The Interaction of Switching and Lead-Lag Effects in the Australian Stock Market

Abstract

This study draws on the lead-lag literature to extend the Barberis and Shleifer (2003) model of switching. While the Barberis and Shleifer model assumes stocks in a given category are of equal importance, this study assumes a category comprises leader stocks and follower stocks. The sentiment of investors towards categories may then be governed by the relative performance of the leader stocks of two categories and may imply a switch into the leader stocks of a particular category first, followed by a subsequent lead-lag effect for that category. Empirical tests using daily returns to Australian industry portfolios suggests that this model of switching involving heterogeneous stocks within a category is a more accurate representation of how switching occurs in equity markets.

Keywords: categories, relative returns, cross-correlation

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1.0 Introduction

This study extends the Barberis and Shleifer (2003) model of switching, BS hereafter. That model assumes that some investors categorize similar stocks into distinct groups and based on the recent relative performance of two groups may increase their exposure to a particular group by simultaneously decreasing their exposure to an alternate group. A key assumption in the model is that investors regard stocks within a so-called category as being of equal importance so that a category's performance in a given period is measured by the simple average of returns to the constituent stocks.

The model of switching proposed here draws on the lead-lag literature, most notably Hou (2007) to suggest that stocks within a category may comprise leader stocks and follower stocks. Leader stocks within a category are those stocks such that any information revealed about those stocks has a significant influence on subsequent returns to the remaining stocks, or follower stocks, of that category. At the same time information about follower stocks tends not to significantly influence subsequent returns to leader stocks. Prior research has shown that key determinants of leadership are size in the context of an index category (Lo and MacKinlay: 1990) or analyst coverage, institutional ownership and trading volumes in the context of categories comprising stocks of a given size (Brennan *et al*: 1993, Badrinath *et al*: 1995 and Chordia and Swaminathan: 2000, respectively). Importantly, for this study, Hou (2007) shows that lead-lag effects, based on size, exist within industry categories.

We propose that investors who switch between categories may concentrate on the relative performance of the leader stocks of the categories in question. As leader stocks generally are the largest stocks in a category by market capitalization, this is intuitively

sensible as it says that investors focus on the most well-known stocks in a category or those that are likely to contribute heavily to the overall performance of their investment portfolios since most investors try to at least match the return to the market portfolio. Investors then overweight their allocation to the leader stocks of categories, for example industries, that they believe are likely to perform well in the near future, by simultaneously reducing their exposure to the leader stocks of categories they believe are simultaneously likely to perform relatively poorly. Then investors may, with a lag, invest in the corresponding smaller follower stocks of the now in-favour category consistent with a lead-lag effect. This version of switching is likely to be a more accurate version of how switching occurs in practice because the smaller stocks of a category may have different characteristics compared with larger stocks, for example they may be thinly traded or have high bid-ask spreads making them costly to trade. However, conditional on an earlier shock to the corresponding leader stocks, these follower stocks may have predictably strong returns.

We show that our model of switching, which we call the SLF model for Switching with Leader stocks and Follower stocks incorporated, makes it easier to identify switching in the Australian stock market, at least based on daily stock returns because switching is largely concentrated amongst the most heavily traded stocks in the Australian stock market and not among larger groups of stocks that the BS model implies. We also show that the trading strategy implied by our model of switching gives rise to higher profits than that implied by the BS model.

The rest of the paper is structured as follows. Section 2 reviews the existing literature on lead-lag effects and switching and argues for a theoretical model that incorporates both of these phenomena. Section 3 presents the SLF model that allows for switching and lead-lag effects and describes the corresponding methodology we use in our empirical work. Section 4 describes the data and empirical tests of the SLF model conducted in this study. Section 5

presents our results while section 6 concludes including a description of the limitations of the study and the practical importance of our findings.

2. Literature Review

As mentioned earlier this study aims to develop a new model of switching by incorporating relevant aspects of the lead-lag literature into the BS (2003) model of switching. The BS model of switching is significant because it is the only theoretical asset-pricing model thus far to state that investors consider the recent relative performance of well defined groups of stocks, for example banking stocks and metals and mining stocks as compared with the momentum literature which considers the relative performance of less well defined groups of stocks. That literature considers the relative performance of winner stocks and loser stocks but the stocks comprising those groups can change over time making it more difficult to implement trading strategies over those groups of stocks. As a result the BS model should imply trading strategies that are more easily implementable due to more reliable return predictability.

The main empirical implication of the Barberis and Shleifer model is that there should be negative lagged cross-correlation between categories.[1] This negative cross-correlation arises due to the purchase of stocks in a category that has performed well recently that causes the prices of these stocks to appreciate, funded by the simultaneous sale of stocks in a category that has performed relatively poorly recently so that these stocks depreciate in price. Importantly the model suggests that the action of purchasing or selling stocks in a category

[1] The De Long et al. (1990) and Hong and Stein (1999) models that precede Barberis and Shleifer (2003) share some common features with that model. For example, all of these models involve the interaction of two types of traders, trend chasers who trade on momentum, and rational traders who know the true fundamental value of stocks. However rational traders are unable to bring prices back to fundamental value because of the fear that trend chasers will drive prices even further from true fundamental value in the short term and they then assume short investment horizons as a result. Prices can then consistently differ from true fundamental value due to limits to arbitrage (Shleifer & Vishny, 1997).

may depend, for some investors, on the relative performance of the two categories even if both have performed well in absolute terms in the recent past.

Empirical testing of the BS model[2] has focused on the value and growth categories or the small-cap and large-cap categories and their importance in asset-pricing models. For example the lagged average return to value, growth, small-cap and large cap funds (Teo & Woo, 2004) or the lagged change in demand for value stocks relative to growth stocks or for small-cap stocks relative to large cap-stocks (Kumar, 2006) has been shown to provide additional explanatory power for the cross-section of stock returns, over and above the four factors of Carhart (1997).

Additionally, Pomorski (2004) and Kumar (2006) found that demand for a particular category is both positively related to prior returns to that category and negatively related to prior returns to an alternate category, again consistent with the predictions of the BS model.[3] Teo and Woo (2004) and Kumar (2006) also showed returns for a particular category are both positively related to prior returns to that category and negatively related to returns to an alternative category.[4]

Finally, Barberis *et al*. (2005)[5] and Boyer (2004) showed that the correlation of returns to a reclassified stock increased with the category it had just joined and decreased with the category it had just left, in line with the hypothesis in the BS model that investors trade categories of stocks.

[2] The most prominent empirical studies on switching are Teo and Woo (2004), Pomorski (2004), Boyer (2004), Barberis *et al.* (2005) and Kumar (2006).
[3] Pomorski (2004) finds this relationship even after allowing for the four factors of Carhart (1997).
[4] Teo and Woo (2004) find this result after allowance for the four factors of the Carhart (1997) model.
[5] The study by Barberis *et al.* (2005) differs from the other empirical studies of switching in that it uses the S&P 500 and non S&P 500 stocks as the categories in its analysis. It also analyzes daily, weekly and monthly returns and finds evidence of switching using all three of these frequencies. This study can serve as motivation for our use of daily returns later. We use industry categories in our analysis and not index constituents versus non-constituents.

In addition, because most asset-pricing models use monthly returns, the empirical tests of switching have also used monthly returns, which is equivalent to searching for switching in the month following the release of relevant information.

We believe that there is scope for investigating faster switches than those documented in the current literature. These faster switches could be consistent with trend chasing where investors expect strong returns from a particular category to continue in the short term. In this study we propose using daily returns, rather than monthly returns to investigate these faster switches. There is also scope for investigating whether categories other than value and growth are appropriate and relevant. We believe that for faster switches industry categories rather than value and growth categories are more likely to give better results as the constituent stocks are then more similar to one another and information about a particular stock can be more accurately extrapolated to the other stocks in the category. Thus a switch may be more likely to be observed using this alternative categorization.

While the switching literature has demonstrated the importance of categories in asset pricing consistent with the BS model, the lead-lag literature shows that the assumption of the BS model that all stocks in a category can be regarded as effectively equivalent, may not hold. This literature suggests that some stocks in a category, or leader stocks, act as a predictor for future returns to other stocks in the category, or follower stocks. In terms of incorporating lead-lag effects into switching models this may imply that some investors switch between categories based on the relative performance of the leader stocks of two categories. Then if this generates strong performance for the leader stocks of a particular category these investors may generate a lead-lag effect for that category. At the same time the leader stocks of the alternate category may depreciate in price and perhaps the follower stocks also if they are sold to fund investment in the follower stocks of the now in-favour category.

Generally lead-lag effects are found where stocks with relatively large market capitalizations lead stocks with relatively smaller market capitalizations either in an index (Lo & MacKinlay, 1990) or in an industry (Hou, 2007). However Brennan *et al*: 1993, Badrinath *et al*: 1995 and Chordia & Swaminathan: 2000, have respectively shown that stock attributes such as analyst coverage, institutional ownership and trading volumes influence lead-lag effects over and above what would be explained by a size factor alone.[6]

Reasons for observing lead-lag patterns generally focus on the illiquidity of relatively small stocks (Boudoukh *et al*., 1994) so that they are expensive to buy due to high bid-ask spreads, or the fact that they are less important to the composition of many investors' portfolios than larger stocks[7] and therefore incorporated into these portfolios relatively slowly (Conrad and Kaul: 1988, Lo and MacKinlay: 1990, Brennan *et al*: 1993, Chordia and Swaminathan: 2000 and Hou: 2007). These reasons should provide sufficient motivation for us to focus on the leader stocks of different categories when trying to identify switching in equity markets rather than including smaller stocks that may be illiquid or likely to be relatively less important than leader stocks for many investors.[8]

In this study we explore the significance of leader stocks in driving switching between categories and whether the relative performance of the leader stocks of two categories can induce strong performance in the leader stocks of a now in-favour category followed by a lead-lag effect for that category. More broadly we examine the role of leader stocks in asset-pricing and return predictability.

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[6] Size or market capitalization is strongly correlated with each of analyst coverage, institutional ownership and trading volume. However Brennan *et al*: 1993, Badrinath *et al*: 1995 and Chordia & Swaminathan: 2000 respectively show that when portfolios are formed from stocks with high analyst coverage, high institutional ownership or high trading volumes for their size relative to when portfolios are formed from stocks with low levels of these attributes for their size.

[7] For example investors trying to replicate an index need to hold the larger stocks in that index to be ensured of an accurate replication.

[8] A third explanation for lead-lag effects, by Boudoukh *et al*: 1994 is that they arise due to high contemporaneous correlation between leader and follower portfolios and, at the same time, strong autocorrelation in follower portfolios. This explanation however focuses on the definition of lead-lag effects rather than a genuine cause for them.

3. Theoretical development

In this section we present an extension of the BS model of switching. The BS model assumes that investors that switch between categories regard all stocks in a category as being equivalent. They therefore hold similar positions in all stocks of that category at any point in time. They also take the simple average of the returns to the stocks comprising a category in order to determine a category's overall return again reflecting the equivalence of all stocks in a category.

In our model we relax this assumption of homogeneity of stocks within a category. Taking into account the illiquidity of relatively small stocks and the fact that they are often less important in investors' portfolios we propose that switcher investors mainly consider the relative performance of the leader stocks of two categories in deciding whether and when to switch between two categories. In addition we propose that when a decision to switch is made the initial positions are mainly taken in the larger more liquid stocks of the now in-favour category and then with a lag into the smaller less liquid stocks which gives rise to a lead-lag effect for the now in-favour category.

Our model, which we call the SLF model for Switching with Leader stocks and Follower stocks incorporated, has one important new parameter, a heterogeneity parameter, h, that allows these additional features to be included. This parameter is described in the next section.

3.1 The Switching with Leader stocks and Follower stocks incorporated Model (SLF)

3.1.1 Definition of heterogeneity

In the BS model, each category comprises *n* stocks. We now assume that of the *n* stocks in a category, $\frac{n}{2}$ are leader stocks and $\frac{n}{2}$ are follower stocks.[9] Suppose in the calculation of a category return, the weight placed by switcher investors on each leader stock is *a* and the weight on each follower stock is *b*. Since these weights must sum to one, the following relation must be satisfied:

$$\frac{n}{2}(a+b)=1 \tag{1}$$

$$a,b \geq 0;\ a \geq b \tag{2}$$

We also require from Equation (2) that both *a* and *b* are greater than or equal to zero, so that no stock can contribute a negative weight in the calculation of the category return. Also, *a* should be greater than or equal to *b* so the weight on a leader stock is always greater than or equal to the weight on a follower stock. The heterogeneity of stocks in this category, *h*, is then defined as follows:

$$h=\frac{n}{2}(a-b) \tag{3}$$

Thus heterogeneity is a measure of the discrepancy in weights placed on leader stocks compared with follower stocks. It can be shown that *h* has a minimum value of zero and a maximum value of one. For a fixed *h*, solving Equations (1) and (3) simultaneously gives the following expressions for *a* and *b*, as shown below:

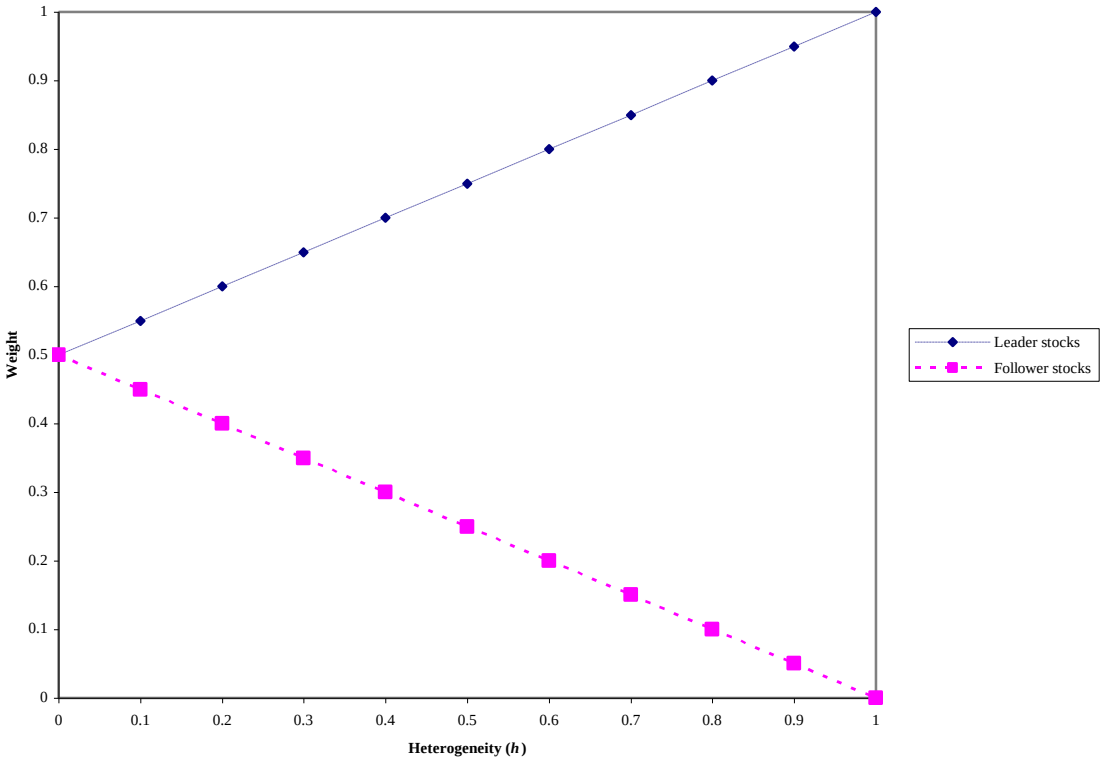
$$a=\frac{1+h}{n} \tag{4}$$

$$b=\frac{1-h}{n} \tag{5}$$

[9] The specification of an equal number of leader and follower stocks is not a crucial assumption but it does simplify the calculations that appear here.

In Figure 1 below we show the weight placed by switcher investors on leader and follower stocks in calculating category returns, for values of *h* ranging from zero to one. We further assume in Figure 1, that there are two stocks in a category.

Figure 1: Weight on leader and follower stocks in computing category returns, as the heterogeneity of stocks in a category changes



From Figure 1, when *h*=0 the weight placed on leader and follower stocks in calculating a category return, is equal. The stocks are homogeneous as assumed in the BS model. As heterogeneity increases, the weight on leader stocks increases linearly and simultaneously the weight on follower stocks decreases. Thus more weight is being placed on the leader stocks in determining the category return. At *h*=1, full weight is placed on leader stocks and zero weight on follower stocks. At this point switcher investors ignore the performance of follower stocks completely and focus on leader stocks only in determining how a category, from their perspective, has performed. These statements confirm that *h* is a measure of the perceived importance of stocks within a category.

The parameter h is regarded as constant over time. However in practice it may be relevant only after an event to a leader portfolio, at which time the distinction between leader stocks and follower stocks becomes most apparent to investors as they decide which stocks of the in-favour category they want to invest in. The assumption of a constant h simplifies the analysis but still permits lead-lag and switching effects in our model.

3.1.2 Demand Functions in the SLF model

As in the BS model, we write down an explicit expression giving the number of shares held by switcher investors of stocks in categories X and Y at any point in time. As there are n stocks in each category, or $2n$ stocks overall writing these demand functions and putting them into a column vector yields a $2n$ x 1 vector, denoted N_t^S in Barberis and Shleifer (2003). Here we use the notation $N_t^{S,BS}$ for the $2n$ x 1 vector of demand functions used in the BS model and $N_t^{S,SLF}$ for the $2n$ x 1 vector of demand functions used in the SLF model.[10]

These demand functions are important as they significantly influence the amount by which equilibrium stock prices differ from true fundamental value as shown in the following expressions:[11]

$$P_t^{BS} = D_t + \gamma V N_t^{S,BS} \tag{6}$$

$$P_t^{SLF} = D_t + \gamma V N_t^{S,SLF} \tag{7}$$

[10] In all cases by convention we write the demand functions for each of the leader stocks for category X first, followed by the demand functions for the follower stocks of category X, followed by the demand functions for the leader stocks of category Y and then the demand functions for each of the follower stocks of category Y. In the BS model the demand functions for the leader and follower stocks of a category will be identical as all stocks in a category are considered to be identical.

[11] Equation (6) is derived in Barberis and Shleifer (2003). Equation (7) for equilibrium prices in the SLF model has a similar form because the SLF model, like the BS model also emphasizes the role of switcher investors in determining equilibrium prices. However it also emphasizes the importance of leader stocks in asset-pricing which gives rise to a different equilibrium solution.

These equations say that switcher investors can cause equilibrium prices to differ from true fundamental value, given by D_t in both of Equations (6) and (7) above. The reason is that whereas normally we would expect fundamental traders who trade against switcher investors to bring stock prices back to a level consistent with their riskiness under some circumstances they cannot do that and observed prices deviate from their fundamental value. Such mispricings may occur when fundamental traders themselves start behaving like switcher investors.[12] Alternatively if fundamental traders are trying to match the return to an index and some stocks in the index are overpriced with the likelihood that switcher investors will cause the price to go higher at least in the short term, then in that case fundamental traders cannot afford not to include those overstocked stocks in their portfolio. Importantly yhe fundamental traders are not bringing prices back to fundamental value and mispricings may persist.

The demand functions used in the SLF model and the BS model[13], for comparison, are shown in Table 1. Switcher investors' demand functions for the leader stocks of categories *X* and *Y* at time *t* are denoted $N^S_{X,Lead,t}$ and $N^S_{Y,Lead,t}$ respectively, and are given in Equations (8) and (9) below.

$$N^S_{X,Lead,t} = \frac{1}{n} * \left[\sum_{s=1}^{q} \theta^{k-1} * \left(\frac{R^{SLF}_{X,t-s} - R^{SLF}_{Y,t-s}}{2} \right) \right] \tag{8}$$

$$N^S_{Y,Lead,t} = \frac{1}{n} * \left[\sum_{s=1}^{q} \theta^{k-1} * \left(\frac{R^{SLF}_{Y,t-s} - R^{SLF}_{X,t-s}}{2} \right) \right] \tag{9}$$

[12] The equations in Table I show that switcher investors behave like trend chasers so that normally rational investors start behaving like trend chasers expecting short term trends to continue in the longer term.

[13] Some constants have been removed in the demand functions for the BS model that appear in Table 1, however the important features of that model can still be generated without those constants.

Equations (8) and (9) show that in the SLF model demand for leader stocks of either category are dependent on the recent relative returns to the two categories with most weight being given to the most recent relative returns since the weighting parameter, θ , satisfies $0 < \theta < 1$.

However the definition of category returns now involves the parameter *h* as shown in Equations (10) and (11) . In those equations stock *i* belongs to the set of leader stocks for category *X* (denoted *XL*), *j* is a stock in the set of follower stocks for category *X* (denoted *XF*), *k* is a stock in the set of leader stocks for category *Y* (denoted *YL*) and *l* is a stock in the set of follower stocks for category *Y* (denoted *YF*).

$$R_{X,t}^{SLF} = \frac{1+h}{n}\left(\sum_{i \in XL} R_{i,t}\right) + \frac{1-h}{n}\left(\sum_{j \in XF} R_{j,t}\right) \tag{10}$$

$$R_{Y,t}^{SLF} = \frac{1+h}{n}\left(\sum_{k \in YL} R_{k,t}\right) + \frac{1-h}{n}\left(\sum_{l \in YF} R_{l,t}\right) \tag{11}$$

Importantly when calculating a category return, since $h \geq 0$, this implies the weight on leader stocks is always greater than the weight on follower stocks except when *h*=0 in which case the weights are equal. This is one important difference from the BS model. In addition the difference in returns to *X* and *Y* now depends on the parameter *h* as shown in Equation (12):

$$R_{X,t}^{SLF} - R_{Y,t}^{SLF} = \frac{1+h}{n}\left(\sum_{i \in XL} R_{i,t} - \sum_{k \in YL} R_{k,t}\right) + \frac{1-h}{n}\left(\sum_{j \in XF} R_{j,t} - \sum_{l \in YF} R_{l,t}\right) \tag{12}$$

Table 1: Demand functions used in the BS and SLF models[#]

Item	Notation	BS	SLF
Category return	$R_{X,t}$	$\frac{1}{n}\left(\sum_{l\in X} R_{l,t}\right)$	$\frac{1+h}{n}\left(\sum_{i\in XL} R_{i,t}\right)+\frac{1-h}{n}\left(\sum_{j\in XF} R_{j,t}\right)$
Demand function for leader stocks of *X*	$N^{S}_{X,Lead,t}$	$\frac{1}{n}\left(\sum_{k=1}^{q}\theta^{k-1}\left(\frac{R_{X,t-k}-R_{Y,t-k}}{2}\right)\right)$	$\frac{1}{n}\left(\sum_{k=1}^{q}\theta^{k-1}\left(\frac{R_{X,t-k}(h)-R_{Y,t-k}(h)}{2}\right)\right)$
Demand function for follower stocks of *X*	$N^{S}_{X,Foll,t}$	$\frac{1}{n}\left(\sum_{k=1}^{q}\theta^{k-1}\left(\frac{R_{X,t-k}-R_{Y,t-k}}{2}\right)\right)$	$\frac{1}{n}*\left[\begin{array}{l}\frac{1}{1+h}*\left(\sum_{k=1}^{q}\theta^{k-1}\left(\frac{R_{X,t-k}(h)-R_{Y,t-k}(h)}{2}\right)\right)+\\ \frac{h}{1+h}*\left(\sum_{k=2}^{q+1}\theta^{k-1}\left(\frac{R_{X,t-k}(h)-R_{Y,t-k}(h)}{2}\right)\right)\end{array}\right]$
Demand function for leader stocks of *Y*	$N^{S}_{Y,Lead,t}$	$-N^{S,BS}_{X,Lead,t}$	$-N^{S,SLF}_{X,Lead,t}$
Demand function for follower stocks of *Y*	$N^{S}_{Y,Foll,t}$	$-N^{S,BS}_{X,Foll,t}$	$-N^{S,SLF}_{X,Foll,t}$
Equilibrium pricing relationship	P_t	$P_t^{BS}=D_t+\gamma VN_t^{S,BS}$	$P_t^{SLF}=D_t+\gamma VN_t^{S,SLF}$

XL and *XF* above refer to the leader and follower stocks of category *X*.

Equations (8) - (12) imply that switcher investors' demand for leader stocks of a category depend on *h*, their perception of the different importance of stocks within a category. If stocks within a category are homogeneous so that *h*=0, Equations (8), (9) and (12) show that this demand is an equally weighted average of the past relative performances of the leader stocks of categories *X* and *Y*, and the past relative performances of the follower stocks of categories *X* and *Y*. As heterogeneity increases and *h*>0, the demand for leader stocks today depends more on the prior relative performance of the leader stocks of *X* and *Y* and less on the prior relative performances of the follower stocks of the two categories. Finally when *h*=1, demand for leader stocks today is fully dependent on prior relative performance of leader stocks. The important point is that owing to the increased importance placed by switcher investors on leader stocks, as the parameter *h* increases, so the demand for

leader stocks depends more on how the leader stocks of the two categories have performed in the immediate past.

The demand functions in the SLF model for follower stocks in categories *X* and *Y*, as at time *t* are denoted $N^S_{X,Foll,t}$ and $N^S_{Y,Foll,t}$ respectively, and are given in Equations (13) and (14) below. They are now also functions of *h*.

$$N^S_{X,Foll,t} = \frac{1}{1+h} * N^S_{X,Lead,t} + \frac{h}{1+h} * N^S_{X,Lead,t-1} \tag{13}$$

$$N^S_{Y,Foll,t} = \frac{1}{1+h} * N^S_{Y,Lead,t} + \frac{h}{1+h} * N^S_{Y,Lead,t-1} \tag{14}$$

In particular current demand for follower stocks is now a weighted average of the contemporaneous demand for the corresponding leader stocks and demand for the corresponding leader stocks lagged one period.

The inclusion of lagged leader demand gives rise to lead-lag effects in the SLF model. The strength of lead-lag effects is governed by the level of heterogeneity of stocks in a category. In a category of extremely heterogeneous stocks (e.g. *h*=1), lead-lag effects are more pronounced than in a category of mildly heterogeneous stocks (e.g. *h*=0.5). If stocks are homogeneous (*h*=0), there are no lead-lag effects, and current demand for leader and follower stocks are equal. Figure 2 shows the weight placed on current and lagged demand for leader stocks in determining today's demand for follower stocks of a particular category. We assume in Figure 2 that *n*=2 so that there are two stocks in a given category.

From Figure 2 it is seen that the weight placed on lagged demand for leader stocks is never greater than 0.5. This occurs at *h*=1 when demand for follower stocks is 50% of current demand for leader stocks and 50% of demand for leader stocks lagged one period.[14] For *h*=0.5 current demand for follower stocks is 67% of current demand for leader stocks and

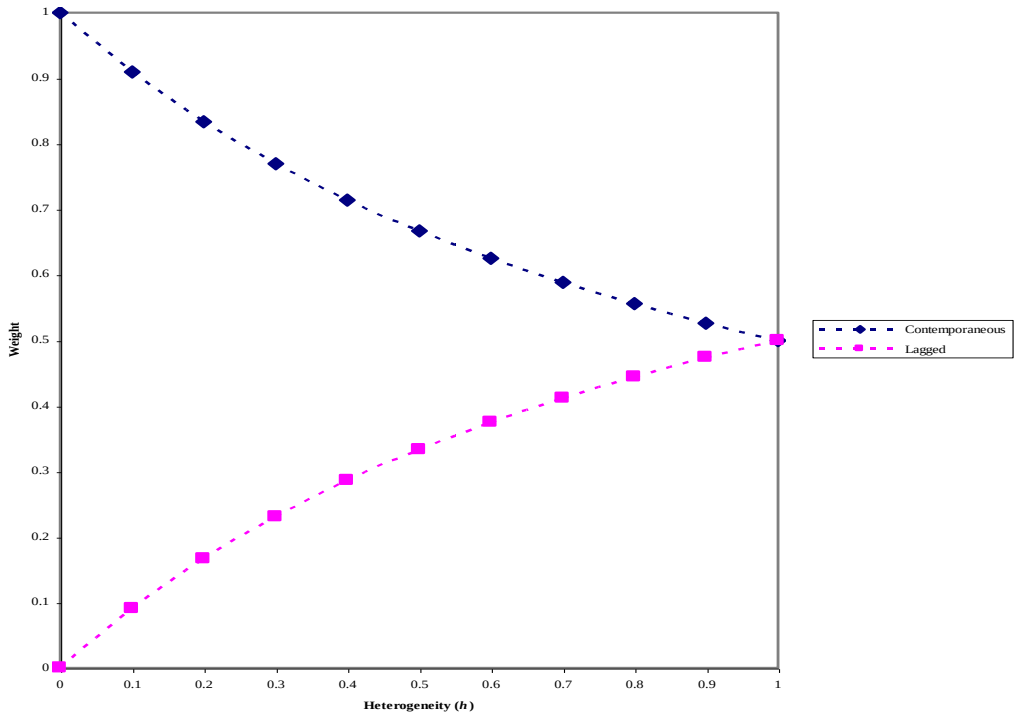
[14] This equal weighting is not necessary. The general conditions that the demand function for follower stocks needs to specify, and are given in footnote 31.

33% of demand for leader stocks, one period ago. For 0<*h*<1, there is a dependency on lagged demand for leader stocks but now the weight on lagged demand for leader stocks is less than 0.5 and the weight on contemporaneous demand for leader stocks exceeds 0.5. If *h*=0, demand for follower stocks is equal to current demand for leader stocks and there is no relationship with what the demand for leader stocks was, one period ago. These demand functions emphasize lead-lag effects within categories, motivated by the lead-lag literature discussed in Section 2.[15]

Specifying the demand function for leader and follower stocks as in Equations (8)-(12) implies that the BS model coincides with the SLF model when *h*=0 so that if stocks within a category are homogeneous then the SLF model gives the same implications as the BS model. In the more general case where stocks are heterogeneous, the two models will give different results. The demand functions in the SLF model involve an initial primary switch into the leader stocks of an in-favour category followed by a lead-lag effect for the now in-favour category whereas the BS model emphasizes a uniform switch from one category to another.

[15] More generally a specification for the demand function for follower stocks is given as follows:
$N^S_{X,Foll,t} = a(h) * N^S_{X,Lead,t} + b(h) * N^S_{X,Lead,t-1}$;
This needs to satisfy all of the following conditions for all $h \in [0,1]$:
(i) $a(h) + b(h) = 1$;
(ii) $a(0) = 1$ and $b(0) = 0$ for consistency with the BS model;
(iii) $a'(h) < 0$ and $b'(h) > 0$

Figure 2: Weight placed on current and lagged demand for leader stocks in determining current demand for follower stocks



3.1.3 Time series properties of equilibrium returns in the SLF model

As for the BS model, we define equilibrium returns in the SLF model as the difference of successive price observations, as shown below:

$$R_t^{SLF} = P_t^{SLF} - P_{t-1}^{SLF} \tag{15}$$

Note that R_t^{SLF} is a $2n$ x 1 vector of returns to all stocks in categories X and Y. We then define switching and lead-lag effects in the SLF model, $S_{SLF}(z,h)$ and $F_{SLF}(z,h)$, respectively, as follows:

$$S_{SLF}(z,h) = Corr\left(R_{Y,Lead,t+z}(h), R_{X,Lead,t}(h)\right) \text{where } z \in \{1,2,3,...,20\} \tag{16}$$

$$F_{SLF}(z,h) = Corr\left(R_{X,Foll,t+z}(h), R_{X,Lead,t}(h)\right) \text{where } z \in \{1,2,3,...,20\} \tag{17}$$

By the definition of Equation (16) switching refers to the magnitude of the downward cycle in prices for the leader stocks of an out-of-favour category coinciding with the upward cycle in prices for the leader stocks of an in-favour category. Equation (17) defines lead-lag effects to be the lagged cross-correlation between leader and follower stocks of either an in-favour or out-of-favour category, with the former leading. The $F_{SLF}(z,h)$ function can be calculated for h=0 to give a measure of lead-lag effects in the BS model. However there are no genuine lead-lag effects in the BS model because there is no concept of leader and follower stocks in the BS model. The increase in the $F_{SLF}(z,h)$ function as h increases does however show the extent to which lead-lag effects are induced by the relative performance of the relevant leader stocks.

We perform simulations of the SLF model using different parameter values to calculate the $S_{SLF}(z,h)$ and $F_{SLF}(z,h)$ functions respectively. To perform the simulations we note that $N_t^{S,SLF}$, the 2n x 1 vector of demand functions in the SLF, can be written in the following form:

$$N_t^{S,SLF} = \sum_{i=1}^{q+1} \omega_i R_{t-i}^{SLF} \tag{18}$$

Then substituting Equation (18) into Equation (7) and then substituting the result into Equation (15) gives:

$$\begin{aligned} R_t^{SLF} &= \varepsilon_t + \gamma V \left(\sum_{i=1}^{q+1} \omega_i \left[R_{t-i}^{SLF} - R_{t-1-i}^{SLF} \right] \right) \\ &= \varepsilon_t + \sum_{i=1}^{q+2} \Lambda_i R_{t-i}^{SLF} \end{aligned} \tag{19}$$

Where:

$$\Lambda_i = \begin{cases} \gamma V \omega_1 & \text{if } i = 1 \\ \gamma V \left(\omega_i - \omega_{i-1} \right) & \text{if } i = 2,3,\ldots,q+1 \\ -\gamma V \omega_{q+1} & \text{if } i = q+2 \end{cases} \tag{20}$$

And: ε_t is a 2n x 1 vector of firm-specific shocks.

Equations (19) and (20) show that equilibrium returns in the SLF model follow a VAR process with order q+2. Having established that the $S_{SLF}(z,h)$ and $F_{SLF}(z,h)$ can be found by calculating the autocorrelation matrices of the VAR(q+2) process.[16] The technique is the multivariate analog of a well known similar calculation for AR(p) processes that give rise to the Yule-Walker equations.

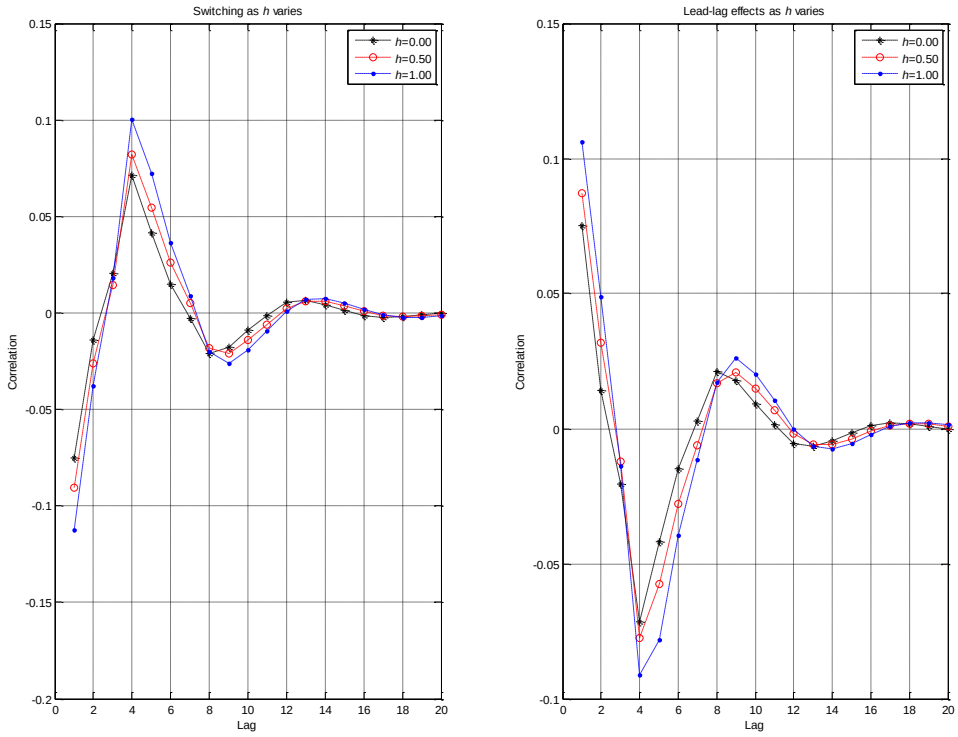
Figure 3 shows the effect of increasing h from a value of 0 to 0.5 and from 0.5 to 1 in simulations holding all other parameters fixed.[17] In these simulations switching between leader stocks becomes more prevalent as h increases. This is because as h increases the importance of leader stocks as being indicative of the future prospects for their respective categories also increases. As a result, when a switch is made into a category it is made initially into the leader stocks of the in-favour category that are most well-known to investors and most liquid.

Lead-lag effects induced by the relative performance of the relevant leader stocks also increase as h increases. The reason is that as h increases switcher investors take relatively large positions in leader stocks, reflecting the importance of leader stocks in their investment decisions and the liquidity of leader stocks. Then, with a lag, which allows for confirmation that the original signal pertaining to leader stocks which led to the initial switch is correct, they move into the corresponding smaller and less-liquid follower stocks.

These simulation results suggest that if leader stocks drive switching behavior in equity markets, as suggested by our SLF model, then a distinction needs to be made between the leader stocks and follower stocks of a category and making this distinction should make it easier to identify switching in equity markets, relative to the BS model. This is discussed more in the next section on our data and methodology.

[16] See Hamilton (1994), pp. 264-266 for more technical details on this procedure.
[17] Details of the parameters used in this simulation are available from the author on request.

Figure 3: Switching and lead-lag effects for h = 0, 0.5, 1.



4. Data and Methodology

4.1 Data

This study uses Australian equity data for the 15 years from 1st January 1990 to 31st December 2004. Daily returns to stocks are analyzed using data from the IRESS database. The use of Australian stock market data in a study of switching is significant as the Australian equity market is heavily influenced by two sectors, Resources and Industrials, and switching is expected between these sectors. The resources sector comprises mainly metals and mining companies while the industrials sector comprises mainly banks and financial institutions. Switching between these sectors is expected because the major banking stocks in Australia are a very safe investment and provide stable franked dividends while the more volatile mining stocks can provide very high returns in certain periods of the business cycle.

However, when these volatile stocks are forecast to depreciate investors can move back into the safer banking stocks. We do not restrict our analysis to banks and metals but also look at other industries in the Australian market. We expect banks, as a relatively safe investment, could be part of other switching strategies with other high-returning but volatile industries.

Our use of daily returns in this study is also significant because most prior studies of switching have used monthly and quarterly returns. Although the use of relatively noisy daily returns could make it more difficult to find evidence of return predictability we believe switching should occur relatively soon after good news to a particular industry, for example. One month or one quarter between observations may be too long between observations as a switch may have occurred soon after a particular event and the effects of any switch may have dissipated by the time the next observation is recorded.

Finally, we use industry categories in this study. An advantage of defining categories in this way is that stocks within groups are expected to have highly correlated fundamental cashflows owing to their exposure to similar risk factors (Moskowitz & Grinblatt, 1999). Investors are thus relatively more likely to use industries as categories, at least in a short term context. There is also a growing body of literature documenting the significance of industries in asset pricing (Moskowitz & Grinblatt, 1999; Grundy & Martin, 2001; Swinkels, 2002; Hurn & Pavlov, 2003; Hou & Robinson, 2006; and Hou, 2007).

4.1.1 Selection of industries for this study

In this study we examine the ten industry groups[18] whose stocks make the highest contribution to the total market capitalization of the ASX 200 index, as at the 28th of February 2005. The industries selected should also comprise a minimum of 5 stocks. This helps to ensure that the industry portfolios in our analysis are not unduly influenced by firm-specific

[18] Industry groups have six digit GICS (General Industry Classification System) codes, for example 151040 for Metals and Mining stocks.

or idiosyncratic risk. In any case, even if the industry portfolios are influenced by idiosyncratic risk, the main concern is whether investors can consistently profit from going long in a particular industry and simultaneously short in another particular industry whenever there is a positive shock to the former. If there is a consistent ability to make profits in this way then this return predictability can be exploited by investors. Finally the return series for an industry portfolio is constructed by taking an equally weighted average of the constituent stocks for which a valid return is available.[19] These industry returns are used in our tests of the BS model.

For testing the SLF model we construct return series for the leader and follower portfolios of each industry. Again these are constructed by taking the equally weighted average of the constituent stocks for which a valid return is available. Since there is a minimum of five stocks in each industry, our algorithm for choosing leader and follower stocks to be discussed later, implies that there are at least two stocks in the leader and follower portfolios for all industries. As before with the industry portfolios, two stocks in these leader and follower portfolios may imply that any return predictability we find could be attributable to firm-specific factors and not a widely pervasive switching phenomenon. However we do use a long time series of returns in our analysis which mitigates the influence of firm-specific factors. We also perform our analysis using market-adjusted returns so that any switches we find are not a restatement of general trends in the market portfolio overall.

Finally stocks in our industry, industry-leader and industry-follower portfolios are chosen from the ASX 200 only, because these stocks are expected to be reasonably liquid.

[19] All industry, industry-leader and industry-follower return series analyzed are stationary with a p-value of less than 1%. Three versions of the augmented Dickey Fuller test are used: (i) with no deterministic trend; (ii) with a constant term only and (iii) with a constant term and time trend.

Concerns that trading strategies involving follower (small-cap) stocks are impractical, for example due to bid-ask bounce or non synchronous trading, should thus be alleviated.[20]

4.1.2 Selection of Leader stocks and Follower stocks within a category

We use the algorithm of Hou (2007) to choose leader and follower stocks for a given industry and say that the largest 30% of stocks, by market capitalization, for a given industry, are that industry's leader stocks. The middle 40% of stocks are mid-cap stocks and the bottom 30% are the small-cap or follower stocks for that industry. Constituent stocks of the industry, industry-leader and industry-follower portfolios are shown in Appendix A.[21]

4.1.3 Descriptive Statistics

Table 2 below shows summary statistics for our industry portfolios. It shows that our sample covers 76% of the ASX 200 by market capitalization. Banks and metals and mining are the largest industries represented on the ASX 200 and account for approximately 38% of the index. The SLF model implies that switches are most likely to occur between the most liquid segments of the equity market. To that extent switches are most likely to involve the largest industries listed in Table 2 below and later results show that three of the four largest industries (banks, metals and mining and media) feature prominently in switching activities.

Table 2

[20] Even if follower stocks are generally affected by bid-ask bounce, lead-lag effects can still be discovered if follower stocks seem to systematically respond to shocks to leader stocks.

[21] Like Hou (2007) we ignore mid-cap stocks in our analysis to ensure that so-called leader stocks are genuinely distinct from follower stocks. We also use two other leader-follower selection algorithms to perform our analysis. In the first of these, we take leader stocks to be the largest 30% of stocks in an industry and the follower stocks to be the next 40% of stocks, by market capitalization, of stocks in that industry. Another algorithm we use takes leader stocks for an industry to be those stocks in that industry that also belong to the top 20% of stocks in the index while follower stocks for that industry must belong to that industry and be in the next 40% of stocks in the index, by market capitalization. Results using these leader-follower classifications are available from the author on request.

Summary Statistics on the Industry Portfolios

Industry	Number of stocks in ASX 200 as at 28.02.2005 (1)	Percentage contribution to the ASX 200 as at 28.02.2005 (2)	Mean return (Percent) (3)	Standard Deviation (Percent) (4)	Autocorrelation			
					ρ_1	ρ_2	ρ_3	ρ_4
Commercial Banks	8	22.6%	0.04	0.82	0.09***	-0.02	0	0.01
Metals and Mining	26	15.8%	0.04	1.19	0.06***	-0.03**	0.03*	0
Real Estate	24	9.9%	0.02	0.67	-0.03*	0	-0.01	-0.04**
Media	12	6.4%	0.05	1.30	0.06***	0.01	0.03*	-0.04**
Insurance	8	6.0%	0.02	1.37	-0.01	-0.02	0.02	0
Food and Staples Retailing	5	4.0%	0.05	1.05	0.02	-0.01	-0.01	-0.02
Oil and Gas	10	3.2%	0.03	1.51	-0.03*	0.01	-0.06***	0.01
Transportation Infrastructure	8	2.9%	0.07	1.33	-0.07***	-0.01	0	-0.02
Construction Materials	5	2.5%	0.02	1.20	-0.02	-0.01	-0.02	-0.01
Beverages	5	2.5%	0.03	0.99	0.03	-0.04**	-0.03*	-0.01

Note. Constituent stocks for these industries are provided in Appendix A. ***, ** and * denote significant at 1%, 5% and 10% respectively.

These switches, involving the larger industries may be due to fund managers temporarily moving a small amount of capital out of a large industry into another whose short term prospects are considered to be very good. Broad exposure to the market portfolio would thus be maintained while taking advantage of temporary mispricings. At the same time these switches could involve well known rather than obscure stocks so that the probability of switching is relatively higher.

Table 2 also shows that there is significant positive first-order autocorrelation in returns to banks, media and metals and mining, and significant negative autocorrelation for the oil and gas, real estate and transport industries. The three industries with significant and positive first-order autocorrelation feature prominently in switches described later. This reflects the fact that one element of switching is consistent with momentum investing while the other element involves selecting from where the funds required for those momentum trades will come.

Table 2 also shows that the first four autocorrelations for metals and mining and oil and gas have alternate signs indicating highly volatile returns. As detecting switching is equivalent to finding evidence of return predictability this should imply it should be difficult to detect switching involving these industries. However while the unconditional autocorrelations vary significantly, the autocorrelations conditional on a particular shock occurring, may not behave in the same way. These are more relevant in determining whether evidence of switching, involving these industries, can be found.

Table 3

Autocorrelations in Daily Returns for Industry Leader and Follower Portfolios[#]

Industry	**Normalized Herfindahl Index**	**Leader portfolio**				**Follower portfolio**			
		ρ_1	ρ_2	ρ_3	ρ_4	ρ_1	ρ_2	ρ_3	ρ_4
Banks	0.1	0.09***	-0.03*	0.01	-0.01	-0.04**	-0.02	0	0
Beverages	0.3	0.05***	-0.02	-0.04**	-0.02	-0.08***	-0.05***	-0.02	0
Constru-ction	0.1	-0.02	-0.06*	0.01	0.02	-0.05***	-0.03*	-0.02	-0.01
Food	0.19	-0.01	-0.03*	-0.04**	-0.02	-0.03	-0.03	0.01	-0.03
Insurance	0.09	-0.06***	-0.05***	0.09***	-0.07***	0.01	-0.03	0	0
Media	0.23	0.03**	-0.03*	-0.02	-0.01	0.04**	0.05***	0.01	-0.03*
Metals and Mining	0.14	0.13***	-0.03**	-0.01	-0.01	-0.07***	-0.04**	0	-0.02
Oil and Gas	0.09	0.05***	-0.03*	-0.04**	-0.03*	-0.1***	-0.01	-0.03	0
Real Estate	0.2	0.01	-0.01	-0.05***	-0.04**	-0.11***	-0.03	0.02	0
Transport	0.19	0.01	0	-0.01	-0.05**	-0.08***	-0.03	-0.03	-0.02

Note. Constituent stocks for these industries are provided in Appendix A. ***, ** and * denote significant at 1%, 5% and 10% respectively.

Table 3 shows the autocorrelation properties of our industry-leader and industry-follower portfolios. It shows that in daily returns, there is strong positive first-order autocorrelation in many industry-leader portfolios. However the table also shows that daily returns to leader portfolios are volatile and this first-order autocorrelation for many of these portfolios becomes negative second-order autocorrelation. Further, Table 3 shows that daily returns to industry follower portfolios are quite volatile. Unlike industry-leader portfolios however,

industry-follower portfolios often display negative first-order autocorrelation probably due to bid-ask bounce or speculative trading in these small stocks. These results are consistent with the contention in the SLF model that switching is more likely to occur between the leader stocks of two industries as these stocks are more liquid and less volatile and therefore it is easier to trade these stocks with confidence.

The normalized Herfindahl indices[22] in Table 1 indicate the biggest discrepancies in size between the leader and follower portfolios are in the beverages, media, food, transport and metals and mining industries. Thus if we identify switches involving these industries we might expect them to be consistent with the SLF model whereby the switches are implemented firstly through the relevant leader stocks, and then with a lag through the relevant follower stocks. However, of these, metals and mining and media are the largest industries and possibly the most familiar to investors. If our hypothesis of the familiarity of leader stocks to investors also affecting switching activities is correct, we would expect these industries to be most likely to be involved in switching activities and for these switches to occur through the leader stocks first, followed by the follower stocks.

4.2 Methodology

We use the vector autoregression (VAR) technique to test the BS model and, consistent with the SLF model, to test for switching between the leader stocks of the industry categories we examine. We also estimate a third set of vector autoregressions designed to test the potential profitability of the SLF model compared with the BS model. These three

[22] See Hou and Robinson (2006) for further discussion on the Herfindahl index. The website http://en.wikipedia.org/wiki/Herfindahl_index also contains a useful background discussion. As a guide, the United States Department of Justice regards a Herfindahl index of below 0.10 as characteristic of an unconcentrated index, an index of between 0.10 and 0.18 as moderate concentration and an index above 0.18 as high concentration.

VAR systems are estimated for raw returns and for market-adjusted returns[23], for each of the 45 industry pairings described in Section 4.1. Further details on the VAR systems and the hypotheses tests performed are given below.

4.2.1 Testing the BS Model

To test the BS model, we first define the 2 x 1 vector z_t,

$$z_t = \begin{bmatrix} R_{X,t} \\ R_{Y,t} \end{bmatrix} \tag{21}$$

and estimate:

$$z_t = c + \Phi_1 z_{t-1} + \Phi_2 z_{t-2} + \ldots + \Phi_p z_{t-p} + \varepsilon_t \tag{22}$$

with $\varepsilon_t \sim \text{i.i.d}\, N(0,\Omega)$. The dimensions of c are 2 x 1, while Ω, $\Phi_1, \Phi_2, \ldots, \Phi_p$ are all 2 x 2 matrices. We use p=5 in our regressions so we are looking for evidence of switching within five days of a positive shock to a category.

We define the elements of the kth coefficient matrix, Φ_k, as

$$\Phi_k = \begin{bmatrix} d_{k:11} & d_{k:12} \\ d_{k:21} & d_{k:22} \end{bmatrix} \tag{23}$$

and calculate the following for l=1,2,3,4,5:

$$M_X(l) = \sum_{k=1}^{l} d_{k:11},\ M_Y(l) = \sum_{k=1}^{l} d_{k:22},\ S_{XY}(l) = \sum_{k=1}^{l} d_{k:12},\ S_{YX}(l) = \sum_{k=1}^{l} d_{k:21} \tag{24}$$

Here $M_X(l)$ can be interpreted as momentum or autocorrelation in X and represents the cumulative response of category X to a shock to itself l periods earlier. $M_Y(l)$ represents a similar quantity for category Y while $S_{XY}(l)$ represents the cumulative response of category X to a shock to Y l periods ago and $S_{YX}(l)$ represents the cumulative response of category Y to

[23] Market-adjusted returns are calculated by subtracting the market return on a given day from the raw return on the same day to a category or a category's leader stocks or a category's follower stocks.

a shock to category *X* *l* periods ago. Having defined those terms, we can say that a switch occurs from *X* to *Y*, *l* periods after a positive shock to *X*, if all of the following are satisfied:

$$M_X(l) > 0,\ M_Y(l) > 0,\ S_{XY}(l) < 0 \tag{25}$$

Similarly a switch occurs from *Y* to *X*, *l* periods after a positive shock to *X*, if all of the following are satisfied:

$$M_X(l) > 0,\ M_Y(l) > 0,\ S_{YX}(l) < 0 \tag{26}$$

We expect both $M_X(l)$ and $M_Y(l)$ to be positive, that is, following a positive shock to a category *l* days ago, we expect subsequent returns to that category to become even higher reflecting momentum in that category, perhaps generated by excessive investor interest.

If switching occurs from *X* to *Y* we expect $S_{XY}(l)$ to be negative reflecting that when there is a positive shock to *Y*, *l* days ago, this leads to a shift out of category *X* and into *Y*, depressing *X*'s return. Similarly, a negative value for $S_{YX}(l)$ could reflect a shift out of *Y* into *X* when there is a positive shock to *X*, *l* days earlier.

We focus on switches where all conditions in Equation (25) or Equation (26) are satisfied and the average p-value is less than 0.10[24]. We also show the *p*-values for each individual condition in Equation (25) or Equation (26), for each of these switches. We also

[24] Ideally we would report one p-value covering simultaneous testing of all restrictions. If all tests were two-sided a Wald test as in Hamilton (1994), p.299, equation (11.1.38) could be used. As the tests are all one-sided we calculate p-values of the hypotheses separately and report the average p-value. However we note that the individual p-values are not independent. Schweder and Spjotvoll (1982) and Rogers (1986) show formally how to deal with simultaneous one-sided restrictions.

highlight the potential profitability of these switches by plotting the cumulative response of categories *X* and *Y*, in the five days following a relevant shock.

4.2.2 Testing the SLF model

4.2.2.1 Testing for switching between *X-Leaders* and *Y-Leaders*

To test for switching from one set of leader stocks to another, we define a 2 x 1 vector l_t,

$$l_t = \begin{bmatrix} R_{X,Lead,t} \\ R_{Y,Lead,t} \end{bmatrix} \tag{27}$$

and estimate

$$l_t = c + \Phi_1 l_{t-1} + \Phi_2 l_{t-2} + \ldots + \Phi_p l_{t-p} + \varepsilon_t \tag{28}$$

with $\varepsilon_t \sim \text{i.i.d}\, N(0,\Omega)$. The dimensions of c are 2 x 1, while Ω, $\Phi_1, \Phi_2, \ldots, \Phi_p$ are all 2 x 2 matrices. Again we set p=5 and we define the elements of the kth coefficient matrix, Φ_k, as:

$$\Phi_k = \begin{bmatrix} d_{k:11} & d_{k:12} \\ d_{k:21} & d_{k:22} \end{bmatrix} \tag{29}$$

and calculate the following for l=1,2,3,4,5:

$$M_{XL}(l) = \sum_{k=1}^{l} d_{k:11},\ M_{YL}(l) = \sum_{k=1}^{l} d_{k:22},\ S_{XYL}(l) = \sum_{k=1}^{l} d_{k:12},\ S_{YXL}(l) = \sum_{k=1}^{l} d_{k:21} \tag{30}$$

Here $M_{XL}(l)$ is the cumulative impact of a shock to *X-Leaders*, l days ago, on returns to *X-Leaders* in the l days following. $M_{YL}(l)$ is similarly defined in respect of *Y-Leaders*. $S_{XYL}(l)$ is the cumulative impact of a shock to *Y-Leaders*, l periods ago, on *X-Leaders* in the l periods following. $S_{YXL}(l)$ is similarly defined for the effect of a shock to *X-Leaders* on *Y-Leaders*.

Similar to the discussion in section 4.2.1 for the BS model we expect $M_{XL}(l)$ and $M_{YL}(l)$ to be positive, reflecting that when there is a positive shock to *X-Leaders* or *Y-Leaders*, this makes these portfolios subsequently appreciate in price. A negative value for

$S_{XYL}(l)$ may imply a switch from *X-Leaders* to *Y-Leaders* when the latter performs relatively well, while a negative value of $S_{YXL}(l)$ may imply a switch from *Y-Leaders* to *X-Leaders* when *X-Leaders* performs relatively well.

We say a switch occurs from *X-Leaders* to *Y-Leaders* l periods after a positive shock to X if all of the following are satisfied:

$$M_{XL}(l) > 0,\ M_{YL}(l) > 0,\ S_{XYL}(l) < 0 \tag{31}$$

Similarly, a switch is said to occur from *Y-Leaders* to *X-Leaders* l periods after a positive shock to X if all of the following are satisfied:[25]

$$M_{XL}(l) > 0,\ M_{YL}(l) > 0,\ S_{YXL}(l) < 0 \tag{32}$$

4.2.2.3 Testing the economic significance of switches identified in the SLF model

We now estimate VAR systems that enable us to see the effect of a positive shock on a particular day to the leader stocks of a category on: (i) those same stocks, in the subsequent five days; (ii) the leader stocks of the alternate category, in the subsequent five days and (iii) on the follower stocks of the in-favour category in the subsequent five days. We do this by using a cumulative impulse response analysis. The aim is to see the potential profitability of the trading strategies implied by the SLF model as this model implies the optimal way to switch from one category to another is to switch into the leader stocks of the in-favour category first, and then with a lag into the smaller less liquid follower stocks of the now in-favour category. We estimate

$$f_t = c + \Phi_1 f_{t-1} + \Phi_2 f_{t-2} + \ldots + \Phi_p f_{t-p} + \varepsilon_t \tag{33}$$

where , f_t , is

[25] The issue of simultaneous one-sided restrictions is relevant here as well. Please refer to Schweder and Spjotvoll (1982) and Rogers (1986) for more details on dealing with this problem. Similarly to the analysis of BS we focus on switches for which all conditions in either Equation (31) or (32) are satisfied and such that the average *p*-value is less than 0.10.

$$f_t = \begin{bmatrix} R_{X,Lead,t} \\ R_{X,Foll,t} \\ R_{Y,Lead,t} \\ R_{Y,Foll,t} \end{bmatrix} \tag{34}$$

and $\varepsilon_t \sim \text{i.i.d}\, N(0,\Omega)$. The dimensions of c are 4 x 1, while Ω, $\Phi_1, \Phi_2, ..., \Phi_p$ are all 4 x 4 matrices. As with the previous systems in respect of lead-lag effects, the BS model and switching from one set of leader stocks to another, we use p=5.

We plot the potential profitability of each significant switch identified in either the BS model or SLF model. The potential profitability of the BS model is shown by a cumulative impulse response of both the in and out-of-favour categories, in response to a positive shock to the former.

5. Results

An overview of the switches found in daily raw returns is shown in Table 4. Panel A of Table 4 shows significant switches identified in the BS model, that is those switches for which all conditions in either Equation (25) or Equation (26) are satisfied while Panel B of Table 4 shows significant switches identified under the SLF model, that is those switches for which all conditions in either Equation (31) or Equation (32) are satisfied. The p-values corresponding to the conditions underlying these switches are shown in Table 6. In addition we show the values of l corresponding to these switches, i.e. we identify how soon after a relevant shock and for how long switching activities persist.

Table 4 shows that in daily raw returns the BS model identifies five significant switches. The strongest switches are from banks to media stocks and from banks to metals. From Table 6, if there is a positive shock to media stocks, then media stocks appreciate

Table 4

Switching in Daily Raw Returns[#]

Panel A: Summary of switching patterns under the BS model

	Banks	Beverages	Construction	Food	Insurance	Media	Metals	Oil and Gas	Real Estate	Transport
Banks		*				***	***			
Beverages										
Construction										
Food						*				
Insurance										
Media							**			
Metals										
Oil and Gas										
Real Estate										
Transport										

Panel B: Summary of switching patterns between leader portfolios

	Banks	Beverages	Construction	Food	Insurance	Media	Metals	Oil and Gas	Real Estate	Transport
Banks		**				**	***	***		
Beverages	**					**		**		
Construction										
Food										
Insurance										
Media										
Metals	***	**				**				
Oil and Gas						**				
Real Estate										
Transport										

Switching occurs out of the industry given in the row and into the industry given in the column

Note. The vector autoregression (VAR) in Equation (22) is estimated. A summary of the results using daily raw returns and daily market adjusted returns is given in Panels A and B respectively. An item appears below when all conditions in either Equation (5) or Equation (6) are satisfied and the average p-value is less than or equal to 0.10. ***,** and * denote an average p-value of less than 0.01, 0.05 and 0.10 respectively.

Table 5

Switching in Daily Market-Adjusted Returns[#]

Panel A: Summary of switching patterns under the BS model

	Banks	Beverages	Construction	Food	Insurance	Media	Metals	Oil and Gas	Real Estate	Transport
Banks		*				***	*			
Beverages	*									
Construction										
Food										
Insurance										
Media		**		**			*			
Metals	**			*						
Oil and Gas										
Real Estate										
Transport										

Panel B: Summary of switching patterns between leader portfolios

	Banks	Beverages	Construction	Food	Insurance	Media	Metals	Oil and Gas	Real Estate	Transport
Banks				***			***	**		
Beverages	*					*				
Construction										
Food						**	*			
Insurance										
Media	*						*			
Metals	***	**		**						
Oil and Gas		*								
Real Estate										
Transport										

Switching occurs out of the industry given in the row and into the industry given in the column

Note. The vector autoregression (VAR) in Equation (28) is estimated. A summary of the results using daily raw returns and daily market adjusted returns is given in Panels A and B respectively. An item appears below when all conditions in either Equation (5) or Equation (6) are satisfied and the average p-value is less than or equal to 0.10. ***,** and * denote an average p-value of less than 0.01, 0.05 and 0.10 respectively.

Table 6

Statistical Significance of Each Condition in Significant Switches

Panel A: Daily raw returns

Switch out of *X*	Switch into *Y*	BS				SLF			
		Mom(*Y*)	Switch(*XY*)	Mom(*X*)	*l*	Mom(*YL*)	Switch(*XYL*)	Mom(*XL*)	*l*
Banks	Beverages	**0.28**	**0.00**	**0.00**	1	0.00	0.07	0.00	1:2
Banks	Media	**0.02**	**0.00**	**0.00**	1:5	0.04	0.00	0.00	1:5
Banks	Metals	**0.00**	**0.01**	**0.00**	1:5	0.00	0.00	0.00	1:5
Food	Media	**0.00**	**0.18**	**0.08**	1:2	-	-	-	-
Media	Metals	**0.00**	**0.11**	**0.00**	1:3	-	-	-	-
Banks	Oil & Gas	-	-	-	-	0.01	0.00	0.00	1
Beverages	Banks	-	-	-	-	0.00	0.07	0.00	2
Beverages	Media	-	-	-	-	0.05	0.00	0.00	1
Beverages	Oil & Gas	-	-	-	-	0.00	0.10	0.00	1
Metals	Banks	-	-	-	-	0.00	0.00	0.00	1:5
Metals	Beverages	-	-	-	-	0.00	0.09	0.00	1:2
Metals	Media	-	-	-	-	0.04	0.00	0.00	1
Oil & Gas	Media	-	-	-	-	0.05	0.03	0.00	1

Panel B: Daily market-adjusted returns

Switch out of *X*	Switch into *Y*	BS				SLF			
		Mom(*Y*)	Switch(*XY*)	Mom(*X*)	*l*	Mom(*YL*)	Switch(*XYL*)	Mom(*XL*)	*l*
Banks	Beverages	0.05	0.16	0.00	1	-	-	-	-
Banks	Media	0.01	0.01	0.00	1:3	-	-	-	-
Banks	Metals	0.14	0.04	0.00	1	0.00	0.01	0.00	1:5
Beverages	Banks	0.00	0.23	0.05	1	0.00	0.10	0.10	3
Media	Beverages	0.06	0.05	0.01	1	-	-	-	-
Media	Food	0.03	0.01	0.01	1	-	-	-	-
Media	Metals	0.19	0.00	0.01	1	0.00	0.03	0.26	1
Metals	Banks	0.00	0.00	0.14	1	0.00	0.25	0.00	1:5
Metals	Food	0.03	0.02	0.11	1	0.00	0.07	0.00	1
Banks	Food	-	-	-	-	0.00	0.01	0.00	1
Banks	Oil & Gas	-	-	-	-	0.00	0.05	0.00	1:2
Beverages	Media	-	-	-	-	0.16	0.03	0.00	1
Food	Media	-	-	-	-	0.12	0.01	0.01	1
Food	Metals	-	-	-	-	0.00	0.18	0.00	1
Media	Banks	-	-	-	-	0.00	0.00	0.28	1
Metals	Beverages	-	-	-	-	0.00	0.25	0.00	1:2
Oil & Gas	Beverages	-	-	-	-	0.00	0.28	0.00	1

Note. A significant switch is one where the average *p*-value of all conditions in either Equation (25) or Equation (26) for the BS model, or Equation (31) or Equation (32) for the SLF model, is less than 0.10. The *p*-value of each condition for each condition for each of these switches is shown here. The values of *l* correspond to when, after a relevant shock, evidence of switching is found. Where the switch satisfies multiple values of *l*, *p*-values are shown for the lowest value of *l*, i.e. the first day for which evidence of switching is found.

in price and remain at that higher level for at least another five days while banking stocks drop in price and remain at that lower level for at least five days. A similar pattern is observed with respect to banking stocks and metals and mining stocks, when there is a shock to the latter.

Table 4 also shows that the SLF model identifies many more switches than the BS model. From Table 6, most of these additional switches are difficult to profit from as the appreciation of the in-favour category and simultaneous depreciation of the out-of-favour category lasts for one day only, after which the volatility of daily returns makes it very difficult to reliably profit from the strategy. However, while it may be difficult to profit from switching between the leader stocks of these industry portfolios, these switches may induce lead-lag effects in the in-favour category from which investors can profit. This is discussed more in the next section. Even with this restriction, the SLF model identifies a very important switch, from metals to banks, which the BS model did not. This switch lasts for at least five days meaning investors may be able to profit from selling metals and mining stocks and buying banking stocks, within five days of a positive shock to the latter.

Table 5 shows that in daily market-adjusted returns, the BS model identifies 9 significant switches. Of these only one, from banks to media stocks, lasts for more than one day. In these switches, if there is a shock to the in-favour category over and above what is being experienced by the market portfolio, then the in-favour category continues to outperform the market portfolio in the subsequent days, while the out-of-favour category proceeds to underperform the market portfolio. These switches may therefore be important to index funds who might try to implement a switch, lock in some abnormal profits from the switch, and then proceed to invest in their normal fashion.

The SLF model identifies 13 switches in daily market-adjusted returns, more than the BS model. This is perhaps not surprising as switching is more likely to be seen between

highly liquid segments of the equity market and the leader stocks of industry portfolios are expected to be highly liquid, certainly more liquid than the categories underlying the BS model. Although most switches identified in the SLF model are short-term switches it is significant that the SLF model identifies relatively long switches, lasting five days, from banks to metals and vice versa. The BS model, by contrast, only identifies the switch from banks to metals, lasting for only one day. This switch is an expected switch as described in Section 4.1 and yet only the SLF model seems to identify it clearly.

Overall these results seem to suggest that the SLF model identifies switches more easily than the BS model. While many of the additional switches identified seem to be short term switches that could be difficult to implement, the SLF model also seems to identify longer-term switches that are more easily implementable.

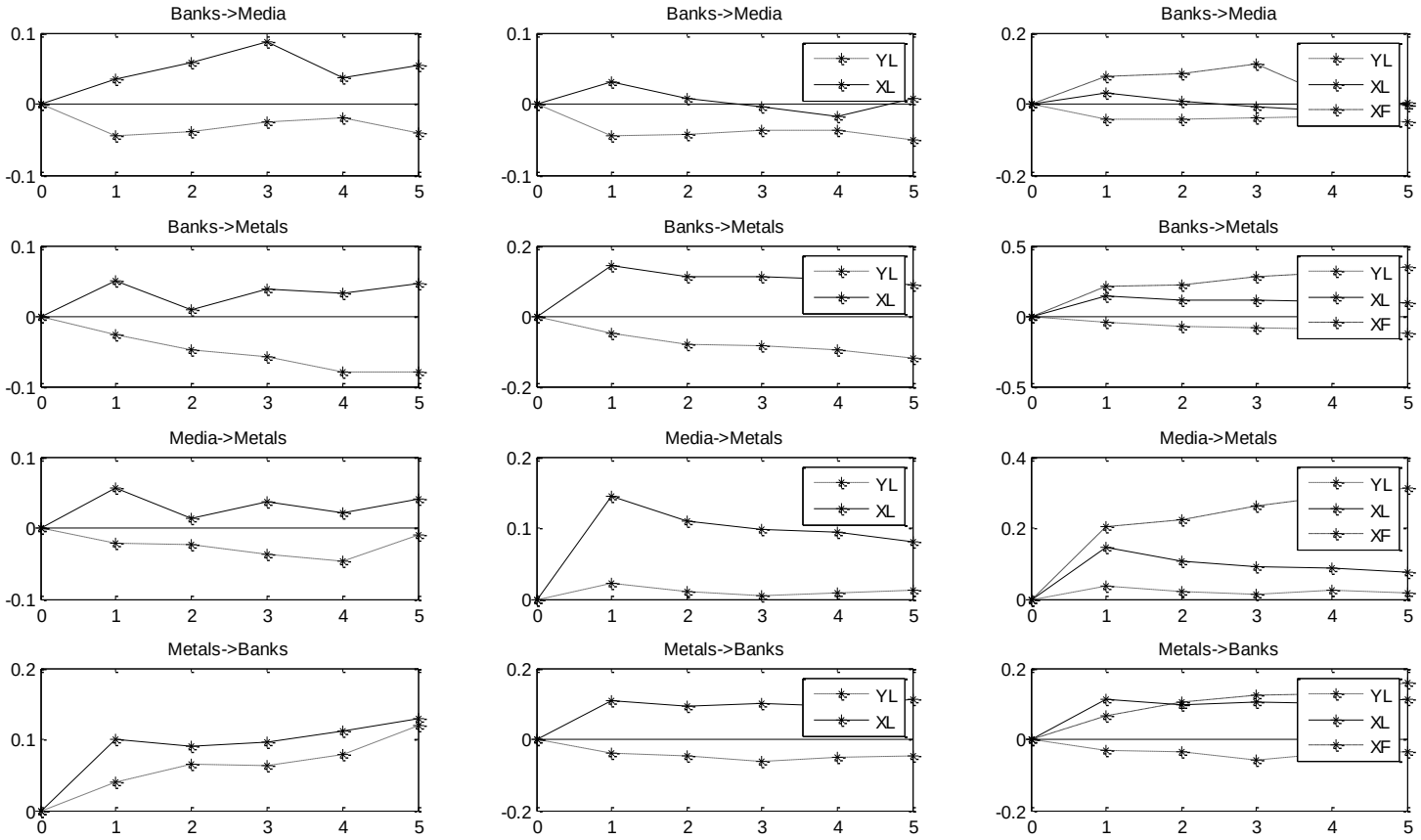
In the next section, we discuss the profitability of the switches identified in Tables 4 and 5. This is important because even if switches last for only one day, if the potential profit from implementing the switch is sufficiently high, then it may be worthwhile to implement that switch.

5.1 Profitability of switching strategies

In this section, we plot, for selected switches the profitability implied by the BS model, the potential profitability from switching between the leader stocks of the relevant categories and the potential profitability from switching between the leader stocks of the relevant categories as well as from any induced lead-lag effects. These are effectively impulse response analyses for the systems in Equations (22), (28) and (33) respectively.

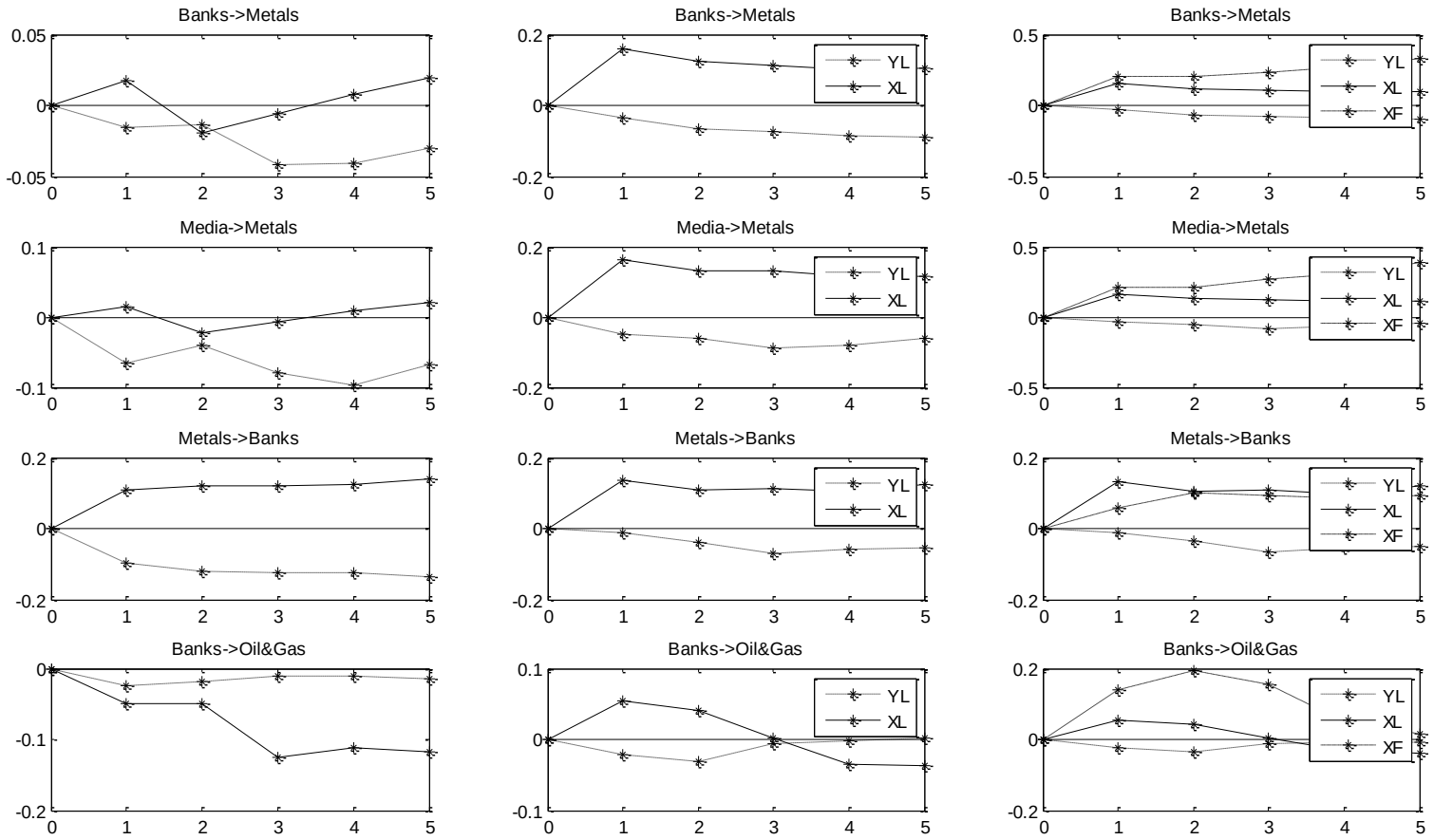
We plot the implied profitability of the following switches based on daily raw returns: (i) Banks to media; (ii) Banks to metals; (iii) Media to metals; (iv) Metals to banks.

Figure 3: Potential profitability of selected switches based on daily raw returns



The graphs in the first column correspond to the BS model and the effect of a category-wide shock.
The graphs in the second and third column refer to the SLF model and the impact of a shock to the relevant leader stocks.

Figure 4: Potential profitability of selected switches based on daily market-adjusted returns



The graphs in the first column correspond to the BS model and the effect of a category-wide shock.
The graphs in the second and third column refer to the SLF model and the impact of a shock to the relevant leader stocks.

Figure 3 shows the implied profitability of these switches. It is important to recall here that for the BS model when we are looking at responses to a category-wide shock we are looking at the average of the responses to shocks to the relevant leader stocks and to the relevant follower stocks. By comparison in the SLF models we only look at responses to shocks to the relevant leader stocks. For the switch from Banks to media in the BS model, in response to a 100 basis point shock to the latter, banking stocks fall by a total of 4 basis points in the next five days while media stocks appreciate by 5.5 basis points over the same time period. However in response to a shock of 100 basis points to the media-stock leaders, banking stock leaders fall by approximately 5 basis points while media leaders, after appreciating for the first day, start to depreciate back to the pre-shock level. This may suggest that it is the positive response of the media industry's follower stocks that drives the media category's overall positive performance.

In the switch from Bank to metals, it is clear that while the BS model easily identifies this switch, the SLF model gives a different picture of the profitability. For example the BS model suggests that Metals appreciate by approximately 5 basis points and banking stocks fall by approximately 8 basis points in response to a 100 basis point shock to the former. However in response to a 100 basis point shock to the leader stocks of metals, these leader stocks appreciate by 20 basis points. Further this same shock induces a very strong lead-lag effect and the follower stocks of metals increase by up to 34 basis points. The SLF model more easily identifies the switch and gives rise to greater profitability by distinguishing between shocks to leader stocks and shocks to follower stocks.

The BS model does however identify a switch from media to metals when the SLF model does not. It seems that when there is a shock to metals' leaders, this does not give rise to switching but perhaps when there is a shock to metals' followers, there may be though the reasons for this need to be investigated further. Finally the BS model fails to identify a

switch from metals to banks but the SLF model easily detects this switch, again by distinguishing between shocks to leader stocks and shocks to follower stocks.

In Figure 4, based on daily market-adjusted returns this feature is again noticeable, as is the very strong appreciation in the follower stocks following any switch induced by a shock to the leader stocks of metals. For example in response to a shock to the leader stocks metals of 100 basis points in excess of the return to the market portfolio, while the leader stocks of media underperform the market by up to 6 basis points, the leader stocks of metals outperform the market by 11 basis points and the follower stocks of metals outperform the market by up to 39 basis points. A similar strong price appreciation is seen in the switch from Banks to Oil and Gas, although for a much shorter time frame.

Overall these results clearly show that the relative performance of leader stocks can induce strong lead-lag effects, as predicted by the SLF model.

5.2 Limitations of the Present Study

There are a number of limitations in our empirical analysis. First, we have not allowed for transaction costs which will dilute the profitability of the switching strategies we describe. A second limitation is that we have not considered whether the stocks in particular industries have sufficient liquidity to be bought or sold or short-sold, as required in these strategies, particularly the smaller follower stocks of the industries we analyze. This will impact on the set of stocks that can be involved in our switching strategies. Third, the variability of profits from the switching strategies we describe has not been documented. Each of these issues can be analyzed separately and are left for further studies.

Further, we have not discussed the possibility of correlated simultaneous shocks to for example the leader and follower stocks of a category, focusing instead on a shock to the leader stocks only of a particular category. Alternatively there could be correlated

simultaneous shocks to the leader stocks of two categories. We have not considered this case either. The most significant limitation, perhaps, is that some of the switches identified could be spurious. For example if we identify a switch from *X-Leaders* to *Y-Leaders*, from *Z-Leaders* to *Y-Leaders* and from *Z-Leaders* to *A-Leaders*, this pattern could also be obtained if there were only two genuine switches from *X-Leaders* to *Y-Leaders* and from *Z-Leaders* to *-Leaders* and with *X-Leaders* and *Z-Leaders* both strongly contemporaneously correlated. This emphasizes the need to understand the reasons *why* switches occur from one category to another. This important area is left for future research.

6. Conclusion

This study has extended the theoretical model of switching by Barberis and Shleifer (2003). Our model, called the SLF model for Switching with Leader stocks and Follower stocks incorporated suggests that switching between categories is driven by the relative performance of the leader stocks of two alternate categories which may then induce lead-lag effects in the now in-favour category. We thus distinguish between leader stocks and follower stocks in our analysis. We showed, based on daily returns to industry, industry-leader and industry-follower portfolios, that the SLF model identifies more instances of switching and gives rise, in some cases, to significantly higher profits than those possible under the BS model.

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Appendix - A

List of Companies Analyzed

Table A1

Constituent Stocks of the Ten Industries in the Analysis and the Selection of Leader Stocks and Follower Stocks within each Industry

INDUSTRY : BANKS		
Issuer Name	***Quintile***	***Hou***
COMMONWEALTH BANK OF AUSTRALIA.	1	Leader
NATIONAL AUSTRALIA BANK LIMITED	1	Leader
AUSTRALIA AND NEW ZEALAND BANKING GROUP LIMITED	1	
WESTPAC BANKING CORPORATION	1	
ST GEORGE BANK LIMITED	1	
BENDIGO BANK LIMITED	3	
ADELAIDE BANK LIMITED	3	Follower
BANK OF QUEENSLAND LIMITED.	3	Follower
INDUSTRY: METALS AND MINING		
BHP BILLITON LIMITED	1	Leader
RIO TINTO LIMITED	1	Leader
WMC RESOURCES LIMITED	1	Leader
BLUESCOPE STEEL LIMITED	1	Leader
ALUMINA LIMITED	1	Leader
NEWCREST MINING LIMITED	1	Leader
ZINIFEX LIMITED	2	Leader
SIMS GROUP LIMITED	3	Leader
ONESTEEL LIMITED	3	
ILUKA RESOURCES LIMITED	3	
LIHIR GOLD LIMITED	3	
OXIANA LIMITED	3	
CENTENNIAL COAL COMPANY LIMITED	4	
SMORGON STEEL GROUP LIMITED.	4	
PORTMAN LIMITED	4	
EXCEL COAL LIMITED	4	
CONSOLIDATED MINERALS LIMITED	4	
JUBILEE MINES NL	4	
MINARA RESOURCES LIMITED	4	Follower
GRD LIMITED	5	Follower
AQUARIUS PLATINUM LIMITED	5	Follower
KIMBERLEY DIAMOND COMPANY NL.	5	Follower

LION SELECTION GROUP LIMITED	5	Follower
KINGSGATE CONSOLIDATED LIMITED.	5	Follower
CROESUS MINING NL	5	Follower
CAPRAL ALUMINIUM LIMITED	5	Follower
INDUSTRY: REAL ESTATE		
WESTFIELD GROUP	1	Leader
STOCKLAND	1	Leader
GENERAL PROPERTY TRUST	1	Leader
LEND LEASE CORPORATION LIMITED	2	Leader
MACQUARIE GOODMAN GROUP	2	Leader
CENTRO PROPERTIES GROUP.	2	Leader
MIRVAC GROUP	2	Leader
INVESTA PROPERTY GROUP	2	MidCap
MULTIPLEX GROUP	2	MidCap
DB RREEF TRUST	2	MidCap
MACQUARIE OFFICE TRUST	2	MidCap
CFS GANDEL RETAIL TRUST	2	MidCap
MACQUARIE COUNTRYWIDE TRUST	3	MidCap
COMMONWEALTH PROPERTY OFFICE FUND	3	MidCap
ING INDUSTRIAL FUND	3	MidCap
ING OFFICE FUND	3	MidCap
MACQUARIE DDR TRUST	3	MidCap
MACQUARIE PROLOGIS TRUST	3	Follower
AUSTRALAND PROPERTY GROUP	4	Follower
GALILEO SHOPPING AMERICA TRUST	4	Follower
FKP PROPERTY GROUP	4	Follower
VALAD PROPERTY GROUP	4	Follower
BUNNINGS WAREHOUSE PROPERTY TRUST	5	Follower
THAKRAL HOLDINGS GROUP	5	Follower
INDUSTRY: MEDIA		
NEWS CORPORATION (CLASS B NON-VOTING SHARES)	1	Leader
NEWS CORPORATION (CLASS A VOTING SHARES)	1	Leader
PUBLISHING & BROADCASTING LIMITED	1	Leader
FAIRFAX (JOHN) HOLDINGS LIMITED	2	Leader
WEST AUSTRALIAN NEWSPAPERS HOLDINGS LIMITED	2	MidCap
MACQUARIE COMMUNICATIONS INFRASTRUCTURE GROUP	2	MidCap
TEN NETWORK HOLDINGS LIMITED	3	MidCap
APN NEWS & MEDIA LIMITED	3	MidCap
SOUTHERN CROSS	3	Follower

BROADCASTING (AUSTRALIA) LIMITED		
SEVEN NETWORK LIMITED	4	Follower
STW COMMUNICATIONS GROUP LIMITED	5	Follower
AUSTEREO GROUP LIMITED	5	Follower
INDUSTRY: INSURANCE		
AMP LIMITED	1	Leader
QBE INSURANCE GROUP LIMITED	1	Leader
INSURANCE AUSTRALIA GROUP LIMITED	1	MidCap
PROMINA GROUP LIMITED	1	MidCap
AXA ASIA PACIFIC HOLDINGS LIMITED	2	MidCap
HHG PLC	2	MidCap
TOWER LIMITED	4	Follower
OAMPS LIMITED	5	Follower
INDUSTRY: FOOD		
WOOLWORTHS LIMITED	1	Leader
COLES MYER LTD.	1	Leader
FOODLAND ASSOCIATED LIMITED	2	MidCap
AWB LIMITED	3	Follower
METCASH TRADING LIMITED	4	Follower
INDUSTRY: OIL AND GAS		
WOODSIDE PETROLEUM LIMITED	1	Leader
SANTOS LIMITED	1	Leader
ORIGIN ENERGY LIMITED	2	Leader
OIL SEARCH LIMITED	2	MidCap
CALTEX AUSTRALIA LIMITED	2	MidCap
HARDMAN RESOURCES LIMITED	3	MidCap
AUSTRALIAN WORLDWIDE EXPLORATION LIMITED	4	MidCap
ARC ENERGY LIMITED	5	Follower
ROC OIL COMPANY LIMITED	5	Follower
TAP OIL LIMITED	5	Follower
INDUSTRY: TRANSPORTATION		
MACQUARIE INFRASTRUCTURE GROUP	1	Leader
MACQUARIE AIRPORTS	2	Leader
TRANSURBAN GROUP	2	MidCap
PATRICK CORPORATION LIMITED	2	MidCap
HILLS MOTORWAY GROUP	2	MidCap
CONNECTEAST GROUP	4	MidCap
PRIME INFRASTRUCTURE GROUP	4	Follower
ADSTEAM MARINE LIMITED	4	Follower
INDUSTRY: CONSTRUCTION		
RINKER GROUP LIMITED	1	Leader
BORAL LIMITED.	2	Leader
JAMES HARDIE INDUSTRIES N.V.	2	MidCap
CSR LIMITED	2	Follower

ADELAIDE BRIGHTON LIMITED	4	Follower
INDUSTRY: BEVERAGES		
FOSTER'S GROUP LIMITED	1	Leader
COCA-COLA AMATIL LIMITED	2	Leader
SOUTHCORP LIMITED	2	MidCap
LION NATHAN LIMITED	2	Follower
MCGUIGAN SIMEON WINES LIMITED	4	Follower

Note. Leader stocks and follower stocks using the Hou (2007) algorithm, a modified Hou (2007) algorithm (Robust1), and a modified Lo and MacKinlay (1990) algorithm (Robust2), are shown. Also shown is the quintile each stock belongs to. Stocks in the ASX200 as at 28 February 2005 were divided into five quintiles based on market capitalization. Quintiles 1 and 5 comprise the largest and smallest stocks respectively.