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Nicholas Tsounis
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# Advances in Longitudinal Data Methods in Applied Economic Research

## 2020 International Conference on Applied Economics (ICOAE)

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*Editors*
Nicholas Tsounis
Laboratory of Applied Economics,
Department of Economics
University of Western Macedonia
Kastoria, Greece

Aspasia Vlachvei
Laboratory of Applied Economics,
Department of Economics
University of Western Macedonia
Kastoria, Greece

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# Preface

This year conference is co-organised by the Hellenic Open University (HOU) and the Department of Economics of the University of Western Macedonia, Greece. Unfortunately, due to the coronavirus pandemic the conference has not taken place in Heraklion, Crete, where it would have been hosted by the Hellenic Open University at Archanes after the kind invitation by Prof. George Agiomirgianakis who is also co-chair of the conference, but it is a virtual conference.

The aim of the conference is to bring together economists from different fields of Applied Economic Research in order to share methods and ideas.

The topics covered include:

- Applied Macroeconomics
- Applied International Economics
- Applied Microeconomics including Industrial Organisations
- Applied work on International Trade Theory including European Integration
- Applied Financial Economics
- Applied Agricultural Economics
- Applied Labour and Demographic Economics
- Applied Health Economics
- Applied Education Economic

All papers presented in ICOAE 2020 and published in the conference proceedings were peer reviewed by anonymous referees. In total, 54 works were submitted from 13 countries while 40 papers were accepted for presentation and publication in the conference proceedings.

**The acceptance rate for ICOAE 2020 was 74%**.

The full text articles will be published online by Springer in the series "Springer Proceedings in Business and Economics"

The organisers of ICOAE 2020 would like to thank:

- The Scientific Committee of the conference for their help and their important support for carrying out the tremendous work load organising and synchronising

the peer-reviewing process of the submitted papers in a very specific short period of time.
- The anonymous reviewers for accepting to referee the submitted conference papers and submit their reviews on time for the finalisation of the conference programme.
- The keynote speaker, Dr. Giovanni Cerulli from the Research Institute on Sustainable Economic Growth, National Research Council of Italy, for accepting to present his work on the Covid-19 outbreak.
- The organising committee for its help for the success of the conference.
- Dr. Eirini Arvanitaki, Mr. Gerassimos Bertsatos, Mr. Lazaros Markopoulos, and Mr. Stelios Angelis for secretarial and technical support.

Kastoria, Greece Nicholas Tsounis

Kastoria, Greece Aspasia Vlachvei

# Contents

# Forecasting the South African Financial Cycle: A Linear and Non-Linear Approach

**Milan Christian de Wet**

**Abstract** Identifying optimal models to forecast economic cycles has been a point of great consideration in literate. A key point of debate in the literature is whether linear or non-linear models perform best at forecasting economic cycles. The literature largely forces on the forecasting of business cycles, and very limited work has been done on financial cycle forecasting. Given the proven destructiveness of financial cycles, the ability to accurately forecast future financial cycle movements in an economy could aid policymakers in managing such cycles. This article evaluates the forecasting performance of both the non-linear Markov Regime-Switching Autoregressive methodology and Smooth Transition Autoregressive methodology relative to the benchmark ARIMA model in forecasting the aggregate South African financial cycle over different time horizons. A fixed window rolling forecast approach is followed, whereby the performance of forecasting the aggregate South African financial cycle 3-steps forward, 6-steps forward, 12-steps forward, 18-steps forward and 24-steps forward is evaluated. The findings indicate that the linear ARIMA model outperforms the non-linear MSMV-AR and LSTAR models at forecasting short periods ahead such as 3–6 months ahead. However, both the MSMV-AR and LSTAR models outperform the ARIMA model, given a longer time horizon such as 12–24 months. Hence, to forecast the aggregate South African financial cycle 3–6 months ahead policymakers should use an ARIMA. However, the MSMV-AR and LSTAR models should be used to forecast the aggregate South African financial cycle 12–24 months ahead.

**Keywords** Non-linear forecasting · Financial cycles · Markov switching · STAR · Regime shifts

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M. C. de Wet (✉)
University of Johannesburg, Johannesburg, South Africa
e-mail: Miland@uj.ac.za

 
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## 1 Introduction

Financial crises have plagued the economies for the past four decades, of which the 2007/2008 financial crisis was the most severe. The financial crisis of 2007 triggered the most severe global economic contraction since the great depression. The financial crisis of 2007 had a negative economic impact on almost all advanced economies and the majority of emerging economies in the world, with only a few exceptions. Furthermore, the financial crisis in Japan during the 1980s and 1990s had severe implications for the Japanese economy. Emerging markets, in particular, have been plagued by disruptive financial crises, such as the Mexican financial crisis that began in 1994, the Asian crisis that began in 1997 and the Argentinian crisis that began in 2001 to name a few. All these examples proved to be a result of an unsustainable financial build-up of some sort. This signals the need for policymakers to improve their understanding of financial conditions and to obtain a means to improve their ability to manage cyclical fluctuations and the effect of such fluctuations.

For the most part, before 2007, policymakers neglected the role played by financial factors and the potentially disruptive impact fluctuations in these factors might have on the real economy (Borio, 2014; Strohsal, Proano, & Wolters, 2019). A possible reason why policymakers neglected financial conditions is that policymakers largely believed that financial conditions are driven by real economic conditions, and not the other way around (Borio, Drehmann, & Xia, 2018). Therefore, the need to understand the state of financial conditions in an economy seemed less important. Over the past four decades, however, financial crises around the world have proven otherwise.

The 2007/2008 financial crisis caught the attention of policymakers, resulting in the realization that the old school of thought, which places all the attention on the real economy, is not completely accurate and effective. The 2007/2008 financial crisis provided clear evidence that financial factors of an economy could be disconnected from the real economy, and extremely disruptive when in disequilibrium. Therefore, financial factors could not merely be monitored and managed through simply monitoring and managing real economic conditions. Hence, specific attention needs to be paid to the cyclicality and cyclical state of financial variables in an economy to fully gauge the financial state of an economy and thereby employing effective management in this regard. After the 2007 financial crisis, policymakers need to re-evaluate how they consider financial factors and how they should go about monitoring and managing financial factors in such a way that extensive financial build-ups and financial disequilibrium are mitigated or avoided. This is to avoid potential future damage that could be caused by such build-ups and disequilibria. The ability to accurately forecast financial cycle movements could aid in this regard.

The value of information that timely and accurately indicates the future development of economic cycles is vast. The importance of such information has led to extensive research on developing means to forecast future moves in aggregate economic cycles. Therefore, the forecasting of economic cycles has received a significant amount of attention since the initial groundwork on cyclical research by Burns and Mitchell (1946). The main reason for this interest is the major economic benefits that lie within the ability to accurately and timely forecast future cyclical fluctuations. The ability to timely and accurately predict future turning points in economic cycles will afford policymakers a means to make more timely policy decisions relating to cyclical fluctuations, and other economic participants to better position themselves for future fluctuations. From cyclical forecasting research, a large number of forecasting models have been suggested, implemented and tested on a wide range of economic cycles, of which business cycles are by far the economic cycle subject to the most research. Major debates in the literature and practice prevail around which models perform best at forecasting economic cycles. Empirically, a lot of mixed results on this topic exists, indicating that optimality varies from cycle to cycle.

For example, the debate between linear and non-linear forecasting models. Botha, Greyling, and Marais (2006) groups econometric models to forecast economic cycles into two major groups, namely linear models and non-linear models. Botha et al. (2006) states that one of the major debates in the literature regarding the forecasting of economic cycles is around the forecasting performance of linear and non-linear models as a means to forecast economic cycles. The debate thus considered whether forecasting models should allow for non-linearities amongst the relational dynamics between a financial cycle under analysis and corresponding endogenous and exogenous explanatory variables during different cyclical phases. Furthermore, within each of these broad two groups, a range of models exists, and even within each group, a lack of consensus exists on which models perform optimally at forecasting economic cycles.

Varying viewpoints and empirical results make it challenging for policymakers, as well as other economic participants, such as asset managers, business managers and risk managers, to depend on a given set of forecasts, hindering optimal decision-making and actions from these various parties. This limitation is amplified when considering financial cycles, given that very limited research has been done to identify optimal models to forecast financial cycles. This study will contribute to the body of knowledge on economic cycles forecasting through identifying a model that performs optimally at forecasting the aggregate South African financial cycle. Henceforth, this study will be structured as follows. Firstly, a literature overview is provided in Sect. 2. Then a data description will be provided, and the methodological approach to be followed in this study will be stipulated in Sect. 3. In Sect. 4, the results will be presented, and a corresponding discussion of results will be provided. Finally, the conclusion will be provided in Sect. 5.

## 2 Literature Overview

Despite very limited to no work done on forecasting aggregate financial cycles, the body of knowledge on research done on forecasting business cycles, as well as various financial variables, is vast. Even though not an exhaustive list, examples of empirical work done in this field are the work done by Laubscher (2019), Nyberg (2018), Wai, Kun, Ismail, and Karim (2015), Singh (2012), Baharumshah and Liew (2006), Botha et al. (2006), Teräsvirta, Van Dijk, and Medeiros (2005), Marcellino (2005), Moolman (2004), Crawford and Fratantoni (2003), Sarantis (2001), Rech (2002), Tkacz (2001) and Clements and Krolzig (1998). Given the lack of literature on financial cycle forecasting, the literature on business cycle forecasting will be utilized as an empirical base.

Several researchers such as Botha et al. (2006), Teräsvirta et al. (2005), Moolman (2004), Sarantis (2001), and Clements and Krolzig (1998) consider the linear autoregressive integrated moving average (ARIMA) as a benchmark model for research on forecasting performance. The forecasting with linear econometric models typically utilizes linear co-movements of economic elements with the forecasted variable under consideration (Teräsvirta et al., 2005). Writes that linear forecasting models include econometric models such as ARIMA, classic linear multiple regression models, probit and logit regression models and vector autoregressive (VAR) models. Linear models, such as linear regression models, assume linear relational dynamics between a cyclical measure and given explanatory variables, thus not accounting for any asymmetries. As a result, linear models do not account for any cyclical asymmetries.

However, economic cycles do not typically evolve in linear fission, but often exhibits asymmetrically sharp movements during cyclical downturns relative to upturns (Bouali, Nasr, & Trabelsi, 2016; Nyberg, 2018). A large amount of empirical research work exists which supports this statement (Baharumshah & Liew, 2006; Clements & Krolzig, 1998; Crawford & Fratantoni, 2003; Moolman, 2004; Sarantis, 2001; Singh, 2012; Teräsvirta et al., 2005; Wai et al., 2015). For example, it is found that variables have a much harsher reaction to cyclical contractions relative to a cyclical upturn, showing that asymmetries do exist (Balcilan, Gupta, & Miller, 2015; Botha et al., 2006; Moolman, 2004).

By assuming cyclical symmetry when forecasting, forecasting accuracy might be suboptimal, leading to the need for non-linear models as a means to forecast economic cycles (Botha et al., 2006; Moolman, 2004; Nyberg, 2018). Bouali et al. (2016) stated that non-linear models used for economic cycle modelling typically allow regime changes and are therefore capable of accommodating relational asymmetries across cyclical regimes. Non-linear models employed to capture such asymmetries include Markov regime-switching (MRS) models and a range of smooth transition autoregressive (STAR) models (Teräsvirta et al., 2005). Provided the range of possible models that can be used as a means to forecast economic cycles, it is of interest to identify an optimal forecasting model and have been the focal point of several empirical studies.

Within this strand of research, the forecasting performance of various models forecasting a range of different variables have been conducted. Studies range from forecasting broad-based economic conditions such as business cycles to forecasting specific variables such as oil, house prices, currencies, and equity prices. A study conducted by Clements and Krolzig (1998) is one of the first studies set out to comprehensively identify an optimal forecasting method for business cycles. Clements and Krolzig (1998) considered the forecasting ability of the Markov Regime-Switching Autoregressive model (MS-AR), the Smooth Transition Autoregressive (STAR) model and several traditional linear models at forecasting the US business cycle. Out of the two non-linear models, Clements and Krolzig (1998) found that the MS-AR model, encompassing of three different regimes and four lagged autoregressive terms generally outperforms the SETAR model in estimating key elements of the US business cycle. They further found that both the MS and STAR models outperform linear models such as the popular autoregressive moving average (ARMA) model. This finding concurs with the findings by researchers such as Wai et al. (2015), Crawford and Fratantoni (2003) and Sarantis (2001).

Nyberg (2018) compared the forecasting ability of the non-linear Markov Switching model to that of the linear Vector Autoregressive model and found that the non-linear Markov Switching model is superior at forecasting both the US business cycle and US interest rates. The study by Li et al. (2005) addressed the same, however, focusing on not only industrialized economies but also on newly industrialized economies and developing economies. They considered the performance of Markov-switching models in modelling the business cycles of the USA, Japan, Taiwan, South-Korea, Malaysia and Indonesia. Li et al. (2005) found that the MS model sufficiently captures the growth and contraction periods in the business cycles of the industrialized and developing countries' business cycles. Contrary to this finding though, they found that the implemented MS model does not sufficiently capture the business cycle growth and contraction regimes of the newly industrialized countries that they analysed.

Li et al. (2005) argue that the shift to industrialization for these countries caused structural breaks, resulting in the ineffectiveness of the MS model in identifying business cycle regime shifts. Li et al. (2005) therefore adjusted for structural breaks by dividing the business cycles into two distinct periods, a pre-industrialized period and a post-industrialized period. They found evidence that an MS two-regime two AR lag approach effectively identifies growth and contraction periods in the business cycle of the newly industrialized countries under analysis. Teräsvirta et al. (2005) compared the forecasting performance of linear autoregressive models and the non-linear STAR model at forecasting a range of macroeconomic time series. Teräsvirta et al. (2005) found evidence that the STAR model predominantly outperforms linear autoregressive methodology. However, studies by Marcellino (2005), Rech (2002) and Tkacz (2001) disagree with Teräsvirta et al. (2005), generally found no clear evidence that the non-linear models perform better than a linear autoregressive approach at forecasting economic variables.

Singh (2012) conducted a study that aims to determine whether non-linearities exist in the economic growth cycles of OECD countries. Evidence of non-linearity will indicate that non-linear models might be necessary to effectively model economic growth rate cycles. Singh (2012) found evidence through employing a range of STAR family models that the hypothesis of linearity in the economic growth cycle of almost every country under analysis could be rejected, and therefore, characteristics of non-linearities do exist in the economic growth cycles of these economies. This implies that non-linear models might be more accurate in modelling economic growth cycles than linear models.

Baharumshah and Liew (2006) conducted a study, aiming to determine whether the traditional AR model or Exponential Smooth Transition Autoregressive (ESTAR) model best performs in modelling and forecasting the path of East Asian currencies. In this study, they found that the non-linear parameters of each currency pair were statistically significant, providing evidence that the long-run equilibrium in all the Asian currency pairs under analysis follows a non-linear path. Furthermore, they found that the residual variance ratio of the ESTAR model applied to each currency pairs relative to the residual variance ratio of the AR model that corresponds to that the ESTAR model is below one. This indicates that for each currency pair, the ESTAR model renders a lower variance in the residual and therefore the ESTAR model proved to result in lower forecasting errors (Baharumshah & Liew, 2006).

Balcilan et al. (2015) analysed the modelling and forecasting performance of the ESTAR and STAR non-linear models versus the linear AR model on US house prices. They found that given a long-time horizon, non-linear models perform better than linear models in point forecasting the underlying financial variable. Balcilan et al.'s (2015) findings on forecasting short-term price moves do however not conform to the findings above. However, Balcilan et al. (2015) found no evidence that non-linear models perform better at forecasting house prices over a short-time horizon relative to linear models. Balcilan et al. (2015) also found little evidence that the non-linear models implemented in their study outperform the linear models when it comes to density forecasting, regardless of the time horizons. This indicates that the ability of the non-linear models to forecast the probability distribution of the underlying financial variable, relative to linear models, is limited. In comparing the modelling and forecasting performance of the two non-linear models, Balcilan et al. (2015) found that the Logistic Smooth Transition Autoregressive model (LSTAR) outperforms that of the ESTAR model.

Relating to the cyclical movements of US house prices, Crawford and Fratantoni (2003) found that regime-switching models do better in depicting realized house price patterns, relative to ARIMA and GARCH family models. They argued that regime-switching models can effectively be utilized to create a cyclical framework for historic house price time-series data because these models identify the turning points, amplitude, and frequency of cyclical moves better. Yet, corresponding to the findings by Balcilan et al. (2015), Crawford and Fratantoni (2003) found no clear evidence that regime-switching models perform better in point forecasting US house prices, relative to the linear ARIMA model.

Based on the contradicting findings in empirical literature considered, it is not clear that non-linear models will necessarily outperform linear models at forecasting economic variables. This is because some researchers found that non-linear models outperform linear models, and other researchers found no such evidence. It is thus not apparent that non-linear models will necessarily outperform linear models at forecasting South African economic cycles. This necessitates research that specifically focusses on South African economic cycles.

Extensive research has been done on the South African business cycle, for example, the work by Laubscher (2019), Botha et al. (2006), Boshoff (2005) and Moolman (2004). Moolman (2004) modelled the South African business cycles through a Markov regime-switching model. Botha et al. (2006) added to the study conducted by Moolman (2004), testing whether the South African business cycle is best estimated and forecasted through linear or non-linear models. Du Plessis (2004) considered the South African Business cycle and how dependent this cycle is on its own duration.

The study by Botha et al. (2006) contributes to the debate of whether linear or non-linear models perform best in estimating business cycles. Moreover, by focusing on the South African business cycle, the findings of this study are of particular importance to this study. Botha et al. (2006) found that non-linear models outperform linear models in forecasting the South African business cycle. Furthermore, Botha et al. (2006) found that the ESTAR model is the most effective model out of all the non-linear models to forecast the South African business cycle.

The findings by Moolman (2004) support the findings by Botha et al. (2006). Based on the mean absolute percentage error (MAPE) statistic and the square root of the mean squared error (RMSE) statistic, Moolman (2004) concluded that the Markov regime-switching model performed much better than the linear AR(4) model in terms of turning point prediction accuracy. The findings by Botha et al. (2006) and Moolman (2004) are insightful because the findings in the broader body of literature are inconclusive on whether linear or non-linear models perform best at forecasting business cycles. This indicates that non-linear models perform best in the South African context. Boshoff (2005) touched on the topic of South African financial cycles by estimating how well these variables aided as leading indicators for the South African business cycle. However, this study did not go through the process of determining the optimal variables to include in the aggregate South African financial cycle and chosen a few ad hoc financial variables to represent the South African financial cycle. Furthermore, the study by Boshoff (2005) did not forecast the South African financial cycle and only used the cycle to predict the business cycle.

Very little to no research work has been done in an attempt to accurately forecast an aggregate South African financial cycle through different methods and thereby comparing the performance of the range of available forecasting methods to forecast the aggregate South African financial cycle. Given the proven role that changes in aggregate financial conditions have on the future economic path, timely and accurately forecasting cyclical fluctuations in financial conditions are essential to policymakers. Considering the large number of forecasting methods available in the literature, research on determining optimal ways to forecast a methodically constructed aggregate South African financial cycle will aid policymakers to better estimate future cyclical fluctuations in aggregate South African financial conditions. This research will attempt to address the research gap by comparing the forecasting performance of an optimally estimated linear ARIMA model to the forecasting performance of the non-linear MS-AR and STAR models at forecast aggregate South African financial cycles over different forecasting periods.

## 3 Data Description and Methodology

This study will utilize the aggregate South African financial cycle constructed by de Wet (2020), and the aggregate financial cycle constructed by de Wet (2020) will be used as the aggregate South African financial cycle in this study. The cyclical measure constructed by de Wet (2020) consists of 59 variables which in turn reflect 7 major financial components. The financial components reflected by this measure are South African credit conditions, South African property market conditions, South African interest rate conditions, balance sheet conditions of the South African financial sector, South African equity market conditions, South African economic confidence levels, and South African foreign financial positions. The aggregate South African financial measure, to be forecasted in this paper, is thus a single aggregate measure that reflects the cyclical movement of seven key South African financial components. de Wet (2020) made use of a principal component analysis and a dynamic factor model to aggregate 59 variables into a single measure. Furthermore, de Wet (2020) employed a Christiano Fitzgerald filter as a cyclical extraction method. The aggregate South African financial cycle typically expands as credit levels and asset prices increase (de Wet, 2020). Furthermore, the aggregate South African financial cycle typically expands due to an aggregate bank balance sheet expansion but contracts due to increase in interest rate (de Wet, 2020). This measure ranges from January 1975 to January 2017, and the data frequency is monthly. de Wet (2020) implemented a Dynamic Factor model to construct a single aggregate South African financial conditions index and made use of a Christiano Fitzgerald bandpass filter to extract the cyclical component from the aggregate conditions index to provide an aggregate South African financial cycle measure. The aggregate South African financial cycle from 1975 to 2017 is depicted in Fig. 1. The cyclicality over time is clear, and the cyclical measure provides a smooth representation of the cyclicality in aggregate South African financial conditions over time.

A number of models will be used to forecast the aggregate South African financial cycle. The forecasting performance of each model will be compared to determine the most accurate model to forecast the aggregate South African financial cycle, provided varying forecasting timeframes. As done by a number of researchers such as Botha et al. (2006), Teräsvirta et al. (2005), Moolman (2004) Sarantis (2001) and Clements and Krolzig (1998), the forecasting performance of the linear ARIMA model will be used as a benchmark. The aggregate South African financial cycle will then be forecasted with the non-linear MS-AR model estimated to achieve objective three. In addition to the non-linear MS model, the aggregate South African financial cycle will be forecasted with an optimal STAR family model. The forecasting results of these non-linear models will be compared to that of the ARIMA model to determine whether accounting for non-linearities improves the performance of forecasting aggregate South African financial cycles.

A fixed window rolling forecasting approach will be followed, and the study will consider the performance of each model to forecast the aggregate South African

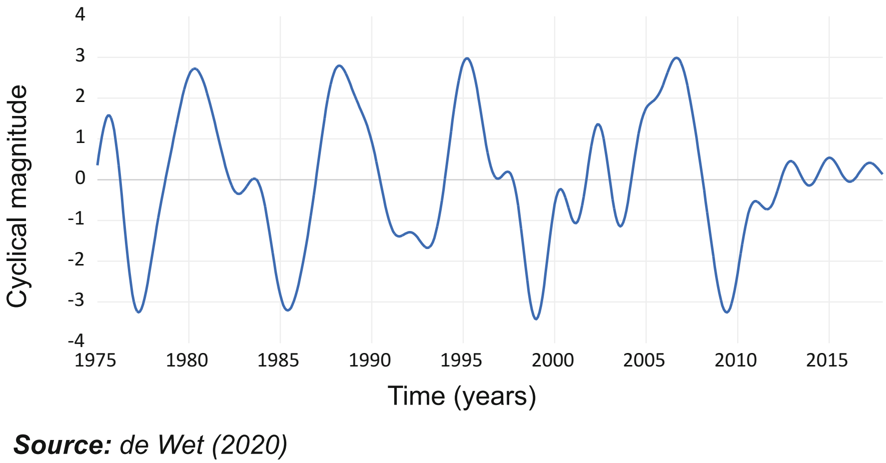


**Fig. 1** The aggregate South African financial cycle. ***Source:*** de Wet (2020)

financial cycle over different time horizons. According to Clark and McCracken (2009), a fixed window rolling forecasting approach is an approach that uses a fixed estimation sample size of a time series to forecast a continuum of a fixed $n$-step ahead forecasts over time. The alternative to a fixed window rolling forecast is a recursive forecasting approach (Clark & McCracken, 2009). With such a forecasting approach, the estimation sample is heterogenic over time and grows as time progresses. The argument against such a forecasting approach is that the data points in the estimation sample can become irrelevant and redundant as the estimation sample grows (Clark & McCracken, 2009). The heterogenic forecasting sample also hinders the ability to compare the forecasting results of various models and various timeframes. This motivates why a fixed window rolling forecasting approach will be adopted in this study.

The consensus in the literature is to use a third of the total number of observations in a time series as an estimation sample, leaving two-thirds of the total series to forecast (Clark & McCracken, 2009). The estimation outputs will thus be based on a third of the full data set. This forecasting process is best explained by the hand of an example. Assume a time series consists of 105 monthly closing price observations, dating from 31 January 2010 to 31 October 2018, and a 4-step ahead forecast is conducted. The fixed estimation sample will consist of 35 observations, thus approximately 2 years and 11 months. The estimation period for the first 4-step ahead forecasted point will range from 31 January 2010 to 31 December 2012. Thus, the model under consideration will be estimated with data points ranging from 31 January 2010 to 31 December 2012. The 4-step ahead forecasted data point will represent a forecasted data point for 30 April 2013. The model under consideration will then be re-estimated for the next 4-step ahead forecasted data point with the estimation period ranging from 28 February 2010 to 31 January 2013. The 4-step ahead forecasted data point will represent a forecasted data point for 31 May 2013.

Note how the estimation sample size remains 35 months, and the forecasted data points remain 4-step ahead forecasted values.

This process will be repeated, and a 4-step ahead forecasted data point for each month up to 31 October 2018 will be obtained. This will result in a continuous series with data points that are forecasted four-steps ahead. In this study, fixed window rolling forecasts with ARIMA, MS-AR and STAR models will be done 1-step ahead, 3-steps ahead, 6-steps ahead, 12-steps ahead, 18-steps ahead and 24-steps ahead. The forecasting performance of each model with different forecasting time horizons will be analysed and compared. This will indicate which model performed best at forecasting the aggregate South African financial cycle and whether different models perform better at forecasting different forecasting time frames.

## *3.1 ARIMA Methodology*

The autoregressive integrated moving average (ARIMA) model where AR refers to autoregressive terms, I refer to the level of integration of a given variable, and MA the moving average of a given variable which measures the stochastic white noise error of the model as an amalgamation of previous errors. The ARIMA model is a very well-known statistical method and widely used in literature. An ARIMA ($p$, $d$, $q$) indicates that $p$ number of autoregressive should be included in the model, the variables need to be differenced $d$ amount of times for the variable to be stationary and $q$ number of moving average terms needs to be included in the model (Brooks, 2019). The ARIMA model, where the variable has been differenced $d$ amount of times to be stationary, can be written in the following linear equation according to Brooks (2019):

$$\mathrm{ASAFC}_t = c + \varnothing_1 \mathrm{ASAFC}_{t-1} + \varnothing_p \mathrm{ASAFC}_{t-p} + \beta_1 \mu_t + \beta_q \mu_{t-q} \tag{1}$$

where $\mathrm{ASAFC}_t$ is the dependent variable at time $t$, $c$ represents the intercept of the model, $\varnothing_p$ is the coefficients of the various autoregressive terms of the dependent variable $\mathrm{ASAFC}_t$, and $\beta_q$ represents the coefficients of the various moving average term $\mu_t$.

According to Gujarati and Porter (2009), a one-period ahead forecast of the dependent variable $\mathrm{ASAFC}_t$ can be forecasted with the ARIMA models depicted in (1) as follows:

$$\mathrm{ASAFC}_{t+1} = c + \varnothing_1 \mathrm{ASAFC}_t + \varnothing_p \mathrm{ASAFC}_{t-p} + \beta_1 \mu_t + \beta_q \mu_{t-q} \tag{2}$$

To determine $I$, the integration level of dependent variable $Y_t$, a Dickey-Fuller unit root will be conducted to determine at which level variable $Y_t$ is stationary as suggested by Gujarati and Porter (2009). Furthermore, as suggested by Gujarati and Porter (2009), the optimum number of autoregressive terms to include in the model will be done by making use of the partial autocorrelation function (PACF).

This function indicates the partial correlation of the dependent variable with its own lags by controlling lag values of relatively shorter lags when considering relatively longer lags (Gujarati & Porter, 2009). The optimal amount of moving average terms to be included in the model will be determined through the autocorrelation function (ACF), which differs from the PACF by not controlling for relatively shorter lags when considering longer lags (Gujarati & Porter, 2009). These measures will indicate how many AR terms and MA terms to include to estimate an optimal ARMA model. However, Gujarati and Porter (2009) state that conclusions based on these measures can be subjective and therefore suggested additional measures such as the Akaike Information Criterion (AIC), Schwartz Criterion (SC) and Hannan Quinn Criterion (HQC) to determine the optimal ARMA model. Henceforth, in addition to ACF and PACF, the AIC, SC and HQC will be used to determine the optimal ARMA model.

## *3.2 Non-linear Models*

In this section, a methodological outline will be provided for both the MS-AR method and the STAR method to be employed in this study. These models make it posable for autoregressive parameters in a model to change over time (Botha et al., 2006).

### 3.2.1 MS-AR Models

In this study, four variants of the MS-AR model will be considered with various lag-lengths. The variations are an MS-AR model with a fixed mean and fixed variance, an MSM-AR model with a regime-dependent mean and fixed variance, an MSV-AR model with a fixed mean and regime-dependent variance and an MSMV-AR model with a regime-dependent mean and regime-dependent variance. Two extensions to the STAR model will be considered in this study, namely the logistic smooth autoregressive (LSTAR) model and an exponential transition function, which will result in the estimation of an exponential smooth autoregressive (ESTAR) model. Both these extensions will be considered, and the optimal version will be used to forecast aggregate South African financial cycles. An optimal MS-AR model to estimate the aggregate South African financial cycle will be identified based on the Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC) and Hannan Quinn Criterion (HQC). The model with the lowest information criterion value will be selected as the optimal model, and further analysis will be based on the results rendered by the optimal model (Brooks, 2019). This selection approach is similar to the selection approach followed by Tastan and Yildirim (2008). Furthermore, it will be assumed that the aggregate South African financial cycle has two states, namely an expansion and a contraction.

The MS-AR model with a fixed mean and fixed variance is specified as follows:

$$y_t = \beta_{s1}\left(y_{t-1} + y_{t-2} + \cdots + y_{t-k}\right) + \beta_{s2}\left(y_{t-1} + y_{t-2} + \cdots + y_{t-k}\right) + \varepsilon_t \tag{3}$$

where, $s_t \in \{1, 2\}$ signifies the regime state under consideration, i.e. state one and two, $k$ signifies the optimal lag length, $\varepsilon_t$ is a non-state-dependent error term and $x_t$ is a vector of explanatory variables. Equation (3) can be restated to accommodate for a regime-switching mean and in this setting can be re-specified as follows (Tastan & Yildirim, 2008):

$$y_t = c_{ts} + \beta_{s1}\left(y_{t-1} + y_{t-2} + \cdots + y_{t-k}\right) + \beta_{s2}\left(y_{t-1} + y_{t-2} + \cdots + y_{t-k}\right) + \varepsilon_t \tag{4}$$

where $C_{ts}$ is a state-dependent, $s$, intercept, allowing for a state-dependent mean. Lastly, (3) can be restated to accommodate for a regime-switching mean and a regime-switching variance and in this setting can be re-specified as follows:

$$\begin{aligned} y_t - \mu_{st} = c_{ts} + \beta_{s1}\left(y_{t-1} + y_{t-2} + \cdots + y_{t-k} - \mu_{st-1}\right) + \\ \beta_{s2}\left(y_{t-1} + y_{t-2} + \cdots + y_{t-k} - \mu_{st-2}\right) + \varepsilon_t \end{aligned} \tag{5}$$

Assuming that $S_t$ is a first-order Markov process meaning that the current regime is a function of the preceding regime $S_{t-1}$, then the transition probabilities of progressing from one regime to another regime can be stated as follows (Tastan & Yildirim, 2008):

$$p_{ij} = \Pr\left(S_t = j | S_{t-1} = i\right), \sum_{j=1}^{n} p_{ij} = 1, \forall i, j \in \{1, 2, \ldots, n\} \tag{6}$$

Thus for a cycle that exhibits two states, an expansion and a contraction, where $S_t = \{1, 2\}$, respectively, the transition matrix is as follows (Tastan & Yildirim, 2008):

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{7}$$

where each entry, $p_{11}$ depicts the conditional probability of remaining in an expansion once in an expansion, $p_{12}$ depicts the conditional probability of moving from an expansion to a contraction, $p_{21}$ depicts the conditional probability of moving from a contraction to an expansion and $p_{22}$ depicts the conditional probability of remaining in a contraction once in a contraction.

### 3.2.2 STAR Models

Following Teräsvirta et al. (2005), the STAR model is specified as follows:

$$s_t = \beta_0 + \beta\text{'}_1 w_t + \left(\varnothing_0 + \varnothing_1' w_t\right) \partial \left(s_{t-d}\right) + \varepsilon \tag{8}$$

where $w_t = (1, s_{t-1}, \ldots, s_{t-k})'$, consisting of $k$ lags of the aggregate South African financial cycle, $\partial$ is a transition function and $s_{t-d}$ is the transition variable and $d$ is the delay parameter. Furthermore, $\varnothing_1 = (\varnothing_1, \varnothing_2, \ldots, \varnothing_p)^{\text{'}}$ and $\beta_1 = (\beta_1, \beta_2, \ldots, \beta_k)'$ are parameter vectors. The transition function can be normal, logistic or exponential (Sarantis, 2001). A normal transition function will result in the estimation of a standard STAR model, a logistic transition function will result in the estimation of a logistic smooth autoregressive (LSTAR) model and an exponential transition function will result in the estimation of an exponential smooth autoregressive (ESTAR) model.

Modelling a STAR model requires three procedures (Teräsvirta et al., 2005). The first procedure is to estimate an autoregressive model and determine the optimal number of autoregressive lags which will become $k$ in (8). The second procedure is to establish whether the variable under consideration exhibits non-linear characteristics within a STAR set-up. If the variable under analysis exhibits non-linear characteristics, the use of the non-linear STAR model to forecast such variables will be justified (Sarantis, 2001). If the variable under analysis does not exhibit non-linear characteristics, modelling and forecasting with a non-linear model will be pointless and a linear model, such as an AR model, will be stuffiest. Thirdly, a sequence of nested tests will be conducted to determine whether the LSTAR model or the ESTAR model is optimal.

To carry out process two and three, the following auxiliary regressions will be estimated as specified by Teräsvirta et al. (2005):

$$V_t = \beta_0 + \beta\prime_1 w_t + \beta\prime_2 w_t s_{t-d} + \beta\prime_3 w_t s_{t-d}^2 + \beta\prime_4 w_t s_{t-d}^3 + \mu_t \tag{9}$$

where $V_t$ is the residuals of the linear AR(4) model specified in (1). A range of $d$ values will be considered, and the axillary model will be reiterated for each value. Sarantis (2001) suggested an integral of $1 \leqq d \geq 6$. The smooth threshold linearity test will be conducted to determine whether the South African financial cycle has non-linear characteristics.

The null hypothesis for the smooth threshold linearity test is as follows:

$$H_0 : \beta\prime_2 = \beta\prime_3 = \beta\prime_4 = 0$$

Rejecting the null hypothesis will indicate that the variable under analysis does exhibit non-linear characteristics.

To establish whether the ESTAR model or the LSTAR model is optimum, the Terasvirta sequential test will be conducted as suggested by Teräsvirta et al. (2005). The null hypotheses for this test are as follows:

$$H_0 : \beta_3 = 0$$

$$H_0 : \beta_2 = 0 \mid \beta_3 = 0$$

$$H_0 : \beta_1 = 0 \mid \beta_3 = \beta_2 = 0$$

The selection rule states that if $H_0 : \beta_1 = 0 \mid \beta_3 = \beta_2 = 0$ has the smallest $p$-value, then an ESTAR model should be used. If any of the other null hypotheses have the lowest $p$-value, then an LSTAR model should be estimated. Furthermore, the optimum lag number for $d$ will be established based on the $d$ with the lowest $p$-value, thus the most significant $d$.

Estimation of the STAR, LSTAR and ESTAR models will provide two sets of beta coefficients for each threshold variable (Teräsvirta et al., 2005). The first set of coefficients will indicate the relationship between a given threshold variable and the aggregate South African financial cycle during linear periods in the aggregate financial cycle. The second set of coefficients will indicate the relationship between a given threshold variable and the aggregate South African financial cycle during non-linear periods in the aggregate financial cycle (Teräsvirta et al., 2005). Linear periods refer to consecutive periods in the aggregate South African financial cycle where no cyclical regime change occurred, for example, a pivot from an expansion to a contraction phase. On the other hand, non-linear periods refer to periods where the aggregate South African financial cycle series pivoted from one cyclical regime to another, for example moving from an expanding to a contracting regime (Teräsvirta et al., 2005). Thus, the set of beta coefficients for threshold variables during non-linear periods indicate the relational dynamics between the aggregate South African financial cycle and a corresponding threshold variable during a period where a cyclical change took place.

### LSTAR

The LSTAR model allows asymmetrical adjustments to the non-linear process. Therefore, if non-linear shifts in the aggregate South African financial cycle does not occur symmetrically during different regimes, then the LSTAR model will be more effective in forecasting turning points in the aggregate South African financial cycle (Teräsvirta et al., 2005). Teräsvirta et al. (2005) state that the LSTAR model follows the following form:

$$\partial\left(s_{t-d}\right)=\left(1+\exp\left\{-\gamma\prod_{k=1}^{K}\left(s_{t-d}-c_k\right)\right\}\right)^{-1}, \tag{10}$$

$$\gamma>0, c_1\leq\cdots\leq c_K$$

where $\gamma$ measures the speed of moving from one regime to the other. Teräsvirta et al. (2005) write that the most common value for $k$ in the transition function $\gamma > 0$, $c_1 \leq \ldots \leq c_K$ is $k = 1$. Teräsvirta et al. (2005) explain that if $k = 1$, then parameters $\varnothing + \lambda G(s_{t-d,h}; \gamma, c)$ change monotonically from $\varnothing$ to $\varnothing + \lambda$ meaning that as $\lambda$ converge to zero, the LSTAR model develops into a linear AR model and becomes a two-regime TAR model if the closer $c_1$ converges to 1.

ESTAR

According to Enders (2004), the ESTAR model is symmetrical if $\text{ASAFC}_{t-1} = c$, allowing the model to approximate gravitational attraction, making the model optimal if the series depicts various levels of autoregressive decay at cyclical pivot points. Enders (2004) states that the STAR model can be transformed to an exponential form by making

$$\gamma=\left[1+\exp(-s(s_{t-0}-c)^2\right]_{y>0} \tag{11}$$

Since $\lambda$ is constant, movements of $\gamma$ towards 0 or $\infty$ make the ESTAR model a AR(p) process, whereas divergence of $\lambda$ from 0 or $\infty$ makes the process non-linear.

### *3.3 Determining Forecasting Performance*

To determine which model performs the best at forecasting the aggregate South African financial cycle, five information criteria will be used, namely root mean square error (RMSE), mean absolute error (MAE), the mean absolute percentage error (MAPE) and Theil's $U$ statistic. These performance measures are often used in literature, such as the work by Wai et al. (2015), Nyberg (2018), Baharumshah and Liew (2006), Botha et al. (2006) and Moolman (2004), as a means to determine the forecasting performance of models. It is argued, however, that forecasting performance measures should be used in combination to get a consensus view, and not in isolation. This will increase the validity of one's findings, hence all five measures will be used. The formulas for each measure are as follows, as seen in Brooks (2019):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=T_1}^{T}\left(y_{t,s} - f_{t,s}\right)^2}, \tag{12}$$

where $y_{t,s}$ is the actual value at time $t$ and $f_{t,s}$ is the forecasted value at time $t$. Furthermore, $n$ represents the total number of observations in the time series.

$$\text{MAPE} = \frac{100}{n}\sum_{t=T_1}^{T}\left|\frac{y - f_{t,s}}{Y_{t,s}}\right|, \tag{13}$$

$$\text{Theil}'\text{s } U_1 \text{statistic} = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{f_{t,s}-y_{t,s}}{y_{t-1}}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{f_{t,n}-y_{t,s}}{y_{t-1}}\right)^2}} \tag{14}$$

where $y_{t-1}$ is the actual value one period prior to the period under consideration and $F_{t,n}$ represents the naïve forecasted value.

Given that RMSE and MAPE indicate the error of a given forecasting process, the lower the values generated by RMSE and MAPE, the better the forecasting accuracy (Brooks, 2019). The average of each measure over time will be considered. The Theil's $U$ statistic provides a slightly different measure than the other four measures considered in this study. It indicates whether the forecasting model performs better than a naïve forecasting approach. A Theil's $U$ coefficient smaller than one indicates that the errors rendered by the forecasting model are lower than that of a naïve forecasting approach and are thus superior to a naïve forecasting approach (Brooks, 2019). On the other hand, if the Theil's $U$ coefficient is larger than one, then a naïve forecasting approach outperforms the forecasting ability of the forecasting model under consideration (Brooks, 2019). The Theil's $U$ statistic will therefore not be used to compare the various forecasting models to each other, but rather to determine whether the model under consideration is more effective than using a naïve forecasting approach. Provided that a rolling forecasting approach will be taken for the various $n$-ahead forecasting time horizons, the average of the various forecasting performance measures over time, for a given forecasting horizon, will be considered.

**Table 1** Phillip-Perron unit root test and the Breakpoint Augmented Dickey-Fuller unit root test results

| **Breakpoint Augmented Dickey-Fuller test results** | |
|---|---|
| | $T$-statistic |
| Augmented Dickey-Fuller test statistic | −8.519 |
| Test critical value at a 99% level | −3.445 |
| Test critical value at a 95% level | −2.868 |
| Test critical value at a 90% level | −2.570 |
| **Phillips-Perron test results** | |
| | $T$-statistic |
| Phillips-Perron test statistic | −4.269 |
| Test critical value at a 99% level | −3.445 |
| Test critical value at a 95% level | −2.867 |
| Test critical value at a 90% level | −2.570 |

***Source:****Author's calculation*

# 4 Results, Findings, and Discussion

Firstly, the results rendered by the ARIMA model will be considered, followed by the results rendered by the STAR model. Then the results from the MS-AR model will be considered, followed by the forecast performance evaluation.

## *4.1 ARIMA Model Outputs*

First, the order of integration, *I*, of the aggregate South African financial cycle will be established. Research has shown that the standard Augmented Dickey-Fuller unit root test is often sub-par when working with a time series that exhibits cycles and regime-switching properties (Nelson, Piger, & Zivot, 2000). Nelson et al. (2000) suggest using the Phillip-Perron unit root test or a breakpoint Augmented Dickey-Fuller unit root test which allows for endogenous probabilistic trend fluctuations in a series when testing a cyclical series for stationarity. Therefore, the Phillip-Perron unit root test and the Breakpoint Augmented Dickey-Fuller unit root test will be used to test the level of integration of the aggregate South African financial cycle. Table 1 depicts the results rendered by these tests. These tests indicate whether the aggregate South African financial cycle is stationary and if not, how many times the series needs to be differenced to be stationary. This will indicate the level of integration (I).

In absolute terms, both the Breakpoint Augmented Dickey-Fuller test statistic and the Phillips-Perron test statistic are larger than the critical value at a 99% confidence level. Thus, the null hypothesis of a unit root can be rejected, and it could be concluded that the aggregate South African financial cycle is stationary at level. The order of integration (*I*) is thus 0, and the series does not need to be differenced. Given that the I in the ARIMA model is now established, the optimal number of AR

**Table 2** ACF and PACF for the aggregate South African financial cycle series

| Autocorrelation | Partial correlation | Number of lags | AC | PAC | Prob |
|---|---|---|---|---|---|
| .\|***** | .\|***** | 1 | 0.916 | 0.986 | 0.000 |
| .\|*** | ***\|. | 2 | 0.820 | −0.771 | 0.000 |
| .\|**** | .\|*** | 3 | 0.871 | 0.767 | 0.000 |
| .\|*** | **\|. | 4 | 0.822 | −0.698 | 0.000 |
| .\|. \| | .\|. \| | 5 | 0.113 | 0.055 | 0.000 |
| .\|. \| | .\|. \| | 6 | 0.045 | 0.046 | 0.000 |
| .\|. \| | .\|. \| | 7 | 0.030 | 0.037 | 0.000 |
| .\|. \| | .\|. \| | 8 | 0.040 | 0.036 | 0.000 |
| .\|. \| | .\|. \| | 9 | 0.006 | 0.013 | 0.000 |
| .\|. \| | .\|. \| | 10 | 0.020 | 0.003 | 0.000 |

***Source:****Author's calculation*

and MA terms must now be determined. A correlogram will be used to display the ACF and PACF of the aggregate South African financial cycle series. The rule of thumb is that the ACF and the PACF should die down to zero if the time series is stationary. Furthermore, spikes in the ACF on the correlogram indicates the optimal MA specification and spikes in the PACF on the correlogram indicates the optimal AR specification. Table 2 depicts ACF and PACF outputs and the corresponding correlogram.

Based on the correlogram depicted in Table 2, both the ACF and PACF die down to zero fairly quickly, indicating that the aggregate South African financial cycle series is stationary. This corresponds with the results rendered by the ADF and PP unit root tests. Based on the correlogram depicted in Table 2, the ACF function spikes at the first four lags and then dies out after the first three lags. Furthermore, the PACF spikes up to four lags and then dies down. This indicates that an AR(4)MA(4) specification will be optimal. Table 3 depicts the AR(4)MA(4) model outputs and based on these outputs, it can be seen that all the AR and MA terms are significant at a 99% confidence level.

The model depicted in Table 3 has an adjusted $R$-squared of 0.851, meaning that the explanatory variables in the model explained 85.1% of the change in the aggregate South African financial cycle. Given this high explanatory power, the AR(4)MA(4) model will be used to forecast the aggregate South African financial cycle, and the forecasting performance of this model will be assessed. As done by a number of researchers such as Botha et al. (2006), Teräsvirta et al. (2005), Moolman (2004) Sarantis (2001) and Clements and Krolzig (1998), the forecasting performance of the ARMA model will be used as a benchmark. The forecasting performance of non-linear models will be compared to that of the ARMA model to determine whether accounting for non-linearities improves the performance of forecasting the aggregate South African financial cycle.

**Table 3** ARIMA results

| Variable | Coefficient | *P*-value |
|---|---|---|
| *C* | 0.062 | 0.607 |
| AR (1) | 3.909 | 0.000*** |
| AR (2) | 4.271 | 0.000*** |
| AR (3) | −3.834 | 0.000*** |
| AR (4) | −0.962 | 0.000*** |
| MA (1) | 1.086 | 0.000*** |
| MA (2) | −0.167 | 0.001*** |
| MA (3) | −0.540 | 0.000*** |
| MA(4) | 0.092 | 0.000*** |
| Adjusted *R*-squared: 0.851 | | |

*, ** and *** denote statistical significance at a 99%, 95% and 99% confidence level, respectively, based on *p*-values
***Source:****Author's calculation*

**Table 4** Outputs rendered by the STAR model

| | Coefficient | *P*-value |
|---|---|---|
| **Variables during the linear phase** | | |
| AR(1) | 0.998 | 0.000*** |
| AR(2) | 0.942 | 0.009*** |
| AR(3) | −1.081 | 0.000*** |
| AR(4) | −0.713 | 0.001*** |
| **Variables during non-linear phase** | | |
| AR(1) | −0.727 | 0.021** |
| AR(2) | −0.923 | 0.011** |
| AR(3) | 0.343 | 0.027** |
| AR(4) | −0.161 | 0.033** |
| **Non-threshold variable** | | |
| *C* | −0.004 | 0.013** |
| *Threshold:* 2.471 and *P-value of threshold:* 0.000*** | | |
| *Adjusted R-squared:* 0.906 | | |

*, ** and *** denote statistical significance at a 99%, 95% and 99% confidence level, respectively, based on *p*-values
***Source:****Author's calculation*

## *4.2 STAR Model Outputs*

The results in the previous section indicated that four AR lag terms are optimal and therefore the base STAR($n$) model will be a STAR($n$) model with four lags, STAR($n$). The results for the standard STAR(4) are presented in Table 4. The top part of the table depicts the coefficients of each AR term exhibited during linear periods in aggregate South African financial cycles. Based on the $P$-values of each AR term, all four AR terms are statistically significant.

**Table 5** Smooth threshold linearity test results

| Null hypothesis | $P$-value |
|---|---|
| $H04$: $b1 = b2 = b3 = b4 = 0$ | 0.000*** |
| $H03$: $b1 = b2 = b3 = 0$ | 0.005*** |
| $H02$: $b1 = b2 = 0$ | 0.009*** |
| $H01$: $b1 = 0$ | 0.002** |

*, ** and *** denote statistical significance at a 99%, 95% and 99% confidence level, respectively, based on $p$-values
***Source:****Author's calculation*

The middle part of the table depicts the coefficients of each AR term exhibited during non-linear periods in aggregate South African financial cycles. Based on the $P$-values of each AR term, all four AR terms are statistically significant during non-linear periods. The lower part of the table depicts the coefficient of the non-threshold variable, the transition threshold value, and the adjusted $R$-squared. The threshold value is 2.471, indicating that the probability of a cyclical change increases significantly when the cycle reaches the 2.471 level. Also, the adjusted $R$-squared of 0.906 indicates that 90.6% of the variance in the aggregate South African financial cycle is explained by the variables in the model. This is an improvement in the linear ARIMA model which had an adjusted $R$-squared of 85.1%. This indicates that the consideration of non-linearity improves the explanatory power of a model.

From this STAR(4) model, a smooth threshold linearity test is conducted within the STAR(4) model set-up to determine whether aggregate South African financial cycles exhibit non-linear characteristics. Furthermore, a Terasvirta sequential test is conducted, as suggested by Teräsvirta et al. (2005), to determine whether the transition function is a normal, logistic or exponential. If the transition function is normal, then the STAR model is the optimal smooth transition model; if the transition function is logistic, then the LSTAR model is the optimal smooth transition model and if the transition function is exponential, then the ESTAR model is the optimal smooth transition model. Once this has been determined, the $P$-values for a range of delay factors, estimated as part of the linearity test, are considered to determine the optimal $d$ in (8) and (9). These tests will aid in selecting the optimal smooth transition model, which in turn will ultimately be used to forecast aggregate South African financial cycles. Table 5 depicts the results rendered by the smooth threshold linearity test.

All four hypotheses in Table 5 can be rejected at a 99% confidence interval. The results in Table 5, therefore, indicate that the beta coefficients of $w_t s_{t-d}^2$ and $w_t s_{t-d}^3$, the two non-linear measures in the auxiliary regression, represented by (9), are highly significant (Teräsvirta et al., 2005). The aggregate South African financial cycle, therefore, does exhibit non-linear characteristics, making it appropriate to model the aggregate South African financial cycle with the STAR methodology. Table 6 represents the results rendered by the Terasvirta sequential tests.

Provided that $H2$: $b2 = 0 \mid b3 = 0$ is significant at a 99% confidence level, as depicted in Table 6, and has a lower $p$-value than $H1$: $b1 = 0 \mid b2 = b3 = 0$, a

**Table 6** Terasvirta sequential test results

| Null hypothesis | $P$-value |
|---|---|
| $H3$: $b3 = 0$ | 0.035** |
| $H2$: $b2 = 0 \mid b3 = 0$ | 0.000*** |
| $H1$: $b1 = 0 \mid b2 = b3 = 0$ | 0.009*** |

*, ** and *** denote statistical significance at a 99%, 95% and 99% confidence level, respectively, based on $p$-values
***Source:****Author's calculation*

**Table 7** $P$-values for the range of delayed factors considered in this study based on linearity test

| $d$ lag | $P$-value |
|---|---|
| 1 | 0.046** |
| 2 | 0.003*** |
| 3 | 0.018** |
| 4 | 0.025*** |
| 5 | 0.028** |
| 6 | 0.037** |

*, ** and *** denote statistical significance at a 99%, 95% and 99% confidence level, respectively, based on $p$-values
***Source:****Author's calculation*

logistic transition function is optimum. The aggregate South African financial cycle will thus be modelled and forecasted by the LSTAR model. Finally, Table 7 depicts the $P$-values of a range of delay factors derived from the linearity test.

Based on the results in Table 7, $d = 2$ is the most significant given that $d = 2$ has the lowest $p$-value. The delay factor for the STAR model in this study will thus consist of two lags. Given the results considered, one now knows that there are non-linearities in the aggregate South African financial cycle and that the transition function exhibits logistic characteristics. Furthermore, the optimum $d$ in (8) and (9) is established. This allows for the estimation of an optimal smooth transition model which is an LSTAR(4) model with a two-lag delay factor. Table 8 depicts the results estimated by the LSTAR(4) model.

All the threshold variables during a linear period in the aggregate financial cycle are significant at a 99% confidence level, provided that each variable exhibited a $p$-value smaller than 0.01. The beta coefficients indicate that, during a linear period, a one unit increase in the aggregate South African financial cycle one, two, three and four periods back will lead to a 0.878, 0.599, −0.757, −0.640 unit change in the current value of the aggregate South African financial cycle, respectively. Thus, an increase in the aggregate South African financial cycle in time $t_1$ will typically have a positive impact on the aggregate South African financial cycle in the following two periods but then have a negative impact three and four periods ahead.

During a non-linear period, a one unit increase in the aggregate South African financial cycle one, two, three and four periods back will lead to a −0.421, −0.337, 0.248 and −0.454 unit change in the current value of the aggregate South African

**Table 8** Outputs rendered by the LSTAR model

| | Coefficient | *P*-value |
|---|---|---|
| **Variables during the linear phase** | | |
| AR(1) | 0.878 | 0.000*** |
| AR(2) | 0.599 | 0.000*** |
| AR(3) | −0.757 | 0.000*** |
| AR(4) | −0.640 | 0.000*** |
| **Variables during non-linear phase** | | |
| AR(1) | −0.421 | 0.020** |
| AR(2) | −0.337 | 0.042** |
| AR(3) | 0.248 | 0.030** |
| AR(4) | −0.454 | 0.022** |
| **Non-threshold variable** | | |
| *C* | −0.006 | 0.014** |
| *Absolute threshold value*: 2.786 and *P-value of threshold:* 0.000*** | | |
| *Adjusted R-squared:* 0.936 | | |

*, ** and *** denote statistical significance at a 99%, 95% and 99% confidence level, respectively, based on *p*-values
***Source:****Author's calculation*

financial cycle, respectively. This mostly indicates that an inverse relationship exists between the aggregate South African financial cycle at time $t_1$ and lags of itself, except for the third AR lag term. The cyclical series is in a transition period during a non-linear phase, thus an inverse relationship between the current period and the preceding periods is expected. Consider now the threshold value and Adjusted *R*-squared depicted in the bottom part of Table 8. The absolute threshold value is 2.786, indicating the typical level at which aggregate South African financial cycles reach a pivot point. This indicates that the probability of a cyclical change increases significantly when aggregate South African financial cycles reach the 2.786 or −2.786 level. Also, the adjusted *R*-squared of 0.936 indicates that the threshold variables in the model perform well in explaining movements in the aggregate South African financial cycle.

## *4.3 MS-AR Model Outputs*

The results from the various criterion for the various MS-AR-type models are presented in Appendix. The HQC, AIC and SIC prove to be the lowest for the MSMV(2)-AR(3) model. Thus, given that all the three information criteria are lowest for the MSMV(2)-AR(3) model, the optimal specification to model the aggregate South African financial cycle is an MS model with three AR lags, a regime-dependent mean and a regime-dependent variance with two states. Hence, the results of the MSMV(2)-AR(3) model will further be considered, and the MSMV(2)-AR(3)

**Table 9** Estimation output of the MSMV(2)-AR(3) model

| Variable | MSMV(2)-AR(3) |
|---|---|
| $\mu_{s1}$ | 0.099*** |
| $\mu_{s2}$ | −0.162*** |
| $\beta_{1s1}$AR(1) | 1.966*** |
| $\beta_{2s1}$AR(2) | 1.162*** |
| $\beta_{3s1}$AR(3) | −1.105*** |
| $\beta_{1s2}$AR(1) | 2.063*** |
| $\beta_{2s2}$AR(2) | 1.753*** |
| $\beta_{3s2}$AR(3) | −0.986** |
| $\sigma_{s1}$ | −3.661*** |
| $\sigma_{s2}$ | −5.787*** |
| **Transition matrix parameters** | |
| P11-C | 2.974*** |
| P21-C | −3.198*** |
| **Typical duration (in months)** | |
| Expanding phase | 49.31 |
| Contracting phase | 35.79 |
| **Transition probabilities** | |
| $p_{11}$ | 0.951 |
| $p_{12}$ | 0.049 |
| $p_{22}$ | 0.891 |
| $p_{21}$ | 0.109 |

** and *** denote statistical significance at a 95% and 99% confidence level, respectively, based on *p*-values
***Source:****Author's calculation*

model will be used to forecast the aggregate South African financial cycle. The outputs from the MSMV(2)-AR(3) model are depicted in Table 9.

In the MSMV(2)-AR(3) model, the mean, $\mu_s$, and variance, $\sigma_s$, and cyclical persistent terms, $\beta_{1s}$AR(1), $\beta_{2s}$AR(2) and $\beta_{3s}$AR(3), depend on the unobservable Markov state variable that may assume two values, $s_t \in \{1, 2\}$. Firstly, consider the results from the regime-dependent means, $\mu_{s1}$ and $\mu_{s2}$. The regime-dependent means of both regimes, $\mu_{s1}$ and $\mu_{s2}$, are statistically significant at a 99% confidence level and have opposite signs. Thus, the point estimates of the regime-dependent means are statistically different from each other. This provides evidence that supports the assumption that two distinct regimes characterize the aggregate South African financial cycle. This justifies the use of an MSMV(2)-AR(3) model that accounts for a regime-dependent mean.

The regime-dependent mean in regime 1, $\mu_{s1}$, is positive, and the regime-dependent mean in regime 2, $\mu_{s2}$, is negative. Given that $\mu_{s1} > \mu_{s2}$, the evidence is provided that one can interpret regime 1 as the expanding regime and regime 2 as the contracting regime (Tastan & Yildirim, 2008). Secondly, consider the variance parameter, $\sigma_{s1}$, and $\sigma_{s2}$. Both these parameters are statistically significant at a 99% confidence level with different magnitudes. In absolute terms $\sigma_{s1} < \sigma_{s2}$, as stated by Tastan and Yildirim (2008), indicates that there is volatility asymmetry between regimes. These results indicate that volatility is lower during an expanding phase relative to the volatility in a contracting phase. This result was expected and corresponds to empirical literature providing evidence that cyclical contractions in both financial conditions, i.e. the 2007 financial crisis, and real economic conditions, i.e. business cycle contractions, are more violent and harsh relative to expansions (Tastan & Yildirim, 2008; McQueen & Thorley, 1993). These asymmetries provide additional justification for the use of non-linear MS-AR methodology that accounts for asymmetries and accounts for a regime-dependent variance.

The transition matrix parameters, P11-C and P21-C, in Table 9 are both statistically significant at a 99% confidence level and have opposite signs. The positive P11-C and negative P21-C signifies that increases in the aggregate South African financial cycle are associated with higher probabilities of remaining in the expanding regime, lowering the transition probability out of regime 1 and increasing the transition probability from regime 2 into regime 1. Furthermore, the results from this model indicated that an aggregate South African financial cycle expansion lasts approximately 49.31 months, thus 4 years and 1.31 months and a contraction last approximately 35.79, thus 3 years. These results thus indicate that an expansion in the aggregate South African financial cycle has a longer duration than a contraction. The aggregate South African financial cycle thus exhibits a level of durational asymmetry.

The various models employed to estimate the aggregate South African financial cycle will now be used to forecast the aggregate South African financial cycle, and the forecasting performance of the various models will be compared to identify the optimal model to forecast the aggregate South African financial cycle.

### 4.4 Forecasting Performance Evaluation

In this section, the rolling forecasting performance of the linear AR(4)MA(4) model, the LSTAR(4) model and the MSMV(2)-AR(3) model will be established and compared. A fixed window rolling forecasts with each model will be done 1-step ahead, 3-steps ahead, 6-steps ahead, 12-steps ahead, 18-steps ahead and 24-steps ahead. The RMSE, MAPE and Theil $\boldsymbol{U_1}$ coefficient are considered to identify the model with the best forecasting performance, given the different forecasting horizons. Table 10 depicts the forecasting performance measures rendered by each of the three models for the various forecasting time horizons.

Consider the results for a three-step and six-step forward forecasting horizon in Table 10. These are the two shortest forecasting time horizons in this study, and based on the RMSE and MAPE the linear ARIMA model produced the most accurate forecasts for this time horizon. The benchmark ARMIA model thus outperforms the non-linear models at forecasting short periods. This corresponds to the findings by Balcilan et al. (2015) who found that non-linear models typically do not outperform standard ARIMA models in forecasting short periods ahead. A possible explanation for this can be that aggregate South African financial cycles exhibit

**Table 10** Forecasting performance measures

| | RMSE | MAPE | Theil $U_1$ coefficient |
|---|---|---|---|
| **Three-steps forward** | | | |
| AR(4)MA(4) | 7.86E-05[a] | 0.070[a] | 2.64E-05[a] |
| MSMV(2)-AR(3) | 0.014 | 3.890 | 0.005 |
| LSTAR(4) | 0.010 | 3.366 | 0.004 |
| **Six-steps forward** | | | |
| AR(4)MA(4) | 0.001[a] | 0.116[a] | 0.000[a] |
| MSMV(2)-AR(3) | 0.027 | 6.943 | 0.009 |
| LSTAR(4) | 0.038 | 8.629 | 0.013 |
| **Twelve-steps forward** | | | |
| AR(4)MA(4) | 0.312 | 44.634 | 0.104 |
| MSMV(2)-AR(3) | 0.109 | 19.027 | 0.012[a] |
| LSTAR(4) | 0.064[a] | 11.547[a] | 0.037 |
| **Eighteen-steps forward** | | | |
| AR(4)MA(4) | 0.315 | 45.978 | 0.105 |
| MSMV(2)-AR(3) | 0.046[a] | 12.749[a] | 0.020[a] |
| LSTAR(4) | 0.297 | 43.968 | 0.101 |
| **Twenty-four-steps forward** | | | |
| AR(4)MA(4) | 1.307 | 107.760 | 0.433 |
| MSMV(2)-AR(3) | 0.132[a] | 15.730[a] | 0.045[a] |
| LSTAR(4) | 0.818 | 86.382 | 0.271 |

***Source:****Author's calculation*

[a]Indicates the lowest measure and thus the model with the best forecasting performance

linearities over short periods. In other words, aggregate South African financial cycles do not reach a cyclical turn every 3–6 months, thus not exhibiting non-linearities. Therefore, by accounting for non-linearities does not improve forecasting accuracy, as such non-linearities are seldom over short periods. Furthermore, the simplicity of ARIMA modelling and forecasting can attribute to the forecasting accuracy of such models (Balcilan et al., 2015; Crawford & Fratantoni, 2003). In combination, the simplicity of ARIMA forecasting and the possible non-linearities exhibited by aggregate South African financial cycles over short periods can explain why the ARIMA model outperforms MS-AR and LSTAR models over a 3 and 6-step forecasting horizon.

On the other hand, based on the RMSE and MAPE, both the non-linear MSMV(2)-AR(3) and LSTAR(4) models produced more accurate forecasts for 12-, 18- and 24-steps ahead forecasting time horizon than the linear AR(4)MA(4) model. Based on the RMSE and MAPE, the forecasting accuracy of the linear AR(4)MA(4) model deteriorates drastically as the forecasting time horizon increases. The mean absolute percentage error is as high as 107.760% for a 24-period ahead forecast, indicating how inaccurate the AR(4)MA(4) model becomes at forecasting aggregate South African financial cycles. This corresponds to the findings of a large number of researchers such as, but not limited to, the work done by Wai et al. (2015), Baharumshah and Liew (2006), Botha et al. (2006), Teräsvirta et al. (2005), Moolman (2004), Crawford and Fratantoni (2003) and Clements and Krolzig (1998) who found evidence that forecasting gains can be generated by exploiting non-linear structures offered by STAR and MS-AR models.

Forecasting 12-steps ahead, the LSTAR(4) model generated the most accurate forecasts according to the RMSE and MAPE. The Theil $\boldsymbol{U_1}$ coefficient indicates that the MSMV(2)-AR(3) model performs slightly better at forecasting aggregate South African financial cycles 12-steps ahead. It might, therefore, be useful to use both the LSTAR and the MSMV(2)-AR(3) models to forecast the aggregate South African financial cycle 12-steps ahead. According to all three performance measures, the MSMV(2)-AR(3) model outperforms the LSTAR (4) and AR(4)MA(4) models at forecasting the aggregate South African financial cycle 18- and 24-steps ahead. These are the longest forecasting time horizons considered in this study. This shows that the MSMV(2)-AR(3) model renders the most accurate forecasts of the aggregate South African financial cycle given a longer-term time horizon. This corresponds to the work done by Clements and Krolzig (1998) who found evidence that MS-AR models outperform STAR models at forecasting economic variables. The Theil $\boldsymbol{U_1}$ coefficient indicates that the linear AR(4)MA(4) model as well as the non-linear MSMV(2)-AR(3) and the LSTAR(4) models outperforms the naïve forecasting approach over all time horizons.

## 5 Conclusion

The aim of this article was to identify the best model to forecast aggregate South African financial cycles over various time periods, specifically distinguishing between the forecasting performance of linear vs non-linear models. The forecasting performance of the linear ARIMA model was used as a benchmark and the forecasting performance of the LSTAR and MS-AR models was measured relative to that of the ARIMA model. The RMSE, MAPE and Theil U coefficient were used as forecasting performance measures because these measures are widely accepted and used in forecasting literature to establish and compare the forecasting performance of various models to one another.

The results rendered by the LSTAR model indicate that the threshold level of the aggregate South African financial cycles is 2.891 in absolute terms. This indicates that the aggregate South African financial cycle tends to reach a pivot point when it reaches a level of 2.891 or −2.891. Therefore, the probability of a cyclical change increases considerably when the aggregate South African financial cycle reaches 2.891 or −2.891. Furthermore, the results rendered by the smooth threshold linearity test indicate that non-linearities are present in the aggregate South African financial cycle series. This corresponds to the research done by Singh (2012). This indicates that the modelling of aggregate South African financial cycles with linear models might be suboptimal and that it might be necessary to account for non-linearities in the modelling of aggregate South African financial cycles. It also indicates that the use of non-linear models to forecast aggregate South African financial cycles might improve forecasting accuracy. It was therefore expected that the non-linear MS-AR and LSTAR models will outperform the benchmark ARIMA model.

Interestingly, evidence indicates that the linear AR(4)MA(4) model outperforms the LSTAR(4) and MSMV(2)-AR(3) models at forecasting the aggregate South African financial cycle three- and six-steps ahead. Thus, given a short forecasting horizon, no forecasting gains are achieved by accounting for non-linearities. However, for longer forecasting time horizons the non-linear MSMV(2)-AR(3) and the LSTAR(4) models outperform the linear AR(4)MA(4) model. Thus, as the forecasting time horizon increases, forecasting gains are achieved by exploiting the non-linear structure of the LSTAR and MSMV-AR models. Furthermore, evidence is found that the MSMV(2)-AR(3) model outperforms the LSTAR(4) model at forecasting aggregate South African financial cycles 18- and 24-steps ahead. Policymakers and other economic participants which are exposed to the aggregate South African financial cycle should use the AR(4)MA(4) model to forecast the aggregate South African financial cycle 3–6 months ahead. However, the MSMV(2)-AR(3) model should be used to forecast the aggregate South African financial 12–24 months ahead.

## A.1 Appendix: Selection Criterion for Various MS-AR Models

| | HQC | AIC | SIC |
|---|---|---|---|
| MS(2)-AR(1) | −0.804 | −0.823 | −0.774 |
| MS(2)-AR(2) | −6.369 | −6.395 | −6.329 |
| MS(2)-AR(3) | −9.002 | −9.034 | −8.951 |
| MS(2)-AR(4) | −7.908 | −7.947 | −7.848 |
| MSM(2)-AR(1) | −1.724 | −1.747 | −1.689 |
| MSM(2)-AR(2) | −9.443 | −9.478 | −9.387 |
| MSM(2)-AR(3) | −8.442 | −8.482 | −8.377 |
| MSM(2)-AR(4) | −5.885 | −5.914 | −5.840 |
| MSV(2)-AR(1) | −1.207 | −1.233 | −1.167 |
| MSV(2)-AR(2) | −7.384 | −7.422 | −7.321 |
| MSV(2)-AR(3) | −9.384 | −9.422 | −9.323 |
| MSV(2)-AR(4) | −5.639 | −5.671 | −5.589 |
| MSMV(2)-AR(1) | −1.212 | −1.234 | −1.177 |
| MSMV(2)-AR(2) | −9.021 | −9.057 | −8.966 |
| MSMV(2)-AR(3) | −10.374[a] | −10.448[a] | −10.206[a] |
| MSMV(2)-AR(4) | −5.546 | −5.572 | −5.506 |

***Source:****Author's calculation*
[a]Optimal model based on criterion

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# From Clubs to Communities. From Tourists to International Friends. Crisis Legacy in Music Organizations with Revenue Management and Relationship Marketing

**Angela Besana and Annamaria Esposito**

**Abstract** The prompt and cost-effective segmentation of audiences and stakeholders is, today, as essential as revenue diversification in US symphony orchestras and opera houses.

The lack of resources was particularly heavy during crisis years and as from 2008. Fundraisers of these music organizations engaged both with clubs and communities. At the same time, marketing officers explored new audiences and their segmentation.

Relationship marketing was a pivotal strategy, in order to enhance stakeholders' engagement and loyalty.

The crisis legacy allowed these organizations to survive with revenue management and relationship marketing.

The purpose of this study is a profiling of a sample of 120 USA symphony orchestras and opera houses, with different marketing and fundraising. Thanks to a k-means cluster analysis of diversified revenues, expenses and gains from 2008 to 2015, the paper will separate this sample into two poles, according to average variations of economic performances and to the focus on relationship marketing in the whole period. One pole grew as concerns relationships, revenue management and diversification. The other pole was affected by diminishing intensity of marketing and increasing fundraising and, as a consequence, retrenchment of some revenues except for contributions. Relationship marketing was in this cluster supported by volunteers. This pole profited by the highest increase in gains.

**Keywords** Economics · Marketing · Classical music · USA · Cluster analysis

A. Besana (✉) · A. Esposito
Dipartimento di Business, Law, Economics and Consumer Behaviour Business, Diritto, Economia e Consumi, International University of Languages and Media, Libera Università di Lingue e Comunicazione IULM, Milan, Italy
e-mail: angela.besana@iulm.it; annamaria.esposito@iulm.it



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## 1 Introduction

Since 2008, the beginning of the latest financial and real crisis, US symphony orchestras and opera houses have struggled to survive in a very competitive scenario, with revolutionary implications for their strategies. During the crisis, marketing and fundraising have not always revealed themselves as efficient strategies in a very uncertain climate. Revenues have been falling and revenue diversification has been not easily implemented and it has been often eluded. Single ticket and group sales have not fully compensated the drop of subscriptions (Besana, 2012; Besana & Esposito, 2019; Pompe, Tamburri, & Munn, 2019; Voss, Voss, Yair, & Lega, 2016). Besides, contributed and investment incomes have not easily recovered after years of fluctuations.

As a consequence, orchestras and opera houses have been innovatively thinking about their marketing and fundraising, with attention to new segments and stakeholders and with a different and versatile implementation thanks to social media. Since these *hard times*, the audience development has concerned both local communities and tourists on the marketing side (Besana & Esposito, 2019; Poon & Lai, 2008). On the fundraising side, donors' exploitation has not more concerned clubs, corporations and grant-making foundations, and also national and international friends (Cancellieri & Turrini, 2016; Kemp & Poole, 2016; Pompe & Tamburi, 2016).

Orchestras and opera houses usually engage with their local communities thanks to education and entertainment programmes: performances, musical activities, rehearsals and concerts in offices halls of private and public buildings and other events, deepening the experience of orchestral music and music education for communities who would typically not otherwise engage with the music organization (League of American Orchestras, 2009; Ravanas, 2007, 2008; Tamburri, Munn, & Pompe, 2015). Tourists are included in the audience development, especially as for guided tours in mostly well-known North American cities, with an ad hoc marketing of bundles of attractions and hotels (Besana & Esposito, 2019).

As a crisis legacy for revenue management and diversification, the 'public good content' has been stressed by the Fundraiser, asking for private philanthropy, worldwide sponsorships and donations, the 'creative and experience content' has been stressed by the Marketing Expert, instead, at the best supported by ICTs and social media.

Fundraising may be thought full-grown and mature, as any segments of foundations (from corporate to community, from independent to family ones), corporate donors and philanthropists, they have been cashed for decades. While grants, donations, and sponsorships, they are the main share of revenues (Besana, 2012; Besana & Esposito, 2019), international friends might be the frontier of fundraising, whose goals can match with marketing ones, when the tourist can get on to the international friend.

Above all, social media have revealed themselves as leading and innovative tools for more than one decade, in order to increase both marketing-oriented and fundraising-oriented audiences and segment them (Esposito, 2016; Roberts, 2014; Van Bree, 2009).

Thanks to a k-means cluster analysis of diversified revenues, expenses and gains from 2008 to 2015, the paper will separate this sample into two poles, according to average variations of economic performances and to the focus on relationship marketing in the whole period. One pole grew as concerns relationships, revenue management and diversification. The other pole was affected by diminishing intensity of marketing and increasing fundraising and, as a consequence, retrenchment of some revenues except for contributions. Relationship marketing was in this cluster supported by volunteers. This pole profited by the highest increase in gains.

## 2 Relationship Marketing in US Opera Houses and Symphony Orchestras: From Engagement to Loyalty Inside and Outside

Relationship marketing is a strategy designed to foster stakeholders' engagement and loyalty (Berry, 1995; Christopher, Payne, & Ballantyne, 1991) as it is essential and indispensable to deal with different groups of stakeholders (Peck, 1996) and with the wide range of connections between these groups (Christopher et al., 1991; Doyle, 1995; Gummesson, 1996).

During the latest crisis, diminishing resources push music organizations to differentiate, segment and maximize their relations with past and new stakeholders, with the commitment of employees, whose roles are clearly separated, either for marketing or fundraising. Without a trade-off in the allocation of resources for marketing and fundraising, fundraisers and marketing officers must focus on building effective relationships among and with staff and volunteers, in order to enhance their engagement and ultimately to improve their performance (Bussell & Forbes, 2006; Kumar & Pansari, 2016).

Volunteers, coming from different sectors of civic society, can act as fundraisers, soliciting grants and contributions of money and goods and services from potential donors. They can also be in charge of some general activities related to the accomplishment of the organization mission.

On the one hand, for instance, orchestras and opera houses can offer to participate in the effort to improve lives through programmes, on the other hand, staff and volunteers can deliver ushering, ticket taking and other services, administrative support in the office; organizing and executing fundraising events and special events (like anniversaries, dinners with main conductors, videomaking of concert halls); promoting main and ancillary activities to their friends, and in addition they could be involved in facilitating experiences that make performances truly memorable.

Managing relationship marketing (Berry, 1995; Das, 2009) is important to define strategies able to attract, maintain, and enhance long-lasting relationships with paid and especially unpaid staff over time. In fact, relationship can become the salient attribute linking staff and volunteers to the organization and, in the same time, the pillar of the original motivation of volunteers (Arnett, German, & Hunt, 2003).

From this standpoint, relationship marketing allows orchestras and opera houses to understand who staff and volunteers are and what drives them in their activities, allowing organizations to identify the strategies more appropriate to manage each of them. In addition, relationship marketing helps to meet the needs of stakeholders, to provide them with information directly suited to their interests, values and visions about the organizations (Bussell & Forbes, 2006, 2007), and to spread an inside-awareness of the social values which lead the achievement of the mission (Andreasen, Kotler, & Parker, 2003).

Adopting a marketing approach allows non-profit to generate stakeholders' trust and commitment (Hussain, Rawjee, & Penceliah, 2014), and to exploit strategically valuable sustainable resources and capabilities, among employees and volunteers. Furthermore, according to Scholars (Colbert, 2001; Hill, O'Sullivan, & O'Sullivan, 1995; Radbourne & Fraser, 1996), the more the organization learns about and monitors the stakeholders' needs, preferences, attitudes and concerns, the more their satisfaction and commitment levels grow. In the same direction, if the mission is properly internally communicated, it can intercept the stakeholders' needs and commitment, leading orchestras and opera houses to reach sustainable management.

## 3 Method

*990 Forms* of the fiscal years 2015 and 2008 are analysed for the IRS—USA Internal Revenue Service—category 'A69-Symphony Orchestra' and 'A6A-Opera': 100 organizations for every category, from the highest to the lowest total income. These reports can be downloaded from the Guidestar website www.guidestar.org and the main websites of organizations themselves.[1] The sample sums up to 158 organizations, whose available 990 Forms were downloadable at www.guidestar.org or their websites.

According to 990 Forms Glossary and Accounting Standards, contributions for US not-for-profit organizations include the direct public support from individuals, grant-makers, foundations, sponsors like corporations and the Government grant for projects of public interest. In the accounting lines of revenues, contributions can be summed up with the programme service revenue, which is money for sold and rendered services.

Contributions and programme service revenue are 85% of total revenues of the here-investigated sample. Next to them, ancillary revenues come from interests and

[1]The Guidestar website collects 990 Forms of USA Not-For-Profits. Not-For-Profits are listed for the relevancy to the keyword. 990 Forms report Statements of Revenues and Expenses and Financial Statements of USA Not-For-Profits.

gains of financial assets, sales of assets, rental income, fundraising from special events and other residual revenues.

The composition of revenues will be here investigated for 2015–2008 percent change of main categories: Contributions with the target of the willingness-to-donate, Programme Service Revenue with the target of willingness-to-pay, Investment Income and Other Revenue.

Expense categories include the following: *Programme Service Expense* related to marketing and management of the core business; *Fundraising expense* and *Management and general expense*, a miscellaneous cost that is not related to the previous accounting lines.

Next to revenue and expense categories, the *(Net) Gain or Loss of the year* as the difference—positive or negative between revenues and costs is also here investigated.

For expense categories and gains (or losses), 2015–2008 percentage changes will be, at the same time, calculated in order to focus on trends of economic performances during and soon after the crisis times.

In order to gain the impact of employees (like fundraisers and marketing officers) and volunteers on economic performances, the ratio of volunteers/employees was added as concerns 2015s data. At the end of the crisis, this ratio is meaningful in order to show how much volunteers and employees have led, and they are leading engagement and loyalty from the inside of the organization, fundraising and marketing from the outside of the organization.

All the monetary data are, first of all, filed in Excel, and 2015–2008 percentage variations are calculated for main items: programme service revenues, contributions, investment income, other revenue, programme service expense, management and general expense, fundraising expense, gain or loss.

Secondly, together with volunteers'/employees' ratios, these variations are clustered in order to obtain meaningful groups with relevant and separating features.

We have adopted the K-means clustering as an iterative follow-the-leader strategy.

## 4 Key Findings and Discussion: The Fundraiser and the Revenue Manager on the Stage of US Classical Music

K-means clustering of the above-mentioned sample of 158 is significant for 120 organizations, which are divided into two clusters. Average performances of two clusters are shown in Table 1. Membership of clusters is reported in Appendix.

The most crowded cluster (74 organizations) is the *Fundraiser* who shows a very important increase in the fundraising expense, +17.45% and as a consequence, in contributions, +18.42%. Save for a very modest increase in the programme service expense (+0.87%), any other item is decreasing. Gains are consistently increasing,

**Table 1** The *crisis legacy* for 120 USA symphony orchestras and opera houses (average 2015–2008% change)

| | Fundraiser −74 organizations | Revenue manager −46 |
|---|---|---|
| Contributions | +18.49 | +12.82 |
| Programme service revenue | −13.81 | +21.99 |
| Investment income | −28.20 | +75.85 |
| Other revenue | −31.70 | +50.69 |
| Programme service expense | +0.87 | +13.26 |
| Management and general expense | −11.94 | +44.82 |
| Fundraising expense | +17.45 | +40.17 |
| Gain or loss | +46.69 | +9.50 |
| Volunteers/employees | 9.15 | 1.04 |

Source: Elaboration with Jump Statistics Software

+46.69%. Volunteers are here essential, nine times employees. They play the role of fundraisers, calling for donations, sponsorships and grants. Social media are mature gatekeepers, in order to promote special events, campaigns, community empowerment. Communities are engaged with plentiful programmes in private and public buildings where orchestra and opera officers tell their histories, seasons, special events and where rehearsals, edutainment and fundraising campaigns take place. Main organizations of big cities like Chicago, Dallas and Los Angeles are included in this cluster. Nevertheless, middle-sized and small American towns are included, too, where performances are together with lunch, dinner, coffee and 'gelato' timing, behind the scenes, with intimate concerts, music and wellness programmes.

Revenue diversification is significant in the second cluster, the *Revenue Manager*. The investment income increase of +75.85% is here matching with increasing other revenue, programme service revenue and contributions, these ones not so high as in the other pole of the Fundraiser. Expenses are increasing and so are gains, but not with the same percentage of the Fundraiser. Some of these organizations count on employees, who show proficiency in investing in financial markets as well as partnershiping with donors' clubs and international friends worldwide. This cluster includes giants like the Met. Several middle-sized and small opera houses and symphony orchestras are here included, whose halls see music travellers of different music genres and whose social media marketing is well-developed in order to engage citizens and tourists, donors, clubs, sponsors and international supporters. Plan Your Visit is provided with information about parking, accessibility, hotels, attractions, programmes notes and comments. Tourists are not more a frontier for marketing in these organizations.

# 5 Conclusion

Today marketing and fundraising of US symphony orchestras and opera houses, they both include diversified tactics and strategies: audiences and philanthropists are investigated as for their willingness-to-pay and willingness-to-donate. Tourists do not more represent the frontier of their flexible subscriptions. Social media are levers of all their audiences and stakeholders.

As a matter of fact, thanks to a price strategy that implies discrimination both for audiences and philanthropists, symphony orchestras and opera houses are connecting with communities, and they are emphasizing relationships, whose performances are particularly meaningful for the Fundraiser cluster. When frontiers of marketing are open to new, innovative and international segmentation and they include tourists, the Revenue Manager is the prevailing profile.

Considering the latest 10 years, it can be confirmed that marketing is as essential as fundraising. Revenue management implies the key consideration that fundraising performances can support or compensate marketing ones, especially when marketing of the place is maximizing occupancy of the houses. Focus on several and multiple stakeholders is the main objective, and marketing is separated from fundraising so that the location can maximize occupancy and revenues.

Research limitations refer, first of all, to the opportunity of the here-investigated organizations to develop new targets like tourists, when US destinations are very different as for tourism: some of them are very attractive as they refer to main opera houses and concert halls like the Met and Carnegie in New York, while some of them remain attractions for business travellers, who are not mainly concerned with opera and classical music as the most important motivation of their journey. Secondly, the here-investigated period was a matter of a real and financial crisis, whose implications hit the whole US economy in spite of skills and marketing efforts of opera and symphony managers. The general lack of resources was deeply affecting all not-for-profit organizations.

Managerial implications imply that managers of these music organizations should continually stress the importance of the selection of new targets. Above all, their segmentation should, at the same time, exploit their willingness-to-pay on the fundraising side (international friends) and on the marketing side (tourists). Social media will facilitate these segmentation and exploitation as they result efficient and pervasive communication channels.

## A.1 Appendix

### *A.1.1 Cluster Fundraiser*

ARIZONA OPERA COMPANY—PHOENIX
BALTIMORE OPERA COMPANY INC—BALTIMORE

BANGOR SYMPHONY ORCHESTRA—BANGOR
BOSTON LYRIC OPERA COMPANY—BOSTON
CALIFORNIA SYMPHONY ORCHESTRA INC—WALNUT CREEK
CANTON SYMPHONY ORCHESTRA ASSOCIATION—CANTON
CHEYENNE SYMPHONY SOCIETY INC—CHEYENNE
CHICAGO SINFONIETTA—CHICAGO
CHICAGO SYMPHONY ORCHESTRA—CHICAGO
CINCINNATI OPERA ASSOCIATION INC—CINCINNATI
CINCINNATI SYMPHONY ORCHESTRA—CINCINNATI
COBB SYMPHONY ORCHESTRA—MARIETTA
DALLAS SYMPHONY ASSOCIATION—DALLAS
DES MOINES METRO OPERA INC—INDIANOLA
DETROIT SYMPHONY ORCHESTRA INC—DETROIT
ERIE PHILHARMONIC INC—ERIE
FAIRFAX SYMPHONY ORCHESTRA—FAIRFAX
GREAT FALLS SYMPHONY ASSOCIATION INC—GREAT FALLS
GREATER AKRON MUSICAL ASSOCIATION INC—AKRON
GREENSBORO SYMPHONY ORCHESTRA INC—GREENSBORO
JACKSONVILLE SYMPHONY ASSOCIATION INC—JACKSONVILLE
JOHNSTOWN SYMPHONY ORCHESTRA—JOHNSTOWN
LANCASTER SYMPHONY ORCHESTRA—LANCASTER
LENAWEE SYMPHONY ORCHESTRA SOCIETY INC—ADRIAN
LONG BEACH SYMPHONY ASSOCIATION—LONG BEACH
LOS ANGELES OPERA COMPANY—LOS ANGELES
LYRIC OPERA OF CHICAGO—CHICAGO
MADISON OPERA—MADISON
MEMPHIS ORCHESTRAL SOCIETY INC—MEMPHIS
MOBILE SYMPHONY INC—MOBILE
MUSIC CENTER OF SOUTH CENTRAL MI—BATTLE CREEK
NASHVILLE OPERA ASSOCIATION—NASHVILLE
NASHVILLE SYMPHONY ASSOCIATION—NASHVILLE
NEVADA OPERA ASSOCIATION—RENO
NEW HAVEN SYMPHONY ORCHESTRA INC—NEW HAVEN
NEW JERSEY SYMPHONY ORCHESTRA—NEWARK
NEW MEXICO SYMPHONY ORCHESTRA—ALBUQUERQUE
NEW ORLEANS OPERA ASSOCIATION—NEW ORLEANS
NEW YORK CITY OPERA INC—NEW YORK
NEWBERRY OPERA HOUSE FOUNDATION—NEWBERRY
NORTH ARKANSAS SYMPHONY ORCHESTRA—FAYETTEVILLE
OMAHA SYMPHONY ASSOCIATION—OMAHA
OPERA BIRMINGHAM—BIRMINGHAM
OPERA COLORADO—DENVER
OPERA OMAHA—OMAHA
OPERA SAN JOSE INCORPORATED—SAN JOSE
OPERA SOUTHWEST—ALBUQUERQUE

OREGON SYMPHONY ASSOCIATION—PORTLAND
PALM BEACH OPERA INC—WEST PALM BEACH
PENSACOLA OPERA INC—PENSACOLA
POCKET OPERA INC—SAN FRANCISCO
PORTLAND OPERA ASSOCIATION—PORTLAND
ROANOKE SYMPHONY ORCHESTRA—ROANOKE
SACRAMENTO PHILHARMONIC ORCHESTRA ASSOCIATION INC—SACRAMENTO
SAINT LOUIS SYMPHONY ORCHESTRA—SAINT LOUIS
SAN ANTONIO OPERA—SANT ANTONIO
SAN DIEGO SYMPHONY ORCHESTRA ASSOCIATION—SAN DIEGO
SANTA BARBARA SYMPHONY ORCHESTRA ASSOCIATION—SANTA BARBARA
SARASOTA OPERA ASSOCIATION INC—SARASOTA
SEATTLE OPERA—SEATTLE
SHEBOYGAN SYMPHONY ORCHESTRA INC—SHEBOYGAN
SPRINGER OPERA HOUSE ARTS ASSOCIATION INC—COLUMBUS
STOCKTON SYMPHONY ASSOCIATION INC—STOCKTON
SYRACUSE OPERA COMPANY INC—SYRACUSE
THE ATLANTA OPERA INC—ATLANTA
THE HENDERSONVILLE SYMPHONY ORCHESTRA INC—HENDERSONVILLE
THE OPERA ASSOCIATION OF CENTRAL OHIO—COLUMBUS
TOLEDO OPERA ASSOCIATION—TOLEDO
TRAVERSE SYMPHONY ORCHESTRA—TRAVERSE CITY
TULSA OPERA INC—TULSA
VIRGINIA OPERA ASSOCIATION—NORFOLK
WHATCOM SYMPHONY ORCHESTRA—BELLINGHAM
WICHITA GRAND OPERA INC—WICHITA
WILLIAMSPORT SYMPHONY ORCHESTRA—WILLIAMSPORT

### *A.1.2 Cluster Revenue Manager*

ALBANY SYMPHONY ORCHESTRA INC—ALBANY
BERKELEY SYMPHONY ORCHESTRA—BERKELEY
BOSTON YOUTH SYMPHONY ORCHESTRA INC—BOSTON
BUFFALO PHILHARMONIC ORCHESTRA SOCIETY INC—BUFFALO
CHATTANOOGA SYMPHONY AND OPERA ASSOCIATION—CHATTANOOGA
DAYTON PHILHARMONIC ORCHESTRA ASSOCIATION—DAYTON
DUBUQUE SYMPHONY ORCHESTRA—DUBUQUE
EL PASO SYMPHONY ORCHESTRA ASSOCIATION INC—EL PASO

EUGENE SYMPHONY ASSOCIATION INC—EUGENE
FLORENTINE OPERA COMPANY INC—MILWAUKEE
GLENS FALLS SYMPHONY ORCHESTRA INC—GLEN FALLS
HAWAII OPERA THEATRE—HONOLULU
HOUSTON GRAND OPERA ASSOCIATION INC—HOUSTON
KALAMAZOO SYMPHONY ORCHESTRA—KALAMAZOO
KANSAS CITY SYMPHONY—KANSAS CITY
KENTUCKY OPERA ASSOCIATION—LOUISVILLE
KNOXVILLE SYMPHONY SOCIETY INC—KNOXVILLE
LYRIC OPERA OF KANSAS CITY—KANSAS CITY
METROPOLITAN OPERA ASSOCIATION INC—NEW YORK
MONTEREY COUNTY SYMPHONY ASSOCIATION INC—CARMEL
OPERA AMERICA INC—NEW YORK
OPERA CAROLINA—CHARLOTTE
OPERA COMPANY OF PHILADELPHIA—PHILADELPHIA
OPERA IN THE HEIGHTS—HOUSTON
OPERA NORTH—LEBANON
PEORIA SYMPHONY ORCHESTRA FOSTER ARTS CENTER—PEORIA
PIEDMONT OPERA INC—WINSTON SALEM
PITTSBURGH OPERA INC—PITTSBURGH
PORTLAND MAINE SYMPHONY ORCHESTRA—PORTLAND
QUAD CITY SYMPHONY ORCHESTRA ASSOCIATION—DAVENPORT
RHODE ISLAND PHILHARMONIC ORCHESTRA & MUSIC SCHOOL—EAST PROVIDENCE
SAN FRANCISCO OPERA ASSOCIATION—SAN FRANCISCO
SANTA ROSA SYMPHONY ASSOCIATION—SANTA ROSA
SEATTLE YOUTH SYMPHONY ORCHESTRAS—SEATTLE
SHREVEPORT OPERA—SHREVEPORT
SKYLIGHT OPERA THEATRE—MILWAUKEE
SOUTH BEND SYMPHONY ORCHESTRA ASSOCIATION INC—SOUTH BEND
SYMPHONY SOCIETY OF SAN ANTONIO
TACOMA OPERA ASSOCIATION—TACOMA
THE LOUISVILLE ORCHESTRA INC—LOUISVILLE
THE LOUSIANA PHILHARMONIC ORCHESTRA—NEW ORLEANS
THE MINNESOTA OPERA—MINNEAPOLIS
THE STAMFORD SYMPHONY ORCHESTRA INC—STAMFORD
UTAH FESTIVAL OPERA COMPANY—LOGAN
WEST SHORE SYMPHONY ORCHESTRA—MUSKEGON
WOODLAND OPERA HOUSE INC—WOODLAND

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# Measuring Dynamic Capabilities-Based Synergies in M&A Deals with Real Options: Amazon's Acquisition of Whole Food

**Andrejs Čirjevskis**

*"Amazon buying Whole Foods is incredibly interesting, highly strategic, and definitely not standard" Josh Chapman, Toptal Finance Expert*

(Clarence-Smith, 2020)

**Abstract** Acquisition-based dynamic capabilities have become well established as a new imperative for organizing M&A processes. However, understanding the full benefits and possible limits of real options applications to measure a dynamic capability-based (managerial) synergy remains a challenge. The paper draws on real options theory to describe some of these benefits and limits to value a synergy in highly strategic and not standard M&A deals. The acquisition of Whole Foods by Amazon makes it possible to combine two streams of research on dynamic capabilities and real options in a cohesive whole. More specifically, the author develops three propositions to justify the role of dynamic capabilities as antecedents of success or failures of M&A deals and to demonstrate real options application to measure synergies of M&A deals.

**Keywords** Merger and acquisition · Dynamic capabilities · Synergy · Real options

## 1 Introduction: Purpose, Motivation, and Originality

"Synergies do not magically materialize. By definition, they are possibilities, not certainties" (Ficery, Herd, & Pursche, 2007, p. 35). While there is some evidence of synergy in the aggregate across all acquisitions, most mergers fail in delivering any

A. Čirjevskis (✉)
RISEBA University of Applied Sciences in Business, Arts and Technology, Riga, Latvia
e-mail: andrejs.cirjevskis@riseba.lv



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synergy (Damodaran, 2005, p. 47). This paper aims to justify the role of dynamic capabilities as antecedents of success or failures of M&A deals and to demonstrate real options application to measure managerial synergies in M&A deals. In the current paper, the author argues that the intersection between dynamic capabilities frameworks and real options theory can shed light on the antecedents of successes and failures of M&A deals.

The interaction between dynamic capabilities and real option valuation enables the acquirer to elect and exercise those options that have a high probability to provide managerial synergies and let expire the options that have low probability. The paper develops three propositions as follows. The probability to exercise a real option in the M&A deal can be measured by exploring similarities and complementarity of the dynamic capabilities of acquirers and targets. The managerial synergies are provided by the successful integration of the dynamic capabilities of an acquirer and a target. Such type of synergy can be assessed and measured by real option application.

The motivation for this research is as follows. First, the majority of papers on the synergetic effects of M&A deals typically focus on a particular type of synergy (Loukianova, Nikulin, & Vedernikov, 2017), while the current paper proposes a model that accounts for the cumulative simultaneous effect of different types of operating, financial, and dynamic capabilities-based synergies. Second, even though the dynamic capabilities framework and its empirical applications (Capron & Anand, 2007; Teece, 2007, 2011) make dynamic capabilities more *visible*, the real option application making dynamic capabilities *measurable* in the M&A deals. The originality of this research is an application of the real option pricing theory to recent Amazon's acquisition of Whole Foods to measure the synergies as an added value to the acquirer's shareholders.

The author selected Amazon's acquisition of Whole Food due to following reasons. The synergy is reflected in additional value created by unifying the companies. For the M&A deal to be successful, this value of a newly merged company should be larger than the value of the stand-alone companies before M&A (Loukianova et al., 2017). So, what does Amazon hoped to gain with this merger? This paper analyzes Amazon acquisition's antecedents through the lenses of dynamic capabilities framework and real options theory.

The paper has the following structure. The first section introduces the concept of dynamic capabilities as antecedents of successful M&A deals, synergies that arise from an M&A deal, and discusses the applicability of the real options approach for their assessment. The role of dynamic capabilities in the M&A deal is discussed in terms of abilities to integrate two merging companies in search of synergies. The sections are devoted, respectively, to develop three propositions which can be justified empirically by analysis of recent Amazon's acquisition of Whole Food case. The following section provides an application of the real options theory to Amazon's dynamic capabilities in the case of Whole Food acquisition. The method was used ex-post to find synergy values in a recent Amazon's M&A deals (2017–2018) and produced sound results.

On average, the author found that the option premiums exceeded the actual takeover premium suggesting that, from an option pricing point of view, this acquisition was not overpaid. At the end of the paper, the author discusses theoretical and managerial contributions. In conclusion subchapter, the author highlights the research limitations and future works.

## 2 Key Literature Review

Dynamic capabilities are the renewing and regenerative capabilities that enable firms to change their operating processes incrementally and radically. Real options valuation provides an appropriate platform for firms to measure managerial flexibilities. "The two distinct concepts of dynamic capability and real options have received notable attention from strategic management scholars in recent years. These two streams of research in strategic management literature are certainly not mutually exclusive" (Jahanshahi & Nawaser, 2018, p. 395).

Nevertheless, there are many differences between real options theory and dynamic capability framework like the difference in the origin, in the aims, and in the context of usage, there are many similarities within two concepts. Both are necessary for managing changes, both are created by managers, and both are new and growing concepts (Jahanshahi & Nawaser, 2018). Dynamic capabilities are necessary *to exploit* real options opportunities, whereas real options are necessary *to evaluate* opportunities (Jahanshahi & Nawaser, 2018).

### *2.1 Exploring Dynamic Capabilities in Merger and Acquisition Deals*

The recent scientific discussion in the field of strategic management broadly favors the idea of dynamic capabilities to overcome potential rigidities of organizational capability building (Schreyogg & Kliesch-Eberl, 2007). "The theoretical and practical importance of developing and applying dynamic capabilities to sustain a firm's competitive advantage in complex and volatile external environments has catapulted this issue to the forefront of the research agendas of many scholars" (Zahra, Sapienza, & Davidsson, 2006, p. 917).

Stefano et al. argue that despite the exceptional rise in interest and influence of dynamic capabilities, criticisms of the dynamic capabilities' perspective continue to mount (Stefano, Peteraf, & Verona, 2014). Common concerns are related to a lack of consensus on basic theoretical elements and limited empirical progress (Stefano et al., 2014). Specific capabilities that have been identified and studied involve research and development (Helfat, 1997), product innovation (Danneels, 2002), ambidextrous organizational structures (O'Reilly & Tushman, 2013), network responsiveness (Kleinbaum & Stuart, 2014), and human capital management (Chatterij & Patro, 2014).