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Galin Todorov

NATIONAL OUTPUT AND MARKET RETURN INTEGRATION OF G-7 COUNTRIES: A PERSPECTIVE FROM PRINCIPAL COMPONENT ANALYSIS

ABSTRACT

This study explores the evolution of integration in output trends, cycles, and market returns for G-7 countries. We use unobserved component model to decompose national output levels and identify quantitatively significant trend and cycle components. For all countries, trend components dominate both in terms of magnitude and importance due to the permanent nature of the shocks they capture. Using principal component analysis, we reveal the existence of common factors driving the volatility in trends, cycles, and market returns. A central contribution of our work is the construction of quantifiable measures of output trend, cycle, and market return integration, referred to as indices of integration. Our indices display high volatility with no trend. In addition, a null hypothesis for white noise could not be rejected for the trend and cycle integration indices. Our study is not able to establish a relationship between integration and national output and market return levels.

Key Words: international business cycles, index of integration, principal component analysis, unobserved components

Galin Todorov
University of Wisconsin-Whitewater, USA

Correspondence: Galin Todorov
University of Wisconsin-Whitewater, USA
E-mail: todorovg@uww.edu

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INTRODUCTION

The continuing process of national output and market return integration is one of the most distinctive features of the modern global economy. Theory suggests numerous benefits of integration: efficient production, greater output, improved capital allocation, more efficient financial system, and accelerated economic growth (Baele, Ferrando, and Hördahl., 2004).

Accounting for 47% of world output in 2015 (Bosworth, 2016), a center part in the process of global integration belongs to the G-7 countries, the seven worlds' most advanced national economies. Therefore, logical questions that arise from both academic and policy perspective are how the process of national output and market return integration among these countries evolved over time, as well as what its effect is on national output levels and market returns.

Although a substantial body of literature has been developed to study national output integration, most existing work has been mostly focused on exploring bilateral business cycle synchronization. Evidence that business cycle synchronization is increasing over time, however, are ambiguous. Stock and Watson (2005), for instance, find no evidence of rising synchronization. Kose, Otrok, and Whiteman (2008) and Bagliano and Morana (2010), on the other hand, report some evidence of increasing synchronization. Results reported by Narayan and Popp (2009) point to the existence of symmetry in business cycles, while evidence offered by Antonakakis and Scharler (2012) point to a rather heterogeneous pattern of synchronization.

Recent literature, however, provides evidence that business cycles synchronization represents only one source of output integration. Blonigen, Piger, and Sly (2014), for instance, demonstrate that most national outputs for G-7 countries are due to the permanent effects of shocks captured by stochastic trend components. Consequently, the extent of integration among countries' level of output would be understated if only cycle fluctuations are considered; therefore, our first goal in this study is to address this shortcoming and expand the scope of national output integration by considering both trend and cycle components. Like Blonigen, Piger, and Sly (2014), we utilize the unobserved component model to decompose quarterly real GDP date for G-7 countries into trend and cycle components. By doing so, we investigate the integration not only in terms of cycles, but also their trends as well.

The unobserved component model was first introduced by Harvey (1985) and has been extensively used in the identification of trends and cycles. Sinclair (2009), for instance, used it in the study of output fluctuations, and Blonigen, Piger, and Sly (2014) used it in the study of co-movement of shocks. Morley, Panovska, and Sinclair (2017) also used it to study the global financial crisis, and Hall and Lagoa (2014) used it to explore the Eurozone inflation; a detailed survey of relevant unobserved component literature is offered in Oh, Zivot, and Creal (2008).

Literature on market return integration is abundant as well, yet most studies are largely based on bilateral correlation measure. Quinn and Voth (2008), for instance, report on several developed countries that since the 1990s, national stock market correlations are at a historically high-level. Analyses by Pukthuanthong and Roll (2009) and Berger, Pukthuanthong, and Yang (2011) report evidence of increasing stock market integration for developed countries, while Volosovych (2011) reports evidence of increasing bond market integration. Some studies focus on the relationship between stock market integration and business cycle synchronization. Davis (2014) shows that increasing equity market integration results in business cycle divergence while Qadan and Yagil (2015) find that international stock market correlations relate strongly to real economic activity. Pyun and An (2016) report that during the global financial crisis, the business cycle co-movements between the US and the rest of the world were stronger when the level of capital market integration between them was higher.

Literature, however, recognizes numerous potential deficiencies of correlations as measures of financial integration. Wilcox (2005), for instance, claims that outliers and heavy-tailed distributions may alter the robustness of sample correlations. Boyer, Gibson, and Loretanl (1999) add that conditional heteroscedasticity and high volatility may demean the reliability of conclusions based on sample integration; Forbes and Rigobon (2002) report that correlation estimates of national market returns are biased upward when volatility in one market increases market volatility elsewhere; and Carrieri, Errunza, and Hogan (2007) and Huber and Ronchetti (2009) explain that correlations between country national returns are not adequate measures of either diversification benefits, or financial integration. In a similar manner, Obstfeld and Taylor (2004) further recognize that higher correlation between market returns might be a result of common shocks among a group of countries and do not necessarily imply integration.

In this study, we aim at addressing the deficiencies imposed by bilateral correlations by exploring integration without using any bilateral correlation based tools. Correspondingly, our second goal is to expand the understanding of integration by quantifying and comparing the levels and evolution of integration in GDP cycles, GDP trends, and market returns for the set of G-7 countries, as opposed to focusing on any bilateral measures. A key feature of our work is the use of the principal component analysis (PCA), which allows us to separately quantify the level of overall integration in cycles, trends, and returns valid for the entire set of G-7 countries. PCA has been used extensively in the studies of integration. Analyses by Pukthuanthong and Roll (2009) and Berger, Pukthuanthong, and Yang (2011) use market returns and PCA to develop a new indicator of financial integration and Volosovych (2011) uses bond returns and PCA to create an index of integration. Some studies assign meaning to the first component. Meric, Eichhorn, McCall, and Merice (2011) and Merice et al. (2012) analyze national market returns and refer to the first component as an indicator of common sources of variability. Volosovych (2011), in a similar manner, suggests that the fraction of total variability in data accounted for by the first component reflects the extent of market integration.

In this study, PCA is used to separately identify the principal components defining the trend and cycle GDP components, as well as the components defining the market returns in each year. Like Volosovych (2011), the fraction of data variability explained by the first component is framed into indices of trend, cycle, and market return integration. Our indices take values between zero and one and provide for a quantifiable measure of integration.

Using unobserved component model, we are able to identify quantitatively significant trend and cycle components for all countries. The trend components, however, dominate both in terms of magnitude and importance due to the permanent nature of the shocks they capture. This underscores the proposition that the extent of integration among countries' level of output would be understated if only cycle fluctuations are considered. Our indices of trend, cycle, and market return integration display high volatility with no trend. In addition, a null hypothesis for white noise could not be rejected for the trend and cycle integration indices. Our study is not able to establish a relationship between integration and national output levels.

The reminder of this paper is organized as follows. The following section briefly reviews the literature exploring the relationship between cross-border economic and

financial activity, integration, and national output levels. Section 3 describes the data and outlines the methodology used in this study. Section 4 presents the results from our empirical work; lastly, Section 5 concludes.

LITERATURE REVIEW

In this section, we briefly review the academic work exploring the relationship between cross-border economic and financial activity, integration, and national output levels. International trade lays at the heart of economic integration. The relationship between trade intensity and business cycle synchronization has been a widely studied subject that originated with the work of Mundell (1961) and McKinnon (1963). The effect of trade intensity on integration, however, seems to be ambiguous.

Traditional trade theory relies on the prediction of the Hecksher-Ohlin theorem. The theory is well supported by a wide array of empirical studies (Frankel and Rose, 1997, 1998; Imbs, 2004; Inklaar, Pin, and Haan, 2008), and postulates that greater trade intensity results in greater inter-industry specialization across countries. Thus, countries experience heterogenous industry-specific supply shocks resulting in diverging business cycles and thus reduced output integration.

Krugman (1979), however, suggests that trade may be due to economies of scale and preference for variety and hence could occur within industries. If such intra-industry specialization dominates trade flows, then greater trade intensity results in greater intra-industry specialization (Giovanni and Levchenko, 2010; Ng, 2010). Thus, countries experience homogeneous industry-specific supply shocks resulting in converging business cycles and hence increased output integration.

Turning to financial markets, literature offers ambiguous evidence on the relationship between cross-border financial activities, integration, and output levels. Literature (e.g., Mundell, 1961; McKinnon, 1963) suggest that for economies with free-floating exchange rates, largely unrestricted capital mobility, and sound institutional fundamentals, the equity markets would be well integrated. The extent of integration, however, may vary due to wealth and balance-sheet effects. Davis (2014) suggests that wealth effect would amplify the extent of financial integration. For instance, a stock market decline in home country would result in a decline in investors' (both domestic and foreign) wealth and hence reduced investment (or disinvestment) abroad, thus causing a stock market decline abroad. International real business cycle (IRBC) literature offers

evidence that wealth effects may also be a reason for a negative effect of equity market integration on business cycle co-movemen;this is because equity market financing implies that the proceeds from a project are shared proportionately by the investor and the financier. Baxter and Cruccini (1995) also attribute the negative relationship to a wealth effect. Evidence for negative impact of the wealth effect can also be found in Kehoe and Perri (2002), as well as in Heathcote and Perri (2003).

Davis (2014) also suggests balance-sheet effects would also amplify the extent of financial integration. For instance, a stock market decline in home country would cause credit constrained financial intermediaries to face relatively large losses in home country. Thus, to cover losses, they may decrease lending or sell assets abroad, hence causing a stock market decline abroad. Models accounting for information asymmetry and financial frictions, offer evidence for a positive impact of equity market integration on business cycle co-movement due to balance sheet effects. Davis (2014) further explains that if a credit constrained financial intermediary faces relatively large losses in home country, the supply of credit would decrease both at home and abroad, resulting in a decline in both domestic and foreign output. Hence, a positive relationship between market integration, business cycles co-movement and output levels.

In summary, theory is ambiguous on the relationship between cross-border economic and financial activities and integration. A dominant effect of intra-industry specialization would increase business cycle synchronization, while a dominant effect of inter-industry specialization would decrease it. Wealth and balance sheet effects increase equity market integration, while a dominant balance sheet effect increases business cycle synchronization, while a dominant wealth effect decreases it.

DATA AND METHODOLOGY

In this section, we review the empirical methods and data utilized in this study. First, we begin by explaining how the trend and cyclical components are derived; next, we proceed in subsections with details on the principal component analysis and the construction of the indices of integration; lastly, the proceeding subsection offers details on the data employed in this study.

Trend and cycle components

We study the national output integration among G-7 countries by exploring the synchronization of trend and cycle GDP components. Since the two GDP components are not directly observed, they need to be derived from real GDP data. Here, like Blonigen, Piger, and Sly (2014), we estimate the two components using an unobserved-components (UC) model.

Consistent with the literature by Harvey (1985) and Oh, Zivot, and Creal (2008), the UC model identifies the trend component as the accumulation of permanent, long-run effects of shocks on output while the cycle component represents the accumulation of temporary, short run effects of shocks on output.

Within the UC framework, the log GDP ($Y_{i,t}$) for each country I in period t, is additively divided into trend ($T_{i,t}$) and cycle ($C_{i,t}$) components:

$$Y_{i,t} = T_{i,t} + C_{i,t} \qquad (1)$$

with the trend component specified as a random walk with a drift process:

$$T_{i,t} = a_i + T_{i,t-1} + v_{i,t} \qquad (2)$$

and the cycle component is specified as an AR (1) process:

$$C_{i,t} = \beta_i + \beta_{1i} C_{i,t-1} + \varepsilon_{i,t} \qquad (3)$$

where $v_{i,t} \sim i.i.d.\ N(0,\sigma^2_{Vi})$, $\varepsilon_{i,t} \sim i.i.d.\ N(0,\sigma^2_{\varepsilon i})$ are independent trend and cycle shocks.

The UC model described by Eqs. *(1)- (3)* is estimated via maximum likelihood and the trend and cycle components are derived using the Kalman Filter. The estimated trend and cycle components are used in the construction of two separate trend and cycle data sets which are subsequently explored using the principal component analysis.

Principal component analysis (PCA)

The Principal Component Analysis (PCA) is a completely non-parametric statistical technique that is used to decrease dimensionality and identify patterns in data Jolliffe,

2002; Rencher and Christensen, 2012). Its objective is to derive linear combinations of uncorrelated, optimally-weighted observed variables, called principal components (PCs), such that each PC explains the maximum amount of variation remaining in the data subject to it being uncorrelated with all previous PCs.

The principal components are ranked by the variation explained. The first component is the one with the largest variance. It accounts for the greatest possible fraction of the total variation in the original dataset. Each remaining component is constructed such that it accounts for the maximum possible fraction of the total variation that remains unexplained by all previous components. Consequently, each successive component accounts for a progressively smaller amount of the total data variation. In practice, only the first few components, and often only the first one are found significant and thus retained for further analysis (refer to Marida, Kent, and Bibby, 1979; Rencher and Christensen, 2012).

Using the PCA method, the principal components defining the market returns, as well as the trend and cycle data sets in each year are extracted separately. For each data set, the portions of total variability explained by the first principal component in each year are used as a proxy for the level of integration. For each data set, those values are stacked together to construct dynamic measures of integration, representing our indices of market, trend, and cycle integration.

Data

We pursued our work utilizing quarterly real GDP data for G-7 countries. Data spans from 1963 (Q1) to 2016 (Q4) and comes from OECD Main Economic Indicators (database). Quarterly data is preferred since it allows us to capture patterns of fluctuation in trend and cycles that may be obfuscated (averaged away) by a longer frequency data. All data is seasonally adjusted and denominated in constant 2010 US dollars and hence particularly useful for cross-country analysis from the prospective of an US stakeholder. We also utilized monthly prices of the MSCI Bara indices for all G-7 national markets for the period between January 1970 and December 2016. We chose monthly market data since it implicitly accounts for differences in trading days and is less affected by random noise. MSCI indices are established consistently across countries and provide an adequate ground for exploration of cross-market relations. They are all value weighted and calculated with dividends reinvested. To avoid double counting, stock prices of companies

set up abroad are not included. All indices are in US dollars, which provides additional comparability across markets and implicitly takes care of currency market effects. Further details on the construction of the indices of integration are provided in Appendix A and technical details on PCA are offered by Jolliffe (2002) and Jackson (2003) among others.

EMPIRICAL RESULTS AND DISCUSSION

In this section, we report and discuss the results from our empirical work. The first subsection begins by describing the quantitative importance of trend and cycle components, while the next subsection introduces the results from the estimation of the indices of trend, cycle, and market integration.

Trend and cycle components

Plots of the log of real GDP, as well as the trend and cycle components for the US and the remaining G-7 countries are offered in the panels of Figure 1. The graphs suggest that the magnitude of the trend component significantly exceeds that of the cycle component. This emphasizes the importance of the trend component and confirms that the evolution of GDP is primarily governed by permanent shocks.

For all seven countries, the cycle components are characterized with great variability, yet relatively small magnitude. Most of the values fall within the range between 0.05 and -0.05, further illustrating the relatively minor importance of cycle fluctuations. A notable exception is the particularly steep decline in 2008-2009, illustrating that some of the effects of the downturn were short-lived.

In summary, the analysis in this subsection suggests considerable quantitative importance of the trend component and relatively minor importance of the cycle component. The effects of the temporary shocks captured by the cycle component are characterized with great volatility. However, the effects of the shocks captured by the trend component are those responsible for long run output growth and tend to dominate in importance due to the permanent nature of their effects.

Indices of trend, cycle, and market integration

In this subsection, we explain the application of the principal component analysis in the derivation of the indices of trend, cycle, and market integration. The principal component analysis of the trend data set reveals one significant principal component, and hence one

common factor, driving trend component variability in 38 of the 53 years in our sample. In the remaining 15 years, variability is driven by two significant components, and hence two common factors.

Since theory suggests that the patterns of trade specialization are the main drivers of economic integration, most likely the most influential common factor, captured by the first principal component, summarizes the competing effects of intra-and-inter-industry specialization. The second component could be due to various regional and political factors.

The second column of Table 1 reports the values of the index of trend integration. Each value represents the fraction of total variability in country trend data in a year, explained by the first principal component and hence the level of trend integration in that year. In all years, this fraction is greater than 0.5, implying that in all years, trade specialization effects account for more than 50% of the total variation in the data set. In 45 of those years, the fraction is greater than 0.7 and hence more than 70% of total variability of trend components can be related to trade specialization effects.

The evolution of the index of trend integration is depicted in panel 1 of Figure 2. The plot illustrates significant volatility, albeit within a relatively tight range. This suggests that periods with dominating intra-industry specialization alternate with periods with dominating inter-industry specialization. The graph is characterized with several particularly steep declines, followed by steep increases. Notable peaks are observed in 1971 (0.9836), and 2010 (0.9867). In these years, the influence of the trade specialization effects was the strongest and almost all the variability in trend components could be attributed to them. The peaks in integration are also suggestive of peaks in intra-industry specialization. Hence, most likely, the trade effects in these years were dominated by intra-industry specialization.

Similarly, notable troughs are observed in 1975 (0.6371), 1980 (0.5332), 1992 (0.5286), 2001 (0.5638), and 2011 (0.586). In these years, the influence of the trade specialization effects was the weakest, and only about half of the variability in trend components could be attributed to them. The troughs in integration are also suggestive of peaks in inter-industry specialization. Hence, most likely the trade specialization effects in these years were dominated by inter-industry specialization. The relative variability of the index suggests that the influence of trade effects is not steady and consistent, but rather volatile and unpredictable.

The graph illustrates that the integration in trend is not increasing over time, but rather follows an unstable path with many ups and downs. Hence, we are unable to say if over time the effect of intra-or inter-industry specialization increases. In addition, the level of integration in 1964 (0.8386) is greater than the level of integration in 2016 (0.6989), further illustrating the uneven path of integration and suggesting that the influence of trade effects in 2016 is weaker than in 1964.

The principal component analysis of the cycle data set reveals one significant principal component, and hence one common factor, driving cycle component variability in only three of the 53 years in our sample. In 31 years, variability is driven by two significant components, and hence two common factors; and in 19 years, variability is driven by three significant components and hence three common factors.

Since theory suggests that the patterns of trade specialization are the main drivers of economic integration, regardless whether in cycles or trend, most likely the most influential common factor, captured by the first principal component, summarizes the competing effects of intra-and-inter-industry specialization. The second and third components could again be due to various regional and political factors.

The third column of Table 1 reports the values of the index of cycle integration. Each value represents the fraction of total variability in cycle component data in a year, explained by the first principal component and hence the level of cycle integration in that year. In all years, this fraction is greater than 0.4, implying that in all years, trade specialization effects cause more than 40% of the total variation in the data set. In only four of those years, the fraction is greater than 0.7. This suggests weaker cycle integration (relative to trend) among country cycle GDP components, as only in four years, more than 70% of total variability of cycle components can be related to trade specialization effects.

The evolution of the index of trend integration is depicted in panel 2 of Figure 2. Similarly, to trend integration, the cycle integration index displays significant volatility and is characterized with several particularly steep rises, followed by steep declines. This again suggests that periods with dominating intra-industry specialization alternate with periods with dominating inter-industry specialization. Notable peaks are observed in 1973 (0.929), and 2009 (0.8784). In these years, the influence of the trade specialization effects was the strongest and almost all the variability in cycle components could be attributed to them. The peaks in integration are also suggestive of peaks in intra-industry specialization.

Hence, most likely, the trade effects in these years were dominated by intra-industry specialization.

Similarly, notable troughs are observed in 1986 (0.5286), 1980 (0.5332), and 2012 (0.4926). In these years, the influence of the trade specialization effects was the weakest, and only about half of the variability in cycle components could be attributed to them. The troughs in integration are also suggestive of peaks in inter-industry specialization. Hence, most likely the trade specialization effects in these years were dominated by inter-industry specialization.

Similarly, to the trend index, the relative variability of the cycle index suggests that the influence of trade effects is not steady and consistent, but rather volatile and unpredictable. The graph illustrates that the integration in cycles is not increasing over time, but rather follows an unstable path with many ups and downs. Hence, we are unable to say if over time the effect of intra-or inter-industry specialization increases. The level of integration in 1964 (0.59), however, is lower than the level of integration in 2016 (0.8047). Hence illustrating a somewhat increased influence of the common in 2016.

The principal component analysis of the market return data set reveals one significant principal component, and hence one common factor, driving trend component variability in 13 of the 47 years in our sample. In 32 years, variability is driven by two significant components, and hence two common factors; and in only two years, variability is driven by three significant components and hence three common factors.

Since theory suggests that wealth and balance effect represent the main drivers of national equity market integration, most likely the most influential common factor, captured by the first principal component, summarizes the wealth and balance sheet effects. The second and third components could be due to various regional and sector specific factors.

The fourth column of Table 1 reports the values of the index of market integration. Each value represents the fraction of total variability in market data in a year, explained by the first principal component and hence the level of market integration in that year. In all years, this fraction in is greater than 0.45 thus implying that in all years, wealth and balance effects capture more than 45% of the total variation in the data set. In 26 of those years, the fraction is greater than 0.7. This suggests considerable integration (relative to trend and cycle components) among national market returns, as in those 26

years, more than 70% of total variability of market return data can be related to wealth and balance sheet effects.

The evolution of the index of market integration is depicted in panel 3 of Figure 2. The plot illustrates significant volatility, yet no particularly steep rises or declines. This suggest period with relatively strong wealth and balance-sheet effects alternate with periods with relatively weaker effects. Notable peaks are observed in 2008 (0.9829), 2009 (0.9684), and 2011 (0.9011). In these years, the influence of the wealth and balance sheet effects was the strongest and almost all the variability in cycle components could be attributed to them. Similarly, notable troughs are observed in 1982 (0.4532), 1991 (0.4533), and 2014 (0.5863). In these years, the influence of the wealth and balance sheet effects was the weakest, and only about half of the variability in market data could be attributed to them.

Similarly, to the other two indices, the relative variability of the market integration index suggests that the influence of wealth and balance sheet effects is not steady and consistent, but rather volatile and unpredictable. The graph illustrates that the market integration follows an unstable path with many ups and downs. Hence, we are unable to say if over time the effect of wealth and balance sheet effects increases or decreases. The level of integration in 1970 (0.6234), however, is quite like the level of integration in 2016 (0.607). Hence illustrating a somewhat increased influence of those effects in 2016.

Table 2 offers the results from the Dicky-Fuller test for unit root and portmanteau (Q) test for white noise performed on the indices of trend, cycle, and market integration. For all indices, the Dicky-Fuller test overwhelmingly rejects the null for a unit root in favor of the alternative that the processes of trend and cycle integration are stationary, hence confirming the lack of trend. For the indices of trend and cycle integration, the portmanteau (Q) test fails to reject the null that autocorrelation functions have no significance for any number lags, hence implying that the two processes represent random white noise. This is important because it implies that the evolution of trend and cycle integration cannot be predicted or forecasted. Hence, searching for determinants of integration would yield conflicting and inconsistent results as no variable would have a statistically significant effect. Additionally, the processes of trend and cycle integration cannot be used as determinants of other variables, as their effects would never be statistically significant. Thus, no relationship could be established between trend and cycle integration and national output levels.

For the index of market integration, however, the portmanteau (Q) test, rejects the null for no autocorrelation functions at any number of lags, hence implying that the process is not a random white noise. Nevertheless, estimation of various specification addressing the effect of integration on output using various estimation techniques yielded insignificant coefficients (possibly due to the short index series). Hence, no relationship could be established between the process of market integration and national output levels and market returns.

In summary, our analysis in this section clearly reveals the existence of common trend, cycle, and market return factors, causing some degree of national output and market return integration. The processes of integration are highly volatile, and no conclusion can be drawn that national output and market return integration are increasing over time. In addition, no relationship could be established with other variables like national output.

CONCLUSION

This study explores the evolution of integration in output trends, cycles, and market returns for G-7 countries. We use unobserved component model to decompose national output levels and identify quantitatively significant trend and cycle components. For all countries, trend components dominate both in terms of magnitude and importance due to the permanent nature of the shocks they capture. Using principal component analysis, we reveal the existence of common factors driving the volatility in trends, cycles, and market returns. Theory suggests the most significant trend and cycle factors most likely represent trade effects due to intra-and-inter industry patterns of specialization, while the most significant market factor is most likely due to wealth and balance sheet effects. A central contribution of our work is the construction of quantifiable measures of output trend, cycle, and market return integration, referred to as indices of integration. Our indices display high volatility with no trend. In addition, a null hypothesis for white noise could not be rejected for the trend and cycle integration indices. Our study is not able to establish a relationship between integration and national output and market return levels.

A logical extension of the research presented in this article is further exploring the factors affecting the levels of integration, as well as the dynamics of their effects. Investigation of integration benefits by exploring the effects of integration on various

macroeconomic variables may be also worthwhile. Finally, this analysis could be extended to a variety of economic aggregates of interest.

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Table 1. Estimates from the Principal Component Analysis

The table provides estimates of the indices of trend, cycle, and market integration

Year	Index of Trend Integration	Index of Cycle Integration	Abbreviation
1964	0.8386	0.59	
1965	0.8209	0.4875	
1966	0.9	0.5352	
1967	0.8305	0.4861	
1968	0.8072	0.5241	
1969	0.887	0.702	
1970	0.8306	0.4799	0.6234
1971	0.9836	0.702	0.488
1972	0.893	0.5943	0.5485
1973	0.9109	0.929	0.6238
1974	0.7196	0.4548	0.8043
1975	0.6371	0.7	0.4808
1976	0.9414	0.5862	0.5589
1977	0.8051	0.6338	0.7075
1978	0.9453	0.6	0.804
1979	0.8665	0.7175	0.5493
1980	0.5332	0.56141	0.571
1981	0.7125	0.51	0.6312
1982	0.8375	0.4926	0.453
1983	0.8756	0.4416	0.7504
1984	0.7173	0.6174	0.5654
1985	0.9251	0.4699	0.8413
1986	0.8614	0.4145	0.7266
1987	0.8614	0.5678	0.6497
1988	0.9	0.64	0.7015
1989	0.9233	0.5059	0.7132
1990	0.6448	0.5839	0.6567
1991	0.628	0.6836	0.453
1992	0.5286	0.5246	0.5673
1993	0.5961	0.5054	0.6887
1994	0.904	0.4742	0.5006
1995	0.842	0.453	0.6114
1996	0.7376	0.61	0.7655
1997	0.9199	0.6669	0.7089
1998	0.6988	0.4814	0.5915
1999	0.8876	0.5076	0.7028
2000	0.93	0.7152	0.5769
2001	0.5638	0.4613	0.9342
2002	0.8846	0.5709	0.8844
2003	0.6472	0.5258	0.958
2004	0.8667	0.6856	0.8358
2005	0.9485	0.6842	0.7448
2006	0.953	0.52	0.8044
2007	0.7856	0.5158	0.7386
2008	0.721	0.7523	0.9829
2009	0.9474	0.8784	0.9684
2010	0.9867	0.6427	0.78
2011	0.586	0.53	0.9011
2012	0.6574	0.4926	0.7755
2013	0.86	0.5185	0.8144
2014	0.824	0.6038	0.5863
2015	0.8639	0.6255	0.7874
2016	0.6989	0.8047	0.607

(Continue from Table 1)

Notes:

* Index of Trend Integration – each value represents the fraction of total variability in country Trend GDP components explained by the first principal component in each year.

**Index of Cycle Integration - each value represents the fraction of total variability in country Cycle GDP components explained by the first principal component in each year.

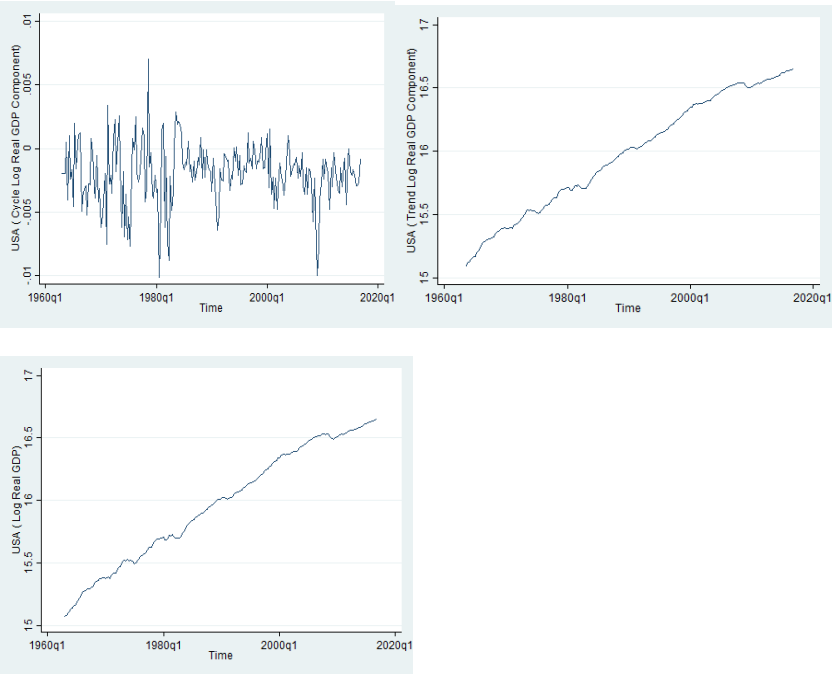
***Index of Market Integration - each value represents the fraction of total variability in national market returns explained by the first principal component in each year.

Table 2. Descriptive Statistics of the Indices of Trend, Cycle, and Market Integration

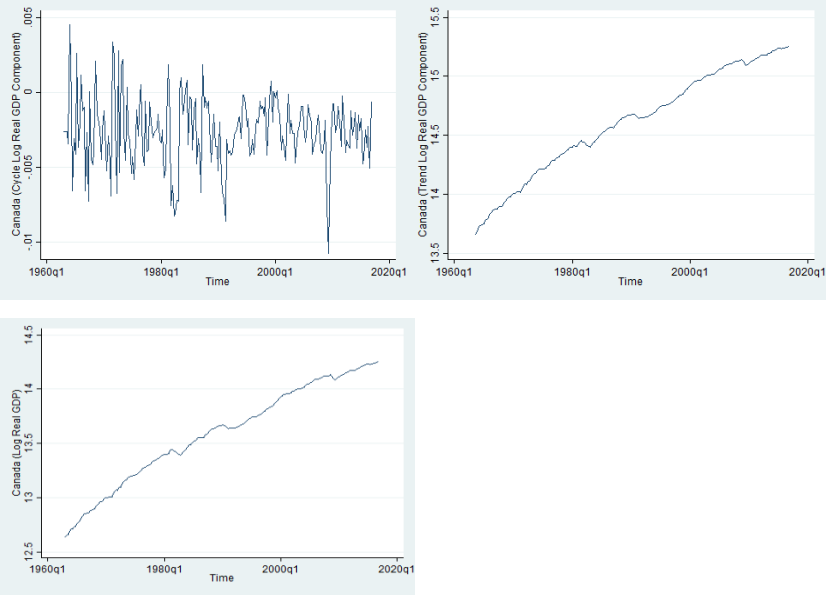
Statistic	Index of Trend Integration	Index of Cycle Integration	Index of Market Integration
Dicky-Fuller Test Mackinnon p-value	0.00	0.00	0.02
Portmanteau (Q) Test Prob > chi2(24)= 0.7637	0.7637	0.758	0.019

Figure 1. Trend and Cycle Components by Country

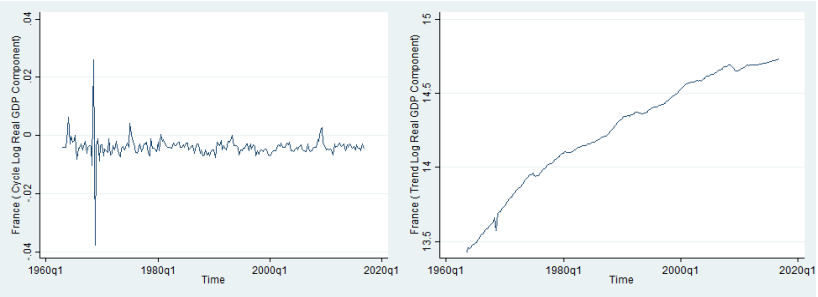
Panel 1: USA

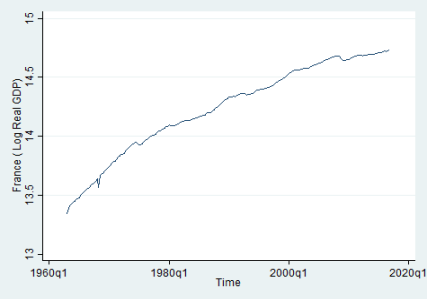


Panel 2: Canada

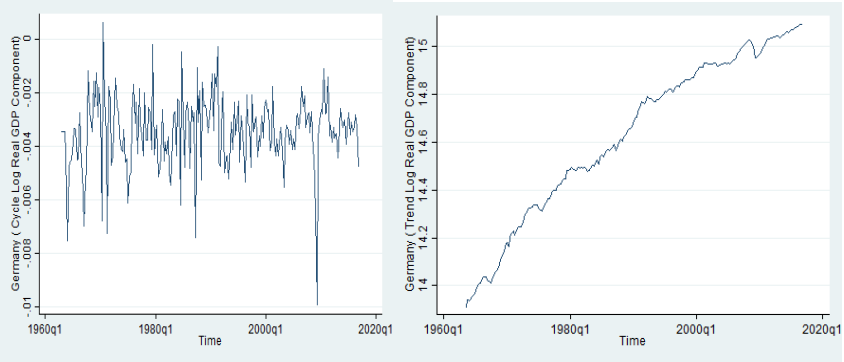


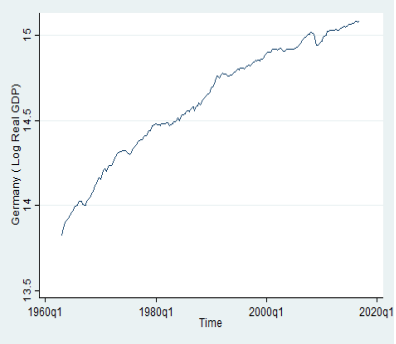
Panel 3: France



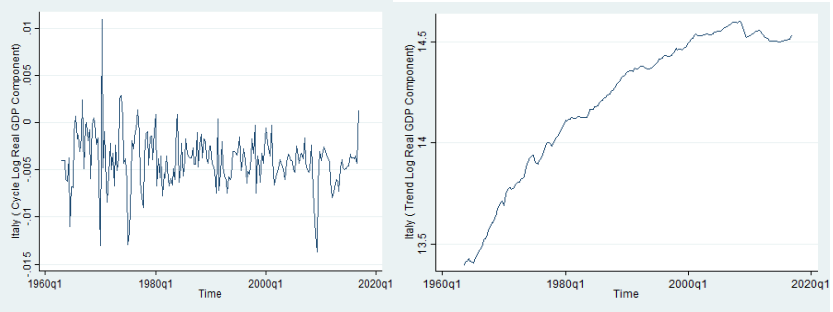


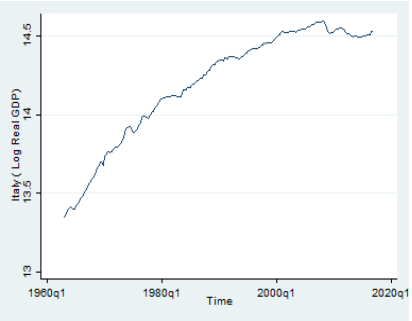
Panel 4: Germany



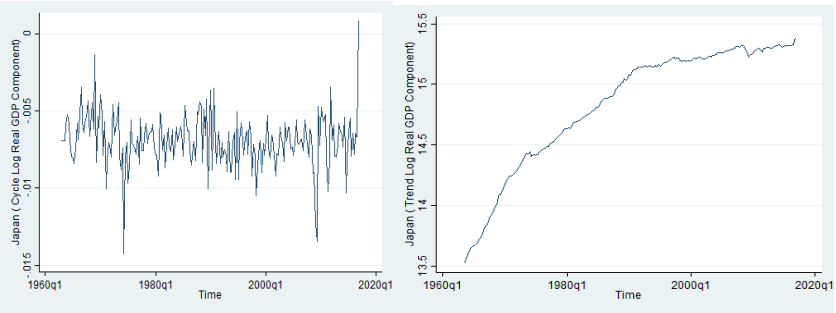


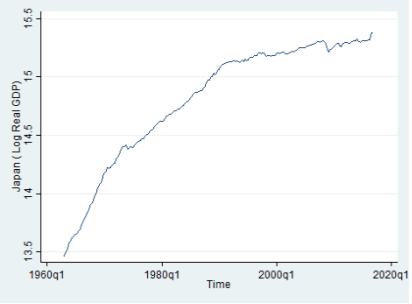
Panel 5: Italy



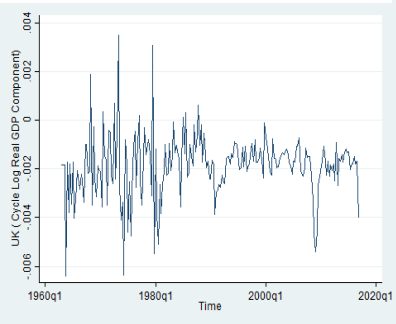


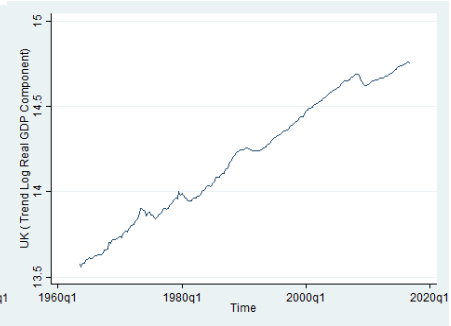
Panel 6: Japan





Panel 7: United Kingdom





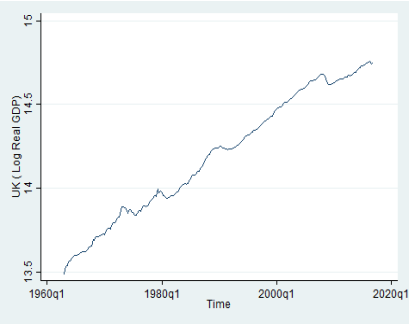
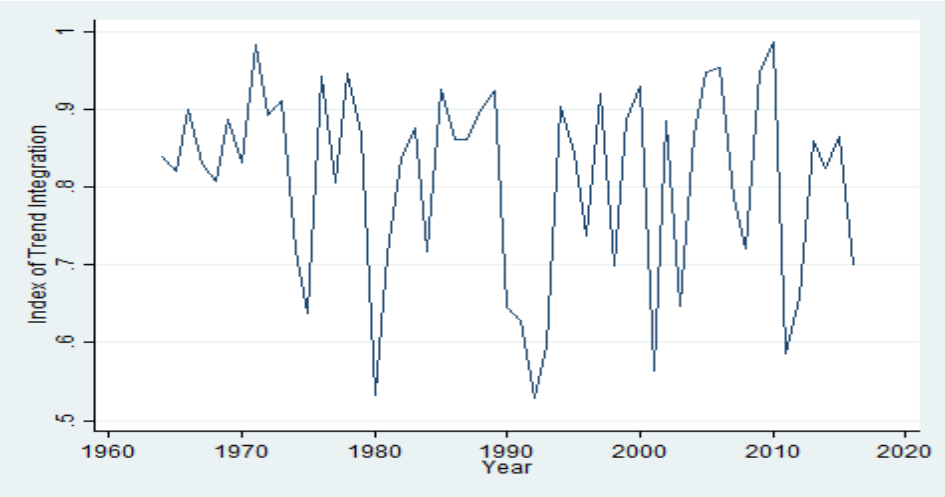
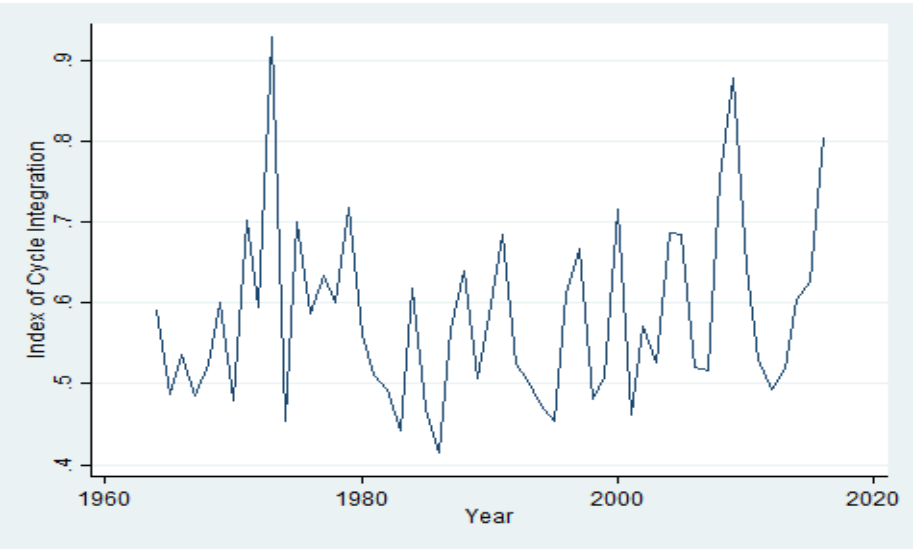


Figure 2. Indices of Integration

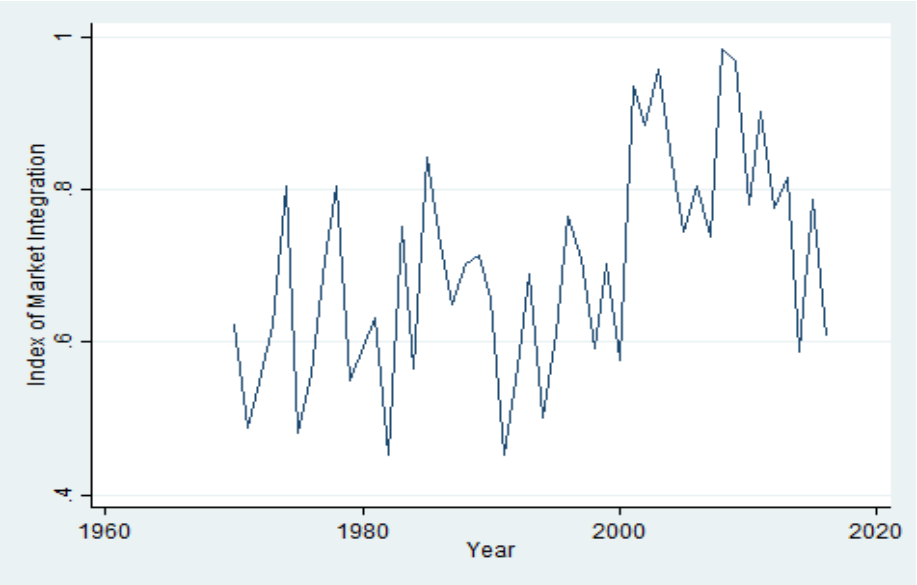
Panel 1: Estimated yearly values of the Index of Trend Integration from 1964 to 2016



Panel 2: Estimated yearly values of the Index of Cycle Integration from 1964 to 2016



Panel 3: Estimated yearly values of the Index of Market Integration from 1970 to 2016



Appendix A. Construction of Indices of Integration

Here we describe my approach to applying the PCA and quantifying the trend, cycle, and market integration indices. The procedure is repeated for each data set separately.
The steps in the process are outlined as follows:

1. we perform PCA on country data separately for each year. This provides for as many principal components as there are countries in the data set. Each principal component is based on an eigenvector with a respective eigenvalue.

2. Rank PCs according to size of eigenvalues. Each eigenvalue measures the variation explained by a particular PC and the sum of all eigenvalues equals the total variation in the data set.

3. Obtain the proportion of total variation explained by those principal components that are significant. This is done by dividing the respective eigenvalue by the sum of all eigenvalues.

4. Repeat this procedure separately for each year. Obtain the fraction of total variation explained by each significant component for each year and stack the corresponding values in vectors to form indices. An index only takes values between 0 and 1.