

A Note on the Technology Herd: Evidence from Large Institutional Investors

Josine Uwilingiye, Department of Economics and Econometrics, University of Johannesburg, Auckland Park, 2006, South Africa.

Esin Cakan*, Department of Economics, University of New Haven, CT 06516, USA

Rıza Demirer, Department of Economics & Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102, USA.

Rangan Gupta, Department of Economics, University of Pretoria, Pretoria, 0002, South Africa.

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ABSTRACT

Purpose: The purpose of this paper is to examine intentional herding among institutional investors with a particular focus on the technology sector that was the driver of the “New Economy” in the USA during the dot-com bubble of the 1990s.

Design/methodology/approach: Using data on technology stockholdings of 115 large institutional investors, the authors test the presence of herding by examining linear dependence and feedback between individual investors’ technology stockholdings and that of the aggregate market. Unlike other models to detect herding, the authors use Geweke (1982) type causality tests that allow authors to disentangle spurious herding from intentional herding via tests of bidirectional and instantaneous causality across portfolio positions in technology stocks.

Findings: After controlling information-based (spurious) herding, the tests show that 38 percent of large institutional investors tend to intentionally herd in technology stocks.

Originality/value: The findings support the existing literature that investment decisions by large institutional investors are not only driven by fundamental information, but also by cognitive bias that is characterized by intentional herding.

JEL classification: G02, G11, G14, C18

Keywords: Herding, Institutional investors, Causality, Technology stocks

* Corresponding author. Email: ecakan@newhaven.edu.

1. Introduction

The empirical validity of the efficient market hypothesis (EMH) has been questioned in numerous studies in the literature since it was developed by the renowned financial theorist Eugene Fama (Fama, 1970). Early studies including Fama and French (1988), Lo and Mackinlay (1999) and Lo *et al.* (2000) document predictable patterns in stock prices, contradicting the weak form of market efficiency. Similarly, studies including Bondt and Thaler (1985), Howe (1986), Jegadeesh and Titman (1993) and Soares and Serra (2005) argue that investors either overreact or underreact to public information, challenging the semi-strong form of the EMH. At the same time, other studies show that prices may not fully reflect private information, supported by higher returns obtained by corporate insiders (e.g. Jaffe, 1974; Del Brio *et al.*, 2002). Questioning the fundamental assumptions of efficiency, Grossman and Stiglitz (1980), among others, argue that prices cannot perfectly reflect all available information since information is costly and the incentives to acquire information do not necessarily align with the concept of public availability of information, underscoring the proportion of informed to uninformed traders in the market as a key factor for market efficiency.

The empirical evidence against market efficiency both in the U.S. and in international markets is further supported by the fact that the EMH has largely failed to explain the evolution of bubbles and subsequent crashes often experienced in financial markets. For instance, in late 1990s, excessive speculation on the potential growth in the so-called “New Economy” led to a surge of investment in technology companies, which at the time were projected to remain profitable over the long term. During that period, technology stocks experienced a historic surge in their share prices and the internet sector earned over 1000% returns on their public equity in a two-year period (Ofek and Richardson, 2003). Though many investors earned abnormal returns during this period, the profitability of the underlying firms was not sustained and both investors and technology companies incurred enormous losses, eventually leading to a burst of the dot-com bubble. Clearly, this was a period that posed a significant challenge to the theory of market efficiency and Shiller (2000) argued that the growth in stock prices during the internet bubble was triggered by irrational behavior among individual investors.

A number of studies including Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmangan (1998), Wermers (1999), Shiller (2002) and Brunnermeier and Nagel (2004) posit that the investors’ decisions are not only driven by information on fundamentals, but also human

emotions. To that end, herding is proposed as a form of cognitive bias in which individual investors mimic the investment decisions of others (group of investors) rather than using their own rational decisions. In fact, the strand of the literature on herding behavior has experienced a boom over the past decade, particularly following the global financial crisis of 2007/2008. Bikhchandani and Sharma (2001) classify herding into two categories: intentional and spurious. Information based (spurious) herding can simply develop as a result of market reaction to common information when investors face similar information sets and make rational decisions which are likely to be correlated. Intentional herding, on the other hand, is driven by cognitive bias according to the theory of behavioral finance and occurs when market participants opt to act irrationally (or rationally according to several theories) by imitating the actions of others.

The literature groups the drivers of such behavior into three categories. The first is information cascades which occur when an individual investor ignores his or her own private information and mimics the action of other investors (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992). The second is reputation-based herding, whereby investors imitate each other in order to preserve their reputation (Scharfstein and Stein, 1990; Truman, 1994 and Graham, 1999). The third group includes compensation based herding that arises when uninformed investors imitate each other's trades incentivized by the compensation schemes offered to them (Brennan, 1993). Apart from presenting a challenge to the concept of market efficiency, intentional herding, particularly by institutional investors, poses significant challenges to investors and policy makers as it has often been considered one of the sources of asset price bubbles and excessive volatility in financial markets. It can also be argued that intentional herding negatively affects the informational efficiency of the market, thus leading to market anomalies, as investors suppress their personal information and simply go along with the market consensus via correlated trades.

The booming literature on herding behavior has produced numerous studies, along with alternative models to detect such behavior, with applications to stock, bond and commodity markets both in the U.S. and internationally. The consensus is that such behavior is more prevalent during periods of market stress or of high volatility (e.g. Demiret et al., 2010; Lao and Singh, 2011; Balcilar et al., 2013, among others), while there is also evidence that herding can create excess volatility (Blasco, et al., 2012). In studies that focus particularly on institutional behavior, Walter and Weber (2006) document evidence of herding and positive-feedback trading among German mutual fund managers, while the findings in Sias (2004) show that institutional investors not only follow other institutional investors in the same security, but also follow their own prior trades in the same security. This study also notes that herding relates more to previous

institutional demand rather than lagged returns. Using a similar approach, Choi and Sias (2009) present evidence of industry herding, implying that institutional investors tend to follow each other in and out of the same industry. Challenging earlier findings on institutional investors, Li et al. (2016) show that herding behavior is more pronounced among individual investors rather than institutionals as the former group tends to rely more on public information and market sentiment. Similarly, Hsieh (2013) argues that institutional trading significantly improves stock price efficiency, while Balagoyzian and Cakan (2016) document limited evidence of herding during the technology bubble.

The literature on herding among institutional investors has primarily utilized tests based on holding data to detect herding. The most commonly used metric for herding in this regard is the measure by Lakonishok, Shleifer and Vishny (1992) (LSV) and Sias (2004) that is based on the changes in asset positions across investors in two consecutive periods. The main weakness of these models, however, is that they do not necessarily differentiate spurious herding and intentional herding, thereby providing an incomplete assessment of herd behavior. In this paper, we propose an alternative approach to detecting intentional herding via Geweke (1982) type causality tests that allow us to disentangle spurious herding from intentional herding by simultaneously examining bidirectional and instantaneous causality across portfolio positions. Geweke causality is commonly used in neuroscience studies to test the connectivity between different neural systems (Barnett et al., 2010; Zhang et al., 2010 and Friston et al., 2013) with few marcoeconomic applications (Calderon and Liu, 2003; Aizenman and Noy, 2006). This type of causality is particularly suitable in tests of intentional herding as it allows discarding the correlated signal that represents the reaction of investors to the same information. We test herding by examining the linear feedback (causality) in individual institutional investors' stock holdings and that of the aggregate market. As the test allows us to examine not only instantaneous causality, but also total correlation (lagged plus instantaneous), this approach is capable of differentiating spurious herding from intentional herding and thus provides a more meaningful assessment of herding.

Similar to the previous studies on institutional herding, our empirical tests utilize holding data, however this time, with a particular focus on large institutional investors and technology stocks. Large institutional investors (with at least \$1 billion under discretionary management) include mostly asset management companies, investment banks, brokers, private wealth management companies and other uncategorized investment companies that include pension funds, endowment funds, most of hedge funds and financial corporations. We particularly focus on the

technology industry as it is one of most volatile sectors in the United States with a higher market capitalization (Fidelity Investments) and has been considered the driver of technological transformations in the economy. We decompose linear dependence and feedback into three parts, thus allowing us to interpret the following research questions in the context of herding: (i) Do individual institutional investors' technology stock holdings granger cause that of the aggregate market? (ii) Does the aggregate market's technology stock holding granger cause individual institutional investors' stock holdings? (iii) Is there instantaneous causality or correlation between individual institutional investors' decisions to hold technology stock with the aggregate market's decisions?

Our analysis of quarterly holdings data for large independent investment advisors from January 1980 and September 2012 suggests that there is a tendency of individual institutional investors to mimic the actions of the rest of investors when it comes investment decisions on the technology industry. After controlling information based (spurious) herding, our tests show that 38% of large institutional investors tend to intentionally herd in technology stocks. Overall, the findings support the existing literature that investment decisions by large institutional investors are not only driven by fundamental information, but also by cognitive bias that is characterized by intentional herding. The remainder of the paper is organized as follows. In the next section, we describe the data and methodology used in this study. Section 3 follows with the presentation and discussion of the results, and Section 4 concludes.

2. Data and Methodology

2.1 Data

The empirical analysis utilizes quarterly holdings data for large independent investment advisors (e.g. asset management companies, investment banks and brokers) and other uncategorized investment firms (e.g. pension funds, endowment funds, most hedge funds and financial arms of corporations) from January 1980 and September 2012 (130 quarters). Data on institutional common stock holdings and transactions reported quarterly by financial institutions with \$100 million or more under management on their SEC 13(f) forms is obtained from the Thomson Reuters database. Since the main focus of the study is on institutional herding among large investors, following Zykaj et al. (2016) and Balagoyzyan and Cakan (2016), we limit our sample to large independent investment advisors and other uncategorized investment companies with at

least \$1 billion under discretionary management.¹ Furthermore, in order to avoid survivorship bias, we only include investors whose equity portfolios in September 2012 had at least 80 quarters of continuous data, leaving us with 115 investors in all.

2.2 Methodology

The testing methodology is based on Geweke (1982) type causality tests to detect dependence and feedback in time series, applied in this context to investors' technology portfolio stock holdings and that of the aggregate market. The methodology developed by Geweke (1982) tests linear dependence and feedback between two multiple time series X and Y in frequency domain; and linear dependence is decomposed into three parts; linear feedback from X to Y, linear feedback from Y to X and instantaneous linear feedback between X and Y. Geweke (1982) suggests the following approach to test linear dependence and feedback between two stationary time series X and Y.² Consider a bivariate vector autoregressive (VAR) model with two endogenous stationary time series variables X_t and Y_t observed at time $t=1, \dots, T$. The vector autoregressive (VAR) of order p can be written as:³

$$Z_t = \sum_{i=1}^p \Pi_i Z_{t-i} + v_t \quad (1)$$

where $E(v_t) = 0$ and $E(v_t v_s') = 0$ when $t \neq s$ and $E(v_t v_s') = \Sigma_v$ when $t = s$. The partition of the vector $Z_t : m \times 1$ into two vectors $X_t : k \times 1$ and $Y_t : l \times 1$ ($m = k + l$) is represented by the following equations:

$$X_t = \sum_{s=1}^p E_{2s} X_{t-s} + \sum_{s=1}^p F_{2s} Y_{t-s} + v_{1t}, \quad \text{var}(v_{1t}) = \Sigma_{11} \quad (2)$$

$$Y_t = \sum_{s=1}^p G_{2s} Y_{t-s} + \sum_{s=1}^p H_{2s} X_{t-s} + v_{2t}, \quad \text{var}(v_{2t}) = \Sigma_{22} \quad (3)$$

where v_{1t} is serially uncorrelated with v_{2t} . The variance-covariance matrix Ψ of the residuals

v_{1t} and v_{2t} is $\Psi = \text{var} \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix} = \begin{bmatrix} \Sigma_{11} & C \\ C' & \Sigma_{22} \end{bmatrix}$ and C is the covariance between v_{1t} and v_{2t} .

According to this specification, it can be said that "Y does not granger cause X" if the coefficients for the lags of (F_{2s}) are statistically insignificant, hence

¹ This dataset was also used in Reza, Sias, and Turtle (2016) and Balagoyzian and Cakan (2016).

² Note that Geweke (1982) causality approach requires the series to be stationary in wide-sense; have autoregressive representation, and they should be purely nondeterministic.

³ The optimal lag length is the same for series X_t and Y_t included in the VAR.

$$X_t = \sum_{s=1}^p E_{1s} X_{t-s} + \varepsilon_{1t}, \quad \text{var}(\varepsilon_{1t}) = \Sigma_{10}. \quad (4)$$

Similarly, X does not granger cause Y when all the coefficients of (H_{2s}) are not statistically significant, leading to Equation 3 written as a restricted model where y is influenced by its own lags only

$$Y_t = \sum_{s=1}^p G_{1s} Y_{t-s} + \varepsilon_{2t}, \quad \text{var}(\varepsilon_{2t}) = \Sigma_{20} \quad (5)$$

Geweke (1982) also derives the equations to test instantaneous linear feedback by first pre-multiplying the following matrix with the system of Equation (2) and (3)

$$\begin{bmatrix} I_k & -\Sigma_{12}\Sigma_{22}^{-1} \\ -\Sigma_{12}'\Sigma_{11}^{-1} & \Sigma_l \end{bmatrix}$$

and obtain the new system presented as:

$$X_t = \sum_{s=1}^p E_{3s} X_{t-s} + \sum_{s=0}^p F_{3s} Y_{t-s} + \eta_{1t}, \quad \text{var}(\eta_{1t}) = \Sigma_{13} \quad (6)$$

$$Y_t = \sum_{s=1}^p G_{3s} Y_{t-s} + \sum_{s=0}^p F_{3s} X_{t-s} + \eta_{2t}, \quad \text{var}(\eta_{2t}) = \Sigma_{23} \quad (7)$$

Using the residuals for the VAR estimates, Geweke (1982) demonstrates that the linear feedback between Y to X and X to Y, and the instantaneous linear feedback between X and Y can be tested for each hypothesis described below:⁴

H₀: “X does not granger cause Y”

$$F_{X \rightarrow Y} = \ln[\Sigma_{10} / \Sigma_{11}] \sim \chi_p^2 \quad (8)$$

H₀: “Y does not granger cause X”

$$F_{Y \rightarrow X} = \ln[\Sigma_{20} / \Sigma_{22}] \sim \chi_p^2 \quad (9)$$

H₀: “No instantaneous causality between X and Y”

$$F_{X,Y} = \ln(\Sigma_{11} \Sigma_{12} / |\Psi|) \sim \chi_1^2 \quad (10)$$

H₀: “No linear association between X and Y”

$$F_{X,Y} = \ln(|\Sigma_{10}| \times |\Sigma_{20}| / |\Psi|) \sim \chi_{(2p+1)}^2 \quad (11)$$

Following this specification, the total linear feedback between vectors X and Y can be obtained using the following combination: $F_{X,Y} = F_{X \rightarrow Y} + F_{Y \rightarrow X} + F_{X,Y}$.⁵

⁴ Note that all the tests follow the chi-square distribution asymptotically as indicated in Geweke (1982).

3. Results and Discussion

We start our analysis by examining the univariate characteristics of each investor's technology portfolio stock holdings and that of the aggregate market obtained by excluding each individual investor one at a time. The Augmented Dickey Fuller test (ADF) shows the two series to be nonstationary at level $I(1)$. As the implementation of Geweke (1982) approach requires the series to be stationary in a wide-sense, we difference both series once. We then test linear dependence and feedback using Geweke causality approach explained earlier. We use the stationary series to test herding behavior of investors as they represent overall short-run fluctuations in investors decisions to get in and out of technology stocks. Next, we carry out the estimation of VAR models for each set of investor's technology portfolio stock holdings and that of the aggregate market. The optimal lag lengths to include in the VARs models were chosen using both the Akaike information criteria (AIC) and final prediction error (FPE).

The results of the tests of linear dependence and feedback between the two series for each of the 115 large institutional investors are presented in Table 1. As explained earlier, the causality tests provide inference on whether there is a causal relationship running between individual institutional investors' technology stock holdings to the aggregate market or vice versa. In the context of herding, evidence of such causality may be a manifestation of herding behavior as investors base their investment decisions on market consensus. Similarly, instantaneous causality along with bidirectional causality between individual institutional investor stock holdings and the rest of the market implies correlated behavior of all institutional investors to hold technology stock.

We observe in Table 1 that the majority of institutional investors (barring 12 cases) in the sample make similar decisions as the null of no instantaneous feedback is rejected at least at the 10 percent level of significance. In addition, no bidirectional causality between the individual institutional technology stock holdings and the rest of the market is rejected at least at the 10% level of significance in 34 out of 115 (30 percent) cases. This implies that investors react to the same information, consistent with the definition of spurious herding. In the case of unidirectional causality, however, the results point to the presence of intentional herding, as we observe causal links from individual investors' stock holdings to the rest of investors in 44 out of 115 cases (38 percent) at the 10 percent level of significance. At the same time, 14 out of 115

⁵ STATA command "gwke82" implemented by Dicle and Levendis (2013) is used for the estimations.

investors are found to be independent in their decision making, as implied by insignificance in total correlation. Overall, our findings largely points to the presence of spurious herding driven by the market's reaction to common information, while intentional herding is also found to play an important role on the investment decisions by institutional investors in technology stocks.

4. Conclusion

This paper contributes to the herding literature from a different perspective by proposing an alternative methodology to detect herding via causality tests applied to stock holdings data. Unlike most commonly used methodologies to detect herding, the causality based approach allows us to distinguish intentional herding from spurious herding by accounting for correlated behavior that can be driven by the reaction of investors to common information. Using data on the technology stock holdings of 115 large institutional investors, we find (i) no clear evidence of individual investors to Granger cause the rest of the investors' technology stock holdings; (ii) evidence of instantaneous causality that is indicative of spurious herding via correlated trades; and (iii) evidence of intentional herding as the aggregate market's stock holdings is found to Granger cause individuals' stock holdings. Overall, the findings show that despite the significant presence of spurious herding that can be considered rational, a significant percentage of investors in the technology industry also tend to herd intentionally. This means that investment decisions by large institutional investors are not only driven by fundamental information, but also by cognitive bias that is characterized by intentional herding.

References

- Aizenman, J. and Noy, I. (2006). FDI and Trade--Two-Way Linkages? *The Quarterly Review of Economics and Finance* 46(3): 317-337.
- Balagoyzian, A. and Cakan, E. (2016). Did large institutional investors flock into the technology herd? An empirical investigation using a vector Markov-switching model. *Applied Economics* 48(58):5731-5747.
- Balcilar, M., Demirer, R., Hammoudeh, S. 2013. Investor herds and regime-switching: Evidence from Gulf Arab stock markets. *Journal of International Financial Markets, Institutions & Money* 23, 295-321.
- Banerjee, A. (1992). A simple model of herd behavior. *Quarterly Journal of Economics* 107: 797-817.
- Barberis, N., Shleifer, A., and Vishny, R. (1998). A Model of Investor Sentiment. *Journal of Financial Economics* 49: 307-343.
- Barnett, L., Barrett, A. B., and Seth, A. K. (2009). Granger causality and transfer entropy are equivalent for Gaussian variables. *Physical review letters* 103(23): 238701.
- Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascade. *Journal of Political Economy* 100 (5): 992-1026.
- Bikhchandani, S., Sharma, S. (2001). Herd behaviour in financial markets. *IMF Staff Papers* 47(3): 279-310.
- Blasco, N., Corredor, P., & Ferreruela, S. 2012. Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, 12(2), 311-327.
- Brennan, M. (1993). Agency and asset pricing, Unpublished manuscript, UCLA and London Business School.
- Brunnermeier, M. and Nagel, S. (2004). Hedge funds and the technology bubble. *Journal of Finance* 59(5): 2013-2040.
- Calderón, C., and Liu, L. (2003). The direction of causality between financial development and economic growth. *Journal of Development Economics* 72(1): 321-334.
- Choi, N. and Sias, R. W. (2009). Institutional industry herding. *Journal of Financial Economics* 94(3): 469-491.
- Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998). Investor Psychology and Security Market under- and overreactions. *Journal of Finance* 53 (6): 1839-1885.
- De Bondt, W.F. M, and Thaler, R. (1985). Does the stock market overreact? *The Journal of finance* 40.3 (1985): 793-805.
- Del Brio, E. B., Miguel, A. and Perote, J. (2002). An Investigation of Insider Trading Profits in the Spanish Stock Market. *The Quarterly Review of Economics and Finance* 42: 73-94.
- Demirer, R., Kutan, A. & Chen, C. 2010. Do Investors Herd in Emerging Stock Markets? Evidence from the Taiwanese Market. *Journal of Economic Behavior & Organization*, 76, 283-295.
- Dicle, Mehmet F and Levendis, John. (2013) Estimating Gewekes(1982) Measure of Instantaneous Feedback. *Stata Journal* 13 (1):136-140
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance* 25 (2) 383-417.

- Fama, E. F. and French, K. R. (1988). Dividend Yields and Expected Stock Returns. *Journal of Financial Economics* 22: 3-25.
- Friston, K., Moran, R. and Seth, A. K. (2013). Analysing connectivity with Granger causality and dynamic causal modelling. *Current Opinion in Neurobiology* 23(2): 172-178.
- Geweke, John (1982) . Measurement of linear dependence and feedback between multiple time series. *Journal of the American Statistical Association* 77 (378): 304-313
- Graham, J.R. (1999). Herding among Investment Newsletters: Theory and Evidence. *Journal of Finance* 54:237–268.
- Grossman, S. J. and Stiglitz, J. E. (1980). On the impossibility of informationally Efficient Markets. *The American Economic Review* 70(3): 393-408.
- Howe, J. S. (1986). Evidence on stock market overreaction. *Financial Analysts Journal* 42(3): 74–77.
- Hsieh, S-F. (2013). Individual and institutional herding and the impact on stock returns: Evidence from Taiwan stock market. *International Review of Financial Analysis* 29: 175-188.
- Jaffe, J. (1974). Special information and insider trading. *Journal of Business* 47:411–428.
- Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* 48:65–91.
- Lakonishok, J. , Shleifer, A. and Vishny, R. W. (1992). The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics* 32: 23-43.
- Lao, P., Singh, H., 2011. Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics* 22, 495–506.
- Lo, A. W. , Mamaysky, H. and Wang, J. (2000). Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. *Journal of Finance* 4: 1705-1765.
- Ofek, E. and Richardson, M. (2003). DotCom mania: The rise and fall of internet stock prices. *Journal of Finance* 58, 1113-1137.
- Scharfstein, D. and Stein, J. (1990). Herd Behavior and Investment. *American Economic Review* 80 (3): 465-479.
- Shiller, R. (2000). Irrational Exuberance. Princeton University Press, Princeton.
- Shiller, R. J. (2002). Bubbles, human judgment, and expert opinion. *Financial Analysts Journal* 58(3), 18-26.
- Sias, R. (2004). Institutional herding. *Review of Financial Studies* 17:165–206.
- Soares, J.V. and Serra, A.P. (2005). Over-reaction and Underreaction: Evidence for the Portuguese Stock Market. *Caderno de Valores Mobiliarios*, 22:55-84.
- Trueman, B. (1994). Analyst Forecasts and Herding Behavior. *Review of Financial Studies* 7 (1): 97-124.
- Tversky, A and Kahneman, D (1994). Judgment under Uncertainty: Heuristics and Biases. *Sciences* 185(4157): 1124-1131
- Walter, A. and Weber, F. M. (2006) Herding in the German Mutual Fund Industry. *European Financial Management* 12: 375-406.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance* 54 : 581–622.

Zhang, L., Zhong, G., Wu, Y., Vangel, M. G., Jiang, B., and Kong, J. (2010). Using Granger-Geweke causality model to evaluate the effective connectivity of primary motor cortex (M1), supplementary motor area (SMA) and cerebellum. *Journal of biomedical science and engineering* 3, 848.

Zyckaj, B., Sias, R. and Turtle, H. J. (2016). Hedge Fund Crowds and Mispricing. *Management Science* 62: 764–784.

Table 1: Geweke (1982) causality test

Portfolio	Lags	Granger causation H ₀ : "Does not Granger cause"		Instantaneous Feedback: H ₀ : "No instantaneous causality between the two series"	Total correlation H ₀ : "No linear association between two series"
		Investor->Market	Market->investor		
260	3	3.5091(0.3196) $\chi^2(3)$	6.7244 (0.0812) * $\chi^2(3)$	133.5430(0.0000) *** $\chi^2(1)$	143.7765(0.0000) *** $\chi^2(7)$
885	2	0.2738(0.8721) $\chi^2(2)$	5.0898(0.0785) * $\chi^2(2)$	40.1794(0.0000) *** $\chi^2(1)$	45.5429(0.0000) *** $\chi^2(5)$
1300	5	14.0813(0.0151) ** $\chi^2(5)$	18.8182(0.0021) *** $\chi^2(5)$	17.8612(0.000) *** $\chi^2(1)$	50.7607(0.0000) *** $\chi^2(11)$
4690	2	3.8231(0.1478) $\chi^2(2)$	0.5263(0.7686) $\chi^2(2)$	0.0295(0.8636) $\chi^2(1)$	4.3789(0.4962) $\chi^2(5)$
4850	4	10.5057(0.0327) ** $\chi^2(4)$	4.0283(0.4022) $\chi^2(4)$	63.4062(0.0000) *** $\chi^2(1)$	77.9403(0.0000) *** $\chi^2(9)$
4900	2	0.1596(0.9233) $\chi^2(2)$	9.0587(0.0108) ** $\chi^2(2)$	80.4207(0.0000) *** $\chi^2(1)$	89.6390(0.0000) *** $\chi^2(5)$
8100	2	1.9865(0.3704) $\chi^2(2)$	4.3421(0.1141) $\chi^2(2)$	0.9862(0.3207) $\chi^2(1)$	7.1236(0.1983) ** $\chi^2(5)$
8240	2	0.6724(0.7145) $\chi^2(2)$	7.1236(0.0284) ** $\chi^2(2)$	33.4315(0.0000) *** $\chi^2(1)$	41.2276(0.0000) *** $\chi^2(5)$
8250	2	2.8028(0.2463) $\chi^2(2)$	6.0937(0.0475) ** $\chi^2(2)$	7.9346(0.0048) *** $\chi^2(1)$	16.8311(0.0048) *** $\chi^2(5)$
9400	2	1.5930(0.4509) $\chi^2(2)$	5.3672(0.0683) * $\chi^2(2)$	51.2247(0.0000) *** $\chi^2(1)$	58.1849(0.0000) *** $\chi^2(5)$
10465	8	24.7009(0.0017) *** $\chi^2(8)$	35.1852(0.0000) *** $\chi^2(8)$	22.6308(0.0000) *** $\chi^2(1)$	82.5169(0.0000) *** $\chi^2(17)$
11800	4	1.5067(0.8255) $\chi^2(4)$	16.9928(0.0019) *** $\chi^2(4)$	34.4685(0.0000) *** $\chi^2(1)$	52.9680(0.000) *** $\chi^2(9)$
12160	4	5.2776(0.2600) $\chi^2(4)$	30.1455(0.0000) *** $\chi^2(4)$	18.0662(0.0000) *** $\chi^2(1)$	53.4893(0.0000) *** $\chi^2(9)$
12280	2	1.2488(0.5356) $\chi^2(2)$	6.3089(0.0427) ** $\chi^2(2)$	26.4346(0.0000) *** $\chi^2(1)$	33.9923(0.0000) *** $\chi^2(5)$
12480	3	14.8190(0.0020) *** $\chi^2(3)$	5.4718(0.1403) $\chi^2(3)$	65.7909(0.0000) *** $\chi^2(1)$	86.0817(0.0000) *** $\chi^2(7)$
16120	8	28.5298(0.0004) *** $\chi^2(8)$	19.3426(0.0131) ** $\chi^2(8)$	73.7510(0.0000) *** $\chi^2(1)$	121.6234(0.0000) *** $\chi^2(17)$
16180	2	1.0518(0.5910) $\chi^2(2)$	3.7573(0.1528) $\chi^2(2)$	73.4450(0.0000) *** $\chi^2(1)$	78.2541(0.0000) *** $\chi^2(5)$
18740	2	1.0159(0.6017) $\chi^2(2)$	8.8485(0.0120) ** $\chi^2(2)$	142.8800(0.0000) *** $\chi^2(1)$	152.7444(0.0000) *** $\chi^2(5)$
21350	2	3.0011(0.2230) $\chi^2(2)$	11.2909(0.0035) *** $\chi^2(2)$	6.3501(0.0117) ** $\chi^2(1)$	20.6421(0.0009) *** $\chi^2(5)$
22300	4	7.2434(0.1236) $\chi^2(4)$	17.4893 (0.0016) *** $\chi^2(4)$	144.1016(0.0000) *** $\chi^2(1)$	168.8344(0.0000) *** $\chi^2(9)$
22620	2	6.1846(0.0454) ** $\chi^2(2)$	8.3708(0.0152) ** $\chi^2(2)$	15.3263(0.0001) *** $\chi^2(1)$	29.8816(0.0000) *** $\chi^2(5)$
23000	2	2.4657(0.2915) $\chi^2(2)$	7.5527(0.0229) ** $\chi^2(2)$	145.6524(0.0000) *** $\chi^2(1)$	155.6708(0.0000) *** $\chi^2(5)$

23270	3	7.0139(0.0715) *	16.5915(0.0009) ***	8.2250(0.0041) **	31.8305(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
23800	3	2.5426(0.4676)	16.1691(0.0010) ***	38.1601(0.0000) ***	56.8719(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
24310	2	5.0889(0.0785) *	7.2929(0.0261) **	103.6243(0.0000) ***	116.0061(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
26455	3	10.1839(0.0171) **	15.6477(0.0013) **	216.9020(0.0000) ***	242.7336(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
27330	2	0.7545(0.6857)	9.9952(0.0068) ***	103.7865(0.0000) ***	114.5362(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
27500	2	9.9575(0.0069) ***	25.8314(0.0000) ***	39.9882(0.0000) ***	75.7771(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
27800	2	5.1647(0.0756) *	7.2673(0.0264) **	98.2879(0.0000) ***	110.7199(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
27900	3	6.0629(0.1086)	10.0830(0.0179) **	17.9898(0.0000) ***	34.1357(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
27940	2	9.8268(0.0073) ***	4.1328(0.1266)	6.0593(0.0138) **	20.0189(0.0012) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
28050	2	1.2268(0.5415)	6.8797(0.0321) **	77.9693(0.0000) ***	86.0757(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
29285	5	71.4393(0.0000) ***	32.4444(0.0000) ***	119.8791(0.0000) ***	223.7627(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
29900	2	1.5473(0.4613)	4.2313(0.1206)	80.4144(0.0000) ***	86.1929(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
30095	3	3.7930(0.2847)	14.6432(0.0021) **	25.9005(0.0000) ***	44.3367(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
36765	3	4.5956(0.2039)	15.4278(0.0015) ***	8.9403(0.0028) ***	28.9637(0.0001) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
36830	8	29.5326(0.0003) ***	53.7852(0.0000) ***	19.0003(0.0000) ***	102.3182(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
39300	2	1.6422(0.4399)	2.0503(0.3587)	66.3319(0.0000) ***	70.0244(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
39400	2	1.6827(0.4311)	0.3316(0.8472)	18.8835(0.0000) ***	20.8978(0.0008) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
39530	2	0.3350(0.8458)	0.2520(0.8816)	48.8808(0.0000) ***	49.4678(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
39580	6	37.9730(0.0000) ***	2.4575(0.8732)	23.1928(0.0000) ***	63.6232(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
40480	7	29.2730(0.0001) ***	65.9144(0.0000) ***	20.6153(0.0000) ***	115.8027(0.0000) ***
		$\chi^2(7)$	$\chi^2(7)$	$\chi^2(1)$	$\chi^2(15)$
41145	4	5.9885(0.2000)	9.3000(0.0540) *	106.9554(0.0000) ***	122.2440(0.0000) ***
		$\chi^2(4)$	$\chi^2(4)$	$\chi^2(1)$	$\chi^2(9)$
41300	6	16.0492(0.0135) **	16.2757(0.0123) **	100.2034(0.0000) ***	132.5283(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
41500	5	6.8485(0.2322)	18.6852(0.0022) ***	37.1096(0.0000) ***	62.6433(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
42200	2	0.5753(0.7500)	1.2571(0.5334)	0.0535(0.8172)	1.8858(0.8647)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
43350	2	6.7440(0.0343) **	16.7250(0.0002) ***	42.0423(0.0000) ***	65.5113(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$

		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
43485	4	6.0133(0.1982)	5.2281(0.2647)	0.0846(0.7711)	11.3260(0.2540)
		$\chi^2(4)$	$\chi^2(4)$	$\chi^2(1)$	$\chi^2(9)$
43885	2	1.4891(0.4750)	7.3712(0.0251) **	99.4894(0.0000) ***	108.3496(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
44700	2	0.2534(0.8810)	0.1335(0.9354)	42.5589(0.0000) ***	42.9458(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
45495	5	33.5369(0.0000) ***	48.5811(0.0000) ***	17.6040(0.0000) ***	99.7220(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
45590	3	24.8670(0.0000) ***	14.6145(0.0022) **	185.8132(0.0000) ***	225.2947(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
47320	3	4.6497(0.1993)	16.1545(0.0011) ***	3.2254(0.0725) *	24.0297(0.0011) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
47650	2	0.4109(0.8143)	4.6552(0.0975) *	9.2239(0.0024) ***	14.2899(0.0139) **
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
47833	2	1.3407(0.5115)	4.2666(0.1184)	61.9777(0.0000) ***	67.5850(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
48170	6	21.2106(0.0017) ***	4.8776(0.5596)	37.9604(0.0000) ***	64.0486(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
48360	2	3.4029(0.1824)	7.9950(0.0184) **	44.9043(0.0000) ***	56.3022(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
49050	3	3.4626(0.3257)	28.8512(0.0000) ***	35.6015(0.0000) ***	67.9152(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
50050	2	2.4390(0.2954)	22.7253(0.0000) ***	11.3160(0.0008) ***	36.4803(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
50100	6	9.4477(0.1499)	28.3450(0.0001) ***	53.9729(0.0000) ***	91.7655(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
51795	2	0.1030(0.9498)	0.4888(0.7832)	5.2920(0.0214) **	5.8838(0.3177)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
51870	2	4.0635(0.1311)	8.8944(0.0117) **	60.3935(0.0000) ***	73.3513(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
52130	8	32.1951(0.0001) ***	17.4142(0.0261) **	57.8322(0.0000) ***	107.4415(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
52600	2	2.6607(0.2644)	1.7494(0.4170)	147.5024(0.0000) ***	151.9124(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
53000	3	0.6312(0.8893)	1.8054(0.6138)	83.6658(0.0000) ***	86.1024(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
53300	2	0.3354(0.8456)	2.2057(0.3319)	0.0598(0.8068)	2.6010(0.7612)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
53625	2	1.3931(0.4983)	5.4941(0.0641) *	58.0270(0.0000) ***	64.9142(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
54000	5	5.8015(0.3260)	19.6970(0.0014) ***	34.5466(0.0000) ***	60.0451(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
54600	5	12.7091(0.0263) **	10.6629(0.0585) *	127.1929(0.0000) ***	150.5649(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
55140	2	7.4864(0.0237) **	8.0425(0.0179) **	32.3398(0.0000) ***	47.8688(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
57070	3	11.4531(0.0095) ***	8.5263(0.0363) **	167.8652(0.0000) ***	187.8446(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$

57200	2	5.7114(0.0575) *	24.0323(0.0000) ***	41.1292(0.0000) ***	70.8729(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
57500	2	3.0536(0.2172)	9.3701(0.0092) ***	96.8252(0.0000) ***	109.2489(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
58500	2	0.3073(0.8576)	1.6205(0.4448)	16.0736(0.0001) ***	18.0013(0.0029) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
58950	8	5.5764(0.0615) **	14.6629(0.0007) ***	121.6790(0.0000) ***	141.9183(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
59500	2	12.2997(0.0021) ***	1.5989(0.4496)	65.6176(0.0000) ***	79.5163(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
60500	2	1.8666(0.3933)	0.0636(0.9687)	16.7124(0.0000) ***	18.6426(0.0022) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
63050	3	15.1576(0.0017) ***	11.3007(0.0102) **	119.0069(0.0000) ***	145.4651(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
64200	6	52.3856(0.0000) ***	69.6489(0.0000) ***	8.2695(0.0040) ***	130.3039(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
64400	3	23.5865(0.0000) ***	10.7864(0.0129) *	55.0533(0.0000) ***	89.4263(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
66635	2	0.1684(0.9192)	3.0460(0.2181)	158.9676(0.0000) ***	162.1821(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
67600	3	4.6478(0.1995)	10.6339(0.0139) *	68.5540(0.0000) ***	83.8357(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
69100	2	3.1718(0.2048)	8.9412(0.0114) *	22.4252(0.0000) ***	34.5382(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
70590	2	1.2844(0.5261)	6.4350(0.0401) **	63.7509(0.0000) ***	71.4703(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
71110	2	0.6705(0.7152)	4.6917(0.0958) *	158.5872(0.0000) ***	163.9494(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
71200	8	38.5521(0.0000) ***	13.4585(0.0970) *	44.4818(0.0000) ***	96.4923(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
72400	2	0.7884(0.6742)	16.6035(0.0002) ***	104.4345(0.0000) ***	121.8264(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
72480	8	26.6564(0.0008) ***	9.9801(0.2664)	65.3333(0.0000) ***	101.9697(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
72750	2	0.1007(0.9509)	0.8297(0.6604)	3.1920(0.0740) *	4.1224(0.5319)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
74530	4	9.1782(0.0568) *	14.5316(0.0058) ***	11.7453(0.0006) ***	35.4550(0.0000) ***
		$\chi^2(4)$	$\chi^2(4)$	$\chi^2(1)$	$\chi^2(9)$
75075	2	1.2055(0.5473)	1.2904(0.5246)	0.3283(0.5667)	2.8242(0.7271)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
76045	6	9.8485(0.1312)	27.5243(0.0001) ***	50.6507(0.0000) ***	88.0235(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(9)$
78500	2	1.7546(0.4159)	0.6613(0.7185)	0.9929(0.3190)	3.4088(0.6372)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
78993	3	3.6975(0.2960)	0.6854(0.8766)	99.7413(0.0000) ***	104.1241(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
79010	2	0.9627(0.6179)	2.6941(0.2600)	0.0785(0.7793)	3.7353(0.5881)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
79350	2	4.8780(0.0873) *	16.6715(0.0002) ***	43.6126(0.0000) ***	65.1621(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$

		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
79400	2	1.4000(0.4966)	0.6826(0.7108)	1.3157(0.2514)	3.3983(0.6388)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
79600	8	34.6918(0.0000) ***	10.6989(0.2193)	0.3070(0.5795)	45.6977(0.0002) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
81860	4	5.5356(0.2366)	27.4952(0.0000) ***	29.9413(0.0000) ***	62.9721(0.0000) ***
		$\chi^2(4)$	$\chi^2(4)$	$\chi^2(1)$	$\chi^2(9)$
81900	2	2.5290(0.2824)	2.9702(0.2265)	2.0513(0.1521)	7.5505(0.1828)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
82080	4	12.6086(0.0134) **	16.5483(0.0024) ***	30.0850(0.0000) ***	59.2419(0.0000) ***
		$\chi^2(4)$	$\chi^2(4)$	$\chi^2(1)$	$\chi^2(9)$
82615	3	5.1468(0.1614)	7.1292(0.0679) *	56.6341(0.0000) ***	68.9102(0.0000) ***
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
82690	5	15.6778(0.0078) **	7.0360(0.2180)	75.8431(0.0000) ***	98.5569(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
83360	2	1.2403(0.5379)	6.8280(0.0329) **	128.0621(0.0000) ***	136.1304(0.0000) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
83900	5	9.8409(0.0799) *	13.1371(0.0221) **	33.8120(0.0000) ***	56.7899(0.0000) ***
		$\chi^2(5)$	$\chi^2(5)$	$\chi^2(1)$	$\chi^2(11)$
85640	2	0.2264(0.8930)	3.4431(0.1788)	5.0739(0.0243) **	8.7434(0.1197)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
85680	3	6.9027(0.0751) *	0.5159(0.9154)	0.8017(0.3706)	8.2203(0.3136)
		$\chi^2(3)$	$\chi^2(3)$	$\chi^2(1)$	$\chi^2(7)$
89180	8	46.7618(0.0000) ***	63.0436(0.0000) ***	31.9812(0.0000) ***	141.7866(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
90300	4	5.5996 (0.2311)	16.5435(0.0024) ***	63.5346(0.0000) ***	85.6778(0.0000) ***
		$\chi^2(4)$	$\chi^2(4)$	$\chi^2(1)$	$\chi^2(9)$
91480	2	0.0860(0.9579)	0.2388(0.8874)	3.5751(0.0587) *	3.8999(0.5639)
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
91845	6	24.2385(0.0005) ***	11.2341(0.0814) *	174.7216(0.0000) ***	210.1942(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
91910	8	24.7781(0.0017) ***	23.6657(0.0026) ***	128.5638(0.0000) ***	177.0077(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$
92060	6	34.9802(0.0000) ***	12.1855(0.0580) **	35.1327(0.0000) ***	82.2984(0.0000) ***
		$\chi^2(6)$	$\chi^2(6)$	$\chi^2(1)$	$\chi^2(13)$
92200	2	3.3845(0.1841)	3.6945(0.1577)	18.2400(0.0000) ***	25.3190(0.0001) ***
		$\chi^2(2)$	$\chi^2(2)$	$\chi^2(1)$	$\chi^2(5)$
93405	8	10.7455(0.2165)	11.6932(0.1654)	132.1444(0.0000) ***	154.5831(0.0000) ***
		$\chi^2(8)$	$\chi^2(8)$	$\chi^2(1)$	$\chi^2(17)$

Note: ***, **, and * represent rejection of the null at 1%, 5% and 10% levels of significance, respectively.