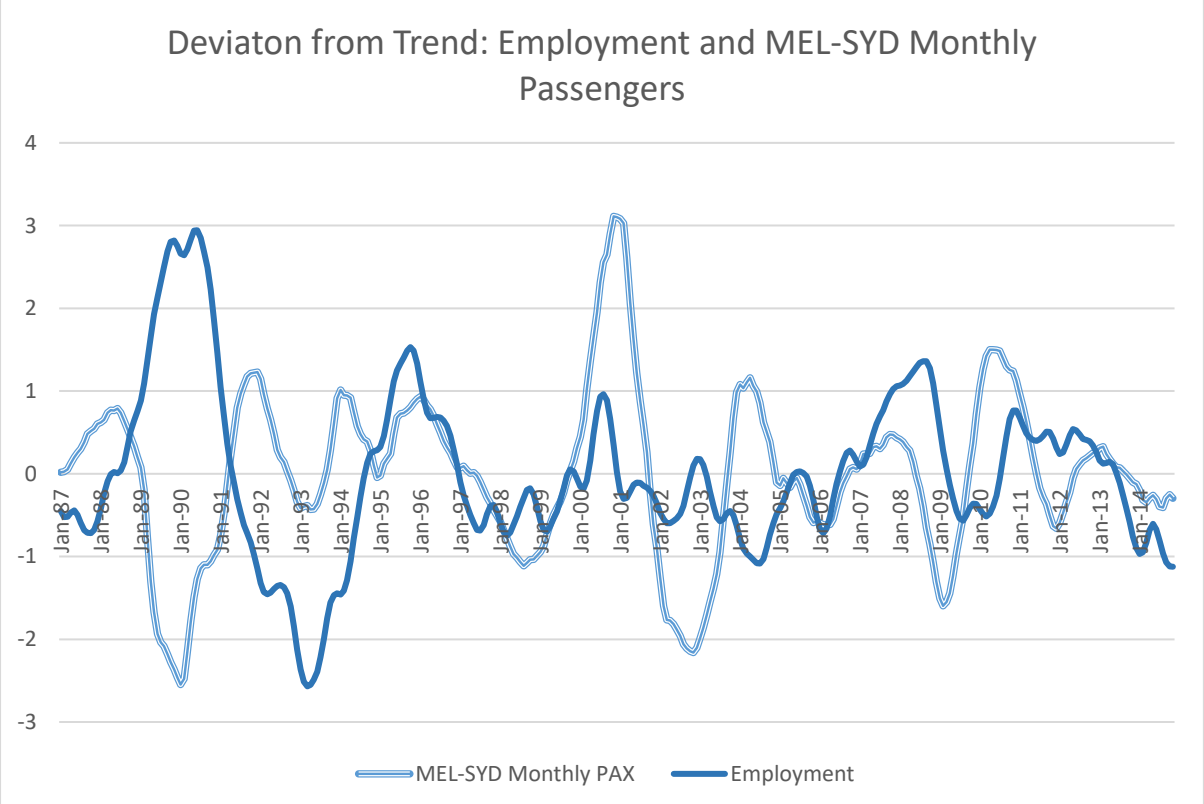
Monthly Domestic Load Factor
Employment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MEL-SYD Monthly PAX
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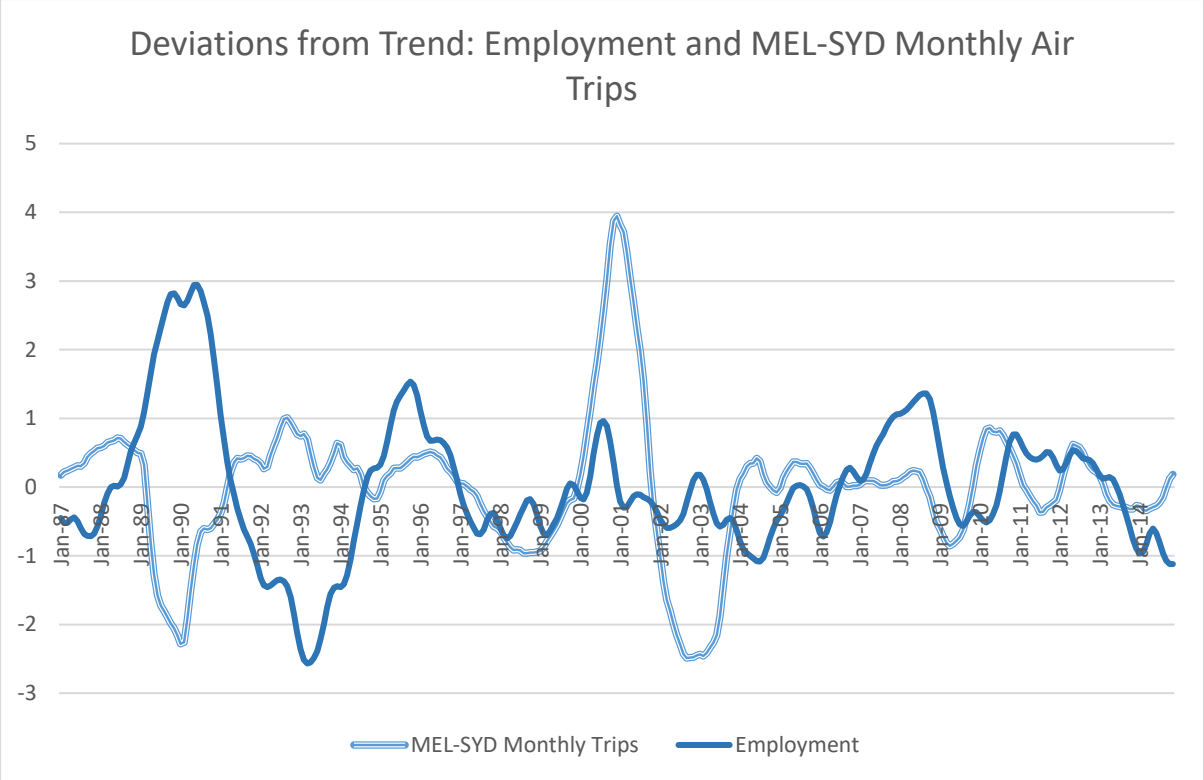
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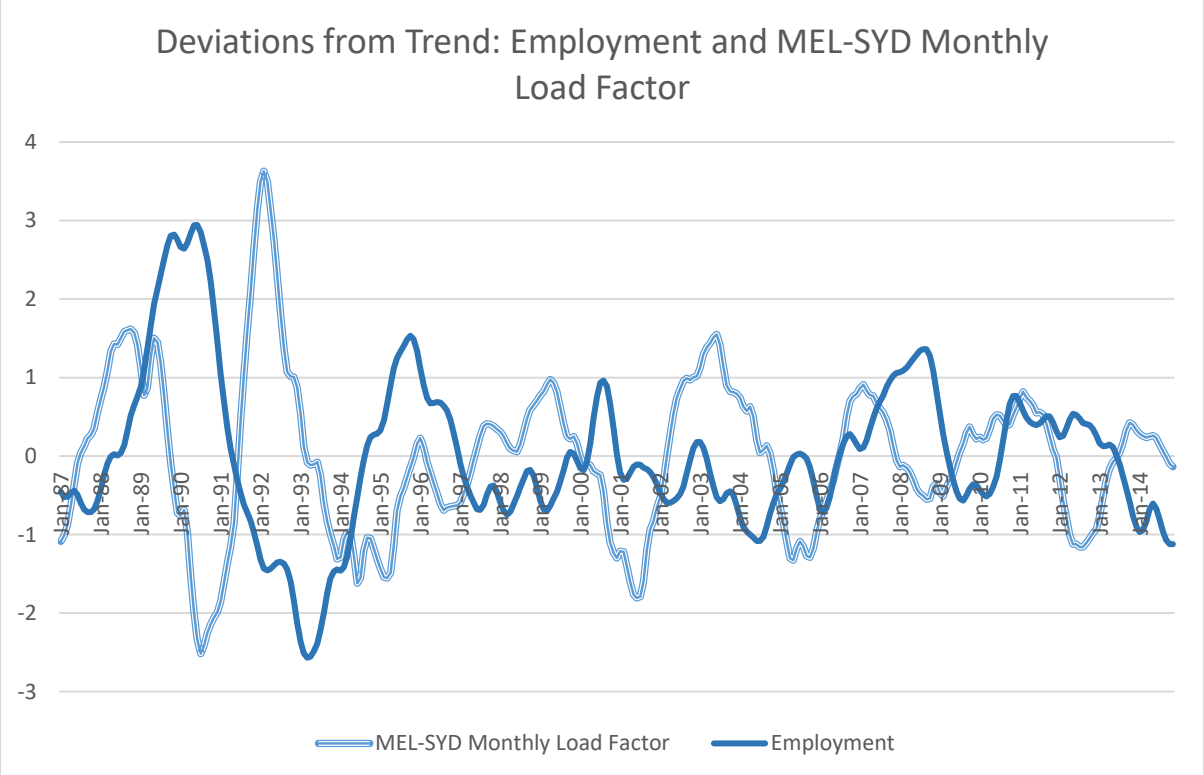
MEL-SYD Monthly Trips
Employment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MEL-SYD Monthly Load Factor
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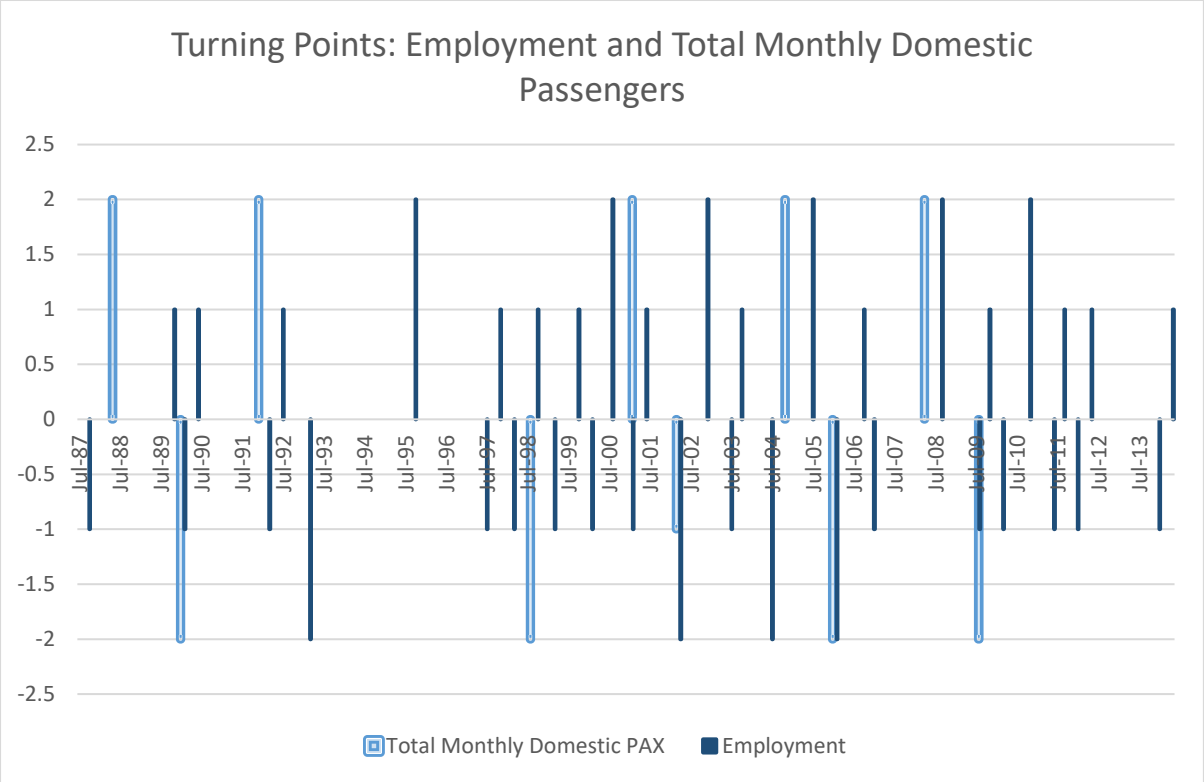
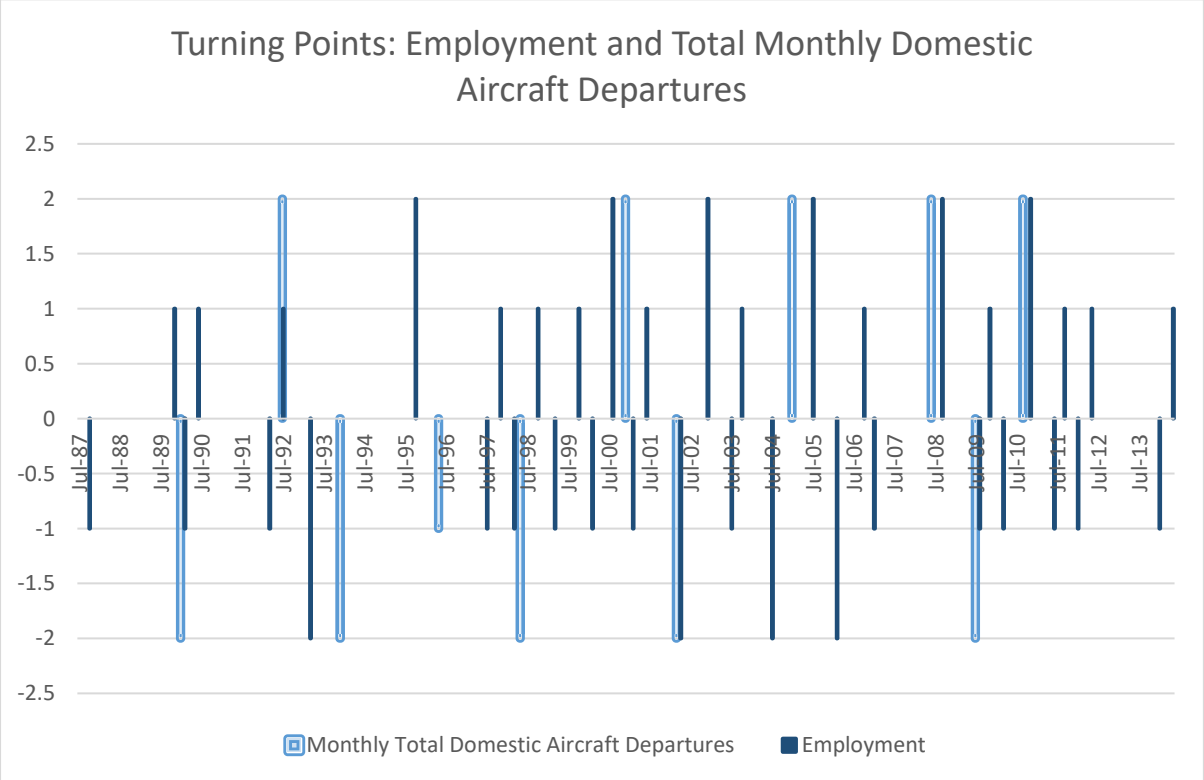
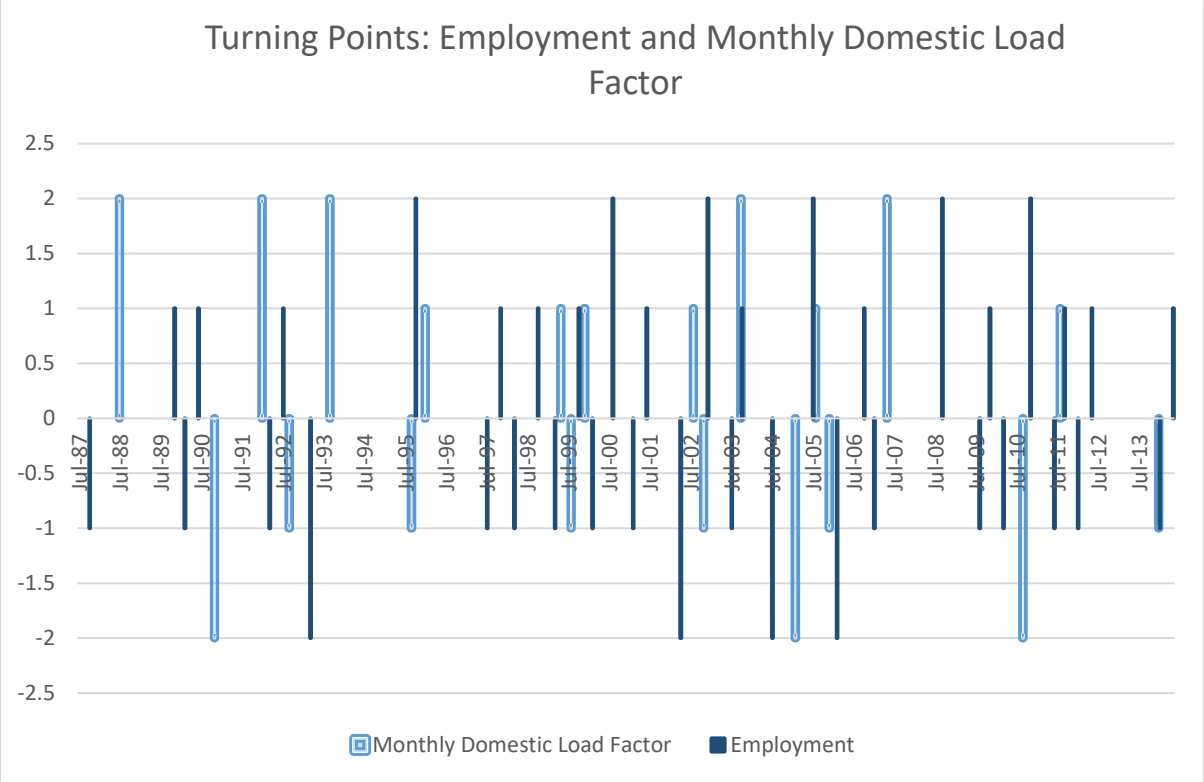
Turning Points: Employment



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Monthly Domestic Load Factor
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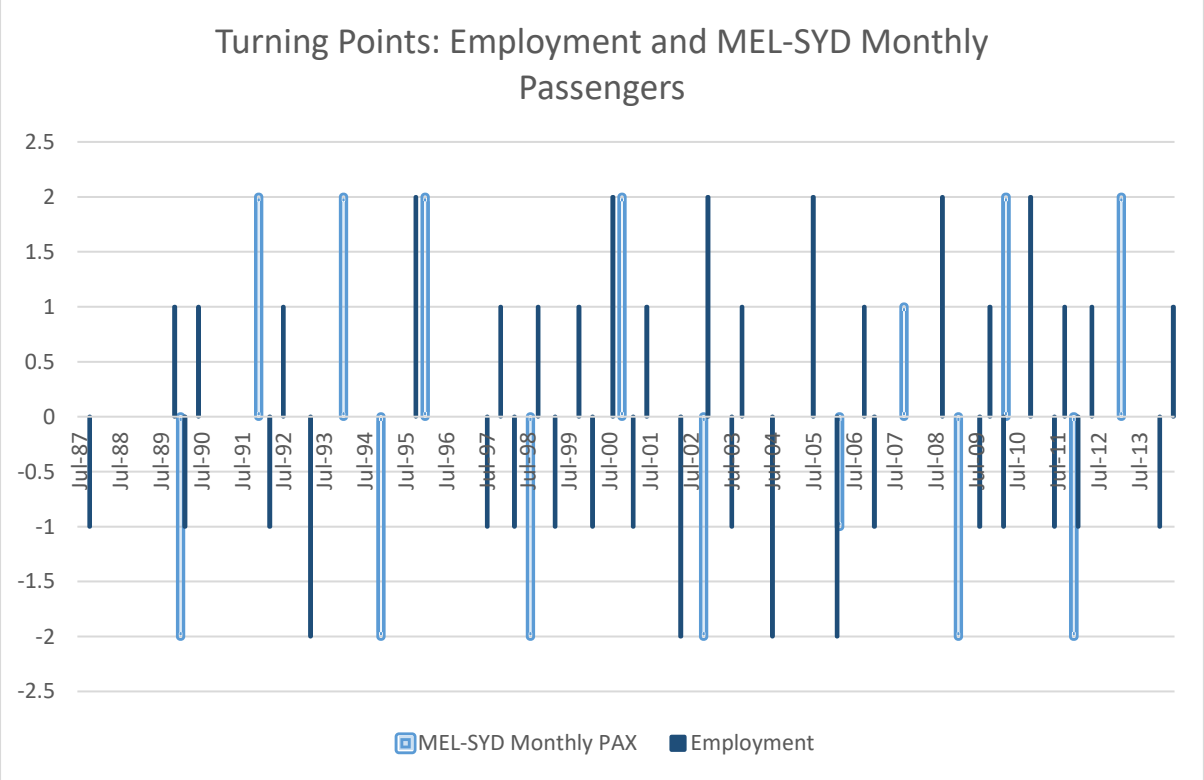
Turning Points: Employment and MEL-SYD Monthly Passengers
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MEL-SYD Monthly PAX
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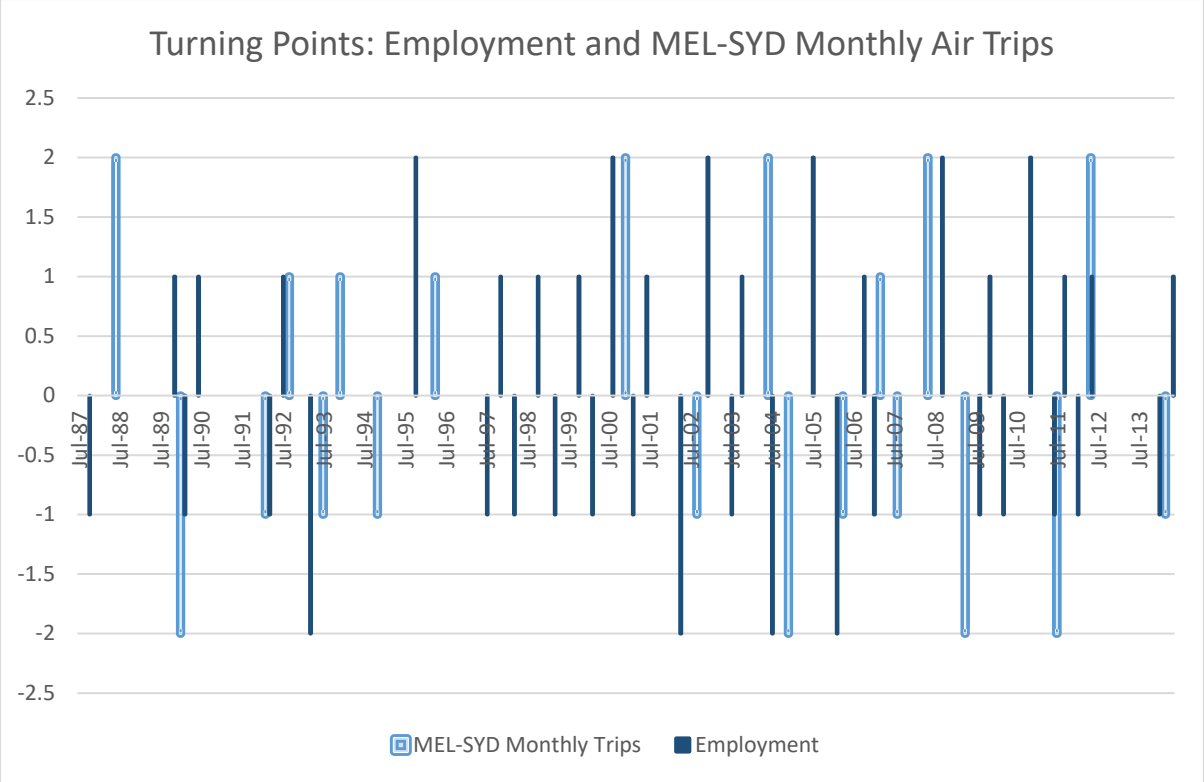
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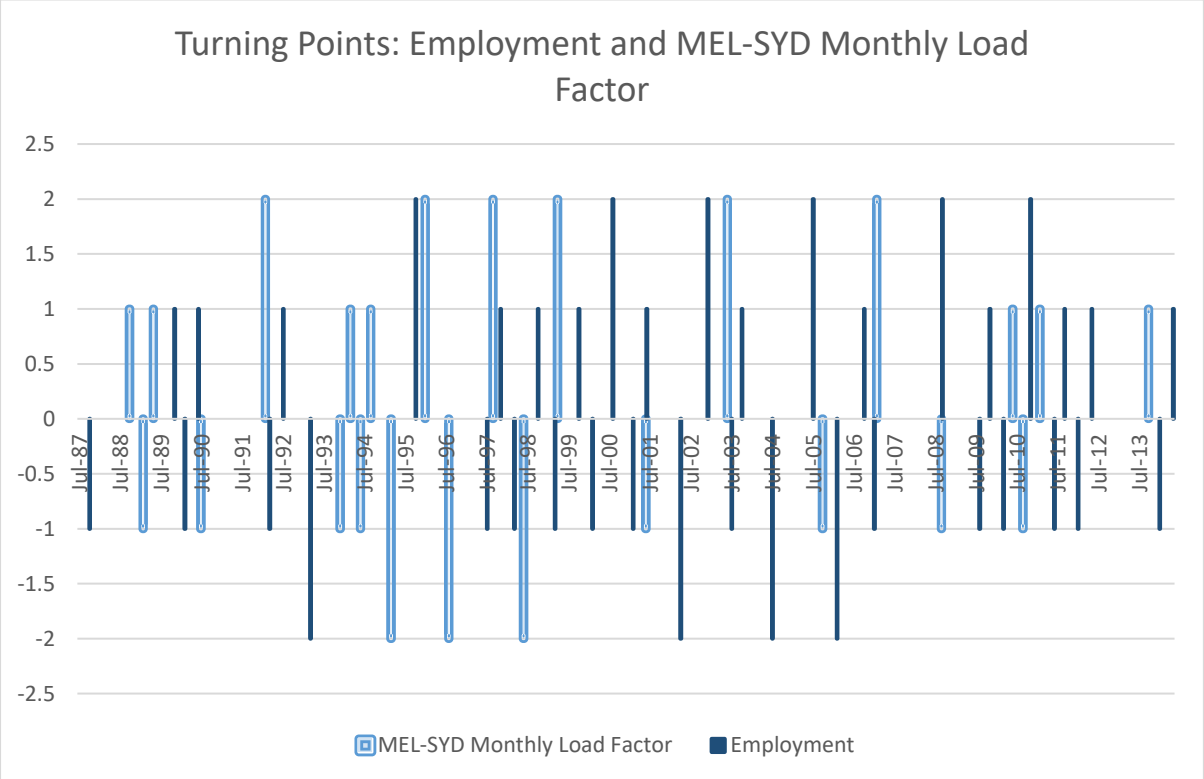
MEL-SYD Monthly Trips
Employment


Turning Points: Employment and MEL-SYD Monthly Load Factor
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MEL-SYD Monthly Load Factor
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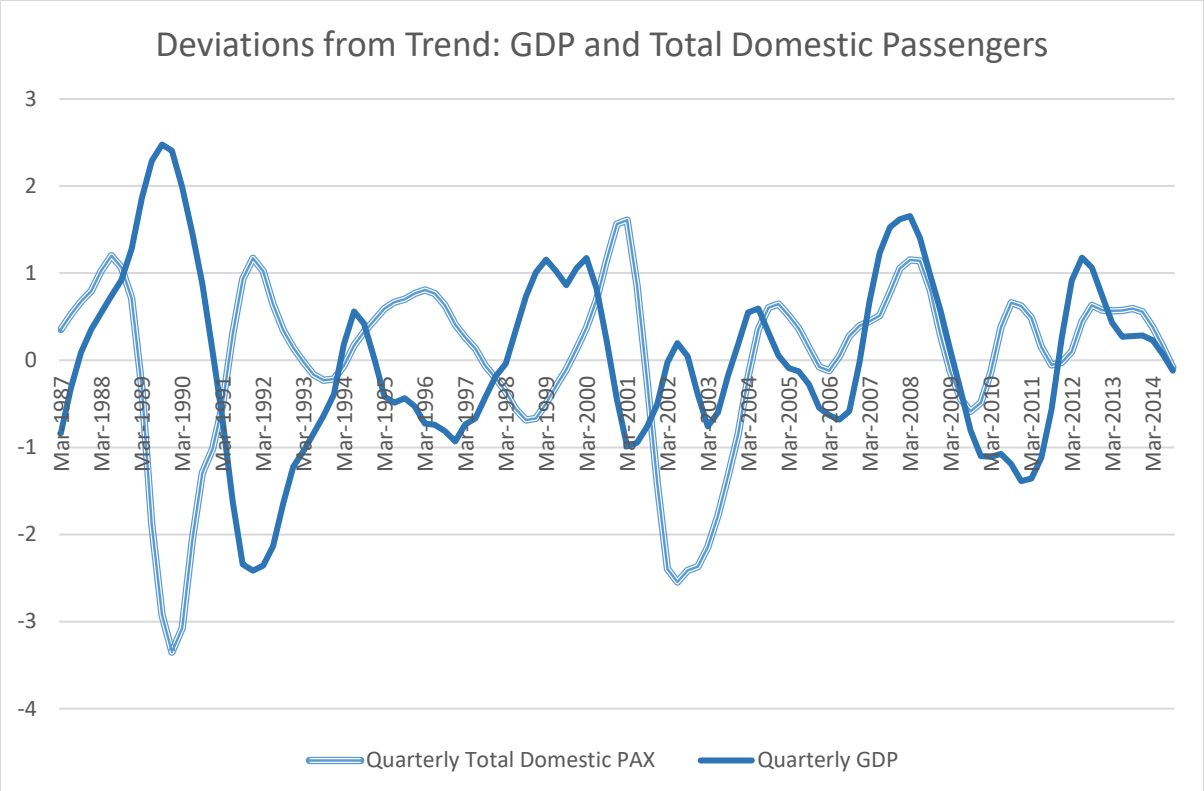
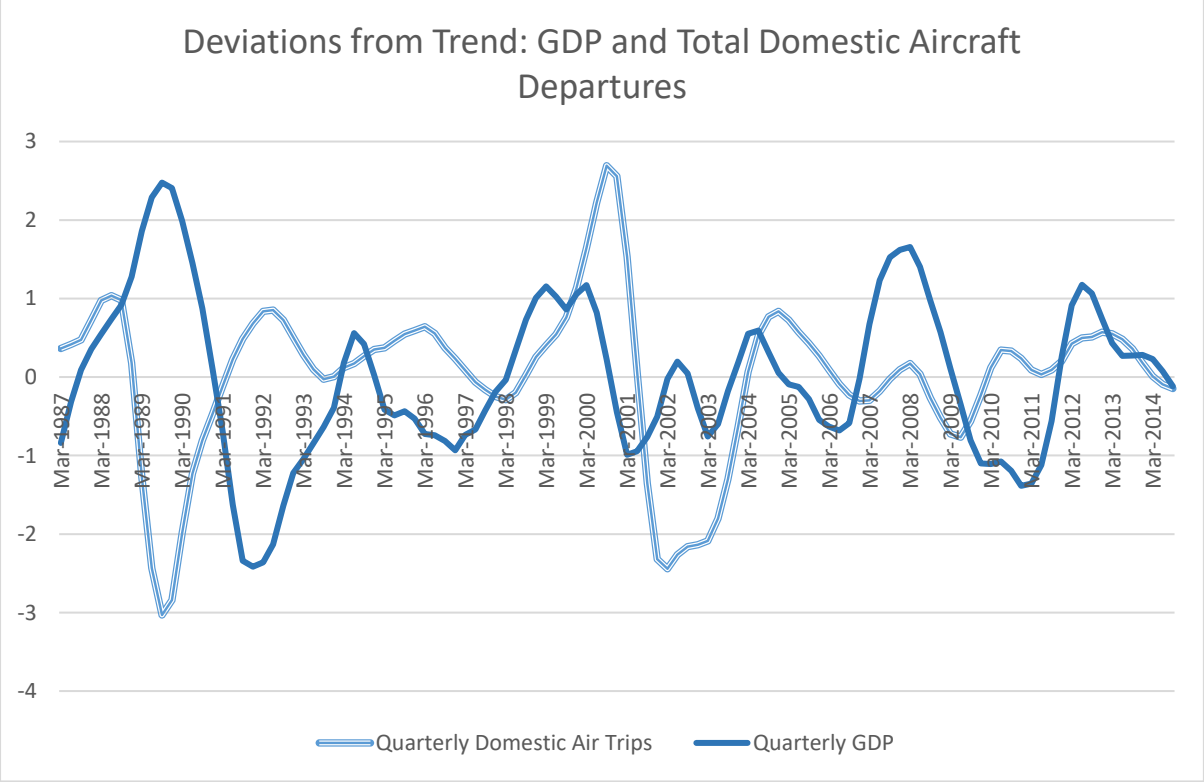
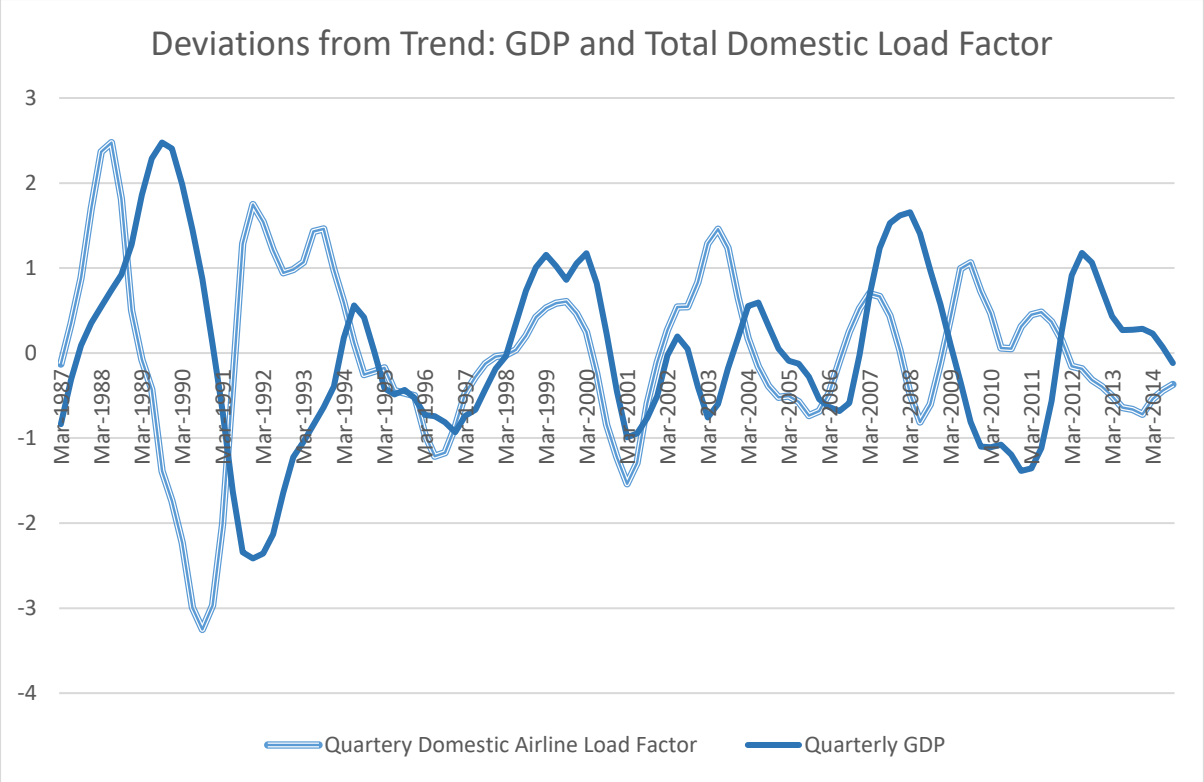
Deviations from Trend: GDP






Deviations from Trend: GDP and Total Domestic Load Factor
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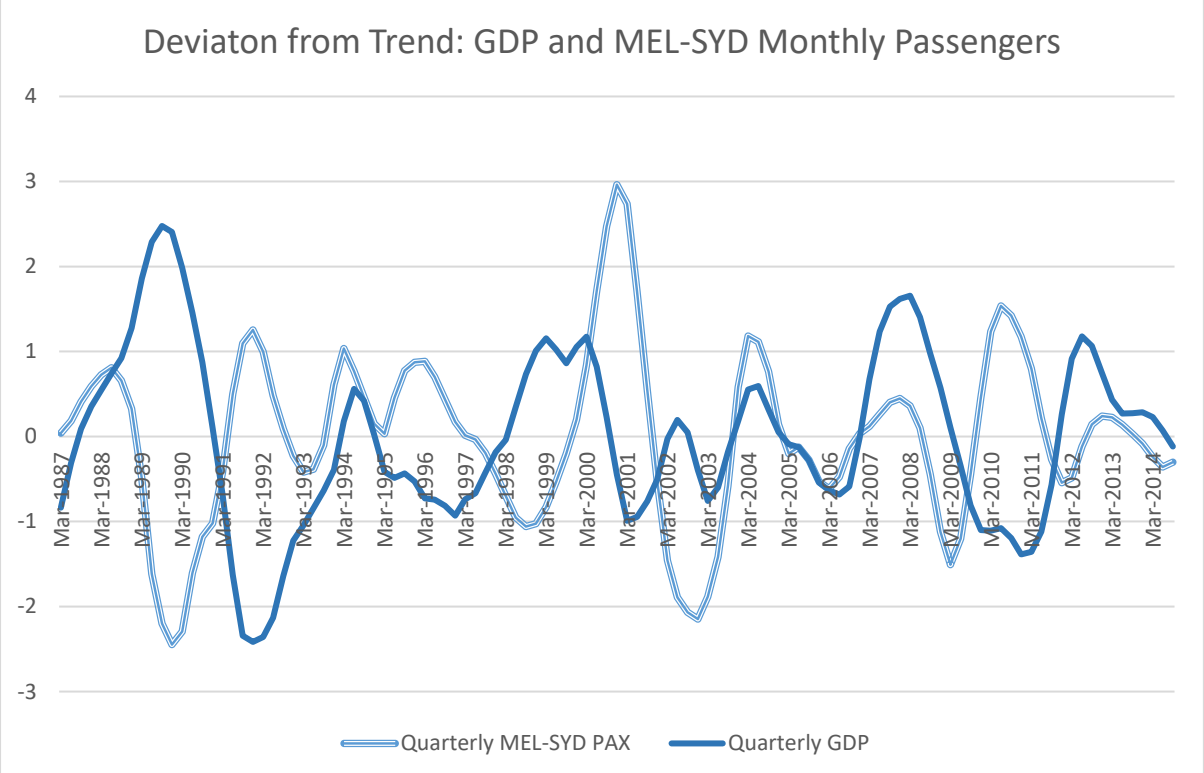
Quartery Domestic Airline Load Factor
Quarterly GDP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Quarterly MEL-SYD PAX
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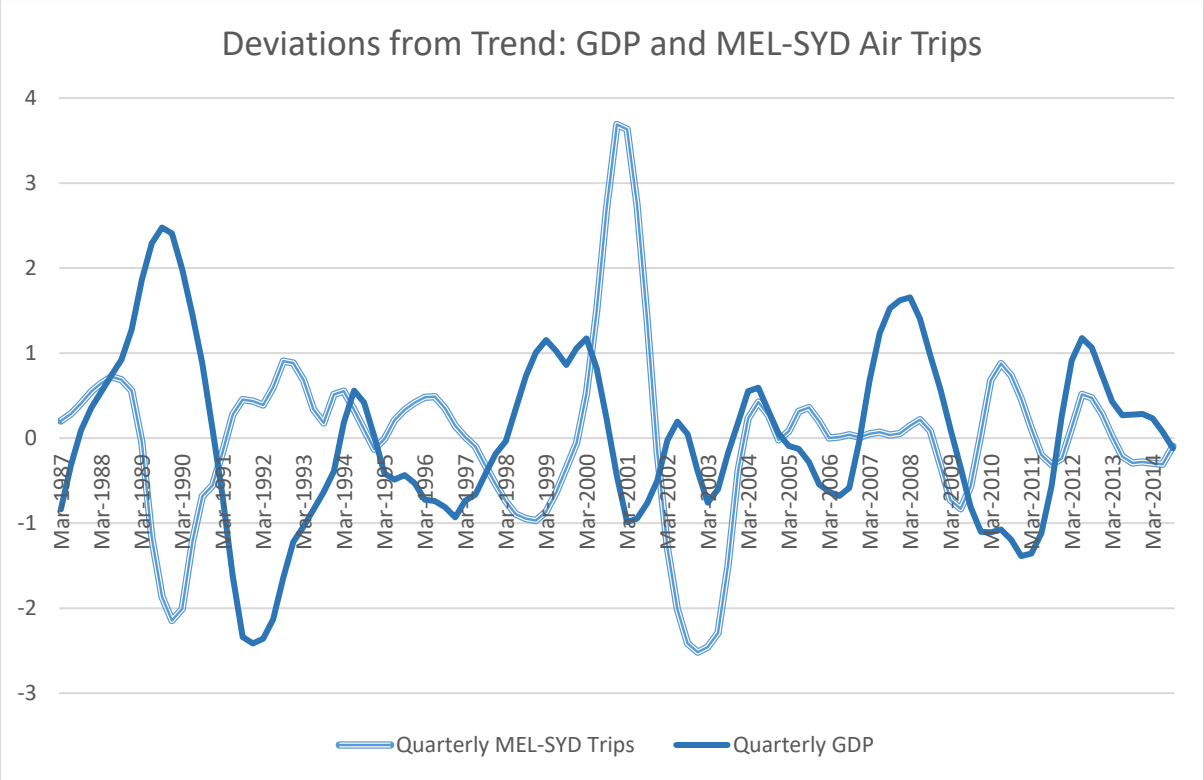
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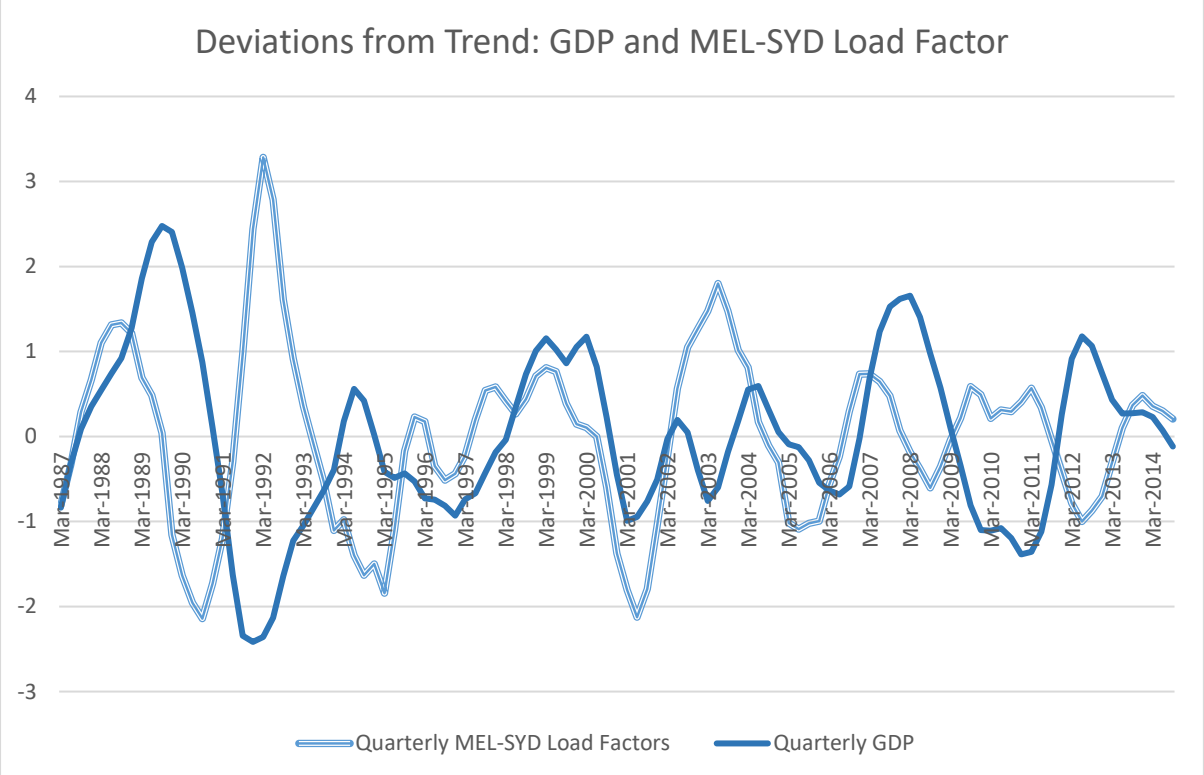
Quarterly MEL-SYD Trips
Quarterly GDP


Deviations from Trend: GDP and MEL-SYD Load Factor
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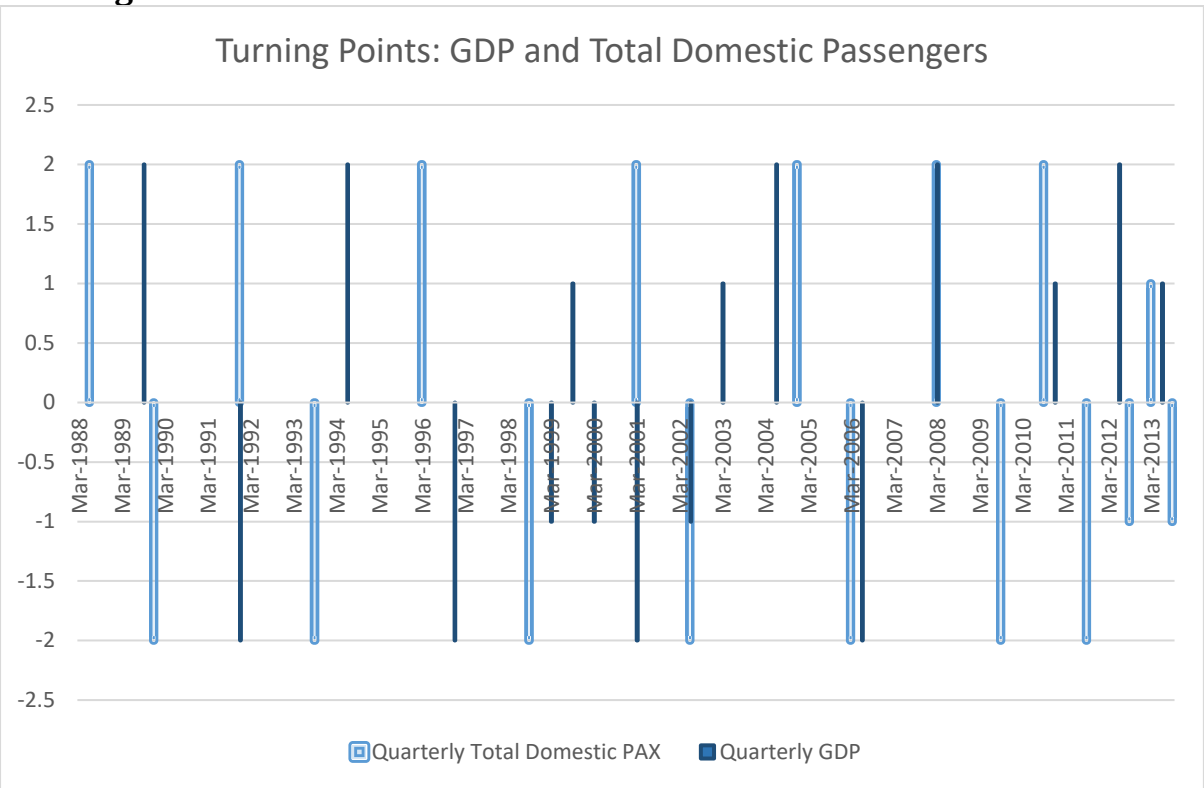
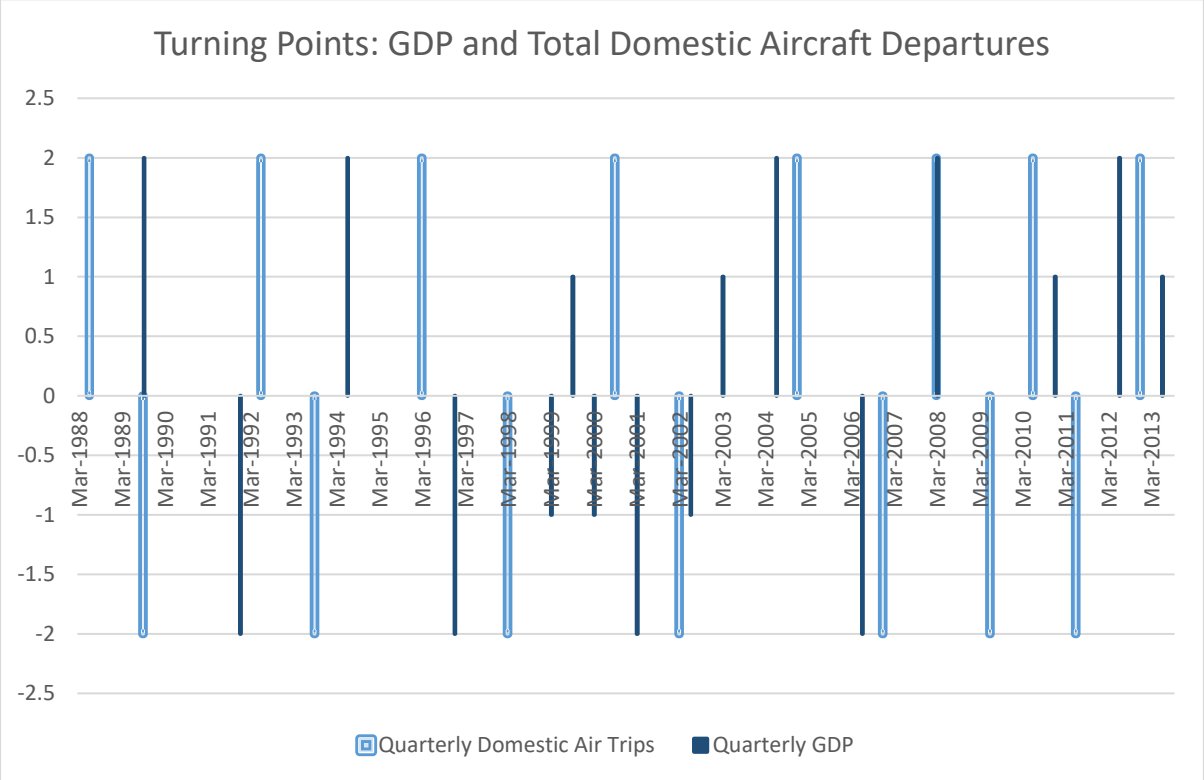
Quarterly MEL-SYD Load Factors
Quarterly GDP

Turning Points: GDP





Turning Points: GDP and Domestic Load Factor
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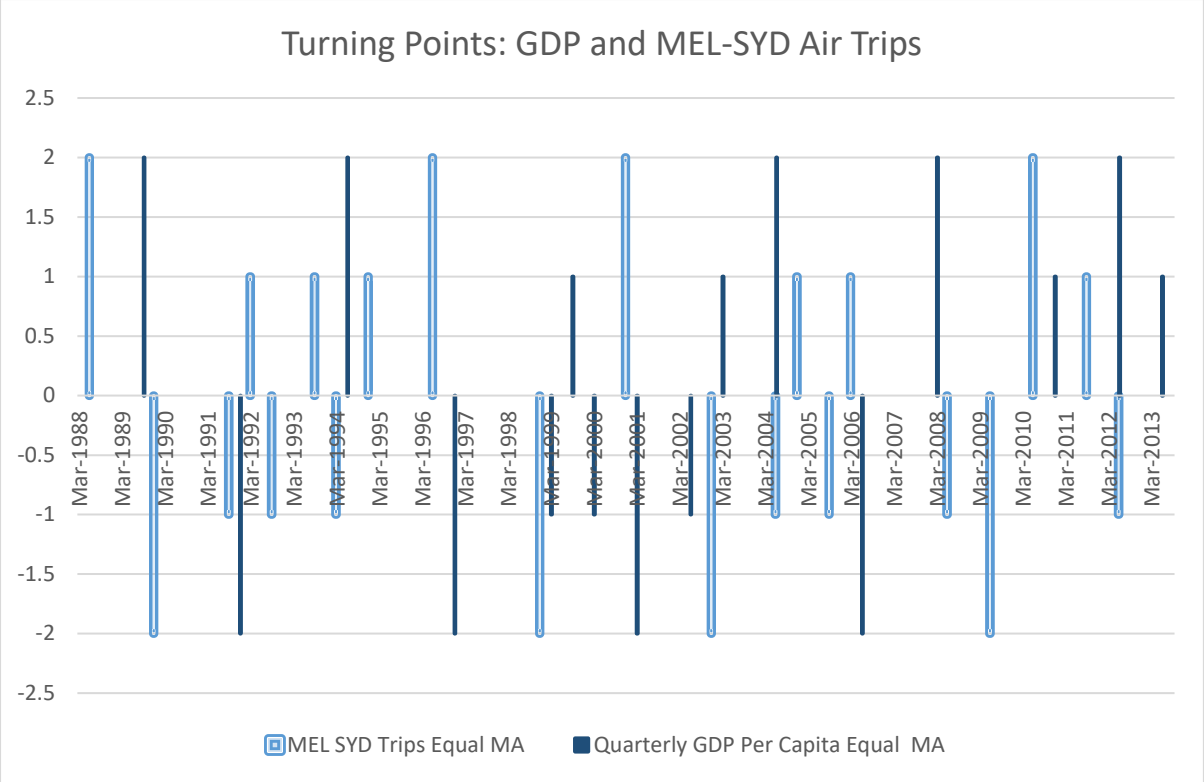
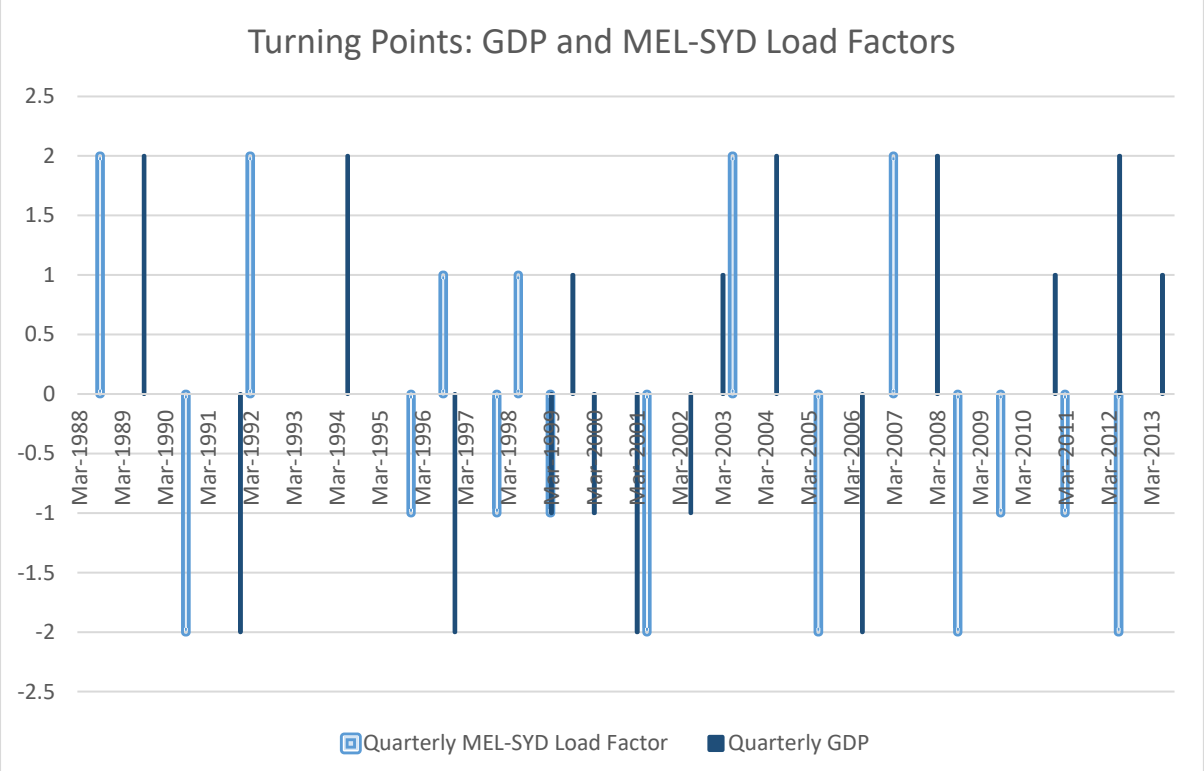
Mar-2007
Mar-2008
Mar-2009
Mar-2010
Mar-2011
Mar-2012
Mar-2013
Quarterly Domestic Airline Load Factor
Quarterly GDP
Deviaton from Trend: GDP and MEL-SYD Monthly Passengers
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
Sep-1988
Sep-1989
Sep-1990
Sep-1991
Sep-1992
Sep-1993
Sep-1994
Sep-1995
Sep-1996
Sep-1997
Sep-1998
Sep-1999
Sep-2000
Sep-2001
Sep-2002
Sep-2003
Sep-2004
Sep-2005
Sep-2006
Sep-2007
Sep-2008
Sep-2009
Sep-2010
Sep-2011
Sep-2012
Quarterly MEL-SYD PAX
Quarterly GDP


Turning Points: GDP and MEL-SYD Air Trips
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
Mar-1988
Mar-1989
Mar-1990
Mar-1991
Mar-1992
Mar-1993
Mar-1994
Mar-1995
Mar-1996
Mar-1997
Mar-1998
Mar-1999
Mar-2000
Mar-2001
Mar-2002
Mar-2003
Mar-2004
Mar-2005
Mar-2006
Mar-2007
Mar-2008
Mar-2009
Mar-2010
Mar-2011
Mar-2012
Mar-2013
MEL SYD Trips Equal MA
Quarterly GDP Per Capita Equal MA


Turning Points: GDP and MEL-SYD Load Factors
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
Mar-1988
Mar-1989
Mar-1990
Mar-1991
Mar-1992
Mar-1993
Mar-1994
Mar-1995
Mar-1996
Mar-1997
Mar-1998
Mar-1999
Mar-2000
Mar-2001
Mar-2002
Mar-2003
Mar-2004
Mar-2005
Mar-2006
Mar-2007
Mar-2008
Mar-2009
Mar-2010
Mar-2011
Mar-2012
Mar-2013
Quarterly MEL-SYD Load Factor
Quarterly GDP