

DEPARTMENT OF ECONOMICS



***MACQUARIE ECONOMICS  
RESEARCH PAPERS***

*Information Spillovers and Size-sorted  
Portfolios: Structural Evidence from Australia*

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**Number 10/2006**  
ISSN 1834-2469

December 2006

# INFORMATION SPILLOVERS AND SIZE-SORTED PORTFOLIOS: STRUCTURAL EVIDENCE FROM AUSTRALIA<sup>\*</sup>

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A portfolio of small capitalization stocks formed from securities listed on the Australian Stock Exchange (ASX) fails to adjust to market-wide news instantaneously and displays a significant amount of predictability from lagged returns on large and medium size firms. Despite apparently large excess payoffs generated by filter rules, the lagged adjustments become economically insignificant once transaction costs associated with taking a position in each constituent security are taken into account. I suggest that the observed predictability is largely due to a lack of small cap portfolio derivatives which could facilitate index arbitrage and enhance price discovery in the Australian market.

**JEL Classifications:** C30, C32, G10

**Keywords:** Size-sorted portfolios, ASX, structural GARCH, predictability

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<sup>\*</sup> The first drafts of this paper were completed independently of similar work by Rigobon and Sack (2003).

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## **1. Introduction**

I conduct structural tests of the lead-lag effect using three size-sorted portfolios from the Australian stock market and find that even after accounting for contemporaneous correlations, small capitalization stocks lag large- and medium-sized firms. It appears that small stocks take between one and two weeks to fully adjust to market-wide news shocks and fail to even partially respond instantaneously to this information. Although the lagged adjustment processes are statistically significant, a series of filter rule tests, when applied to the return series of the entire index, fail to generate excess profits and suggest that the market is informationally efficient. However, this finding is due to the large transaction costs that one incurs by engaging in a trading strategy of buying and selling all size-sorted portfolio constituent securities simultaneously, mainly due to the lack of adequate size-sorted portfolio derivatives. Given that futures contracts on the top fifty and the top two hundred stocks exist and are actively traded in Australia, I believe that the market would benefit significantly, by way of price discovery and market efficiency, through the introduction of a small cap index futures contract.

The lead-lag effect of size-sorted portfolios relates to the finding that returns on small capitalization firms are predictable from lagged returns on large stocks, but not the other way around (Lo and MacKinlay 1990). Empirical evidence that supports this effect has been reported in a number of US and international studies (e.g. Meh 1993; Jegadeesh and Titman 1995; Chang, McQueen and Pinegar 1999) and also in the context of conditional volatility (e.g. Conrad, Gultakin and Kaul 1991; Kroner and Ng 1998). In this paper, and in contrast to the existing literature which is mainly based on reduced-form statistical models, I examine the lead-lag effect using a new structural GARCH approach (Rigobon and Sach 2003; Milunovich 2004).

The structural GARCH framework has two main advantages over the reduced-form approaches that are commonly applied in the literature. First, it overcomes the endogeneity problem and provides unbiased estimates of

contemporaneous regression coefficients. Using a structural GARCH model I am thus able to estimate and test lagged as well as contemporaneous interactions among size-sorted portfolios, something that has not been done previously in this context. Second, I conduct volatility spillover tests on both structural and reduced form variance equations. Differentiating between the two can be important and provides new insights into the pattern of volatility transfers among the portfolios. For example, while spillovers in the reduced form volatility are important for financial applications (e.g., portfolio selection, risk management), structural volatility spillovers relate to transfers of uncertainty among the most fundamental source of risk: news shocks. Given that this study presents a first attempt at investigating the lead-lag effect on Australian data, it also contributes new international evidence to the literature.

The rest of the paper is organized as follows: a brief literature review is given in Section II. I introduce the econometric model in Section III and present empirical findings in Section IV. Section V concludes.

## **2. 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<sup>1</sup> has been studied and tested on a wide range of financial variables and size-sorted portfolios are not an exception. Lo and MacKinlay (1988) are amongst the first to test Bachelier's hypothesis in this context using five size-sorted portfolios from the NYSE and AMEX. They strongly reject the random walk hypothesis in portfolio data and illustrate that portfolio returns exhibit strong positive serial correlations, even though individual returns are on average weakly and negatively autocorrelated. Lo and MacKinlay hypothesize that this controversy is due to cross-autocorrelations between individual security returns. In a related study, Lo and MacKinlay (1990) report several substantial differences in the behaviour of small and large capitalization portfolios. They demonstrate that returns for small stocks are more predictable

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<sup>1</sup> This hypothesis essentially asserts that future stock market returns are unpredictable.

than those of large firms. They also present evidence suggesting the existence of a lead-lag structure between small and large capitalization stocks that is asymmetric in nature: small stocks appear to lag large firms but not the other way around.

A number of recent studies have followed in the steps of Lo and MacKinlay and examined the lead-lag relationship in various stock markets. For instance, Fargher and Weigard (1998) investigate the impact of technological and regulatory changes on the lead-lag effect and find that the effect has diminished in the more recent past. They explain their findings using an argument of improved market efficiency and better dissemination of information. McQueen, Pinegar and Thorley (1996) study 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 of small firms instantaneously. Evidence is also found to support the lead-lag hypothesis in Asia-Pacific markets. Chang, McQueen and Pinegar (1999) report asymmetric cross-autocorrelations in six Asian markets including Hong Kong, Japan, Singapore, South Korea, Taiwan and Thailand. However, they confirm McQueen, Pinegar and Thorly's asymmetric reaction to good news only for Taiwan. Chang, McQueen and Pinegar do not find sufficient evidence to infer that the degree of cross-autocorrelation had weakened since 1987.

Conducting research on the conditional second moment matrix, Conrad, Gultekin and Kaul (1991) find evidence of GARCH volatilities and volatility spillovers in the US size-sorted portfolios. Briefly, a volatility spillover is said to have occurred when a change in price volatility in one market produces a lagged impact on volatility in another market, over and above local effects. Conrad et al. (1991) relate their empirical findings to a theoretical model of Ross' (1989), in which price volatility is associated with the rate of information flow. Similar to the findings reported by Lo and MacKinlay, Conrad et al. document 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) confirm Conrad, Gultekin and Kaul's findings using several MGARCH models. Reyes (2001) reports similar findings in size-sorted indices listed on the

Tokyo Stock Exchange. Pardo and Torro (2003) study dynamic relationships between large and small firms using volatility impulse response functions. They find that bad news causes volatility spillovers in both directions.

Overall, international evidence suggests that spillovers exist in both means and variances of size-sorted portfolios and that the spillovers stem from large capitalization to small capitalization firms. Although the stylised facts presented above seem to be generally accepted, there is a number of conflicting opinions as to what causes them. Boudoukh, Richardson and Whitelaw (1994) broadly categorise these competing theories into three camps, which they refer to as: heretics, loyalists and revisionists.

According to Boudoukh et al., studies that attribute the lead-lag effect in size-sorted portfolio to either over-reaction or partial adjustment in the price of small firms to common market information are labelled “heretics”. Because large firms are believed to adjust to new information instantaneously, the cross-autocorrelations are due to the slow adjustment of small firms to shocks in common factors. Of the heretics, studies by Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) are amongst the most prominent ones. Recent empirical evidence that supports this theory comes from Richardson and Peterson (1999) who show that in the US large firms Granger cause small firms but not vice versa.

The second group of theorists, referred to as “loyalists” in the Boudoukh et al. classification, believe that the market processes information rationally and that short-horizon correlations are not due to fundamentals but market frictions and microstructure effects. Market imperfections such as non-synchronous trading, bid-ask spreads, various trading mechanisms, systematic changes in inventory holdings and non-instantaneous information flows are commonly cited. Lo and MacKinlay (1990) examine the non-synchronous trading arguments and conclude that even after assuming excessively high levels of non-trading probabilities it is unlikely that non-synchronous trading is the cause of the lead-lag effect. Similarly, Mech (1993) is concerned with transaction costs being a source of the lead-lag effect, a theory supported by his cross-sectional data tests. Boudoukh,

Richardson and Whitelaw (1994) themselves assume a loyalist position and develop a model that allows for heterogenous non-trading. However, their empirical findings lead them to conclude that non-synchronous trading cannot account for all of the lead-lag effect.

The last camp, labelled “revisionists”, hypothesize that markets are efficient and that completely frictionless markets can generate short-horizon returns that are autocorrelated. Time varying risk premiums can be explained by inter-temporal asset pricing models such as the conditional APT and consumption based CAPM. In this literature Conrad and Kaul (1989) and Conrad, Gultekin and Kaul (1991) claim that predictable variations at short-horizons are attributable to changes in expected returns. Connolly and Conrad (1991) use cointegration and simulation tests to compare a time varying factor model to a lagged price adjustment model and conclude in favour of the time varying factor model. Similarly, Hameed (1997) uses principal component analysis to extract factors and shows that the time varying factor model provides a better fit than a price adjustment model.

Given that all three theories are supported by some empirical evidence, it is unclear which of the three camps best explains the observed empirics. One would also surmise that some of these theories can be complementary.

## **2. Econometric specification: A structural GARCH model**

A structural GARCH model can be derived from a structural vector auto-regression (SVAR) by assuming that structural innovations follow a GARCH process (Rigobon and Sack 2003; Milunovich 2004). This is not an unrealistic assumption given that the reduced form innovations, which are often found to display GARCH behaviour, are linear combinations of the structural shocks.

I derive a structural GARCH model for three size-sorted portfolios in the following way: if  $\mathbf{r}_t$  is a  $(3 \times 1)$  matrix of size-sorted portfolios, ordered from the largest capitalization index to the smallest, and  $\mathbf{u}_t$  is a vector of structural innovations then an SVAR process of order  $p$  can be written as:

$$\mathbf{B}_0 \mathbf{r}_t = \mathbf{C} + \sum_{i=1}^p \mathbf{B}_i \mathbf{r}_{t-i} + \mathbf{u}_t \quad (1)$$

where the structural innovation vector  $\mathbf{u}_t$  has the following properties:  $\mathbf{u}_t \sim (\mathbf{0}, \mathbf{G})$  and  $\mathbf{G}$  is a diagonal  $(n \times n)$  matrix. Thus, the structural shocks,  $\mathbf{u}_t$ , are uncorrelated random variables, with a mean of zero and a covariance matrix  $\mathbf{G}$ . In order to derive the structural GARCH model equation (1) can be rewritten as:

$$\mathbf{B}_0 \mathbf{r}_t = \mathbf{C} + \sum_{i=1}^p \mathbf{B}_i \mathbf{r}_{t-i} + \mathbf{g} \boldsymbol{\varepsilon}_t \quad (2)$$

where  $\mathbf{g}$  is a diagonal matrix of standard deviations such that  $\mathbf{G} = \mathbf{g} \mathbf{g}'$ ,  $\mathbf{u}_t = \mathbf{g} \boldsymbol{\varepsilon}_t$  and  $\boldsymbol{\varepsilon}_t$  is an  $(n \times 1)$  vector of  $N(\mathbf{0}, \mathbf{I}_n)$  variables. Allowing the covariance matrix  $\mathbf{G}$  to vary over time, conditional on the information set  $\mathfrak{I}_{t-1}$  yields a structural GARCH model:

$$\begin{aligned} \mathbf{B}_0 \mathbf{r}_t &= \mathbf{C} + \sum_{i=1}^p \mathbf{B}_i \mathbf{r}_{t-i} + \mathbf{u}_t^* \\ &= \mathbf{C} + \sum_{i=1}^p \mathbf{B}_i \mathbf{r}_{t-i} + \mathbf{g}_t \boldsymbol{\varepsilon}_t. \end{aligned} \quad (3)$$

with  $\mathbf{u}_t^* = \mathbf{g}_t \boldsymbol{\varepsilon}_t$ . The conditional covariance matrix for the structural process is therefore:

$$\begin{aligned} \text{Var}(\mathbf{B}_0 \mathbf{r}_t | \mathfrak{I}_{t-1}) &= \text{Var}_{t-1}(\mathbf{B}_0 \mathbf{r}_t) \\ &= E_{t-1}(\mathbf{g}_t \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \mathbf{g}_t') \\ &= E_{t-1}(\mathbf{g}_t \mathbf{I}_n \mathbf{g}_t') \\ &= E_{t-1}(\mathbf{G}_t). \end{aligned} \quad (4)$$

In order to complete the above model, I specify  $\mathbf{G}_t$  as a GARCH( $p, q$ ) process:

$$diag(\mathbf{G}_t) = \boldsymbol{\omega} + \sum_{i=1}^p \boldsymbol{\alpha}_i (\mathbf{u}_{t-i} \circ \mathbf{u}_{t-i}) + \sum_{i=1}^q \boldsymbol{\beta}_i diag(\mathbf{G}_{t-i}) \quad (5)$$

where  $diag()$  operator stacks main diagonal elements into a column vector, ‘ $\circ$ ’ is the element by element multiplication operator,  $\boldsymbol{\omega}$  is a  $(3 \times 1)$  vector of constants,  $\boldsymbol{\alpha}$ ’s and  $\boldsymbol{\beta}$ ’s are  $(3 \times 3)$  parameter matrices. As equation (5) suggests, even though the structural innovations are uncorrelated, they are not necessarily independent because higher order dependencies may arise from the conditional second moment equations. Because  $\mathbf{G}_t$  depends on information up to and including the time period  $t-1$ , equation (5) also implies that the conditional expectation of  $\mathbf{G}_t$ , and thus the conditional variance of the structural process is simply  $\mathbf{G}_t$ :

$$E_{t-1}(\mathbf{G}_t) = Var_{t-1}(\mathbf{B}_0 \mathbf{r}_t) = \mathbf{G}_t \quad (6)$$

The reduced form covariance matrix can then be seen to be a linear combination of structural GARCH covariance matrix elements:

$$\begin{aligned} Var_{t-1}(\mathbf{r}_t) &= Var_{t-1}(\mathbf{B}_0^{-1} \mathbf{u}_t^*) = \mathbf{B}_0^{-1} E_{t-1}(\mathbf{u}_t^* \mathbf{u}_t^{*'}) \mathbf{B}_0^{-1'} \\ &= \mathbf{B}_0^{-1} (\mathbf{G}_t) \mathbf{B}_0^{-1'} \\ &= \mathbf{H}_t. \end{aligned} \quad (7)$$

Although an unrestricted SVAR model such as the one in equation (1) cannot be estimated directly,<sup>2</sup> Rigobon and Sach (2003) show that GARCH volatility generates additional moment conditions which in conjunction with restrictions implied by equation (7) allow identification of all structural parameters, up to a permutation matrix.

### 3. Data summary and empirical findings

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<sup>2</sup> This is due to the endogeneity problem; see for example Judge et al (1982), pp. 338-406.

The dataset consists of daily observations on the closing price, dividends paid and market capitalization for 466 securities listed on the ASX and included<sup>3</sup> in the All Ordinaries Share Price Index. I use Wednesday closing prices and dividend payments to calculate simple weekly<sup>4</sup> returns for each stock over the period December 1987–April 2003. I then construct three size-sorted portfolios that comprise of twenty stocks of large, medium and small market capitalization respectively.

There are two main reasons why I chose to limit the number of firms in each portfolio to twenty and not use ASX published size-sorted indices. Firstly, I want to keep the same number of securities in each index. 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 these indices. This in turn can make small capitalization stocks appear to have smaller risk profiles than medium and large capitalization stocks and significantly affect estimation results. Secondly, given the above argument the number of stocks included in each index is, to a large extent, determined by the number of large capitalization stocks 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 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 be likely to result in a mix 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 the 11 percent of the cumulative sample market value. Similarly, the small capitalization index is composed of the first twenty stocks above 3.5 percent

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<sup>3</sup> As of 26 October 2002, the All Ordinaries is a capitalization weighted index that accounts for more than 90 percent of the total market capitalization in Australia.

<sup>4</sup> I use weekly returns rather than daily 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.

of the cumulative market value. Thus, 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 Medium Cap and ASX Small Cap indices.

I construct the portfolio as equally-weighted indices of their constituent securities and rebalance them every six months in order to maintain the appropriate firm size in each portfolio. Further, I also control for the non-synchronous trading problem (Fisher, 1966) by computing weekly portfolio returns using only those securities that actively trade on the last two consecutive trading days. This procedure was shown to eliminate the effect of stale prices by Mech (1993). Table 1 presents summary statistics for the three portfolios.

**Table 1. Summary statistics for the size-sorted portfolios**

	Median (%)	St. Dev. (%)	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	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.  $\rho$ 's represent autocorrelation coefficients while Q(5) is the Ljung-Box Q-statistics calculated on the first five  $\rho$ 's, 5% critical value for the Q-statistic is 11.07.

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 large Q-statistics, while the large cap index shows no discernable serial correlation pattern. After squaring the returns, all three series appear to be strongly autocorrelated, which is indicative of time varying volatility.

The median weekly return and standard deviation estimate are highest for the small firm portfolio.

### 3.1. Empirical findings

Table 2 presents maximum likelihood estimates of the structural mean equation parameters, see equation (2). 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 a notable exception of the small cap index lagged two periods. The medium capitalization index, on the other hand, appears to lag large firms while the small cap index lags both the large and medium size portfolios. These findings are largely in line with the lead-lag hypothesis proposed by Lo and MacKinlay (1990).

**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
$r_{2t-2}$	-0.04	-0.872	0.384	$r_{2t-2}$	0.05	1.180	0.238	$r_{2t-2}$	0.15	2.793	0.005
$r_{3t-2}$	-0.01	-0.134	0.893	$r_{3t-2}$	0.04	1.259	0.208	$r_{3t-2}$	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.

Turning to the contemporaneous regression coefficients, the large firm portfolio seems to respond to the information conveyed by the medium capitalization index. Similarly, the medium cap index is contemporaneously affected by the return on the large cap portfolio. In contrast to these two portfolios, the small capitalization index does not adjust contemporaneously to either of the other two indices with 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 market-wide information contemporaneously. The entire adjustment process of the small firms studied here occurs with a time lag of between one and two weeks. This new finding has not been reported in the literature previously.

Additional to the above analysis, it is of interest to identify the structural innovations that drive the size-sorted portfolio returns process. In order to do this I use a diversification argument. Large and medium size firms tend to be well diversified, both operationally and regionally and, as such, are mainly determined by macroeconomic conditions and market-wide news. Sensitivities to regional, sectoral or idiosyncratic news are largely diversified away. Since the estimated contemporaneous  $\mathbf{B}_0$  matrix is block diagonal, the first two structural innovations can be thought of as two components of a market-wide news factor. The third structural innovation that relates only to small stocks (with statistical significance) can then be interpreted as the small capitalization index idiosyncratic noise. Although it is uncorrelated with the market-wide news it is not independent of it, as shown below in Table 3. Its conditional volatility is determined by market-wide news volatility spillovers.

There are two potential sources of volatility spillovers in a structural GARCH model. As equation (9) indicates, a reduced form GARCH variance is a weighted average of the structural form variance matrix. Thus, the first source of volatility spillover comes from the estimated contemporaneous matrix  $\mathbf{B}_0$  which forms the weights, while the second source can be identified as volatility spillovers in the structural GARCH variances. The estimated  $\mathbf{B}_0$  matrix is block

diagonal, which means that there are bidirectional volatility spillovers between the reduced large and medium capitalization firms from this source. The small capitalization firms, on the other hand, appear neither to transmit nor receive volatility from this source. The small cap index receives volatility spillovers from its structural variance equation that is the conditional variance of its structural news shocks, as shown in Table 3.

**Table 3: Structural GARCH estimates – variance equations**

Dependent Variable: Structural Variance 1 – $g_{1t}$			Dependent Variable: Structural Variance 2 – $g_{2t}$			Dependent Variable: Structural Variance 3 – $g_{3t}$		
	Coeff.	Prob.		Coeff.	Prob.		Coeff.	Prob.
Const.	0.19	0.088	Const.	0.11	0.166	Const.	0.68	0.051
$u_{1t-1}^{*2}$	0.08	0.016	$u_{1t-1}^{*2}$	0.00	0.718	$u_{1t-1}^{*2}$	0.08	0.061
$u_{2t-1}^{*2}$	-0.03	0.254	$u_{2t-1}^{*2}$	0.07	0.013	$u_{2t-1}^{*2}$	0.14	0.048
$u_{3t-1}^{*2}$	0.02	0.359	$u_{3t-1}^{*2}$	0.00	0.992	$u_{3t-1}^{*2}$	0.05	0.491
$g_{1t-1}$	0.86	0.000	$g_{2t-1}$	0.88	0.000	$g_{3t-1}$	0.61	0.000

Note: Each structural conditional variance equation is specified as a GARCH (1,1) with additional volatility spillover terms:  $g_{it}^2 = \omega + b_1 g_{it-1}^2 + a_{11} u_{1t-1}^{*2} + a_{12} u_{2t-1}^{*2} + a_{13} u_{3t-1}^{*2}$  where  $u_{1t}^*$ ,  $u_{2t}^*$  and  $u_{3t}^*$  are structural innovations associated with equations on the large, medium and small cap portfolios. t-statistics and p-values reported are based on robust Bollerslev-Wooldridge (1992) standard errors.

The structural variance associated with the first component of the market-wide news factor, does not appear to receive any cross-equation volatility spillovers. It has statistically significant ARCH and GARCH parameters and a volatility half-life<sup>5</sup> of slightly more than eleven weeks. Similarly there are no cross-equation volatility spillovers in the second component of the market-wide news factor. It however exhibits more persistence than the first equation with an estimated half-life of thirteen and a half weeks. The last structural variance equation that is associated with the small capitalization index appears to be driven

<sup>5</sup> Half-life of a volatility shock is calculated as:  $\ln(0.5)/\ln(\sum \alpha_j + \sum \beta_j)$ .

exclusively by volatility spillovers received from the other two equations. Its own ARCH parameter is statistically insignificant although the equation exhibits a moderate level of persistence given by a GARCH parameter of 0.61. This implies that, although the small firms' idiosyncratic noise presents a constant source of risk in the small stocks, it does not affect its time varying risk profile. The time varying risk in the small stocks is driven primarily by the market-wide news volatility shocks.

### *3.2. Filter rule profitability tests*

In this section I test the information spillover patterns uncovered above for economic significance via a series of filter rule profitability tests. I focus on the statistically significant lagged spillovers found in the small cap stocks (see Table 2) as they have the best chance of generating returns in excess of those produced by a buy and hold strategy.

The filter rule tests I implement are simple in design and limited to long positions; short selling of ordinary shares is not allowed on the ASX. 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 threshold. I consider a number of threshold levels ranging from 0.5 percent to 2 percent and buying the small capitalization stocks following three events: 1) the previous week's large capitalization return exceeds the threshold, 2) the previous week's medium capitalization return exceeds the threshold and 3) both the previous week's medium and large capitalization returns exceed the threshold. Once the small capitalization index is bought, I then compute returns for several holding periods, ranging from one to five weeks. Table 4 below presents the outcomes of these filter trading strategies for a holding period of three weeks<sup>6</sup>.

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<sup>6</sup> Results for other holding periods are available upon request.

**Table 4. Filter rule profitability tests.**

Filter Rule	Average Return %	Cumulative Return %	No. of Trades
<b>1</b> a. Large Cap > 2%	2.95	421.40	143
b. Mid Cap > 2%	2.18	252.74	116
c. Large & Mid Cap > 2%	4.29	197.56	46
<b>2</b> a. Large Cap > 1.5%	2.33	462.28	198
b. Mid Cap > 1.5%	2.37	411.89	174
c. Large & Mid Cap > 1.5%	3.80	315.07	83
<b>3</b> a. Large Cap > 1%	1.95	536.09	275
b. Mid Cap > 1%	2.12	526.52	248
c. Large & Mid Cap > 1%	2.85	415.42	146
<b>4</b> a. Large Cap > 0.5%	1.84	626.89	340
b. Mid Cap > 0.5%	1.84	642.82	349
c. Large & Mid Cap > 0.5%	2.20	482.08	219

Note: Holding period is 3 weeks. Unconditional return over the whole sample was 203%.

Profitability of the trading strategies and the number of generated buy signals vary considerably across different rules. The greatest average per trade return is generated by a filter that signals a buy decision when both the medium and large capitalization indices increase by more than 2% over the previous week. However, since this rule produces only 46 buy signals over the whole sample period, it results in the smallest cumulative trading return of 198%. The unconditional return over the same period, which corresponds to a buy and hold strategy return is 203%. The largest cumulative return of 643% is given by a strategy that buys the small capitalization index after the medium capitalization portfolio has increased by more than 0.5% in the previous week.

Although, the above results seem to indicate that it is possible to generate filter trading profits well in excess of the buy and hold strategy, one must consider that Table 4 does not take into account trading costs. In fact, since there is no single financial derivative contract available on the size-sorted portfolio studied in this paper, or any other size-sorted portfolio in Australia, every filter rule studied here involves buying and selling twenty small capitalization securities separately.

For example, the average weekly return on strategy **4b** in Table 4 is 1.84%, which implies that the overall one way trading fee must not exceed 0.92% for this strategy to be profitable. Given that there are twenty securities which must be traded, the one way trading fee must be less than 0.046% of the amount invested for this strategy to generate any return above zero. This is clearly in excess of any discount brokerage fees available in Australia.

#### **4. Conclusions**

I use a novel structural framework to study information spillovers among three size-sorted portfolios constructed from securities listed on the Australian Stock Exchange. The main advantage of this approach, over the existing models, is that it permits unbiased estimation of contemporaneous regression parameters, and hence facilitates tests of structural rather than reduced form parameters.

My findings indicate that not only does the small capitalization index lag the large and medium capitalization indices with statistical significance; but that it fails to even partially adjust to their returns contemporaneously. This finding provides further empirical support for the Lo and MacKinlay (1990) partial-adjustment hypothesis. However, as I demonstrate using a series of filter rule profitability tests, the partial-adjustment mechanism does not generate trading profits in excess of those given by a buy-and-hold strategy. Although the filter rules typically forecast the direction of the small portfolio return accurately, large transaction costs associated with trading a number of small capitalization stocks simultaneously render the return on these strategies economically insignificant. Hence, I suggest that the observed predictability of the small cap index return is largely due to the lack of a small cap portfolio futures contract in Australia that would facilitate index arbitrage and hence price discovery. In the presence of these arguments, the question that one might pose is whether it is possible to replicate the small cap index studied here using a smaller number of securities which would entail lower transaction fees and could possibly result in positive excess profits. I leave this issue to be addressed by future research.

The analysis of conditional volatility suggests that even though the three size-sorted portfolios are subject to their own sources of unconditional risk, the fundamental cause of time varying uncertainty in all three indices can be traced to market-wide news shocks.

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