# Essays on US Business Cycle Investigated from Keynesian Perspective

Minsu Kim

School of Economics

University of Nottingham

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# Abstract

This thesis investigates the US business cycle from the (old) Keynesian perspective. It is in line with the [86]Keynes (1936) in following aspects. (1) The analyses are focused on the cyclical fluctuations. The underlying assumption behind this practice is that economic fluctuations are mainly ascribed to cyclical components. (2) Business cycles are only analysed using demand-side factors. This practice corresponds to the Keynes' proposition that demand generates supply. (3) The main mechanism of business cycles is based on the [86]Keynes'(1936) intuition that investment is driven by businessmen's expectations and the major source of the expectations is current consumption.

Three chapters are connected to each other. In chapter 3, I detrend the US real GDP to obtain a reasonable business cycle. In this course, I detect three break points in the trend. In chapter 4, I investigate the main driver of business cycles using the data which is detrended using the break points detected in chapter 3. In chapter 5, I apply the mechanism that is studied in chapter 4 to forecasting.

In chapter 2, I review the literature of modern business cycle models, that is, dynamic stochastic general equilibrium models (DSGE) from an empirical perspective which is corresponding to the Old Keynesian idea. I discuss the limitation of DSGE models for the two empirical facts, consumption-investment comovement and flat Phillips curve.

In chapter 3, I decompose the US real GDP using a deterministic (log) linear trend with three breaks. The practice is chosen as it yields a cycle that is important in magnitude, which corresponds to the Keynesian perspective in that economic fluctuations are mainly ascribed to a cyclical component. The measured business cycle displays a boom-bust pattern with sporadic downward pluckings. The estimated boom-bust cycle is far from a stationary process in that it is long-lasting,

large in size and displays sharp reversions to the trend. To support the estimated result, I provide following evidence: (1) I also estimate the cyclical components of well-known US coincident indicators using the detected break points. The estimated cycles of US coincident indicators are close to the estimated cycle of real GDP. (2) the US business cycles estimated using the HP filter with large smoothing parameter and the bandpass filter with an alternative bandwidth also corresponds to the cycle estimated through a linear deterministic trend with breaks. (3) When applying the same estimation strategy, boom-bust cycles are found in Korea and Japan real GDP. To justify the estimated results, I also show that the estimated trend and cycle provide a new and reasonable view for the well-known macroeconomic puzzle: the slow recovery of the US economy from the 2008-9 Global Financial Crisis. The estimation results of this chapter imply that the Global Financial Crisis is the collapse of a huge boom rather than a big recession, therefore, a recovery does not follow. Meanwhile, non-stationary cycles provide an important implication in the business cycle literature. They allow for a long-lasting and large business cycle observed in reality without unrealistically large shocks or endogenous amplification mechanisms.

In chapter 4, I investigate the main driver of business cycles using the data which is detrended using the break points detected in chapter 1. I argue that consumption shocks are the main driver of business cycles from the perspective of [86]Keynes (1936) and [115]Pigou (1927). I reconcile their ideas based on their commonality highlighting the role of businessmen's expectations as an important driver of business cycles. The reconciled idea describes a boom-bust cycle generated by consumption shocks and their propagation to investment. To examine the idea, I estimate the effects of consumption shocks. The estimated effects predict a a boom-bust cycle close to the benchmark investment cycle. A unit shock to consumption generates a long-lasting and important responses of consumption and investment even though the secular trend of each variable is already removed. This result is corresponding to boom-bust cycles but in contrast with a well-known hump-shaped responses of output to a demand shock. The studied model is close to the Keynes-Hansen-Samuelson multiplier accelerator model ([122]Samuelson, 1939) in that investment is the function of consumption changes. The main differences are in two points: (1) marginal effect of output changes on consumption is smaller than in the Keynesian cross. (2) Consumption shocks are the most important among demand shocks.

In chapter 5, I apply the mechanism that is studied in chapter 4 to forecasting. I forecast short-term US GDP growth. The trend growth is forecasted using the HP filter with a large smoothing parameter. The cyclical changes (=demeaned output growth) are forecasted using the consumption-investment relationship that is studied in chapter 4. The forecasting performance of the model is comparable to the one of the Survey of Professional Forecasters.

# Acknowledgements

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I would like to thank from deep inside all the scholars who openly share their knowledge online. Without them, I would not have finished this thesis. In chapter 2, the estimation of SVAR models are conducted using the Matlab codes of [87]Kilian and Lutkepohl (2017) [1]. In chapter 3, dynamic factor models are estimated using the modified Matlab codes of [121]Ritschl et al. (2016) [2]. I have also learned a lot from the lecture materials and codes that are found online.

[1] https://sites.google.com/site/lkilian2019/textbook

[2] The codes are obtained in the Review of Economics and Statistics Dataverse (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZYTP50).

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

This thesis investigates the US business cycle from the (old) Keynesian perspective. It is in line with [86]Keynes (1936) in following aspects. (1) The analyses are focused on the cyclical fluctuations. The underlying assumption behind this practice is that economic fluctuations are mainly ascribed to cyclical components. Following [86]Keynes (1936), the thesis does not address the mechanism determining the long-run trend. And the trend is estimated through purely empirical methods. (3) Business cycles are only analysed using demand-side factors. I follow Keynes' proposition that demand generates supply unlike a typical neoclassical model in which output is limited by production capacity (4) The main mechanism of business cycles is based on the [86]Keynes'(1936) intuition that investment is driven by businessmen's expectations and the major source of the expectations are current consumption. However, the model is distinguished from the New Keynesians in that price stickiness is not required to generate business cycles and it does not employ the neoclassical model in which output is determined in the step of production.

Three chapters are connected to each other. In chapter 3, I detrend the US real GDP to obtain a reasonable business cycle. In this course, I detect three break points in the trend. In chapter 4, I investigate the main driver of business cycles using the data which is detrended using the break points detected in chapter 3. In chapter 5, I apply the mechanism that is studied in chapter 4 to forecasting.

In chapter 1, I decompose the US real GDP using a deterministic (log) linear trend with three breaks. The practice is chosen as it yields a cycle that is important in magnitude, which corresponds to the Keynesian perspective in that economic fluctuations are mainly ascribed to a cyclical component. The measured business cycle displays a boom-bust pattern with sporadic downward pluckings. The estimated boom-bust cycle is far from a stationary process in that it is long-lasting, large in size and displays sharp reversions to the trend. To support the estimated result, I provide following evidence: (1) I also estimate the cyclical components of well-known US coincident indicators using the detected break points. The estimated cycles of US coincident indicators are close to the estimated cycle of real GDP. (2) the US business cycles estimated using the HP filter with large smoothing parameter and the bandpass filter with a longer bandwidth also corresponds to the cycle estimated through a linear deterministic trend with breaks. (3) When applying the same estimation strategy, boom-bust cycles are found in Korea and Japan real GDP. To justify the estimated results, I also show that the estimated trend and cycle provide a new and reasonable view for the well-known macroeconomic puzzle: the slow recovery of the US economy from the 2008-9 Global Financial Crisis. The estimation results of this chapter imply that the Global Financial Crisis is the collapse of a huge boom rather than a big recession, therefore, a recovery does not follow.

The non-stationary is in contrast with the common assumption of business cycle and decomposition literature. Since [95]Lucas (1973) described a business cycle as a stationary process moving around a linear time trend, a cyclical component has been commonly assumed to be stationary. However, a business cycle is only transitory by its definition and it does not necessarily need to be stationary. The economic terminology ’transitory’ is not equivalent to the statistical terminology ’stationary.’ Meanwhile, non-stationary cycles provide an important implication in the business cycle literature. They allow for a long-lasting and large business cycle observed in reality without unrealistically large shocks or endogenous amplification mechanisms.

In chapter 2, I review the literature of modern business cycle models, that is, dynamic stochastic general equilibrium models (DSGE) from an empirical perspective which is related with the Old Keynesian idea. I discuss the limitation of DSGE models for the two empirical facts, consumption-investment comovement and flat Phillips curve.

In chapter 3, I argue that consumption shocks are the main driver of business cycles based on the intuitions of Keynes (1936) and Pigou (1927). I reconcile their ideas based on their commonality highlighting the role of businessmen's expectations as an important driver of business cycles. The reconciled idea describes a boom-bust cycle generated by consumption changes and their propagation to investment through the adjustment of businessmen's expectation. To examine the idea, I estimate the effects of consumption changes on investment changes using a set of reduced-form investment models. The estimated effects predict a boom-bust cycle of investment which is close to the benchmark investment cycle. Then I estimate the effects of consumption shocks on investment. The effects of consumption shocks also predict a boom-bust cycle close to the benchmark investment cycle. And a unit shock to consumption generates a long-lasting and important responses of consumption and investment even though the secular trend of each variable is already removed. This result is corresponding to boom-bust cycles but contrasting to a well-known hump-shaped response of output to a demand shock. Finally, I discuss the validity of the required assumption that consumption is predetermined for investment.

The investigated model is close to the Keynesian cross. The closest one is the Keynes-Hansen-Samuelson multiplier accelerator model ([122]Samuelson, 1939) in that investment is the function of consumption changes. The main differences are in two points: (1) marginal effect of output changes on consumption is smaller than in the Keynesian cross. In the Keynesian cross, consumption is the function of output as output is equal to domestic income. In reality, however, the source of consumption is personal income, not domestic income. And the correlation between output changes and disposable personal income (DPI) changes is moderate. Moreover, marginal effect of DPI changes on consumption is also small. The well-known fact is that consumption is smoother than DPI. The combination of these two facts yields the small marginal effect of output changes on consumption. (2) Consumption shocks are the most important among demand shocks. In the Keynesian cross, the effect of every demand shock is identical regardless of its target. A demand shock directly increases output and then amplifies the effect through the multiplier effect. In this model, however, the multiplier effect is small as the marginal effect of output changes on consumption is small. Only exogenous consumption shocks and their propagation to investment generates significant effects.

In chapter 3, I forecast output growth as the sum of the trend growth and the cyclical changes (= demeaned output growth) from the Keynesian perspective. I first decompose output growth into the trend growth and the cyclical changes and then forecast each component using different methods. For the trend growth, I estimate a highly smooth time-varying trend using the HP filter with a large smoothing parameter. Then I simply extend the estimated trend growth. For the cyclical changes, a bottom-up procedure is employed. In the procedure, I first forecast the components of demeaned GDP growth and then aggregate them to obtain the forecast of the cyclical changes of GDP. To this end, I employ the relationship between consumption and investment, which is studied in chapter 3 where I demonstrate that consumption changes lead to investment changes. The forecasting performance of the model is comparable to the one of the Survey of Professional Forecasts (SPF). However, SPF is better in nowcasting the sharp decline during the Global Financial Crisis.

This thesis is simplified by abstracting away from the three main feature of Keynesian economics: (1) Okun's law (2) Phillips curve (3) sensitivity of investment to real interest rate. Abstracting from the first two features means that it also abstracts from the natural rate hypothesis. However, the simplification does not appear harmful as it may be taken as corresponding to the weakening belief of nowadays in those features. The systematic relationship between output and unemployment does not seem to be confirmed by empirical evidence ([89]Knotek 2007; [102]Meyer and Tasci 2012). The Phillips curve is not part of original Keynes' idea. Moreover, the flattening Phillips curve since mid-1990s cast doubt on the relationship between inflation and business cycles ([49]Farmer 2013). The weak relationship between interest rate and investment has long been discussed since [123]Shapiro (1986) and [29]Chirinko(1993).

# Chapter 2

# Review of modern business cycle models from empirical perspective

Since 1980s, business cycle models based on neoclassical growth models have become a major workhorse of business cycle studies. Two major streams of them are Real Business Cycle Theory initiated by [91]Kydland and Presscot (1982) and new Neoclassical Synthesis, which is now generally referred to as New Keynesian model introduced by [62]Goodfriend and King (1997). Those models are highly attractive in that they provide empirical implications with the help of fast-improving computation ability as well as theoretical backgrounds based on micro-foundations.

In this chapter, I review the previous studies from an empirical perspective which is corresponding to the [? ]Keynes(1936)' idea. I discuss two issues of modern general equilibrium models. The one is the comovement of consumption and investment. Since [7]Barro and King (1984) pointed out the issue, DSGE models with investment dynamics have been hard to replicate the fact, which is generally called the Barro-King curse. The other one is regarding the flat Phillips curve. Since the rise of natural rate hypothesis, it has been the key ingredients of Keynesian economics. The flat Phillips curve implies the possibility that demand side effect may not be related with price dynamics in the short run, which is consistent with the original Keynes' idea. Based on the review, I provide some implications to business cycle research.

## 2.1 The comovement of consumption and investment

A widely recognised stylised fact of the US business cycle since [91]Kydland and Prescott (1982) is the comovement of consumption and investment. This comovement is easily observed in original US data and cyclical data detrended by various decomposition methods. Unfortunately, this pattern is very hard to replicate using DSGE models unless neutral technology shocks are introduced. This fact has become an important obstacle to DSGE users who stand against neutral technology shocks.

The puzzle is early explained by [7]Barro and King (1984), thus it is called the Barro-King curse. In an efficient equilibrium, the marginal rate of substitution between consumption and leisure must equal the marginal product of labour. This condition implies that for any shocks that only indirectly affect the marginal product of labour, such as investment shocks do, consumption and hours move in opposite directions. That is, the rise in marginal product of labour necessarily leads to increase in leisure and decrease in consumption. Therefore, neutral shocks are only known mechanism which can boost consumption and investment at the same time.

### 2.1.1 The rise and fall of technology shocks

Despite the merit, technology shocks are subject to critiques of academic scholars due to their ambiguous definition and measurement. [91]Kydland and Prescott (1982) employ the Solow residuals as a proxy for technology shocks. However, there are skeptical views of whether the Solow residuals are a proper measurement of technological changes. [80]Jorgenson and Griliches (1967) and [135]Griliches (1996) point out that the Solow residual measures more than underlying technological changes. They are considered as the composite of other shocks. [119]Rebelo (2005) document that technology shocks can be explained by policy shocks and other various effect. Moreover, even for neutral technology shocks, [30]Christiano and Fitzerald (1998) show that investment increases even more than does consumption in a two-sector neoclassical model. Another issue concerning technology shocks is regarding recession. Unlike booming seasons, it is not easy to explain why adverse technological progress occur during recession in such sharp manner. This point is well illustrated in [98]Mankiw(1989).

A good example of adverse shocks is oil shock. However, oil shocks are only attributed to a faction of recession events. These critiques led to various versions of DSGE models which employ alternative shocks.

### 2.1.2 The empirical problem of alternative shocks in DSGE models

RBC models have embraced various shocks as alternatives to technology shocks. The most popular one among them is investment shock suggested by [82]Justiniano et al. (2011). The shock is motivated by [86]Keynes (1936)'s marginal product of capital, and [65]Greenwood et al. (1988). The model replicate an actual US real GDP growth in yearly frequency well. However, the model fails to generate the comovement of consumption and investment. In a neoclassical model, consumption and investment are bounded by its production capacity of this period. Therefore, a sudden increase in investment necessarily leads to subdued consumption.

To resolve the opposite movement of investment and consumption, endogenous capital utilization is introduced in [82]Justiniano et al. (2011) following the tradition of [65]Greenwood et al. (1988). For a given technology level and the corresponding output, consumption and investment necessarily move in opposite directions. Endogenous capital utilization mitigate the problem by increasing output as a response to shocks. However, it may help prevent consumption growth from going negative, but cannot generate comovement of consumption and investment. A representative agent have to decide between consumption and saving for a given production capacity for the society. Later literature add add more features in RBC models such as adjustment cost to investment ([66]Greenwood et al. 2000) and wealth effect [79]Jaimovich and Rebelo 2009). By doing so, they reduce the movement of consumption and investment in opposite direction. However, it is hard to say they comove as two components increase at different timing.

Another well-known shock is news shock ([10]Beaudry and Portier 2004). The idea is an attempt to model the expectation-driven business cycle within RBC frameworks. In their model, a forecast of future technological improvement first leads to a boom, and the realisation that a forecast is too optimistic leads to a recession. Same as investment shocks, however, an increase in investment driven by expectation necessarily leads to a decrease in consumption. Similar results are found in other literature studying news shocks ([79]Jaimovich and Rebelo 2009), [8]Barsky and Sims 2011). The modification of RBC models mitigate the comovement problem to some extent, but news shock s themselves are the solution.

The most recent idea is to model uncertainty shocks ([15]Bloom et al. 2018). In the literature, increase in uncertainty makes it optimal for firms to wait, leading to significant falls in hiring, investment and output. At the same time, consumption overshoot as investment fall. The increase in consumption appears very weird in a highly uncertain environment although it is an expected result for a RBC model. The shock can also be applied to consumer preference ([52]Fernandez-Villaverde and Guerron-Quintana,2020). Increase in uncertainty may reduce consumption while raising precautious savings. In a general equilibrium model, an increase in savings means increase in investment and therefore two components move in opposite direction.

Another interesting idea is to model sunspot shocks ([12]Benhabib and Wen, 2004). In the model, forecasting errors of an agent generate unexpected variation of investment. To reduce the negative comovement between consumption and investment, capacity utilisation and externalities are employed in the model. However, it fails to generate positive comovement between consumption and investment.

In standard new neoclassical syntheses models (or new Keynesian models) with capital accumulation, the dynamics of GDP components fundamentally cannot be different from those of RBC models. This is because RBC models and new Keynesian models are all built upon neoclassical growth models. Any demand shocks affecting consumption lead to decreasing or subdued investment or vice versa. These results can be found in the well-literature of New Keynesian models. A handful of previous literature attempted to resolve the problem within the New Keynesian framework such as [59]Furlanetto, Natvik and Seneca 2013, [28]Chiarini, Ferrara and Marzano, 2020). They employ rule of thum consumption and entrepreneur's tax evasion as well as endogenous capital utilization to resolve the Barro-King curse. However, it is hard to say that those models are successful to replicate actual data. Those models are at best stop consumption from reducing while investment increase.

### 2.1.3 Implication to business cycle research

The Barro-King curse represents a fundamental difference in perspective between the original Keynesian and modern business cycle theory. Keyens (1936) sees business-cycle as the results of interaction between individuals who has different purpose and objects. The difference is obvious between consumers and entrepreneurs. Therefore, in this logic, increase in consumption is likely to lead to increase in investment as Keynes(1936) explains in Chapter 12 as the current consumption is the most reliable information for the future consumption unless additional private information is in hand. However, it is not common to have private information about future and that is why firms often lose money in the market. And increase in investment leads to increase in income and consumption, which is the multiplier effect that Keynes emphasizes. That is, the Keyne's idea is all about interaction among different people. On the other hand, neoclassical models with a representative agent plays both roles of consumer and investor. For a given technology level, the agent should decide between consumption and investment. Therefore, both components are hard to move together.

## 2.2 Flat Phillips curve

Since the New neoclassical synthesis is introduced by [62]Goodfriend and King (1997), New Keynesian models have become a major workhorse for the scholars who study the effect of public policy. This new kind of Keynesian models is in line with a traditional Keynesian theory in that it recognises the role of demand shocks and acknowledges the role of cyclical fluctuations to explain business cycles. A major difference is the role of demand shocks on price. This feature is the legacy of the augmented Phillips curve and the neoclassical synthesis, but not the one of the Keynes' original idea. It is also considered as the weakness of the traditional Keynesian theory which does not explain the dynamics of price.

### 2.2.1 Insensitivity of inflation to business cycles

The crucial part of New Keynesian model is the response of output to demand shocks and stickiness in price, which generates important cyclical fluctuations. Instantaneous frictions in price adjustment generate deviations from a trend and therefore business cycles. A problem is that inflation is stable since mid-1990s while output display a large movement, in particular, during recessions. Booms in late 1990s and mid 2000s were not accompanied by inflation. And deflation is also hard to find during recessions. And the recent inflation is ignited by increase in oil price rather than demand shocks. The flattening Phillips curve has been documented by previous literature (see [40] Del Negro et al. 2020). The causes of flat Phillips curve are being discussed by scholars. The most popular one is a more responsive monetary policy and anchoring inflation expectations ([101]McLeay and Tenreyro, 2020)

### 2.2.2 Implications to Keynesian models

An important implication of flat Phillips curves is that New Keynesian models converge to the original Keynesian model in which demand shocks do not affect inflation in the short-run. [40]Del Negro et al. (2020) mention this point that a New Keynesian model approaches to a original Keynesian model in which demand shocks generate business cycle regardless of price. This kind of view is not novel as the Natural rate hypothesis itself is just an assumption and it always has been doubted by some scholars. One of early one is [129]Summers (1991) who emphasises that the Natural rate hypothesis is not the essential part of the original Keynes' idea and does not correspond to actual data.

Recently, alternative views argue for demand-driven business cycles not causing inflation. Some papers that attempt demand shocks within RBC frameworks as discussed above can be considered as this kind. More obvious one is [11]Beaudry and Portier (2014) who try to figure out the mechanism that demand shocks do not cause inflationary pressure within a New Keynesian model. Another one is [49][50]Farmer (2013, 2018) who replaces Phillips curve with a belief function to determine expectations of nominal income growth in new Keynesian models. By doing so, demand shocks can generate business cycles without causing inflation or deflation. The recent empirical finding to advocate this view is from [2]Angeletos et al. (2020) who argue that promising candidates for main business cycle shocks are non-inflationary demand shocks.

# Chapter 3

# Boom-bust cycles in US real GDP

The only agreed hypothesis among students of business cycle research is that the long-run trend varies smoothly over time[1]. However, there exist contrasting views on the shape of trend and thereby what the main source of economic fluctuations is: one view mainly attributes economic fluctuations to cycles (Keynesian and Monetarism), and the other mainly attributes economic fluctuations to trends (Real Business Cycle). In the trend-cycle decomposition literature, the extreme version of the first view is decomposition using a deterministic linear trend (DLT) and that of the second view is the Beveridge-Nelson (BN) decomposition. The other methods are located somewhere between them.

It is hard to conclude which view is right given the empirical evidence currently available. Therefore, the choice of decomposition methods tends to depend on the view of the researcher. In this chapter, I decompose US output into the trend and cycle components following the first view. This kind of cycle estimate has an important implication for macroeconomic policies as it tends to justify the policy intervention. A significant deviation from the trend implies disequilibrium in an economy and thereby may require a remedy to correct it. The decomposition yields the boom-bust cycle with sporadic downward pluckings [2]. This pattern corresponds to a

[1] "The maintained hypothesis, based upon growth theory considerations, is that the growth component of aggregate economic time series varies smoothly over time." ([91]Kydland and Prescott 1997).

[2] [57]Friedman (1969) coined the terminology and described the pattern as follows: "Consider an elastic string stretched taut between two points on the underside of a rigid horizontal board and glued lightly to the board. Let the string be plucked at a number of points chosen more or less at random with a force that varies at random, and then held down at the lowest point reached. The result will be to produce a succession of apparent cycles in the string whose amplitudes depend on the force used in plucking the string. The cycles are symmetrical about their troughs; But there is no necessary connection between the amplitude of an expansion and the amplitude of the

common perception of a business cycle [3] and to the perspective of early scholars such as Pigou and Hayek.

While admitting the extremeness of DLT, I still argue that DLT can provide us with a good implication in business cycle research for the following reasons:(1) Estimated cycles necessarily contain actual cycles. The method attributes all the economic fluctuation to a cyclical component. Therefore it would not distort the cyclical pattern even though it may overestimate the scale. (2) A cyclical component may be non-stationary. If this is the case and the trend is stochastic, the decomposition is not feasible without prior information as both the trend and the cycle are non-stationary stochastic processes. A cyclical component is commonly assumed to be stationary as it is 'transitory'. In a strict sense, however, the economic terminology 'transitory' is not equivalent to the statistical terminology 'stationary'. The former only implies the trend-reverting property which is not equivalent to the mean-reverting property of a stationary process. Moreover, the invariant autocovariance of a stationary process generates a smooth mean-reversion while 'transitory' does not imply anything about the pattern of trend-reversion (3) The cyclical patterns estimated with an unobserved component model (UC) and by DLT are almost identical as observed by [131]Watson (1986) and [33]Clark (1987). [110]Perron and Wada (2009) document that this still holds for a longer series when a break in trend is accounted for. This implies a negligible gap between a stochastic trend and a deterministic trend in the decomposition of real GDP only if the cyclical and the trend components are uncorrelated[4]

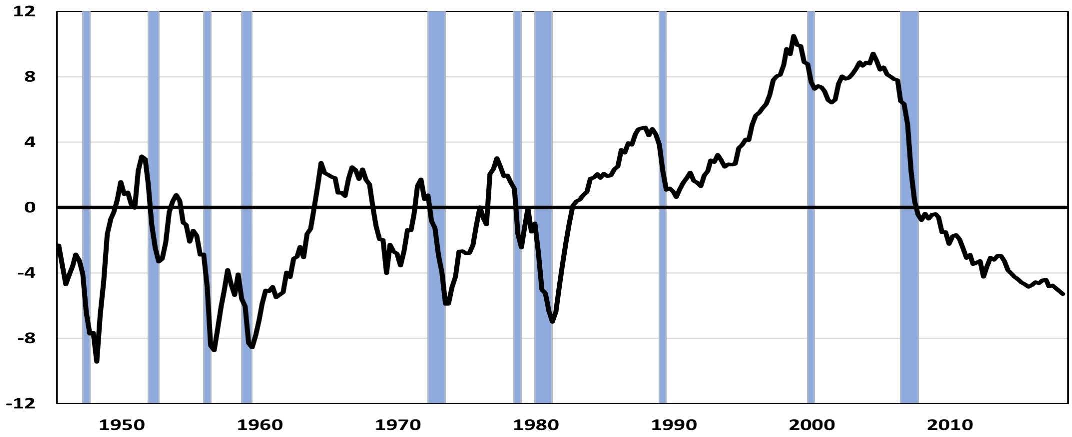
The critical drawback of DLT with breaks is that it requires the detection of break points prior to the decomposition. However, economic scholars have not reached an agreement over the number and the timing of break points in the trend of US output.)[110]Perron and Wada (2009 suggest one break point in 1973:1. As observed in Chan and Grant (2017)[64], however,

succeeding contraction." (p.17)

[3]"Very few economic commentators regard the recession of 2001 as resulting from a negative technology shock. A more common view among economists is that the collapse of investment observed in 2001 resulted from some combination of changes in expectations about the profitability of new investments as well as a possible feedback from a period of very high investment in the late nineties and early in 2000." ([10]Beaudry and Portier (2004, p.1184)

[4][104]Morley 2003 document that the difference between UC models and BN filter is ascribed to the assumption of the correlation between trend and correlation. The ARIMA model with the assumption of independence between trend and correlation yields the estimate identical to the one of a UC model.

Figure 3.1: Estimate of US business cycle using DLT with a single break in 1973:1




*Note:* Units are per cent deviation from trend. Shaded bars correspond to NBER recession dates. X-axis: periods (1947:1 to 2019:4. The model is estimated using the code of [25]Chan and Grant 2018)

the single-break DLT yields a negative deviation from trend widening over time since the 2007-8 Global Financial Crisis (GFC, henceforth) as shown in Figure 3.1. The decomposition result is not sensible in that the US economy was in recovery from the GFC. This implies that the estimated growth of trend since the GFC is too high and therefore more break points need to be considered. The timing of detected points also vary across papers[5]. This implies that detection is still a difficult task and thus none of the existing detection methods are more reliable than the others. This difficulty would supposedly be raised because the magnitude of a break in trend is small relative to that of cyclical movement.

For this reason, instead of detecting break points directly, I detect the points where the cycle returns to trend. The detected points allow for the estimation of segmented trends[6]. The magnitude of a break is estimated ex-post as the difference in mean growth between neighbouring segments. To detect the return points, I first estimate the overall pattern of the US business cycle. The pattern of cycles can be observed in the arithmetic mean of output growth. The predicted business cycle has a boom-bust pattern with sporadic downward pluckings. From the estimated pattern, I detect the return points which allow for the segmentation of data. Then

[5][109]Perron (1989) 1973:1, [97]Luo and Starz (2014) 2006:1, [3]Antolin-Diaz et al. (2017) 2000:2, [64]Grant and Chen (2017) 2007:1

[6]In this method, the trend slope of each segment is estimated as the mean growth of the segment. When the segmentation is corresponding to the cyclical pattern, the sum of cyclical movements is zero within a segment. It allows for the estimation of trend growth which is not affected by cyclical movements.

I calculate the arithmetic mean of each segment to find the trend slope. The estimated trend ends up with three breaks which are two more than [110]Perron and Wada (2009) employ. Once the trend component is estimated, the cycle can be estimated as the residual.

In the estimated business cycle, the widening deviation disappears and displays the boom-bust pattern with sporadic downward pluckings as I estimate in advance. The cycle is far from a stationary process, which contrasts with the common assumption of the decomposition literature. And the estimated business cycle provides some clues to help explain a well-known puzzle that is often discussed in macroeconomics: the slow growth of US output in the post-2009 recovery. The existing answers to the puzzle are hysteresis ([130]Summers 2015 ) that began after the GFC and, the slower productivity growth and demographic change ([63]Gordon 2015 [51]Fernald et al. 2017) that started before the GFC. However, the view reflected in my estimate is different. The estimated trend shows that US growth has declined in a step-wise manner over a long time. The difference is attributed to the different views on the late 1990s-boom in US. I see the boom as a deviation from the trend while the major views see it as a significant change in the trend. Again I see the GFC as the event of abrupt trend-reversion while the major views see it as another significant change in the trend.

Finally, I provide evidence to support the estimation results of this chapter. I document that the estimated cycle accords well with the ones of well-known coincident indicators and also with the ones estimated by the Hodrick-Prescott filter and bandpass filter when using alternative values for the smoothing parameter and the bandwidth limits. Additionally, to see whether the boom-bust pattern is common across countries, I apply the decomposition of South Korea (Korea, henceforth) and Japan's real output. The cycles of Korea and Japan also display boom-bust patterns like the US cycle. The estimation results also provide a clue to another puzzle: the asymmetric effect of financial crises on Korea and Japan. The estimation results suggest that the effect of a financial crisis is proportional to the existing disequilibrium. Korea experienced the bust of a large scale boom during the 1997-8 Asian Financial Crisis. After the boom is bust, the new boom generated until 2007 was relatively small. On the other hand, Japan did not experience the bust during the Asian Financial Crisis and kept a substantial size of boom to bust in 2008.

This paper is related to papers that study the decomposition of output via the estimation of linear trend ([131]Watson 1986, [33]Clark 1987 and [110]Perron and Wada 2009). Their estimated cyclical patterns are close to mine. Just by adding more breaks in trends and relaxing the stationarity assumption of cycles, however, I achieve a non-stationary cycle which provides a new perspective on the US business cycle.

The remainder of this paper is organized as follows. Section 2 introduces the strategy to decompose US output into trend and cyclical components and presents the decomposition results. Section 3 discusses why a non-stationary cycle is reasonable in contrast with the view of previous decomposition literature. Section 4 demonstrates that the estimated trend and cycle can provide some clues to help explain the slow recovery from the 2008-9 Global Financial Crisis. Section 5 provides evidence to support the estimation results. Section 6 concludes.

## 3.1 Measurement of US business cycle

### 3.1.1 Preliminary test

In this subsection, I attempt to detect break points using [5][6]Bai and Perron methods (1998, 2003) to detect break points[7]. The method is the most popular and known to be the most reliable method in econometrics.

The results are presented in Table 3.1. As presented, detected points vary for different periods. It is most common that no points are detected. The point which is the most frequently detected is the second quarter of 2000. The point is not detected for samples which ends earlier than the fourth quarter of 2012. And the point is not coincident with the one advocated by the developer of the method, Pierre Perron. He keeps advocating the point in the first quarter of 1973 in his two important papers ([109]Perron 1989, and [110]Perron and Wada 2009). The point is chosen from his intuition rather than from his detection method.

Th results indicate that the strategy of applying the conventional test is not satisfactory and a

[7]I employ the matlab code distributed by Pierre Perron at https://blogs.bu.edu/perron/codes/

new perspective over detection points in US GDP growth is required.

Table 3.1: Detection Results

| Periods | Detected points |
|---|---|
| 1947.2Q to 2019.4Q | 2000.2Q |
| 1961.1Q to 2019.4Q | 1973.2Q |
| 1985.1Q to 2019.4Q | 2006.1Q |
| 1991.1Q to 2019.4Q | 1996.1Q, 2000.2Q |
| 1963.1Q to 2003.4Q | 1965.4Q |

Break points are detected at 5% significance level.

### 3.1.2 Model

A model of economic time series with DLT including n breaks is considered. The model describes log real GDP $y_t$, as the sum of a trend $\tau_t$ and a cyclical component $\mathbb{c}_t$.

$$\begin{aligned} y_t &= \tau_t + \mathbb{c}_t \\ \tau_t &= \mu + \theta_1 1(t > T_{b1}) + \cdots + \theta_n 1(t > T_{bn}) + \tau_{t-1} \\ &\text{where} T_{b1} < T_{b2} < \cdots < T_{bn} \end{aligned} \tag{3.1}$$

The constant mean and breaks can be reduced into a time-varying mean, $\mu_t$.

$$\mu_t = \mu + \theta_1 1(t > T_{b1}) + \cdots + \theta_n 1(t > T_{bn})$$

where 1(A) is the indicator function for the event A, and each $T_b$is the observation corresponding to the time of a break. Then, the trend can be reduced.

$$\tau_t = \mu_t + \tau_{t-1}$$

Taking a first-order difference of $y_t$ yields the following process.

$$\Delta y_t = \mu_t + \Delta \mathbb{c}_t \tag{3.2}$$

The cyclical component does not require modelling. Once $\mu_t$ is estimated $\Delta\mathbb{c}_t$ is estimated as the residual. By definition, $\mathbb{c}_t$ cannot diverge over time and returns to zero at a certain point.

### 3.1.3 Decomposition

To see the trend and cycle decompositions implied by the specification, I use US real GDP 1947:1-2019:4 seasonally adjusted. I first estimate the overall pattern of the US business cycle. Then using that prior information, the trend and cycle components are estimated.

**Segmentation of data: what does the US business cycle look like?**

In this subsection, I estimate the overall look of the US cyclical pattern and detect segment points from the look. The estimation of DLT with breaks is equivalent to that of segmented trends. The trends slope of each segment is estimated as an arithmetic mean of growth within the segment. In this case, to achieve the unbiased estimate of trend slope, the sum of cyclical movements within a segment should be zero. Therefore, segment points should be corresponding to the cyclical pattern. Therefore, to detect proper segment points, the cyclical pattern needs to be estimated first.

There are four well-known business cycle pattern hypotheses: (1) boom-bust cycle (Pigou, Hayek) (2) Plucking model (Friedman) (3) periodic business cycle called limit cycle (Kalecki) (4) random fluctuations (Real Business Cycle, New Keynesian). Which pattern would be close to the US business cycle?

I estimate the cyclical pattern of the US economy using a simple arithmetic mean. The mean of output growth consists of three terms.

$$\frac{1}{T}\sum_{t=1}^{T}\Delta y_t = \mu_t + \frac{\mathbb{c}_T}{T} - \frac{\mathbb{c}_0}{T} \tag{3.3}$$

Among them, $-\frac{\mathbb{c}_0}{T}$ do not affect the identification of the cyclical pattern. $-\frac{\mathbb{c}_0}{T}$ also does not fluctuate as it monotonically increases or declines over time. The economic fluctuations can be observed in $\frac{\mathbb{c}_T}{T}$. Over time the magnitude of fluctuation decreases. However, it does not affect the fluctuation pattern itself. A problem is that $\frac{\mathbb{c}_T}{T}$ approaches zero for a large T. To tackle this issue, I divide the whole sample into two parts. According to the estimation results of [3]Antolin-Diaz (2017), the trend growth significantly declines between 1984-1990. Thus, I split the sample into 1950 to 1985 and 1985 to 2015. The pattern of the $\mu_t$ is not certain. As I assume a DLT, the trend growth does not change over unless it faces a break. Therefore, the trend growth is likely to stay still within a subsample.

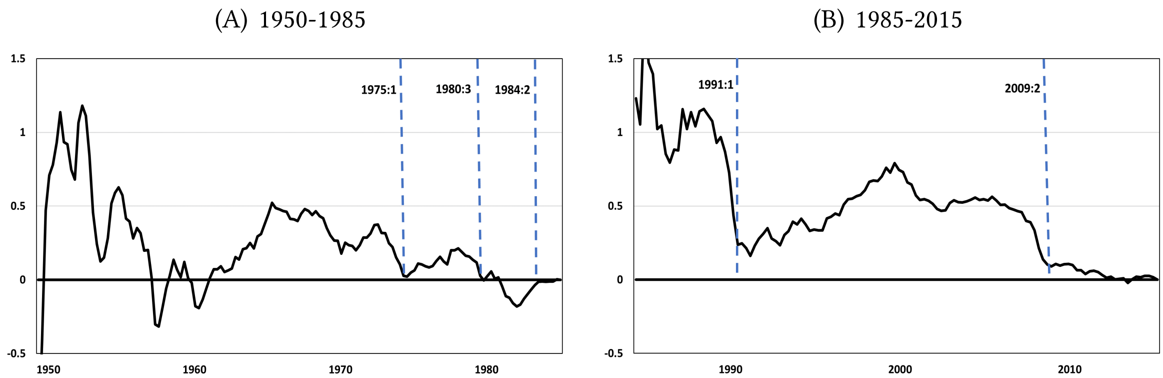
For large number $T_1$ and $T_2 < T_1$, as $T_2$ approaches to $T_1$ only if there is no large break between $T_1$ and $T2$,

$$\frac{1}{T_2}\sum_{t=1}^{T_2}\Delta y_t - \frac{1}{T_1}\sum_{t=1}^{T_1}\Delta y_t \approx \frac{\mathbb{C}_{T_2}}{T_2} \tag{3.4}$$

Two graphs are drawn for 1950 to 1989 and 1985 to 2015 using the equation (4).

The estimated pattern is present in Figure 3.2. The boom-bust patterns are repeated with some downward pluckings. From the view, I choose suspected segment points in 1975:1, 1980:3, 1984:2, 1991:1 and 2009:2. Using the five suspected segment points, I estimate the US business

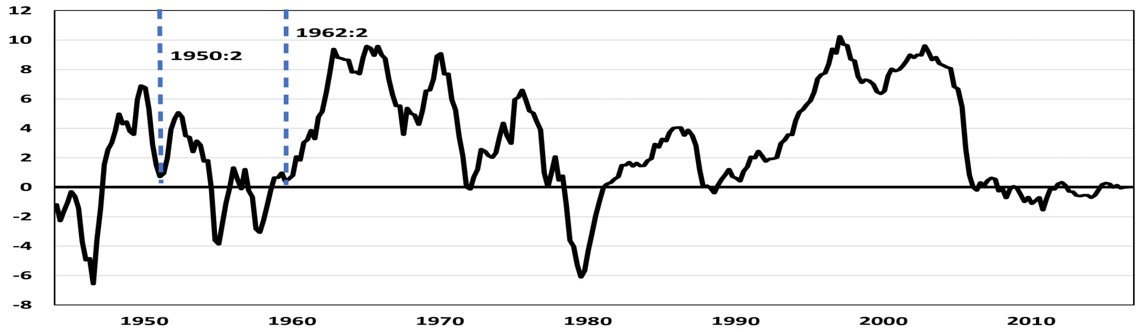
Figure 3.2: Predicted cyclical pattern of US GDP




*Note:* X-axis: Time horizon in quarters

cycle. The result is present in Figure 3.3. The business cycle displays a boom-bust pattern with sporadic downward pluckings. Form the view, I choose two more suspected segment points in 1950:2, 1960:2. I choose total seven segment points. Five are bust points: 1950:2, 1975:1, 1980:3, 1991:1 and 2009:2. Two are plucking-recovery points: 1962:2 and 1984:2.

Figure 3.3: Preliminary estimation of cycle with five segment points




*Note:* Y-axis, per cent deviation from the trend, X-axis: Time horizon in quarters

### Estimation of trend and cycle

Once the time series is segmented according to the detected points, the trend growth of each segment can be estimated as the mean growth. If you get n break points, there are n+1 segmentations ,and $\hat{\mu_1} \ldots \hat{\mu_{n+1}}$ should be estimated. For an arbitrary $k$th segment,

$$\frac{1}{\tilde{T}}\sum_{i=1}^{\tilde{T}} \Delta y_i = \mu_k + \frac{1}{\tilde{T}}\sum_{i=1}^{\tilde{T}} \Delta \mathbb{c}_i = \hat{\mu_k} + \frac{1}{\tilde{T}}\sum_{i=1}^{\tilde{T}} \Delta \hat{\mathbb{c}}_i$$

$$\hat{\mu_k} = \frac{1}{\tilde{T}}\sum_{i=1}^{\tilde{T}} \Delta x_i - \frac{1}{\tilde{T}}\sum_{i=1}^{\tilde{T}} \Delta \hat{\mathbb{c}}_i \tag{3.5}$$

As seen in equation (5), the estimation of an unconditional mean is sensitive to cycles. To avoid this sensitivity, the segmentation should be corresponding to the cyclical pattern so that $\sum_{i=1}^{\tilde{T}} \Delta \hat{\mathbb{c}}_i$ becomes zero. Then it will minimise the bias in the estimate of $\hat{\mu_k}$.

Once trend growth is estimated, the estimate of a cycle is achieved as the sum of demeaned output growth.

$$\mathbb{c}_T = \sum_{t=1}^{T} (\Delta y_t - \hat{\mu_t}) \tag{3.6}$$

I first estimate the business cycle using the seven segmented points detected above: 1950:2, 1962:2, 1975:1, 1980:3, 1984:2, 1991:1, 2009:2. The estimated results is present in Figure 3.4. In panel (B), the estimated trend growth is present. In overall, the estimated trend growth is very smooth. The breaks in 1962:2, 1975:1 and 1980:3 do appear very small. These breaks may be attributed to measurement errors rather than to actual structural breaks. Therefore, I merge those segments into a long segment spanning from 1950:4 to 1980:3. Then I estimate the trend again with four segment points in 1950:2, 1984:2, 1991:1 and 2009:2.

Figure 3.4: Preliminary estimation of cycle and trend growth with seven segment points

(A) Cycle　　(B) Trend growth


*Note:* Unit: (A) per cent deviation from trend (B) per cent, annualised rate. X-axis: periods (1947:1 to 2019:4.)

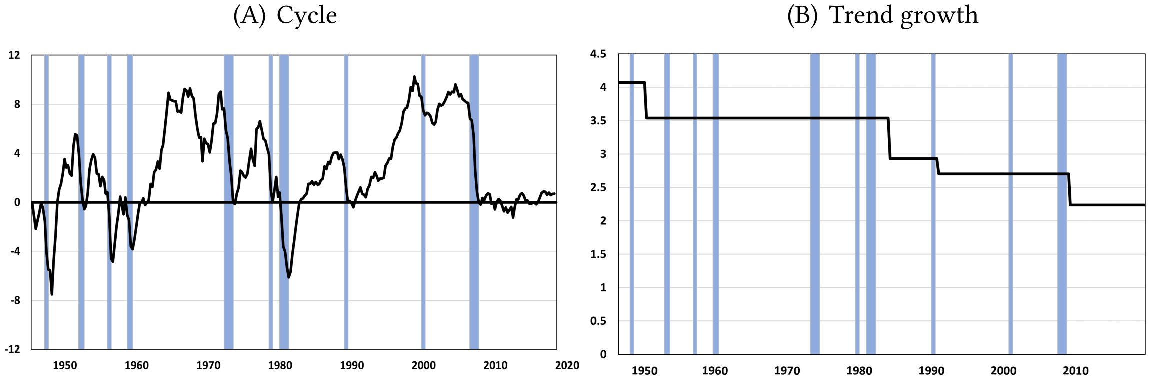
The final estimation results are present in Figure 3.5. The estimated cycle is present in panel (A) of Figure 3.5. As predicted in Figure 3.2 and Figure 3.3, the cycle of US output follows the boom-bust pattern with sporadic downward pluckings. And results break points are in 1984:3, 1991:2 and 2009:3. There is also a significant change in trend growth in 1950:3. However, the estimated break in 1950:3 is not reliable as the first segment is truncated with small number of data left in the segment.

To support the estimation results, I apply the Bai and Perron method(Bai and Perron 1997, 2003) to the GDP growth data detrended as above. The method is applied to various sample periods presented in Table 3.1. Unlike the results in Table, no break points are detected for various samples. It means that the break points are reasonable.

## 3.2 Supporting evidence

The detection of break points employed in the previous section is likely to be affected by the researcher's subjective judgement. Therefore, to support the estimation results, I provide following evidence. (1) I estimate the cyclical components of well-known US coincident indicators using the detected break points. The estimated cycles of US coincident indicators are close

Figure 3.5: Cycle and trend growth of US GDP




*Note:* Unit: (A) per cent deviation from trend (B) per cent, annualised rate. Shaded bars correspond to NBER recession dates. X-axis: periods (1947:1 to 2019:4.)

to the estimated cycle of real GDP. (2) the US business cycles estimated using the HP filter with large smoothing parameter and the bandpass filter with a longer bandwidth also corresponds to the cycle estimated through a linear deterministic trend with breaks. (3) When applying the same estimation strategy, boom-bust cycles are found in Korea and Japan real GDP.

### 3.2.1 Consistency with coincident indicators

In this subsection, I document that the cycles of well-known US coincident indicators display the same pattern with the cycle of US real output. If the economic indicators produced with different sources of data display the same pattern, the pattern is likely to be true.

(1) one of the most well-known coincident indicators is the coincident index compiled by the Conference Board (TCB). The index is the composite of four indexes: number of employees on non-agricultural payrolls, personal income less transfer payments, industrial production and, manufacturing and trade sale. The period is from 1959:1 to 2018:2. (2) Another well-known coincident indicator is the coincident index compiled by the the Philadelphia Federal Reserve (TPFR). The TPFR index is a good comparison as unlike the TCB index, it only comprises labour market indicators such as nonfarm payroll employment, average hours worked in manufacturing, unemployment rate and, wage and salary disbursements deflated by the consumer price index. Therefore, it is less likely to correspond to the cycle of real output which is value-added statistics. If they accord well, it can be taken as strong evidence for the true cycle. The period is

from 1980:1 to 2019:4. (3) Industrial production (IP) is one of the most well-known coincident indices among individual monthly indicators. IP is regarded as a good proxy for economic activity. The manufacturing and utility sector only make up for approximately 20 per cent of GDP. IP tends to well keep track of economic activity as they are closely related with other sectors via the supply chain despite its small share in GDP relative to the service sector. The period is from 1948:1 to 2019:4. (4) Personal income less transfer payments (PI) is the indicator that is conceptually closest to GDP and is likely to display a pattern that is similar to that of GDP. However, PI is compiled mainly using compensation of employee data unlike GDP which mainly depends on expenditure data. The period is from 1948:1 to 2019:4.

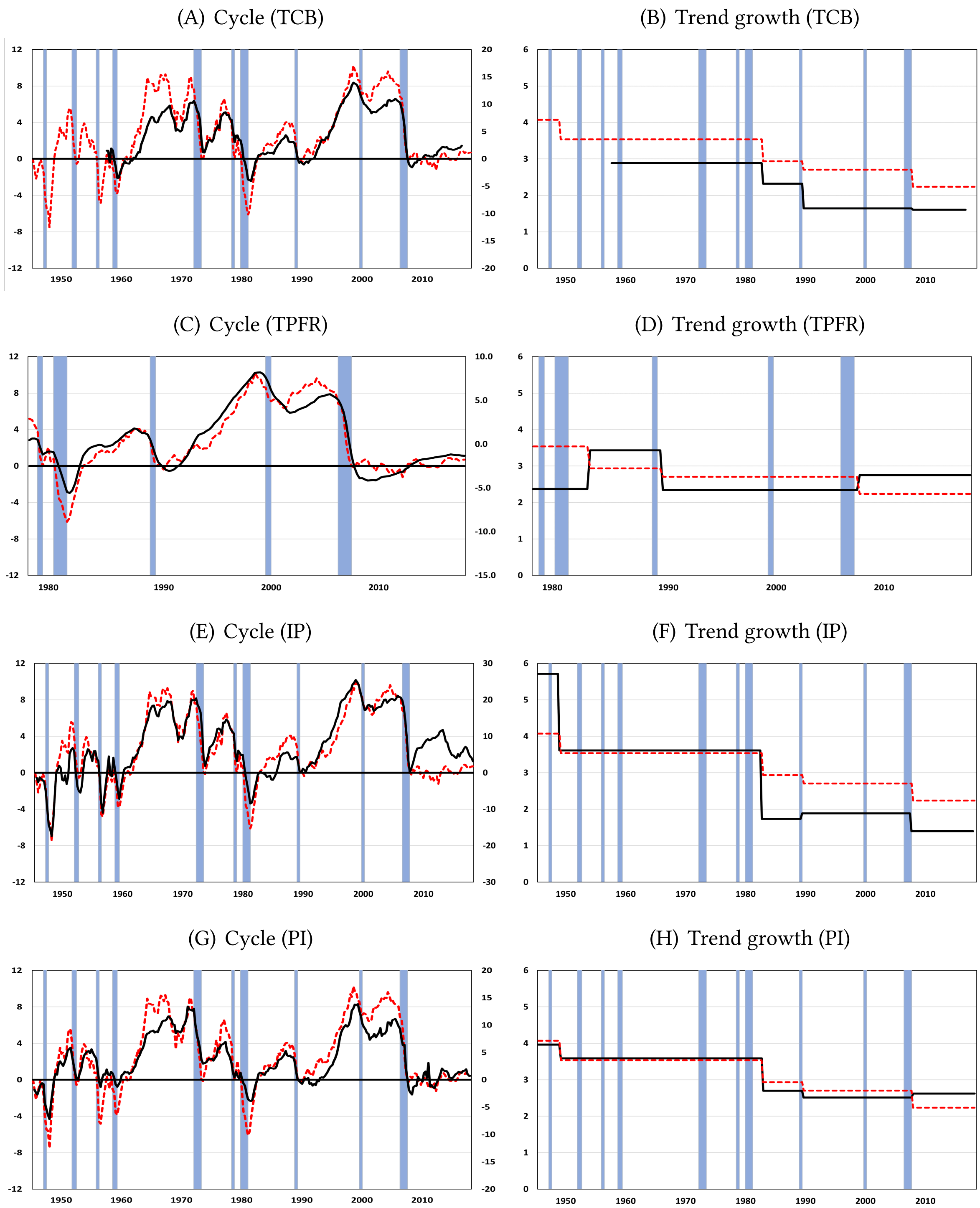
I decompose these indicators[8] using the method introduced in section 2. The segment points of real output are equally applied to the coincident indicators. The decomposition results are present in Figure 3.6. The cyclical patterns of those indicators are corresponding to the one of real GDP. This indicates that they all have the same implied cycle. Despite the similar cycle across indicators, the pattern of trend growth is quite different across indicators. The trend growth of real output monotonically decreases over time. And there are breaks with a substantial size in 1984:2 and 2009:2. However, these are not always the case for the other indicators.

### 3.2.2 Comparison with other decompositions

In this subsection, I demonstrate that other well-known statistical methods such as the Hodrick-Prescott (HP) filter ([77]Hodrick and Prescott, 1997) or the bandpass (BP) filter ([9]Baxter and King, 1999; [32]Christiano and Fitzerald, 2003 ) can yield the similar results of this chapter just by adjusting the smoothing parameter or the bandwidth. Popular statistical decomposition methods such as the HP filter or the BP filter have parameters affecting the pattern of trends or cycles. Prior to the implementation of the HP filter, the smoothing parameter value ($\lambda$) should be determined. The larger the value is, the smoother the trend is. For the quarterly data, $\lambda$ is commonly 1600 following the guidance of [77]Hodrick and Prescott (1997). However,

[8]The indicators except for PI are transformed into quarterly series by averaging within a quarter. PI is compiled in both monthly and quarterly.

Figure 3.6: Cycle and trend growth of coincident indicators




*Note:* Solid line: cycle and trend of coincident indicators, Dashed line cycle and trend of real GDP. Unit: (A) (C) (E) (G) per cent deviation from trend, right axis for solid line, left axis for dashed line (B)(D) (F) (H) per cent, annualised rate. Shaded bars correspond to NBER recession dates. X-axis: periods (1959:1 to 2018:2 for TCB, 1980:1 to 2019:4 for TPFR, 1948:1 to 2019:4 for IP and PI. TCB is The Conference Board coincident index. TPFR is The Philadelphia Federal Reserve coincident index. IP is industrial production index. PI is Personal Income less transfer payments) their choice of the value was purely ad-hoc and empirical[9]. Prior to the implementation of BP filter, the bandwidth should be determined. The convention for real GDP is between 6 and 32 quarters. If a longer frequency cycles exist and choose a larger upper limit, the longer frequency cycles can be obtained. [9]Baxter and King (1999) first obtained the above bandwidth from the definition of a business cycle which is made by [17]Burn and Mitchell (1946) seven decades ago. Therefore, it is not certain whether their definition of business cycle well represents the current business cycle.

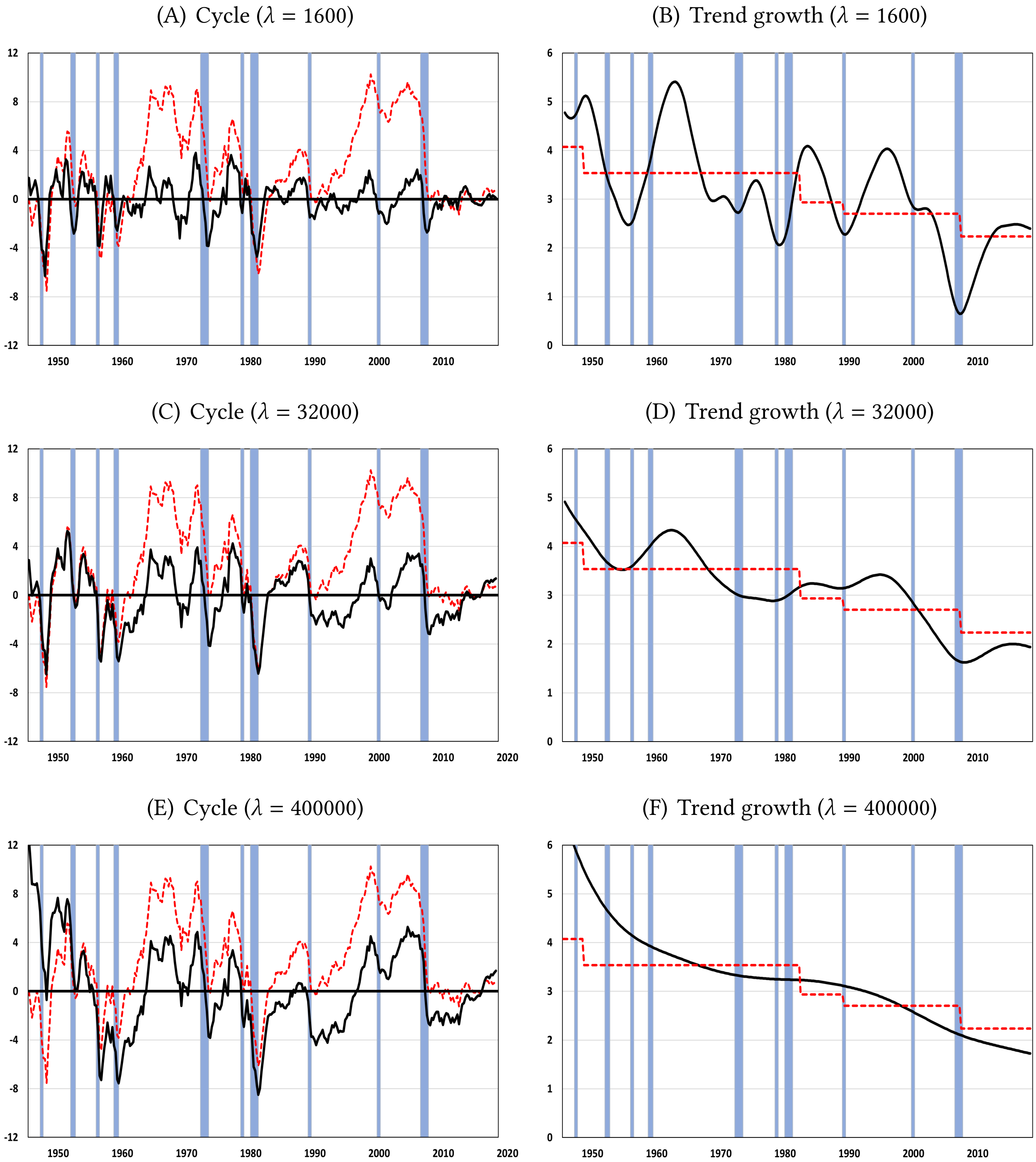
With the HP filter and the BP filter, various trends or cycles can be obtained depending on the view of a researcher. The view of this chapter is in favour of smooth trends and, persistent and important cycles. Therefore, larger values for $\lambda$ and the upper limit of the band can be chosen. Some scholars share a similar view of this chapter in choosing $\lambda$. For the value of $\lambda$, [73]Harvey and Timbur (2008) suggest 32000, [43]Drehmann et al. (2011) 400000 and [110]Perron and Wada (2009) 800000. I will employ 32000 and 400000 as there is little difference between 400000 and 800000. To decide a proper bandwidth, I will exploit the estimation results of this chapter. The most recent cycle in my estimate starts at 1991:2 and ends at 2009:2, therefore the cycle is as long as 73 quarters. Therefore, for the value of the upper limit, I will choose 80 quarters which is much larger than 32. By doing so, the filter passes lower frequency signals.

The results of HP filtering are present in Figure 3.7. As the value of $\lambda$ increases, the trend becomes smoother and the cycle becomes more persistent and more important. The estimates of cycles with $\lambda$ = 32000 and 400000 display a similar pattern to the one estimated in this chapter. The estimated cycles locate around zero unlike those of this chapter as HP filter necessarily generates stationary cycles. The results of BP filtering[10] are present in Figure 3.8. When raising the upper limit of the band to 80 quarters, the estimated cycles become more persistent and more important. The cyclical pattern is similar to that of mine except that the cycles locate around zero. The BP filter is also supposed to generate stationary cycles.

[9]The optimal value of $\lambda$ is the ratio of the variance of the cyclical component to the variance of the second difference of the trend (the inverse signal-to-noise ratio). [77]Hodrick and Prescott (1997) speculate that the value of US GDP would be about 1600.

[10]Technically, I employ the Christiano-Fitzerald filter.

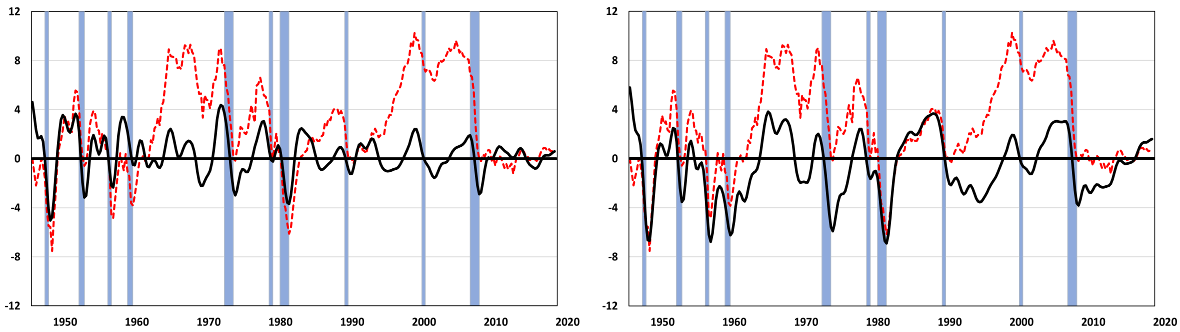
Figure 3.7: HP filtered cycles for various smoothing parameters




*Note:* Solid line: cycle and trend by HP filter, Dashed line cycle and trend by linear deterministic trend. Unit: (A) (C) (E) per cent deviation from trend (B) (D) (F) per cent, annualised rate. Shaded bars correspond to NBER recession dates. X-axis: periods (1947:1 to 2019:4.)

Figure 3.8: Bandpass filtered cycles

(A) 6-32 quarters (B) 6-80 quarters




*Note:* Solid line: cycle generated by Christiano-Fitzerald filter, Dashed line: cycle by linear deterministic trend. Unit: per cent deviation from trend. Shaded bars correspond to NBER recession dates. X-axis: periods (1947:1 to 2019:4.)

### 3.2.3 Application to Korea and Japan real output

In this subsection, I apply the decomposition strategy to the real output of Korea and Japan to see whether the boom-bust pattern is common across countries. I use Korean real GDP 1960:1-2019:4 and Japanese real GDP 1955:2-2019:4 seasonally adjusted. In the Japanese national account, 2008SNA and 1993SNA are disconnected. Therefore, I employ the growth rate of 1994:1-2019:4 from 2008SNA and the growth rate of 1955:3-1993:4 from 1993SNA. From the estimated cyclical patterns, real output of Korea is segmented in 1963:4, 1968:2, 1972:3, 1974:4, 1998:2 and 2009:1 and real output of Japan is segmented in 1959:1 1974:1, 1981:3, 1984:2, 1989:2, 2009:1 and 2019:4.

Estimated results are present in Figure 3.9. As depicted in panel (A) and (C) The cycles of Korea and Japan also display boom-bust patterns like the US cycle. However, sporadic pluckings are not observed in the cycles of Korea and Japan. Unfortunately, the results of this chapter do not explain the difference from the US cycle. A small size negative deviation is observed in the cycle of Japan between 1984:4 and 1987:4, which is allegedly related to the uncertainty surrounding the Plaza accord in 1985 which is finished by the Louvre accord in 1987.

The trend growth of the two countries also monotonically declines over time in a step-wise manner. Korea experienced the most significant drops right after the 1997 Asian Financial Crisis and after the GFC. And the other break occurred after the first Oil Crisis. The biggest drop in Japanese trend growth happened after the first Oil Crisis. And the second largest drop came with the formation and the collapse of the asset price bubble between 1986 and 1991. The trend growth of Japan slightly revived after the GFC. It may be the effect of Abenomics or just the effect of measurement error. As mentioned in section 2, the break in 1963:4 of Korea and the one in 1959:1 of Japan are not reliable as the segments are truncated with a small number of data left.

### Asymmetric effect of Global Financial Crisis on Korea and Japan

The estimated results can be applied to a puzzle: "Why was Japan hit so hard by the global financial crisis? ([85]Kawai and Shinji, 2009 ; [126]Sommer 2009; [58]Fukao and Yuan 2009[11])" Looking at its neighbour country, the issue becomes more interesting. Korea appears to have experienced a relatively mild recession during the GFC compared to Japan as shown in panel (A) of Figure 3.10. Why was Japan hit so hard? Or how could Korea avoid the effect of the GFC? A decade ago from the GFC, Korea had already experienced a severe recession during the Asian Financial Crisis and then a relatively mild recession during the GFC[12]. On the other hand, Japan experienced a mild recession during 1997 Asian Financial Crisis and it instead suffered a large swing during the GFC [13]. This implies that a country that suffers a lot from the first crisis is likely to have a relatively weak effect of the second crisis when there are two consecutive crises and vice versa. The effect of a crisis is proportional to the extent of existing disequilibrium. Once the disequilibrium is cleared during the first crisis, it commonly takes time for disequilibrium to mount again. Therefore, the disequilibrium would be small when facing the second crisis, which leads to the small effect of the crisis. The estimated cycles of Korea and Japan in Figure 3.9 describe this pattern.

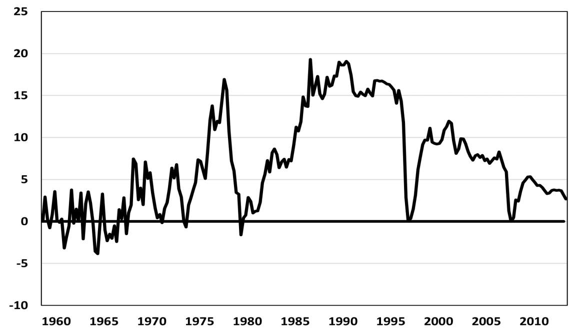
[11]They all attribute the issue to the great dependence on the export of Japan.

[12]This appears the case for Thailand, Indonesia, and Malaysia when looking at panel (B) of Figure 3.9

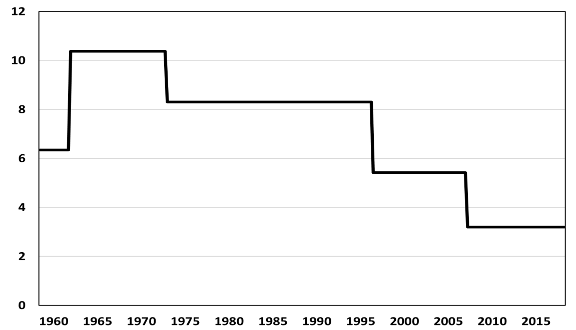
[13]Japan was not subject to a credit crunch as Japan was a lender rather than a borrower in the international financial market and was holding a largest amount of reserve in the world worth US $218 billion at the end of 1996 ([134]Yamazawa, 1998)

Figure 3.9: Cycles and trend growth of Korea and Japan

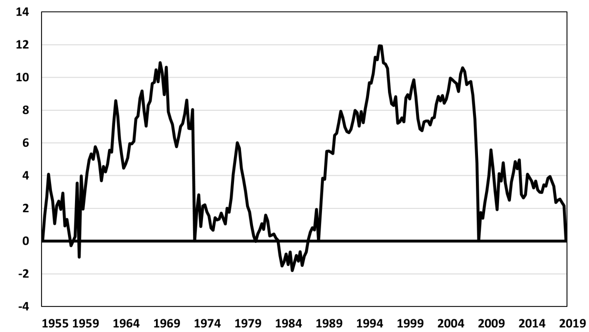
(A) Korea: cycle



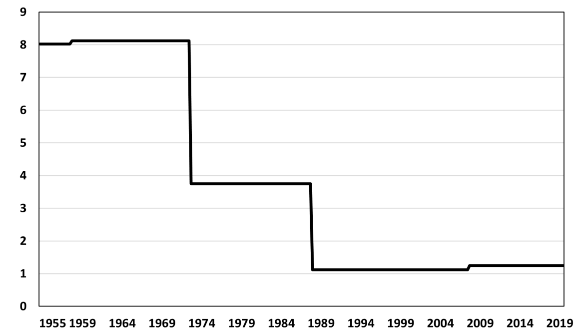

(B) Korea: trend growth




(C) Japan: cycle



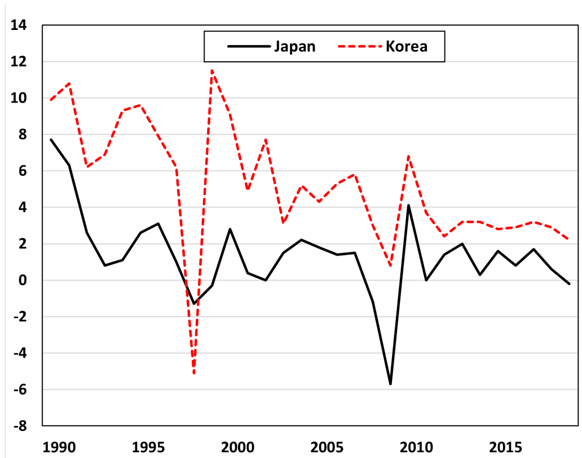

(D) Japan: trend growth



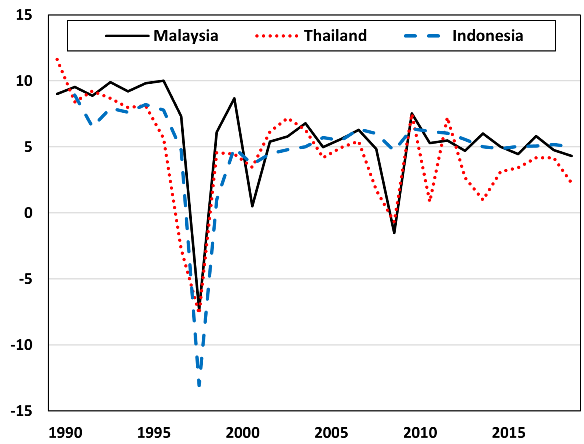

*Note:* Unit: (A) (C) per cent deviation from trend (B) (D) per cent, annualised rate. X-axis: periods (1960:1 to 2019:4 for Korea, 1955:2 to 2019:4 for Japan.)

Figure 3.10: Effect of Global and Asian Financial Crisis on Selected Asian Countries

(A) Korea and Japan




(B) Other Asian countries




*Note:* Y-axis: gdp growth(per cent) X-axis: periods (1990 to 2019), annual

## 3.3 Growth slowdown in the wake of 2008-9 Global Financial Crisis

To justify the estimated results, I also show that the estimated trend and cycle provide a new and reasonable view for the well-known macroeconomic puzzle: the slow recovery of the US economy from the 2008-9 Global Financial Crisis. The Global Financial Crisis is the collapse of a huge boom rather than a big recession, therefore, a recovery does not follow.

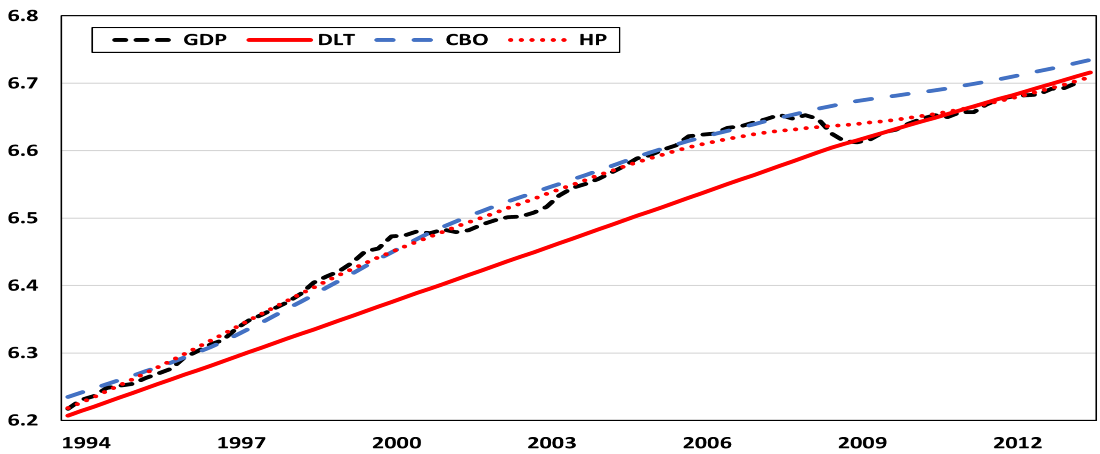
The slow recovery of US economy from the GFC has been explained by two major views. One is hysteresis ([130]Summers 2015) and the other is the slow growth of productivity ([63]Gordon 2015, [51]Fernald et al. 2017). The former view argues that the slowdown occurred right after the GFC and the latter ones argues that it started before the GFC. Meanwhile, [3]Antolin-Diaz et al., 2017 provide the evidence supporting the latter.

The estimation result of this chapter provides a different perspective on the timing of the growth slowdown of US GDP. The estimated trend growth in panel (B) of Figure 3.5 shows that US growth has been subject to a step-wise slowdown since the mid-1980s. The most of slowdown occurred right after the early 1980s recession and right after the GFC. This result implies that the growth slowdown may follow a large scale recession.

The gap between this chapter and major views is attributed to the contrasting views on the 1990s boom of US economy. I regard it as the growth over trend. On the other hand, major views regard it as a significant change in trend. The boom follows the growth slowdown of the 1980s. And the revival of US growth between the mid-1990s and mid-2000s has been regarded as the resurgence of productivity as argued by [81]Jorgenson (2001). However, this view is not robust for the following reasons. First, the Solow paradox [14] itself reflects the doubt about the effect of information technology on productivity. Second, European countries have not experienced a productivity or growth acceleration, unlike US ([16]Bloom et al. 2012). [1]Acemoglu et al. (2014) also question the effect of information technology because there is little evidence of

[14]It refers to the slowdown in productivity growth in the United States in the 1970s and 1980s despite rapid development in the field of information technology (IT) over the same period. The concept is attributed to Robert Solow, in reference to his 1987 quip, "You can see the computer age everywhere but in the productivity statistics." ([125]Solow, 1987 )

Figure 3.11: Trend between 1994:1 and 2013:4




*Note:* DT: deterministic trend, CBP: Congressional Budget Office, HP: Hodrick Prescott filter. y-axis: log real GDP(real GDP in 1947:1 = 100), x-axis: periods (1994:1 to 2013:4.)

faster productivity growth in industries that intensively use IT after the late 1990s.

In this vein, it is not reasonable to see the 1990s boom as a significant change in trend. The GFC is just a bust of boom and, therefore, a rapid recovery has not followed. The growth hike in the 1990s and the plummet during the GFC just constitute a lap of a cycle. As seen in Figure 3.11, the US GDP between 1994 to 2013 can be fitted with only one linear line with a slight change in slope in 2009:3. The actual output keeps deviating from the trend line until the GFC. On the other hand, the trend estimated by the Congressional Budget Office and the one estimated using the Hodrick-Prescott filter closely track the real output. The difference represents the contrasting views on the 1990s-boom.

## 3.4 Advocation of non-stationary cycles

As seen in panel (B) of Figure 3.5, the estimated cycle follows a pattern that is far from a stationary process. The cycle is highly persistent and abruptly reverts to the trend, unlike a stationary process that gradually reverts to the mean. And the distribution of values is highly skewed toward the zone above the trend. This is a stark difference from the estimates from other statistical methods [15]. In this subsection, I will discuss why non-stationary cycles are

[15]In a UC model, the cyclical component is assumed to be stationary. Beveridge-Nelson (BN) filter and Hodrick-Prescott (HP) filter also yield stationary cycles though they do not explicitly assume it. For the BN filter, the current cyclical component is simply proportional to the current innovation, thereby, it is stationary. HP filter

reasonable for real output.

### 3.4.1 Origins of stationary cycles

The assumption of stationary cycles is often taken for granted in the business cycle and trend-cycle decomposition literature. Where does the convention come from? First, stationary cycles have been adopted as cycles are transitory by definition. The convention was first built on the natural rate hypothesis which sees cycles as a temporary deviation from the real output corresponding to the natural rate of unemployment. In this context, the stationary cycle of output was first introduced by [95]Lucas (1973) . Later, [107]Nelson and Plosser (1982) explicitly set 'stationary' as equivalent to 'transitory'. Second, the structure of an economic time series which is first introduced in [71]Harvey (1985) has now become the standard in the trend-cycle decomposition literature. In his model, the trend and cyclical components are modelled as non-stationary and stationary respectively. The assumption helps decompose a time series without any prior information as the trend and the cycle contain different processing patterns.

### 3.4.2 Defects of the stationarity assumption

The validity of the stationarity assumption can be examined by reviewing its origins. As mentioned above, transitory cycles are considered as stationary. However, it is not clear whether the economic terminology 'transitory' can correspond to the statistical terminology 'stationary'. The term 'transitory' is pertinent to the concept of trend-reversion. On the other hand, 'stationary' requires mean-reversion and invariant autocovariance. Trend-reversion is not equivalent to mean-reversion. A trend goes through any points including the mean of a cycle. Moreover, the invariant autocovariance generates the pattern of smooth reversion to the mean. On the other hand, the term 'transitory' can have any pattern of reversion. It allows for abrupt changes which are often observed during recessions. Moreover, the [71]Harvey (1985)'s model is only built on the statistical consideration without any economic grounds. The modelling intuition of [71]Harvey (1985) came from a typical statistical model of seasonal

also yields stationary cycles after detrending ([88]King and Rebelo 1993).

adjustment such as [76]Hilmer and Tiao (1982). The model consists of three components - trend, seasonality, and irregularity. [72]Harvey and Todd (1983) adopted the same specification and then [71]Harvey (1985) switched the seasonal component into a cyclical component. And the stationarity assumption is given to the cyclical component in this course. However, it is not clear whether economic cycles necessarily need to be stationary like seasonality [16].

### 3.4.3 Evidence for non-stationary cycles

There exist evidence for non-stationary cycles in previous economic literature. First, the well-known classical business cycle hypotheses are far from stationary. The cycles described by Pigou, Hayek and Friedman are all far from a stationary process. The boom-bust style cycle described by Pigou and Hayek should locate above trend. On the other hand, the Plucking model of Friedman describes cycles that mostly locate below trend and displays an abrupt return to trend. Second, the commonly used estimate of a cycle is also different from a typical stationary process. The cycle estimated using the Congressional Budget Office's estimate of potential output (as of 2020) is skewed toward the zone above trend until the early 1970s and then toward the zone below trend. Third, non-stationary cycles can reconcile two properties of real output that appear contradictory to each other. Early studies of [19]Campbell and Mankiw(1987) and, Campbell and Mankiw(1989) demonstrate that output fluctuations are highly persistent. Meanwhile, [34]Clark (1989), [14]Blanchard and Quah(1989), [35]Cochrane (1988) and [36]Cochrane (1994) demonstrate that real output has an important trend-reverting component, which supports the existence of significant deviation from trend. These two pieces of evidence appear contradictory to each other as the first one is taken as the evidence for permanent shocks as the main source of a business cycle and the second one is taken as the evidence for transitory shocks as the main source of a business cycle. Therefore, to reconcile these two empirical observations, a possible option is a non-stationary cycle. Non-stationary cycles are transitory by definition. And they also can be highly persistent, which makes them

[16] As seasonality is the relative size of each season, the sum of seasonal factors is zero within a calendar period such as a year, a month and a week. Therefore, it is reasonable that stationarity is assumed for the seasonal component.

look like permanent changes. Fourth, another interesting evidence can be found in the long-memory literature. [42]Diebold and Rudebusch (1989) test the existence of a unit root in US real output using fractionally integrated ARIMA (ARFIMA) models. They cannot reject the null hypothesis that a unit root exists as the estimated long-memory parameter ranges from 0.5 to 0.9 where the value is 1 for the existence of a unit root. The result implies the existence of a persistent dynamics in US real output, however, not as persistent as a unit root. [127] Sowell (1992) applies ARFIMA models to the first difference of log US real output, which allows for the test of the existence of a deterministic trend as well as the existence of a unit root with drift. In his specification, the differenced long-memory parameter is -1 for a deterministic trend and 0 for a unit root with drift. The estimated parameter ranges from -0.59 to 0, which leads to the open conclusion that both specifications are possible. This implies that the dynamics of economic fluctuations can be neither a pure unit root nor a pure stationary process.

A problem is that modelling an integrated process with a trend-reverting property is not possible. However, it does not mean that such data does not exist in reality. The well-known controversy over the pattern of a stock price is relevant to this issue: Are stock prices a random walk [17] or a mean (trend)-reverting process[18] [19]? In a statistical view, the issue is a dichotomy as a random-walk process cannot have a trend-reverting property. However, the fact that scholars have not reached out an agreement implies the existence of a non-stationary process with a trend-reverting property.

## 3.5 Conclusion

Inspired by [110]Perron and Wada (2009), I decompose US real output using a DLT with three breaks. The estimated cycle follows the boom-bust pattern with sporadic downward pluckings. The estimation results have an important implication in economic literature as it revives the intuition of early economists such as Pigou and Hayek against the current major

[17] [47] Fama 1970; [120] Richardson and Stock 1989; [24]Cecchetti, Lam, and Mark 1990

[18] The mean-reverting means that a detrended stock price is mean-reverting. Therefore, it can be taken as trend-reverting.

[19] [116]Poterba and Summers 1988; [48]Fama and French (1988)

views that see economic fluctuation just as the results of random supply or demand shocks. First, economic fluctuations may result from the mount of shocks over time. The existence of non-stationary cycles indicates that shocks can be accumulated to generate an important magnitude of deviation without a large transitory shock. Second, the currently existing disequilibrium can be larger than the current business cycle models predict. This highlights the role of policy intervention.

The study of this chapter has the following caveats other than the extremeness of DLT. First, the results of this chapter are purely empirical. And therefore they do not have any theoretical ground to support them as they are not relevant to any existing business cycle theories. The only specific ideas describing the properties of the trend in real output would be the Okun's definition of potential output and the natural rate hypothesis of Friedman. However, I do not see that the estimated cycle of this chapter has any systematic relationship with inflation or unemployment[20]. Therefore, new theoretical supports are required to justify the estimation results. Second, I abstract from the real-time estimation. From a practical perspective, real-time measurement is important for timely policy intervention. Unfortunately, more consideration is required to estimate DLT with breaks in real-time than popular methods which are a kind of moving average type filters. Systematic research of real time estimation of DLT with breaks is required to enhance the practical use of the method.

[20]Including the cycle estimate of this chapter, no existing estimates of cycles have a stable relationship with inflation or unemployment. Recent studies document that the estimated cycles do not have an ability to forecast inflation ([108]Orphanides and van Norden 2005;[45]Edge and Rudd 2016; [84]Kamber et al. 2018;[117]Quast and Wolters 2020). It has become obvious with the flattened Phillips curve. And the systematic relationship between real output and unemployment is fundamentally ad-hoc and empirically appears unstable over time. Therefore, it is not reliable ([102]Meyer and Tasci 2012). This leads to skepticism about the natural rate hypothesis - Is there any long-run trend where an economy returns to? ([38]Coeur 2017 ).

# Chapter 4

# Keynes-Pigou Cycle: US Boom-bust Cycles Investigated from Keynesian Perspective

## 4.1 Introduction

The findings of [2]Angeletos et. al. (2020) support the existence of a main business-cycle driver but rule out the well-known economic shocks for this role[1]. In contrast, they choose models that allow for demand-driven cycles under flexible prices as promising candidates. The purpose of this chapter is to investigate the demand-driven business cycle mechanism in this context.

In chapter 2, I demonstrated that the US business cycle displays a boom-bust pattern with sporadic pluckings. Then what is the source of the boom-bust cycle? To answer the question, I decompose the components of output using the strategy introduced in chapter 2. The decomposition results show that the cycles of consumption and investment are close to the one of output in pattern, and they are close to each other in pattern and magnitude. This result implies two possible cases. First, the existence of shocks driving the fluctuations in both consumption and investment. This view corresponds to common business cycle models

[1] technology or other shocks that map to TFP movements; news about future productivity; and inflationary demand shocks of the textbook type.

assuming that neutral technology shocks are the main driver of business cycles. However, the assumption cannot be applied to the transitory cycles. Second, consumption shocks drive the fluctuations of investment or vice versa. This chapter investigates the second case from the perspective of [86]Keynes (1936) and [115]Pigou (1927).

In this chapter, I argue that business cycles are generated by consumption shocks and their propagation to investment. This propagation channel amplifies the boom-bust cycle of consumption. The idea that the boom-bust cycle driven by the expectations of businessmen has early been discussed by [115]Pigou (1927). However, his intuition has not developed to a detailed idea which elaborates the causes of fluctuations in businessmen's expectation[2]. Meanwhile, [86]Keynes (1936) also emphasizes the role of businessmen's expectations as a major source of economic fluctuations. Moreover, he argues that current consumption affects investment by adjusting the businessmen's expectations of future consumption[3]. The idea of this chapter is the combination of intuitions from the two economists. In this sense, I name it 'Keynes-Pigou cycle.'

In this context, the analyses in this chapter are conducted from the Keynesian perspective. First, all the employed variables are detrended using the strategy introduced in chapter 2. The practice is based on the view of Keynes who distinguished short-run fluctuations from long-run growth. Therefore, all the results can be interpreted as transitory. Second, the output fluctuations are obtained by aggregating the fluctuations of GDP components. To achieve the additivity across the components, I employ the contribution of each component to GDP growth instead of the component growth. Contribution to GDP growth and growth data are fundamentally equivalent in that both are standardised changes. I denote contribution to GDP growth as (scaled) changes throughout this chapter following [20]Campbell and Deaton (1989) and [21]Campbell and Mankiw(1990).

To demonstrate the causal relationship between consumption and investment, I estimate a system of reduced form investment models using ordinary least square (OLS). In those models, the changes in non-residential, residential, and inventory investments are represented as the

[2] [115]Pigou (1927) mainly discusses the causes of forecast errors.

[3] However, his idea of business cycles is close to the plucking model of Friedman.

function of current consumption changes. As I assume that consumption is predetermined for investment and the changes in the components of investment do not contemporaneously affect each other, the models can be estimated using OLS. And then I predict the cycle of investment using the estimated models. The predicted cycle of investment is close to the one estimated through decomposition. This result supports Keynes' intuition that current consumption is an important determinant of current investment.

Then I estimate the effects of consumption shocks on investment changes. As consumption changes include endogenous effect, I estimate exogenous consumption shocks using the specification introduced by [106]Nelson (1987), which accounts for endogenous income effects and the persistence of consumption. The estimated consumption shocks are very close to the consumption changes. Then I estimate the above investment models using the exogenous consumption shocks and acquire the results that are close to the ones obtained using consumption changes.

Then I show that the response of investment to a consumption shock is long-lasting and important in magnitude as observed in the benchmark boom-bust cycle of investment. I first estimate the responses of investment using the estimated exogenous shocks and the OLS models employed in Section 4.5. Then I hire structural vector autoregression (SVAR) models. Vector autoregression (VAR) is just a generalised system of unrestricted OLS equations. [124]Sims (1980) advocates SVAR against incredible restrictions imposed on empirical models. The models of this chapter cannot be free from the Sim's criticism though I carefully construct them from the perspective of Keynes. The estimated responses show that a consumption shock generates long-lasting dynamics of investment like a random walk. The result contrasts with the well-known hump-shaped response of output to a demand shock. However, the result cannot be interpreted as a permanent change as all the variables are detrended prior to conducting the analysis.

To solve the systems without the issue of simultaneity, I assume that consumption is predetermined for investment. However, current investment changes lead to an identical change in current GDP. current GDP changes are likely to affect current personal income, which may affect current consumption. Thus, simultaneity may arise. However, there are two suspected points that disconnect the channel. First, the effect of GDP changes on personal income changes is uncertain. In reality, unlike a typical neoclassical model, the source of personal income is diverse and thus it is affected by various factors. The correlation between GDP changes and the changes in disposable personal income is less than 0.5. Second, the effect of current income changes on current consumption changes is small. A well-known fact is that consumption is far smoother than income ([20]Campbell and Deaton, 1989 )[4]. It means that the feedback effect from investment to consumption is small and the possibility of simultaneity is low. To support it, I estimate the effect of current investment changes on current consumption changes. To reduce the effect of the potential simultaneity, I estimate the effect indirectly. I first estimate the effect of the changes in each investment component on income changes and then the effect of disposable personal income changes on consumption. Then I obtain the effect of changes in each investment component on consumption changes by multiplying the two effects. The estimated effect is very small for each investment component.

It is hard to find papers studying the effect of consumption shocks on investment. Relatively close are ones that study the effect of consumption shocks on output ([69]Hall(1984);[13]Blanchard 1993;[36]Cochrane, 1994a;[37]Cochrane, 1994b). However, those studies raised the issues without elaborating on the underlying mechanism. [12] Benhabib and Wen (2004), [133]Wen (2006), [52]Fernandez-Villaverde and Guerroni-Quintana(2020) study the effect of consumption shocks using Real Business Cycle (RBC) models. However, consumption shocks do not appear successful to replicate the dynamics of actual data which display the comovement of consumption and investment. [94]Lorenzoni(2009)/citeLorenzoni.2009 also study the effect of consumption shocks. However, his model does not employ the investment dynamics and, thus, cannot study the consumption-investment relationship. Another related strand of papers studies the effect of investment shocks on business cycles. These papers are inspired by [86]Keynes' (1936) intuition that regards the shocks to the marginal efficiency of investment as a major source

[4]As I detrend variables using a linear deterministic trend with breaks, all the fluctuations except for the upward sloping trend are left in each variable. It means that the detrended consumption is still smoother than the detrended income.

of output fluctuations. [65]Greenwood, Hercowitz and Huffman (1988), and [82]Justiano et al. (2011) demonstrate that shocks to the marginal efficiency of investment account for most of the output fluctuations of the US economy in a neoclassical and a new neoclassical synthesis model respectively. However, they assume artificial investment shocks to generate output fluctuations without investigating the source of investment shocks. On the other hand, this chapter empirically demonstrates that consumption shocks are the main source of investment shocks.

The remainder of this paper is organized as follows. Section 2 introduces the important features of data employed in this chapter. Section 3 discusses how the intuitions of Keynes and Pigou are reconciled to provide a new perspective of business cycles. Section 4 discusses modelling the effect of consumption on investment based on the intuition of Keynes. Section 5 estimates the effect of consumption shocks on investment. Section 6 discuss robustness. Section 7 concludes.

## 4.2 Data

For the analysis of this chapter, I use US real GDP growth and contribution of its components to GDP growth 1950:3-2019:4 seasonally adjusted[5]. The data is obtained from the US Bureau of Economic Analysis. The data from 1947:2 to 1950:2 is abstracted as the detrending results are unreliable. The employed detrending method is a kind of segmented trend estimation. As discussed in chapter 2, the first segment is truncated with the small number of data left in the segment and, thus, the estimated trend growth is unreliable.

The employment of contribution data has been adopted by [18]Campbell and Deaton (1989) and [21]Campbell and Mankiw (1990). They name contribution to output growth 'scaled changes'[6]. In the following analyses, (scaled) changes in a GDP component indicates the contribution of the component to GDP growth. And I use lowercase letters to denote (scaled) changes of variables and uppercase letters to denote the corresponding level variables. For example,

[5]The data is collected in July 2021.

[6]A difference from this chapter is that they compute contribution to output growth using the constant weighted real GDP and its components while I use the chain-weighted real GDP and its components

$c_t$ denotes the (scaled) changes in consumption and $C_t = C_{t-1} + c_t$. $C_t$ is the % deviation of consumption from the trend of real output.

### 4.2.1 Use of contribution to output growth

Contrary to the common convention of using growth rate in analysis, I employ contribution to output growth for the components of output. Contribution data has several advantages over growth rates. First, the size of value can be directly compared across GDP and components as they are all measured in the unit of GDP growth. Therefore, the magnitude of cycles that are built using contribution data also can be directly compared. Second, additivity holds across the components. For example, the aggregation of cycles of non-residential, residential and inventory investment yields the cycle of gross investment. Finally, the estimated coefficients of regression can be directly compared. For any variables, regression coefficients can be read as %p change of output growth for the one %p change of output growth [7].

Growth rate and contribution to output growth are fundamentally equivalent in that both are a kind of standardised changes. For example, if $X_i$ is a component of output Y, then both growth rate and contribution can be written in the form of $w_i(t)\Delta X_i(t) * 100$ where $w_i(t)$ is the weight used for standardisation at time t. For growth rate, $w_i(t)$ is $X_i(t-1)$, while for contribution to output growth, $w_i(t)$ is

$$\frac{P_i^*(t)}{\sum_{i=1}^{n}(P_i^*(t)X_i(t-1))}$$

where $P_i^*(t)$ is the weight of component i at time t. The value is $P_i(t-1) + P_i(t)/\Pi(t)$ for a Fisher index where $\Pi(t) = P(t)/P(t-1)$ and $P(t)$ is the GDP deflator at time t. The value is $P_i(t-1)$ for a Laspeyres index, and $P_i(t)$ for a Passche index. $P_i$ and $X_i$ are the price and quantity of the component i.

The weight is the composite of level values and thus it smoothly varies. Therefore, most of the variations ascribe to $\Delta X_i(t)$. As shown in Table 1, the correlation between growth rate and contribution is close to 1 for every component.

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[7]For a similar reason, this practice is employed by [20][21]Campbell and Mankiw (1989, 1990)

Table 4.1: Correlation between output growth and contribution to output growth

| | Consumption | Investment | Non-residential | Residential |
|---|---|---|---|---|
| Corr | 0.9979 | 0.9936 | 0.9853 | 0.9684 |

### 4.2.2 Detrending

The variables used in this chapter are all detrended using a linear deterministic trend with breaks following the strategy introduced in chapter 2. This practice is based on the Keynesian perspective that the mechanism of short-run fluctuation is distinct from the one of long-run growth and what matters are short-run fluctuations.[8].

An important merit of detrended data is that the estimation results can be interpreted as cyclical movements without confusion with the trend changes such as the effect of neutral technology shocks. Despite the advantage, I admit that the estimation results may be contaminated by ad-hoc detrending. In my defense, ad-hoc and empirical detrending has become a common practice that has continued since various methods of trend estimation were introduced[9]. And in chapter 2, I demonstrate that the decomposition using a deterministic linear trend with breaks yield boom-bust cycles that is corresponding to a well-known classical hypothesis and a common perception of business cycles. Moreover, a deterministic linear trend is the most harmless method from a Keynesian perspective. The method ascribes all the economic fluctuations to the cyclical component and the trend component only accounts for a monotonic upward trend. Therefore, the method does not distort the cyclical pattern even though it may overestimate the magnitude.

[8]Keynes supported his philosophy by saying "We are all dead in the long-run."

[9]see [95]Lucas(1973) for linear trends, [77]Hodrick and Prescott(1997) for the HP filtering, and [71]Harvey (1985) for unobserved component models.

## 4.3 Keynes-Pigou Cycle

### 4.3.1 Motivating Observations

The components of US real GDP are decomposed into the cycle and trend components using the strategy introduced in chapter 2. The break points of US real GDP that are detected in chapter 2 are employed[10]. The break points are assumed to be identical across the US real GDP and its components. An economic time series $y_t$ is assumed to consist of the trend $\tau_t$ and cyclical components $\mathbb{c}_t$.

$$y_t^j = \tau_t^j + \mathbb{c}_t^j \quad \text{where} \quad j = GDP, C, I, G$$

Taking a first-order difference of $y_t^j$ yields the following process.

$$\Delta y_t^j = \mu_t^j + \Delta \mathbb{c}_t^j$$

$\Delta y_t^j$ is the contribution of each component to output growth. $y_t^j$ can be taken as the level of a component whose price is adjusted to the price of real output. The additivity of components into a real GDP still holds for the trends and cycles.

$$\tau_t^{GDP} = \tau_t^C + \tau_t^I + \tau_t^G + \tau_t^{NX}$$

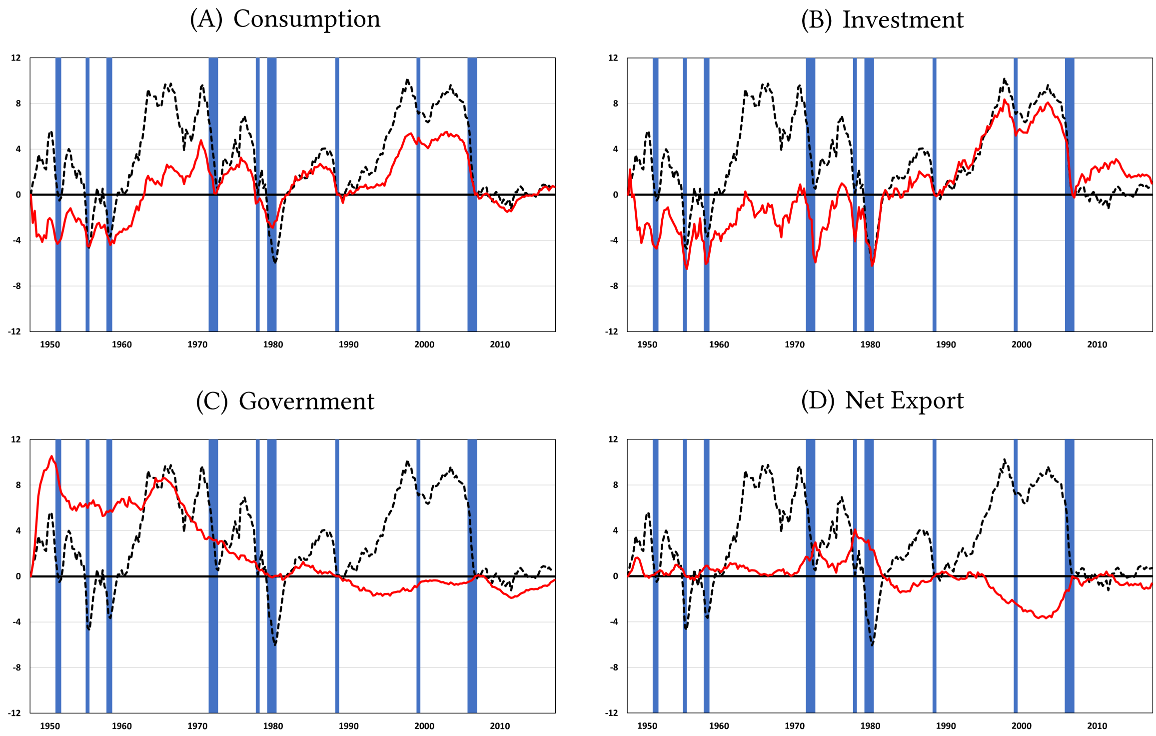
$$\mathbb{c}_t^{GDP} = \mathbb{c}_t^C + \mathbb{c}_t^I + \mathbb{c}_t^G + \mathbb{c}_t^{NX}$$

Estimated cycles are present in Section 4.3.1. As depicted in panel (A) and (B), the cycles of consumption and investment are very close to the one of real GDP and they all follow boom-bust patterns with sporadic downward pluckings. This is consistent with the well-known business cycle facts that consumption and investment are procyclical and largely coincident with GDP. These results suggest two possible cases. First, the existence of shocks driving the fluctuations in both consumption and investment. This view corresponds to common business

[10] They are in 1984:3, 1991:2 and 2009:3

cycle models that assume the existence of neutral technology shocks. Second, consumption shocks drive the fluctuations of investment or vice versa. I investigate the second case from the perspective of [86]Keynes (1936) and [115]Pigou (1927).

Figure 4.1: Cyclical movements of GDP components




*Note:* Solid line: the estimated cycle of each component, Dashed line: the estimated cycle of GDP. Units are per cent deviation from real GDP trend. Shaded bars correspond to NBER recession dates. X-axis: periods (1950:3 to 2019:4.)

### 4.3.2 Reconciling Keynes and Pigou

The US business cycle depicted in Section 4.3.1 follows a boom-bust pattern as described by [115]Pigou (1927). On the other hand, the business cycle pattern that attracted the [86]Keynes'(1936) attention is the downward deviations from the full employment output which appears similar to the downward pluckings described by [56]Friedman (1968)[11]. The two types of business cycle are in stark opposition as the boom-bust cycle moves above trend while downward pluckings locate below trend.

Despite the contrasting views on the pattern of business cycles, [115]Pigou (1927) and

[11] "The right remedy for the trade cycle is ... to be found ... in abolishing slumps and thus keeping us permanently in a quasi-boom." ([86] 1936, p.159)

[86]Keynes (1937) have a commonality in that both highlight the importance of businessmen's expectations as an important driver of business cycles. Pigou argues that a business cycle is driven by businessmen's over-optimism and perception of errors [12] [13]. Keynes similarly argues that the animal spirits of businessmen are a crucial factor determining the marginal efficiency of capital [14]. This intuition of Keynes and Pigou has been empirically studied by a handful of previous studies [15].

The expectation of businessmen links Keynes' and Pigou's views that appear different from each other. In Pigou's intuition, the businessmen's expectation generates a boom-bust pattern of business cycles. And Keynes provides an idea that the change in present consumption affects the businessmen's expectations. By reconciling two economists, a boom-bust cycle generated by consumption shocks is achieved.

### 4.3.3 Effects of consumption shocks on investment changes

Table 4.2: Cross-correlation between consumption changes and investment changes

| Lag | Investment | Fixed investment | Non-residential | Residential | Inventory |
|---|---|---|---|---|---|
| -3 | 0.057 | 0.138 | 0.250 | -0.070 | -0.015 |
| -2 | 0.120 | 0.283 | 0.326 | 0.096 | -0.026 |
| -1 | 0.504 | 0.370 | 0.343 | 0.229 | 0.415 |
| 0 | 0.204 | 0.594 | 0.457 | 0.486 | -0.115 |
| 1 | 0.324 | 0.260 | 0.097 | 0.338 | 0.254 |
| 2 | 0.111 | 0.199 | 0.024 | 0.322 | 0.016 |
| 3 | -0.083 | 0.030 | -0.115 | 0.195 | -0.127 |

Lag indicates the relative lag of investment changes to consumption changes.

[12]Pigou (1927, pp.29) "the varying expectations of business men ... and not anything else, constitute the immediate and direct causes or antecedents of industrial fluctuation."

[13]In the same period, a boom-bust pattern business cycle is formulated by [74]Hayek (1933) while the Pigouvian cycle has been left as an intuition until recently. However, the source of business cycles is over-optimism in Pigou's idea of a business cycle while it is the low interest rate in Austrian business cycle theory

[14]However, [75]Hicks (1937) did not agree to the idea and ignored the effect of animal spirits when he modelled the Keynes' idea. " Surely there is every reason to suppose that an increase in the demand for consumers' goods, arising from an increase in employment, will often directly stimulate an increase in investment, at least as soon as an expectation develops that the increased demand will continue. If this is so, we ought to include I in the second equation, though it must be confessed that the effect of I on the marginal efficiency of capital will be fitful and irregular." (p.156)

[15][46]Eisner(1978), [39]Cummins, Hassett, and Oliner (2006), Guiso, Pistaferri, and Suryanarayanan (2006), [4]Arif and Lee (2014), [67]Greenwood and Hanson (2015), [60]Gennaioli, Ma and Shleifer (2016)

In this subsection, I provide evidence supporting the role of consumption shocks. First, I reexamine the well-known stylised facts of business cycles. The substantial correlation between consumption changes and the changes in investment components implies the potential causality between them. And the different patterns of correlation between fixed investment changes and inventory changes imply that one neutral technology shock is not enough to account for the two distinguished patterns even though the Real Business Cycle theory is right. Second, I estimate the responses of output changes to consumption shocks and investment shocks using SVAR models with two variables. It supports the propagation of consumption shocks but does not support the propagation of investment shocks.

The key features of the Keynes-Pigou cycle are (1) the highly persistent movements of consumption cycles and (2) the effect of consumption changes on investment changes. I already demonstrate that the US consumption cycle is highly persistent and assume that consumption changes are predetermined. Therefore, if the second feature is true, the investment cycle will also display highly persistent movements.

It is hard to find papers studying the effects of consumption shocks on investment. [13]Blanchard (1993),[36][37] Cochrane (1994a, 1994b) demonstrate that long-lasting responses of output and consumption to a consumption shock using SVAR models [16].

Both Consumption and investment are known to be coincident and procyclical with output ([92]Kydland and Prescott 1990). These facts are based on the data detrended using Hodrick-Prescott filtering . And they are confirmed by the data detrended using the bandpass filter ( [128]Stock and Watson 1999). This result is largely consistent with the results of [22]Canova (1998) who employs various detrending methods even though the detail of cyclical patterns varies across methods. There is a different finding. [12]Benhabib et al. (2004) find that consumption leads output and investment by one or two quarters using the band-pass filtered data.

In Table 4.2, the cross-correlation between consumption and investment is present which is estimated using the data of this chapter. Unlike well-known stylised facts, consumption

[16]In a standard neoclassical model, consumption shocks contemporaneously reduce investment. However, the response of investment is not consistent with well-known stylised facts of business cycles that both consumption and investment are procyclical.

leads investment by one quarter. It is corresponding to the finding of [12]Benhabib et al. (2004). However, the result is changed if inventory investment is excluded from aggregate investment. Fixed investment, non-residential and residential investment are all coincident with consumption. On the other, inventory changes lags consumption changes and it is negatively correlated with consumption changes at lag 0. The different correlation pattern between fixed investment changes and inventory changes implies that a neutral technology shock is not enough to account for these two different patterns. In typical neoclassical models, a neutral technology shock contemporaneously affects consumption and investment through the production function.

To document the causal relationship between consumption changes and investment changes, I conduct simple experiments using bivariate-SVAR models including GDP and consumption. I estimate VAR(1) using OLS. To identify consumption shocks, I set a common shock that contemporaneously affects GDP and consumption. As consumption is a component of GDP, the common shock can be taken as a consumption shock if the coefficient of consumption changes on GDP growth is one. The other shock only affects GDP. Thus, it can be regarded as a composite of the other demand shocks. The identification scheme is summarized in Equation 4.1.

$$\begin{pmatrix} u_t^y \\ u_t^c \end{pmatrix} = \begin{pmatrix} -b_{22}u_t^c + w_t^{nc} \\ w_t^c \end{pmatrix} \tag{4.1}$$

where $u_t^y$, $u_t^c$ are reduced-form residuals of output and consumption, and $w_t^c$ and $w_t^{nc}$ are structural shocks to consumption and non-consumption respectively. As consumption is a component of GDP, $-b_{22}$ should be unity. This identification is similar to the one employed by [13]Blanchard (1993) and [37]Cochrane(1994). Consumption shocks are not confused with neutral technology shocks as the secular trend is already removed from each variable. The estimation results can be written in a structural form as follows:

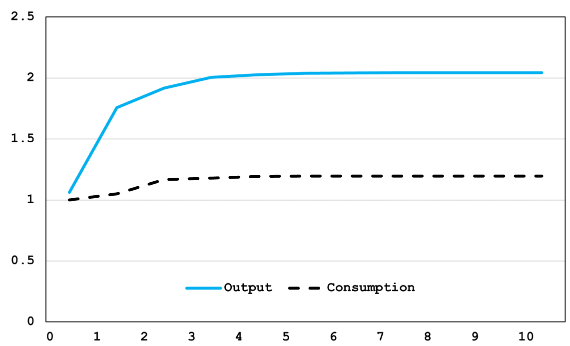
$$\begin{aligned} y_t &= 1.0617c_t + 0.2203y_{t-1} + 0.2643c_{t-1} + w_t^{nc} \\ c_t &= 0.0841y_{t-1} - 0.0648c_{t-1} + w_t^c \end{aligned}$$

Where $c_t$ and $y_t$ are consumption changes and output growth respectively. $w_t^c$ and $w_t^{nc}$ are a structural shock to consumption and a structural shock to non-consumption respectively.

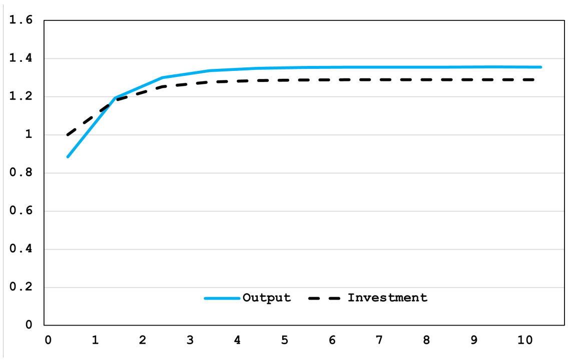
The coefficient of $c_t$ on $y_t$ is close to unity. This indicates that a consumption shock is economically identified. Both $y_t$ and $c_t$ contemporaneously change by about 1%p for a 1%p consumption shock. Moreover, in the second equation, the coefficients on $y_{t-1}$ and $c_{t-1}$ are close to zero. This indicates that detrended consumption is close to a random walk as Hall (1978)[68] argues. This result indicates that the consumption shocks are accumulated to create a long-lasting cycle over time.

Figure 4.2: Response of output to a demand shock

(A) Consumption shock




(B) Investment shock




*Note:* Vertical axis: per cent point, Horizontal axis: time horizon in quarters.

Estimated responses to a consumption shock are present in panel (A) of Figure 4.2. The cumulative effect on GDP is 2.04%p while the effect on consumption is 1.20%p. The gap between the two responses is around 0.84%p. This means that a consumption shock affects other components besides consumption. This implies the propagation of consumption shocks to other components.

I also discuss the effect of investment shocks as investment shocks are a more popular mechanism than consumption shocks in the business cycle literature. Nevertheless, it is hard to find studies that empirically investigate the effect of investment shocks on GDP and its components. [53]Fisher (2006) only documents that investment shocks generate persistent effects on output. However, the specific mechanism should depend on neoclassical models.

According to a typical neoclassical model, investment shocks contemporaneously cause a crowd-output effect on consumption. Then it again leads to the growth of consumption over time, which makes the consumption changes negatively correlated with the investment changes at lag 0 and the consumption changes lag the investment changes. The results contradict the well-known stylised facts and the cross-correlation presented in Table 4.2.

I identify investment shocks the same way as before. The estimated structural equations are as below:

$$y_t = 0.8848 i_t + 0.3670 y_{t-1} - 0.0341 i_{t-1} + w_t^{ni}$$
$$i_t = 0.2023 y_{t-1} - 0.0407 i_{t-1} + w_t^{i}$$

Where $i_t$ and $y_t$ are investment changes and output growth respectively. $w_t^i$ and $w_t^{ni}$ are a structural shock to investment and a structural shock to non-investment respectively.
The estimation results are also economically identified as the coefficient of $i_t$ on $y_t$ is 0.88 which is close to unity. The response of output to an investment shock is close to the response of investment to an investment shock in size as depicted in panel (B) of Figure 4.2. The estimated responses imply that investment shocks barely propagate to consumption and other components. Therefore, investment shocks are not a good candidate for a main source of business cycles.

## 4.4 Businessmen's expectation is not just psychological

In this section, I introduce the intuitions in detail which is behind the reduced form models and the short-run restrictions employed in the next section.

Keynes and Pigou highlight the role of businessmen's expectation as a major source of economic fluctuations. How can we quantify the expectation of businessmen? The problem of psychological factors is that they are hard to identify or to measure as they are unobservable in macro level. [10]Beaudry and Portier (2004) try to quantify this psychological factor by identifying news shocks. [103]Milani (2011) tries to measure it via the estimation of expectation shocks. However, the model-based estimation or identification of shocks is highly dependent on the assumptions of the model. Thus, it is hard to get consistent estimation results as the estimation results can vary across models and assumptions.

To tackle the issue, I employ current consumption changes as proxies for shocks on businessmen's expectation based on the Keynes'(1936)[86] intuition. The formation of expectation depends on the observed facts and on the forecasts[17]. It is reasonable that the expectation should mainly depend on the observation of current demand that is the most certain information. In particular, Keynes emphasizes the role of current consumption [18].

Extending his intuition, I set Investment as the function of expected final demand instead of consumption. The final demand comprises consumption, investment, export, and government spending. The superscript e indicates that it is an expected value for the future. In following discussion, I is investment, FD is final demand, C is consumption, EX is export, G is government spending, NR is non-residential investment, R is residential investment, INV is inventory, ND is non-durable consumption, D is durable consumption, and S is service consumption. Lowercase letters variables denote the changes in the corresponding level variables.

$$I_t = F(FD^e) = F(C^e, I^e, EX^e, G^e)$$

The crucial issue is to model expected value of each demand component. The expected value of a variable can be represented as the function of the current variable. For example, the expected consumption is

$$C^e = E_t[C_{t+k}] = E_t[C_t + c_{t+1} + \cdots + c_{t+k}]$$

[17]"The formation of expectation depends partly on existing facts which we can be assumed to be known, and partly future events which can only be forecasted with more or less confidence. However, it would be foolish, in forming our expectations, to attach great weight to matters which are very uncertain. It is reasonable, therefore, to be guided to a considerable degree by the facts about which we feel somewhat confident, even though they may be less decisively relevant to the issue than other facts about which our knowledge is value and scanty.... Our conclusion must mainly depend upon the actual observation of markets and business psychology." ([86]Keynes 1936, p. 75)

[18]"Moreover, the expectation of future consumption is so largely based on current experience of present consumption that a reduction in the latter is likely to depress the former, with the result that the act of saving will not merely depress the price of consumption-goods and leave the marginal efficiency of existing capital unaffected, but may actually tend to depress the latter also. In this event it may reduce present investment-demand as well as present consumption demand."(Keynes, 1936, p.105)

where $c_t = C_t - C_{t-1}$. t represents the current time and t+k represents the arbitrary time in the future. In difference terms,

$$c^e = C^e - C_{t-1} = c_t + c_{t+1} + \cdots + c_{t+k}$$

For a random walk consumption as argued by Hall (1978), $c_t = \epsilon_t$. Then

$$c^e = E_t[c_t + \cdots + c_{t+k}] = c_t$$

For the consumption with habit, $c_t = a_1 c_{t-1} + \epsilon_t$.

$$c^e = (1 + a_1 + \cdots + a_1^k)c_t + (1 + a_1 + \cdots + a_1^k)\epsilon_t + \cdots + \epsilon_{t-k}$$

$$c_e = b_0 c_t$$

Under the assumption that the lag order of $i_t$, $ex_t$ and $g_t$ is less than 2, the expected investment in change or export in change can be written as the function of the current variables.

$$i^e = b_1 i_t$$

$$ex^e = b_2 ex_t$$

$$g^e = b_3 g_t$$

Equation (1) can be written in first-difference terms.

$$i_t = f(c^e, i^e, ex^e, g^e) = \hat{f}(c_t, i_t, ex_t, g_t)$$

Investment comprises the three components: non-residential, residential and inventory investment. Each component has a different characteristic. And as shown in Section 4.3.3, the comovement pattern with consumption is different between fixed investment and inventory changes. Therefore, a different specification can be considered for each component.

In following subsections, I assume that investment components do not affect each other contemporaneously for the following reasons. First, investment is very volatile and unpredictable relative to consumption. Therefore, the expectation of investment has little point. In particular, expecting future inventory is of no use as it is highly volatile and it is hard to see inventory changes effective demand. Second, it is hard to identify the effect of current investment changes in reduced-form models as they are highly correlated with current consumption changes.

### 4.4.1 Non-residential investment

Non-residential investment is commonly considered as a business investment. Therefore, it is the most closely related to the current demand. Previous studies report that a lagged variable explain the investment movement well ([31]Christiano et. al. 2005;[44]Eberly, Rebelo and Vincent 2012). The non-residential investment can be represented as the function of the expected final demand and the lagged non-residential investment.

$$NR_t = F^{NR}(NR_{t-1}, E_t[C^e, EX^e, G^e])$$

The equation can be written in first-difference terms.

$$nr_t = f^{nr}(nr_{t-1}, E_t[c^e ex^e g^e]) = \hat{f}^{nr}(nr_{t-1}, c_t, ex_t, g_t) \tag{4.2}$$

### 4.4.2 Residential investment

Residential investment is modelled as the function of housing sales. As an ad-hoc consideration, a lagged term of residential investment is added like in the model of residential investment.

$$R_t = F^R(R_{t-1}, HS^e)$$

where HS is housing sales.

In difference terms,

$$r_t = f^r(r_{t-1}E_t[hs^e]) = \hat{f}^r(r_{t-1}, hs_t) \tag{4.3}$$

A critical issue is to link the housing sales to GDP components. In a typical economic model, housing is classified as a part of durables ([114]Piazzesi and Schneider 2016). It is reasonable as residential structures are highly durable [19]. And the purchase of a new house is likely to be subject to the decision making which is similar to that of durables. [96]Luengo-Prado (2006) demonstrates that according to the Federal Reserve Board's 1998 Survey of Consumer Finances (SCF), collateral borrowing, mainly obtained to purchase housing and automobiles, is the principal type of borrowing undertaken by households. If the purchase of housing is correlated with the purchase of automobiles, durable consumption can be a good proxy for housing sales as the volatility of automobile consumption account for most of durable consumption's volatility[20].

$$r_t = \hat{f}^r(r_{t-1}, d_t)$$

To make it matched to other components, I employ aggregation consumption instead of durable consumption. As durable consumption is highly correlated with aggregate consumption[21], it would not make a big difference.

$$r_t = \hat{f}^r(r_{t-1}, c_t) \tag{4.4}$$

### 4.4.3 Inventory

The stockout avoidance theory ([83]Kahn (1987)) is employed to explain the dynamics of inventory investment. [132]Wen (2005) demonstrates that the theory has much better potential than other competing theories for explaining the features of observed inventory fluctuations[22]

[19]However, housing is also different from other durables as it works as an asset whose value tends to increase over time.

[20]The standard deviation is 0.94 for automobiles, 0.43 for furnishing and durable household equipment, 0.19 for recreational goods and vehicles, and 0.13 for other durable goods when using the data of contribution to GDP growth between 1950:3 and 2019:4.

[21]The correlation between aggregate consumption and durable consumption is 0.863.

[22]I assume that INV>0 at all time, then the demand is equivalent to the actual sales. This assumption makes sense as US inventory stock always larger than trend for the given period. In this case, the trend can be taken as

$P$ is production, $\theta$ is demand (sales) for the product, and $INV$ is inventory stock.

$$P_t = E_{t-1}[\theta_t] - INV_{t-1}$$

$$INV_t = P_t + INV_{t-1} - \theta_t$$

$$INV_t = E_{t-1}[\theta_t] - \theta_t$$

When the production depends on the expectation of sales at t-1, inventory stock is the difference between the expectation and the actual sales. Taking a first-order difference of $INV_t$ leads to

$$inv_t = (E_{t-1}[\theta_t] - E_{t-2}[\theta_{t-1}]) - (\theta_t - \theta_{t-1})$$

I assume that $E_t[\theta_t] = h(\theta_t)$ and $h(\cdot)$ is a linear function, and then $E_{t-1}[\theta_t] - E_{t-2}[\theta_{t-1}] = h(\Delta\theta_t)$. Then it leads to

$$E_{t-1}[\Delta\theta_t] - \Delta\theta_t = f^{inv}(\Delta\theta_{t-1}, \Delta\theta_t)$$

The remarkable difference from the other investment components is that there is no need to make expectation of the future demand. To manage the inventory stock, the expectation of the current demand is required. And the expectation is made at the previous period.

An issue is to find a proxy for sales. The demand for goods is hard to predict using GDP components as the demand includes raw materials as well as finished goods. Considered is the fact that the demand for raw materials also depends on the demand for finished goods. In this vein, in the inventory literature, the total sales is defined as GDP minus inventory investment. I assume that the changes in investment components does not affect each other. Therefore I employ consumption as a proxy for total sales. It is reasonable as there is little incentive to stock inventory for fixed investment as it is a more planned expenditure than consumption. For fixed investment, the decision making entities are equivalent in both demand and supply side

the optimal cut-off point.

and thus forecasting errors are unlikely. Government spending and export are also not included as they are more planned demand and thus unlikely to affect inventory stocks. Therefore, assuming $\Delta\theta_t = g(c_t)$,

$$inv_t = f^{inv}(g(c_t), g(c_{t-1})) = \hat{f}^{inv}(c_t, c_{t-1}) \tag{4.5}$$

## 4.5 Examination of the Keynes' intuition

### 4.5.1 Model

In this subsection, I estimate the reduced form investment models using OLS. The estimated model will be used to predict the investment dynamics. By comparing the predicted investment cycle and the cycle estimated through decomposition, the prediction ability of the models can be assessed. The OLS estimation has two merits over SVAR. First, the causal relationship between current consumption changes and current investment changes can be statistically tested. Second, the prediction of investment can be achieved only depending on observed data without additional assumptions.

The OLS estimators are unbiased as I assume that consumption is predetermined for investment, and the changes in investment components does not mutually affect each other contemporaneously. As specified in the section 4, three investment models are set out.

$$nr_t = \alpha_1 nr_{t-1} + \alpha_2 c_t + \alpha_3 ex_t + \alpha_4 g_t + \eta_{1t} \tag{4.6}$$

$$r_t = \beta_1 r_{t-1} + \beta_2 c_t + \eta_{2t} \tag{4.7}$$

$$inv_t = \gamma_1 c_t + \gamma_2 c_{t-1} + \eta_{3t} \tag{4.8}$$

Table 4.3: Non-residential Investment

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag(1) | 0.403*** | 0.402*** | 0.402*** | 0.403*** |
| | (0.045) | (0.048) | (0.045) | (0.045) |
| c | 0.241*** | 0.241*** | 0.241*** | 0.241*** |
| | (0.026) | (0.026) | (0.026) | (0.026) |
| ex | 0.294*** | 0.295*** | 0.295*** | 0.294*** |
| | (0.050) | (0.050) | (0.050) | (0.050) |
| g | | -0.021 | | |
| | | (0.035) | | |
| sg | | | -0.071 | |
| | | | (0.133) | |
| ndg | | | | -0.047 |
| | | | | (0.113) |
| $R^2$ | 0.484 | 0.485 | 0.485 | 0.485 |
| Obs | 276 | 276 | 276 | 276 |

Dependent variable is non-residential investment changes for all specifications. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

### 4.5.2 Estimation

The estimation results of non-residential investment are present in Table 4.3. I employ three specifications. One without $g_t$, one with $g_t$, one with $sg_t$ and one with $ndg_t$ where $sg_t$ and $ndg_t$ are state government spending changes and non-defense federal government spending changes. At some periods, government spending excessively increase and then decrease due to the sudden change of military spending. To avoid this issue, $sg_t$ and $ndg_t$ are employed instead of $g_t$.

Regardless of specification, the coefficients of $c_t$ is about 0.24. The estimated coefficients of government spending ($g_t$ , $sg_t$ and $ndg_t$) are all insignificant. Therefore I choose the model (1) to predict the the cycle of non-residential investment. In Table 4.4, the estimation results of residential and inventory investment changes are present. In the model of residential investment, the estimated coefficients of $r_{t-1}$, $d_t$ and $c_t$ are all significant at 1 per cent significance level.

In Table 4.4, presented are the estimation results for residential investment changes and inventory changes. The coefficients of regressors are all insignificant at 5% significant level. And

Table 4.4: Residential and Inventory Investment

| | Dependent Variables | | |
|---|---|---|---|
| regressor | r | r | inv |
| Lag(1) | 0.422*** | 0.401*** | |
| | (0.048) | (0.048) | |
| c | | 0.182*** | -0.151** |
| | | (0.022) | (0.068) |
| c(-1) | | | 0.473*** |
| | | | (0.065) |
| d | 0.282*** | | |
| | (0.035) | | |
| $R^2$ | 0.443 | 0.448 | 0.167 |
| Obs | 276 | 276 | 276 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

the signs are corresponding to the prediction discussed in Section 4.4. I predict the residential investment changes using $c_t$ to match it to other models. The inventory investment is well fitted with $c_t$ and $c_{t-1}$.

### 4.5.3 Prediction of cycles

The goal of this chapter is to measure the effect of consumption shocks. I predict the changes in investment components with consumption changes as below. $nr_t$ and $r_t$ are AR(1) models, the effects of consumption shocks can be written in the form of autoregressive distributed lag (ADL) models. I truncate the lags at t-4 as the coefficients become close to zero there. For the purpose of comparison, I also predict the effects of export shocks.

$$nr_t^c = 0.241c_t + 0.097c_{t-1} + 0.039c_{t-2} + 0.016c_{t-3} + 0.006c_{t-4}$$

$$nr_t^{ex} = 0.294ex_t + 0.118ex_{t-1} + 0.048ex_{t-2} + 0.019ex_{t-3} + 0.008ex_{t-4}$$

$$r_t^c = 0.182c_t + 0.073c_{t-1} + 0.029c_{t-2} + 0.012c_{t-3} + 0.005c_{t-4}$$

$$inv_t^c = -0.151c_t + 0.473c_{t-1}$$

Once $nr_t$, $r_t$ and $inv_t$ are predicted, the predicted cycle of each component can be achieved by summing the predicted values, $p(j)$, recursively from the front.

$$\hat{\mathbb{C}}_T^j = \sum_{t=1}^{T}(p_t(j)) \quad j = \text{NR(nr), R(r) and INV(inv)}$$

The predicted cycle of investment can be achieved by aggregating all the predicted cycles of components.

$$\hat{\mathbb{C}}_t^I = \hat{\mathbb{C}}_t^{NR} + \hat{\mathbb{C}}_t^R + \hat{\mathbb{C}}_t^{INV}$$

The predicted cycles are present in Figure 4.3. The predicted cycle of gross investment is panel(E) is close to the cycle estimated in section 3. Once the effects of export shocks are considered, the gap between the prediction and the estimation decreases. The predicted cycles of the components are also close to their estimates. This indicates that consumption changes are the main source of investment fluctuations.

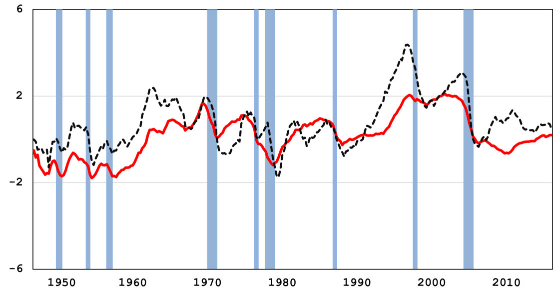
## 4.6 Measuring the effects of consumption shocks

In this section, I estimate the effect of consumption shocks. In previous section, I demonstrate that consumption changes are the main driver of investment cycles. To understand the source of business cycle, however, exogenous consumption shocks are required as consumption changes are affected by the endogenous effects.

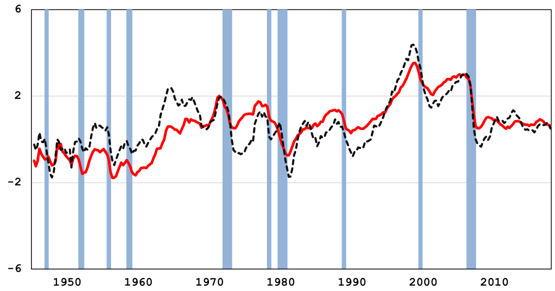
To estimate exogenous consumption shocks and the responses to consumption shocks, I

Figure 4.3: Predicted investment cycles

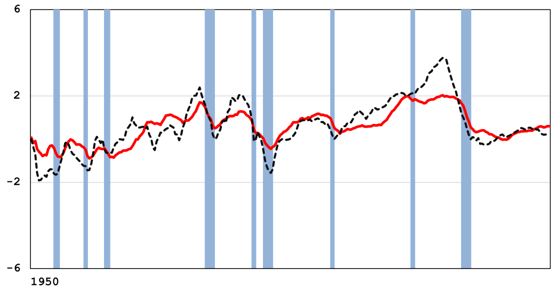
(A) Non-residential(c)



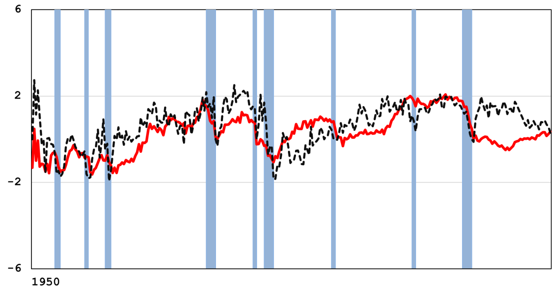

(B) Non-residential(c+ex)



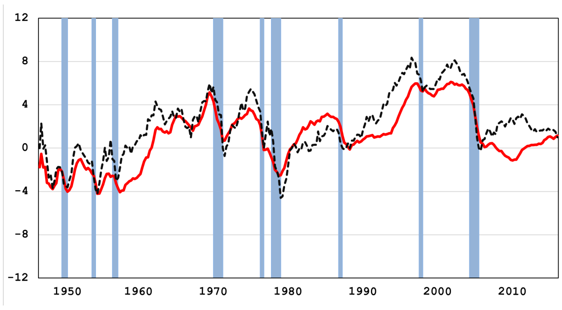

(C) Residential



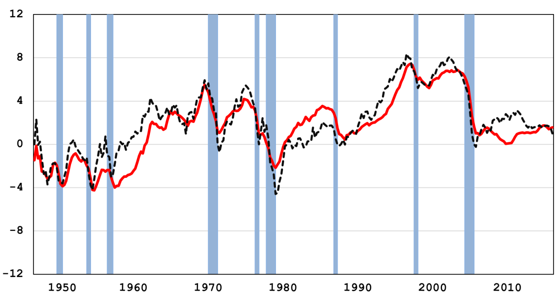

(D) Inventory




(E) Total (c)

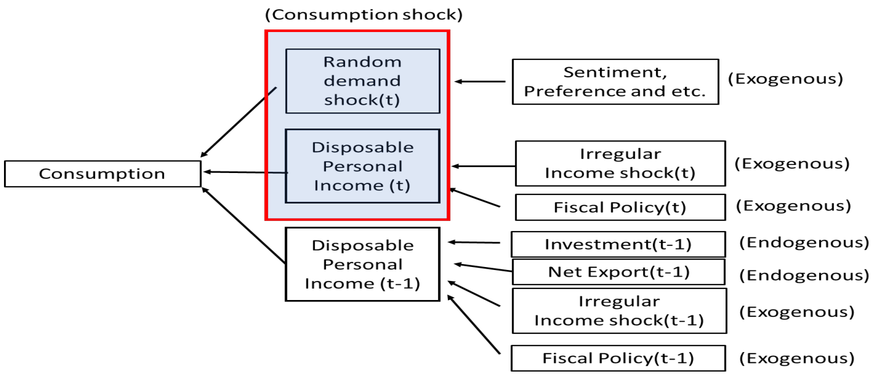



(F) Total (c+ex)




*Note:* Note: X-axis: time horizon in quarters. Y-axis: per cent. Dashed line: predicted cycle. Solid line: cycle estimated through decomposition of contribution data

Figure 4.4: The sources of consumption shocks




*Note:* The shaded area represent the estimated consumption shocks

employ two methods. First, I directly estimate consumption shocks using the consumption-income relationship. Then I estimate the responses of investment to consumption shocks using the models estimated in the previous section. Second, consumption shocks are identified and the responses to consumption shocks are estimated using SVAR models. Two shocks are very close to each other and therefore, the estimated effects are also close to each other.

### 4.6.1 Reduced-form

**Estimation of consumption shocks**

In this subsection, I identify exogenous consumption shocks. The consumption changes employed in the previous subsection are not exogenous shocks as they contain the endogenous effect of lagged investment changes and lagged net export even though I assume that consumption changes are predetermined for investment. Additionally I also assume that consumption is predetermined for net export[23]. Therefore, to obtain exogenous consumption shocks, the endogenous effects should be excluded.

The identification of consumption shocks can be achieved under two assumptions. (1) output changes only affect consumption changes through disposable personal income changes. There may be additional effects that occur through wealth changes or inflation changes. However, they are not considered here as such endogenous effects are not clear in the previous literature. (2) consumption is predetermined for investment and net export. Behind this as-

[23]This assumption appears harmless as the share of net export is very small.

sumption, there are two logics. First, the correlation between output and disposable personal income are as moderate as around 0.5. It means that only a part of output changes leads to disposable personal income changes [24]. Second, the correlation between consumption changes and income changes is low, around 0.3. A well-known fact is that consumption is smoother than income. The validity of this assumption will be discussed in Section 4.6.

Under the above assumptions, I define consumption shocks as the ones that include all the exogenous and contemporaneous effects on consumption excluding endogenous effects. The definition is described in the diagram of Figure 4.4. The shaded box represents the consumption shocks that include three contemporaneous effects (1) structural consumption shocks in a strict sense such as consumer sentiment shocks and preferences shocks. (2) irregular income shocks which affects consumption through income changes. It can be regarded as distribution shocks affecting the distribution among households, firms and governments. (3) exogenous demand component such as fiscal policy effect. Therefore, exogenous shocks can be obtained only if lagged disposable person income changes are controlled for.

This definition also corresponds to the specifications employed in the previous literature. Consumption changes are commonly assumed to be the function of the lagged consumption changes and the current and lagged income changes. [68] Hall (1978) first suggest a random-walk consumption independent of income in short-run. However, the following literature document that consumption change are the function of lagged consumption changes[25], current income changes[26] and lagged income changes [27]. Among them, I exclude the current income term as there are no endogenous effects through current income changes on current consumption changes by the assumption mentioned above.

Consumption is modelled as the function of the lagged consumption changes and the lagged disposable personal income (DPI) changes. DPI changes are denoted as dpi. The contribution of DPI to GDP growth can be obtained by using the formula $dpi_t = \Delta DPI(t)/GDP(t-1)$

[24]In a typical neoclassical model, output is equated with personal income. In reality, however, output equals gross national income. And gross nation income is different from personal income. And the latter is the source of consumption

[25][105]Muellbauer 1988) for habit formation, [23]Carroll et al. (2020) for sticky expectation

[26][20][21]Campbell and Mankiw (1989, 1990)

[27][54]Flavin (1981), [70]Hall and Mishikin (1982), [106]Nelson(1987)

as DPI is deflated by the GDP deflator. Then the consumption changes are modelled as

$$c_t = \delta_1 c_{t-1} + \delta_2 dpi_{t-1} + v_t \tag{4.9}$$

$v_t$ is an exogenous consumption shock. As all the endogenous effects work through $dpi$, this model captures all the endogenous effect. Therefore, the model is enough to estimate exogenous and contemporaneous consumption shocks.

The estimated model of Equation 4.9 is

$$\hat{c}_t = \underset{(0.058)}{0.052} c_{t-1} + \underset{(0.044)}{0.207} dpi_{t-1}$$

The coefficient of $dpi_{t-1}$ is significant at 5 per cent significance level while the one of $c_{t-1}$ is not significant. The predicted consumption changes using the estimation model represent contemporaneous shocks on consumption changes.

The estimated consumption can also be estimated using the components of output growth. The model can be written in a structural form. $dpi$ is the function of GDP component changes.

$$dpi_t = \delta_3 c_t + \delta_4 i_t + \delta_5 g_t + \delta_6 nx_t + v_{2t} \tag{4.10}$$

Once the $dpi_t$ in equation Equation 4.9 is replaced with equation Equation 4.10, it yields,

$$c_t = (\delta_1 + \delta_2\delta_3)c_{t-1} + \delta_2\delta_4 i_{t-1} + \delta_2\delta_5 g_{t-1} + \delta_2\delta_6 nx_{t-1} + \delta_2 v_{2t-1} + v_t \tag{4.11}$$

The difference between two models is $\delta_2\delta_5 g_{t-1} + \delta_2 v_{2t-1}$. Therefore, the consumption shocks estimated using Equation 4.9 is purely contemporaneous shocks. The shocks estimated using Equation 4.11 are overestimated. Another merit of Equation 4.9 relative to Equation 4.11 is that it helps avoid the collinearity issue among regressors.

Table 4.5: Estimation of Investment models

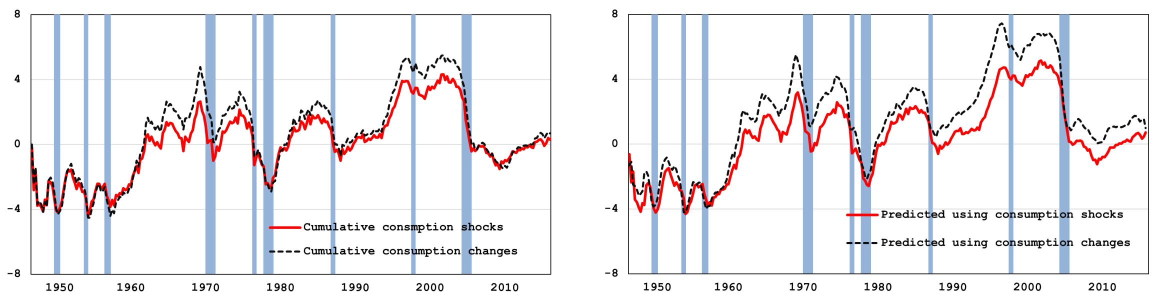
| | Dependent Variables | | |
|---|---|---|---|
| regressor | nr | r | inv |
| Lag(1) | 0.440*** | 0.410*** | |
| | (0.045) | (0.047) | |
| c | 0.250*** | 0.204*** | -0.125* |
| | (0.027) | (0.026) | (0.071) |
| c(-1) | | | 0.508*** |
| | | | (0.070) |
| ex | 0.304*** | | |
| | (0.051) | | |
| $R^2$ | 0.479 | 0.463 | 0.170 |
| Obs | 275 | 275 | 275 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Effects of consumption shocks**

Figure 4.5: Predicted cycles using consumption shocks

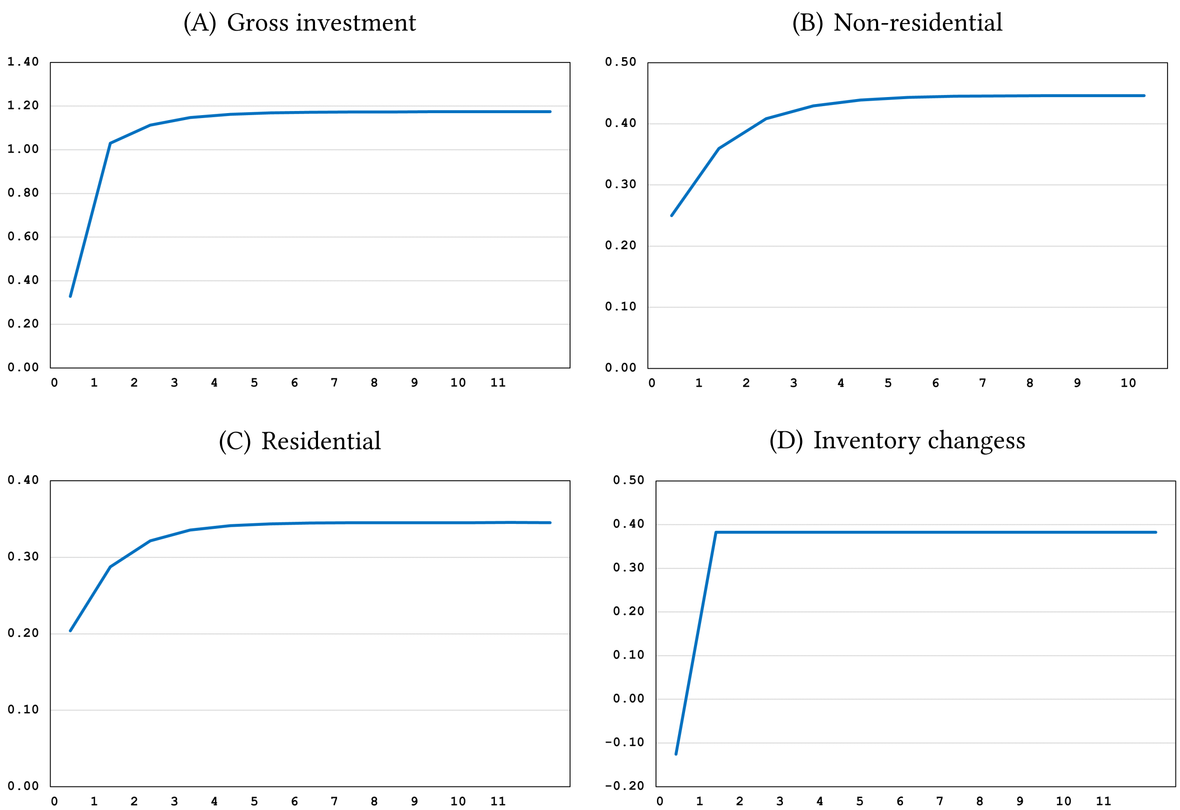
(A) Cumulative consumption shocks (B) Predicted investment cycle




I first predict an investment cycle using the estimated consumption shocks. The estimated investment cycle is close to the benchmark investment cycle. Then I estimate a response of investment to a consumption shock. The estimated response of investment is long-lasting. This result is corresponding to a boom-bust cycle, however, contrasting to a well-known hump-shape response to a demand shock.

I first estimate the reduced-form investment models of Equation 4.6, Equation 4.7 and Equation 4.8 using the exogenous consumption shocks estimated in the previous subsection. The estimation results are present in Table 4.5. The results are almost identical to the ones that are present in Table 4.3 and Table 4.4. It is not surprising as the estimated shocks are very close

Figure 4.6: Responses of investment to consumption shocks




*Note:* % p response to a consumption shock of 1% p output growth in size.

to consumption changes.

The cumulative consumption shocks and the investment cycle predicted using consumption shocks are present in Figure 4.5. When comparing the cycles predicted using consumption changes, the difference is very small. This indicates that consumption shocks are the main driver of business cycle.

### 4.6.2 SVAR

In this subsection, I demonstrate that consumption shocks generate a long-lasting and important responses of consumption and investment as described in the estimated boom-bust cycles of them. As consumption and investment components are already detrended, the estimation results should be transitory. This estimation result indicates that consumption shocks generate long-lasting non-stationary cycles of output. This result is contrasting to the well-known facts that demand shocks generate hump-shaped response of output [28].

**The VAR**

The basic VAR specification is

$$B(L)Y_t = W_t \quad \text{(Structural Form)}$$

$$A(L)Y_t = U_t \quad \text{(Reduced Form)}$$

where $Y_t \equiv [c_t, nr_t, r_t, inv_t]'$ is a four-dimensional vector in the contribution to real GDP growth, quarterly data. No constant term is required they are all detrended as explained in the previous section. $W_t \equiv [w_t^c, w_t^{nr}, w_t^r, w_t^{inv}]$ is the corresponding to the vector of structural shocks, which have zero cross correlations. $U_t \equiv [e_t^c, e_t^{nr}, e_t^r, e_t^{inv}]$ is the corresponding vector of reduce-form residuals, which in general will have nonzero cross correlations. $B(L) \equiv B_0 - B_1 L - \cdots - B_q L^q$ is the matrix of coefficients for a structural-form equation. $A(L) \equiv I_4 - A_1 L - \cdots - A_q L^q$ is the

[28] [14] Blanchard (1989)

matrix of coefficients for a reduced-form equation. $B_0$ is the structural matrix containing the parameters governing the simultaneous relationship.

### Identification

The identification of structural shocks follows the Keynesian perspective introduced in section 4. $B_0 U_t = W_t$ such that

$$\begin{pmatrix} u_t^c \\ u_t^{nr} \\ u_t^r \\ u_t^{inv} \end{pmatrix} = \begin{pmatrix} w_t^c \\ -b_{21}u_t^c - b_{23}u_t^r - b_{24}u_t^{inv} + w_t^{nr} \\ -b_{31}u_t^c + w_t^r \\ -b_{41}u_t^c - b_{43}u_t^r + w_t^{inv} \end{pmatrix} \tag{4.12}$$

The structural matrix $B_0$ can be estimated using the method of moments approach. The estimation is based on the second moment matrix of the VAR innovations, $\Sigma_u$, which may be expressed in terms of the structural model parameters as $B_0 \Sigma_u B_0' = \Sigma_w$. The computational efficiency may be increased by directly imposing the restrictions that the off-diagonal elements of $\Sigma_w$ are zero and that the diagonal elements of $B_0$ are unity, and only solving for the remaining elements.

To identify the parameters in $B_0$, some restrictions are required. As all the variables are detrended and the cyclical movements are left, short-run restrictions are only valid. (A1) $b_{12}$, $b_{13}$ and $b_{14}$ are set to zero as I assume that current consumption changes are predetermined. Correspondingly, $b_{21}$, $b_{31}$ and $b_{34}$ are set to be non-zero. According to the initial assumption that the changes in investment components does not mutually affect each other contemporaneously. Therefore, the other parameters should be set to zero. However, for exact identification I set three more parameters as zero which are more likely to be zero compared to the other parameters. (A2) $b_{34}$ is set to zero as it is unlikely that inventory investment contemporaneously affect residential investment. (A3) $b_{32}$ and $b_{42}$ are set to zero as non-residential investment is unlikely to affect the residential and inventory investment in a contemporaneous manner. The estimation through overidentification will be discussed in the next section.

The structural matrix subject to the restrictions is as below. This is a non-recursive restrictions. Therefore, I solve them using a non-linear least square solver [29].

**Estimation**

The identified structural parameters in $B_0$ are as below.

$$\hat{B}_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -0.1924 & 1 & 0 & -0.0068 \\ -0.1809 & 0 & 1 & 0 \\ 0.2543 & -0.0011 & 0.0093 & 1 \end{bmatrix} \tag{4.13}$$

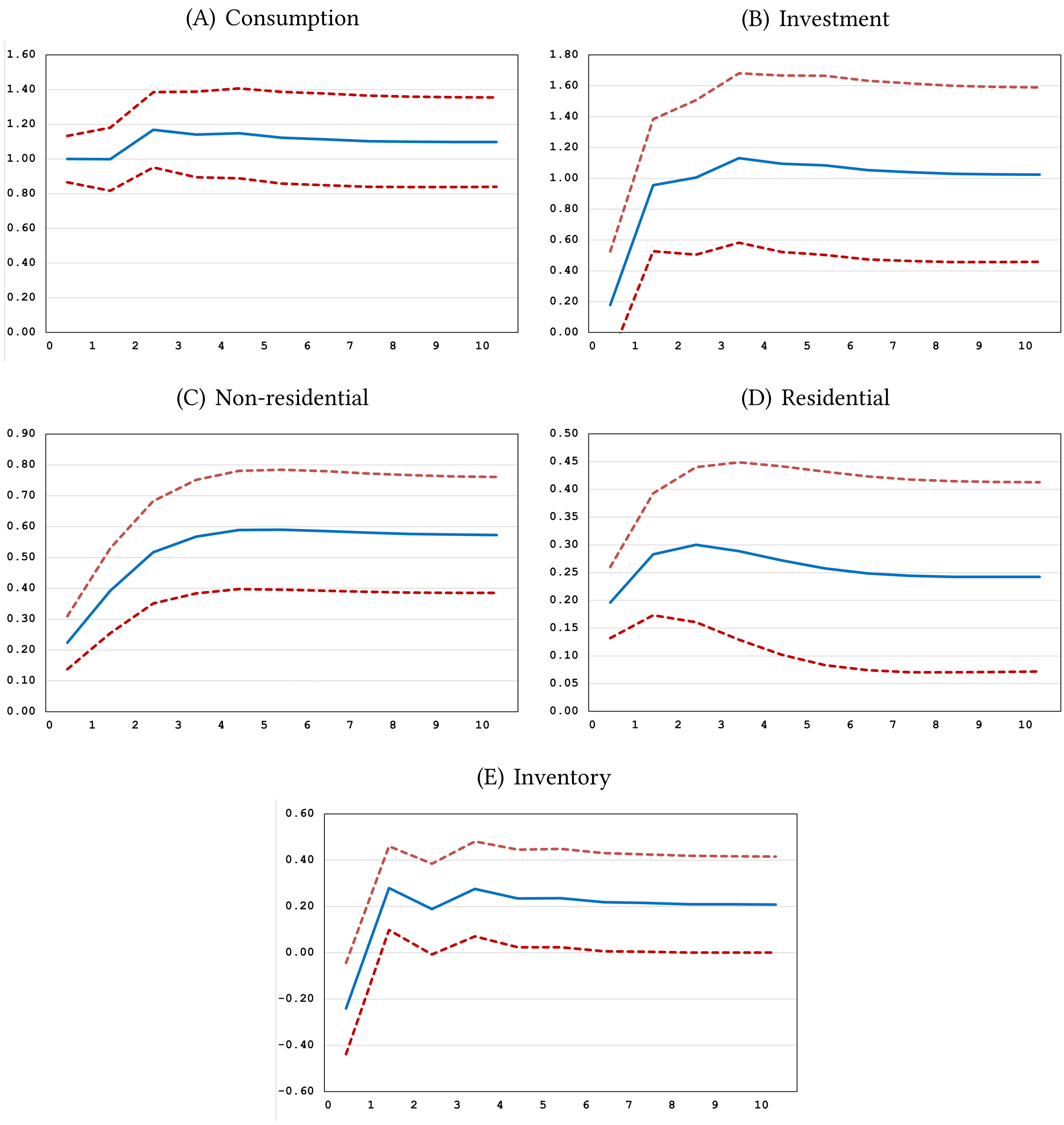
The effect of unit consumption shock is estimated as shown in Figure 4.7. The estimated responses can be aggregated as discussed in Section 4.2. As seen in panel (A), consumption immediately rises as much as 1%p and stay at 1.1%p. This result is corresponding to [68]Hall (1978)'s random walk model like the estimated result in section 3. Investment also rises in the similar magnitude following consumption. Therefore, output rise around 2%p responding to a 1%p consumption shock. The estimated model can be written in a structural form as below:

$$\begin{aligned}
c_t &= -0.058c_{t-1} - 0.016nr_{t-1} + 0.405r_{t-1} + 0.077inv_{t-1} + w_t^c \\
nr_t &= 0.225c_t + 0.004nr_{t-1} + 0.063c_{t-1} + 0.125r_{t-1} + 0.0361inv_{t-1} + w_t^{nr} \\
r_t &= 0.196c_t - 0.009c_{t-1} - 0.031nr_{t-1} + 0.163r_{t-1} + 0.015inv_{t-1} + w_t^r \\
inv_t &= -0.2123c_t + 0.1855c_{t-1} - 0.0188nr_{t-1} + 0.165r_{t-1} - 0.139inv_{t-1} + w_t^{inv}
\end{aligned}$$

The estimation results raise the suspected over-parameterization issue in particular for the effect of $r_{t-1}$ on $c_t$. It is unclear how $r_{t-1}$ affects $c_t$. However, it does not make a big difference in the estimated responses. The second order effect of residential investment shocks are small as the standard deviation of $r_t$ is smaller than those of consumption and the other investment components. To sort our the suspected over-parameterisation of residential investment, I employ fixed gross investment that is the aggregation of non-residential and residential investment.

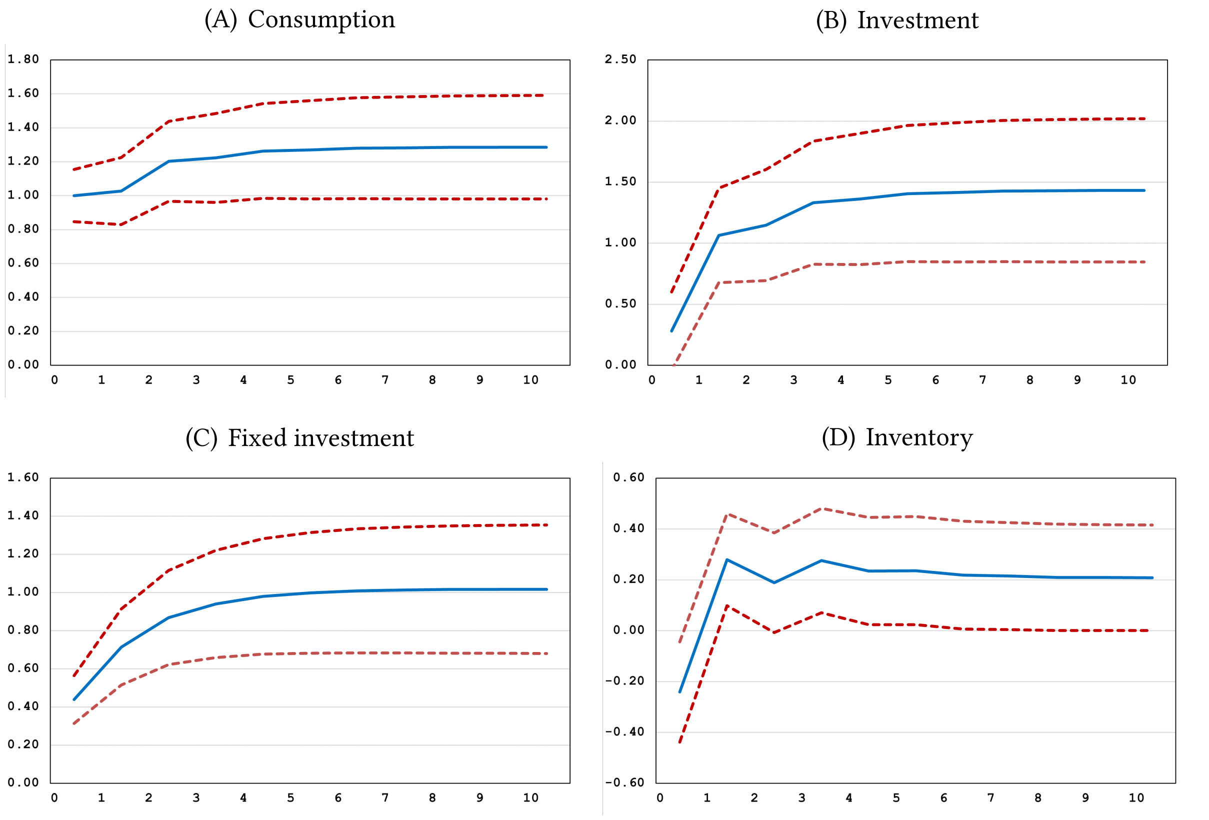
[29]By rearranging the order of variables, it can be a recursive matrix. And then it can be solved using the choleski decomposition.

Figure 4.7: Response to a consumption shock (4 Variable)




*Note:* X-axis: time horizon in quarters. Y-axis: cumulative response in unit of %p change in output growth. Dashed lines are 95% confidence intervals constructed using standard errors generated from 2000 bootstrap replications.

Figure 4.8: Response to a consumption shock (3 Variable)




*Note:* X-axis: time horizon in quarters. Y-axis: cumulative response in unit of %p change in output growth. Dashed lines are 95% confidence intervals constructed using standard errors generated from 2000 bootstrap replications.

The overall results are similar to the previous ones. A 1%p consumption shock generates a long-lasting responses of consumption and investment. The responses are bigger than before as the endogenous effects through the income changes are better estimated.

The estimation results are more reasonable than the previous ones.

$$c_t = -0.033c_{t-1} + 0.134fix_{t-1} + 0.084inv_{t-1} + w_t^c$$

$$fix_t = 0.447c_t + 0.029c_{t-1} + 0.149fix_{t-1} + 0.052inv_{t-1} + w_t^{fix}$$

$$inv_t = -0.1572c_t + 0.2013c_{t-1} + 0.057fix_{t-1} - 0.134inv_{t-1} + w_t^{inv}$$

### 4.6.3 Comparison of OLS coefficients and structural parameters

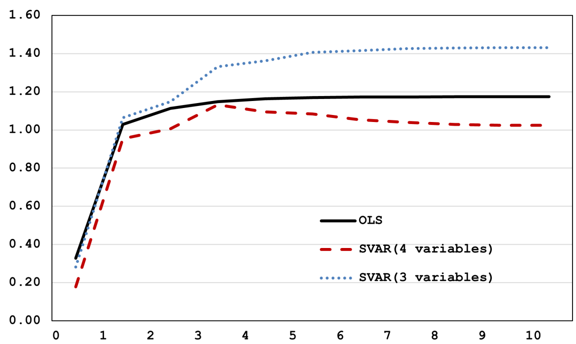
To justify the estimation results, I compare the OLS estimates of coefficients with SVAR structural parameters of $fix_t$, $nr_t$, $r_t$, and $inv_t$. Both estimates represent the marginal effect of a consumption shock on the current changes in investment components. The estimated parameters of the structural matrix is relatively free from the simultaneity and collinearity issue. As present in the table, there are no substantial differences between OLS estimates and SVAR structural parameters. There is little gap between OLS and 3-variable SVAR. This indicates that the estimation results of both models are reliable.

Table 4.6: SVAR parameters vs. OLS coeffcients of consumption

| | fixed investment | Non-residential | Residential | Inventory |
|---|---|---|---|---|
| SVAR(4-variable) | 0.421 | 0.225 | 0.196 | -0.212 |
| SVAR(3-variable) | 0.447 | | | -0.157 |
| OLS | 0.454 | 0.250 | 0.204 | -0.125 |

In Figure 4.9, the estimated responses of investment to a consumption shock are compared across models. Despite small differences in magnitude, they all display long-lasting responses. The results contradict the well-known facts that the a demand shock generates a hump-shaped response of output. Therefore, when consumption shocks display a non-staionary boom-bust pattern, investment also follows a non-staionary boom-bust pattern.

Figure 4.9: Comparison of estimated responses of investment

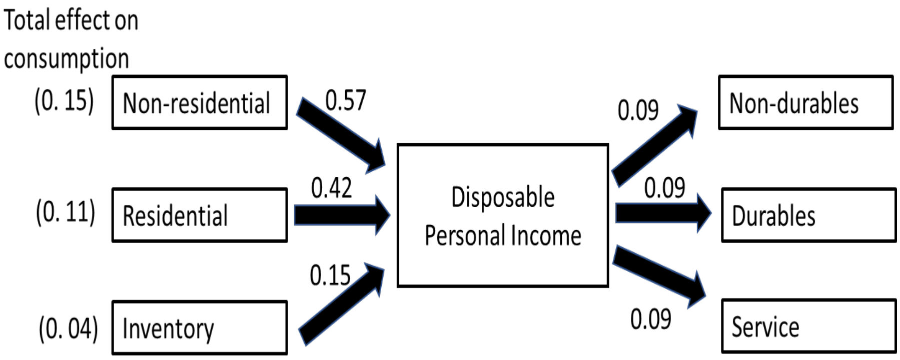



*Note:* % p response to a consumption shock of 1% p output growth in size.

## 4.7 Robustness

### 4.7.1 Simultaneity

Figure 4.10: The effect of investment changes on consumption changes




*Note:* Every number indicates the % p response to the 1% p change in an independent variable.

In this chapter, I assume that consumption is predetermined for investment. This assumption is relevant to an important econometric issue: simultaneity between consumption and investment. As the changes in current consumption leads to an identical changes in GDP which is likely to increase in DPI, the simultaneity arises unless the effect on income is offset by another effect. [30]

First, the increase in investment necessarily leads to the increase in GDP as investment is a component of GDP. However, the effect on DPI changes is not just as clear. As a major source of DPI, labour income itself is not stable relative to GDP. And personal income is affected by various factors as well as labour income. Second, the increase in DPI does not necessarily lead to an increase in consumption. Consumers adjust their expenditure through borrowings and savings regardless of the current income.

In this subsection, I examine the effect of investment changes on consumption changes. To reduce the effect of potential simultaneity, I employ two strategies. First, I estimate the effect of DPI changes on consumption and the effect of investment on DPI changes. By doing so, the effect of correlation between consumption and investment less intervene in estimation. Second, I employ the components of consumption. By employing components, the effect of accidental

[30]The rule-of-thumb consumers [20][21](Campbell and Mankiw 1989, 1990) or credit constraint hypotheses support the substantial causality from current DPI change to current consumption change.

correlation between consumption changes and DPI changes can be reduced. For example, an increase in PDI does not necessarily lead to an increase in non-durables, durables and services proportionally. The effect on each component would be randomly determined. Therefore, it reduces the possibility of simultaneity. This procedure is illustrated in Figure 4.10.

The estimation results are present in tab:2:7 and summarised in Figure 4.10. The effects of nr, r, and inv on dpi are 0.57, 0.42, and 0.15 respectively. Just a part of changes in investment components leads to changes in DPI. And then I estimate the effect of dpi on consumption changes. The effects on non-durables, durables and service changes are 0.09 respectively. The combined effect of 1 per cent point change in DPI on consumption is 0.22 per cent point. This is equivalent to the effect on aggregate consumption.

The effect of changes in each investment component on consumption changes can be obtained through the multiplication of the effect on dpi and the effect of dpi on the changes in total consumption which is 0.27. The total effects is 0.11 for non-residential and residential changes and 0.04 for inventory changes. This means that 1%p shocks on each investment component leads to 0.15, 0.11, and 0.4%p increase in consumption respectively. These effects are small and are unlikely to cause significant bias.

The possibility of simultaneity bias in the estimation results cannot be excluded. However, the suspected direction of bias is upward[31]. Therefore, the actual effect should be smaller than the above estimation results. The effect of consumption changes on DPI changes is likely to be positive. The effect of DPI on investment components is unclear. If DPI only affects investment components through the increase in consumption, the effects on non-residential and residential should be positive. The effect of DPI on inventory may be negative. In this sense, the effect of inventory on consumption may only be underestimated.

When there exists simultaneity, the estimated results are upwardly biased as below.

$$i_t = \delta c_t + \psi z_t + v_t$$

[31]Current changes in fixed investment are positively correlated with current changes in consumption.

Table 4.7: The effect of investment changes on consumption changes

| | Dependent Variables | | | | |
|---|---|---|---|---|---|
| regressor | dpi | nd | d | s | c |
| nr | 0.574*** | | | | |
| | (0.141) | | | | |
| r | 0.418** | | | | |
| | (0.182) | | | | |
| inv | 0.150** | | | | |
| | (0.067) | | | | |
| dpi | | 0.086*** | 0.091*** | 0.087*** | 0.265*** |
| | | (0.014) | (0.026) | (0.013) | (0.040) |
| $R^2$ | 0.1210 | 0.1277 | 0.0420 | 0.1368 | 0.1382 |
| Obs | 276 | 276 | 276 | 276 | 276 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

$$c_t = \theta i_t + \varepsilon_t$$

$$E[\hat{\delta}] = \frac{Cov(i_t, c_t)}{Var(c_t)} = \delta + \frac{Cov(c_t, v_t)}{Var(c_t)}$$

$$c_t = \frac{\theta\psi}{1-\theta\delta} z_t + \frac{1}{1-\theta\delta} \nu_t + \frac{\theta}{1-\theta\delta} \varepsilon_t$$

$$Cov(c_t, v_t) = \left(\frac{\theta}{1-\theta\delta}\right) Var(v_t)$$

$$\text{bias} = \frac{\theta}{1-\theta\delta}\frac{Var(v_t)}{Var(c_t)}$$

The estimated $\theta$ is 0.04-0.15, $\delta$ is 0.27 and $\delta\theta$ is close to zero. $Var(c_t)$ is 0.248. The estimated $Var(v_t)$ for nr, r and inv are 0.048, 0.042 and 0.144 respectively[32]. The estimated bias is around 0.02 for nr, r and inv. Therefore, the magnitude of biases is considered as negligible.

[32]I employ the reduced form models employed in section 5.1 to estimate $upsilon_t$. I suspect the potential bias would not make a big difference in the volatility.

## 4.8 Comparison with (old) Keynesian economics.

The model introduced in this chapter is just a Keynesian cross. The closest one is the Keynes-Hansen-Samuelson multiplier accelerator model ([122]Samuelson, 1939) in that investment is the function of consumption changes.

The crucial difference between two models arises from the view of output-personal income relationship. In a typical macroeconomic model, the source of consumption is national income and it is equated to output. When output changes directly lead to income changes, the multiplier effect works well to amplify the effect of demand shocks.

In reality, however, the source of consumption is disposable personal income. And the relationship between output and disposable personal income is variant in short-run even though they would definitely move together in a longer horizon. Besides, once the intertemporal choice of consumers is considered, the uncertainty increases in the relationship between output and consumption. Therefore, the multiplier effects is not guaranteed.

In the Keynes-Pigou cycle, the boom-bust cycle of consumption and its propagation to investment is the main source of business cycles. Due to the sharp decline in consumption during a bust season, the sharp decline in output can be generated without the help of multiplier effect. However, this chapter is silent of the more fundamental sources of consumption shocks.

## 4.9 Conclusion

In this chapter, I argue that consumption shocks are the main driver of business cycles based on the intuitions of [86]Keynes (1936) and [115]Pigou (1927). I reconcile their ideas based on their commonality highlighting the role of businessmen's expectations as an important driver of business cycles. The reconciled idea describes a boom-bust cycle generated by consumption changes and their propagation to investment through the adjustment of businessmen's expectation. To verify their idea, I estimate the effect of consumption shocks on investment changes using a set of reduced-form investment models. The estimated effects predict a boom-bust cycle of investment Then I estimate the response of investment to a consumption shock using

SVAR models. A shock to consumption generates a long-lasting and important responses of consumption and investment even though the secular trend of each variable is already removed. This result is corresponding to boom-bust cycles but contrasting to a well-known hump-shaped response of output to a demand shock.

The study of this chapter has two important caveats. First, this chapter is silent of the source of consumption shocks. As shown in the section 2, the main source of a boom-bust business cycle is the boom-bust cycle of consumption. And the consumption cycle is mostly generated by exogenous shocks. Therefore, to better understand the business cycle mechanism, the sources of consumption shocks need to be investigated. The second caveat concerns the estimated trend. The results of this chapter highly depend on the assumption that the trend is a DLT with breaks. However, this assumption is purely empirical and ad-hoc. Therefore, the estimation results of this chapter cannot be justified without clarifying the nature of trend. This issue is closely related to the natural rate hypothesis suggested by [56]Friedman (1968).

# Chapter 5

# Forecasting Short-term US GDP from Keynesian perspective

## 5.1 Introduction

An innovation of Keynesian economics is to distinguish short-run economic fluctuation from long-run growth. This convention leads to the development of different mechanisms in the business cycle literature and in the growth literature respectively. In forecasting studies, it implies that the forecasting methods should be different between short-run fluctuations and long-run trend growth.

To build a novel forecasting procedure, I bring the implication of chapter 2 and chapter 3. First, I assume that the trend of US GDP is very smooth so that economic fluctuation is mainly attributed to cyclical components. A linear trend with breaks, however, is not appropriate for real time forecasting as explained below. To estimate highly smooth trends, I employ HP filter with very large smoothing parameters. Second, I apply the consumption-investment relationship which is studied in chapter 3. So I first forecast consumption using a mixed frequency dynamic factor model, and then forecast investment using consumption forecasts. In this sense, this chapter is built upon the previous two chapters.

In this chapter, I forecast output growth as the sum of the trend growth and the cyclical changes (= demeaned output growth) from the Keynesian perspective. I first decompose output growth into the trend growth and the cyclical changes and then forecast each component using different methods. For the trend growth, I simply extend the estimated trend growth under the assumption that the trend growth does not change in short-run. For the cyclical changes, a bottom-up procedure is employed. In the procedure, I first forecast the components of demeaned GDP growth and then aggregate them to obtain the forecast of the cyclical changes of GDP. To this end, I employ the relationship between consumption and investment, which is studied in chapter 3 where I demonstrate that consumption changes lead to investment changes. First, I forecasts the (demeaned) consumption changes[1] using a Mixed-Frequency Dynamic Factor Model (MF-DFM) with a set of monthly indicators that are demeaned in the same way as output growth is demeaned. Then, I forecasts (demeaned) investment changes and net export changes using the forecast of consumption changes. Once the consumption changes, investment changes and net export changes are forecasted, the forecasts of cyclical changes can be obtained by aggregating the forecasts of its components. Additivity holds across the GDP components as I employ contribution to GDP growth data instead of growth data[2].

An important issue of the forecasting strategy is in the decomposition of employed variables. In chapter 2, I demonstrated that the decomposition of US output growth using a deterministic linear trend (DLT)[3] with breaks leads to a reasonable cyclical pattern of the US economy that describes a boom-bust pattern. Moreover, once the trend is assumed to be a DLT with breaks, forecasting the trend growth becomes simple as the close future trend growth is just the current trend growth. However, the critical drawback of DLT with breaks is that it requires the detection of break points prior to estimation. Well-known break point detection methods are not appropriate for real-time detection as documented by [3] Antolin-Diaz et al. (2017). Therefore, previous studies commonly employ a stochastic trend to track the variation of trend in real time. However a stochastic trend is highly sensitive to cyclical factors, which does not corresponding to this thesis which advocates a DLT with breaks from the Keynesian perspective.

[1]In this chapter, the term '(scaled) changes' means contribution to GDP growth. See the section 3.2 in chapter 3 for the discussion of this practice.

[2]In chapter 3, I document that growth and contribution are fundamentally identical in that both are standardised changes

[3]Technically, it is a log-linear trend in that logs are taken of variables. However, it is commonly denoted as linear-trend in the previous literature.

For the decomposition of variables, I employ the Hodrick-Prescott (HP) filter with a large smoothing parameter[4] to obtain trend growth as smooth as the growth of DLT. The HP filter is a kind of moving-average filter, it tends to generate a large swing around a big recession such as the Global Financial Crisis (GFC). To prevent such a large and sudden change, I exclude outliers prior to decomposition using a simple detection method that exclude the values out of 1.5 time interquartile range with the median value. The estimated trends shows a good performance of tracking the DLT with breaks estimated in chapter 2.

To evaluate the performance of the model, I run a horse race (pseudo out of sample forecasting) between the model and one of the representative judgemental forecasts[5], the Survey of Professional Forecasts (SPF) over the forecasting horizons from the current quarter to one year ahead. The SPF has advantages that it is regularly published and easily accessible from the website of the Philadelphia Fed. The forecasting performance of the model is comparable to that of the SPF across the forecasting horizons. However, for nowcasts, it shows the relatively weak performance tracking the large swing during the Global Financial Crisis. When decomposing the forecasts into trend growth and cyclical changes, the weak performance is ascribed to the limited information for forecasting of consumption changes and to the high dependence of forecasting on smooth consumption changes. For the choice of a smoothing parameter for the HP filter, an increase in the value from 1600 to 32000 substantially improves forecasting performance. However, further additional increases do not improve performance.

It is hard to find papers which employ a bottom-up procedure of forecasting GDP growth. [55]Frale et al. (2011) aggregate the growth of components using optimal weight reflecting the relative precision of each component. However, their practice is a model averaging method rather than a bottom-up procedure. In this chapter, on the other hand, the forecast of GDP

[4]Several previous studies suggest large smoothing parameters to obtain a highly smoothing trend. For the value, [73]Harvey and Timbur (2008) suggest 32000, [43]Drehmann et al. (2011) 400000 and [110]Perron and Wada (2009) 800000.

[5]Judgemental forecasts are forecasts based on subjective judgements such as intuition and subjective probability. More precise terminology would be "judgementally adjusted forecasts" as those forecasts are the result of combination of all the available information. The well-known judgemental forecasts are known to over-perform the forecasts obtained from other methods such as statistical models and DSGE models. ([93]Lawrence et al. ,2006; [27]Chauvet and Potter, 2013). The most commonly employed for the forecasts of output growth are the Green Book forecasts, the Blue Chip economic indicators and the Survey of Professional Forecasts.

growth is the direct aggregation of its components. The additivity holds across components as I use contribution of its components to GDP growth. This chapter is also related to empirical literature studying the performance of MF-DFMs ([61] Giannone et al. 2008 and many) and MF-DFMs with time-varying parameters ([41] Del Negro and Otrok 2008, [99] Marcellino et al., 2016; [121]Ritschl et al., 2016; [3]Antolin-Diza et al., 2017). Unlike the previous studies that are purely empirical, the forecasting strategy of this chapter is based on the economic logic derived from the Keynes' intuition. Another relevant studies include forecasting in the presence of structural breaks. To tackle the issue, various methods have been introduced [6]. This chapter is close to [3] Antolin-Diaz, (2017) in that I estimate a time-varying mean. On the other hand, the other papers mainly focus on the reduces the effect of structural breaks.

The remainder of this chapter is organized as follows. Section 2 introduces the framework employed to forecast output growth. Section 3 applies the model to forecast US output growth and, then evaluate its forecasting performance. Section 4 concludes.

## 5.2 Framework

### 5.2.1 Decomposition and forecasting of trend growth

A model of economic time series with a trend whose slope is time-variant is considered. The model describes log real GDP $y_t$, as the sum of a trend $\tau_t$ and a cyclical component $\mathbb{c}_t$.

$$y_t = \tau_t + \mathbb{c}_t$$

$$\tau_t = \mu_t + \tau_{t-1}$$

Taking a first order difference of $y_t$ yields the following process.

$$\Delta y_t = \mu_t + \Delta \mathbb{c}_t \tag{5.1}$$

[6][113]Persaran and Timmerman (2002) and [78]Inoue and Rossi (2017) for recursive modelling, [112]Pesaran, Pettenuzzo and Timmermann (2007) for Bayesian model averaging, [90]Koop and Potter (2007) and [26] Chauvet and Piger, 2008 for the combination of time-varying parameters and markov swtiching, dynamic factor models with a time-varying intercept ([3]Antolin-Diaz, 2017), [111]Pesaran, Pick and Pranovich (2013) for model averaging using optimum weights

Once $\mu_t$ is estimated $\Delta \mathbb{c}_t$ is estimated as the residual.

The decomposition of output growth as (1) is conducted using the HP filter. The assumption of a smooth trend is imposed by assuming that the sum of squares of the second differences of $\Delta y_t$ is small. For a given smoothing parameter $\lambda$, a estimate of the trend is obtained by minimising:

$$\arg\min_{\mu} \left( \sum_{t=1}^{T} (\Delta y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T} [(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2 \right)$$

where T is the sample size.

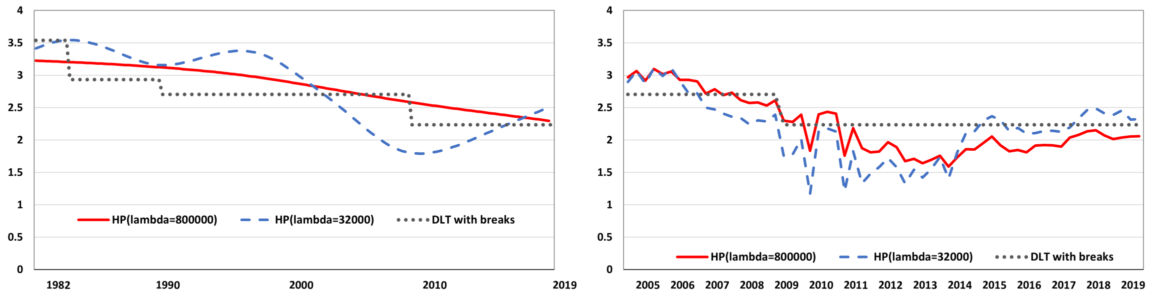
The smoothness of trend is governed by $\lambda$. The larger $\lambda$ is, the smoother the estimated trend is. For $\lambda$ , 1600 is widely used since [77]Hodrick and Prescott (1997) suggested the value. However, the intuition behind the value is different form the assumption of this chapter. [9] Baxter and King (1999) document that the HP filter with $\lambda = 1600$ is close to a approximate high-pass filter with cutoff frequency of 32 periods, that is, 8 years for quarterly data. As the US business cycle estimated in chapter is as long as up to around 20 years, $\lambda = 1600$ is not appropriate for the study of this chapter. To approximate the cycle, a far larger value of $\lambda$ is required. In previous studies, several alternative values have been suggested: [73]Harvey and Timbur (2008) suggest 32000, [43]Drehmann et al. (2011) 400000 and [110]Perron and Wada (2009) 800000. I will employ 800000 and discuss the results from the choice of different values.

To achieve highly smooth values for the trend growth, I remove outliers from the data. As the HP filter is a kind of moving average filter, a big recession generates a sharp decline and recovery in trend growth around the recession. To tackle the issue, I simply replace the values outside of the 1.5 times interquartile range with the median. As seen in Figure 5.1, the trend growth estimated with the HP filter using $\lambda = 800000$ is close to the trend growth estimated with DLT with breaks which is estimated in chapter 1. The $\lambda = 32000$ generates a cyclical trend growth relative to the one estimated using $\lambda = 800000$.

I forecast the trend as the most recent value of the estimated trend as I assume that the trend is a DLT with breaks. Therefore, the trend growth is expected to stay still in short run unless a break occurs.

Figure 5.1: Estimates of trend growth

(A) 2019:4 (B) Real time




*Note:* X-axis: time horizon in quarters (1982:1-2019:4 for panel (A), 2005:1-2019:4 for panel (B). Y-axis: per cent

### 5.2.2 Forecasting of cyclical changes

In this subsection, I introduce the model to forecast cyclical changes of output. As the model concerns the short-run fluctuations, all the employed variables are demeaned the same way as output growth is demeaned in section 2 using the same $\lambda$ across the variables. And all the employed quarterly variables are demeaned contribution to GDP growth. In this sense, I denote them (scaled) changes as I do in chapter 3.

#### Causal relationship between consumption and investment

I follow the intuition of [86]Keynes(1936) discussed in chapter 3 that consumption changes are the main driver of business cycles. I first forecast consumption changes using MF-DFMs. Then I estimate the changes in investment components and net export changes using the forecasts of consumption changes.

To forecast the changes in investment components, I employ three reduced-form investment models that considered in chapter 3.

$$nr_t = \alpha_1 nr_{t-1} + \alpha_2 c_t + \alpha_3 ex_t + \eta_{1t} \tag{5.2}$$

$$r_t = \beta_1 r_{t-1} + \beta_2 c_t + \eta_{2t} \tag{5.3}$$

$$inv_t = \gamma_1 c_t + \gamma_2 c_{t-1} + \eta_{3t} \tag{5.4}$$

where $c$ is consumption changes, $nr$ is non-residential investment changes, $r$ is residential investment changes, $inv$ is inventory changes, and $ex$ is export changes. The government spending is not considered as the coefficients on government spending are not statistically significant as like in chapter 3. Moreover, the published information of the planned government spending ahead would be more helpful than using a statistical method[7].Additionally, I add an ad-hoc net-export model as follows.

$$nx_t = \delta_1 c_t + \delta_2 c_{t-1} + \eta_{4t} \tag{5.5}$$

**Forecasting**

Once the above models are estimated, the forecasts of each component can be achieved. As $nr$ and $r$ are AR(1) models, the effects of consumption changes and export changes can be approximated to autoregressive distributed lag (ADL) models. I truncate the lags at t-4 as the coefficients become close to zero there. Inventory changes and net export changes are forecasted using Equation 5.4 and Equation 5.5.

$$\begin{aligned}
\hat{nr}_{t+h} =& \hat{\alpha}_2\hat{c}_{t+h} + \hat{\alpha}_1\hat{\alpha}_2\hat{c}_{t+h-1} + \hat{\alpha}_1^2\hat{\alpha}_2\hat{c}_{t+h-2} + \hat{\alpha}_1^3\hat{\alpha}_2\hat{c}_{t+h-3} + \hat{\alpha}_1^4\hat{\alpha}_2\hat{c}_{t+h-4} \\
& \hat{\alpha}_3\hat{ex}_{t+h} + \hat{\alpha}_1\hat{\alpha}_3\hat{ex}_{t+h-1} + \hat{\alpha}_1^2\hat{\alpha}_3\hat{ex}_{t+h-2} + \hat{\alpha}_1^3\hat{\alpha}_3\hat{ex}_{t+h-3} + \hat{\alpha}_3^4\hat{\alpha}_3\hat{ex}_{t+h-4} \\
\hat{r}_{t+h} =& \hat{\beta}_2\hat{c}_{t+h} + \hat{\beta}_1\hat{\beta}_2\hat{c}_{t+h-1} + \hat{\beta}_1^2\hat{\beta}_2\hat{c}_{t+h-2} + \hat{\beta}_1^3\hat{\beta}_2\hat{c}_{t+h-3} + \hat{\beta}_1^4\hat{\beta}_2\hat{c}_{t+h-4} \\
\hat{inv}_{t+h} =& \hat{\gamma}_1\hat{c}_{t+h} + \hat{\gamma}_2\hat{c}_{t+h-1} \\
\hat{nx}_{t+h} =& \hat{\delta}_1\hat{c}_{t+h} + \hat{\delta}_2\hat{c}_{t+h-1}
\end{aligned}$$

where j=0, 1, 2, 3 and 4 which is a forecasting horizon. As consumption is close to a random walk, $\hat{c}_{t+1} \cdots \hat{c}_{t+4}$ are close to zero, which means that consumption only can be nowcasted. For given forecasting horizons, export data is only available up to t-1 and thus, export changes barely help to forecast non-residential investment changes. Therefore, the forecasting mainly

[7]I abstract away from the practice, as it is not the interest of this chapter

depends on consumption changes.

Once the components of GDP growth are forecasted, the forecasts of GDP growth are obtained by summing all the components.

$$\Delta\hat{\mathbb{C}}_{t+h} = \hat{c}_{t+h} + \hat{nr}_{t+h} + \hat{r}_{t+h} + \hat{inv}_{t+h} + \hat{nx}_{t+h} \tag{5.6}$$

### 5.2.3 Forecasting consumption changes

#### Model

A Bayesian approach to dynamic factor model employed in this chapter largely follows [121]Ritschl et al. (2016) as I estimate factors using the modified codes of theirs[8]. I abstract from the time-varying factors and auto-correlated disturbances and add the time-varying volatility of idiosyncratic disturbances.

$$X_s = \Lambda f_s + v_{1s} \tag{5.7}$$

$$f_s = \phi_1 f_{s-1} + \cdots + \phi_q f_{s-q} + v_{2s} \tag{5.8}$$

$X_s$: vetor of monthly indicators$(n \times 1)$

$\Lambda$: matric of factor loadings$(n \times 1)$

$v_{1s}$: vector of idiosyncratic components$(n \times 1)$

$f_s$: vector of common factors$(1 \times 1)$

$v_{2s}$: vector of shocks to factors$(r \times 1)$

$$v_{is} \sim N(0, h_{is}^2) \quad \text{and} \quad i = 1j, 2 \tag{5.9}$$

$$h_{is} = h_{is-1} + \eta_{is}, \quad \text{where } \eta_{is} \sim N(0, \Omega_{\eta_i}) \tag{5.10}$$

[8] The codes are obtained in the Review of Economics and Statistics Dataverse (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZYTP50).

$h_{is}$: stochastic volatility of factor$(r \times 1)$

$\Omega_{\eta_i}$: diagonal matrix of volatilities of $h_{is}(r \times r)$

I hire only one factor in this study for the following reasons.First, two factors are not identifiable when employing stochastic volatility as [99]Marcellino et al. (2016) note. Second, the second factor tends to deteriorate forecasting accuracy while it improves nowcasting accuracy as seen in [61]Giannone et al. (2008). Finally, economic interpretation is complex for two factors. Having two factors indicate that there are two common factor driving an economy. It is hard to explain what each factor means.

And the factor dynamics follow the first order autoregressive process. It reveals coherent performance over time. And it is easy to interpret the movement in economic perspective. It can be simply decomposed into a current shock and persistence of past shocks. For AR(2), persistence of past shocks become much complex structure and thus it does not match to economic intuition.

To bridge GDP and factors, frequency of both variables should be matched as quarterly. Aggregation formula of monthly factors follows [100]Mariano and Murasawa (2003).

$$f_s^Q = \frac{1}{3}(f_{s-4} + 2f_{s-3} + 3f_{s-2} + 2f_{s-1} + f_s) \tag{5.11}$$

Prediction of GDP growth is a linear function of the expected common factors and the other regressors as follows:

$$c_t = \beta f_t^Q + \xi_t \tag{5.12}$$

### Prior

Before proceeding to the estimation, I specify prior assumptions. In the previous literature, consumption is close to a random walk. Therefore, I wish to estimate the model mainly depends on data with as simple structure as possible. In this sense, I use uninformative priors for the parameters.

For the factor loadings, the relevant prior for each individual factor loading ($\lambda_i$) is

$$\lambda^{prior} = N(\underline{\lambda}, \underline{V}_{\lambda}),$$

where $\underline{\lambda} = 0$ and $\underline{V}_{\lambda} = 100$.

For the AR parameters $\phi_1, \phi_2, \ldots, \phi_q$ of the factor equation, we specify the following priors:

$$\phi^{prior} \sim N(\underline{\phi}, \underline{V}_{\phi})$$

where $\underline{\phi} = 0_{q\times 1}$ and

$$\underline{V}_{\phi} = \psi \begin{bmatrix} 1 & 0 & \ldots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \ldots & \ddots & 0 \\ 0 & \ldots & 0 & \frac{1}{q} \end{bmatrix}$$

I choose $\psi_1 = 0.2$. I tighten the priors as autoregressive lags are distant, which follows the previous literature that argues that consumption is close to a random walk.

For the variance of the innovations in $\eta_{it}$, I specified the following prior:

$$\sigma_{\eta_i}^{2\,prior} = IG\left(\frac{\tilde{\alpha}_{\eta_i}}{2}, \frac{\tilde{\delta}_{\eta_i}}{2}\right)$$

I choose $\tilde{\alpha}_{\eta_i} = 101$ and $\tilde{\delta}_{\eta_i} = 0.1$.

**Estimation**

I estimate the model by Gibbs sampling. In my case, the estimation procedure is subdivided into four blocks. Each block is estimated conditional the estimated values of the first block or the ones of the previous iterations unless available

1. Estimate factor loadings: $\lambda_j$ for j=1,...,n

2. Estimate constant parameters: $\phi_m$, $\Omega_g$ for m = 1,...,q and g = $\nu_{1s}, \eta_{1s}, \eta_{2s}$

3. Estimate stochastic volatilities: $h_{ir}$ for i= 1,2 and s=q+1,...,S

4.Estimate factors: $f_s$ for s= q+1,...,S

After the estimation of the fourth block, we start the next iteration step again at the first block by conditioning on the last iteration step. I obtain estimates for lag length q=1, taking 10,000 draws and discard first 1000 as burn-in.

## 5.3 Empirical Application: Short-term Forecasts of US GDP

I apply the model to the problem of forecasting US GDP growth at short horizons. The growth of every monthly indicator is demeaned and then standardized using its standard deviation. The full data set starts in January 1982 and end in December 2019.

To evaluate the forecasting performance, I conduct a pseudo out-of-sample forecast exercise in which I assess the point forecasting performance of my model compared to the performance of SPF. To make sure that the results from my models are based on an information set comparable to that available to the SPF forecasters, my model outcomes are based on data available up to the end of the first week of the second month of each quarter, just after the release of the Employment Report.

### 5.3.1 Data

Table 4.1: The dataset of monthly indicators

| | Indicators | Publishing lag |
|---|---|---|
| (1) | real personal consumption growth | two month |
| (2) | real personal consumption growth: goods | two month |
| (3) | real personal consumption growth: service | two month |
| (4) | real disposable personal income | two month |
| (5) | industrial production | one month |
| (6) | consumer sentiment complied by the University of Michigan | one month |
| (7) | consumer sentiment complied by the Conference Board | one month |

To forecast US output growth, I use US real GDP growth and contribution of GDP components to GDP growth 1982:1-2019:4 seasonally adjusted[9]. The data is obtained from the US

[9]The data is collected in July 2021.

Bureau of Economic Analysis. Additivity holds across the components as Contribution data is employed. I will forecast contribution of each GDP components, and then the forecasts of GDP growth are obtained by aggregating the contributions of components. In following analyses, (scaled) changes in a GDP component denotes the demeaned contribution of the component to GDP growth.

As documented in chapter 3, the detrended consumption is close to a random-walk as [68]Hall (1978) argues. Therefore, the up-to-date monthly data is crucial for the nowcasting of consumption growth. In Table 4.1, present are the monthly indicators that are selected to nowcast consumption changes. The first four rows are consumption and its components. These three variables help construct a factor close to the actual consumption changes. Their publication lags are two month, thus, they are not involved in nowcasting. Industrial production index and two consumer sentiment indices are exploited to nowcast consumption changes.

The growth of selected monthly indicators are all demeaned in the same way employed in section 3. The $\lambda$ for monthly indicators should be different from the $\lambda$ for quarterly data. To decide $\lambda$ for monthly data, I employ the formula suggested by [118]Ravn and Uhlig (2002).

$$\lambda_{monthly} = \lambda_{quarterly} \cdot 3^4$$

### 5.3.2 Overall evaluation of the model

To evaluate the forecasting performance of the model, I conduct a pseudo out-of-sample forecasting exercise. Forecast accuracy is measured by the relative root mean squared forecast error (RMSE) and relative root mean absolute forecast error. The relative RMSE is calculated as the ratio of two RMSEs (= RMSE of a evaluated model/RMSE of the benchmark model) and the relative RMAE is calculated as the ratio of two RMAEs (= RMAE of a evaluated model/RMAE of the benchmark model). The evaluation sample starts from the first quarter of 2005 to the lasts quarter of 2019. As a benchmark of nonpredictability, I compute the forecasts for a naive constant-growth model.

In Table 4.2, the forecasting performance of the model and SPF are present. In the upper

Table 4.2: Forecasting Performance: SPF vs. Model

| | Horizon | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|
| | Whole periods (2005:1-2019:4) | | | | | |
| SPF | RMSE | 0.65 | 0.74 | 0.95 | 0.98 | 0.99 |
| | RMAE | (0.81) | (0.80) | (0.90) | (0.96) | (0.98) |
| Model | RMSE | 0.70 | 0.85 | 0.97 | 0.99 | 0.99 |
| | RMAE | (0.78) | (0.85) | (0.95) | (0.98) | (0.98) |
| | Excluding GFC and COVID-19 | | | | | |
| SPF | RMSE | 0.86 | 0.83 | 0.88 | 0.95 | 0.97 |
| | RMAE | (0.93) | (0.85) | (0.89) | (0.95) | (0.97) |
| Model | RMSE | 0.85 | 0.87 | 0.93 | 0.93 | 0.95 |
| | RMAE | (0.89) | (0.85) | (0.94) | (0.97) | (0.98) |

Notes: 0 horizon indicates nowcast and 1 to 4 indicate 1 to 4 quarter ahead forecasts. GFC indicates 2008:9 and 2009:1. COVID-19 indicates 2020:1-2020:4. RMSE is relative root mean squared forecasting error. RMAE is relative mean absolute error.

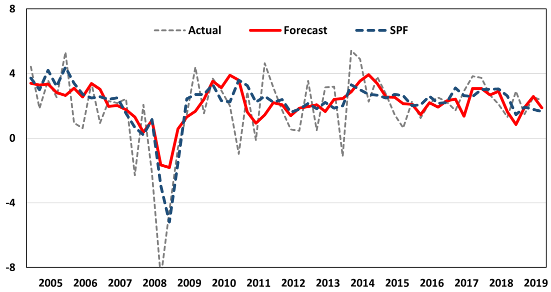
part of the table, the evaluation is conducted for the whole sample period. In the lower part, the GFC(2008:2009:1) and COVID-19(2020:1-2020:4) periods are excluded. Such periods generate exceptionally large forecasting errors. When using RMSEs for evaluation, small number of large errors may highly affect the overall performance. The RMSEs of horizon 3 to 5 are close to 1 for both model and SPF because forecasting errors during the GFC and the COVID-19 are larger than the sum of the forecast errors during the rest of the periods.

For the whole period, the forecasting performance of both SPF and model are far better than the benchmark model. For the nowcasts, RMSEs are 30 per cent lower than the one of constant-growth model. When comparing SPF and the model, for both RMSE and RMAE, SPF is better than the one of the model. However, the gap is not substantial. When excluding the GFC and the COVID-19, the performance gap between the model and SPF is reduced. In terms of RMAE, the performance of the model is very close to the one of SPF.

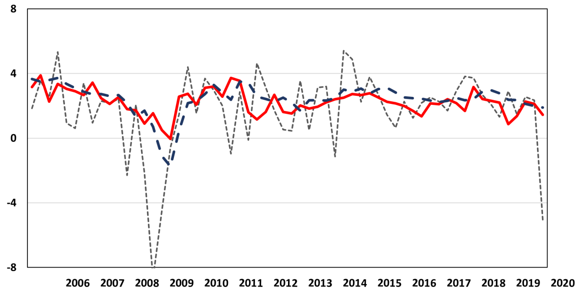
The nowcasts of SPF track the sharp fall of output growth well compared to those of the model. The model tends to generate a smooth movements of forecasts as the forecasts of output growth depends on the forecasts of consumption changes. As consumption smoothly varies, the forecasts of output also tend to vary smoothly.

Figure 5.2: Forecasts by horizons

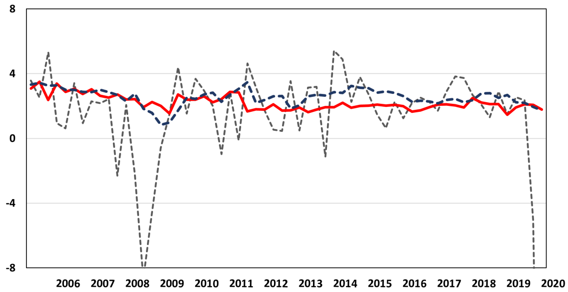
(A) Nowcast



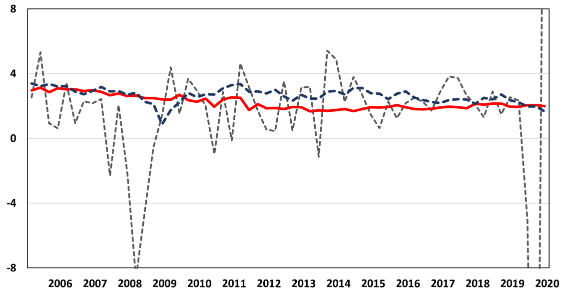

(B) h=1



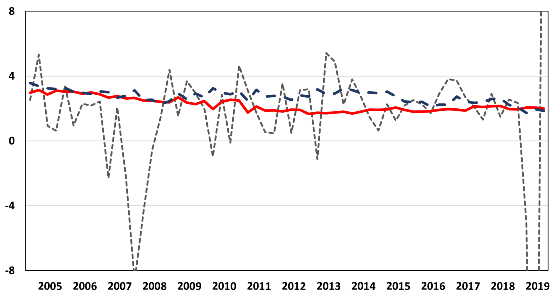

(C) h=2




(D) h=3



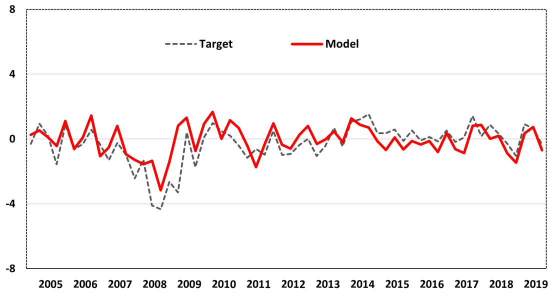

(E) h=4



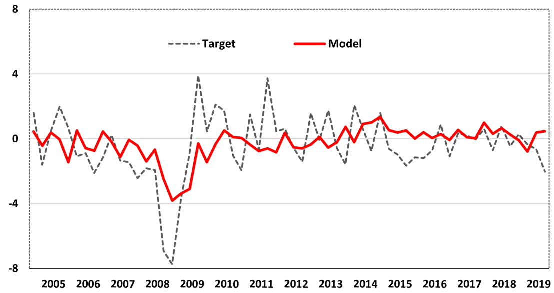

*Note:* y-axis: per cent, x-axis: time horizons (2005:1-2019:4)

Figure 5.3: Nowcasts by components of GDP

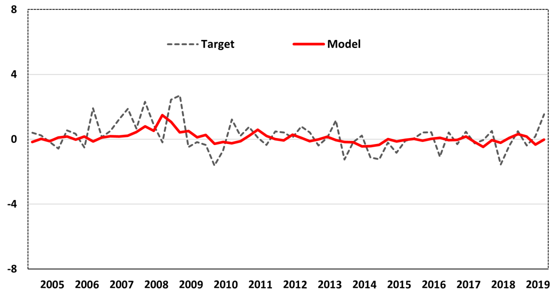
(A) Consumption changes




(B) Investment changes




(C) Net export changes




*Note:* y-axis: per cent, x-axis: time horizons (2005:1-2019:4), Target denotes the estimated cycle through decomposition of contribution data

### 5.3.3 Contribution of components

In this subsection, I evaluate the forecasting performance of the model by components. The nowcast of consumption growth is present in panel (A) of Figure 5.3. The employed MF-DFM tracks the variations of consumption well in overall. During the GFC, however, the performance is limited. In particular, the second dip in 2009:2 is not forecasted at all, which leads to additional forecasting errors in other components. It is hard to improve the performance through the modification of model as consumption is known to be close to a random walk. Therefore, additional monthly indicators containing information of consumption would be required to improve the performance.

The nowcast of investment is present in panel (B) of Figure 5.3. The result displays the moderate performance. It tracks the overall direction of movements well. Therefore, it makes no large errors. However, the nowcast shows the limited ability to catch the short-run fluctuations of investment. It is a natural consequence of the forecasting depending on consumption changes as consumption changes are smooth. To better catch the high fluctuations of investment changes, additional information need to be augmented to the basic model.

The nowcast of net export is present in panel (C) of Figure 5.3. The nowcast of net export is also very smooth as it is forecasted depending on the nowcast of consumption like the nowcast of investment. To improve the performance, additional information would be required.

### 5.3.4 Role of trend and cycle

In this subsection, I separate the forecasts of trend growth and the cyclical changes. To this end, I assume that the forecasts of one year ahead output growth is the trend growth. AS the currently available information of the output cycle is unlikely to affect the forecasts of one year ahead output growth. Therefore, it is reasonable to see the one year ahead forecasts as the the current view of forecasters over the trend growth. This is the case for the model based forecasts.

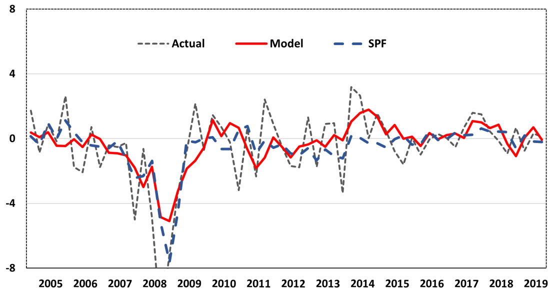
The forecasts of cyclical changes of the model and SPF are very close to each other. As seen in panel (A) of Figure 5.4, two forecasts of cyclical changes are very close to each other. (1) The apparent superiority of SPF is that it catches the sharp decline during the GFC well compared to the model. The model generates relatively smooth forecasts as the forecasts mainly depend on the forecasts of consumption changes. The well-known facts are that consumption is smoother than output. (2) In general, except for the GFC, the model better tracks the cyclical variations of GDP than SPF. The trend growth forecast of SPF is higher than one of the model between 2009 and 2015. During the period, the output growth is higher than the one after the period. The model regards it as the increase in cyclical changes while SPF regards it as the changes in trend growth.

### 5.3.5 Role of smoothing parameter

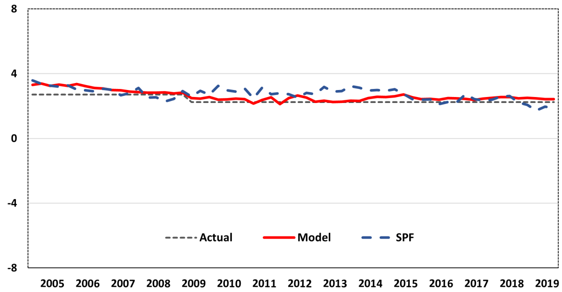
In this subsection, I assess the role of the smoothing parameter, $\lambda$. The results indicate that the estimate of smooth trend helps forecasting output growth. When increasing $\lambda$ from 1600

Figure 5.4: Comparison of trend growth and cycle changes

(A) Cycle changes




(B) Trend growth

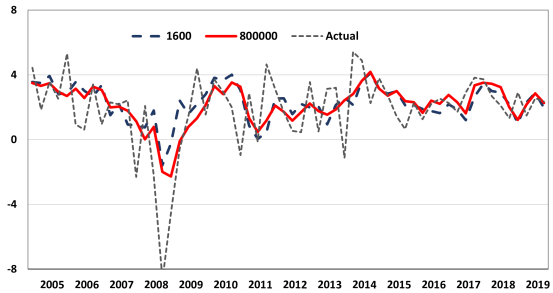



*Note:* y-axis: per cent, x-axis: time horizons (2005:1-2019:4), Acutal denotes the cyclical changes and trend growth estimated in chapter 1

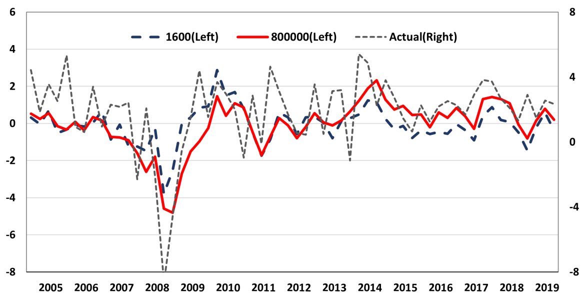
to 32000, the forecasting performance meaningfully improves across the forecasting horizons. When increasing the number from 32000 to larger ones, the forecasting performance does not improve any more.

Figure 5.5: Comparison of trend growth and cycle changes by smoothing parameters

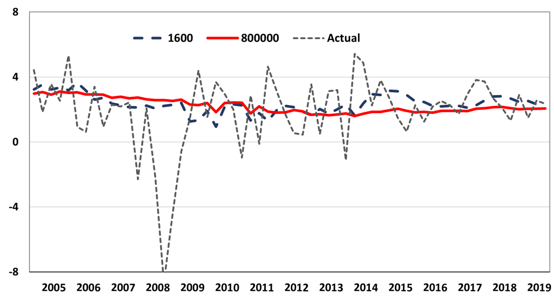
(A) Total




(B) Cycle changes




(C) Trend growth




*Note:* y-axis: per cent, x-axis: time horizons (2005:1-2019:4), Acutal denotes the cyclical changes and trend growth estimated in chapter 1

As seen in the panel (C) of Figure 5.5, for $\lambda = 800000$, a smoother trend is obtained than $\lambda = 1600$ and, at the same time, more volatile cyclical changes are obtained. On the other hand, $\lambda = 1600$ generates a volatile trend compared to the one generated by $\lambda = 800000$ while cyclical

Table 4.3: Forecasting Performance by smoothing parameters

| | | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|
| | | Whole periods (2005:1-2019:4) | | | | |
| $\lambda$=1600 | RMSE | 0.74 | 0.84 | 0.97 | 0.99 | 0.99 |
| | RMAE | (0.85) | (0.89) | (0.96) | (1.01) | (0.98) |
| $\lambda$=32000 | RMSE | 0.68 | 0.84 | 0.97 | 0.99 | 0.99 |
| | RMAE | (0.79) | (0.86) | (0.94) | (0.98) | (0.99) |
| $\lambda$=400000 | RMSE | 0.67 | 0.82 | 0.97 | 0.99 | 0.99 |
| | RMAE | (0.79) | (0.86) | (0.94) | (0.98) | (0.99) |
| $\lambda$=800000 | RMSE | 0.70 | 0.85 | 0.97 | 0.99 | 0.99 |
| | RMAE | (0.78) | (0.85) | (0.95) | (0.98) | (0.98) |
| | | Excluding GFC and COVID-19 | | | | |
| $\lambda$=1600 | RMSE | 0.90 | 0.89 | 0.95 | 0.98 | 0.98 |
| | RMAE | (0.93) | (0.93) | (0.98) | (1.05) | (1.05) |
| $\lambda$=32000 | RMSE | 0.84 | 0.86 | 0.91 | 0.94 | 0.94 |
| | RMAE | (0.87) | (0.88) | (0.93) | (0.98) | (0.98) |
| $\lambda$=400000 | RMSE | 0.86 | 0.85 | 0.93 | 0.95 | 0.95 |
| | RMAE | (0.91) | (0.86) | (0.94) | (0.97) | (0.97) |
| $\lambda$=800000 | RMSE | 0.85 | 0.86 | 0.93 | 0.95 | 0.96 |
| | RMAE | (0.86) | (0.86) | (0.94) | (0.98) | (0.97) |

Notes: 0 horizon indicates nowcast and 1 to 4 indicate 1 to 4 quarter ahead forecasts. GFC indicates 2008:9 and 2009:1. COVID-19 indicates 2020:1-2020:4. RMSE is relative root mean squared forecasting error. RMAE is relative mean absolute error.

changes are relatively smooth. They reflect the relative differences between Keynesian and Real Business Cycle theories. Interestingly, the forecasting results are close to each other except for the period around the GFC.

## 5.4 Conclusion

In this chapter, I introduce a novel method forecasting output growth. From the Keynesian perspective, (1) the short-run fluctuations and the trend growth are forecasted respectively using a different mechanisms. (2) The bottom-up procedure of forecasting is employed. The forecasts of output growth are obtained by aggregating the forecasts of components growth. Forecasting using contribution to GDP growth data allow for the additivity across the components. (3) Employed is the intuition of [86]Keynes'(1936) that current consumption affect current investment by adjusting the businessmen's expectation. Unlike a statistical methods, it reduces the effect of noise in data. To evaluate the forecasting performance of the model, I conduct pseudo out-of-sample forecasting for the horizon from 0 to 4. The results shows that the forecasting performance of the model is comparable to that of SPF.

One thing to improve is the real time detrending method. Intuitive and simple implementation of the HP filter is a strong advantage of the method. However, there are well-known disadvantages of the HP filter. (1) spurious cycle (2) end-point distortion. US output growth has a smoothly declining pattern. Therefore, such disadvantages do not affect the forecasting performance much. However, such disadvantages may be serious for the output growth with fluctuations or breaks in large magnitude.

# Chapter 6

# Conclusion

In this thesis, I investigate US business cycle from the Keynesian perspective. In chapter 1, I decompose US real GDP into the trend and cyclical components through the estimation of a linear deterministic trend with three breaks. The measured business cycle displays the boom-bust pattern with sporadic downward pluckings. In chapter 2, I argue that consumption shocks are the main driver of business cycles based on the intuition of [86]Keynes (1936) and [115]Pigou (1927). I reconcile their ideas based on their commonality highlighting the role of businessmen's expectations as an important driver of business cycles. The reconciled idea describes a boom-bust cycle generated by consumption shocks and their propagation to investment. To support the idea, I document that the estimated response to consumption shocks displays a boom-bust cycle. In chapter 3, I employ the consumption-investment relationship that is studied in chapter 2 to forecast short-run US GDP. The forecasting performance of the model is comparable to the one of the Survey of Professional Forecasters.

The studies in this thesis have two important caveats. First, this thesis does not elaborate the sources of consumption shocks. As shown in chapter 2, the main source of a boom-bust business cycle is the boom-bust cycle of consumption. And the consumption cycle is mostly generated by exogenous consumption shocks. Therefore, to better understand the business cycle mechanism, the sources of consumption shocks need to be investigated. The second caveat concerns the estimated trend. The results of this chapter highly depend on the assumption that the trend is a DLT with breaks. However, this assumption is purely empirical and ad-hoc.

Therefore, the estimation results of this chapter cannot be justified without clarifying the nature of trend. This issue is closely related to the natural rate hypothesis suggested by [56]Friedman (1968).

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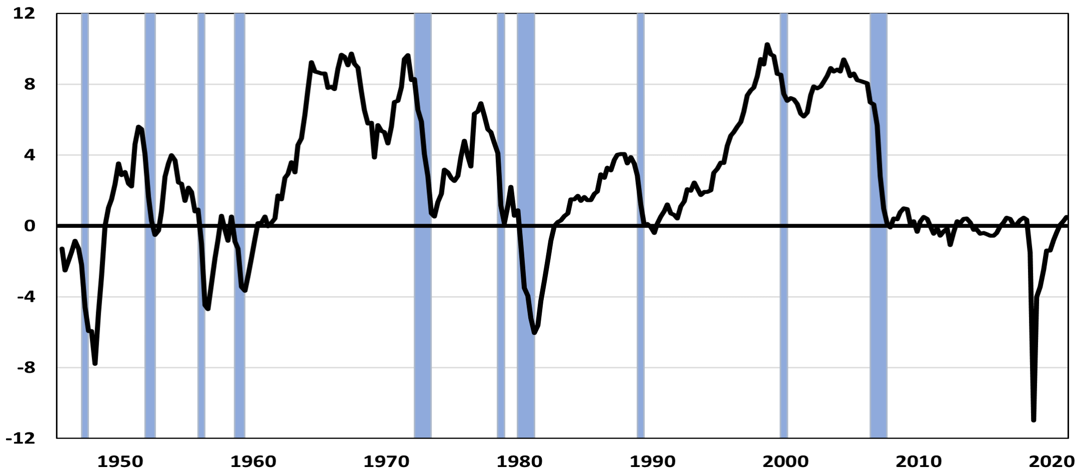
# Appendices

# Appendix A

# Effect of COVID-19

Figure A1: Effect of COVID-19




*Note:* Unit: per cent deviation from trend. Shaded bars correspond to NBER recession dates. X-axis: periods (1947:1 to 2022:4)

In this section, the effect of COVID-19 is investigated. The currently available data of US real output is up to 2021:3. To see the longer horizon trend, I exploit the forecast data of the Survey of Professional Forecasts compiled by the Federal Reserve of Philadelphia, which is available from 2021:4 to 2022:4. There is little difference in the mean growth between the pre-COVID segment and the post-COVID segment. Therefore I merge those two segments. As depicted in Figure A1, the COVID-19 period constitutes a downward plucking of enormous magnitude. Like other pluckings, the plucking ends up with an abrupt reversion to the trend. It is still not certain whether the plucking leads to another slowdown of growth in the post COVID-19 era.

# Appendix B

# Estimation

The estimation largely follows [121]Ritschl et al. (2016) as I estimate models using the modified codes of theirs[1]

## B.1 the Constant Parameters

To estimate the factor loadings, I rewrite equation (1) as:

$$y_i = \lambda_i f + \chi \tag{B.1}$$

where $y_i$ is $S \times 1$ and $f$ which is $S \times 1$ for $i = 1, 2, \ldots, N$. Thus, the posterior for the factor loadings is

$$\lambda_i \sim N(\bar{\lambda}, \bar{V}_{i,\lambda}) \tag{B.2}$$

where

$$\bar{\lambda}_i = (\underline{V}_{\lambda}^{-1} + ((\sigma_{i,\chi}^2)^{-1} f'f)^{-1})(\underline{V}_{\lambda}^{-1}\underline{\lambda} + ((\sigma_{i,\chi}^2) f'y_i))$$

$$\bar{V}_{\lambda} = (\underline{V}_{\lambda}^{-1} + ((\sigma_{i,\chi}^2) f'f))^{-1})$$

[1]The codes are obtained in the Review of Economics and Statistics Dataverse (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZYTP50).

To estimate the AR-parameters of the factor $\phi_1, \ldots, \phi_q$, we find useful to rewrite equation (4.7) as:

$$f = X_f \phi + \nu \tag{B.3}$$

where $f = [f_{q+1}, \ldots, f_S]'$ is $(S-q) \times 1$, $\phi = [\phi_1, \ldots, \phi_q]'$ is $q \times 1$,$\nu = [\nu_{q+1}, \ldots, \nu_S]'$ is $(S-q) \times 1$ and

$$X_f = \begin{bmatrix} f_q & f_{q-1} & \cdots & f_1 \\ f_{q+1} & f_q & \cdots & f_2 \\ \vdots & \vdots & \vdots & \vdots \\ f_{S-1} & f_{S-2} & \cdots & f_{S-q} \end{bmatrix}$$

which is $(S-q) \times q$. Thus, the posterior of the AR-parameters of the factor is:

$$\phi \sim N(\bar{\phi}, \bar{V}_\phi) \tag{B.4}$$

where

$$\bar{\phi} = (\underline{V}_\phi^{-1} + (X_f' \Sigma^{-1} X_f)^{-1})(\underline{V}_\phi^{-1} \underline{\phi} + (X_f' \Sigma^{-1} f))$$

$$\bar{V}_\phi = (\underline{V}_\phi^{-1} + (X_f' \Sigma^{-1} X_f)^{-1})$$

where $\Sigma = diag(\sigma^2_{q+1,f}, \ldots, \sigma^2_{S,f})$ with $\sigma_{s,f} = e^{hs}$.

## B.2 Estimating the stochastic volatility

To estimate the stochastic volatility $h_s$, I condition on the factor $f_s$, the AR coefficients in $\phi$, and the variance $\sigma^2_\eta$. Given the factor, the AR coefficients, and the variance of the innovations, we can observe as

$$f_s^* = f_s - \phi_1 f_{s-1} - \cdots - \phi_q f_{s-q} = e^{h_{2s}} \zeta$$

where $\zeta \sim N(0,1)$ This nonlinear measurement equation can be linearised by squaring and taking logarithms

$$log(f_s^*)^2 = 2h_s + log(\zeta_s^2)$$

Because $(f_s^*)^2$ can be very small, an offset constant is used to make the estimation procedure more robust, resulting into the following approximating linear state-space framework.

$$f_s^{**} = 2h_s + e_s \tag{B.5}$$

$$h_s = h_{s-1} + \eta_{2s} \tag{B.6}$$

where $f_s^{**} = log[(f_s^*)^2 + \bar{c}]$, $e_s = log(\zeta_s^2)$. The offset constant $\bar{c}$ was introduced by Fuller (1996, pp. 494-7) and is set to 0.001. Although the representation is linear, it is not Gaussian, as the innovation of the system in (B.5) can be found by approximating $e_s$ by a mixture of normal densities as shown by Kim et al. (1998). They match a number of moments of the $log\chi(1)^2$ distribution using a mixture of seven normal densities with component probabilities $q_j$, and means $m_j$ and variance $v_j^2$, $j = 1, \dots, 7$, as tabulated in Table A-1. Hence,$e_s$ can be approximated as

$$f(e_s) \approx \sum_{j=1}^{7} q_j f_N((e_s | m_j - 1.2704, v_j^2)$$

As alternative way to express this is

$$e_s | s_s = j \sim N(m_j - 1.2704, v_j^2), \tag{B.7}$$

$$Pr(s_s = j) = q_j, \tag{B.8}$$

where $s^S$ is a matrix of unobserved indicator states $s_{i,s} \in 1, \dots, 7$, selecting at every period which number of the normal distribution mixture is used for the approximation of $e_s$.

Conditional on $f_s^{**}$ and $h_s$ for $s = 1, \dots, S$, it is possible to sample the indicator states $s^S$. This is done by independently drawing each $s_t$ from the probability mass function defined

$$Pr(s_s = j | f_s^{**}, hs) \propto q_j f_N(f_s^{**} | 2h_s + m_j - 1.2704, v_j^2),$$

with $j = 1, \ldots, 7$ and $s = 1, \ldots, S$. The normal approximation to the $\log\chi(1)^2$ innovations transforms the system in (B.5) into a Gaussian one. Due to this fact, the sampling algorithm of Carter and Kohn (1994) can be used agains to obtain draws for $h_s$ for $s = 1, \ldots, S$.

## B.3 Estimating the Latent Factor

To estimate the common latent factor we condition on the parameters of the model and the factor loadings $\lambda$. The state equation is

$$F_s = \Phi F_{s-1} + \tilde{v}_s \tag{B.9}$$

where $F_s = [f_s, f_{s-1}, \ldots, f_{s-q+1}]$ is $q \times 1$, which is denoted as the state vector, $\tilde{v}_s = [v_{2s}, 0, \ldots, 0]'$ is $q \times 1$ and

$$\Phi = \begin{bmatrix} \phi_1 & \phi_2 & \ldots & \phi_q \\ & I_{q-1} & & 0_{q-1\times 1} \end{bmatrix}$$

To calculate the common factor, I use the algorithm suggested by Carter and Kohn (1994). This procedure draws the vector $F = [F_1, F_2 ... F_S]$ from the joint distribution given by:

$$p(F|\Lambda, Y, \Xi) = p(F_S|\Lambda, y_S, \Xi) \prod_{s=1}^{S-1} p(F_S|F_{s+1}, \Lambda, \Xi, Y_s) \tag{B.10}$$

where $Y^s = [Y_1 Y_2 \ldots Y_s]$. Because the error terms in equation (B.9) are Gaussian equation, (B.10) can be rewritten as

$$p(F|\Lambda, Y, \Xi) = N(F_{S|S}, P_{S|S}) \prod_{t=1}^{S-1} N(F_S|F_{s|s,F_{s+1}}, P_{s|s,F_{s+1}}) \tag{B.11}$$

with

$$F_{S|S} = E(F_S|\Lambda, \Xi, Y) \tag{B.12}$$

$$P_{S|S} = Cov(F_s|\Lambda, \Xi, Y) \tag{B.13}$$

and

$$F_{s|s,F_{s+1}} = E(F_s|F_{s+1}\Lambda, \Xi, Y) \tag{B.14}$$

$$P_{s|s,F_{s+1}} = Cov(F_s|F_{s+1}, \Lambda, \Xi, Y) \tag{B.15}$$

We obtain $F_{S|S}$ and $P_{S|S}$ from the last step of the Kalman filter iteration and use them as the conditional mean and covariance matrix for the multivariate normal distribution $N(F_{S|S}, P_{S|S})$ to draw $F_S$. To illustrate the Kalman Filter, we work with the state-space system equation (B.9). We begin with the prediction steps.

$$F_{s|s-1} = \Phi F_{s-1|s-1} P_{s|s-1} = \Phi P_{s-1|s-1}\Phi + Q_s \tag{B.16}$$

where

$$Q_s = \begin{bmatrix} \sigma^2_{s,f} & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

which is q × q. To update these predictions we first have to derive the forecast error:

$$\kappa_s = Y_s - H_s F_{s|s-1} \tag{B.17}$$

its variance

$$\Sigma = H_s P_{s|s-1} H_s' + \Omega_{chi} \tag{B.18}$$

and the Kalman gain:

$$K_s = P_{s|s-1} H_s' \Sigma^{-1} \tag{B.19}$$

Thus, the updating equations are:

$$F_{s|s} = F_{s|s-1} + K_s \kappa_s \tag{B.20}$$

$$P_{s|s} = P_{s|s-1} + K_s H_s P_{s|s-1} \tag{B.21}$$

To obtain draws for $F_1, F_2, \ldots, F_{S-1}$ we sample from $N(F_{s|s,F_{s+1}}, P_{s|s,F_{s+1}})$, using a backwards moving updating scheme, incorporating at time t distribution about $F_t$ contained in period t+1. More precisely, we move backwards and generate $F_s$ for $s = S-1, \ldots, 1$ at each step while using information from the Kalman filter and $F_{s+1}$ from the previous step. We do this until 1.

The updating equations are:

$$F_{s|s,F_{s+1}} = F_{s|s} + P_{s|s}\Phi' P^{-1}_{s+1|s}(F_{s+1} - F_{s+1|s}) \tag{B.22}$$

and

$$P_{s|s,F_{s+1}} = P_{s|s} - P_{s|s}\Phi' P^{-1}_{s+1|s}\Phi P_{s|s} \tag{B.23}$$

Table A1: Selection of Mixing Distributions

| $\omega$ | $q_j = Pr(\omega = j)$ | $m_j$ | $v_j^2$ |
|---|---|---|---|
| 1 | 0.00730 | -10.12999 | 5.79596 |
| 2 | 0.10556 | -3.97281 | 2.61369 |
| 3 | 0.00002 | -8.56686 | 5.17950 |
| 4 | 0.04395 | 2.77786 | 0.16735 |
| 5 | 0.34001 | 0.61942 | 0.64009 |
| 6 | 0.24566 | 1.79518 | 0.34023 |
| 7 | 0.25750 | -1.08819 | 1.26261 |

Source: Kim et al. (1998).