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

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ABSTRACT

This paper examines intentional herding among institutional investors with a particular focus on the technology sector that was the driver of the "New Economy" in the United States during the dot-com bubble of the 1990s. Using data on technology stockholdings of 115 large institutional investors, we 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, we use Geweke (1982) type causality tests that allow us to disentangle spurious herding from intentional herding via tests of bidirectional and instantaneous causality across portfolio positions in technology stocks. After controlling information based (spurious) herding, our tests show that 38 percent of large institutional investors tend to intentionally herd in technology stocks. 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

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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, Hirsheifer 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. Demirer 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 institutional 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 Balagyozyan 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 macroeconomic 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 Balagyozyan 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. Furthermore, in order to avoid survivorship bias, we only include investors whose equity portfolios had at least 80 quarters of continuous data as of September 2012, 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 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.[1] Consider a bivariate vector autoregressive (VAR) model with two endogenous stationary time series variables X_t and Y_t observed at time t=1, …, T. The vector autoregressive (VAR) of order p can be written as:[2]

$$Z_t = \sum_{i=1}^{P} \Pi_i Z_{t-1} + v_t \tag{1}$$

where $E(v_t)=0$ and $E(v_t v_s^{'})=0$ when t≠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:

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

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

where v_{1t} is serially uncorrelated with v_{2t}. The variance-covariance matrix Ψ of the residuals v_{1t} and v_{2t} is $\Psi = \mathrm{var}\begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix} = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$ and Σ_{12} is the covariance between v_{1t} and v_{2t} and Σ_{21} is the covariance between v_{2t} and v_{1t}.

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

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

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

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

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

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 stated as

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

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

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 stated below:[3]

H_0: " X does not granger cause Y "

$$F_{X \to Y} = \ln\left[\Sigma_{10} / \Sigma_{11}\right] \sim \chi_p^2 \tag{8}$$

H_0: "Y does not granger cause X"

$$F_{Y \to X} = \ln\left[\Sigma_{20} / \Sigma_{22}\right] \sim \chi_p^2 \tag{9}$$

H_0: "No instantaneous causality between X and Y"

$$F_{X.Y} = \ln\left(\Sigma_{11} . \Sigma_{12} / \left|\Psi\right|\right) \sim \chi_1^2 \tag{10}$$

H_0: "No linear association between X and Y"

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

Following this specification, the total linear feedback between vectors X and Y can be obtained using the following combination: $F_{X,Y} = F_{X \to Y} + F_{Y \to X} + F_{X.Y}$.[4]

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

Unlike the Granger (1969) causality approach which assumes a simple causal model that mainly tests how the past values of a time series can be used to predict the current values of another time series, the Geweke (1982) causality approach not only tests the simple causal model which represents intentional herding, but also instantaneous causality that can be attributed to spurious herding. Instantaneous causality differs from the simple causal model by incorporating the current values of a time series in predicting the current values of another time series. Since spurious herding relates to the common reaction of market participants to fundamental information that is publicly available, one can argue that this aspect of Geweke causality can be utilized to capture spurious herding by detecting commonalities in asset holdings across institutional investors at a given time point.

Granger (1969) considers the inclusion of instantaneous causality in tests of causal relationships between time series to depend on the frequency of the data examined. For instance, if one uses high frequency data, it is unlikely to observe instantaneous causality as the information adjustment is very slow. In our case, using quarterly frequency data, we expect the institutional investors' decision to hold technology stocks to be rational as they have enough time to use current and past information to make a decision on their technology stock positions. To that end, the use of instantaneous causality to test spurious herding is justified as the reaction of institutional investors' technology stock holdings on the same fundamental information can be captured via instantaneous causality. As mentioned in the paper, the Geweke (1982) causality approach has already been utilized in other contexts (e.g. neuroscience studies). In our case, it offers a useful framework in the context of herding behavior as after controlling for instantaneous causality (i.e. spurious herding), the remaining simple causal model represents intentional herding, which in our case relates to the causal effect of the aggregate market's technology stock positions over individual institutional investors' technology stock holdings.

To the best of our knowledge, this is the first attempt to use Geweke's (1982) approach in behavioral finance to analyze herding in technological stocks, although the method has been used to explore causal relationships across commodity, currency and equity markets (Christner and Dicle, 2011), and hedging in currency and stock markets (Christner et al., 2013). Multivariate extensions of this approach based on directed acyclic graph and Bayesian graphical VARs have also been recently applied in energy finance (Ji, 2012; Ji and Fan, 2015, 2016) and in studies of economic and financial market uncertainties (Balcilar et al., 2016; Bouri et al., forthcoming).

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[4] STATA command **"**gwke82**"** implemented by Dicle and Levendis (2013) is used for the estimations.

3. Empirical Results

As mentioned earlier, the causality approach of Geweke (1982) not only allows to test the simple causal model that explores the predictive power of past values of a time series over the current values of another time series, but also to examine instantaneous causality by incorporating the current value of a time series to predict the current value of another time series. In our context, we associate instantaneous causality with spurious herding as instantaneous causality relates to the commonalities in technology stock holdings across institutional investors at a given time point driven by their reaction to the same, publicly available fundamental information. On the other hand, following the argument by Bikhchandani and Sharma (2001), intentional herding relates more to causality between individual investors' investment choices and that of the aggregate market as this form of herding occurs as investors suppress their personal beliefs and go with the market consensus. Therefore, we use the remaining simple causal model to represent intentional herding, which in our case relates to the causal effect of the aggregate market's technology stock holdings over that of individual institutional investors. We examine the each institutional investor's technology stock holdings series and that of the aggregate market obtained by excluding each individual investor one at a time.

We first test the stationarity of the stock holding series by using the Augmented Dickey Fuller test (ADF) and find that all of the series have unit roots. As the implementation of Geweke (1982) approach requires the series to be stationary in a wide-sense, we take the first differences of all series. Next, we apply the VAR methodology for each set of investor's technology stock holdings and that of the aggregate market. Akaike information criteria (AIC) and final prediction error (FPE) are used to find the optimal lag lengths to be included in the VAR models. We then test linear dependence and feedback via Geweke causality approach applied to stationary series and test herding behavior based on their investment positions in technology stocks.

The causality test results presented in Panel A of Table 1 provide inference on whether there is a causal relationship running from 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 intentional herding behavior as investors base their investment decisions on the market consensus, driving causal links between aggregate and individual investors' stock holdings. Examining the findings for causality from individual investors' holdings to the aggregate market shown in column (1) in Panel A, we observe causality from individual investors' stock holdings to the rest of the investors in 44 out of 115 cases (38 percent) at the 10 percent level of significance. On the other hand, we reject the null of no causality from the aggregate market to the individual investors in 76 out of 115 cases (65 percent) at 10 percent significance level (column 2), implying the presence of intentional herding behavior per the arguments in Bikhchandani and Sharma (2001). The evidence of causality from individual investors to the aggregate market, although relatively weaker than the opposite direction, might indicate the presence of 'informed' traders in the market that other traders choose to follow, thus leading to causal effects running from individual investors to the aggregate market. However, the strong evidence of causality in the opposite direction running from the aggregate market to individual investors' holdings is consistent with the market consensus serving as the driver of decision making at the individual level, consistent with the arguments for intentional herding.

Next, we apply unidirectional causality tests in order to help us disentangle intentional herding from spurious herding by checking causal links of one series with past lags, as discussed earlier. However, these unidirectional causality tests do not allow us to determine whether what we observe is spurious herding. In order to differentiate spurious herding from intentional herding, we follow Geweke test, as explained earlier, and test the presence of instantaneous causality from one series to another. The results from tests of linear dependence and feedback for each of the 115 large institutional investors are reported in Panels B and C in Table 1. We observe in Panel B that the majority of institutional investors (except 12 cases out of 115) make similar decisions as the null of no instantaneous feedback is largely rejected at 10 percent level of significance. The strong evidence of instantaneous causality is consistent of the presence of spurious herding driven by investors' common reaction to publicly available information. These arguments are further supported by the findings in Panel C suggesting that a very small percentage of investors (14 out of 115) act independently in their decision making, as implied by insignificance in total correlation. This implies the presence of correlated trading behavior in technology stocks in market-wide scale, further supporting the presence of intentional herding.

Overall, our findings point 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 tends 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.

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Table 1: Geweke (1982) causality tests

Portfolio	Lags	**Panel A:** Granger causation H0: "Does not Granger cause" (1) Investor->Market	(2) Market->investor	**Panel B:** Instantaneous Feedback: H0: "No instantaneous causality between the two series" (3)	**Panel C:** Total correlation H0:" No linear association between two series" (4)
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) * $\chi^2(3)$	16.5915(0.0009) *** $\chi^2(3)$	8.2250(0.0041) ** $\chi^2(1)$	31.8305(0.0000) *** $\chi^2(7)$
23800	3	2.5426(0.4676) $\chi^2(3)$	16.1691(0.0010) *** $\chi^2(3)$	38.1601(0.0000) *** $\chi^2(1)$	56.8719(0.0000) *** $\chi^2(7)$
24310	2	5.0889(0.0785) * $\chi^2(2)$	7.2929(0.0261) ** $\chi^2(2)$	103.6243(0.0000) *** $\chi^2(1)$	116.0061(0.0000) *** $\chi^2(5)$
26455	3	10.1839(0.0171) ** $\chi^2(3)$	15.6477(0.0013) ** $\chi^2(3)$	216.9020(0.0000) *** $\chi^2(1)$	242.7336(0.0000) *** $\chi^2(7)$
27330	2	0.7545(0.6857) $\chi^2(2)$	9.9952(0.0068) *** $\chi^2(2)$	103.7865(0.0000) *** $\chi^2(1)$	114.5362(0.0000) *** $\chi^2(5)$
27500	2	9.9575(0.0069) *** $\chi^2(2)$	25.8314(0.0000) *** $\chi^2(2)$	39.9882(0.0000) *** $\chi^2(1)$	75.7771(0.0000) *** $\chi^2(5)$
27800	2	5.1647(0.0756) * $\chi^2(2)$	7.2673(0.0264) ** $\chi^2(2)$	98.2879(0.0000) *** $\chi^2(1)$	110.7199(0.0000) *** $\chi^2(5)$
27900	3	6.0629(0.1086) $\chi^2(3)$	10.0830(0.0179) ** $\chi^2(3)$	17.9898(0.0000) *** $\chi^2(1)$	34.1357(0.0000) *** $\chi^2(7)$
27940	2	9.8268(0.0073) *** $\chi^2(2)$	4.1328(0.1266) $\chi^2(2)$	6.0593(0.0138) ** $\chi^2(1)$	20.0189(0.0012) *** $\chi^2(5)$
28050	2	1.2268(0.5415) $\chi^2(2)$	6.8797(0.0321) ** $\chi^2(2)$	77.9693(0.0000) *** $\chi^2(1)$	86.0757(0.0000) *** $\chi^2(5)$
29285	5	71.4393(0.0000) *** $\chi^2(5)$	32.4444(0.0000) *** $\chi^2(5)$	119.8791(0.0000) *** $\chi^2(1)$	223.7627(0.0000) *** $\chi^2(11)$
29900	2	1.5473(0.4613) $\chi^2(2)$	4.2313(0.1206) $\chi^2(2)$	80.4144(0.0000) *** $\chi^2(1)$	86.1929(0.0000) *** $\chi^2(5)$
30095	3	3.7930(0.2847) $\chi^2(3)$	14.6432(0.0021) ** $\chi^2(3)$	25.9005(0.0000) *** $\chi^2(1)$	44.3367(0.0000) *** $\chi^2(7)$
36765	3	4.5956(0.2039) $\chi^2(3)$	15.4278(0.0015) *** $\chi^2(3)$	8.9403(0.0028) *** $\chi^2(1)$	28.9637(0.0001) *** $\chi^2(7)$
36830	8	29.5326(0.0003) *** $\chi^2(8)$	53.7852(0.0000) *** $\chi^2(8)$	19.0003(0.0000) *** $\chi^2(1)$	102.3182(0.0000) *** $\chi^2(17)$
39300	2	1.6422(0.4399) $\chi^2(2)$	2.0503(0.3587) $\chi^2(2)$	66.3319(0.0000) *** $\chi^2(1)$	70.0244(0.0000) *** $\chi^2(5)$
39400	2	1.6827(0.4311) $\chi^2(2)$	0.3316(0.8472) $\chi^2(2)$	18.8835(0.0000) *** $\chi^2(1)$	20.8978(0.0008) *** $\chi^2(5)$
39530	2	0.3350(0.8458) $\chi^2(2)$	0.2520(0.8816) $\chi^2(2)$	48.8808(0.0000) *** $\chi^2(1)$	49.4678(0.0000) *** $\chi^2(5)$
39580	6	37.9730(0.0000) *** $\chi^2(6)$	2.4575(0.8732) $\chi^2(6)$	23.1928(0.0000) *** $\chi^2(1)$	63.6232(0.0000) *** $\chi^2(13)$
40480	7	29.2730(0.0001) *** $\chi^2(7)$	65.9144(0.0000) *** $\chi^2(7)$	20.6153(0.0000) *** $\chi^2(1)$	115.8027(0.0000) *** $\chi^2(15)$
41145	4	5.9885(0.2000) $\chi^2(4)$	9.3000(0.0540) * $\chi^2(4)$	106.9554(0.0000) *** $\chi^2(1)$	122.2440(0.0000) *** $\chi^2(9)$
41300	6	16.0492(0.0135) ** $\chi^2(6)$	16.2757(0.0123) ** $\chi^2(6)$	100.2034(0.0000) *** $\chi^2(1)$	132.5283(0.0000) *** $\chi^2(13)$
41500	5	6.8485(0.2322) $\chi^2(5)$	18.6852(0.0022) *** $\chi^2(5)$	37.1096(0.0000) *** $\chi^2(1)$	62.6433(0.0000) *** $\chi^2(11)$
42200	2	0.5753(0.7500) $\chi^2(2)$	1.2571(0.5334) $\chi^2(2)$	0.0535(0.8172) $\chi^2(1)$	1.8858(0.8647) $\chi^2(5)$

43350	2	6.7440(0.0343) ** $\chi^2(2)$	16.7250(0.0002) *** $\chi^2(2)$	42.0423(0.0000) *** $\chi^2(1)$	65.5113(0.0000) *** $\chi^2(5)$
43485	4	6.0133(0.1982) $\chi^2(4)$	5.2281(0.2647) $\chi^2(4)$	0.0846(0.7711) $\chi^2(1)$	11.3260(0.2540) $\chi^2(9)$
43885	2	1.4891(0.4750) $\chi^2(2)$	7.3712(0.0251) ** $\chi^2(2)$	99.4894(0.0000) *** $\chi^2(1)$	108.3496(0.0000) *** $\chi^2(5)$
44700	2	0.2534(0.8810) $\chi^2(2)$	0.1335(0.9354) $\chi^2(2)$	42.5589(0.0000) *** $\chi^2(1)$	42.9458(0.0000) *** $\chi^2(5)$
45495	5	33.5369(0.0000) *** $\chi^2(5)$	48.5811(0.0000) *** $\chi^2(5)$	17.6040(0.0000) *** $\chi^2(1)$	99.7220(0.0000) *** $\chi^2(11)$
45590	3	24.8670(0.0000) *** $\chi^2(3)$	14.6145(0.0022) ** $\chi^2(3)$	185.8132(0.0000) *** $\chi^2(1)$	225.2947(0.0000) *** $\chi^2(7)$
47320	3	4.6497(0.1993) $\chi^2(3)$	16.1545(0.0011) *** $\chi^2(3)$	3.2254(0.0725) * $\chi^2(1)$	24.0297(0.0011) *** $\chi^2(7)$
47650	2	0.4109(0.8143) $\chi^2(2)$	4.6552(0.0975) * $\chi^2(2)$	9.2239(0.0024) *** $\chi^2(1)$	14.2899(0.0139) ** $\chi^2(5)$
47833	2	1.3407(0.5115) $\chi^2(2)$	4.2666(0.1184) $\chi^2(2)$	61.9777(0.0000) *** $\chi^2(1)$	67.5850(0.0000) *** $\chi^2(5)$
48170	6	21.2106(0.0017) *** $\chi^2(6)$	4.8776(0.5596) $\chi^2(6)$	37.9604(0.0000) *** $\chi^2(1)$	64.0486(0.0000) *** $\chi^2(13)$
48360	2	3.4029(0.1824) $\chi^2(2)$	7.9950(0.0184) ** $\chi^2(2)$	44.9043(0.0000) *** $\chi^2(1)$	56.3022(0.0000) *** $\chi^2(5)$
49050	3	3.4626(0.3257) $\chi^2(3)$	28.8512(0.0000) *** $\chi^2(3)$	35.6015(0.0000) *** $\chi^2(1)$	67.9152(0.0000) *** $\chi^2(7)$
50050	2	2.4390(0.2954) $\chi^2(2)$	22.7253(0.0000) *** $\chi^2(2)$	11.3160(0.0008) *** $\chi^2(1)$	36.4803(0.0000) *** $\chi^2(5)$
50100	6	9.4477(0.1499) $\chi^2(6)$	28.3450(0.0001) *** $\chi^2(6)$	53.9729(0.0000) *** $\chi^2(1)$	91.7655(0.0000) *** $\chi^2(13)$
51795	2	0.1030(0.9498) $\chi^2(2)$	0.4888(0.7832) $\chi^2(2)$	5.2920(0.0214) ** $\chi^2(1)$	5.8838(0.3177) $\chi^2(5)$
51870	2	4.0635(0.1311) $\chi^2(2)$	8.8944(0.0117) ** $\chi^2(2)$	60.3935(0.0000) *** $\chi^2(1)$	73.3513(0.0000) *** $\chi^2(5)$
52130	8	32.1951(0.0001) *** $\chi^2(8)$	17.4142(0.0261) ** $\chi^2(8)$	57.8322(0.0000) *** $\chi^2(1)$	107.4415(0.0000) *** $\chi^2(17)$
52600	2	2.6607(0.2644) $\chi^2(2)$	1.7494(0.4170) $\chi^2(2)$	147.5024(0.0000) *** $\chi^2(1)$	151.9124(0.0000) *** $\chi^2(5)$
53000	3	0.6312(0.8893) $\chi^2(3)$	1.8054(0.6138) $\chi^2(3)$	83.6658(0.0000) *** $\chi^2(1)$	86.1024(0.0000) *** $\chi^2(7)$
53300	2	0.3354(0.8456) $\chi^2(2)$	2.2057(0.3319) $\chi^2(2)$	0.0598(0.8068) $\chi^2(1)$	2.6010(0.7612) $\chi^2(5)$
53625	2	1.3931(0.4983) $\chi^2(2)$	5.4941(0.0641) * $\chi^2(2)$	58.0270(0.0000) *** $\chi^2(1)$	64.9142(0.0000) *** $\chi^2(5)$
54000	5	5.8015(0.3260) $\chi^2(5)$	19.6970(0.0014) *** $\chi^2(5)$	34.5466(0.0000) *** $\chi^2(1)$	60.0451(0.0000) *** $\chi^2(11)$
54600	5	12.7091(0.0263) ** $\chi^2(5)$	10.6629(0.0585) * $\chi^2(5)$	127.1929(0.0000) *** $\chi^2(1)$	150.5649(0.0000) *** $\chi^2(11)$
55140	2	7.4864(0.0237) ** $\chi^2(2)$	8.0425(0.0179) ** $\chi^2(2)$	32.3398(0.0000) *** $\chi^2(1)$	47.8688(0.0000) *** $\chi^2(5)$
57070	3	11.4531(0.0095) *** $\chi^2(3)$	8.5263(0.0363) ** $\chi^2(3)$	167.8652(0.0000) *** $\chi^2(1)$	187.8446(0.0000) *** $\chi^2(7)$

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

79400	2	1.4000(0.4966) $\chi^2(2)$	0.6826(0.7108) $\chi^2(2)$	1.3157(0.2514) $\chi^2(1)$	3.3983(0.6388) $\chi^2(5)$
79600	8	34.6918(0.0000) *** $\chi^2(8)$	10.6989(0.2193) $\chi^2(8)$	0.3070(0.5795) $\chi^2(1)$	45.6977(0.0002) *** $\chi^2(17)$
81860	4	5.5356(0.2366) $\chi^2(4)$	27.4952(0.0000) *** $\chi^2(4)$	29.9413(0.0000) *** $\chi^2(1)$	62.9721(0.0000) *** $\chi^2(9)$
81900	2	2.5290(0.2824) $\chi^2(2)$	2.9702(0.2265) $\chi^2(2)$	2.0513(0.1521) $\chi^2(1)$	7.5505(0.1828) $\chi^2(5)$
82080	4	12.6086(0.0134) ** $\chi^2(4)$	16.5483(0.0024) *** $\chi^2(4)$	30.0850(0.0000) *** $\chi^2(1)$	59.2419(0.0000) *** $\chi^2(9)$
82615	3	5.1468(0.1614) $\chi^2(3)$	7.1292(0.0679) * $\chi^2(3)$	56.6341(0.0000) *** $\chi^2(1)$	68.9102(0.0000) *** $\chi^2(7)$
82690	5	15.6778(0.0078) ** $\chi^2(5)$	7.0360(0.2180) $\chi^2(5)$	75.8431(0.0000) *** $\chi^2(1)$	98.5569(0.0000) *** $\chi^2(11)$
83360	2	1.2403(0.5379) $\chi^2(2)$	6.8280(0.0329) ** $\chi^2(2)$	128.0621(0.0000) *** $\chi^2(1)$	136.1304(0.0000) *** $\chi^2(5)$
83900	5	9.8409(0.0799) * $\chi^2(5)$	13.1371(0.0221) ** $\chi^2(5)$	33.8120(0.0000) *** $\chi^2(1)$	56.7899(0.0000) *** $\chi^2(11)$
85640	2	0.2264(0.8930) $\chi^2(2)$	3.4431(0.1788) $\chi^2(2)$	5.0739(0.0243) ** $\chi^2(1)$	8.7434(0.1197) $\chi^2(5)$
85680	3	6.9027(0.0751) * $\chi^2(3)$	0.5159(0.9154) $\chi^2(3)$	0.8017(0.3706) $\chi^2(1)$	8.2203(0.3136) $\chi^2(7)$
89180	8	46.7618(0.0000) *** $\chi^2(8)$	63.0436(0.0000) *** $\chi^2(8)$	31.9812(0.0000) *** $\chi^2(1)$	141.7866(0.0000) *** $\chi^2(17)$
90300	4	5.5996 (0.2311) $\chi^2(4)$	16.5435(0.0024) *** $\chi^2(4)$	63.5346(0.0000) *** $\chi^2(1)$	85.6778(0.000) *** $\chi^2(9)$
91480	2	0.0860(0.9579) $\chi^2(2)$	0.2388(0.8874) $\chi^2(2)$	3.5751(0.0587) * $\chi^2(1)$	3.8999(0.5639) $\chi^2(5)$
91845	6	24.2385(0.0005) *** $\chi^2(6)$	11.2341(0.0814) * $\chi^2(6)$	174.7216(0.0000) *** $\chi^2(1)$	210.1942(0.0000) *** $\chi^2(13)$
91910	8	24.7781(0.0017) *** $\chi^2(8)$	23.6657(0.0026) *** $\chi^2(8)$	128.5638(0.0000) *** $\chi^2(1)$	177.0077(0.0000) *** $\chi^2(17)$
92060	6	34.9802(0.0000) *** $\chi^2(6)$	12.1855(0.0580) ** $\chi^2(6)$	35.1327(0.0000) *** $\chi^2(1)$	82.2984(0.0000) *** $\chi^2(13)$
92200	2	3.3845(0.1841) $\chi^2(2)$	3.6945(0.1577) $\chi^2(2)$	18.2400(0.0000) *** $\chi^2(1)$	25.3190(0.0001) *** $\chi^2(5)$
93405	8	10.7455(0.2165) $\chi^2(8)$	11.6932(0.1654) $\chi^2(8)$	132.1444(0.0000) *** $\chi^2(1)$	154.5831(0.0000) *** $\chi^2(17)$

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