Investment Management and Financial Innovations, Volume 6, Issue 4, 2009

George Milunovich (Australia)

Size-sorted portfolios and information spillovers: structural evidence from Australia

Abstract

A structural model is proposed to analyze linkages between large, medium and small capitalization securities traded on the Australian Stock Exchange. Small stocks fail to react instantaneously to the information transmitted by large and medium cap firms, and take several weeks to absorb this information in an entirely lagged adjustment process. In contrast, medium firms respond to the information conveyed by large cap securities with about 80 percent instantaneous and 20 percent lagged adjustment. Large stocks are the quickest to respond to new information but slightly overshoot in their immediate reaction to the news transmitted by medium cap firms. A number of trading strategies are constructed on the basis of the uncovered patterns in order to test for the possibility of arbitrage profits. Although the excess returns generated by these strategies are typically positive, they are statistically insignificant, suggesting that the discovered signals are too weak to be successfully used for trading purposes.

Keywords: size-sorted portfolios, information spillovers, structural model, GARCH, predictability.
JEL Classification: C30, C32, G10.

Introduction

I investigate temporal links between three size-sorted portfolios composed of securities traded on the Australian Stock Exchange, namely large, medium and small capitalization stocks. While a number of international studies have delved into the tendency of small cap firms to lag large capitalization stocks, this paper adds to the current literature in three important ways. First, the existing literature (see, for example, Lo and MacKinlay, 1990; Jegadeesh and Titman, 1995; and Kroner and Ng, 1998) examines lagged portfolio spillovers in isolation of their contemporaneous interactions. This approach is incomplete because only a fraction of such linkages is expected to occur with a lag. In this paper, I propose a new method to assess relative significance of both the simultaneous interactions as well as the lagged spillovers. Second, in contrast to the existing literature, which examines the lead-lag effect from a large market, typically the U.S., point of view, this paper provides new empirical evidence from Australia, a relatively small equity market. Third, I apply and extend a new empirical technique in the context of size-sorted portfolio spillovers.

The tendency of small capitalization indices to respond to price changes in large cap portfolios with a lag, but not vice versa, has been termed the lead-lag portfolio effect by Lo and MacKinlay (1990). Although there is a significant number of studies that map out the lagged price discovery processes, they fail to account for instantaneous adjustments that may occur between portfolios of different capitalizations. Thus, extending the analysis to include both instantaneous as well as lagged adjustments will provide additional insights into the issue. For example, finding that small firms respond to price changes of large stocks with no instantaneous and 100 percent lagged adjustment conveys considerably more information than simply knowing that lagged adjustments are statistically significant. However, this kind of decomposition is difficult to achieve in empirical work, primarily due to the endogeneity problem[1].

Put in the context of size-sorted portfolios the endogeneity issue implies that, if two price indices are determined jointly, it is difficult to unbiasedly estimate their unrestricted contemporaneous regression coefficients. In this paper, I apply and extend a relatively new econometric technique known as the structural GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model, which overcomes the endogeneity issue. The structural GARCH model, which was originally proposed by Rigobon and Sack (2003), achieves parameter identification through a time varying nature of conditional variances. This allows one to estimate the entire contemporaneous regression coefficient matrix, provided certain regularity conditions are met. However, the structural GARCH model lacks the ability to identify or "name" structural shocks, without placing some rather stringent restrictions on its parameters. This represents a significant shortcoming in the current application where a decomposition of a portfolio's responses to news transmitted by other portfolios' returns requires such identification. To this end, I use an approach suggested by Dungey et al. (2009) that extends the basic Structural GARCH framework and provides a way to link structural shocks with observable portfolio variables and is based on a variance decomposition technique.

[1] The endogeneity issue, which is frequently encountered in the demand-supply type of equations, refers to the bias encountered when trying to estimate the unrestricted matrix of contemporaneous coefficients in a system of jointly determined equations.

I find that even after accounting for contemporaneous interactions, small capitalization stocks still lag large and medium cap portfolios. In fact, the small stocks fail to even partially respond to the news conveyed by the large and medium cap indices contemporaneously. Over the sample period of December 1987-April 2003, 100 percent of the total response of small stocks, to the information conveyed in price changes of large cap firms, occurred with a lag. The large and medium capitalization indices also exhibited some lagged adjustments, but of much smaller magnitudes. The lagged response of the large cap index over a period of ten weeks following a 1 percent change in medium size stocks is about -0.03 percent, while the instantaneous response amounts to 0.25 percent. These findings suggest that large firms achieve most of its adjustment contemporaneously, but slightly overshoot in their immediate reaction. Similarly, medium size stocks exhibit a small lagged response to a 1 percent change in the large cap index, which accounts for about 20 of the total adjustment.

As a measure of the economic significance of the above reported lagged adjustments, I employ a series of filter trading strategies constructed on the basis of the uncovered patterns. While the filter rules generate positive excess returns over a buy and hold strategy, the returns are statistically indifferent from zero even before taking trading fees into account. This leads us to conclude that although we find statistically significant lead-lag patterns in the Australian data, the uncovered patterns are too weak to be used profitably as trading signals in an investment strategy.

The rest of the paper is organized as follows: Section 1 reviews some relevant literature on the lead-lag effect in size-sorted portfolios. The econometric methodology is discussed in Section 2, while Section 3 details the dataset and presents empirical results. Conclusions are provided in the final section.

1. Literature review: lead-lag effect in size-sorted portfolios

The study of time series properties of security prices has its roots in the seminal work of Louis Bachelier (1900). Bachelier's hypothesis, nowadays better known as the random walk hypothesis[1], has been studied and tested on a wide range of financial variables, and size-sorted portfolios are not an exception. Lo and MacKinlay (1988) were amongst the first to test Bachelier's hypothesis in the portfolio context using five size-sorted indices comprised of stocks listed on the NYSE and AMEX. They strongly rejected the random walk hypothesis in portfolio data and found that portfolio returns exhibit strong positive serial correlations, even though individual returns are on average weakly and negatively autocorrelated. Lo and MacKinlay hypothesized that this inconsistency was due to cross-autocorrelations between individual security returns. In a related study, Lo and MacKinlay (1990) reported substantial differences in the behavior of small and large capitalization portfolios. They demonstrated that returns for small stocks were more predictable than those of large firms. Further, they also presented evidence that suggested the existence of a lead-lag structure between small and large capitalization stocks that was asymmetric in nature: small stocks appear to lag large firms, but not the other way around.

Following in the steps of Lo and MacKinlay (1990), a number of more recent studies examined the lead-lag relationship in several different stock markets as well as over different time periods. For instance, Fargher and Weigard (1998) investigated the impact of technological and regulatory changes on the lead-lag effect and found that the effect diminished in the more recent past. They explained their findings using the argument of improved market efficiency and better dissemination of information. McQueen et al. (1996) studied the asymmetric responses to good and bad news. Small firms appear to respond with a lag to good, but not bad news. That is, adverse information seemed to be impounded in the price change of small firms instantaneously. Evidence was also found to support the lead-lag hypothesis in Asia-Pacific markets. Chang et al. (1999) reported asymmetric cross-autocorrelations in six Asian markets including Hong Kong, Japan, Singapore, South Korea, Taiwan and Thailand. However, they confirmed McQueen et al.'s asymmetric reaction to good news only for Taiwan. Chang et al. did not find sufficient evidence to infer that the degree of cross-autocorrelation had weakened since 1987.

A number of papers have also extended the literature by examining the portfolio lead-lag effect in the context of conditional variances. For example, Conrad et al. (1991) found evidence of GARCH volatilities and volatility spillovers in the US size-sorted portfolios. Further, similar to the findings reported by Lo and MacKinlay, Conrad et al. reported asymmetric spillovers in conditional variances. The direction of asymmetry is the same; volatility spilling over from large to small firms. In a later study, Kroner and Ng (1998) confirmed Conrad et al.'s findings using several different types of M-GARCH models. Reyes (2001) reported similar findings in size-sorted indices listed on the Tokyo Stock Exchange.

[1] This hypothesis essentially asserts that future stock market returns are unpredictable.

2. Econometric specification: a structural GARCH model

A structural GARCH specification is essentially a simultaneous equations model (SEM), or a structural vector auto-regression (SVAR) in which structural innovations are characterized by GARCH processes (Rigobon and Sack, 2003). This is not an unrealistic assumption given that the reduced form innovations which are often found to display GARCH behavior, are linear combinations of the structural shocks.

A tri-variate structural GARCH model used in the current application can be specified in the following way:

$$B_0 r_t = C + \sum_{i=1}^{p} B_i r_{t-i} + u_t = C + \sum_{i=1}^{p} B_i r_{t-i} + g_t \varepsilon_t, \quad (1)$$

where r_t is a (3×1) matrix of size-sorted portfolios, ordered from the largest capitalization index to the smallest, u_t is a vector of structural innovations with the following properties: $u_t | \Im_{t-1} \sim (0, G_t)$ and its conditional variance matrix G_t is a diagonal matrix of order $(n \times n)$, such that $G_t = g_t g_t'$. Further, ε_t is an $(n\times1)$ vector of Normal $(0, I_n)$ variables. The conditional covariance matrix for the structural process is therefore specified as:

$$Var(B_0 r_t | \Im_{t-1}) = Var_{t-1}(B_0 r_t) = E_{t-1}(g_t e_t e_t' g_t') = E_{t-1}(g_t I_n g_t')$$
$$= E_{t-1}(G_t) = G_t, \quad (2)$$

while the reduced or "observed" form conditional covariance matrix can be seen to be a linear combination of the structural covariance elements:

$$Var_{t-1}(r_t) = Var_{t-1}(B_0^{-1} u_t) = B_0^{-1} E_{t-1}(u_t u_t') B_0^{-1'} =$$
$$B_0^{-1}(G_t)\, B_0^{-1'} = H_t. \quad (3)$$

In order to complete the above model, G_t is specified as a GARCH(p,q) process:

$$diag(G_t) = \omega + \sum_{i=1}^{p} \alpha_i (u_{t-1} \cdot u_{t-i}) + \sum_{i=1}^{q} \beta_i diag(G_{t-1}), \quad (4)$$

where $diag(G_t)$ represents a column vector that consists of the main diagonal elements of G_t, "·" is the element by element multiplication operator, ω is a (3×1) vector of constants, α's and β's are (3×3) parameter matrices.

Although an unrestricted SVAR model similar to the one presented in Eq. (1) cannot be estimated directly[1], Rigobon and Sach (2003) show that in the case of the structural GARCH model, i.e. when structural innovations exhibit GARCH variances, the model is identified, up to row permutations of the original model. This implies that although we can estimate the parameters we cannot assign names to the structural innovations, e.g. large, medium or small firm shocks.

2.1. "Naming" of structural shocks. Because I wish to compare instantaneous and lagged responses in one size sorted portfolio for given changes in the other portfolios, one at a time, I use a variance decomposition approach developed in Dungey et al. (2009) that extends the Rigobon and Sack (2003) approach and overcomes the issue of identifying shocks, i.e. linking structural shocks and observable variables. In particular, I name a structural innovation after that size-sorted portfolio which receives the largest portion of its variation from the innovation. For example, the observed variance of any of the three portfolios h_i^2 (i = 1, 2, 3) can be decomposed as follows:

$$h_i^2 = \alpha_i^2 g_i^2 + \beta_i^2 g_2^2 + \gamma_i^2 g_3^2, \quad (5)$$

where g_i^2's (i = 1, 2, 3) represent the variances of structural shocks u_t, and α, β, γ, are the coefficients implied by Eq. (3). The identification of shocks is then achieved by computing percentage contributions of each structural shock u_i to every size-sorted portfolio variance h_i^2 (i = 1, 2, 3). For example, the contributions to the large firm portfolio variance can be calculated as follows:

$$VD_{r_1,u_1} = \frac{\alpha^2 g_1^2}{\alpha^2 g_1^2 + \beta^2 g_2^2 + \gamma^2 g_3^2}$$
$$VD_{r_1,u_2} = \frac{\beta^2 g_2^2}{\alpha^2 g_1^2 + \beta^2 g_2^2 + \gamma^2 g_3^2}\ . \quad (6)$$
$$VD_{r_1,u_3} = \frac{\gamma^2 g_3^2}{\alpha^2 g_1^2 + \beta^2 g_2^2 + \gamma^2 g_3^2}$$

The decision rule then becomes: name the structural shock u_i (i = 1, 2, 3) after the large firm portfolio if $VD_{r_1,u_i} > VD_{r_1,u_j}$ for all $i \neq j$. For example, if the structural shock number one accounts for 40 percent of the variation in the large cap index, while the shocks two and three account for 30 percent of the variation each, we would name the structural shock one the large firm portfolio shock[2].

[1] This is due to the endogeneity problem; see, for example, Judge et al. (1982), pp. 338-406.

[2] This method, however, would not work if a shock was found to contribute the most variation to more than one observable variable.

2.2. A decomposition of portfolio responses into contemporaneous and lagged components. Once the structural shocks have been identified (i.e. named) I decompose the total cumulative response of each size-sorted portfolio, to a 1 percent change in each of the three portfolios, into instantaneous and lagged components by conducting impulse-response analyses. I provide an impulse of 1 percent change to each of the size-sorted portfolios, one at a time via their structural shocks, and then compute the resulting instantaneous and lagged responses in the portfolios. This approach is feasible only in a structural framework and would not be possible in a regular vector autoregression setting[1].

To illustrate this approach I re-write Eq. (1) in its vector moving average form:

$$r_t = B_0^{-1}C + \sum_{i=1}^{p} B_0^{-1}B_i r_{t-1} + B_0^{-1} g_t \varepsilon_t$$

$$r_t = K + \sum_{i=1}^{p} \Pi_{\mathrm{i}} r_{t-1} + B_0^{-1} g_t \varepsilon_t$$

$$\left(I - \sum_{i=1}^{p} \Pi_{\mathrm{i}} L^i \right) r_t = K + B_0^{-1} g_t \varepsilon_t \qquad (7)$$

$$r_t = \left(I - \sum_{i=1}^{p} \Pi_{\mathrm{i}} \right)^{-1} K + \sum_{i=0}^{\infty} \psi^i B_0^{-1} g_{t-i} \varepsilon_{t-i}$$

The instantaneous response of a size sorted portfolio *i* to a 1 percent change in portfolio *j* can be seen as:

$$\frac{\partial r_{i,t}}{\partial r_{j,t}} = \frac{\left[B_0^{-1} g_t e_j \right]_i}{\left[B_0^{-1} g_t \right]_{jj}}, \qquad (8)$$

where e_j is a (3×1) elementary vector that has 1 in position *j* and 0 elsewhere. Similarly the sum of the lagged responses is equal to:

$$\frac{\sum_{n=1}^{\infty} \partial r_{i,t+n}}{\partial r_{j,t}} = \frac{\left[\sum_{nz=1}^{\infty} \psi^i B_0^{-1} g_{t+n} e_j \right]_i}{\left[B_0^{-1} g_t \right]_{jj}}. \qquad (9)$$

3. Data summary and empirical findings

The dataset consists of daily observations on the closing price, dividends paid and market capitalization for 466 securities listed on the Australian Stock Exchange (ASX) and included[2] in the All Ordinaries Share Price Index. I use Wednesday closing prices and dividend payments to calculate simple weekly returns for each stock over the period December 1987-April 2003[3]. Three size-sorted portfolios are constructed that consist of twenty stocks of large, medium and small market capitalization respectively. Weekly returns rather than daily are used in order to lessen market microstructure effects such as large bid-ask spreads, non-synchronous trading and complications arising from seasonality problems, namely the day-of-the-week effect.

The reason for choosing to limit the number of firms in each portfolio to twenty securities is to keep the number of securities in each index the same. The Small Cap Index published by the ASX consists of 200 securities, the ASX Mid Cap Index contains 50 issues, while the ASX Large Cap Index only 20. Having more stocks in the Small and Mid Cap Indices means that idiosyncratic risks are diversified over a larger number of securities in those portfolios. This in turn can make small capitalization stocks appear to exhibit smaller risk profiles on average when compared to medium and large capitalization stocks, an unrealistic scenario. Further, the number of stocks included in each index is to a large extent determined by the total number of large capitalization securities listed on the Australian Stock Exchange. The ASX is a relatively small market and the top twenty firms account for more than 60 percent of the total market capitalization. These twenty stocks clearly distinguish themselves from the rest of the market by their size and including more than twenty stocks in the large capitalization portfolio would likely result in a blend of large and medium capitalization firms.

While I form the large capitalization portfolio from the twenty largest firms listed on the ASX, the medium capitalization portfolio includes the first twenty stocks above 11 percent of the cumulative sample market value. The small capitalization index is composed of the first twenty stocks above 3.5 percent of the cumulative market value. Therefore, the large stock portfolio mirrors the ASX published Large Cap Index while the cut-off points for the medium and small capitalization portfolios roughly coincide with the median cumulative market values of the ASX published Medium and Small Cap indices.

I construct the portfolios as equally-weighted indices of their constituent securities and rebalance them every

[1] A regular vector autoregression impulse-response function exhibits only lagged responses.

[2] As of October 26, 2002, the All Ordinaries is a capitalization weighted index that accounts for more than 90 percent of the total market capitalization in Australia.

[3] This time period was chosen due to limitations the author had in accessing the data.

six months in order to maintain the appropriate firm size in each portfolio. Further, I control for the non-synchronous trading problem (Fisher, 1966) by computing weekly portfolio returns using only those securities that are actively traded on the last two trading days before Wednesday of each week. This procedure was shown to eliminate the effect of stale prices by Mech (1993). Table 1 presents summary statistics for the three portfolios. Consistent with the findings of Lo and MacKinlay (1990) in the US, Australian medium and small firm portfolios show statistically significant serial correlations, according to the large Q-statistics, while the large cap index shows no discernable serial correlation pattern.

Table 1. Summary statistics for the size-sorted portfolios

	Median (%)	Volatility (%)	ρ(1)	ρ(2)	ρ(3)	ρ(4)	Q(4)	JB
r_1	0.20	2.06	0.020	0.025	0.020	-0.026	1.68 (0.79)	40.64 (0.00)
r_2	0.29	1.80	0.157	0.065	0.020	0.000	23.11 (0.00)	30.44 (0.00)
r_3	0.31	2.31	0.238	0.132	0.040	-0.027	60.29 (0.00)	58.30 (0.00)
r_1^2	1.62	7.60	0.131	0.123	0.089	0.084	37.58 (0.00)	
r_2^2	1.28	5.42	0.106	0.048	0.138	0.072	29.84 (0.00)	
r_3^2	2.28	9.74	0.166	0.022	0.015	0.020	22.73 (0.00)	

Note: r_1, r_2 and r_3 are weekly portfolio returns on the large, medium and small capitalization portfolios. ρ's represent autocorrelation coefficients while Q(5) is the Ljung-Box Q-statistics calculated on the first five ρ's, 5% critical value for the Q-statistic is 11.07.

After squaring the returns, all three series appear to be strongly autocorrelated, which is indicative of time varying conditional volatility. The median weekly return and volatility estimates are greatest for the small firm portfolio.

3.1. Empirical findings. Table 2 presents the estimates of the structural mean equation parameters, see Eq. (1). The large capitalization index seems to absorb most of relevant information contemporaneously. None of the coefficients on the lagged explanatory variables are statistically significant at any conventional level of significance, with the exception of the small cap index lagged two periods. In contrast, the medium capitalization index appears to lag large firms while the small firms lag both the large and medium size portfolios. These findings are largely in line with the lead-lag hypothesis proposed by Lo and MacKinlay (1990), and international literature reviewed in Section 1.

As Table 2 suggests, the large firm portfolio responds instantaneously to the information conveyed by the medium capitalization index, at the 5 percent level of significance. Similarly, the medium cap index shows a partial immediate adjustment to the news transmitted by the return on the large cap portfolio. In contrast to these two portfolios, the small capitalization index does not respond contemporaneously to either of the other two indices, at any conventional level of statistical significance. This finding, combined with what we observe in lagged responses, not only supports the partial-adjustment hypothesis but also suggests that small firms fail to even partially adjust to the information conveyed by large and medium firms contemporaneously. The entire adjustment process of the small capitalization index occurs with a time lag, a finding that has not been previously reported in the literature.

Diagnostic tests reported in Table A.1 of the Appendix indicate that the fitted model provides a good representation of the data. In particular, the tests find no residual autocorrelation or GARCH effects, while standardized residuals also appear to be normally and independently distributed.

3.2. The relative significance of contemporaneous versus lagged adjustments. This section presents the newly developed decomposition of the lead-lag effect into the instantaneous and lagged components. Having conducted the variance decomposition analysis and identified[1] structural shocks as large, medium and small firm shocks, I present a decomposition of the lead-lag effect (see Table 3).

[1] The variance decomposition analysis reveals that the first, second and third structural shocks account for the 96%, 87% and 88% percent of the variation in the large, medium and small firms, respectively. Complete variance decomposition analyses are available upon request from the author.

Table 2. Structural GARCH estimates – mean equations

Dependent variable: **Large capitalization index** - r_{1t}				Dependent variable: **Medium capitalization index** - r_{2t}				Dependent variable: **Small capitalization index** - r_{3t}			
	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value		Coeff.	t-stat	p-value
Const.	0.19	2.879	0.004	Const.	0.11	2.044	0.041	Const.	0.05	0.522	0.602
r_{2t}	0.24	2.304	0.021	r_{1t}	0.25	3.060	0.002	r_{1t}	0.31	1.190	0.234
r_{3t}	0.04	0.185	0.853	r_{3t}	0.11	0.970	0.332	r_{2t}	0.11	0.448	0.654
r_{1t-1}	-0.02	-0.347	0.729	r_{1t-1}	0.07	2.266	0.024	r_{1t-1}	0.09	1.748	0.081
r_{2t-1}	-0.04	-0.872	0.384	r_{2t-1}	0.05	1.180	0.238	r_{2t-1}	0.15	2.793	0.005
r_{3t-1}	-0.01	-0.134	0.893	r_{3t-1}	0.04	1.259	0.208	r_{3t-1}	0.08	2.015	0.044
r_{1t-2}	0.02	0.459	0.646	r_{1t-2}	-0.01	-0.366	0.714	r_{1t-2}	0.10	2.328	0.020
r_{2t-2}	0.06	1.300	0.194	r_{2t-2}	0.04	0.842	0.400	r_{2t-2}	0.11	2.030	0.043
r_{3t-2}	-0.08	-2.605	0.009	r_{3t-2}	0.00	-0.023	0.982	r_{3t-2}	0.05	1.168	0.243

Note: r_1, r_2 and r_3 are weekly portfolio returns on the large, medium and small capitalization portfolios. t-statistics and p-values reported are based on robust Bollerslev-Wooldridge (1992) standard errors. A lag length of two (i.e. $p = 2$) was chosen according to the AIC and Hannan-Quinn selection criteria and residual diagnostic tests. Residual diagnostic tests reported in Table A.1 of the Appendix give favorable assessment to the fitted model.

Table 3. Decomposition of portfolio responses into contemporaneous and lagged parts

		INITIAL IMPULSE IS GIVEN BY 1% SHOCK TO		
		Large cap index	Medium cap index	Small cap index
Contemporaneous response	Large cap index	1.00 %	0.25 %	0.00 %
	Medium cap index	0.24 %	1.00 %	0.00 %
	Small cap index	0.00 %	0.00 %	1.00 %
Lag 1 response	Large cap index	0.02 %	0.00 %	0.00 %
	Medium cap index	0.07 %	0.02 %	0.00 %
	Small cap index	0.13 %	0.17 %	0.08 %
Sum of responses for lags 2-10	Large cap index	-0.03 %	-0.03 %	-0.10 %
	Medium cap index	-0.01 %	-0.01 %	-0.03 %
	Small cap index	0.17 %	0.16 %	-0.02 %

Note: The table presents a summary of the impulse-response function, where the impulses are given by structural shocks calibrated to represent 1% changes in the large, medium and small capitalization portfolios.

As evident from the above table, a 1 percent change in the large cap index results in an immediate effect of 0.24 percent in the medium cap index, while a 1 percent impulse to medium capitalization firms produces a similar 0.25 percent increase in the large cap portfolio. Interestingly, changes neither to the large nor to the medium cap firms are capable of producing instantaneous changes in small cap stocks, but result in strong lagged responses.

The total lagged response of the small cap index to a 1 percent change in large firms can be broken down into a 0.13 percent response within a week of the initial shock, and 0.17 percent adjustment over the next nine weeks. The lagged reaction of the medium cap stocks to a 1 percent change in large firms is smaller, with about 0.07 percent change in the first week following the initial shock, and -0.01% effect over the subsequent nine week period. Small firms cause neither instantaneous nor one-week-after-the-shock effect in large and medium cap firms. However, there are marginal responses of -0.03 percent and -0.02 percent in medium and large cap portfolios respectively, over the time span of two to ten weeks following an impulse to small companies.

3.3. Filter rule profitability tests. I test the information spillover patterns uncovered and described above for their economic significance via a series of filter rule tests. I focus on statistically significant lagged spillovers found in the small cap index equation[1] (see Table 2) as they have the best chance of generating returns in excess of those produced by a buy and hold strategy.

Since the estimated coefficients on the lagged large and medium cap index returns are positive a buy signal for the small cap index is generated if the lagged return on the large and/or medium cap index exceeds a certain value, and a sell signal is generated if the return falls below the same threshold. A number of threshold levels ranging from 0.5 percent to 2 percent are considered as triggers for trading in the small capitalization stocks following these three events: 1) previous week's large capitalization return exceeds/falls below the threshold, 2) previous week's medium capitalization return exceeds/falls below the threshold, and 3) both medium and large capitalization returns exceed/fall below the threshold in the previous week. In addition, the investor is assumed to be invested in Australian 90-day Treasury Bills when not holding a position in small stocks.

I assess the effectiveness of the above described trading system by computing excess returns of this strategy over a passive "buy and hold" investment strategy for a number of holding periods ranging from one to five weeks. Table 4 below presents the outcomes of these filter trading rules for a holding period of three weeks[2]. In addition, Table 4 also reports results of a statistical test for the significance of excess returns being different from zero.

Table 4. Filter rule profitability tests

RULE		Annual excess return over a "buy and hold" strategy (%)	Null hypothesis: excess annual return = 0 t-statistic and (p-value)	Number of trading signals
1	a. Large cap > |2%|	1.98	0.399 and (0.689)	239
	b. Mid cap > |2%|	1.48	0.294 and (0.768)	191
	c. Large & Mid cap >|2%|	-0.45	-0.088 and (0.929)	88

[1] Filter rules were also applied to the other two portfolios but resulted in lower trading profits. They are available from the author upon request.
[2] The results for other holding periods do not change the conclusions reached based on the results presented here. Trading profits for other holding periods are available upon request.

Table 4 (cont.). Filter rule profitability tests

RULE		Annual excess return over a "buy and hold" strategy (%)	Null hypothesis: excess annual return = 0 t-statistic and (p-value)	Number of trading signals
2	a. Large cap > |1.5%|	2.79	0.571 and (0.568)	332
	b. Mid cap > |1.5%|	4.18	0.832 and (0.405)	299
	c. Large & Mid cap > |1.5%|	1.42	0.283 and (0.777)	161
3	a. Large cap > |1%|	3.56	0.698 and (0.485)	472
	b. Mid cap > |1%|	5.59	1.109 and (0.268)	426
	c. Large & Mid cap > |1%|	3.21	0.647 and (0.518)	293
4	a. Large cap > |0.5%|	5.45	0.985 and (0.325)	617
	b. Mid cap > |0.5%|	6.06	1.229 and (0.219)	591
	c. Large & Mid cap > |0.5%|	4.78	0.967 and (0.334)	484

Note: Holding period is assumed to be 3 weeks. Excess returns for holding periods less than three weeks have been calculated but they are typically smaller than the returns reported here. The statistical test is performed by regressing excess returns on a constant, and using the Newey-West (1987) HAC consistent covariance estimates to calculate test statistics.

As Table 4 shows, profitability of the trading strategies and the number of generated trade signals vary considerably across different rules. As expected, less stringent rules generate more trading signals. However, it also appears that the less restrictive the trading rule is, the higher the annual excess returns it produces.

The smallest excess return is associated with the strategy 1.c. of Table 4, which trades when both large and medium stocks move by more than 2% in absolute value. On the other hand, the greatest annual excess return is generated by the strategy 4.b that generates a buy signal when medium size stocks' return exceeds 0.5 percent, and a sell signal when the medium cap index falls by more than 0.5 percent.

Although some annual excess returns appear rather large, a formal statistical test is presented in column three of Table 4. None of the twelve trading strategies implemented here provides an annual return, in excess of a buy and hold strategy, that is statistically different from zero. Further, subtracting trading fees, which amount to about 4.0 percent[1] for a round trip brokerage fee, would make these results even more in favor of a simple buy and hold strategy.

Conclusions

A structural method is proposed to investigate information spillovers among three size-sorted portfolios constructed from the securities listed on the Australian Stock Exchange. The main advantage of this approach over the existing models is that it broadens the lead-lag analysis into an investigation of the contemporaneous versus lagged information spillovers. Specifically, it allows us to quantify relative importance of the contemporaneous and lagged information spillovers for each size-sorted portfolio.

It appears that not only does the small capitalization index lag the large and medium size firms with statistical significance, as reported by the existing literature, but that it fails to even partially adjust to their returns contemporaneously. On the other hand, over 80 percent of the total adjustment to new information completed by large and medium size firms occurs instantaneously. This is a new and interesting finding that indicates a degree of segmentation in the Australian stock market based on the market capitalization.

In order to test the uncovered patterns for profitability I construct a series of filter rule trading strategies. Even though the filter rules typically forecast the sign of the small portfolio return correctly, the excess returns are not statistically different from zero, at any conventional level of significance. The economically irrelevant lagged responses found here will likely perpetuate in the future as they do not generate profitable arbitrage opportunities that would eliminate them.

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[1] Round trip discount brokerage fees amount to about 0.20% of the traded value in Australia. Each portfolio consists of 20 securities.

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Appendix

Table A.1. Residual diagnostic tests

	Standardized residual one		Standardized residual two		Standardized residual three	
	Statistic	(p-value)	Statistic	(p-value)	Statistic	(p-value)
Autocorrelation in residuals: Ljung-Box (1979) test H_0: No autocorrelation						
Lag 1	0.396	(0.529)	0.199	(0.656)	0.017	(0.896)
Lag 2	0.403	(0.817)	0.995	(0.608)	0.086	(0.958)
Lag 3	0.480	(0.923)	1.146	(0.766)	0.107	(0.991)
Lag 4	0.482	(0.975)	1.146	(0.887)	0.116	(0.998)
Lag 5	0.765	(0.979)	1.314	(0.934)	0.199	(0.999)
GARCH in residuals: Ljung-Box (1979) test Autocorrelation in squared residuals H_0: No autocorrelation						
Lag 1	0.087	(0.768)	0.132	(0.717)	0.026	(0.871)
Lag 2	1.552	(0.460)	0.560	(0.756)	0.619	(0.734)
Lag 3	2.753	(0.431)	0.706	(0.872)	0.688	(0.876)
Lag 4	2.775	(0.596)	0.712	(0.950)	0.735	(0.947)
Lag 5	2.815	(0.729)	1.107	(0.953)	1.552	(0.907)
Normality in residuals: Jarque-Bera (1980) test H_0: Normality	4.570	(0.102)	5.600	(0.061)	0.118	(0.113)
Independence of residuals: BDS Test H_0: Independence	0.080	(0.936)	-0.685	(0.494)	0.152	(0.879)

Diagnostic tests presented in the above table were conducted on a vector of standardized residuals ε_t as described in Eq. (1). None of the null hypotheses can be rejected at 5% significance level, while only one hypothesis (Normality of Standardized Residual Two) can be rejected at 10%. Overall, these results are strongly in favor of the estimated model.