Special Issue on Applied Economics and Finance

The Causality Between Consumer Confidence Index and Stock Returns: Evidence from Recursive Evolving Granger Causality Test[1]

Tüketici Güven Endeksi ve Hisse Senedi Getirilerinin Nedensellik İlişkisi: Özyinelemeli Granger Nedensellik Testinden Kanıtlar

Efe Caglar CAGLI, Dokuz Eylul University, Turkey, efe.cagli@deu.edu.tr

Abstract: This paper aims to investigate the causal relationship between Consumer Confidence Index and stock returns on Borsa Istanbul (BIST). We analyze the changes in Consumer Confidence Index as a proxy for investor sentiment and changes in the BIST-100 return index, employing both the conventional and time-varying recursive evolving Granger causality tests. The monthly data covering January-2004 – January-2019 are analyzed. The results obtained from the conventional Granger causality test indicate unidirectional Granger causality running from BIST-100 to CCI at the 10% level. However, the recursive evolving window procedure not only detects Granger causality episodes running from BIST-100 to CCI, but also detects a significant episode of Granger causality running from CCI to BIST-100 during the latter period of the sample, between April 2017 and September 2018. These results show the importance of modelling causality in a dynamic framework which accommodates the potential changes in the causal relationship among variables stemming from nonlinearities over the sample period.

Keywords: Consumer Confidence, Turkey, Granger Causality, Recursive Evolving Algorithm

Öz: Bu çalışma, Tüketici Güven Endeksi (TGE) ve Borsa Istanbul (BIST) hisse senedi getirileri arasındaki nedensel ilişkiyi araştırmayı amaçlamaktadır. Yatırımcı duyarlılığını temsilen kullanılan Tüketici Güven Endeksindeki değişimler ve BIST-100 Getiri Endeksindeki değişimler geleneksel ve zamana göre değişen özyinelemeli Granger nedensellik testleriyle analiz edilmiştir. Ocak 2004 – Ocak 2019 dönemini kapsayan aylık veriler analiz edilmiştir. Geleneksel Granger nedensellik testinden elde sonuçlar, BIST-100'den TGE'ye %10 önem seviyesinde Granger nedensellik olduğunu göstermektedir.Bununla birlikte, özyinelemeli Granger nedensellik testi, BIST-100'den TGE'ye Granger nedensellik dönemleri tespit etmenin yanında, örneklem döneminin sonlarına doğru, Nisan 2017-Eylül 2018 arasında, TGE'den BIST-100'e doğru anlamlı bir Granger nedensellik dönemi de tespit etmektedir. Bu sonuçlar, örneklem dönemlerinde doğrusal olmayan yapılardan kaynaklanan nedensellik ilişkilerindeki potansiyel değişimleri dinamik bir çerçeve içerisinde modellemenin önemini göstermektedir.

Anahtar Sözcükler: Tüketici Güveni, Türkiye, Granger Nedensellik, Özyinelemeli Algoritma

1. Introduction

Classical finance theory is developed based on the assumption that perfect market conditions are hold, implying investors behave rationally in informationally efficient markets where asset prices are in equilibrium through arbitrage activities. Contrary to the assumptions and the implications of classical finance theory, behavioral finance lays emphasis on the market imperfections stemming from the limits to arbitrage and psychological factors that lead investors to make irrational decisions. Prospect Theory by Kahneman and Tversky (1979) states that psychological issues play important role in decision making under risk. Ritter (2003) labels the psychological issues as cognitive biases which refers to the following patterns regarding the behavior of investors: Heuristics, overconfidence, mental accounting, framing, representativeness, conservatism, and disposition effect. Given the fact that investors have cognitive biases, financial markets may not be rational.

Thaler (2000) and Shefrin (1999) state that psychological factors should be taken into account in developing models. Investor sentiment as one of the psychological factors reflects the prevailing attitude of investors towards the investment risks and anticipated prices that are not warranted by fundamentals (De Long et al. 1990; Baker and Wurgler 2006, 2007). However, it is not an easy task to measure the investor sentiment which cannot be observed directly in the markets. Direct and indirect proxies are used for measuring the investor sentiment. Direct proxies include consumer and real sector confidence indices, calculated based on the results of the consumer and sector tendency surveys carried out by the academic and governmental statistical institutes. Indirect proxies reflecting the holdings and positions of the investors include closed-end fund discount, turnover ratio, trading volume, mutual fund flows, net stock purchases, volatility premium, long/short position, and so forth.

[1] Bu çalışma Efe Çağlar Çağlı özet bildirisi olarak, "*ICOAEF'18, IV. International Conference on Applied Economics and Finance & EXTENDED WITH SOCIAL SCIENCES, November 28 – 29 – 30, 2018 / Kuşadası – Turkey*" Kongresinde sanal oturumda sunulmuştur ve kongre procedia özet kitapçığında basılmıştır.

It is worth investigating the predictive power of the investor sentiment on stock returns as the predictive ability of the investor sentiment on the stock returns implies that it can be considered as market timing indicator and as a source of systematic risk. There is a myriad of studies examining whether the investor sentiment has a significant impact on the stock returns. Using direct proxies (consumer confidence index, hereafter CCI) for investor sentiment, Otoo (1999), Jansen and Nahuis (2003), Brown and Cliff (2004) provide evidence that stock prices are successful predictors of consumer confidence, but not vice versa. Fisher and Statman (2003), Schmeling (2009), Akhtar et al. (2011), and Zouaoui, Nouyrigat, and Beer (2011) state that CCI has a significant impact on the stock returns.

Following Lee, Shleifer, and Thaler (1991; 1990), Chen, Kan, and Miller (1993) and Baur, Quintero, and Stevens (1996) use closed-end fund discount as indirect proxy for investor sentiment index and conclude that changes in the investor sentiment are not related to changes in the stock prices. Baker and Stein (2004) use liquidity measures for the investor sentiment and report that aggregate measures of equity issuance and share turnover have predictive power on the market returns. Baker and Wurgler (2006, 2007) construct an investor sentiment index that embodies information from various indirect proxies, closed-end fund discount, share turnover, the number of IPOs, the average first-day returns of IPOs, the share of equity issues in total equity and debt issues, and dividend premium. Their findings suggest incorporating investor sentiment in the asset pricing models. The other studies including Chiang, Tsai, and Lee (2011), Chen, Chen, and Lee (2013), and Ni, Wang, and Xue (2015) use different indirect proxies for different markets and confirm the significant impact of the investor sentiment on stock returns on different markets.

The studies on Turkish stock market (Borsa Istanbul) use both direct and indirect proxies for investor sentiment. Olgac and Temizel (2008), Topuz (2011), Bolaman and Mandaci (2014) use CCI as a proxy for investor sentiment to examine the relationship between investor sentiment and stock returns on Borsa Istanbul (BIST). Olgac and Temizel (2008) and Topuz (2011) provide evidence of unidirectional causality running from stock prices to CCI. Bolaman and Mandaci (2014) detect long-run relationship between consumer confidence and BIST-100 index. Korkmaz and Cevik (2009) report a positive relationship between Real Sector Confidence Index (RSCI) and BIST-30. Canbas and Kandir (2007, 2009) use indirect proxies including closed-end fund discounts, mutual funds flow, stock purchases to measure investor sentiment and find that they have significant impact on the stock price indices. Uygur and Tas (2014) use trading volume of BIST-100 index as investor sentiment proxy, and conclude that investor sentiment significantly affects particular sub-sector indices in Borsa Istanbul.

In this paper, we aim to examine the causal relationship between CCI and stock returns on Borsa Istanbul (BIST). For stock returns on BIST, we analyze the changes in the BIST-100 return index. Different from the previous studies, we employ a novel Granger causality framework developed by Shi, Phillips, and Hurn (2018). The framework helps us model time-varying Granger causal relationships and determine origination and termination dates in the causal relationship. Given its dynamic structure, the recursive evolving testing procedure in the framework allows for heteroskedasticity and nonlinearities stemming from structural breaks in the data. Moreover, our data period, between January-2004 and January-2019, covers significant market events, such as, the global financial crisis in 2007-08, the European debt crises in 2011-12, the coup attempt in Turkey in 2016, high volatility in the TL/USD exchange rate in August 2018, and so forth.

The paper is organized as follows: Section 2 documents the econometric methodology, Section 3 presents data and empirical results, and last section concludes the paper.

2. Methodology

Carrion-i-Silvestre, Kim, and Perron (2009) develop GLS-based unit root tests allowing multiple structural breaks which are endogenously determined. By allowing multiple breaks in the data, Carrion-i-Silvestre, Kim, and Perron (2009) state that their tests overcome the shortcomings of conventional unit root tests (e.g. Augmented Dickey and Fuller (1979), Philips and Perron (1988), Kwiatkowski et al. (1992)) which may overreject the null hypothesis of unit root in the presence of structural breaks in the data. We employ Carrion-i-Silvestre, Kim, and Perron's (2009) unit root testing procedures which allow for an arbitrary number of changes up to five structural breaks in both the level and slope of the trend function. We consider *M*-class unit root tests with good power and size properties, $MZ_{\alpha}^{GLS}(\lambda)$, $MSB^{GLS}(\lambda)$, and $MZ_{t}^{GLS}(\lambda)$. Each tests the null hypothesis of unit root against the alternative hypothesis of stationarity.

We estimate the following unrestricted VAR(k) model for testing conventional Granger (1969, 1988) causality among strictly stationary time series:

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_k y_{t-k} + \beta_1 x_{t-1} + ... + \beta_k x_{t-k} + \varepsilon_t \\ x_t &= \alpha_0 + \alpha_1 x_{t-1} + ... + \alpha_k x_{t-k} + \beta_1 y_{t-1} + ... + \beta_k y_{t-k} + \varepsilon_t \end{aligned} \tag{1}$$

where k is the optimal lag length determined by Schwarz Information Criterion. We obtain Wald (W) statistics following χ^2 distribution, with k degrees of freedom, under the null hypothesis of Granger non-causality against the alternative hypothesis of Granger causality:

$$H_0 : \beta_1 = \beta_2 = ... = \beta_k = 0 \tag{2}$$

By imposing zero restriction on the β parameters, we test the null hypothesis of that x does not Granger cause y in the first regression of Equation (1), and that y does not Granger cause x in the second regression of Equation (1).

Given the fact that conventional Granger causality test is sensitive to the time period of estimation, Shi, Phillips, and Hurn (2018) propose a novel recursive evolving window algorithm for detecting changes in causal relationships. The approach has its roots in the work of Phillips, Shi, and Yu (2015) which develops a framework for detecting and dating financial exuberance in real time. The recursive evolving procedure is an extension of both the forward expanding window algorithm by Thoma (1994) and rolling window algorithm by Swanson (1998). Different from the conventional Granger causality test, we estimate W for each subsample regression in the recursive evolving approach and estimate sup W (SW_r) as follows:

$$SW_r(r_0) = \sup_{(r_1,r_2)\in\Lambda_0, r_2=r} \{W_{r_2}(r_1)\} \tag{3}$$

where $\Lambda_0 = \{(r_1, r_2) : 0 < r_0 + r_1 \le r_2 \le 1, \text{and } 0 \le r_1 \le 1 - r_0\}$, r is the observation of interest, r_0 is the minimum window size, r_1 and r_2 are the starting and terminal points of the sequence of regressions, respectively. Origination (r_e) and termination (r_f) dates in the causal relationship are calculated according to the following crossing time equations:

$$\hat{r}_e = \inf_{r\in[r_0,1]} \{r : SW_r(r_0) > scv\} \tag{4}$$

$$\hat{r}_f = \inf_{r\in[\hat{r}_e,1]} \{r : SW_r(r_0) < scv\} \tag{5}$$

where scv is the sequence of the bootstrapped critical values of the SW_r statistics.

3. Data and Empirical Results

We obtain Consumer Confidence Index (CCI) from Turkish Statistical Institute (TURKSTAT). The stock returns on Borsa Istanbul (BIST) are proxied by the BIST-100 return index, obtained from the Electronic Data Delivery System (EDDS) of the Central Bank of the Republic of Turkey (CBRT). The monthly data cover the period from January-2004 to January-2019. We analyze log-difference data and present the descriptive statistics for the time-series in Table 1. Figure 1 shows the movements of the time-series over the sample period.

Table 1. Descriptive Statistics

Statistics	**CCI (Δlog) (%)**	**BIST-100 (Δlog) (%)**
Mean	-0.290	1.196
Median	-0.076	2.147
Maximum	20.621	21.324
Minimum	-12.854	-26.293
Std. Dev.	3.884	7.559
Skewness	0.591	-0.438
Kurtosis	7.682	3.782
Prob. (J-B)	0.000	0.006
Observations	180	180

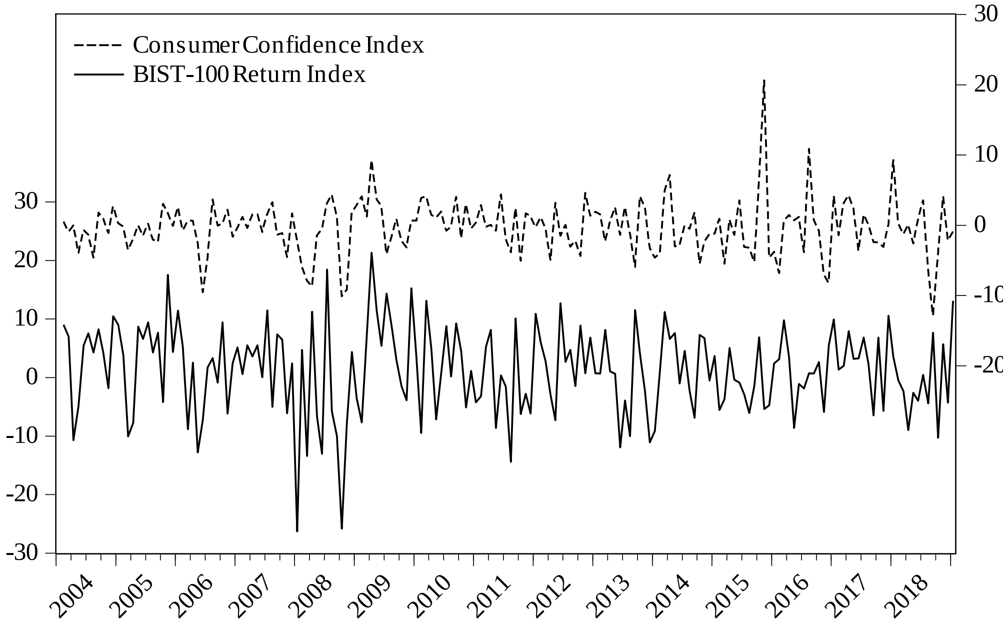

Figure 1: Monthly log differences of BIST-100 return index and Consumer Confidence Index (%)

Note: Solid (left-axis) and dashed (right-axis) lines represent BIST-100 Return index and Consumer Confidence Index, respectively.

We check the stationarity of the time-series using the unit root test procedures developed by Carrion-i-Silvestre, Kim, and Perron (2009). The unit root test statistics reported in Table 2 suggest rejecting he null hypothesis of unit root, indicating that the log-differenced series are stationary over time.

Table 2. Carrion-i-Silvestre, Kim, and Perron (2009) Unit Root Test Statistics

Tests	**BIST-100 (Δlog)**	**CCI (Δlog)**
$MZ_{\alpha}^{GLS}(\lambda)$	-73.603	-57.692
$MSB^{GLS}(\lambda)$	0.0821	0.093
$MZ_{t}^{GLS}(\lambda)$	-6.045	-5.367
Timing of Structural Breaks		
TB_1	2005M09	2005M12
TB_2	2007M12	2007M07
TB_3	2010M01	2012M09
TB_4	2011M07	2014M03
TB_5	2013M05	2015M10

Note: a denotes stationarity ($I(0)$) at the significance level of 1%. *TB* stands for the timing of structural breaks.

Having found that both CCI and BIST-100 are stationary, we estimate Vector Autoregression (VAR) system and conduct the conventional Granger causality analysis between the series. Schwarz Information Criteria suggests estimating VAR(1) system which also satisfies the stability condition.

Table **3** and Table **4** report the estimation results for VAR(1) system and the conventional Granger Causality tests, respectively. The conventional Granger causality test results suggest rejecting the null hypothesis that BIST-100 does not Grager cause CCI at 1% significance level; however, we cannot reject the null hypothesis that CCI Granger causes BIST-100. We evidence unidirectional Granger causality running from BIST-100 to CCI based on the conventional Granger causality tests.

Table 3. VAR (1) Estimation Results

	Dependent Variable	
Variable	**BIST-100**	**CCI**
Intercept	1.837	-0.618
	(1.167)	(0.576)
BIST (-1)	0.030	0.129
	(0.078)	(0.038)
CCI (-1)	-0.064	0.112
	(0.150)	(0.074)
t	-0.008	0.002
	(0.011)	(0.005)

Note: Lag length (1) is determined by Schwarz Information Criterion. *t* is trend. a denotes statistical significance at 1% level. Though not reported here, no root lies outside the unit circle, VAR (1) system satisfies the stability condition. The numbers in parentheses are standard errors.

Table 4. Granger Causality Test Results

Null Hypothesis	χ^2	**Prob.**
CCI Granger causes BIST-100	0.183	0.669
BIST-100 Granger causes CCI	11.370	0.001

Note: Lag length (1) is determined by Schwarz Information Criteria.

We test causal relationship between BIST-100 and CCI and determine origination and termination dates in the causal relationship using the recursive evolving procedure suggested by Shi, Phillips, and Hurn (2018), along with the forward expanding window procedure by Thoma (1994) and rolling window procedure by Swanson (1998). Figure 2 shows the MWald test statistic sequences and bootstrapped 10% critical value sequences for the time-varying Granger Causality tests following the procedures. We can reject the null hypothesis of no Granger causality between the time-series as the MWald test statistics exceed the critical value sequence.

Figure 2 illustrates the results for testing Granger causality between BIST-100 and CCI. According to Panel a of Figure 2, the forward expanding window procedure detects four episodes of Granger causality running from BIST-100 to CCI at the 10% level; the first is detected in February 2008; the second lasts two months between May 2008 and June 2008; the third lasts 34 months between October 2008 and August 2011; and the fourth lasts 64 months, starting in October 2013 and continues until the end of the sample period. However, we cannot reject the null hypothesis that CCI does not Granger cause BIST-100 as the MWald test statistic sequence does not exceed the 10% critical value sequence over the whole sample period.

Panel b of Figure 3 illustrates that rolling window procedure detects three episodes of Granger causality running from BIST-100 to CCI at the 10% level; the first lasts seven months between November 2008 and June 2009; the second lasts two months between August 2015 and September 2015; and the third lasts four months between April 2016 and July 2016. The rolling window procedure also detects two episodes of Granger causality running from CCI to BIST-100 at the 10% level; the first starts in April 2017 and terminates in May 2018; the second lasts three months between July 2018 and September 2018.

Panel c of Figure 3 shows that recursive evolving window procedure detects two main episodes of Granger causality running from BIST-100 to CCI at the 10% level; the first lasts 16 months between November 2008 and February 2010; and the second lasts 47 months, starting in March 2015 and continues until the end of the sample period. The recursive evolving window procedure detects the episode of Granger causality running from CCI to BIST-100 at the 10% level, starting in April 2017 and terminating in September 2018.

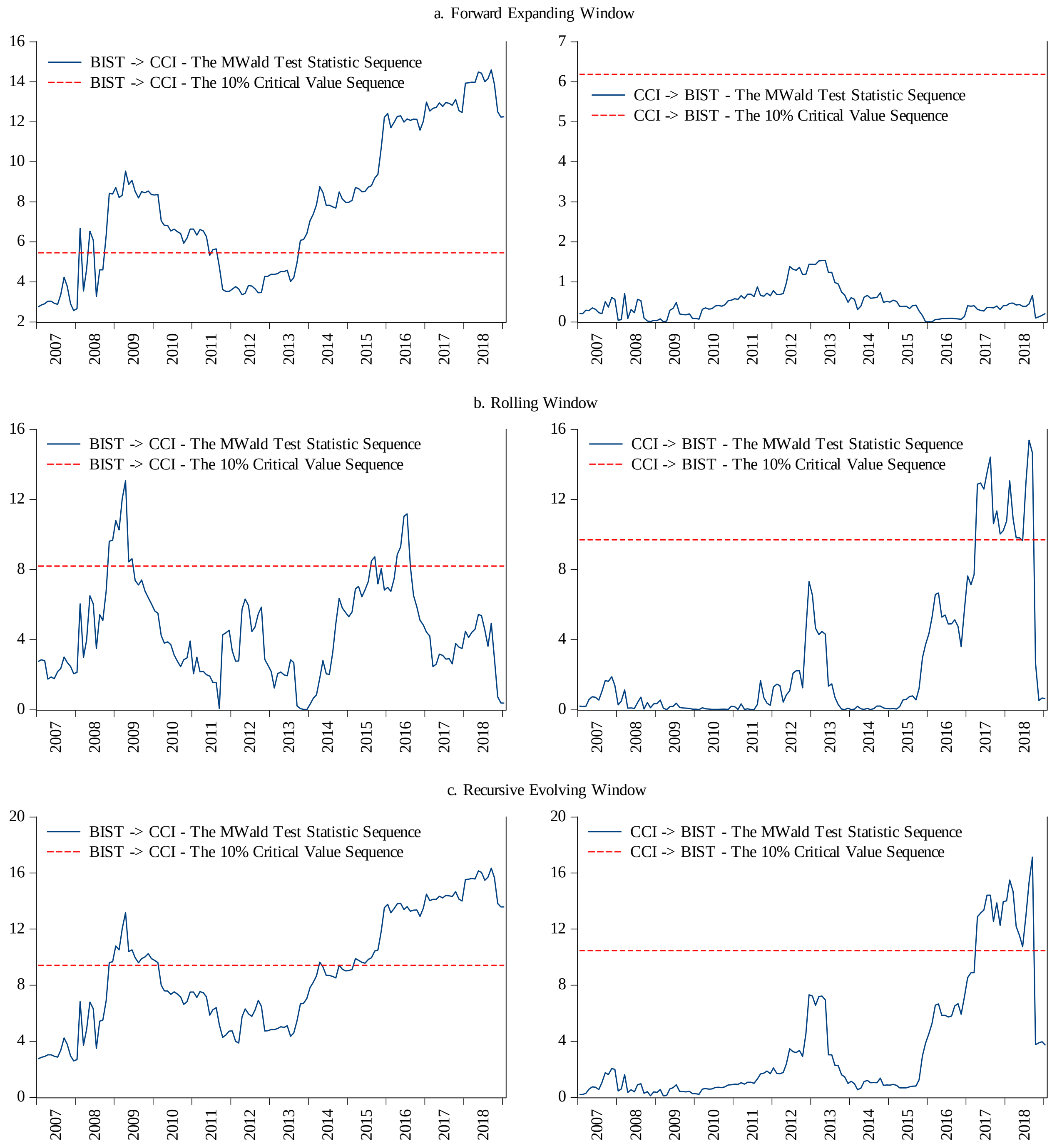

Figure 2. Time-Varying Granger Causality Test Results, BIST-100 → CCI

Note: The lag order is assumed the same for all subsamples and selected using the Schwarz information criteria (BIC) for the whole sample period with a maximum lag length 12. The critical values are obtained from bootstrapping procedure with 499 replications. The empirical size is 10% and is controlled over a three-year period.

4. Conclusion

The above methodology developed by Shi, Phillips, and Hurn (2018) is applied for the first time to examine the causal relationship between the Consumer Confidence Index (CCI) of Turkey and the stock returns on Borsa Istanbul (BIST). The results of the conventional Granger causality test suggest unidirectional Granger causality running from BIST-100 to CCI at the 10% level, which is consistent with those of the the forward expanding procedure of Thoma (1994). The rolling and recursive evolving window procedures not only detect Granger causality episodes running from BIST-100 to CCI, but also detect significant episodes of Granger causality running from CCI to BIST-100 during the latter period of the sample, between April 2017 and September 2018.

The findings that BIST-100 Granger causes CCI during both the early sample period of 2008-2009 and latter sample period of 2014-2018 may be explained by the leading indicator channel (Otoo, 1999) that changes in the stock prices significantly affect the future income, and thus the consumer confidence in general. It is noteworthy that the episodes of Granger causality from BIST-100 to CCI which are detected during the different periods of the sample have different characteristics. We evidenced dramatic decreases in the stock prices in Borsa Istanbul during the Great Recession of 2007-2009, which was triggered by the mortgage delinquencies in the US. However, the stock prices in Borsa Istanbul surged after 2010 owing to the expansionary monetary policy of the Fed; and the market continued its rally in the latter period of the sample until the beginning of 2018 despite the Fed's tapering decision after 2013 and domestic issues, such as political turmoil in 2015-2016 and coup attempt in July 2016. We may conclude that both the bear and bull market conditions in Borsa Istanbul, most likely driven by the global factors, significantly affect the consumer confidence in Turkey during the aforementioned episodes of Granger causality.

On the other side of the relationship, the returns on Borsa Istanbul is found to be sensitive to the consumer confidence during the latter period of sample. Contrary to the findings suggested by the conventional Granger causality test, both the rolling and recursive procedures detect Granger causality running from CCI to BIST-100 in the latter sample period of April 2017–September 2018, during which Turkish Lira depreciated by around 70% against the US Dollar, 5-Year CDS premium of Turkey increased by about 130%, consumer (producer) price index increased from 11.87% (16.37%) to 24.52% (46.15%), and the CBRT hiked the policy interest rates from 8% to 24%. During that period, consumer spending slowed down due to the increasing domestic economic risks in Turkey and consumer confidence index decreased to the level of 60 from 71. The possible explanations for the episode of Granger causality running from CCI to BIST-100 during that period may be that decrease (increase) in consumer confidence level (producer price index) has a decreasing (increasing) effect on the sales revenues (costs of sales) of the corporations, leading stock prices to decline. It seems that trajectory of the Turkish economy was mostly determined by domestic factors rather than global ones during the period, which may also explain why we do not find evidence of Granger causality from CCI to BIST-100 in the Great Recession period during which consumer confidence index level hit the lowest level of 56.

Overall, we evidence that the causal relationship between consumer confidence and stock returns on Borsa Istanbul is subject to change over time, implying that the changes in economic policy, regulatory structure, governing institutions, or operating environments should be taken into account. These results show the importance of modelling causality in a dynamic setting which accommodates the potential changes in the causal relationship among variables stemming from nonlinearities over the sample period. Our results support and extend those of the earlier studies (Topuz, 2011; Bolaman and Mandaci, 2014) concerning the causal relationship between stock returns and consumer confidence index. Finally, the investors, portfolio managers, and policy makers in Borsa Istanbul shall consider consumer confidence index as an important factor driving the stock returns when country-specific risks tend to increase.

REFERENCES

Akhtar, Shumi, Robert Faff, Barry Oliver, and Avanidhar Subrahmanyam. 2011. “The Power of Bad: The Negativity Bias in Australian Consumer Sentiment Announcements on Stock Returns.” *Journal of Banking & Finance* 35 (5). North-Holland: 1239–49. doi:10.1016/J.JBANKFIN.2010.10.014.

Baker, Malcolm, and Jeremy C Stein. 2004. “Market Liquidity as a Sentiment Indicator.” *Journal of Financial Markets* 7 (3). North-Holland: 271–99. doi:10.1016/J.FINMAR.2003.11.005.

Baker, Malcolm, and Jeffrey Wurgler. 2006. “Investor Sentiment and the Cross-Section of Stock Returns.” *The Journal of Finance* 61 (4). John Wiley & Sons, Ltd (10.1111): 1645–80. doi:10.1111/j.1540-6261.2006.00885.x.

———. 2007. “Investor Sentiment in the Stock Market.” *Journal of Economic Perspectives* 21 (2): 129–51. doi:10.1257/jep.21.2.129.

Baur, Michael N., Socorro Quintero, and Eric Stevens. 1996. “The 1986-88 Stock Market: Investor Sentiment or Fundamentals?” *Managerial and Decision Economics* 17 (3). John Wiley & Sons, Ltd: 319–29. doi:10.1002/(SICI)1099-1468(199605)17:3<319::AID-MDE776>3.0.CO;2-0.

Bolaman, Özge, and Pinar Evrim-Mandacı. 2014. “Effect of Investor Sentiment on Stock Markets.” *Finansal Araştırmalar ve Çalışmalar Dergisi* 6 (11): 51–64. doi:10.14784/JFRS.2014117327.

Brown, Gregory W., and Michael T. Cliff. 2004. “Investor Sentiment and the Near-Term Stock Market.” *Journal of Empirical Finance* 11 (1). North-Holland: 1–27. doi:10.1016/J.JEMPFIN.2002.12.001.

Canbaş, Serpil, and Serkan Yılmaz Kandır. 2007. “Yatırımcı Duyarlılığının İMKB Sektör Gelirleri Üzerindeki Etkisi.” *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi* 22 (2): 219–48.

———. 2009. “Investor Sentiment and Stock Returns: Evidence from Turkey.” *Emerging Markets Finance and Trade* 45 (4). Routledge: 36–52. doi:10.2753/REE1540-496X450403.

Carrion-i-Silvestre, Josep Lluís, Dukpa Kim, and Pierre Perron. 2009. “GLS-BASED UNIT ROOT TESTS WITH MULTIPLE STRUCTURAL BREAKS UNDER BOTH THE NULL AND THE ALTERNATIVE HYPOTHESES.” *Econometric Theory* 25 (06): 1754. doi:10.1017/S0266466609990326.

Chen, Mei-Ping, Pei-Fen Chen, and Chien-Chiang Lee. 2013. “Asymmetric Effects of Investor Sentiment on Industry Stock Returns: Panel Data Evidence.” *Emerging Markets Review* 14 (March). North-Holland: 35–54. doi:10.1016/J.EMEMAR.2012.11.001.

Chen, Nai-Fu, Raymond Kan, and Merton H. Miller. 1993. “Are the Discounts on Closed-End Funds a Sentiment Index?” *The Journal of Finance* 48 (2). John Wiley & Sons, Ltd (10.1111): 795–800. doi:10.1111/j.1540-6261.1993.tb04741.x.

Chiang, Ming-Chu, I-Chun Tsai, and Cheng-Feng Lee. 2011. “Fundamental Indicators, Bubbles in Stock Returns and Investor Sentiment.” *The Quarterly Review of Economics and Finance* 51 (1). North-Holland: 82–87. doi:10.1016/J.QREF.2010.11.001.

Dickey, David A., and Wayne A. Fuller. 1979. “Distribution of the Estimators for Autoregressive Time Series With a Unit Root.” *Journal of the American Statistical Association* 74 (366): 427–31. doi:10.2307/2286348.

Fisher, Kenneth L., and Meir Statman. 2003. “Consumer Confidence and Stock Returns.” *The Journal of Portfolio Management* 30 (1). Institutional Investor Journals Umbrella: 115–27. doi:10.3905/jpm.2003.319925.

Granger, C. W. J. 1969. “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods.” *Econometrica* 37 (3): 424–38. doi:10.2307/1912791.

Granger, C.W.J. 1988. “Some Recent Development in a Concept of Causality.” *Journal of Econometrics* 39 (1–2). North-Holland: 199–211. doi:10.1016/0304-4076(88)90045-0.

Jansen, W.Jos, and Niek J Nahuis. 2003. “The Stock Market and Consumer Confidence: European Evidence.” *Economics Letters* 79 (1). North-Holland: 89–98. doi:10.1016/S0165-1765(02)00292-6.

Kahneman, Daniel, and Amos Tversky. 1979. “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica* 47 (2): 263–91. doi:10.2307/1914185.

Korkmaz, T, and Eİ Çevik. 2009. “Reel Kesim Güven Endeksi Ile İMKB 100 Endeksi Arasındaki Dinamik Nedensellik Ilişkisi.” *Istanbul University Journal of the School of Business Administration* 38 (1): 24–37. http://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=13031732&asa=Y&AN=45447045&h=19ywOpql74GNbllYwtqQizTRFtxF%2BGVqPzr3uZPJhjTVGLJfQwQWMDF2zwxy2s%2FmOvNwn%2Bv6xtaQaYg%2BH4Dnhw%3D%3D&crl=c.

Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin. 1992. “Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?” *Journal of Econometrics* 54 (1–3). North-Holland: 159–78. doi:10.1016/0304-4076(92)90104-Y.

Lee, Charles M. C, Andrei Shleifer, and Richard H Thaler. 1990. “Anomalies: Closed-End Mutual Funds.” *Journal of Economic Perspectives* 4 (4): 153–64. doi:10.1257/jep.4.4.153.

Lee, Charles, Andrei Shleifer, and Richard H. Thaler. 1991. “Investor Sentiment and the Closed End Fund Puzzle.” *The Journal of Finance* 46 (1): 75–109. doi:10.2307/2328690.

Long, J. Bradford De, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. 1990. “Noise Trader Risk in Financial Markets.” *Journal of Political Economy* 98 (4): 703–38. doi:10.1086/261703.

Ni, Zhong-Xin, Da-Zhong Wang, and Wen-Jun Xue. 2015. “Investor Sentiment and Its Nonlinear Effect on Stock Returns—New Evidence from the Chinese Stock Market Based on Panel Quantile Regression Model.” *Economic*

Modelling 50 (November). North-Holland: 266–74. doi:10.1016/J.ECONMOD.2015.07.007.

Olgaç, Serkan, and Fatih Temizel. 2008. “Yatırımcı Duyarlılığı Hisse Senedi Getirileri İlişkisi: Türkiye Örneği.” *TISK Akademi* 3 (6): 224–39. http://eds.b.ebscohost.com/eds/pdfviewer/pdfviewer?vid=0&sid=04dfd03b-836e-4019-87dd-a8358863600a%40sessionmgr104.

Otoo, Maria Ward. 1999. “Consumer Sentiment and the Stock Market.” *FEDS Working Paper No. 99-60*. http://www.federalreserve.gov/pubs/feds/1999/199960/199960pap.pdf.

Phillips, Peter C. B., Shuping Shi, and Jun Yu. 2015. “TESTING FOR MULTIPLE BUBBLES: HISTORICAL EPISODES OF EXUBERANCE AND COLLAPSE IN THE S&P 500.” *International Economic Review* 56 (4). Wiley/Blackwell (10.1111): 1043–78. doi:10.1111/iere.12132.

Phillips, Peter C B, and Pierre Perron. 1988. “Testing for a Unit Root in Time Series Regression.” *Biometrika* 75 (2): 335–46. doi:10.1093/biomet/75.2.335.

Ritter, Jay R. 2003. “Behavioral Finance.” *Pacific-Basin Finance Journal* 11 (4). North-Holland: 429–37. doi:10.1016/S0927-538X(03)00048-9.

Schmeling, Maik. 2009. “Investor Sentiment and Stock Returns: Some International Evidence.” *Journal of Empirical Finance* 16 (3). North-Holland: 394–408. doi:10.1016/J.JEMPFIN.2009.01.002.

Shefrin, Hersh. 1999. “Irrational Exuberance and Option Smiles.” *Financial Analysts Journal* 55 (6). Association for Investment Management and Research : 91–103. doi:10.2469/faj.v55.n6.2316.

Shi, Shuping, Peter C. B. Phillips, and Stan Hurn. 2018. “Change Detection and the Causal Impact of the Yield Curve.” *Journal of Time Series Analysis* 39 (6). John Wiley & Sons, Ltd (10.1111): 966–87. doi:10.1111/jtsa.12427.

Swanson, Norman R. 1998. “Money and Output Viewed through a Rolling Window.” *Journal of Monetary Economics* 41 (3). North-Holland: 455–74. doi:10.1016/S0304-3932(98)00005-1.

Thaler, Richard H. 2000. “From Homo Economicus to Homo Sapiens.” *Journal of Economic Perspectives* 14 (1): 133–41. doi:10.1257/jep.14.1.133.

Thoma, Mark A. 1994. “Subsample Instability and Asymmetries in Money-Income Causality.” *Journal of Econometrics* 64 (1–2). North-Holland: 279–306. doi:10.1016/0304-4076(94)90066-3.

Topuz, Yusuf Volkan. 2011. “Tüketici Güveni Ve Hisse Senedi Fiyatları Arasındaki Nedensellik İlişkisi: Türkiye Örneği.” *Ekonomik ve Sosyal Araştırmalar Dergisi* 7 (1): 53–65.

Uygur, Utku, and Oktay Taş. 2014. “The Impacts of Investor Sentiment on Different Economic Sectors: Evidence from Istanbul Stock Exchange.” *Borsa Istanbul Review* 14 (4). Elsevier: 236–41. doi:10.1016/J.BIR.2014.08.001.

Zouaoui, Mohamed, Geneviève Nouyrigat, and Francisca Beer. 2011. “How Does Investor Sentiment Affect Stock Market Crises? Evidence from Panel Data.” *Financial Review* 46 (4). John Wiley & Sons, Ltd (10.1111): 723–47. doi:10.1111/j.1540-6288.2011.00318.x.