Journal of Applied Economics, Vol. V, No. 2 (Nov 2002), 273-292

ASYMMETRIC REACTION TO INFORMATION AND SERIAL DEPENDENCE OF SHORT-RUN RETURNS

Pablo Marshall and Eduardo Walker*

Pontificia Universidad Católica de Chile

This paper studies the daily stock price reaction to new information of portfolios grouped by size quintiles. To that end, cross-correlations, autocorrelations and Dimson beta regressions are analyzed. Based on a sample of shares traded in the Santiago de Chile Stock Exchange for the 1991-1998 period, results show that larger company stock prices –as measured by market capitalization– react to both good and bad news sooner than the smaller ones do. Thus a crossed effect appears, although not as a cascade: only the prices of large firms react earlier than the rest. These effects do not seem to be caused by non-trading. There also are significant asymmetric lagged and cross-effects. Good news has a more pronounced lagged effect than bad news does.

JEL classification codes: G12, G15

Key words: efficient market hypothesis, cross-serial autocorrelation, emerging markets

I. Introduction

The predictability of daily returns has been extensively treated in the literature, where most authors agree on the possibility of predicting short-run returns.[1] If expected returns are assumed constant, then autocorrelation tests also are tests of the Efficient Market Hypothesis (EMH). This assumption may not be totally incorrect if short-term daily returns and horizons are used.

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* Correspondence should be addressed to Escuela de Administración, Pontificia Universidad Católica de Chile, Casilla 76, Correo 17, Santiago, Chile.

[1] See, for example, Lo and Mackinlay (1988, 1990).

However, in this case the issue of transaction costs is critical. Still, there are other arguments that may make the observed levels of autocorrelation compatible with EMH. Boudoukh, Richardson and Whitelaw (1994) argue that serial correlation may arise from measurement problems (asynchronous trading, discrete changes, bid-ask spread); institutional structures (transaction mechanisms and trading times); or from market "microstructure" (inventory and flows of information).[2] Boudoukh, Richardson and Whitelaw (1994) label this school of thought "loyal" to the EMH. They also identify the "Revisionist" and the "Heretic" schools. The former believes in EMH and in that predictability comes from changes in risk premia over time, whereas the latter believes that markets are irrational, and that it is possible to exploit these inefficiencies.

The existence of daily autocorrelation has been documented for quite some time now (for example see Fama, 1976). More recently Campbell, Lo and Mackinlay (1997) analyze autocorrelations for daily returns for individual stocks and stock indexes. They find substantially higher autocorrelation levels for portfolios than for individual stocks, especially in the equal-weighted stock index's weekly returns. For such an index, first-order autocorrelation is 0.35. Given that autocorrelation is larger for equal-weighted stock indexes and that it is not significant at the individual stock level, the conclusion is that "cross-serial correlation" must exist. A more detailed analysis shows that high returns on large companies at time t are associated with high returns on small companies at $t+1$, but not vice versa.[3]

Mech (1993) finds that transaction costs, and not variations in risk premia, lack of transactions or microstructure problems, explain the cross-serial correlation. However, Boudoukh, Richardson and Whitelaw (1994) contradict

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[2] See related references therein.

[3] A data problem caused by asynchronicity is one possible explanation. Lo and McKinlay (1990) find that part of the stylized facts found in the literature may be the result of this phenomenon. However, the probability of non-trading should be "too large" to warrant the levels found for cross-serial correlation, particularly when the time unit is lengthened from day, to week, to month.

Mech and support the "loyal" school, arguing that there is no such cross-serial correlation between large and small companies, and that what really is observed is a combination of "own autocorrelation with contemporaneous cross-correlation". Own autocorrelation is attributable to low trading levels and the risk characteristics of smaller companies.

McQueen, Pinegar and Thorley (1996) change the perspective and analyze the possibility of asymmetric responses to common bad and good news, as captured by the return on a market index. Their empirical evidence indicates that whenever the news is bad all firms' price responses are fast. But when the news is good, smaller companies take longer to react. This contradicts the previous explanations of Mech (1993) and Boudoukh, Richardson and Whitelaw (1994). They thus adopt the "heretic" view. It is interesting to notice that McQueen, Pinegar and Thorley's (1996) results are consistent with a particular bias identified by "Behavioral Finance" researchers, which supposedly affects investor behavior: overconfidence. It consists in assigning "too much weight" to one's own prior beliefs, resulting in an under reaction to new information (see Fama (1998) for a critical review). Under reaction thus implies persistence of the same sign in returns. However, "behavioral investors" are also known for being reluctant to realize their losses, and this eventually implies more persistence in the case of negative impulses, which contradicts the evidence.

Summarizing, the essence of the discussion has to do with the interpretation of the observed auto- and cross-serial correlations, and if they are consistent with the EMH. McQueen, Pinegar and Thorley's (1996) major point is that the EMH-consistent stories related with transaction costs and time-varying risk premia are not compatible with the observed autocorrelation asymmetry. However, as noted by Fama (1998) in a different context, the alternative (behavioral) hypothesis of investor behavior, is not quite successful either. Overconfidence implies under reaction o new information (of any sign), but reluctance to realize losses implies more under reaction (and thus more persistence) in the case of negative impulses. Thus, we shall call this the "Lame Behavioral Hypothesis".

For emerging markets there is little evidence available.[4] Thus, the aim of this study is first to verify the existence of the aforementioned stylized facts for a particular emerging market. Specifically, we study *daily* returns of market-capitalization-based size-quintiles of stocks traded in the Santiago Stock Exchange over the 1991-1998 period. If there is a "leader-follower" relationship between Chilean stocks, we would expect the ones with the larger share of institutional investors (which also are the larger and more liquid stocks) to lead,[5] independently of the interpretation given to this.

Here we do find significant autocorrelation both for returns and for squared returns. Using Dimson (1979) beta regressions, we find that large quintiles adjust faster to common market information than small quintiles. Similarly, the result of applying vector autoregression analyses, as suggested by Chordia and Swaminathan (2000), reveals that large quintiles lead small quintiles. These cross-effects do not have a cascade form: the returns of firms in the two highest quintiles react earlier than the rest.

Our results also show asymmetric effects of good and bad news. An impulse-response analysis of the cumulative lagged dynamic effects of a 1 % change in the returns of large companies implies a return, after the day of the initial impulse and therefore not including such effect, of roughly 1.7 % after 20 days in both large and small firms. This cumulative effect is about –1.0 %, in large and small firms, when the impulse in large firms is negative and equal to –1 %. On the other hand, a 1 % change in the returns of small companies implies a cumulative return of 0.5 % in small companies and a cumulative return of 0.1 % in large companies. A negative change in small companies has no significant lagged effect in either small or large companies.

[4] An exception is Chang, McQueen and Pinegar (1998), who find cross-serial correlation for Asia, some of the same across the ocean between the US and Asia, but no systematic evidence of asymmetry.

[5] See Badrinath, Kale and Noe (1995). They find that monthly returns on stock portfolios with a higher percentage owned by institutional investors lead the rest. However, complementary tests by McQueen, Pinegar and Thorley (1996) challenge these results.

The effect of non-trading is also considered herein, finding it unlikely to explain our results.

Our results contradict the hypothesis of Boudoukh, Richardson and Whitelaw (1994) of no cross-serial correlation, may be consistent with Mech's (1993) transaction costs story, but are most consistent with McQueen, Pinegar and Thorley's (1996), regarding response asymmetry. The evidence does indicate that smaller firms take longer to adjust to new information. Whether this is exploitable depends on the initial shock. If it is not large enough, transaction costs (of about 1 % round-trip) will eliminate any potential profits. However, if the initial shocks are large enough these findings indicate profit opportunities even in the absence of short sales. In any case, the patterns that emerge are consistent with the Lame Behavioral Hypothesis.

This article is organized in five sections. Following this introduction, Section II presents the sample selection criteria and data used in the study. Section III shows the results of adjusting Dimson beta regressions and vector autoregressions with and without crossed effects to explain returns (Section III.D, in particular, analyzes the effects of non-trading). Conclusions are presented in Section IV.

II. Data Description and Sample Selection

The data used herein consists of the daily returns on a sample of stocks traded in the Santiago de Chile Stock Exchange between January 20, 1990 and August 31, 1998. Returns are calculated as the percentage difference between the price logarithms adjusted for dividends, preemptive subscription rights, splits, and the like. On the other hand, only returns arising form transactions on two consecutive working days are considered herein, including Friday to Monday, and any two working days with one or more holidays in between. In other words, we leave out the returns that come from two non-consecutive working days, since they may bias the autocorrelation study.

To avoid survivorship biases in the sample selection, the stocks included each year in the study were selected based on the information available in the previous year. The selected stocks are those traded at least on 50 % of the previous year's working days. The total number of stocks considered at least once is 164. At any given year the figure is in the 60 to 115 range.

Stocks selected each year are grouped into quintiles according to company size, defined as the market capitalization at the beginning of the period. Then, a non-weighted return index is calculated in order for it to represent a typical stock in the respective quintile. The number of companies in each quintile varies between 12 and 23 from one year to another and the average number of companies in each quintile is 18.9. The first quintile groups the smaller-sized companies whereas the fifth includes the largest ones.

Table 1 shows basic statistics for each quintile, namely the market cap percentage, the number of observations, the mean, the standard deviation, the symmetry coefficient, the kurtosis coefficient and the maximum and the minimum. The first quintile, with the smallest firms, has an average market cap equal to 1.46 % of the total whereas the quintile with the largest companies accumulates a market capitalization of 69.32 % of the total.

Table 1. Basic Statistics by Quintiles

Quintile	Cap.	*n*	Mean	St. D.	Sym.	Kurt.	Min.	Max.
Q1	1.46	1,898	0.19	1.32	0.36	6.59	-8.53	7.22
Q2	3.81	1,898	0.15	1.23	0.17	5.83	-7.03	6.19
Q3	8.29	1,898	0.11	1.11	-0.20	7.98	-8.84	5.81
Q4	17.11	1,898	0.10	1.12	0.10	7.27	-7.85	7.53
Q5	69.32	1,898	0.06	1.14	0.18	6.08	-4.96	7.39

Table 2 shows return autocorrelations and squared return autocorrelations, for 1 to 5 lags. Given the sample sizes considered herein, these autocorrelations are significantly different from zero whenever their absolute value is greater than 0.046. The results in Table 2 show substantial first-order return autocorrelation in all five quintiles. For squared returns, autocorrelation is also significant for the five lags considered. Ljung-Box (1978) tests, for both returns and squared returns, show statistically significant autocorrelation even for 20-day-long lags.

Table 2. Autocorrelation Coefficients by Quintiles

	Returns					Squared Returns				
Quint.	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Q1	0.27*	0.08*	0.06*	0.05*	0.05*	0.19*	0.14*	0.11*	0.15*	0.08*
Q2	0.33*	0.08*	0.04	0.09*	0.08*	0.30*	0.14*	0.11*	0.07*	0.09
Q3	0.29*	0.07*	0.07*	0.08*	0.04	0.19*	0.20*	0.15*	0.07*	0.13*
Q4	0.31*	0.11*	0.06*	0.08*	0.08*	0.29*	0.29*	0.18*	0.14*	0.15*
Q5	0.29*	0.06*	0.01	0.05*	0.02	0.37*	0.31*	0.20*	0.15*	0.11*

Note: * stand for significant coefficients at 5%.

III. Methodology and Results

A. Dimson Beta Regressions

In order to analyze the speed of adjustment to new information for the different quintiles, and in order to control for systematic effects we run a market regression model as suggested by Dimson (1979) and Chordia and Swaminathan (2000). The form of the model is:

$$r_{B,t} - r_{A,t} = c + \sum_{l=1}^{4} a_l \, d_{l,t} + \sum_{j=-k}^{k} b_j \, r_{m,t-j} + \varepsilon_t \tag{1}$$

where $r_{B,t}$ and $r_{A,t}$ are the returns of quintiles B and A at day t; c represents a constant; $d_{l,t}$ are day-of-the-week dummies;[6] $r_{m,t}$ is the return of a market index; ε_t is a random disturbance; and a_l, $l = 1,...,4$ and b_j, $j = -k,..,0,..,k$ are unknown coefficients. The regression model (1) allows us to study the relative adjustment speeds of the return quintiles given market returns. More specifically, quintile *B* responds more rapidly to market information than quintile *A* if its contemporaneous sensitivity to common information (represented by the aggregate index return) is greater than that of quintile *A*. Now, as quintile *A* responds more slowly to market information, it should be more sensitive to past information, represented in (1) by the lags in the market index. In sum, quintile *B* responds more rapidly to common information than quintile *A* if $b_0 > 0$ and

$$\sum_{j=1}^{k} b_j < 0 \tag{2}$$

Table 3 shows the results of estimating equation (1) to the quintiles using unweighted and weighted market indexes. The dependent variables are always in the form of the larger minus the smaller quintile. The results for the two market indexes are very similar although considering only the significant coefficients, the regression that uses the unweighted market index shows coefficients that are greater in absolute value. The contemporaneous coefficients are always positive and significant, and the sum of the lagged coefficients is almost always negative and significant when we compare the speed of adjustment of either Q4 or Q5 with respect to Q1, Q2 or Q3. The only cases where the evidence is not as strong is when we compare the speed of adjustment of Q4 with respect to Q1, Q2 or Q3 in the weighted market index models. The results in Table 3 also show that the speed of adjustment is greater in Q5 than in Q4 and that Q1, Q2 and Q3 do not react at different speeds given new information common to all the market. The sum of the lead coefficients is not significant in any of the models.

[6] See Marshall and Walker (2001), who explore the relationship between day-of-the-week and size effects.

Table 3. Dimson Beta Regressions

	Unweighted Index				Weighted Index			
Dep. var.	Lags	Contemp.	Leads	R^2	Lags	Contemp.	Leads	R^2
Q2-Q1	0.10	0.20	-0.08	0.02	0.12	0.09	-0.02	0.01
Q3-Q1	-0.20	0.06	-0.13	0.02	-0.11	-0.01	-0.07	0.01
Q3-Q2	-0.30	-0.14	-0.05	0.02	-0.26	-0.11*	-0.06	0.02
Q4-Q1	-0.44*	0.43**	0.10	0.04	-0.25	0.23**	0.11	0.03
Q4-Q2	-0.54**	0.23*	0.18	0.04	-0.37	0.14*	0.12	0.03
Q4-Q3	-0.25	0.36**	0.23	0.04	-0.11	0.24**	0.18	0.04
Q5-Q1	-0.96**	0.89**	-0.05	0.10	-0.56**	0.54**	0.03	0.09
Q5-Q2	-1.06**	0.69**	0.04	0.11	-0.68**	0.44**	0.05	0.10
Q5-Q3	-0.76**	0.83**	0.09	0.14	-0.42**	0.55**	0.11	0.14
Q5-Q4	-0.51**	0.46**	-0.15	0.06	-0.31**	0.31**	-0.07	0.07

Note: * and ** stand for significant coefficients at 5% and 1%, respectively.

Finally, the R^2 coefficients show small values although quite significant when either Q4 or Q5 are included the model, especially in the latter case.

B. Vector Autoregressions

The Dimson beta regressions show the speed of adjustment to common new information in the market. In contrast, vector autoregressions measure the speed of adjustment of the different quintiles relative to one another. More specifically, vector autoregressions are important in order to quantify the marginal contribution of cross autocorrelations given the own autocorrelations and to measure the ability of large firm returns to predict the returns of small firms. The vector autoregressive model has the form:

$$r_{A,t} = m_{A,t} + \sum_{i=1}^{k} a_i \; r_{A,t-i} + \sum_{i=1}^{k} b_i \; r_{B,t-i} + \varepsilon_{At} \tag{3}$$

$$r_{B,t} = m_{B,t} + \sum_{i=1}^{k} c_i \; r_{B,t-i} + \sum_{i=1}^{k} d_i \; r_{A,t-i} + \varepsilon_{Bt} \tag{4}$$

In this specification, returns of quintile B are said to Granger cause the returns of quintile A if controlling for the predictive power of the lagged returns of A, the lagged returns of B can predict the returns of A. However, Chordia and Swaminathan (2000) propose a modified version of Granger causality by examining whether the sum of the coefficients of the lagged returns of B in equation (3) is greater than zero.[7] Moreover, equations (3) and (4) can be considered jointly to test the ability of the returns of one quintile to predict the returns of the other. This hypothesis is verified by considering the cross-equation test:

$$Z = \sum_{i=1}^{k} b_i - \sum_{i=1}^{k} d_i > 0 \tag{5}$$

Table 4 presents the results of the vector-autoregression models (equations (3) and (4) for the different quintiles. We observe in Table 4 that Q1, Q2 and Q3 tend to “cause” each other. The same is observed for Q4 and Q5, although in the latter case the significance is at the 5% level only. We also observe that the returns of the largest quintiles Q4 and Q5 “cause” small quintile returns Q1, Q2 and Q3 but that the reverse is not true. Although quintile Q1 presents a significant first lag effect in the models for Q4 and Q5, its magnitude is very small and the sum of the 10 lagged coefficients is not significant at the 5% level. The sum of the cross-effects of Q4 and Q5 on Q1, Q2 and Q3 range between 0.40 and 0.54, whereas the magnitude of the sum of the reverse cross-effects fluctuates between 0.25 and 0.32.

[7] The proposed test considers not only predictability but also the sign of the permanent cross-effect of a given return shock.

Table 4. Vector Autoregressions

Dep. Var.	Indep. Var	Lag Dependent First	Lag Dependent Sum	Lag Dependent Vector	Lag Independent First	Lag Independent Sum	Lag Independent Vector	R^2	Z
Q1	Q2	0.19**	0.22*	**	0.20**	0.32**	**	0.14	0.09
Q1	Q3	0.21**	0.29**	**	0.18**	0.28**	**	0.14	0.01
Q1	Q4	0.18**	0.14	**	0.19**	0.49**	**	0.14	0.43**
Q1	Q5	0.16**	0.24*	**	0.25**	0.40**	**	0.15	0.32*
Q2	Q1	0.25**	0.36**	**	0.16**	0.23**	**	0.18	
Q2	Q3	0.26**	0.34**	**	0.15**	0.29**	**	0.17	0.03
Q2	Q4	0.21**	0.17	**	0.21**	0.51**	**	0.19	0.45**
Q2	Q5	0.17**	0.28**	**	0.27**	0.40**	**	0.20	0.36*
Q3	Q1	0.21**	0.26*	**	0.16**	0.26*	**	0.15	
Q3	Q2	0.19**	0.26*	**	0.18**	0.26*	**	0.15	
Q3	Q4	0.16**	0.02	*	0.20**	0.54**	**	0.15	0.48**
Q3	Q5	0.12**	0.09		0.27**	0.51**	**	0.17	0.49**
Q4	Q1	0.28**	0.49**	**	0.06*	0.05		0.14	
Q4	Q2	0.27**	0.47**	**	0.07	0.06		0.14	
Q4	Q3	0.27**	0.48**	**	0.07	0.06		0.14	
Q4	Q5	0.14**	0.34**		0.23**	0.25*	**	0.16	-0.04
Q5	Q1	0.27**	0.36**	**	0.07*	0.08		0.12	
Q5	Q2	0.31**	0.39**	**	-0.01	0.04		0.12	
Q5	Q3	0.30**	0.41**	**	0.01	0.02		0.12	
Q5	Q4	0.27**	0.16	**	0.05	0.29*		0.12	

Note: * and ** stand for significant sum of coefficients at 5% and 1% respectively.

The R^2 coefficients range between 0.11 and 0.13 in the equations for quintiles Q4 and Q5, to 0.14 and 0.18, in the cases of quintiles Q1 and Q2. The last column presents the *Z*-statistic corresponding to the cross-equation test in (5).[8] The results of these tests show that Q4 and Q5 "cause" Q1, Q2 and Q3, but not viceversa, and that the quintiles Q1, Q2 and Q3 do not present significantly different adjustment speeds among each other.

C. Asymmetric Effects and Impulse-Response Analysis

The analysis of the previous subsections shows that the returns of the largest two quintiles lead those of the smaller firms. Provided that they show similar behavior, in this subsection we aggregate quintiles one through three and quintiles four and five to form the averages of small and large firms, respectively. With these two portfolios we redo the analysis allowing for the possibility of asymmetric effects. We test whether lagged positive and negative returns have different effects on current returns. In equations (1), (3) and (4) we extend the specifications to include an additional independent variable for each of the right-hand-side variables previously considered. This additional variable equals the original return when it takes a positive value and zero otherwise.

Table 5 presents the Dimson beta regression models with asymmetric effects. This table indicates that it is still true that given both positive and negative returns the larger firms' contemporaneous reaction to market shocks is faster than that of smaller firms and that the lagged effects are more pronounced for the latter. In particular, results show that the contemporaneous effect of the market return indexes on the excess returns of large over small

[8] This is not a standard test. Chordia and Swaminathan (2000) show that if we are able to reject the null hypothesis against the one-sided alternative using the traditional chi-square distribution, we should most likely be able to reject the stated hypothesis using the exact test. In any case, the same results are obtained when the traditional Chi-square test is computed using both (i) White-corrected standard errors with no cross-equation disturbance correlation and (ii) SUR with no correction for heteroscedasticity.

firms is more important when the market return is positive. This may indicate that smaller and larger firm stock prices react at a more similar speed when market returns are negative, e.g. given bad news. However, Table 5 also indicates that when lagged index returns are negative, the subsequent excess return of large over small firms is positive. This suggests that negative market-wide news takes longer to be impounded in smaller firm stock prices, contradicting the previous interpretation. This apparent contradiction may be explained by the lead coefficients that appear significant only when the market index returns are negative. This indicates that larger firms react faster to bad news than the average firm in the index. This is a plausible explanation since the sum of the lead coefficients is even more significant in the equation that uses the equally-weighted index (that assigns more weight to smaller firms) as the explanatory variable. Thus, the overall evidence indicates that it is not true that smaller firms react relatively more promptly to bad news.

Table 5. Dimson Beta Regressions for Aggregate Indexes

		Unweighted Index				Weighted Index			
Dep. Var.	Effects	Lags	Contemp.	Leads	R^2	Lags	Contemp.	Leads	R^2
(Q4-5) – (Q1-3)		-0.67**	0.57**	0.10	0.12	-0.40	0.36**	-0.06	0.11
(Q4-5) – (Q1-3)	(-)	-0.63**	0.44**	0.42*	0.12	-0.44**	0.29**	0.34**	0.11
	(+)	-0.46**	0.67**	-0.17		-0.34**	0.40**	-0.16	

Note: * and ** stand for significant coefficients at 5% and 1% respectively.

Table 6 presents the vector autoregressions (3) and (4) with asymmetric effects. Each equation considers two additional sets of coefficients in order to capture the differences in the effects of good and bad news. The effects of large over small firm returns are not significantly different when the latter are positive or negative. This is, the lagged reaction of small stocks is similar independently on whether the new information is good or bad.

Table 6. Asymmetric Vector Autoregressions for Aggregate Indexes

Dep. Var.	Indep. Var.	Effects	Lag Dependent First	Lag Dependent Sum	Lag Dependent Vector	Lag Independent First	Lag Independent Sum	Lag Independent Vector	$\overline{R}^2$	Z
Q1-3		(-)	0.25**	0.43**	**				0.22	
		(+)	0.57**	0.67**	**					
Q1-3	Q4-5	(-)	0.03	-0.20		0.21*	0.68**		0.24	0.93**
		(+)	0.39**	0.33*	**	0.23**	0.47**	*		0.41**
Q4-5		(-)	0.16	0.42*					0.15	
		(+)	0.49	0.63**	**					
Q4-5	Q1-3	(-)	0.18	0.67**		-0.03	-0.26		0.16	
		(+)	0.40**	0.60**	**	0.14*	0.05			

Note: * and ** stand for significant sum of coefficients at 5% and 1% respectively.

Regarding the effects of small on large firm returns we obtain the same result previously found for the individual quintiles: the sum of the coefficients is not significant at the 5% level. However, and as before, the first lag coefficient appears significant, albeit in this case only for positive lagged returns. The effect of small firms on large firms disappears for negative lagged returns. Thus, if the small-over-large-firm effect exists, it is small and happens only in the case of good news. One interesting fact found in Table 6 is that the own autocorrelations of portfolio Q1-3 are significant only for the positive lagged returns in the equation that also includes Q4-5 as an explanatory variable.

The *Z* statistics for the relative speed of adjustment hypothesis (5) confirm the results reported in Table 4: returns of portfolio Q4-5 lead those of portfolio Q1-3. Finally, the adjusted R^2 increases by 0.022 in the equation for Q1-3 when Q4-5 is included, whereas including Q1-3 in the equation for Q4-5 yields an improvement of only 0.009.

To illustrate the effects of good and bad news originating in either Q1-3 or Q4-5, Table 7 shows an impulse-response analysis of the cumulative lagged dynamic effects.

Table 7. Cumulative Effects in Impulse-Response Analysis

	Bad News Q4-5		Good News Q4-5		Bad News Q1-3		Good News Q1-3	
Day	Q1-3	Q4-5	Q1-3	Q4-5	Q1-3	Q4-5	Q1-3	Q4-5
1	-0.21	-0.18	0.23	0.40	0.00	0.00	0.38	0.12
5	-0.52	-0.49	0.91	0.99	0.00	0.00	0.36	0.03
10	-0.90	-0.77	1.32	1.36	0.00	0.00	0.54	0.16
15	-1.01	-0.87	1.64	1.57	0.00	0.00	0.52	0.10
20	-1.05	-0.91	1.77	1.68	0.00	0.00	0.50	0.08

A 1 % shock in the returns of large companies implies a return of roughly 1.7 % in both large and small firms after 20 days (a lagged “elasticity” of 1.7).[9] When the impulse is negative and equal to –1 %, the cumulative effect on large and small companies is about –1 %. On the other hand, a 1 % return in small companies implies a cumulative return of 0.5 % in small companies and a cumulative return of 0.1 % in large companies. A negative change in small companies has no significant lagged effect in either small or large companies. The results of the impulse response analysis are also presented in Figure 1 and Figure 2.

D. Non-Trading Bias

The results shown so far may be biased because certain stocks, most likely the smaller firms’ do not trade on some days. There are two aspects of this

[9] A 1 % shock is similar to one standard deviation (see Table 1).

Figure 1. Impulse Response of a 1% Change in Q4-5

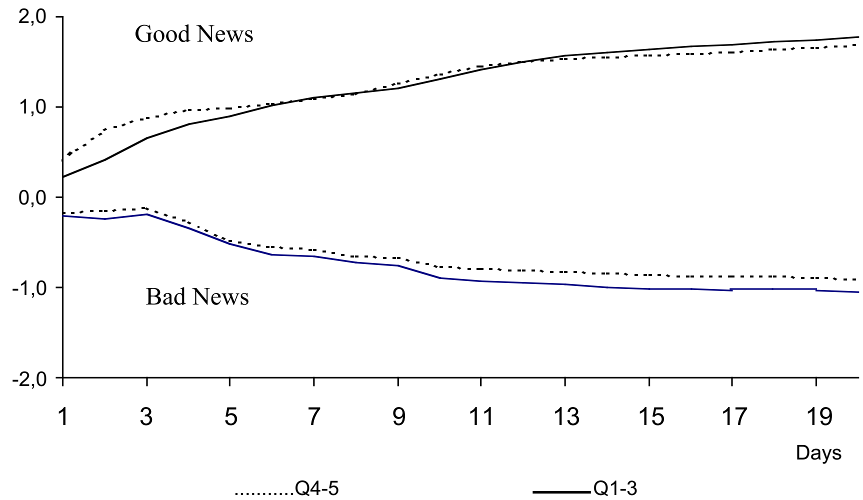
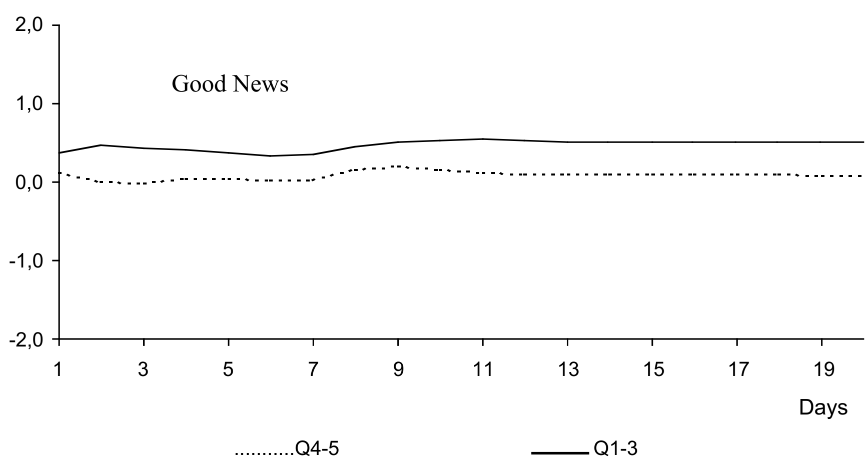


Figure 2. Impulse Response of a 1% Change in Q1-3



non-trading phenomenon that deserve further study. First, whenever a company's stocks are not traded on a certain day, price variations show up on the following trading day. This phenomenon, which might bias autocorrelation and cross-correlation between indexes is controlled for herein by taking only the returns on consecutive working days, Fridays to Mondays, and working days with holidays in between.

The second aspect to consider is the eventual bias resulting from some stocks not trading on a given day. When this happens the respective quintile's index calculation includes only those stocks that did trade. Table 8 shows basic statistics of non-trading indexes in each quintile. These indexes are defined as the proportion of companies in a quintile that did not trade on a given day over the total number of selected companies in the respective quintile. The average non-trading index ranges from 41.34 % in the first quintile to 17.20 % in the fifth.

Table 8. Basic Statistics of Non Trading Indexes

Quintile	n	Mean	St. D.	Symmetry	Kurtosis	Min.	Max.
Q1	1,898	41.34	18.24	-0.04	2.77	0	95.45
Q2	1,898	36.82	14.87	0.17	2.85	0	90.91
Q3	1,898	31.03	14.72	0.47	3.32	0	90.00
Q4	1,898	24.41	13.23	0.26	2.61	0	65.22
Q5	1,898	17.20	8.91	0.38	3.09	0	53.33

In order to study the relationship between the absence of trading and past returns, models in Table 6 were estimated adding non-trading lagged indexes. The results of this exercise are presented in Table 9. In general, although the lagged non trading indexes are statistically significant and the adjusted R^2 measure increases by 1 or 2 %, the coefficients estimated by considering the non-trading effects are not very different from the ones reported in Table 6.

Table 9. Asymmetric Vector Autoregressions for Aggregate Indexes with Non Trading Effects

Dep. Var.	Indep. Var.	Effects	Lag Dependent First	Lag Dependent Sum	Lag Dependent Vector	Lag Independent First	Lag Independent Sum	Lag Independent Vector	$\overline{R}^2$	Z
Q1-3		(-)	0.24**	0.40**	**				0.23	
		(+)	0.51**	0.58**	**					
Q1-3	Q4-5	(-)	0.05	-0.20		0.19*	0.65**		0.25	1.00**
		(+)	0.36**	0.23*	**	0.21**	0.56**	*		0.53**
Q4-5		(-)	0.15	0.41*					0.15	
		(+)	0.48	0.60**	**					
Q4-5	Q1-3	(-)	0.18	0.69**		-0.04	-0.36		0.16	
		(+)	0.40**	0.59**	**	0.13	0.03			

Note: * and ** stand for significant sum of coefficients at 5% and 1% respectively.

IV. Conclusions

This study analyzes the speed at which good and bad news are impounded into daily stock prices by examining autocorrelation and cross-correlation patterns, allowing for the possibility of asymmetric effects. Based on a sample of stocks that traded in the Santiago Stock Exchange over the 1991-1998 period, the results of Dimson beta regressions and vector autoregressions show significant and asymmetric autocorrelation. Good news have a more pronounced lagged effect than bad news. Also, larger companies, as measured by their market capitalization reflect the effects of good and bad news significantly earlier than smaller companies. This implies a cross-effect, but not in a cascade form: only the returns of firms in the two top quintiles lead the rest.

The effect of non-trading is also considered herein. Although the study includes only returns on stocks that had transactions in two consecutive working days, companies not trading on a given day may have different characteristics than those that do and are used to build the quintile's indexes. An analysis of non-trading indexes shows that the correlation of non-trading with past and concurrent returns is very low, so a bias in the results caused by this phenomenon is unlikely.

Our results contradict Boudoukh, Richardson and Whitelaw's (1994) claims, since we find cross-serial correlation not generated by return autocorrelation. They may be consistent with Mech's hypothesis (1993), because lagged responses may be explained by transaction costs. However, the fact that autocorrelation persists for small firms only when their own past returns are positive casts doubts on this interpretation. Thus, our results seem to be most consistent with the heretic vision of McQueen, Pinegar and Thorley (1996) regarding response asymmetry, since the evidence is indicative of asymmetric under reactions. This may be better understood in the context of an overconfidence bias in investor decisions. Overconfidence implies under reaction to new information (of any sign), but reluctance to realize losses implies more under reaction (and thus more persistence) in the case of negative impulses. Thus, the evidence is only consistent with a Lame Behavioral Hypothesis.

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