# Relationship between Business Confidence Indicators and Real GDP? – A Regional Spatial Panel Approach

**Key Words**: Business Confidence, Gross Regional Product, Panel Data Econometrics, Fixed Effects, Random Effects.

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#### ABSTRACT

Timely information about processes occurring in both the national and provincial economy is crucial for the analysis and decision making for economic policy purposes. Annual and quarterly information on GDP is of great relevance to policy makers as it is a broad indicator of domestic activity covering all sectors of the economy. Unfortunately this information on domestic activity is available only on the national economy and is only available on a provincial level with a significant time delay: the provincial release is available only after at least two years after the national release. The information lag creates a significant problem for analysing, forecasting and decision making on a provincial level.

This paper presents a first attempt to model the relationship between regional business confidence and regional GDP growth rates employing a panel data approach that include one-way and two-way fixed and random effects to accounts for either regional and time heterogeneity or homogeneity. Performing real-time provincial analysis will potentially eliminate the time delay. While the results presented in the paper remain tentative due to limited data availability, they provide a benchmark which future research may build on.

The literature suggests that confidence indicators can be useful in calculating and forecasting real GDP growth rates in the short run. The results of the various model specifications suggests that the two-way error component fixed effect regression model is the most representative and robust model given the limited data availability. The presence of fixed effects is apparent since the F test for fixed-effects clearly rejects the null hypothesis of homogeneous cross-sections. This is also evident from the fact that the model has the highest adjusted R<sup>2</sup> value. The business confidence coefficient is equal to 0.013, suggesting a positive relationship as expected.

#### 1. INTRODUCTION

The European Central Bank (ECB) published a working paper in March 2002 stating that there has been a growing literature on confidence indicators and their use in monitoring or forecasting short-term economic developments. The ECB further argues that these indicators are now regularly followed both by public and private institutions to get both an indication of the current economic situation and in some cases to help in predicting short term developments (ECB, Working Paper 133, 2002).

The ECB then published working paper 622 in May 2006 in which they use the European Commission's Economic Sentiment Indicator that combines confidence in the manufacturing, construction, retail and non-retail services with consumer confidence. The ECB argues that one of the main advantages of this methodology is parsimony. However the ECB also use the various confidence surveys separately (ECB, Working Paper 622, 2006).

Latvijas Banka in 2008 released a working paper that closely followed the ECB working paper 622. They state that timely information about processes occurring in the economy is crucial for the analysis and decision making for economic policy purposes. The paper specifically refers to business confidence stating that although the indicator captures only partial information on domestic activity, it has a significant advantage over GDP statistics in terms of availability (Latvijas Banka, 5-2008)

Developing from these strands of work, I investigate the possible relationship between regional business confidence and regional economic growth in the province of KwaZulu-Natal. I first cover briefly some relevant empirical work conducted by mainly the ECB, but also other studies. Against this background I will then proceed to the empirical work, firstly to develop a business confidence index series and an economic growth rate series for each of the five regions in the province, and secondly to construct and evaluate the panel. Thirdly I will focus on the application of panel data econometric techniques to empirically test or evaluate the relationship between regional business confidence and economic growth.

#### 2. LITERATURE OVERVIEW

The ECB in their working paper number 133 (2002) argues that although confidence and survey indicators are broadly used to assess current economic developments and/or undertake short-term forecasts, their use is still controversial. A set of different models (linear or not, with constant or time-varying coefficients) are proposed by practitioners, academics and applied economists to evaluate performances of forecasting models based on confidence indicators, with a view to take into account data properties.

The objective of the ECB working paper number 133 is to determine to what extend confidence indicators can be useful in predicting real GDP growth rate in the short run, restricting the analysis to two European Commission confidence indicators: the Economic Sentiment Indicator (ESI) and the Industrial Confidence Indicator (ICI). The tests were carried out for the six largest euro area countries, which represent almost 90% of the euro area. For each country, the ECB estimate a relationship between real GDP growth and confidence indicators.

The ECB further states that the use of a bottom-up or country specific approach is deemed appropriate given that country specific shocks have occurred in the sample period under investigation and that data at a country level are in general available on a deeper historical basis. The model that the ECB estimated for each of the six euro area countries has the following form.

$$\begin{cases} (1) \quad \Delta \ln GDP_t = \begin{bmatrix} I & \Delta INDIC \end{bmatrix} * \begin{bmatrix} A_t \\ \Gamma_t \end{bmatrix} + w_t = \begin{bmatrix} I & \Delta INDIC \end{bmatrix} * \beta_t + w_t \\ (2) \quad \beta_t = \beta_{t-1} + s_t \end{cases}$$

The core of the model is a measurement equation (equation 1) where the growth rate of real GDP is a function of the variation in the confidence indicator. The vector of coefficients of the system ( $\beta_t$ ) is determined by a transition equation (equation 2)

which is assumed to follow a random walk process. In the case when the parameters are assumed to be constant over time, equation 2 disappears and equation 1 becomes a basic linear relationship between real GDP growth and the variation of confidence indicators. It is expected that gamma ( $\Gamma$ ) will be positive, meaning that an increase in confidence will translate into higher GDP growth. The error terms w and s are white noise orthogonal vectors.

The ECB applies Granger causality tests between the growth rates of real GDP and the first difference of the confidence indicators. The ICI Granger causes real GDP in all countries except Spain. On the contrary, the reverse causations does not hold in all countries. The results, according to the ECB, suggest the usefulness of the ICI and its lagged values in explaining real GDP growth. Regarding the ESI, i.e., ESI Granger causing real GDP, it is found for all countries except for Spain. The results are encouraging as a preliminary hint of the usefulness of confidence indicators in forecasting real GDP growth rates in the short-run.

The second stage of their investigation consisted of regressing real GDP on each of the confidence indicators, using ordinary least squared techniques. The results suggest that both the ICI and ESI are significant determinants of real GDP growth, except for the ICI in Spain and in the Netherlands. The results also are as expected in terms of the relationship between real GDP and confidence being positive. The amplitude of the coefficient is comparable across countries. The fit of the equations are generally good, though the adjusted R square is low. Finally most of the time there seems to be no problems of autocorrelation or heteroskedasticity. In most regressions, the reset test indicates that the models are well specified and the Chow tests testing the prediction ability of the equation at a one or two quarter horizon give good results.

The ECB then conclude by stating that the results show that confidence indicators could be useful in forecasting real GDP growth rates in the short run. However there are some ambiguities in the results, for example in the case of Spain, which suggest that confidence indicators are not useful. It is therefore not guaranteed that the results suggest uniformity over countries and therefore country specific characteristics need to be taking into account.

The ECB then followed up their 2002 working paper in 2006 that focused on shortterm forecasts of euro area real GDP growth using vintage data. In the paper, the ECB use various types of monthly indicators (including confidence indicators), with different combinations of them. The aim of the paper was not to select the 'best' combination of monthly indicators. They ECB argue that the combination which is 'best' depends on one's purpose, and different selection criteria provide different answers. Rather, the selection is guided by the aim to (a) test the validity of pseudo real-time tests as opposed to genuine real-time experiments and (b) quantify the relative importance of the four sources of forecast errors identified. In this view, three characteristics of the explanatory variables are key: size of revisions if any, timeliness and degree of tightness of the link between the variable and GDP growth.

The third equation relates real GDP growth to the European Commission's Economic Sentiment Indicator (ESI), which combines confidence in the manufacturing, construction, retail and non-retail services sector, with consumer confidence.

$$d \log(GDP) = \alpha_0^5 + \alpha_1^5 * ESI + \alpha_2^5 * d \log(GDP(-1))$$

One main advantage of this equation, according to the ECB, is parsimony. One drawback however is that the weights attributed to the various confidence indicators in the ESI are somewhat ad-hoc. The fourth and fifth equations therefore use the different confidence surveys separately.

The fourth equation relates to business confidence surveys for various sectors of activity. Confidence surveys are available for four main sectors of activity: manufacturing, construction, retail trade and other market services. Construction and retail trade confidence were found to be insignificant, reflecting very high volatility of these series. Therefore, our fourth equation is written as:

$$d \log(GDP) = \alpha_0^3 + \alpha_1^3 * d(MAN CONF) + \alpha_2^3 * SER CONF$$

The fifth equation is similar to the second one, but using survey data. Thus, the ECB include consumer confidence (CONS\_CONF), which aims at capturing developments in consumption. Business confidence variables are used to proxy for non-consumption demand variables. Amongst all possible combinations of the various business confidence indicators with consumer confidence, one retaining manufacturing and retail trade confidence gives the most accurate forecasts.

$$d\log(GDP) = \alpha_0^4 + \alpha_1^4 * d(MAN CONF) + \alpha_2^4 * RET CONF + \alpha_3^4 CONS CONF$$

The ECB states that results show that the average reliability measures of pseudo real-time exercises seem valid. In addition, averaging across several equations, forecasts for individual quarters tend to be similar whether they are based on preliminary or revised data. These results therefore provide legitimacy to pseudo real-time exercises. However, the results also call for some degree of caution when selecting short-term forecasting tools from pseudo real-time exercises and when interpreting their results. Indeed, looking at specific equations and specific quarters, significant differences occur between forecasts based on revised series and forecasts based on real time data. The differences are sometimes large enough to give a different picture of activity developments.

Binette and Chang (2013) state that the formulation of monetary policy relies, in part, on the analysis of a variety of information about "current" economic conditions. Through current analysis economists try to understand and gauge the implications of the most recent economic conditions, including the impact of unpredictable events, such as natural disasters and work stoppages. Consequently, timely and accurate data are important for current analysis, since a clear understanding of current events is critical to better predict future developments. This in turn allows for the appropriate monetary policy response, given the forward looking nature of the monetary policy approach.

Binette and Chang (2013) further state that forecasting short-term growth in real GDP presents a number of challenges. Economists have a large number of data series at their disposal, ranging from National Accounts data to credit aggregates.

From this profusion of data, they must extract the right information. As well, many indicators are published with lags, some of which are as long as two months. Economists need to find the best way to address the problems caused by these delays in the publication and revision of data. Another challenge is to develop tools that can use series with different frequencies, since data are published at daily, weekly, monthly or quarterly frequencies. Another challenge involves truncated series resulting largely from redefinitions of variables.

The Bank of Canada has in response the above statements developed Canada's Short-Term Indicator (CSI). CSI is a monthly, dynamic, single-factor model built on the principle that any series can be divided into two components: a component that is common to all variables in the model and an idiosyncratic component. All indicators in CSI are projected based on a common component and on their own individual dynamics, as described by autoregressive (AR) processes in which the current values of the indicators are explained by using only their past values. The empirical analysis uses data available from 1982 through to 2012. Although CSI is a monthly model, its indicators include quarterly variables.

The choice of indicators used in CSI, according to Binette and Chang (2013), has therefore been guided by the following criteria: (i) the variables should be directly related to the Canadian economy; and (ii) forecasts over the past decade should be more accurate than simple benchmarks found in the literature. The current specification of CSI includes 32 indicators most of which are well-known statistics for Canada, such as total hours worked (from the Labour Force Survey), retail trade and housing starts. Other indicators include soft information (such as consumer confidence), financial data and international variables. U.S. data series and the global purchasing managers' index (PMI) for manufacturing are used to proxy foreign demand for Canadian exports.

According to the Bank of Canada overall, the CSI model performs as anticipated. The initial forecasts are not very accurate, with root-mean-square prediction errors (RMSPEs) above 2 per cent, in part, because of the model's inability to predict the severe economic downturn in 2008–09. The accuracy of CSI increases, however, as more information becomes available, and significant improvements occur in weeks 18 and 22 with the release of the monthly GDP data for the first two months of the quarter (early estimates). This should come as no surprise, since GDP at basic prices and GDP at market prices are highly correlated at the quarterly frequency, despite the small conceptual difference.

Latvijas Banka in their 2008 working paper state that quarterly data on Latvia's real GDP are published on the 70th day after the end of the reference period or in other words, GDP figures are available with more than a 2-month lag. Moreover, GDP data are subject to revisions after the annual balancing of the System of National Accounts. As of 2007, the Central Statistical Bureau of Latvia (CSB) also publishes flash estimates of real GDP annual growth based on available statistical data and econometric models. These estimates are published on the 40th day after the end of the reference period and are available one month earlier than the first release.

However, according to the Bank, the history of flash estimates is too short to make any systematic analysis, and preliminary estimations of real GDP are ignored in this paper. To perform the real-time analysis of forecasting performance, the Bank created a real-time database, which contains real GDP series with different vintages. In other words, the Bank do not use just one latest GDP data row but create a set of GDP time series – one for each quarter. Using such database, it is possible to discover historical GDP figures available for analysis at any particular period of time. In addition, the real-time database allows the Bank to find out what and when GDP data revisions were made.

The next step is to choose monthly indicators that could be useful in explaining the dynamics of Latvia's real GDP. The selection of explanatory monthly variables was based on the following criteria. First, the selected monthly indicator should be available as quickly as possible after the end of the quarter, and, definitely, it should be available before the first GDP release. Second, there should be an economic reason for this variable to be a good indicator for real GDP. Third, data on the monthly indicator should be available at least from the beginning of 1996. Business Sentiment of Confidence is one such monthly indicator that fulfills the abovementioned criteria (Latvijas Banka, 2008).

Business confidence indicators are indicators based on qualitative economic surveys intended for short-term economic analysis. The Bank use seasonally adjusted industrial, construction and retail trade confidence indicators as well as the overall economic sentiment indicator (ESI) for Latvia. Confidence indicators are released before the end of the current month (Latvijas Banka, 2008).

The confidence bridge equations for Latvia's real GDP (estimation was made on a quarterly basis for a sample period from the second quarter of 1996 to the fourth quarter of 2007, t-statistics in parenthesis) is displayed below. Residuals of the bridge equations are normally distributed with no signs of autocorrelation but with heteroskedasticity Autocorrelation was detected by the Breusch-Godfrey serial correlation LM test, heteroskedasticity by the White test, and normality by the Jarque-Bera statistics.

$$\Delta \ln y_t = \underbrace{0.014}_{(4.652)} + \underbrace{0.244}_{(1.760)} \cdot \Delta \ln y_{t-2} + \underbrace{0.00008}_{(0.733)} \cdot \Delta ind \_bc_t$$
$$R^2 = 0.074$$
$$SIC = -5.950$$

where  $ind\_bc_t$  denotes the industrial confidence indicator. The inclusion of business confidence indicators gives the worst results in terms of in-sample fit. Moreover, only the industrial confidence indicator and overall ESI enter the bridge equation with a positive (albeit statistically insignificant) sign (Latvijas Banka, 2008).

The Bank argues that another method to incorporate information from various monthly indicators is to use models with unobserved components or state space models. A state space model consists of a measurement equation and a transition equation. The unobserved components are linked to observed monthly variables in the transition equation. At the same time, unobserved monthly components are also constrained by observable quarterly GDP via the measurement equation (Latvijas Banka, 2008).

The choice of monthly indicators for the transition equation was made similarly to the choice of monthly indicators for bridge equations. Four sets of monthly indicators were formed using economic logic: indicators describing GDP from the production side, indicators of expenditure side, financial and price indicators as well as business confidence indicators. The results for the confidence state space model is displayed below:

$$\Delta \ln y_t^m = \underbrace{0.0023}_{(6.672)} + \underbrace{0.612}_{(10.127)} \cdot \Delta \ln y_{t-1}^m + \underbrace{0.00033}_{(2.068)} \cdot \Delta total\_esi_t$$
  
$$\sigma^2 = 9.63 \cdot 10^{-6}$$
  
$$SIC = -15.609$$

where  $total\_esi_t$  is the overall economic sentiment indicator (ESI) for Latvia. In contrast to quarterly bridge equation, the best in-sample fit among confidence indicators is ensured by ESI, although SIC shows that the in-sample explanatory power of this equation is worse than for other state space models (Latvijas Banka, 2008).

The Bank concludes by stating that the results of out-of-sample forecasting exercise are rather similar for both types of models. According to the calculations, models based solely on indicators from the production and expenditure sides (industrial production, retail trade turnover, exports) perform worse or produce results similar to the benchmark model. Consequently, data on the abovementioned monthly indicators do not add much new information to improve the accuracy of Latvia's real GDP forecasts. The same conclusion could be drawn for models with confidence indicators (Latvijas Banka, 2008).

The Bank of Albania (2011) states that various estimating models of quarterly GDP have been developed during the last decade that aim to explore the factors affecting its trend. Their final goal is to provide forecasts at shorter term horizons than those accomplished through macro models, which have more strict requirements regarding the fulfilment of macroeconomic equilibrium conditions. The short term estimating models employ all the available economic information (monthly and quarterly) deriving from the system of official, economic, financial data and from confidence surveys.

Surveys (confidence, sentiment, economy experts) and financial data are known as "soft data" according to the Bank. The survey indicators reflect the assessments of economic agents on the development of the economic activity in general and on specific aspects for the reference period, when no information on the GDP is available for that period. At the same time, the surveys' indicators provide information on the market agent's expectations of the future short-term developments of the economy. Notwithstanding the soft-data indicators are not directly related with GDP components, they provide valuable information for explaining its behaviour, similar to the hard-data indicators (Bank of Albania, 2011).

The surveys' indicators used in this paper result from the quantification of qualitative information acquired from business and consumer confidence surveys. Their usage in the explanatory and short-term GDP forecasting models is based on the assumption that the judgments and opinions of businesses shall be reflected on concrete actions with economic consequences. Thus, the ability of surveys' indicators to assess the economic activity depends on the degree that these opinions will be reflected in concrete actions (Santero and Westerlund, 1996 as referenced in the Bank paper).

The advantages of using survey indicators in the short-term GDP forecast models consist in the fact that: (i) they provide preliminary signals that are obtained directly from the economic agents regarding the short-term evolution of their activity; (ii) they are published in advance of the main macroeconomic aggregates or the hard data indicators; (iii) the results are subject only to minor revisions. The experience of European developed economies has shown that these indicators are broadly used to forecast short-term GDP owing to the available timely economic information (Bank of Albania, 2011).

The Bank concludes by stating that the estimation results show that the models have good statistical qualities. The estimation of the best model or models remains a debatable issue. Two of the main reasons behind this judgment are: firstly, the estimates have been conducted for a relatively short period and secondly, the forecast examinations are focused on the approaching degree of real values to the theoretical ones within the period (in-sample compared to out-of -sample).

# 3. THE DATA

The gross domestic product for each of the three regions is estimated using a national provincial regional structure model. The model uses national gross domestic product estimates as published by Statistics South Africa to estimate the gross domestic product for each of the three regions. The model is very similar to models used by IHS Global Insight and Quantec in their regional economic estimates, for example.

The base year for the model is determined by updating the latest available regional level gross domestic product figures as released by StatsSA from the release date of November 1994 to the start of the model, 2005. This is done by estimating the structural relationships from various national provincial regional proxies such as fuel consumption and buildings reported as completed and applying these to the latest national gross domestic product figures. Table 1 indicates the structural relationships between national fuel consumption and regional fuel consumption over the period. These structural relationships form the basis of the national provincial regional structure model from which the regional gross domestic product are estimated.

	2008	2009	2010	2011
KZN	16.60	16.83	15.09	16.80
Ethekwini	9.68	10.46	8.60	9.75
Msunduzi	1.16	1.43	1.30	1.36
Umthlatuze	1.09	1.07	0.90	0.91

Table 1:	Fuel Consum	otion Structure –	as a % of National

(Dept of Energy, own calculations)

The equation to calculate the estimated regional gross domestic product is as follows:

$$\text{GDP}_{\text{it}} = \text{GDP}_{\text{st}} \times \left[ \frac{\sum_{Psn}^{Pin}}{n} \right]$$

where

i = particular regional economy/proxy
s = national economy/proxy
t = annual period
n = number of national and regional proxies
P = national economic proxies such as fuel consumption
GDP<sub>it</sub> = regional gross domestic product at time t
GDP<sub>st</sub> = national gross domestic product at time t

It is important that only proxies that are relevant, reliable and timeous, that can be disaggregated to a regional level and that have a proven relationship with economic output are used. There are, unfortunately, not many such proxies.

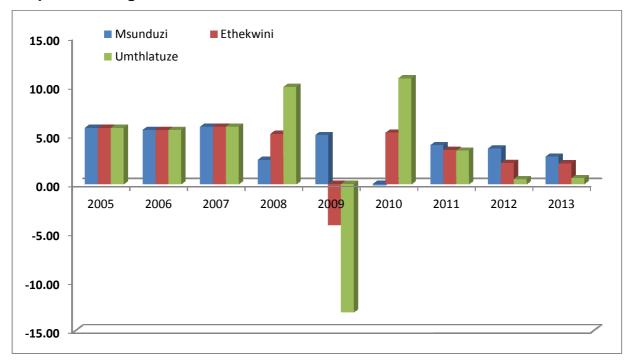
The gross domestic product (growth rate) for each of the five regions is displayed in the table and graph below.

GDP (% pa)	Msunduzi	Ethekwini	Umthlatuze
2005	5.76	5.76	5.76
2006	5.53	5.53	5.53
2007	5.87	5.87	5.87
2008	2.46	5.14	9.93
2009	5.02	-4.20	-13.12
2010	-0.09	5.26	10.83
2011	3.97	3.49	3.43
2012	3.63	2.15	0.49
2013	2.80	2.10	0.60

 Table 2:
 Regional Gross Domestic Product – 2005 to 2013

(Stats SA, own calculations)

The business confidence indicator for each of the five regions is estimated using a primary survey method. The survey is an online anonymous business survey designed specifically to generate data and information on a number of regional economic characteristics and trends, and the general level of business confidence in the particular regional economy. The survey is conducted yearly via the regional chamber of business and other regional business organizations.





It is important to note that the surveys are conducted at the same time each year, i.e., March and April of each year, in order to ensure consistency. The survey as mentioned is conducted using the World Wide Web (web) through a survey company located in Cape Town. Once the questionnaire has been finalized it is then given to this company to upload onto the web and a web address or link is generated. Although the questionnaire is reviewed every year, very little change has been made since 2005, again to ensure consistency. The web link is then sent to the various chambers of business and other business organizations so that they can then distribute the web link to all their members. After two months the survey is closed and the data is collated by the web-based software that underpins the survey and a report and excel database is generated.

<sup>(</sup>Stats SA, own calculations)

In general the response rate is between 1 percent and 2 percent of the total membership of the various chambers of business and business organizations. However there can be questions about the number of responses and thus its level of inference.

The business confidence index is calculated or derived from the gross percentage of respondents responding Good, Fair, Better and Same to the questions: Present business/trading conditions are? and, Your expected sales performance over the next year? The responses of the fourth and fifth last questions are thus used to calculate the business confidence index for the particular year. The equation to calculate the business confidence index thus is as follows:

$$\mathsf{BCI} = \left(\frac{\sum BitCitGitHit}{\sum AitBitCitDitEitFitGitHitIitJit}\right)$$

where

i = particular local economy

t = period

A<sub>it</sub> = excellent response to Present business/trading conditions are?

B<sub>it</sub> = good response to Present business/trading conditions are?

C<sub>it</sub> = fair response to Present business/trading conditions are?

D<sub>it</sub> = poor response to Present business/trading conditions are?

E<sub>it</sub> = very poor response to Present business/trading conditions are?

 $F_{it}$  = much better response to Your expected sales performance over the next year?

 $G_{it}$  = better response to Your expected sales performance over the next year?  $H_{it}$  = same response to Your expected sales performance over the next year?  $I_{it}$  = worse response to Your expected sales performance over the next year?  $J_{it}$  = much worse response to Your expected sales performance over the next year?

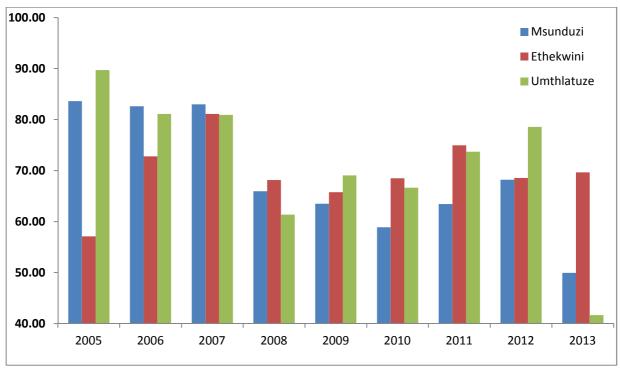
The business confidence index varies between 0 and 100 and should therefore be interpreted as follows, i.e. a value of 50 is indicative of neutrality, 100 indicates

extreme confidence and 0 indicates extreme lack of confidence. The gross domestic product for each of the five regions is displayed in the table and graph below.

GDP (% pa)	Msunduzi	Ethekwini	Umthlatuze
2005	83.60	57.10	89.70
2006	82.60	72.80	81.10
2007	83.00	81.09	80.90
2008	65.95	68.13	61.38
2009	63.50	65.75	69.05
2010	58.88	68.50	66.65
2011	63.45	74.95	73.70
2012	68.20	68.55	78.55
2013	49.95	69.65	41.65

### Table 3: Regional Business Confidence Index – 2005 to 2013

(Own calculations)



Graph 2: Regional Business Confidence Index – 2005 to 2013

(Own calculations)

# 4. CONSTRUCTING AND EVALUATING THE PANEL

The panel extends the regions to include the Newcastle and Hibiscus Coast (Port Shepstone) regions, i.e., five regions, but decreases the number of years from 2005

to 2013 (9 years) to 2011 to 2013 (3 years) since the business surveys were only conducted in the two regions from 2011 onwards. The methodologies used to generate the gross domestic product estimates and the business confidence indices for the two regions are the same as for the other three regions and as discussed in above. The panel is displayed in the below table.

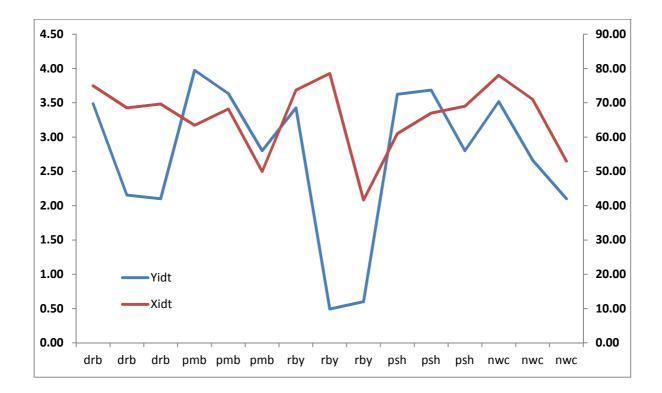
Id	Time	gdp	conf
id	t	Yidt	Xidt
drb	2011	3.49	74.95
drb	2012	2.15	68.55
drb	2013	2.10	69.65
pmb	2011	3.97	63.45
pmb	2012	3.63	68.20
pmb	2013	2.80	49.95
rby	2011	3.43	73.70
rby	2012	0.49	78.55
rby	2013	0.60	41.65
psh	2011	3.62	61.00
psh	2012	3.69	67.00
psh	2013	2.80	69.00
nwc	2011	3.52	78.00
nwc	2012	2.66	71.00
nwc	2013	2.10	53.00

Table 4:Panel for the five regions – 2011 to 2013

(Stats SA, own calculations) (drb = Ethekwini, pmb = Msunduzi, rby = Umthlatuze, psh – Hibiscus Coast and nwc – Newcastle)

The following graph displays the panel graphically.

# Graph 3: The Panel – five regions from 2011 to 2013



The following two tables display the variation for the dependent variable, explanatory variable and regressors. The tables also include the following:

- Overall variation variation over time and regions
- Between variation variation between regions
- Within variation variation within regions over time

 Table 5:
 Variation for the Regional Gross Domestic Product

Id	Time	gdp	Individual Mean	Overall Mean	Overall Dev	Between Dev	Within Dev	Within Dev Mod
id	t	Yidt	Yid	Ŷ	Yidt - Ÿ	Yid - Ŧ	Yidt - Yid	Yidt - Yid + Ÿ
drb	2011	3.49	2.58	2.74	0.75	-0.16	0.91	3.64
drb	2012	2.15	2.58	2.74	-0.58	-0.16	-0.43	2.31
drb	2013	2.10	2.58	2.74	-0.64	-0.16	-0.48	2.26
pmb	2011	3.97	3.47	2.74	1.24	0.73	0.51	3.24
pmb	2012	3.63	3.47	2.74	0.90	0.73	0.16	2.90
pmb	2013	2.80	3.47	2.74	0.06	0.73	-0.67	2.07
rby	2011	3.43	1.51	2.74	0.69	-1.23	1.92	4.66
rby	2012	0.49	1.51	2.74	-2.24	-1.23	-1.01	1.72
rby	2013	0.60	1.51	2.74	-2.14	-1.23	-0.91	1.83
psh	2011	3.62	3.37	2.74	0.89	0.63	0.25	2.99
psh	2012	3.69	3.37	2.74	0.95	0.63	0.32	3.05

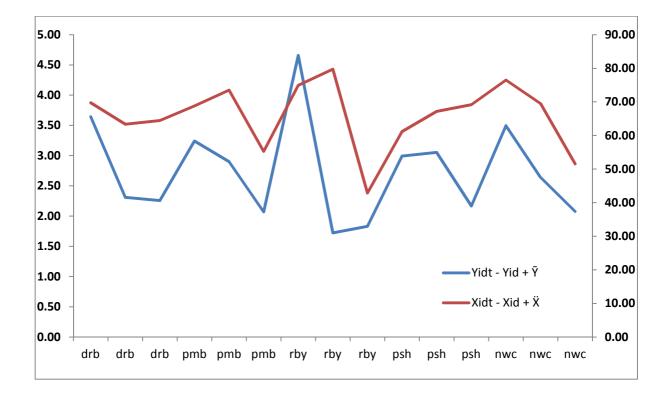
psh	2013	2.80	3.37	2.74	0.06	0.63	-0.57	2.17
nwc	2011	3.52	2.76	2.74	0.78	0.02	0.76	3.49
nwc	2012	2.66	2.76	2.74	-0.07	0.02	-0.10	2.64
nwc	2013	2.10	2.76	2.74	-0.64	0.02	-0.66	2.08

# Table 6: Variation for the Regional Business Confidence

Id	Time	conf	Individual Mean	Overall Mean	Overall Dev	Between Dev	Within Dev	Within Dev Mod
i	t	Xidt	Xid	X	Xidt - X	Xid - X	Xidt - Xid	Xidt - Xid + Ẍ
drb	2011	74.95	71.05	65.84	9.11	5.21	3.90	69.74
drb	2012	68.55	71.05	65.84	2.71	5.21	-2.50	63.34
drb	2013	69.65	71.05	65.84	3.81	5.21	-1.40	64.44
pmb	2011	63.45	60.53	65.84	-2.39	-5.31	2.92	68.76
pmb	2012	68.20	60.53	65.84	2.36	-5.31	7.67	73.51
pmb	2013	49.95	60.53	65.84	-15.89	-5.31	-10.58	55.26
rby	2011	73.70	64.63	65.84	7.86	-1.21	9.07	74.91
rby	2012	78.55	64.63	65.84	12.71	-1.21	13.92	79.76
rby	2013	41.65	64.63	65.84	-24.19	-1.21	-22.98	42.86
psh	2011	61.00	65.67	65.84	-4.84	-0.18	-4.67	61.18
psh	2012	67.00	65.67	65.84	1.16	-0.18	1.33	67.18
psh	2013	69.00	65.67	65.84	3.16	-0.18	3.33	69.18
nwc	2011	78.00	67.33	65.84	12.16	1.49	10.67	76.51
nwc	2012	71.00	67.33	65.84	5.16	1.49	3.67	69.51
nwc	2013	53.00	67.33	65.84	-12.84	1.49	-14.33	51.51

The following graph displays the modified within deviation series for each of the variables.

# Graph 4: Modified Within Deviation Series – five regions from 2011 to 2013



The descriptive statistics for the panel is displayed in the below table.

	GDPF	CONF
Mean	2.737272	65.84333
Median	2.8	68.55000
Maximum	3.974053	78.55000
Minimum	0.492455	41.65000
Std. Dev.	1.083599	10.52622
Skewness	-0.95322	-0.955617
Kurtosis	2.888166	3.078780
Jarque-Bera	2.279375	2.286886
Probability	<mark>0.319919</mark>	<mark>0.318720</mark>
Sum	41.05908	987.6500
Sum Sq. Dev.	16.43861	1551.219
Observations	15	15

 Table 7:
 Descriptive Statistics for the Panel five regions from 2011 to 2013

It must however be stated that the panel does suffer from a lack of time series data which does pose some risks with regard to the investigation of potential nonstationarities. The model therefore potentially will suffer from misspecification bias, poor fit and statistical insignificance for example.

# 5. ECONOMERIC ANALYSIS OF THE PANEL

#### 5.1 Pooled Model

Pooled data occur when we have a "time series of cross sections," but the observations in each cross section do not necessarily refer to the same unit (Baltagi 2009). The pooled model assumes:

- All the usual OLS assumptions are not violated
- The constant is constant across all units i
- That the effect of any given X on Y is constant across observations (assuming, of course, that there are no interactions in X).

However in most panels there is some form of heterogeneity across units and over time suggesting that:

- One possible violation of the above assumptions is that the intercepts vary
- The other possibility is that we have a constant intercept but that the effects of X on Y differs across either units or time

The above possible violations may distort the "true" relationship between the dependent and independent variables across entities. It must, therefore, be noted that this type of model is the most restrictive (it specifies constant coefficients) and therefore not much used in the literature. However for illustrative purposes this model will be included.

Regional gross domestic product  $(Y_{idt})$  will be the dependent variable whilst regional business confidence  $(X_{idt})$  will be the explanatory variable. The regional identifiers are noted as id whilst the time identifiers are noted t. The traditional linear model for the panel will look as follows:

$$Y_{idt} = \alpha + \beta X_{idt} + \varepsilon_{idt}$$

where

 $Y_{idt}$  = regional gross domestic product at time t  $X_{idt}$  = regional business confidence at time t

$$\begin{aligned} & \text{id} = 1,...,N \\ & t = 1,...,N \\ & \epsilon_{\text{idt}} & = \text{error term} \end{aligned}$$

The coefficients ( $\alpha + \beta$ ) will be estimated using Ordinary Least Squares (OLS). The output of the regression (ordinary least square using Eviews) is displayed in the table below.

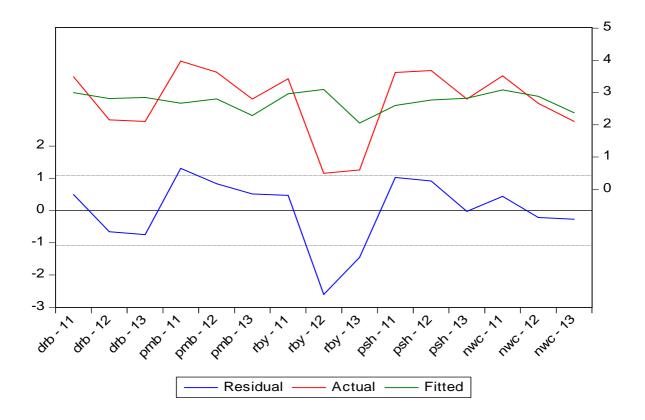
# Table 7: Pooled Regression Equation

Dependent Variable: GDP Method: Panel Least Squares Periods included: 3 Cross-sections included: 5 Total panel (balanced) observations: 15				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CONF C	<mark>0.028279</mark> 0.875292	0.027453 1.829015	1.030094 0.478560	<mark>0.3218</mark> 0.6402
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.075463 0.004345 1.081242 15.19810 -21.38248 1.061093 0.321751	Mean dependent var S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter. Durbin-Watson stat		2.737272 1.083599 3.117664 3.212071 3.116658 1.599470

The model is graphically displayed in the below graph. It must be noted that the model is problematic for the following reasons:

- The  $\beta$  is not statistically significant, p = 0.32
- Very low prediction power,  $R^2 = 0.0043$
- Some evidence of positive serial correlation, Durban-Watson = 1.6
- Sum Squared Error = 15.2

### Graph 5: Pooled Regression Equation



The results suggest that the pooled model is not reliable or valid.

### 5.2 Fixed Effect Model

The fixed effects model is a statistical model that represents the observed quantities in terms of explanatory variables that are treated as if the quantities were nonrandom. The within estimator (fixed effect model) is used to refer to an estimator for the coefficients in the regression model. If we assume fixed effects, we impose time independent effects for each entity that are possibly correlated with the regressors.

By including fixed effects (group dummies), one is controlling for the average differences across regions in any observable or unobservable predictors, such as differences in quality, sophistication, etc. The fixed effect coefficients soak up all the across-group action. What is left over is the within-group action. The one-way error component model allows cross-section heterogeneity in the error term, i.e.,

 $Y_{idt} = \alpha + \beta X_{idt} + F_{id} + \varepsilon_{idt}$ 

where

$$\begin{split} Y_{idt} &= regional \ gross \ domestic \ product \ at \ time \ t \\ X_{idt} &= regional \ business \ confidence \ at \ time \ t \\ F_{id} &= individual \ effects \\ id &= 1,...,N \\ t &= 1,...,N \\ \epsilon_{idt} &= error \ term \end{split}$$

```
\epsilon_{idt} = \mu_i + v_{it}
```

where

 $\mu_i$  = unobservable individual effects

v<sub>it</sub> = well behaved disturbance

The cross section fixed effect model is presented in the table below.

id	t	Yidt	Xidt	ddrb	Dpmb	drby	dpsh
drb	2011	3.49	74.95	1	0	0	0
drb	2012	2.15	68.55	1	0	0	0
drb	2013	2.10	69.65	1	0	0	0
pmb	2011	3.97	63.45	0	1	0	0
pmb	2012	3.63	68.20	0	1	0	0
pmb	2013	2.80	49.95	0	1	0	0
rby	2011	3.43	73.70	0	0	1	0
rby	2012	0.49	78.55	0	0	1	0
rby	2013	0.60	41.65	0	0	1	0
psh	2011	3.62	61.00	0	0	0	1
psh	2012	3.69	67.00	0	0	0	1
psh	2013	2.80	69.00	0	0	0	1
nwc	2011	3.52	78.00	0	0	0	0
nwc	2012	2.66	71.00	0	0	0	0
nwc	2013	2.10	53.00	0	0	0	0

 Table 8:
 Fixed Effect Model with Cross Section Dummies

(ddrb = dummy Ethekwini, dpmb = dummy Msunduzi, drby = dummy Umthlatuze and dpsh - dummy

Hibiscus Coast)

The output of the cross-section fixed effect regression (ordinary least square using Eviews) is displayed in the table below.

	reor regression			
Dependent Variable: GDP				
Method: Panel Least Squares	6			
Periods included: 3				
Cross-sections included: 5				
Total panel (balanced) observ	ations: 15			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CONF	0.039105	0.023636	1.654443	<mark>0.132</mark> 4
DDRB	-0.325125	0.720773	-0.451078	0.6626
DPMB	0.974589	0.733232	1.329167	0.2165
DRBY	-1.148312	0.718241	-1.598784	0.1443
DPSH	0.674983	0.716484	0.942077	0.3708
C	0.127266	1.669961	0.076209	0.9409
R-squared	0.579693	Mean dependent v	ar	2.737272
Adjusted R-squared	<mark>0.346189</mark>	S.D. dependent va	r	1.083599
S.E. of regression	0.876182	Akaike info criterio	n	2.862689
Sum squared resid	<mark>6.909260</mark>	Schwarz criterion		3.145909
Log likelihood	-15.47017	Hannan-Quinn crite	er.	2.859672
F-statistic	2.482585	Durbin-Watson sta	t	<mark>2.926081</mark>
Prob(F-statistic)	<mark>0.111650</mark>			

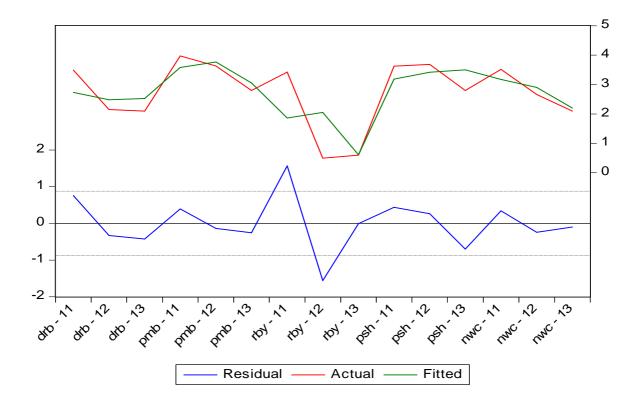
Table 8:	Fixed Effect Regression Equation – Cross Section
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The model is graphically displayed in the below graph. It must be noted that the model is problematic for the following reasons:

- The  $\beta$  is not statistically significant, p = 0.13
- Low prediction power,  $R^2 = 0.23$
- Some evidence of negative serial correlation, Durban-Watson = 2.9
- F statistic (joint significance of explanatory variables) not statistically significant = 0.11

However the cross section fixed effect model is much more reliable that the pooled model, i.e., sum squared error 6.91 vs 15.2.

# Graph 6: Fixed Effect Regression Equation – Cross Section



# 5.3 Within, Q, Estimation

The within estimation makes use of demeaning the data and therefore the individual effects are ignored. The  $\beta$  coefficient is estimated and the individual effects are calculated.

Id	Time	gdp	conf	Individual Mean	Individual Mean	DevGDP	DevConf
id	t	Yidt	Xidt	Ŷid.	Żid.	ӯ = yidt − ýid.	ṡ=xidt−xid.
drb	2011	3.49	74.95	2.58	71.05	0.91	3.90
drb	2012	2.15	68.55			-0.43	-2.50
drb	2013	2.10	69.65			-0.48	-1.40
pmb	2011	3.97	63.45	3.47	60.53	0.51	2.92
pmb	2012	3.63	68.20			0.16	7.67
pmb	2013	2.80	49.95			-0.67	-10.58
rby	2011	3.43	73.70	1.51	64.63	1.92	9.07
rby	2012	0.49	78.55			-1.01	13.92
rby	2013	0.60	41.65			-0.91	-22.98
psh	2011	3.62	61.00	3.37	65.67	0.25	-4.67
psh	2012	3.69	67.00			0.32	1.33
psh	2013	2.80	69.00			-0.57	3.33
nwc	2011	3.52	78.00	2.76	67.33	0.76	10.67

nwc	2012	2.66	71.00		-	-0.10	3.67
nwc	2013	2.10	53.00			-0.66	-14.33
				2.75	65.47		
				Ŷid	Żid		

The output of the within or Q regression (ordinary least square using Eviews) is displayed in the table below.

# Table 8: Within or Q Regression Equation

Dependent Variable: DEVGD Method: Panel Least Squares Sample: 2011 2013 Periods included: 3 Cross-sections included: 5 Total panel (balanced) observ	5			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DEVCONF	<mark>0.039105</mark>	0.019666	1.988393	<mark>0.0682</mark>
С	-1.11E-10	0.188234	-5.90E-10	1.0000
R-squared	0.233206	Mean dependent var		-6.67E-11
Adjusted R-squared	<mark>0.174222</mark>	S.D. dependent var		0.802255
S.E. of regression	0.729028	Akaike info criterion		2.329356
Sum squared resid	<mark>6.909260</mark>	Schwarz criterion		2.423763
Log likelihood	-15.47017	Hannan-Quinn criter.		2.328350
F-statistic	3.953705	Durbin-Watson stat		<mark>2.926081</mark>
Prob(F-statistic)	<mark>0.068243</mark>			

It is now possible to calculate the individual effects:

 $\overline{\alpha} = \overline{y}... - \overline{\beta} \dot{X}..$  $\overline{\mu_{id}} = \overline{y} - \overline{\alpha} - \overline{\beta} \dot{X}_{id}. \text{ for } 1d = 1 \text{ to } 5$ 

# Table 9:Individual Effects

	CITY	Effect
1	drb	-0.360352
2	pmb	0.939362
3	rby	-1.183539
4	psh	0.639756
5	nwc	-0.035227

5.4 Testing the Joint Validity of Fixed Cross and Time Effects

The null hypothesis of no individual (cross and time) effects is tested with the applied Chow or F-test, combining the residual sum of errors for the regression both with constraints and without.

F = 2.7 (cross section fixed effects) which is less than the critical value of 3.86 (F(n-1),(nt-n-k) at the 5% percent probability value thus suggesting that the individual cross effects are not valid and therefore the cities are homogeneous and can be pooled.

F = 2.6 (time fixed effects) which is bigger than the critical value of 3.98 (F(n-1),(nt-n-k) at the 5% percent probability value thus suggesting that the individual time effects are not valid and therefore the cities are homogeneous and can be pooled.

### 5.5 Random Effect Model

Random effects models are also known as multilevel or mixed models. In a random effects model, the unobserved variables are assumed to be uncorrelated with (or, more strongly, statistically independent of) all the observed variables. That assumption will often be wrong but, for the reasons given above (e.g. standard errors may be very high with fixed effects, random effects models lets allows for the estimate effects for time-invariant variables), an random effects model may still be desirable under some circumstances. Random effects models seem to have at least two major advantages over fixed effect models: 1) the possibility of estimating shrunken residuals; 2) the possibility of accounting for differential cross section effectiveness through the use of random coefficients models. Random effects which allows for time-invariant variables to play a role as explanatory variables.

The basic linear random effect model can be presented as follows:

 $Y_{idt} = \alpha + \beta X_{idt} + \epsilon_{idt} + u_{idt}$ 

where

$$\begin{split} Y_{idt} &= regional \ gross \ domestic \ product \ at \ time \ t \\ X_{idt} &= regional \ business \ confidence \ at \ time \ t \\ id &= 1,...,N \\ t &= 1,...,N \\ \epsilon_{idt} &= within \ entity \ error \\ u_{idt} &= between \ entity \ error \end{split}$$

The output of the cross-section random effect regression (ordinary least square using Eviews) is displayed in the table below.

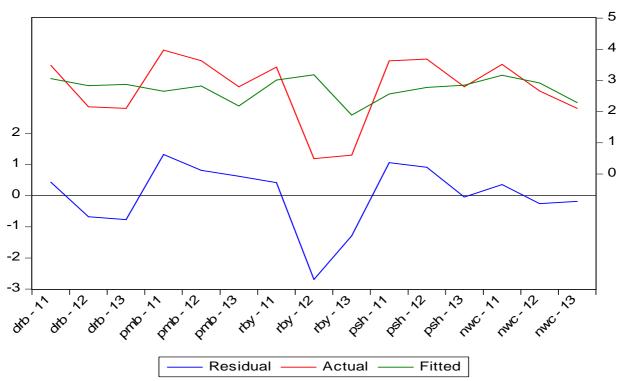
 Table 10:
 Random Effect Regression Equation – Cross Section

Dependent Variable: GDP				
Method: Panel EGLS (Cross-sect	ion random effects)			
Periods included: 3				
Cross-sections included: 5				
Total panel (balanced) observatio	ns: 15			
Swamy and Arora estimator of co	mponent variances			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CONF	<mark>0.035182</mark>	0.023142	1.520247	<mark>0.1524</mark>
С	0.420785	1.573111	0.267486	0.7933
	Effects Sp	ecification		
			S.D.	Rho
Cross-section random			0.712964	<mark>0.3984</mark>
Idiosyncratic random			0.876182	<mark>0.6016</mark>
	Weighted	Statistics		
R-squared	0.154312	Mean dependent var		1.583957
Adjusted R-squared	<mark>0.089259</mark>	S.D. dependent var		0.906243
S.E. of regression	0.864852	Sum squared resid		<mark>9.723600</mark>
F-statistic	2.372104	Durbin-Watson stat		2.088079
Prob(F-statistic)	<mark>0.147502</mark>			
	Unweighte	d Statistics		
R-squared	0.070967	Mean dependent var		2.737272
Sum squared resid	<mark>15.27202</mark>	Durbin-Watson stat		<mark>1.606574</mark>

The model is graphically displayed in the below graph. It must be noted that the model is problematic for the following reasons:

- The  $\beta$  is not statistically significant, p = 0.15
- Low prediction power,  $R^2 = 0.09$
- Some evidence of positive serial correlation, Durban-Watson = 1.61
- F statistic (joint significance of explanatory variables) not statistically significant = 0.15

The cross section random effect model is also less reliable than the cross section fixed effect model, i.e., sum squared error 9.72 vs 6.91, but it is more reliable than the pooled model.



Graph 7: Random Effect Regression Equation – Cross Section

# 5.6 Fixed or Random: Hausman test

To decide between fixed or random effects it is possible to run a Hausman test where the null hypothesis is that the preferred model is random effects vs. the alternative the fixed effects (see Green, 2008, chapter 9). It basically tests whether the unique errors  $(u_{id})$  are correlated with the regressors, the null hypothesis is they are not.

The results of the Hausman test are displayed in the table below. It suggest (p>0.05) that the random effect model is the more appropriate model compared to the fixed effect model.

# Table 11:Hausman Test Results

Cross-section random	0.032764	1	<mark>0.8564</mark>
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Test cross-section random effects			
Equation: POOLE			
Correlated Random Effects - Hausman Test			

# 5.7 Two-Way Error Component Regression Model – Fixed Effects

The two-way error component model with individual and time fixed effects are displayed in the table below.  $\mu_{id}$  (dummy for cities) and  $y_{id}$  (dummy for time) are fixed parameters to be estimated.

				-			_		
id	t	gdp	conf	ddrb	dpmb	drby	dpsh	d2011	d2012
drb	2011	3.49	74.95	1	0	0	0	1	0
drb	2012	2.15	68.55	1	0	0	0	0	1
drb	2013	2.10	69.65	1	0	0	0	0	0
pmb	2011	3.97	63.45	0	1	0	0	1	0
pmb	2012	3.63	68.20	0	1	0	0	0	1
pmb	2013	2.80	49.95	0	1	0	0	0	0
rby	2011	3.43	73.70	0	0	1	0	1	0
rby	2012	0.49	78.55	0	0	1	0	0	1
rby	2013	0.60	41.65	0	0	1	0	0	0
psh	2011	3.62	61.00	0	0	0	1	1	0
psh	2012	3.69	67.00	0	0	0	1	0	1
psh	2013	2.80	69.00	0	0	0	1	0	0
nwc	2011	3.52	78.00	0	0	0	0	1	0

 Table 12:
 Two-Way Error Component Fixed-Effect Regression Model

nwc	2012	2.66	71.00	0	0	0	0	0	1
nwc	2013	2.10	53.00	0	0	0	0	0	0

(ddrb = dummy Ethekwini, dpmb = dummy Msunduzi, drby = dummy Umthlatuze and dpsh – dummy Hibiscus Coast, d2011 = dummy 2011, d2012 = dummy 2012)

The output of the two-way error component regression (ordinary least square using Eviews) is displayed in the table and graph below.

Table 13:	Two-Way Error Co	omponent Fixed-Effect	<b>Regression Model</b>

Dependent Variable: GDP Method: Panel Least Squares Periods included: 3 Cross-sections included: 5 Total panel (balanced) observat	ions: 15			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CONF	0.012984	0.022949	0.565792	<mark>0.5892</mark>
DDRB	-0.228043	0.516728	-0.441322	0.6723
DPMB	0.796969	0.532996	1.495262	0.1785
DRBY	-1.218837	0.513393	-2.374082	0.0493
DPSH	0.631448	0.511073	1.235533	0.2565
D2011	1.349956	0.502809	2.684828	0.0313
D2012	0.263758	0.509124	0.518063	0.6204
С	1.348144	1.400704	0.962476	0.3679
R-squared	0.834098	Mean dependent var		2.737272
Adjusted R-squared	<mark>0.668196</mark>	S.D. dependent var		1.083599
S.E. of regression	0.624179	Akaike info criterion		2.199769
Sum squared resid	<mark>2.727199</mark>	Schwarz criterion		2.577395
Log likelihood	-8.498264	Hannan-Quinn criter.		2.195746
F-statistic	5.027653	Durbin-Watson stat		<mark>2.944459</mark>
Prob(F-statistic)	<mark>0.024577</mark>			

The city fixed effects and time fixed effects are displayed in the below table

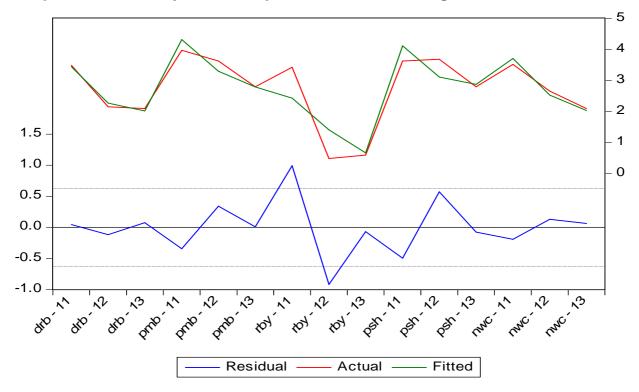
Table 14:         Cross Section and Period Effects
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City	<b>Cross Section Effect</b>	Date	Period Effects
drb	-0.22435	2011/01/01	0.812051
pmb	0.800662	2012/01/01	-0.27415
rby	-1.21515	2013/01/01	-0.53791
psh	0.635141		
nwc	0.003693		

The total average individual effect is as follows:

- Durban = 1.12
- Pietermaritzburg = 2.15
- Richards Bay = 0.13
- Port Shepstone = 1.98
- Newcastle = 1.35

Graph 8: Two-Way Error Component Fixed-Effect Regression Model



5.8 Testing the Joint Validity of Fixed Effects (Individual and Time effects)

The null hypothesis of one common intercept across time and cross-sections versus the alternative of an intercept for each year and cross-section is tested with the applied Chow or F-test, combining the residual sum of errors for the regression both with constraints and without. The test is for the joint significance for the cross-section and time dummies effects.

F = 5.33 (cross section and time fixed effects) which is greater than the critical value of 4.21 (F(n+t-2),((n-1)(t-1)-k) at the 5% percent probability value thus suggesting that the individual cross and time affects are valid and therefore the cities are heterogeneous across time.

5.9 Two-Way Error Component Regression Model - Random Effects

The specification for the two-way random-effects model is

 $\mu_{it} = \mu_i + \sigma_t + v_{it}$ 

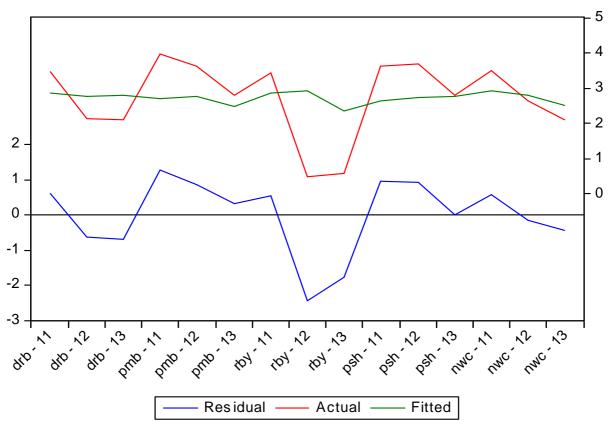
where:

$$\begin{split} \mu_{it} &= \text{error term} \\ \mu_i &= \text{unobserved individual effect} \\ \sigma_t &= \text{unobserved time effect} \\ v_{it} &= \text{stochastic disturbance} \end{split}$$

The output for the two-way random-effects regression (general least square using Eviews) is displayed in the table and graph below.

# Table 15: Two-Way Error Component Random-Effect Regression Model

Dependent Variable: GDP Method: Panel EGLS (Two-way i Sample: 2011 2013 Periods included: 3 Cross-sections included: 5 Total panel (balanced) observation Swamy and Arora estimator of co	ons: 15					
Variable	Coefficient	Std. Error	t-Statistic	Prob.		
CONF C	<mark>0.015878</mark> 1.691791	0.020574 1.463687	0.771768 1.155843	<mark>0.4541</mark> 0.2685		
Effects Specification S.D. Rho						
Cross-section random Period random Idiosyncratic random			0.796461 0.734722 0.624179	0.4057 0.3452 0.2491		
	Weighted	Statistics				
R-squared Adjusted R-squared S.E. of regression F-statistic Prob(F-statistic)	0.043810 <mark>-0.029743</mark> 0.599792 0.595626 <mark>0.454053</mark>	Mean dependent var S.D. dependent var Sum squared resid Durbin-Watson stat		0.764719 0.591067 <mark>4.676758</mark> <mark>1.896397</mark>		
Unweighted Statistics						



# Graph 8: Two-Way Error Component Random-Effect Regression Model

The city random effects and time random effects are displayed in the below table

City	Cross Section Effect	Date	Period Effects
drb	-0.19873	2011/01/01	0.698551
pmb	0.677358	2012/01/01	-0.25175
rby	-1.00574	2013/01/01	-0.4468
psh	0.527633		
nwc	-0.00051		

Table 14: Cro	oss Section and	<b>Period Effects</b>
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The total average individual effect is as follows:

- Durban = 1.49
- Pietermaritzburg = 2.4

- Richards Bay = 0.69
- Port Shepstone = 2.22
- Newcastle = 1.7

# 5.10 Model Selection

Eight models have been specified and tested. The table below displays the sum of the squared residuals for each of the eight models. It is clear that the Pooled-Model faired the worse, whilst the two-way error component fixed effect regression model faired the best.

	Sum squared resid
Pooled Model	15.20
Cross Section Fixed Effect Model	6.91
Within, Q, Estimation	6.91
Time Fixed Effect Model	10.28
Cross Section Random Effect Model	9.72
Time Random Effect Model	11.99
Two-Way Error Component Fixed Effect Regression Model	<mark>2.73</mark>
Two-Way Error Component Random Effect Regression Model	4.68

The panel data estimation results for the various model specifications are presented in the table below. It is again evident that the two-way error component fixed effect regression model faired the best. It must be noted that no correction for serial correlation was done, thus it cannot be stated that the models are free from serial correlation problems. Unfortunately, given the limited data available, the method proposed by Baltagi (2001) to correct for serial correlation cannot be performed.

Table 16:	Business Confidence in the KZN Regions (2011 to 2013)
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	Pooled	Fixed Effect	Random Effect		Two Way Random Effects
Constant	0.875	0.127	0.421	<mark>1.348</mark>	1.692

	(0.6402)	(0.9409)	(0.7933)	(0.3679)	(0.2685)
Confidence	0.028	0.039	0.035	<mark>0.013</mark>	0.016
	(0.3218)	(0.1324)	(0.1524)	(0.5892)	(0.4541)
Adjusted R	0.004	0.346	0.089	<mark>0.668</mark>	-0.030
Fixed Effects F test		2.699		<mark>5.33***</mark>	
Random effects LM test			1.370		0.988

P-values reported in parenthesis

\*/\*\*/\*\*\* indicates significance of the coefficients or rejection of the null hypothesis on a 10%/5%/1% level of significance

To summarize, the overall results of the business confidence real GDP growth rate relationship are consistent with some of the empirical findings of previous studies. It is estimated that the business confidence real GDP growth rate coefficient is between 0.013 and 0.039.

# 6. CONCLUSIONS

In this study I used panel data estimation techniques to assess the relationship between business confidence and real GDP growth rates on a regional basis. Due to the fact that these techniques incorporate both time-series and cross-section dimensions of the data, in theory, the degrees of freedom of the estimation should improve, generating more representative coefficient estimates. Another important reason for using these techniques is the fact that the study was able to acknowledge regional heterogeneity, therefore capturing unobservable regional-specific effects.

Unfortunately, given the limited data available, these superior estimates are less likely to have been achieved and the presence of serial correlation could not be corrected for. Nonetheless, the estimation results suggest that, based on a variety of specifications using panel data econometric techniques, regional business confidence and regional real GDP growth rates display a positive relationship

### REFERENCES

Baltagi, B. H., (2009) **Econometric Analysis of Panel Data**. John Wiley & Sons Ltd 4<sup>th</sup> edition

Binette, A. & Chang, J. (2013) "CSI: A Model for Tracking Short-Term Growth in Canadian Real GDP" Bank of Canada

Bank of Albania, (2011) "*Modeling the Quarterly GDP- Role of Economic and Surveys Indicators*" <u>http://www.google.co.za/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0CCcQFjAA&url=http%</u> <u>3A%2F%2Fwww.bankofalbania.org%2Fpreviewdoc.php%3Fcrd%3D5776%26ln%3D2%26uni%3D&ei</u> <u>=g8RsU-WRCMOp7AbQj4DgAQ&usg=AFQjCNE69e6htBk-9Nm\_NG1Xr0ZRHpFH-Q</u>, accessed 9

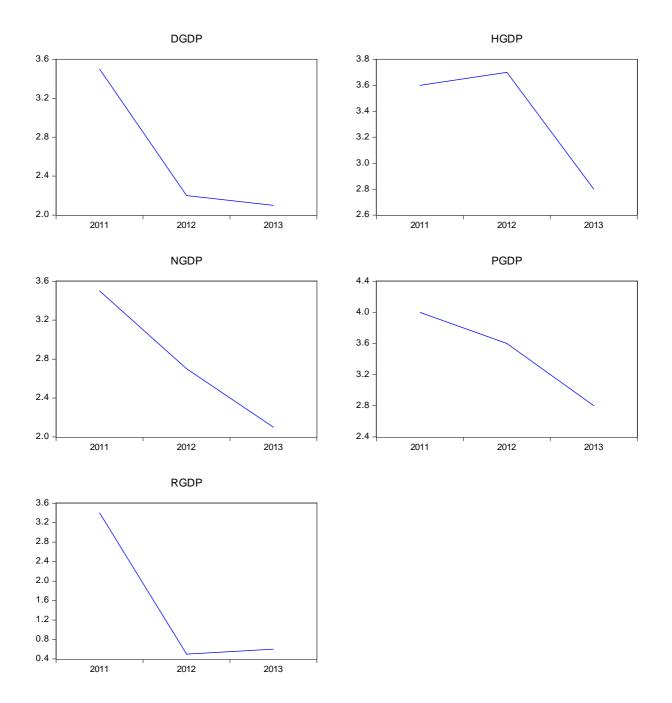
May 2014

European Central Bank, (2003) "Can Confidence Indicators be Useful to Predict Short Term Real GDP Growth?". Working Paper 133

European Central Bank, (2006) "Short-Term Forecasts of Euro Area Real GDP Growth: An Assessment of Real Time Performance Based on Vintage Data". Working Paper 622

Latvijas Banka (2008) "Short-Term Forecasts Of Latvia's Real Gross Domestic Product Growth Using Monthly Indicators" Working Paper 5-2008

# Appendix 1

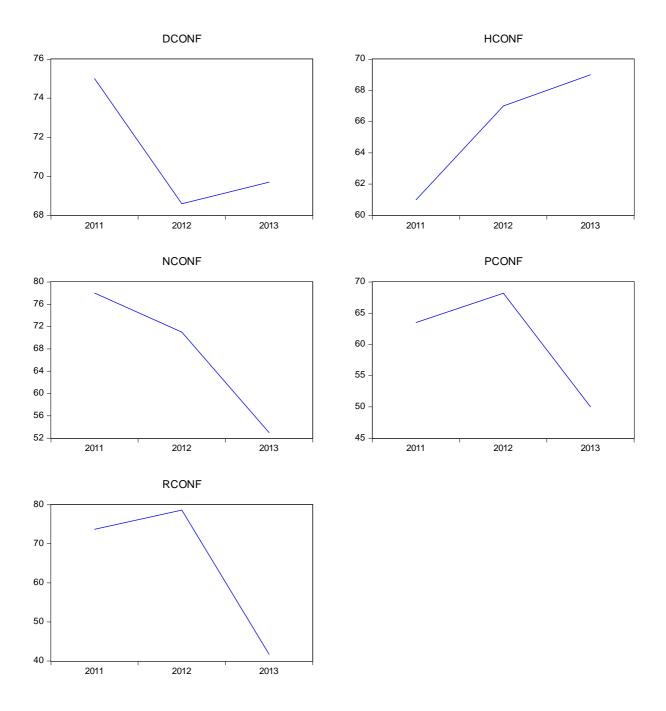


# Real GDP Growth (%) for each of the five cities, 2011 to 2013

(d=Durban, h=Port Shepstone, n= Newcastle, p=Pietermaritzburg and r=Richards Bay)

# Appendix 2

# Business Confidence (number out of 100) for each of the five cities, 2011 to 2013



(d=Durban, h=Port Shepstone, n= Newcastle, p=Pietermaritzburg and r=Richards Bay)