

# MOMENTUM AND MEAN REVERSION ACROSS NATIONAL EQUITY MARKETS\*

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*December 2001*

## ABSTRACT

A number of studies have separately identified mean reversion and momentum. This paper considers these effects jointly: potential for mean reversion and momentum is combined into one index, interpretable as an expected return. Combination momentum-contrarian strategies, used to select from among 18 developed equity markets at a monthly frequency, outperform both pure momentum and pure mean reversion strategies. A breakdown of the combination strategies indicates that both extreme high-expected-return and low-expected-return strategies rely heavily on country-indices with higher standard deviation of return, smaller firm size, and a lower number of firms. These observations suggest a mispricing rather than risk-compensation explanation of returns, with overreaction tied to information-based neglect of countries with fewer and smaller firms.

*Keywords:* Mean Reversion, Momentum, International Asset Pricing, Investment Strategies, Overreaction Hypothesis

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\* The authors thank seminar participants at Erasmus University, the Hong Kong Monetary Authority, and West Virginia University for helpful comments. Part of this work was completed while Balvers visited the Tinbergen Institute and Wu visited the Hong Kong Institute for Monetary Research. They thank these Institutes for their hospitality and financial support. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Tinbergen Institute or the Hong Kong Institute for Monetary Research, its Council of Advisors or Board of Directors.

## INTRODUCTION

Considerable evidence exists that both contrarian and momentum investment strategies produce excess returns. The work of DeBondt and Thaler (1985, 1987), Chopra, Lakonishok, and Ritter (1992), Richards (1997), and others finds that a contrarian strategy of sorting (portfolios of) firms by previous returns and holding those with the worst prior performance and shorting those with the best prior performance generates positive returns. On the contrary, the work of Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), Rouwenhorst (1998), Chan, Hameed and Tong (2000), Grundy and Martin (2001), Jegadeesh and Titman (2001), and others reveals that a momentum strategy of sorting (portfolios of) firms by previous returns, holding those with the best prior performance and shorting those with the worst prior performance generates positive returns.

There is no contradiction in the profitability of both contrarian and momentum investment strategies since contrarian strategies work for a sorting period ranging from 3 years to 5 years prior and a similar 3 to 5 year holding period; while momentum strategies typically work for a sorting period ranging from 1 month (or more commonly 3 months) to 12 months and a similar 1 (or 3) to 12 months holding period.<sup>1</sup> The results correlate well with the findings of mean reversion at horizons of around 3 to 5 years and the findings of continuation for horizons up to 12 months.<sup>2</sup> Furthermore the overreaction hypothesis of DeBondt and Thaler (1985, 1987), as formalized by DeLong *et al.* (1990), and the behavioral theories of Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) imply the observed pattern of momentum/continuation at

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<sup>1</sup> Lehmann (1990) and Jegadeesh (1990) find profitability of contrarian strategies for very short – 1 week to 1 month – periods. We refer to the horizon from one month to up to one year as “short” although some authors [for instance Lee and Swaminathan (2000)] refer to this horizon as “intermediate.”

<sup>2</sup> For the early work on these issues, see for instance Lo and MacKinlay (1988), Fama and French (1988), and Poterba and Summers (1989).

high frequencies and mean reversion at low frequencies.<sup>3</sup>

The purpose of this paper is to explore the implications of an investment strategy that considers momentum potential and mean reversion potential jointly. Chan, Jegadeesh, and Lakonishok (1996, p.1711) state prominently: “Spelling out the links between momentum strategies and contrarian strategies remains an important area of research.” Subsequent research by Lee and Swaminathan (2000), and Jegadeesh and Titman (2001) exploring these links confirms an earlier finding of Jegadeesh and Titman (1993) that particular momentum-sorted portfolios experience eventual partial mean reversion. This finding is important since it suggests that momentum and mean reversion, which in principle may occur in different groups of assets, occur in the same group of assets—supporting the overreaction hypothesis for this group of assets. The reversal result, however, needs further corroboration: it is established for U.S. data only; it is weak in the 1982-1998 period; may not hold for large firms after risk correction; and appears to be insignificant for prior losers (Jegadeesh and Titman, 2001).

Aside from providing further evidence pertaining to the overreaction hypothesis, sorting out the connection between momentum and mean reversion is important for other reasons as well. First, it may help in identifying characteristics that make particular assets susceptible to overreaction; thus providing evidence for or against specific behavioral theories. Second, as momentum and mean reversion potentials interfere with each other, controlling for one should improve estimates of the duration of the other. Third, from an investor’s perspective, it may be worthwhile to combine contrarian and momentum strategies. In regards to this last point, traditional non-parametric approaches make a combination strategy awkward. One could, for instance, construct a portfolio of

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<sup>3</sup> Consistent use of terminology suggests that a process of *mean reversion* leads to profitable *contrarian* investment strategies; a process of *continuation* leads to profitable *momentum* investment strategies. We prefer, however, the more common use of the term “momentum” to indicate both the process and the strategy.

firms with a combination of high returns in the previous 1-12 month period and low returns in the previous 3-5 year period, and buy this portfolio. One problem then is: what should the holding period be – 1-12 months or 3-5 years? More essential than the selection of a particular holding is the actual portfolio choice: how should an investor weigh the importance of momentum potential vis-à-vis mean reversion potential?

We instead utilize the decomposition into permanent and transitory components from Fama and French (1988) and employ a parametric approach, as in Jegadeesh (1990), Pesaran and Timmermann (1995, 2000), and Balvers, Wu, and Gilliland (2000). Specific parameter estimates allow construction of an expected returns index that combines potential for momentum and mean reversion into one number. Investing occurs *at each point in time* in the asset or portfolio of assets with the highest index number at that time (while shorting the assets with the lowest index number).

Applying these investment switching strategies to a sample of developed national equity markets we find that strategies combining momentum and mean reversion typically yield returns of around 1.2 - 1.5 percent monthly and generally outperform pure momentum and mean reversion strategies, which in turn outperform a random-walk-based strategy. The results cannot easily be explained as a reward for taking on systematic risk, but readily support a behavioral overreaction perspective.

The outline of the paper is as follows. In section I we describe the model and a decomposition of expected returns into a common unconditional mean, the country-specific potential for mean reversion, and the country-specific potential for momentum. Section II discusses the Morgan Stanley Capital International (MSCI) data for the index returns in eighteen developed equity markets over the 1970-1999 period and estimation issues, while basic results for pure and combination momentum and mean reversion strategies and random-walk-based strategies are presented in Section III. Illustrative

parameter estimates and impulse responses for a baseline formulation are described in Section IV. Various robustness issues are covered in Section V, and risk and other characteristics describing strategy portfolios are discussed in Section VI; Section VII concludes with an appraisal of the results and further discussion of the implications.

## I. THE MODEL AND A RETURN DECOMPOSITION

### *(a) An integrated mean reversion-momentum model*

We adapt the model of Fama and French (1988) and Summers (1986) to apply in a global context and to allow for momentum as well as mean reversion. First define  $p_t^i$  as the log of the equity price index of country  $i$  with reinvested dividends, so that the continuously compounded return  $r_t^i$  is given as:

$$r_t^i = p_t^i - p_{t-1}^i. \quad (1)$$

Superscripts everywhere indicate an individual country index. Following Fama and French (1988), we separate equity prices into permanent and temporary components. Empirically we consider portfolios for a homogeneous group of countries, which enables us to add some structure to the model. Specifically we assume that all permanent shocks are global; or, in other words, any country-specific shocks are transitory. For country  $i$  we have accordingly

$$p_t^i = y_t + x_t^i, \quad (2)$$

The permanent price component is denoted by  $y_t$  and the temporary component by  $x_t^i$ .

The theoretical motivation for assuming that all permanent shocks are global is based on the idea of “convergence.” Barro and Sala-i-Martin (1995) find that real per capita GDP across the 20 original OECD countries displays absolute convergence, implying that real per capita GDP in these countries converges to the same steady state. This would imply in models such as the Lucas asset pricing model [Lucas, (1978); see also Balvers, Cosimano, and McDonald (1990)] that values of representative firms in these countries should converge as well. As our sample consists of mainly OECD countries we expect the non-global components in equity prices in these countries to be stationary. The permanent component therefore is fully global and given as a random walk with drift as in Fama and French (1988):

$$y_t = y_{t-1} + \mathbf{a}_t . \quad (3)$$

The random term  $\mathbf{a}_t$  is stationary with positive mean but otherwise unrestricted. From equations (1)–(3) it is clear that  $r_t^i - \mathbf{a}_t = x_t^i - x_{t-1}^i$ .

The temporary component  $x_t^i$  is given as:

$$x_t^i = (1 - \mathbf{d}^i) \mathbf{m}^i + \mathbf{d}^i x_{t-1}^i + \sum_{j=1}^J \mathbf{r}_j^i (x_{t-j}^i - x_{t-j-1}^i) + \mathbf{h}_t^i . \quad (4a)$$

Equation (4a) generalizes the Fama and French (1988) and Summers (1986) model by allowing the  $\mathbf{r}_j^i$  to be non-zero. The constant  $\mathbf{m}^i$ , the autoregressive coefficient  $\mathbf{d}^i$ , the momentum coefficients

$\mathbf{r}_j^i$ , and the mean-zero normal random term  $\mathbf{h}_t^i$  (serially and cross-sectionally uncorrelated with variance  $\mathbf{s}_{\mathbf{h}^i}^2$ ), can vary by country.

With enough countries  $i$  the assumption that  $\mathbf{h}_t^i$  is cross-sectionally uncorrelated implies that it is reasonable to set the worldwide average of the country-specific components  $x_t^w$  equal to a constant,

$$x_t^w = \mathbf{m}^w, \quad r_t^w = \mathbf{a}_t. \quad (4b)$$

The second equality follows from the first equality together with equations (1) - (3) applied to the case  $i = w$ , where  $w$  indexes worldwide averages.

Equations (1) - (4) represent an integrated mean reversion-momentum model. From these four equations it is straightforward to find the return in country  $i$  as:<sup>4</sup>

$$r_t^i - r_t^w = -(I - \mathbf{d}^i)(x_{t-1}^i - \mathbf{m}^i) + \sum_{j=1}^J \mathbf{r}_j^i (r_{t-j}^i - r_{t-j}^w) + \mathbf{h}_t^i. \quad (5)$$

### (b) Return decomposition

To simplify notation we redefine variables and use lag operators  $L^j$  to write:

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<sup>4</sup> Note that for empirical purposes  $r_t^i - r_t^w$  is directly observable in the data and that  $x_{t-1}^i$  can be identified from  $x_{t-1}^i = p_{t-1}^i - y_{t-1}$  (equation 2) plus the fact that  $x_0^i = 0$  by construction of the MSCI data (all index values are set equal to 100 in December 1969). Thus,  $x_t^i$  is generated as  $x_t^i = \sum_{s=1}^t r_s^i - r_s^w$ . The  $\mathbf{m}^i$  can be viewed as adjusting for the measurement error introduced by the initialization error of setting  $x_0^i = 0$  for each country  $i$ .

$$R_t^i = - (I - \mathbf{d}^i) X_{t-1}^i + \mathbf{r}^i(L) R_{t-1}^i + \mathbf{h}_t^i, \quad (6)$$

$$\text{where } R_t^i \equiv r_t^i - r_t^w, \quad X_t^i \equiv x_t^i - \mathbf{m}^i, \quad \text{and } \mathbf{r}^i(L) \equiv \sum_{j=1}^J \mathbf{r}_j^i L^{j-1}.$$

Or simply,

$$R_t^i = MRV_t^i + MOM_t^i + \mathbf{h}_t^i, \quad (7)$$

$$\text{with } MRV_t^i \equiv - (I - \mathbf{d}^i) X_{t-1}^i, \quad MOM_t^i \equiv \mathbf{r}^i(L) R_{t-1}^i.$$

The left-hand side of equation (7) represents the excess return for country index  $i$  (excess relative to the world mean return). In obvious notation, the first term on the right-hand side represents the mean reversion component of return and the second term on the right-hand side represents the momentum component of return.

The unconditional expectation of the mean reversion term  $E(MRV_t^i)$  is equal to zero [since  $E(x_{t-1}^i) = \mathbf{m}^i$  from equation (4a)] and, similarly, the unconditional expectation of the momentum component  $E(MOM_t^i)$  is equal to zero. Hence, *average* excess returns  $R_t^i$  are zero and the realized country returns  $r_t^i$  can be cleanly decomposed into the global average return  $r_t^w$ , a mean reversion component, a momentum component, and an idiosyncratic shock component. The formulation is flexible, yielding the momentum formulation of Jegadeesh and Titman (1993) as a special case when  $\mathbf{d}^i = 1$  (for all  $i$ ) and  $\mathbf{r}_j^i = \mathbf{r}^i$  (for all  $i$  and  $j$ ) and the mean reversion formulation of Balvers, Wu, and Gilliland (2000) as a special case when  $\mathbf{r}_j^i = 0$  (for all  $i$  and  $j$ ).

In the empirical implementation we deviate in two important ways from the Fama and French (1988) approach. Fama and French consider returns information instead of price information. As



first-differencing is accompanied by a loss in information about slowly decaying processes (such as, typically, the mean reversion component) we deviate from Fama and French by not differencing the data and focusing on price information instead of returns information.<sup>5</sup> The second deviation in the empirical implementation relative to Fama and French (1988) is that, while we use time series information to estimate parameters as do Fama and French, we take the additional step of assessing the usefulness of the parameter estimates in guiding trading strategies. That is, we employ the parameter estimates (using only past information) for investment decisions and evaluate the resulting excess returns.

The focus on investment strategies designed to exploit mean reversion and momentum is similar to the DeBondt and Thaler (1985) approach designed to exploit reversion and the Jegadeesh and Titman (1993) approach to exploit continuation, with as major difference that these approaches are non-parametric whereas ours is explicitly parametric. For a similar parametric approach see Jegadeesh (1990) and Balvers, Wu, and Gilliland (2000).

## II. DATA AND ESTIMATION ISSUES

### *(a) Data*

Monthly returns data are obtained from the MSCI equity market price indices for a value-weighted world average and 18 countries with well-developed equity markets: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. We use here the prices with reinvested gross dividends [that is, before withholding taxes; see Morgan Stanley Capital

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<sup>5</sup> For a recent approach that avoids first differencing while still utilizing earnings and cost of equity forecasts see Lee, Myers, and Swaminathan (1999).

International (1997) for details] converted to dollar terms. The period covered is from the start of the data series, in December 1969, through December 1999. Table I shows the summary statistics, with average monthly returns for each country and each country's beta with the world index return.<sup>6</sup>

*(b) Estimation Issues*

Estimation of our variant of the Fama-French permanent-transitory components model employs a maximum likelihood estimation procedure. The model parameters to be estimated, in principle, are the  $\mathbf{d}^i$ , the  $\mathbf{s}_{h^i}^2$ , the  $\mathbf{r}_j^i$ , and the  $\mathbf{m}^i$ . This sums to a set of  $18(J+3)$  parameters (where  $J$  represents the number of momentum lags), which is a high number in light of our 18 by 361 panel. Hence, to improve efficiency and avoid multicollinearity problems we set  $\mathbf{s}_{h^i}^2 = \mathbf{s}_h^2$  for all  $i$  and, in most specifications, apply one or more of the following restrictions:  $\mathbf{d}^i = \mathbf{d}$ ,  $\mathbf{r}_j^i = \mathbf{r}_j$ ,  $\mathbf{r}_j^i = \mathbf{r}^i$  (the  $\mathbf{m}^i$  are always allowed to differ by country as they allow for possible “mispricing” at the beginning of the sample period). Thus anywhere between 21 and  $18(J+2)+1$  parameters remain to be estimated.

### III. TRADING STRATEGY RETURNS

The joint consideration of momentum and mean reversion urges us to use a parametric procedure for establishing the trading rules. We follow closely the parametric approach of Balvers, Wu, and Gilliland (2000) who consider a strategy for exploiting mean reversion results, using only

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<sup>6</sup> In principle, a comparison of the average returns by country allows us to check directly an unintended implication of our stylized model—that the (unconditional) average returns are equal across countries. While it is easy to check from Table I that none of the average returns differ significantly from the world average return, we do not take seriously the view that mean returns are equal in all developed national markets. Rather we treat this as a simplifying assumption that is not essential for our results.

prior information. Starting at 1/3 of their sample, they use rolling parameter estimates to forecast expected returns for the upcoming period and then buy the fund with the highest expected return and short-sell the fund with the lowest expected return. We extend this strategy to exploit simultaneously the mean reversion and the momentum effects. Clearly, the “index” that combines the potential for mean reversion and momentum for each country is the conditional expected return presented in equation (5). Accordingly, we employ a trading strategy of buying at each point in time the country index with the highest expected return and short-selling the country index with the lowest expected return, based on equation (5) and using parameters estimated from prior data only. We start the forecast period at 1/3 of the sample, in January 1980, and update parameter estimates as we roll the sample forward.

The empirical model of equation (5) is applied with 12 possible momentum lags and a one-month holding period (or more if the latest available information does not induce a portfolio change) as the baseline case. While six or nine lags are employed more commonly for exploring momentum effects, we allow for additional lags because controlling for mean reversion can be expected to expose additional momentum lags (at lags beyond nine or so, mean reversion that is not controlled for may mask the presence of additional momentum lags). For the sake of comparison to existing approaches, we initially also consider standard variations of pure momentum and mean reversion strategies and related variations of the combined momentum-mean reversion strategy. In Tables II-IV, we display four special cases based on equation (5): the pure momentum model of Jegadeesh and Titman (1993), the pure mean reversion model of Balvers, Wu, and Gilliland (2001), the random walk model of Conrad and Kaul (1998), and the simplest combination mean reversion-momentum model. In these cases we report all reasonable variations in sorting and holding periods.

*(a) Pure momentum strategies*

We first replicate the momentum approach of Jegadeesh and Titman (1993) for our data set of national equity market indices. For the empirical model in equation (5) this is equivalent to setting  $\mathbf{d}^i = 1$  (for all  $i$ ) and  $\mathbf{r}_j^i = \mathbf{r}^i$  (for all  $i$  and  $j$ ); thus (excess) realized returns over the previous  $J$  sorting periods are weighted equally in determining expected future returns. The country index with the highest expected return (based fully on past momentum for this strategy) is chosen as the “Max1” portfolio and the country index with the lowest expected return is chosen as the “Min1” portfolio. The strategy of buying Max1 and shorting Min1 and holding this portfolio for  $K$  periods is referred to as “Max1-Min1” and listed under the appropriate value for  $K$  (similarly “Max3” and “Min3” refer to the strategies of holding the three country indices with, respectively, the highest and the lowest expected returns).

Jegadeesh and Titman (1993) focused only on the permutations of  $J = 3, 6, 9, 12$  and  $K = 3, 6, 9, 12$  which are shaded in Table II. However, since our model is designed for forecasting returns one period (month) ahead, we also add the case of  $K = 1$ , in which the portfolio is held only until the updated return forecast is available. Additionally, we speculate that controlling for mean reversion as we do in our combination model of equation (5) is likely to imply a longer duration of the momentum effect (since positive momentum after, say, 12 months of previous momentum is likely to be offset by the downward pull of mean reversion and thus would not register in a pure momentum approach); accordingly we also add the permutations for  $J = 15, 18, 21, 24$  and  $K = 15, 18, 21, 24$  in Table II.

The results for the period January 1980 – December 1999 (earlier data are reserved for parameter estimation as is needed for other trading strategies) are displayed in Table II. These results generally agree, both quantitatively and qualitatively, with those of Jegadeesh and Titman (1993) for

U.S. equities and those of Rouwenhorst (1998) and Chan, Hameed, and Tong (2000) for international equities. Excess returns per gross dollar invested (net dollar investment is zero) for the Max1-Min1 and Max3-Min3 portfolios are positive for all cases originally considered by Jegadeesh and Titman (shaded) and, in the range most commonly considered,  $J = 6, 9$  and  $K = 6, 9$ , equal to around 10 percent annually and statistically significant for the Max3-Min3 cases. For the case of  $K = 1$  returns are generally substantially lower and sometimes negative which is consistent with Jegadeesh (1990) and Lehmann (1990). As expected without controlling for mean reversion and consistent with Jegadeesh and Titman (2001), excess returns for longer holding periods ( $K > 12$ ) fall rapidly as  $K$  increases to 24. Additionally, increasing the sorting period  $J$  beyond 12 lowers returns substantially.

*(b) Pure mean reversion and random walk strategies*

A further special case of equation (5) arises if we ignore momentum and focus on mean reversion only by setting  $\mathbf{r}_j^i = 0$  (for all  $i$  and  $j$ ). The resulting formulation is comparable to that used in Balvers, Wu, and Gilliland (2000) to detect mean reversion, employing an international sample similar to ours. Their approach requires employing all available (panel) data prior to the forecast period to estimate the mean reversion parameter. Hence, in contrast to the momentum case in Table II we cannot vary  $J$  but we can vary the holding period  $K$  as shown in Table III. Again, the results are consistent with those of Balvers, Wu, and Gilliland and with the earlier work on contrarian strategies exploiting mean reversion by DeBondt and Thaler (1985) and others. The contrarian strategy returns are positive in all cases. For Max1-Min1 the excess returns rise with  $K$  to 11.1 percent at  $K = 6$  and then slowly drop with  $K$  to 7.5 percent for  $K = 24$ . The returns for Max3-Min3 are lower, increasing slowly from 3.4 percent at  $K = 1$  to 5.6 percent at  $K = 15$  and then fall with  $K$  to 4.2 percent at  $K = 24$ . These results correspond reasonably well to the results in Balvers, Wu, and

Gilliland for annual data who find (for  $K = 12$ ) the Max1-Min1 return as 9.0 percent and the Max3-Min3 return as 8.4 percent.

Interestingly, the pure momentum Max1-Min1 strategy for the nine-month holding period ( $K = 9$ ) taking  $J = 6$ , for instance, yields an annualized excess return of 9.3 percent (see Table II), whereas over the same nine-month holding period the, ostensibly opposite, contrarian strategy based on pure mean reversion yields an annualized excess return of 11.0 percent (See Table III). Thus, both momentum strategies and mean reversion strategies can be profitable over the same holding period, but the momentum strategy here considers only returns over the past six months while the mean reversion strategy is predicated on the full return history. Note that, in principle, the two disparate strategies may advocate identical portfolio holdings. Whether this is in fact the case we examine in Section V.

Table III also shows the returns generated with a pure “random walk” strategy. This case is obtained from equation (5) by ignoring all lagged price components. Accordingly, country indices differ by mean return only. This formulation captures the essence of that of Conrad and Kaul (1998). Under this formulation, the random walk strategy selects the country index with the highest expected return obtained by averaging return realizations prior to each forecast period. In a simple efficient markets view, those assets with the highest prior returns are likely to be riskiest and thus are expected to have the highest returns in the future, as argued by Conrad and Kaul (1998). Since all returns prior to the forecast period are used in obtaining the best estimate for expected return, the sorting period  $J$  cannot vary (as is also true for the mean reversion case). Table III reveals that this strategy produces negative returns for all holding periods  $K$ . Clearly, this is an unexpected result given a simple standard efficient markets perspective, but can be understood easily from a mean reversion perspective: higher past realized returns likely indicate that future returns will be lower as equity prices return to trend.

Note that the momentum effect becomes unimportant here since, in contrast with the mean reversion effect, momentum carries little weight in calculating the average return from all past data.

(c) *Combination momentum and mean reversion strategies*

We now present the returns obtained by following a strategy that, based on equation (5) and using only prior information, combines the potential for mean reversion and momentum into one index for each asset, and chooses for each period the asset with the highest expected return, Max1, and shorts the asset with the lowest expected return, Min1 (and similarly for Max3 and Min3). Equation (5) allows for *eight basic ways* of combining the potential for momentum and mean reversion into one index, depending on whether the momentum parameters are allowed to differ by country and/or are allowed to differ by lag and whether the mean reversion parameter is allowed to differ by country. We take here as our baseline the most parsimonious case that encompasses both the pure momentum and mean reversion cases, namely the case of one momentum parameter ( $\mathbf{r}_j^i = \mathbf{r}$  for all  $i$ , and  $j$ ) and one mean reversion parameters ( $\mathbf{d}^i = \mathbf{d}$  for all  $i$ ). The returns for the seven alternative ways of combining momentum and mean reversion are discussed in a robustness section (Section V).

Table IV displays the combination strategy returns based on equation (5) with one momentum parameter and one mean reversion parameter. Returns are positive in all cases. For easy comparison with the pure momentum case, considered for the same permutations of  $K$  and  $J$ , the specific instances in which the combination strategy outperforms the pure momentum strategy are shaded in Table IV. There are 72 permutations of holding period  $K$  and sorting period  $J$ . In 72 of 72 corresponding Max1-Min1 strategies and in 67 of 72 corresponding Max3-Min3 strategies, the combination strategy outperforms the pure momentum strategy. The Max3-Min3 cases where the

momentum strategy works somewhat better are for  $J$  equal to 6 and 9 and  $K$  smaller or equal to 9. For the 16 cases considered by Jegadeesh and Titman (1993), shaded in Table II, the annualized average of the pure momentum return for Max1-Min1 is 6.65 percent and for Max3-Min3 is 7.30 percent, while for these 16 cases the average combination momentum-mean reversion strategy return for Max1-Min1 is 11.05 percent and for Max3-Min3 is 8.84 percent (see Table IV).

Comparing the combination strategy return against the pure mean reversion return is more difficult since sorting period  $J$  does not vary in the mean reversion case. Taking the average for the  $K = 3, 6, 9, 12$  cases considered in Jegadeesh and Titman produces a pure mean reversion Max1-Min1 return of 10.30 percent, only slightly lower than in the combination strategy case, but a pure mean reversion Max3-Min3 return of 4.40 percent, less than half the combination strategy return.

A more relevant comparison, however, may be the comparison for the case of  $K = I$ : since the optimal forecast is updated each month, the most reasonable strategy for maximizing realized excess returns is one where the portfolio, in principle, is adjusted each time when a new forecast is available. This case of one holding period, given our parametric context, is the only variant that can plausibly be motivated. Under the one-holding-period criterion, the Max1-Min1 return averaged over the  $J = 3, 6, 9, 12$  cases considered by Jegadeesh and Titman is 2.83 percent under pure momentum, 8.50 percent under pure mean reversion, and 12.25 percent under the combination strategy; the Max3-Min3 return is 9.03 percent under pure momentum, 3.40 percent under pure mean reversion, and 9.03 percent under the combination strategy.

The Max1-Min1 and Max3-Min3 returns for  $K = I$  increase with  $J$  until  $J = 9$  or  $12$  before diminishing, providing some indication that momentum effects last up to a year when controlling for mean reversion, as opposed to the six to nine months typically considered. In the following, we use as the baseline case the natural case of  $K = I$  and we set  $J = 12$  to allow, in principle, for 12 possible



momentum lags. In this instance, the Max1-Min1 return is 9.5 percent under pure momentum, 8.50 percent under pure mean reversion, and 16.70 percent under the combination strategy; the Max3-Min3 return is 11.20 percent under pure momentum, 3.4 percent under pure mean reversion, and 11.90 percent under the combination strategy.

#### IV. ILLUSTRATIVE PARAMETER ESTIMATION RESULTS

##### *(a) Parameter estimates for the baseline model and pure strategy models*

To illustrate in detail the implications of considering momentum and mean reversion simultaneously, we examine the parameters of the baseline combination model case. To review, the baseline case of equation (5) sets  $\mathbf{d}^i = \mathbf{d}$ ,  $\mathbf{r}_j^i = \mathbf{r}$  (for all countries  $i$  and lags  $j$ ), and  $\mathbf{s}_{h^i}^2 = \mathbf{s}_h^2$ , and assumes a lag structure for the momentum effect with monthly lags up to 12 ( $J = 12$ ), which is suggested by the aforementioned literature on the momentum effect that finds momentum effects of generally less than a year together with the observation that controlling for mean reversion may increase the estimated duration of the momentum effect. Additionally, the holding period is one month ( $K = 1$ ) so that for each period the zero-investment portfolio is chosen based on the best forecast for that period.

The pooled mean reversion parameter in the pure mean reversion case is estimated to be 0.986 and the pooled momentum parameter in the pure momentum case is estimated to be 0.017. For the pure mean reversion scenario, the half-life of the impulse is straightforwardly calculated as  $\ln(0.5)/\ln(0.9855) = 47.46$  months (slightly under four years); for the pure momentum case the half-life is not defined (infinite).

For the baseline case the parameter values are displayed in Table V. The mean reversion

$-\delta$ , indicating the speed of mean reversion,

equals 0.021, the momentum parameter  $\rho$  pooled across lags and countries equals 0.026; both the speed of mean reversion  $1-\delta$  and the strength of the momentum effect  $\rho$  are larger than in the pure strategy cases. The variance of the idiosyncratic return shock  $\mathbf{s}_h^2$  pooled across countries equals 0.0031. Quantitatively, these numbers imply that a cumulative return of 1.0 percent below trend has a mean reversion effect on the expected return for the upcoming period of +0.021 percent. To get an equivalent momentum effect, a returns shock of 0.81 percent in the last twelve months must occur. Alternatively, all else equal, if last period's return (or a return in any of the past 12 months) is 1 percent higher, the expected return for the upcoming month will be  $0.026 - 0.021 = 0.005$  percent higher; if the return 13 months ago is 1 percent higher, the expected return for the upcoming month will be 0.021 percent lower.

Figures 1(1) through 1(3) shows the impulse response of the idiosyncratic part of the expected price index level (for any of the countries) to a shock  $\mathbf{h}_t^i$ , for the parameter values presented above in the pure mean reversion, pure momentum, and baseline combination strategy cases. The half-life for the combination strategy can be seen to be around 40 months, although the mean reversion component by itself implies a half life of  $\ln(0.5)/\ln(0.979) = 32.66$  months. The half-life for the combination strategy is shorter than in the pure mean reversion case, in spite of the momentum component, because its speed of mean reversion  $1-\delta$  is larger. Intuitively, with momentum added in appropriately, several effects alter the calculation of the half-life. First, the continuation due to the initial shock causes the downturn to start later (beyond the 12 months of momentum lags in the baseline case) causing the half-life to be longer; second, as the downturn starts, the momentum effect reinforces it, causing the half-life to be shorter. Note in both Figures 1(1) and 1(2) that the momentum period is longer than the 12 momentum lags assumed. The reason is that, while the exogenous shock directly affects the momentum component for 12 periods only, the endogenous

momentum responses in periods one through 12 imply that even in month 13 and beyond the momentum component may still be positive and exceed the mean reversion component.

Figure 1(4) displays the impulse response graph for a “smoothed” variant of the combination strategy: instead of the 12 momentum lags in the baseline case, here there are 24 momentum lags but with coefficients restricted to fit a second-degree polynomial (that is, we consider a three-parameter Almon lag formulation). The resulting impulse response graph has a maximum around nine months and a half-life of around 36 months. Figure 1(4) shows that the momentum effect by itself lasts around 12 months, longer than what is typically found in studies that do not control for mean reversion.

*(b) Decomposition of return variance*

Table V displays the R-squared for the expected return regression as 0.021 so that only 2.1 percent of return variability is explained by the momentum and mean reversion components combined as follows from equation (6). Hence, from month to month the model explains 2.1 percent of returns variability. As Cochrane (2001, p.446) notes, however, even predictability of 0.25 percent would be enough to explain the excess momentum returns generated in the empirical work of Jegadeesh and Titman (1993) and others.<sup>7</sup> Intuitively, while the predictable variation for the average asset (country index) is small, the predictable variation of an asset deliberately selected for the extreme values of its forecasting variable is much larger.

Taking the variance in equation (7), given that  $\mathbf{d}^i = \mathbf{d}$ ,  $\mathbf{r}_j^i = \mathbf{r}$ , and  $\mathbf{s}_{hi}^2 = \mathbf{s}_h^2$  for all  $i$  and  $j$ ,

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<sup>7</sup> Numerically, following the computation in Cochrane (2001, p.447), multiply the standard deviation of the return  $(0.00316)^{1/2}$  by the standardized expected return of the asset in the top 18<sup>th</sup> of the standard normal distribution, 2.018, and this times the square root of the predictable variation  $(0.021)^{1/2}$ , yielding 0.0162 which is the expected monthly excess return; shorting the bottom 18<sup>th</sup> asset and annualizing implies an expected return of 38.8 percent. This number matches approximately the expected Max1-Min1 return of 39.3 percent in Table VI, Model 1.

produces:

$$Var(R_t) = Var(MRV_t) + Var(MOM_t) + 2Cov(MRV_t, MOM_t) + \mathbf{s}_h^2. \quad (8)$$

The variance consists of a part due to conditional variance  $Var_{t-1}(R_t) = \mathbf{s}_h^2$  and a part due to changing the prediction:  $Var[E_{t-1}(R_t)] = Var(MRV_t) + Var(MOM_t) + 2Cov(MRV_t, MOM_t)$ .

The variance of the momentum component  $Var(MOM_t)$ , averaged across countries, equals  $2.560 \cdot 10^{-5}$ , and the variance of the mean reversion component  $Var(MRV_t)$ , averaged across countries, is  $3.060 \cdot 10^{-5}$ . These numbers together with equation (7), in which both components  $MRV_t$ ,  $MOM_t$  count equally in calculating expected returns, suggest that momentum and mean reversion are of similar importance in affecting the combination strategy portfolio choices. The average return variance  $Var(R_t) = 0.00316$ ; Table V shows accordingly that unpredictable return variation is 98.5 percent, predictable variation due to mean reversion is 1.2 percent, and predictable variation due to momentum is 0.8 percent. These numbers do not add to 100 percent due to the covariance term in equation (8). The covariance between the momentum and the mean reversion effect can be backed out from equation (8):  $Cov(MRV_t, MOM_t) = -0.59 \cdot 10^{-5}$ , implying a correlation between the momentum and the mean reversion effect of -0.21.

We conclude that both mean reversion and momentum appear to be quantitatively important in predicting monthly returns, although the mean reversion effect is quantitatively slightly larger. Additionally, the covariance effect is quantitatively significant, suggesting that discussing momentum and mean reversion jointly is important. The covariance is negative because, all else equal, a, say, positive run in stock returns is associated with positive momentum, but, at the same time, causes

prices to exceed (or be less far below) fundamental values, generating a negative potential for mean reversion (or decreasing the positive potential for mean reversion). Explained alternatively, accumulated positive potential for mean reversion is more likely when a negative returns streak has occurred.

## V. ROBUSTNESS OF THE COMBINATION TRADING STRATEGIES

### *(a) Return results for alternative strategies*

Panel A in Table VI first summarizes again, as models 1-4, the returns for the basic strategies (combination, pure momentum, pure mean reversion, random walk) for the baseline case of a one-month holding period and 12 momentum lags if applicable ( $K = 1$ ,  $J = 12$ ); also listed are the world market beta, expected return, and percentage of portfolio switched each period—this information we use later in the paper to discuss risk, robustness, and transaction costs. As in Balvers, Wu, and Gilliland (2000) we present the perfect foresight strategy results (model 5: ex-post optimal choices) and the results of the baseline strategy employing full sample parameters (model 6: in-sample optimal choices) to provide a sense of proportion. As expected, returns for model 5 are dramatically higher (Max1-Min1 return is 227.5 percent), and returns for model 6 are significantly higher (Max1-Min1 return is 32.2 percent) compared to the baseline combination strategy return (Max1-Min1 return is 16.7 percent).

Model 7 in Panel A reports the returns for the case with 24 momentum lags that are restricted by three Almon lag parameters (the case for which the impulse response graph given in Figure 1(4)). Returns continue to be positive, but not significantly so for the Max1-Min1 strategy. The extension to 24 lags is useful as it is no longer clear, after controlling for mean reversion, whether 12 momentum lags is enough; the results confirm those in Table IV that adding momentum lags beyond

12 does not increase expected returns. The impulse response graph for model 7 in Figure 1(4), however, shows a smoother adjustment path for this model compared to the baseline and allows determination of the duration of the momentum effect after controlling for mean reversion.

Models 8 and 9 in Panel A give the returns on the baseline combination strategy when the starting point varies. Model 8 presents the results when forecasts start at  $\frac{1}{4}$  of the sample so that there are more sample points but obtained from less precise parameter estimates. Returns are slightly higher compared to the baseline case starting at  $\frac{1}{3}$  of the sample. Model 9 presents the results when forecasts start at  $\frac{1}{2}$  of the sample so that there are fewer sample points but obtained from more precise parameter estimates. Returns now are slightly lower compared to the baseline case.

*(b) Return results for natural variations of the combination strategies*

The baseline combination strategy is the simplest strategy allowing combination of momentum and mean reversion. Panel B in Table VI presents the returns of all other basic variations to the combination strategy presented by equation (5). Specifications differ by whether or not the momentum parameter varies across countries and/or lags, and whether the mean reversion parameter varies across countries. Model 1 in Panel B presents again the returns for the baseline case for reference.

In all cases the returns are significantly positive (although only at the 10 percent level using a 1-sided test for the Max1-Min1 returns for models 6 and 7). Three of the seven variations outperform the baseline on the Max1-Min1 strategy and two of the seven variations outperform the baseline on the Max3-Min3 strategy. In general, allowing mean reversion parameters to differ across countries (in models 5-8) lowers returns, while allowing momentum parameters to vary across countries and lags improves returns. The highest returns occur in model 4 with one mean reversion

parameter and 12 x 18 momentum parameters. Here the Max1-Min1 return is 20.3 percent and the Max3-Min3 return is 14.3 percent.

We view the eight specifications of the combined momentum/mean reversion case as each addressing the same “overreaction” phenomenon with a slightly different technique. If we take each specification to provide a similar signal about expected return but with different measurement noise, then a better expected return estimate might be obtained from an (equal-weighted) average of the expected returns over all eight specifications. In averaging, the value of the signal should be unchanged (assuming all specifications are similarly reliable) whereas the variance of the measurement error is reduced. Thus the signal-to-noise ratio improves and decisions based on the resulting average expected return—the *consensus* forecast—should yield a better strategy return. Item 9 in Panel B states the strategy results from implementing the consensus forecast. Results are indeed stronger than in each of the individual eight specifications: the Max1-Min1 return is 21.1 percent and the Max3-Min3 return is 15.5 percent.

Figure 2 provides additional information about the robustness of the combination strategies in Panel B. Instead of focusing only on the one or three countries with the highest expected returns and the one or three countries with the lowest expected returns, Figure 2 ranks 18 strategies:  $\text{Max}(i)$  represents the strategy of investing each period in the country index with the  $i$ th highest expected return for  $i$  from one to 18. Thus  $\text{Return}[\text{Max}(1)]$  is identical to  $\text{Return}[\text{Max1}]$  and  $\text{Return}[\text{Max}(1)] + \text{Return}[\text{Max}(2)] + \text{Return}[\text{Max}(3)] = 3 \text{Return}[\text{Max3}]$ . Figure 2 displays strategies  $\text{Max}(i)$  for  $i$  from one to 18 on the horizontal axis and  $\text{Return}[\text{Max}(i)]$  on the vertical axis. The slope of the regression line is significantly negative for all combination strategies in Panel B (slopes and t-statistics not tabulated here).

To further elaborate on the random-walk perspective of Conrad and Kaul (1998), consider for

the  $\text{Max}(i)$  strategy choices at each point in time the average return, using only past observations, of the country picked. Based on Conrad and Kaul this prior average return would be the best guess as to what the return for the  $\text{Max}(i)$  strategy would be. Figure 3 demonstrates that this prediction is systematically wrong:  $\text{Max}(1)$  has the highest realized return but the lowest prior average return;  $\text{Max}(18)$  has the lowest realized return but the highest prior average return, as follows from comparing Figures 2 and 3. Thus the Conrad and Kaul view is strongly rejected, also from this perspective. On the other hand, given our model of momentum and mean reversion, the prior average return is highly negatively correlated with mean reversion potential (and largely uncorrelated with momentum potential which is concentrated in twelve months thus constituting only a small overlap with the prior average return) so that a positive slope in Figure 3 is expected.

An alternative approach to generating portfolio switching results follows Lo and MacKinlay (1990) [see also Lehmann (1990) for a similar approach]. They simulate investment in each asset (each of 18 country indices here) with weight given by its expected return relative to the average expected return (thus shorting assets with expected return below average), yielding a zero-investment portfolio. For robustness we consider this approach for our baseline model, Model 1 in Panel B. Because the Lo-MacKinlay approach puts less emphasis on the extremes, we expect a lower portfolio return. The results (not reported in a table) show that the return is 10.0 percent, indeed lower than the  $\text{Max}1\text{-Min}1$  return of 16.9 percent and the  $\text{Max}3\text{-Min}3$  return of 11.9 percent. However, as the Lo-MacKinlay portfolios are better diversified, the portfolio return has a lower standard deviation. As a result, the statistical significance of the results is higher than for our extreme portfolios: the t-statistic for the Lo-MacKinlay portfolio result is 3.28 (not tabulated) compared to the t-statistic for  $\text{Max}1\text{-Min}1$  of 2.45 and for  $\text{Max}3\text{-Min}3$  of 2.96 in Table IV.



(c) *Expected returns*

The expected returns in Table VI are generated, based on equation (5), by employing the parameter estimates that apply at each point to calculate the expected return for an “out-of-sample” point, and then averaging over all out-of-sample points. This expected return can thus be interpreted as the expected return that would be generated for a given model by the trading strategy applied over the out-of-sample period, under the assumption that the model is exactly correct—no omitted variables, no nonlinearities, and perfect parameter estimates. This expected return measure is useful as an indicator of what mean return can maximally be expected from the trading strategies based on a particular model specification. The expected return in the baseline case (Model 1 in Panels A and B) equals 39.3 percent for Max1-Min1 (compare this number to that derived in footnote 6) and 36.7 percent for Max3-Min3. Thus, *realized* strategy returns are, respectively, 42.5 percent and 32.4 percent of what would be expected based on the employed model being correct. Given our limited time series, these percentages could reasonably be anticipated, even if the model were correctly specified, based on imperfect parameter estimates alone. Expected returns for the more restrictive model specifications in Panel A (Models 2, 3, and 4) are lower as may be anticipated because less variation in country-specific anticipated returns is generated.

While in general the realized returns are clearly lower than the expected returns, the expected return in the case of full sample estimates (model 6) is approximately equal to the realized return. Two possibilities readily present themselves to explain this: the model is very well specified so that, with good, full sample, parameter estimates the realized return deviates from the expected return only stochastically and should on average equal this realized return; or, the full sample estimation procedure uses sufficient information not available in real time to offset the drawback of an imperfectly specified model and leads to expected returns similar to those expected for a perfectly

specified model.

Expected returns in Panel B are similar for all variants except for the variants with varying momentum parameters across countries and lags, models 4 and 8, where they are about double the expected returns of the other cases. The unrestricted momentum specification in these models allows for additional variability in the momentum component of the anticipated excess returns so that the extreme expected Max1 and Min1 returns are likely to be larger. This feature seems to explain why models 4 and 8 produce higher realized and expected returns, although, likely due to overfitting, their realized returns as a fraction of the expected returns are smaller.

*(d) Transactions Costs*

We also present in Table VI the number of portfolio switches implied by each investment strategy. This allows us to assess transaction costs, which are likely to be substantial for monthly switching. Carhart (1997) points out for instance that for mutual funds following momentum investment strategies the excess returns disappear when transactions costs are considered; Grundy and Martin (2001) conclude similarly for U.S. equities. In the cases of Max3 and Max3-Min3 we count each switch of one of the three or six country indices for  $1/3$  and  $1/6$  of a switch, respectively. A switch entails selling one country index and purchasing another. There is therefore a round-trip transactions cost in the form of a brokerage cost. In addition, there is a loss in the form of the bid-ask spread. Both together may vary from around 1 percent to 2 percent per switch, depending on the time period, the countries involved, and whether short-selling is involved. See for instance McGuinness (1999, pp. 75-76). The last column of Panel A in Table VI indicates that the momentum aspect of the full model accounts for a large percentage of the switches. The percentage of the portfolio switched in each period is 39 percent for the pure momentum model and falls from 16 percent for the baseline

combination model to 11 percent for the pure mean reversion model (all for the Max1-Min1 strategies).

If no adjustment to the strategies were made then the transactions costs might negate a significant part of the excess returns generated by our portfolio switching strategies. Table VII for easy reference shows again the baseline case labeled as model 1. The Max3-Min3 strategy requires a switch 10 percent of the time, or 1.2 times per annum multiplied by two since switches occur in both Max3 and Min3. At a cost per switch of 2 percent the resulting transactions costs of 4.8 percent offset nearly half of the excess return of 11.9 percent. Note by the way that, as Grundy and Martin (2001) point out, establishing that one cannot profit from momentum (or mean reversion) does not imply that momentum (or mean reversion) disappears; it is still a feature of financial markets.

Once transactions costs are considered it is clearly not optimal to switch portfolios the moment the expected return of one country index exceeds the expected return of the currently-held country index. We assume here that the expected returns differential must be 1 percent, half the assumed transactions cost of 2 percent, before a switch occurs.<sup>8</sup> Table VII, model 2 shows the returns resulting from superimposing this transactions cost filter on the switching strategies: in each of the model specifications a switch occurs only if the expected return of the best alternative country index is at least 1 percent higher than the expected return of the country index currently held.

The addition of the filter produces very little change in the expected returns, but the percentage switches falls dramatically. Thus, for instance, the expected return for the Max3-Min3 strategy in the baseline combination model equals 10.8 percent (instead of 11.9 percent without the transactions cost filter); switches occur only 2 percent (instead of 10 percent without the transactions

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<sup>8</sup> This filter is approximately optimal as, for instance, an expected returns differential of 1.0 percent will on average last more than one period (say approximately two periods), causing the opportunity cost (due to the expected returns differential) of not switching to exceed on average a 2.0 percent transactions cost.

cost filter) of the time so that annual transactions costs equal  $12 \times 2 \times 0.02 \times 2$  percent = 1.0 percent, leaving an excess return after transactions costs of 9.8 percent. One way of interpreting this result is that the estimation of the momentum parameters is sufficiently imprecise, so that the substantial reduction in the number of transactions is clearly worth the cost of ignoring small differences in expected returns.

Interestingly Model 3 in Table VII reveals that the pure momentum model fares much worse if a 1 percent filter is imposed: the excess returns are close to zero. This suggests that, while taking into account momentum is important in generating excess returns, it cannot be exploited profitably by itself as Carhart (1997) and Grundy and Martin (2001) find for U.S. data. The pure mean reversion model, Model 4 in Table VII, fares better under the 1 percent filter but not as well as the combination model. Results for the random-walk-based strategy, Model 5 in Table VII, are marginally better under the 1 percent filter but still significantly below the combination strategy results.

*(e) Omitting the first month*

We know from Jegadeesh (1990) and Lehmann (1990) that for short holding and sorting periods—less than a month—reversion rather than continuation is observed. Explanations for this observation include bid-ask bounce and infrequent trading. Accordingly Jegadeesh and Titman (1993) present results for when the holding period is deferred by one month, omitting the first month after the end of the sorting period. To deal with this issue in our framework where the holding period is one month, we simply assign portfolio choices for period  $t+1$  (based on expected returns for time  $t+1$  given information at time  $t$ ) to time  $t+2$ , thus skipping the first month after the sorting period.

Panel B in Table VII gives the baseline strategy returns for this case. Results here are similar to the baseline results: Max1-Min1 is 15.1 percent (slightly lower than in the baseline case) and

Max3-Min3 is 13.3 percent (slightly higher than in the baseline case). Diminished excess returns would be expected based on setting the observation period one month after the designed forecast period; increased excess returns might be expected due to the avoidance of the bid-ask bounce/infrequent trading effect. The result suggests that either both of these effects are quantitatively unimportant or that these effects offset each other.

*(f) Other robustness issues*

We also consider, in Table VIII, for the most relevant portfolio strategies [the first five models in Panel A, a transactions filter case, a case with 24 momentum lags, and all models of Panel B (except the consensus case) in Table VI], the percentage “overlap” with the other portfolio strategies.

Percentage *overlap* for a pair of strategies is defined as the percentage of time that one strategy implies the same choice as the other strategy (for the Max3 case we count 1/3 overlap if only one country matches at a given point in time); the percentage overlap for any pair of strategy outcomes is calculated by averaging the percentage overlap in each period (0, 33.33, 66.67, or 100 percent) over time.

Consider the following hypothesis:

*If mean reversion and momentum truly occur, but if their potential is measured with (possibly substantial) error, then models, or variants of models, with different ways of measuring mean reversion and momentum potential should produce positive excess returns, not as high as theoretically expected, but likely using quite different actual strategy outcomes.*

This hypothesis was already put to the test in Table VI.B where we found that for all eight different varieties of the momentum/mean reversion specification the excess return were significantly positive, but below the return expected in absence of measurement error. We further argued and confirmed in model 9 of Table VI.B that, given measurement error, a consensus forecast should have a lower signal-to-noise ratio and hence produce higher excess returns.

By focusing on overlap we next check an additional implication of the hypothesis, namely that the strategy choices under the different strategies could be substantially different. A further motivation for considering the overlap of the different strategy variants is that finding overlap substantially below 100 percent increases confidence in the robustness of the model: the excess returns in the various specifications of the model are not just generated because the specifications are sufficiently “similar”.

Consider first for reference that, in a purely random drawing of two sets of three country portfolios from a group of 18, the probability that a particular country index, drawn as part of set one, is also part of set two is one-in-six (16.67 percent). Intuitively then the percentage overlap between two unrelated strategies should be around 16.67.<sup>9</sup> Bearing in mind this number as a reference, several conclusions can be drawn from the results displayed in Table VIII.

First, the *confidence in the robustness* of the uniformly significant excess returns for each of the eight combination momentum/mean reversion strategies (models 1 and 8-14) is greatly enhanced. (Note that, while all Max3-Min3 returns are significant at the 1 percent level in a one-tailed test, two of the Max1-Min1 returns are only significant at the 10 percent level). One could question whether these models yield much *independent information* about the returns of the combination

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<sup>9</sup> A precise calculation of the expected fraction overlap between two random strategies gives  $[(3/3) + (2/3)60 + (1/3)210] / \binom{18}{3} = 1/6 = 0.1667$ .

momentum/mean reversion strategies since they may be viewed as a minor tweaking of the momentum and mean reversion specifications, that may lead in practice to very similar portfolio choices. Table VIII reveals that this is not the case: the overlap between the baseline strategy and the other seven combination strategies is on average only about half (53 percent to be exact), and similar numbers apply within the group of seven alternative combination strategies.

Second, comparing the eight combination strategies to the actual ex-post Max3 or Min3 groups (perfect foresight strategy 5), reveals that the overlap is generally above what would be expected in a random drawing (around 22 percent versus 17 percent in a random draw) but not substantially so. Interestingly, the random walk strategy also overlaps with the perfect foresight strategy more than expected (around 22 percent versus 17 percent in a random draw). Apparently, when the random walk strategy does not coincide with the perfect foresight strategy, its return is exceptionally low. Interesting also is the observation that the overlap between the strategy based on the consensus forecast and the perfect foresight strategy is 24 percent for Max3 (22 percent for Min3) [these numbers are not presented in a table] – not higher than for some of the other strategies. Apparently, the consensus strategy picks the outliers correctly more frequently.

Third, the pure random walk strategy (strategy 4 in Table VIII) has less overlap than would be expected by coincidence with all strategies except the pure momentum strategy (and the perfect foresight strategy discussed in the previous paragraph). The reason appears to be that the random-walk-based strategy selects country indices with the highest expected returns based on previously displayed high returns. The resulting choices are likely to be negatively correlated with mean reversion choices (choosing indices with previously high returns).

Fourth, based on the previous argument, combination strategies imply choices that are somewhat more weighted toward mean reversion than to momentum. This can be verified by noticing

that the overlap between the combination strategies (1 and 8-14) and the pure momentum strategy (strategy 2) is above what would be expected randomly but is generally a little lower than its overlap with the pure mean reversion strategy (strategy 3). Not surprisingly, the combination cases with mean reversion coefficient restricted to be equal for all countries (strategies 1, 8, 9, and 10) are more similar to the pure mean reversion case in which the mean reversion coefficient is also restricted to be equal for all countries.

Fifth, the overlap numbers for the Max3 strategies are amazingly similar, qualitatively and quantitatively, to the corresponding overlap numbers for the Min3 strategies. Accordingly we can be more confident that the implications drawn from the numerical regularities are not spurious results of random fluctuations in these overlap numbers.

## **VI. EXPLORING STRATEGY CHARACTERISTICS**

The preceding analysis presents evidence on the joint existence of momentum and mean reversion, but it provides no indication as to the causes of excess returns from exploiting momentum and mean reversion. By examining features of the strategy choices we attempt to identify whether the excess returns are simply equilibrium compensation for loading on standard equilibrium risk factors or whether characteristics—in the sense of Daniel and Titman (1997)—that are not directly tied to factor risk may clarify the return patterns observed here. Unlike Daniel and Titman (1997) who use a linear model to identify if a characteristic provides explanatory power separate from the effect of its corresponding factor, we focus on non-linear features of the relation between a characteristic and its return, as a way of assessing characteristics explanations vis-à-vis risk explanations.

### *(a) Systematic risk factors*



Standard equilibrium risk factors should apply if the developed markets examined here can be considered as integrated. First, consider the conventional single market-beta model. In our global context a country-index market beta is obtained based on the world portfolio return (proxied by the MSCI value-weighted world index return). Assuming that relative purchasing power parity provides a decent description of reality, the world market beta of each portfolio should fully explain cross-sectional average return discrepancies. Column 5 of Table VI lists the world market beta of each trading strategy. The betas for the excess returns strategies, Max1-Min1 and Max3-Min3 are negative in the relevant cases, implying that excess returns adjusted for global beta risk are in fact higher than the original excess returns.

The solid lines in Figure 4 display the global market betas for the Max( $i$ ) through Max(18) strategies based on the realized returns for each of these strategies for the first eight cases in Panel B of Table VI. It is apparent that the betas for the Max( $i$ ) strategies for low  $i$  are no higher than those for high  $i$  and are usually lower. Thus Max-Min strategies tend to have negative betas.

The dotted lines in Figure 4 display the “ex ante” global market betas for the Max( $i$ ) through Max(18) strategies. The ex ante betas are computed by assigning at each time the beta (computed from the entire sample period) of the country picked and then averaging the assigned betas over time.<sup>10</sup> The resulting average beta for each strategy can be interpreted as the ex ante choice of risk, if we assume that individual country betas are known and stable over time. We can then decompose, in principle, which part of the excess return is due to picking *a priori* riskier countries and which part is due to picking *a posteriori* riskier countries.

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<sup>10</sup> The betas averaged over all eighteen Max( $i$ ) strategies come to 0.93 rather than 1.00. The reason is that the market return is taken to be the MSCI world index, which is value weighted and includes more than the eighteen countries in our sample. Countries omitted from our sample typically have betas above 1.00 and the U.S. index (weighted by value in the MSCI index) has beta below 1.00. As a result, equal-weighting the eighteen betas in our sample (as occurs implicitly in averaging the betas in the Max( $i$ ) strategies) yields an average below 1.00.

As Figure 4 shows, the ex ante risk of the Max strategies appears to be *smaller* than that of the Min strategies and the ex post beta realizations seem to be randomly distributed around the ex ante risk measures. Hence, from a simple global CAPM perspective, neither unconditional nor conditional choice of beta risk loadings explains the excess combination momentum-mean reversion strategy returns. Thus, for instance, a conditional CAPM with time-varying covariances, as in De Santis and Gerard (1997), is unlikely to explain the excess strategy returns in our data.

Table IX presents multi-factor risk-adjusted return results for the baseline model (combined momentum and mean reversion), the pure momentum model, the pure mean reversion model, and the Jegadeesh-Titman model with  $J = 6$  and  $K = 6$ . In Panel A returns are adjusted for two factors based on the Fama and French (1998) model: global market risk and “value” risk.<sup>11</sup> Results are thus obtained by regressing the monthly returns of the various Max and Min portfolios on the excess return of the MSCI world index and the excess return of an internationally diversified portfolio long on value and short on growth stocks. The estimated constant terms are the risk-adjusted returns – the “alphas”.

Both the Max1-Min1 and the Max3-Min3 portfolios have negative exposure to world market risk but (moderately) positive exposure to value risk. In all cases, the risk-adjusted returns are similar to the raw returns. In particular, the risk-adjusted baseline returns continue to be large and significant: 18.6 percent for Max1-Min1 and 11.9 percent for Max3-Min3, both significant at the 1 percent level. Observe that the positive alphas result mostly from the Min1 part of the zero-investment strategy.

The risk-adjusted returns for the pure momentum and pure mean reversion models are insignificant. However, for the Jegadeesh-Titman model with  $J = 6$  and  $K = 6$ , the Max3-Min3

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<sup>11</sup> Since size differences are small for the MSCI indices, which are value weighted and only include larger size firms

return is 8.8 percent and significant at the 1 percent level (the Max1-Min1 return is 6.9 percent but insignificant). These results are roughly consistent with the Fama and French (1996) conclusion that mean-reversion effects can be explained as factor risk but the momentum effects cannot [see also Brennan, Chordia, and Subrahmanyam (1998), Carhart (1997), and Jegadeesh and Titman (2001) for similar results; Chordia and Shivakumar (2000) find however that momentum returns are related to the business cycle, a potential risk factor].

Panel B in Table IX presents a related risk correction. It applies the standard Fama and French (1993, 1996) three-factor model to correct for risk, using in addition to the global market factor the value and size factors for U.S. stocks. Results are very similar to the two-factor results.

*(b) Country-specific risk*

Since standard risk corrections cannot explain the positive excess returns from the combined momentum/mean reversion strategies, we next consider alternative explanations. Based on the home bias/international non-diversification puzzle perspective of French and Poterba (1991), it may be appropriate to consider country risk in isolation; risk arbitrage by agents not predisposed to the home bias may be insufficient to eliminate the anomalous pricing of country-specific risk. Accordingly we examine how the Max( $i$ ) strategies load on country-specific risk measured by *standard deviation of return*.

In Figure 5, the eight basic strategy specifications for the combined policy (the first eight strategies displayed in Panel B of Table VI) generate a U-shaped pattern when we view the solid lines, displaying the realized standard deviation of return from strategy Max( $i$ ) as a function of  $i$ . Thus extreme Max or Min strategies are associated with higher realized standard deviation of return. To

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(see MSCI, 1997), one may argue that the traditional size factor can be ignored as in Fama and French (1998).

see if the pattern is systematic consider an ex ante (“perfect foresight”) measure of strategy risk: assign to the choice of country index in each period the country index standard deviation averaged over time; then average over the choices for all time periods (similar to the process of calculating the ex ante betas in Figure 4). The resulting average standard deviation is interpretable as the risk expected based on the average riskiness of the countries selected. The dotted lines in Figure 5 illustrate that (generally) there is a U-shaped pattern for the ex ante standard deviation as well. Hence, typically, *riskier countries* are selected in the extreme Max or Min strategies. Note that the similarity of the ex ante and realized standard deviation patterns suggests that, to the extent that standard deviation is linked to risk, time-varying risk is not a likely factor in explaining the strategy returns.

On the surface, the U-shape of standard deviation against  $\text{Max}(i)$  is easily explained because country indices with a high standard deviation of return are more likely to have extreme return realizations, leading to more extreme potential for momentum and/or mean reversion. We then pick these countries more often as extreme  $\text{Max}(i)$  choices. This does explain why we would expect to see the shape of Figure 5, but fails to account for why high standard deviations of return are associated with both high and low realized returns. We next provide and assess two possible explanations.

First, presume a CAPM context (a similar argument can be made for a multi-factor model, however). To explain why there is no negatively sloped pattern in Figure 4 we must assume that (a) the world index is a poor proxy for the “market.” We further assume that (b) some country indices are inefficient (in the sense that they have negative “true” market betas). Then the Max strategies load heavily on the (unobserved) market factor, producing high average return and high standard deviation of return, while the Min strategies load negatively on the market factor, producing low average return but still generating a high standard deviation of return.

Second, a behavioral explanation is that countries subject to more mispricing/overreaction exhibit excess volatility leading to higher standard deviation of return; these countries also generate more extreme strategy returns: standard deviation is correlated with a characteristic that implies more mispricing on average. Hirshleifer (2001, pp.1574, 1575) discusses the theory that more uncertainty about cash flow, which we may provisionally tie to higher standard deviation of return, promotes mispricing because information signals are less precise leaving more room for overconfidence or other behavioral biases.

Both theories are consistent with Figures 3-5. However, the risk-based theory appears to be inconsistent with the information in Table I. The theory requires that some country indices are inefficient so that a U-shape should be visible when standard deviation is shown in relation to average return. Table I allows comparison of mean return and standard deviation of return across countries. There is no clear positive relation across countries between mean and standard deviation, and, in particular, there is no U-shape.

*(c) Further characteristics describing returns*

Standard small firm effects and liquidity issues are *prima facie* unlikely to be important factors in explaining excess returns: our sample (a) consists of index returns for similar developed markets; (b) consists of indices that include only larger firms; and (c) considers the period after 1980 when international markets in developed economies can be viewed as well integrated.<sup>12</sup>

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<sup>12</sup> Morgan Stanley Capital International (1997, pp. 6-15) states that each MSCI country index is chosen to capture 60 percent of the market capitalization of the country. In doing so, MSCI selects in principle the most liquid securities in each country.

### *Firm size*

While truly small firms are absent from our data, there is still considerable variation in the average firm size by country. Based on Loughran and Ritter (2000) and Fama (1998) firm size is a potential characteristic related to mispricing. Figure 6 displays the average firm size (FS) of each strategy  $\text{Max}(i)$ . The relation between  $\text{FS}(i)$  and  $\text{Max}(i)$  resembles an inverse U-shape.<sup>13</sup> The implication is that firm size appears not to be a risk factor. First, in U.S. data at least (Banz, 1981), the small firm effect is weak among the larger firms (such as we have in our sample). Second, more crucially, the small firm effect implies that, holding other factors equal, smaller-firm countries have larger mean returns; but this appears not to be the case for the Min strategies that tend to rely on small-firm countries according to Figure 6.

### *The number of firms*

The number of firms in a country index also matters. Figure 7 shows that the relation between number of firms,  $\text{FN}(i)$ , and  $\text{Max}(i)$  resembles an inverse U-shape similar to that in Figure 6.

### *Explanations*

A reasonable explanation for the inverse U-shape of both the  $\text{FS}(i)$  and  $\text{FN}(i)$  graphs derives from information-based explanations in the international context [see Gehrig (1993), Kang and Stulz

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<sup>13</sup> We measure firm size of country  $i$  as follows: market capitalization as found by taking the weight of country  $i$ 's capitalization as a percentage of the total capitalization of the eighteen countries in our sample is divided by the number of firms in the index. Further, we use the average relative weights over the pre-testing sample period from 1972 through 1979 (market capitalization data for Hong Kong and Singapore start in January 1972 instead of December 1969). The reason for doing so is to minimize the effect of momentum and mean reversion in affecting market capitalization and to prevent spurious correlation between expected return estimates and the market cap measure if this measure is taken during the testing period.

(1997), Brennan and Cao (1997), and Choe, Kho, and Stulz (1999)]. If we assume that the cost of becoming informed has both a country-specific and a firm-specific component, foreign investment will be limited as a whole (the home bias) and be most likely directed at countries with larger firms [indeed, the empirical evidence of Choe, Kho, and Stulz (1999) and Kang and Stulz (1997) indicates that in the cases of Korea and Japan foreign investors are more likely to invest in larger firms]. Thus, countries with smaller firms will be “neglected” more often by (rational) information traders. But then these countries have a higher proportion of “noise” traders so their stocks are mispriced more on average. Daniel, Hirshleifer, and Subrahmanyam (1998, p.1866) argue similarly that the fixed costs of becoming informed about smaller firms are not easily recovered. Loughran and Ritter (2000) add that higher transactions costs (larger bid-ask spreads) and the larger effect that trades have on price are specific factors decreasing the benefit of acquiring information about small firms.

Along similar lines we can argue also that foreign investors have an incentive to ignore countries with only a few firms, since the fixed cost of gaining country-specific information is split among fewer possible candidate firms. Countries with few firms tend to be “neglected” so we pick them more often as our extreme Max and Min strategy choices, generating the inverse U-shape.

To the extent that standard deviation of return, firm size, and number of firms are highly correlated, Figures 5-7 need not require separate explanations. Table X considers the correlations between these factors. The correlations between firm size and standard deviation (-0.55) and number of firms (0.66) are relatively high. To determine whether the (inverse) U-shapes survive after adjusting for these correlations, we regress firm size against standard deviation and examine the relation between the residual of this regression  $FSErr1(i)$  and  $Max(i)$ . Similarly we regress firm size against number of firms and against standard deviation and number of firms jointly and compare the residuals  $FSErr2(i)$  and  $FSErr3(i)$  against  $Max(i)$ . In each of these three cases the inverse U-

shape remains (results available from the authors). Hence, the link between firm size and the strategy choices remains even after adjusting for firm size's correlation with standard deviation and number of firms.

In the same vein we regress standard deviation against firm size. Examining the relation between the residual  $SDError(i)$  and the strategy choices  $Max(i)$  we now find that the U-shape disappears. Thus, it appears that it is solely the negative correlation with firm size that causes the U-shape for standard deviation. Regressing number of firms against firm size we find that the relation between the residual  $FNError(i)$  and the strategy choices  $Max(i)$  still displays a U-shape although this shape is less clear than in Figure 7. Hence, number of firms may cause a U-shape independently of its correlation with firm size but this is unsettled.

### *Seasonal effects*

A further feature characterizing return abnormalities is a seasonal aspect. A January effect in international equity returns has been well documented. See Gultekin and Gultekin (1983) and Agrawal and Tandon (1994). We find in our 1970-1999 sample that a January effect is present on average, but is only significant for a few of the countries, while, interestingly, a December effect is much more pronounced and present in most of the countries (these results are not shown). Motivated by the demonstration of a reverse January effect in Jegadeesh and Titman (2001) and Grundy and Martin (2001) we examine the January returns for our baseline combination momentum-mean reversion strategy.

As displayed in Figure 8 we find that the Max1 and Max3 strategies generate high January returns and that the Min1 and Min3 strategies generate below average returns in January. The Max1-Min1 strategy produces a large January return of over 50 percent while the Max3-Min3 January



return is 37 percent. Thus our baseline strategies produce a strong January return that explains around a quarter of the total return in both cases. The fact that we do not generate the reverse January effect as in Grundy and Martin (2001) and Jegadeesh and Titman (2001) is probably due to three separate factors. First, our strategies rely on mean reversion as well as on momentum. Second, our international sample differs from the U.S. sample used by Grundy and Martin and Jegadeesh and Titman. Third, our strategies imply a holding period of 1 month as opposed to the 6-month holding period typically considered by these authors.

Part of the explanation for this January effect is the fact that there is substantial cross-sectional variation in January. While returns are consistently high across countries in December, a clear January effect only occurs in some of the countries. It is difficult to attribute the result to small firms [as has been done for U.S. data, see for instance Daniel and Titman (1997)] generating these high returns. First, all firms in the MSCI data may be considered large. Second, we find no clear tie between firm size and January returns in our sample: the correlation between firm size and January excess returns in Table X is -0.27. Nor is there a ready explanation in terms of tax differences across countries, especially because December returns are so high in most countries.

### *Trading volume*

An additional factor that may illuminate the causes of the excess strategy returns is trading volume as recently emphasized by Lee and Swaminathan (2000). Unfortunately we do not have volume data so we can only argue in indirect terms how our results relate to those of Lee and Swaminathan. They find that assets with both high momentum and high volume experience higher subsequent returns and low reversal; assets with high momentum and low volume have lower subsequent returns and high reversal. We can reconcile their results with ours based on a key result

of Gervais and Odean (2001): volume is higher (lower) late in a bull (bear) market when investors become overconfident (underconfident). Then the Lee and Swaminathan results can be viewed as using volume to determine when high momentum firms have (a) low mean reversion potential (and thus relatively low expected returns), or (b) high mean reversion potential and thus high expected returns. In case (a), a firm has performed well over the recent and the more distant past, investors are overconfident and trading volume is high. Based on our expected return index, however, future returns should be relatively low due to reversal. In case (b) the firm has performed well in the recent past but not so well over the more distant past, so investors are less confident and trading volume is lower. Future returns should typically be high in our view since high potential due to both mean reversion and momentum implies high expected returns and little chance of reversals.

*(d) Overreaction*

The existence of momentum and mean reversion does not imply that both occur in the same group of assets. For instance, the basic empirical results of DeBondt and Thaler (1985) and Jegadeesh and Titman (1993) are consistent with particular assets being prone to (slow) mean reversion and particular *other* assets being prone to momentum.

As Hirshleifer (2001, p.1575) points out, the three recent behavioral models of how mistaken beliefs cause momentum and mean reversion: Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999), all imply that “misperceptions that drive momentum are also the drivers of long-term reversal. These models therefore imply that if there is some market segmentation, then those sets of assets with the largest momentum effects should also have the largest reversal effects; *international testing would be of interest.*” (emphasis added).

Jegadeesh and Titman (2001) finds for U.S. equities that holding portfolios of stocks selected

for momentum potential for a longer period eventually erases a substantial part of the excess momentum returns. This result is not robust across pre-war and post-war time periods and across categories of firms (small firms versus large firms). However, it suggests that, indeed, the same assets that experience momentum also tend to experience eventual mean reversion. Our paper directly models “overreaction”—the process by which particular shocks followed (on average) by momentum effects drive long term reversal. The support for this specification confirms the Jegadeesh and Titman (2001) finding and similar findings from a different angle and for a different, international data set.

The overreaction hypothesis can be contrasted with the underreaction hypothesis [see for instance Chan, Jegadeesh, and Lakonishok (1996) and Choe, Kho, and Stulz (1999)] according to which momentum does not imply reversal. Our results strongly suggest that momentum is eventually reversed, rejecting the underreaction view. Related to this observation is the fact that pure momentum strategies underperform strategies in which momentum is followed by mean reversion. The overreaction hypothesis can also be contrasted with the view of Conrad and Kaul (1998) that assets appearing to display high momentum are merely assets with high average returns. In our data, however, picking those assets that have generated higher past returns leads to negative excess returns, a clear indication of overreaction rather than continuation.

Matching the evidence on overreaction with the inverse U-shaped effect of characteristics produces a view that mispricing due to overconfidence or other behavioral biases is larger for countries with smaller and fewer firms. The conclusion of viewing firm size and number of firms as characteristics derives here directly from the nonlinear association between the characteristic and the cross-section of the  $\text{Max}(i)$ -sorted portfolio returns, rather than from the more intricate process of disentangling risk and characteristic effects

## VII. SUMMARY AND APPRAISAL OF RESULTS

A simple trading strategy that draws on the combined promise for momentum and mean reversion in 18 national market stock indices, produces significant excess returns. The strategy is neither contrarian nor momentum-based; it instead uses the information of all previous price observations to aggregate the mean reversion potential with the momentum potential into a single index number. Investing in the national market with the highest index number and short selling the national market with the lowest index number generates an annual excess return of 16.7 percent over the 20-year “out-of-sample” period 1980-1999. This result arises in our baseline model, which presumes a momentum effect of up to twelve months.

The excess return in the joined momentum-mean reversion model is higher than the excess returns found in either of the separate momentum or mean reversion models. The pure momentum and mean reversion returns, in turn, are higher than the returns based on purchasing (short selling) countries with the highest (lowest) historical average returns. The joined momentum-mean reversion model suggests existence of around 12 momentum lags which is longer than the six to nine momentum lags found in previous studies [Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), and Rouwenhorst (1998)]. Similarly, the mean reversion effect seems to develop quicker, with a half-life of around 33 months (compared to over 36 months in Balvers, Wu, and Gilliland, 2000). We also find that mean reversion contributes around 1.5 times as much to expected returns as does momentum and that the expected returns from momentum and from mean reversion are negatively correlated with correlation coefficient of  $-0.21$ .

Our parametric approach allows eight basic variations based on whether or not mean reversion and momentum parameters are constrained to be identical across countries and whether or not momentum parameters are constrained to be identical across momentum lags. Each of the eight

variations yields similarly high and significant excess returns. Impressively, these similar returns are generated from quite different country choices: on average across the eight variations the country choices overlap only around half the time. The relatively low overlap leads one to suspect that the strategies are quite noisy proxies for an unobserved superior strategy. This suspicion is reinforced based on the theoretical expected return calculated from parameter estimates which yields expected returns typically around two to three times as high as the realized strategy returns. We thus expect that a consensus forecast obtained by averaging the forecasts of the eight variations should produce a higher signal-to-noise ratio and lead to higher strategy returns. Indeed, the consensus strategy outcome is higher than for any of the pure strategy variations, generating a Max1-Min1 return of 21.1 percent.

The excess strategy returns have no simple explanation. In contrast to the returns from momentum strategies which tend to disappear when transactions costs are considered, this is not the case for the combination momentum-mean reversion strategies—if a simple one percent filter is appended to the combination strategy the frequency of portfolio shifts decreases dramatically whereas the excess return hardly changes. Standard risk factors also do not account for any of the profitability of the combination strategies: neither global market risk nor the Fama-French risk factors lower risk-adjusted returns. Further, realized beta risk is similar to beta risk chosen ex ante (and both are close to zero for the Max-Min strategies) suggesting that time variation in market risk exposure also can not explain the returns.

Characteristics of the strategy choices generating extreme returns suggest behavioral explanations. Specifically, we find (inverse) U-shape patterns, instead of linear patterns, of key characteristics against strategies ranked from Max(1) to Max(18) (i.e., Min1). The U-shapes suggest mispricing—high exposure to particular characteristics is associated with both extremely high and

extremely low returns. The characteristics found to generate (inverse) U-shapes are firm size, standard deviation of return, and number of firms in the index. However, after correction for correlation among these characteristics, only firm size and (possibly) number of firms remain as drivers of mispricing.

As an additional diagnostic factor, further examination of the properties of the excess strategy returns show that there is a clear January effect in that Max1-Min1 returns in January are over 50 percent (accounting for about one-fourths of the excess returns), which contrasts with the pure momentum results of Jegadeesh and Titman (2001) and Grundy and Martin (2001) who find negative January returns for U.S. data.

What do we learn from these results? First, we obtain strong support for the overreaction view versus the underreaction view and versus Conrad and Kaul's (1998) random walk perspective. As such we corroborate the results of Jegadeesh and Titman (2001) but for international data. Related to the overreaction finding, we confirm that momentum and mean reversion occur in the same assets. Accordingly, in establishing the strength and duration of the momentum and mean reversion effect it becomes important to control for each factor's effect on the other, especially since the two factors are (negatively) correlated. We find, accounting for the full price history, that controlling for mean reversion appears to extend the momentum effect, and controlling for momentum seems to accelerate the mean reversion process. Most of the results further strengthen our belief in the robustness of both the momentum effect and the mean reversion effect: the data are international, we utilize a parametric approach that is different from approaches typically used to document momentum or mean reversion, and all of our combination strategy formulations yield significant excess returns.

A second lesson we learn from the results is that, while it is extremely difficult to find risk factors that account for the excess returns, the results are easily reconciled with behavioral

approaches. As noted elsewhere the overreaction result is consistent with the implications of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). Further, the fact that both the Max and the Min combination strategies rely on countries with fewer and smaller firms, suggests that these countries may be neglected more readily by information traders, causing the proportion of trades subject to behavioral biases to be larger, so that mispricing is more common.

Additionally, the results of Lee and Swaminathan (2000) that assets with both high momentum and trading volume experience lower subsequent returns (and vice versa for assets with high momentum but low trading volume) match our results exactly (in that future returns are lower as a result of the mean reversion component) if we rely on Gervais and Odean (2001) who find that volume is higher later in a bull market, when investors become overconfident. Lastly, our finding after risk adjustment in Table IX that excess returns from the zero-investment Max-Min strategy are mostly due to the Min component suggests mispricing by noise traders that is harder to arbitrage by rational information traders when assets are overpriced because of short selling constraints. This explanation is consistent with Dechow et al. (2001) who show that short sellers select value stocks and tend to profit from mean-reversion in equity prices.

A third lesson is that, from an investor's perspective, judicious accounting for momentum and mean reversion, and shifting portfolios in the direction of those assets with the highest combined potential, can generate high excess returns, even after transactions cost, and apparently without an increase in risk.

A final lesson is that the maintained hypothesis in the model, derived from the literature on economic growth, that "absolute convergence" occurs between developed economies, appears to be a fruitful one in the international asset pricing context. As a tentative thesis we may put forward the

view that traders react myopically to local innovations, underestimating the process that leads to the spread of the innovation to (international) competitors.



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**Table I Summary Statistics of National Stock-Index Returns**

This table reports summary statistics for monthly return data from Morgan Stanley Capital International over the period 1970.1 to 1999.12. In computing the world market betas, the U.S. treasury-bill rate is used as the risk-free rate of return.

Country	Mean Return (percent per month)	Standard Error (percent per month)	$\beta$ with World Index
AUSTRALIA	0.70	7.53	1.05
AUSTRIA	0.79	6.00	0.50
BELGIUM	1.23	5.32	0.81
CANADA	0.86	5.53	0.97
DENMARK	1.13	5.33	0.65
FRANCE	1.07	6.61	1.02
GERMANY	1.04	5.89	0.84
HONG KONG	1.50	11.24	1.26
ITALY	0.64	7.53	0.81
JAPAN	1.13	6.53	1.08
NETHERLANDS	1.29	5.11	0.92
NORWAY	0.94	7.85	1.00
SINGAPORE	1.11	8.74	1.19
SPAIN	0.89	6.53	0.82
SWEDEN	1.38	6.39	0.91
SWITZERLAND	1.10	5.45	0.90
UNITED KINGDOM	1.08	6.66	1.11
UNITED STATES	1.05	4.42	0.90
WORLD	1.01	4.12	1.00

**Table II Performance of Portfolio Switching Strategies: Jegadeesh and Titman (1993) Approach**

This table reports the mean returns (annualized) of Max1, Max1-Min1, Max3 and Max3-Min3 portfolios formed according to the Jegadeesh and Titman (1993) momentum strategy. The shaded areas ( $J=3,6,9,12$ ;  $K=3,6,9,12$ ) are the combinations of  $J$  (index sorting period) and  $K$  (index holding period) originally examined by Jegadeesh and Titman (1993) for U.S. stock data.

	$K=1$		$K=3$		$K=6$		$K=9$		$K=12$		$K=15$		$K=18$		$K=21$		$K=24$	
	Mean Return	t-ratio	Mean Return	t-ratio	Mean Return	t-ratio	Mean Return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	Mean Return	t-ratio	mean return	t-ratio
$J=3$																		
Max1	0.192	3.316	0.165	3.301	0.176	3.802	0.171	3.873	0.158	3.589	0.142	3.470	0.133	3.376	0.137	3.650	0.124	3.424
Max1-Min1	-0.004	-0.056	0.038	0.650	0.070	1.418	0.080	1.903	0.065	1.670	0.023	0.663	0.005	0.171	0.015	0.525	-0.010	-0.372
Max3	0.164	3.637	0.158	3.781	0.155	3.803	0.159	4.109	0.153	3.867	0.135	3.590	0.142	3.858	0.142	3.973	0.135	3.894
Max3-Min3	0.025	0.558	0.034	0.889	0.045	1.367	0.058	2.136	0.046	1.795	0.013	0.564	0.013	0.578	0.014	0.722	0.007	0.401
$J=6$																		
Max1	0.171	2.687	0.206	3.647	0.188	3.729	0.175	3.545	0.148	3.063	0.131	2.985	0.138	3.316	0.134	3.330	0.125	3.225
Max1-Min1	-0.011	-0.137	0.056	0.803	0.084	1.478	0.093	1.827	0.050	1.045	0.008	0.180	0.010	0.272	0.012	0.336	-0.002	-0.064
Max3	0.211	4.528	0.216	4.844	0.195	4.629	0.177	4.159	0.156	3.749	0.147	3.732	0.146	3.883	0.144	3.956	0.140	3.983
Max3-Min3	0.116	2.290	0.103	2.363	0.106	2.864	0.090	2.573	0.050	1.543	0.026	0.870	0.023	0.865	0.022	0.911	0.022	1.016
$J=9$																		
Max1	0.141	2.228	0.180	3.110	0.161	2.879	0.138	2.577	0.125	2.549	0.124	2.739	0.129	3.031	0.129	3.120	0.122	3.059
Max1-Min1	0.033	0.418	0.101	1.449	0.112	1.763	0.078	1.333	0.035	0.656	0.013	0.273	0.016	0.366	0.011	0.268	-0.003	-0.075
Max3	0.198	3.901	0.189	3.990	0.173	3.801	0.158	3.592	0.146	3.504	0.141	3.606	0.145	3.881	0.141	3.908	0.135	3.872
Max3-Min3	0.108	2.126	0.118	2.594	0.113	2.675	0.082	2.081	0.046	1.292	0.032	0.991	0.028	0.971	0.023	0.881	0.017	0.752
$J=12$																		
Max1	0.184	2.583	0.180	2.838	0.140	2.384	0.135	2.547	0.131	2.625	0.131	2.799	0.141	3.133	0.134	3.088	0.120	2.917
Max1-Min1	0.095	1.107	0.092	1.234	0.049	0.753	0.041	0.714	0.020	0.382	0.000	0.002	0.007	0.167	0.001	0.028	-0.021	-0.586
Max3	0.177	3.374	0.184	3.706	0.163	3.536	0.146	3.339	0.139	3.394	0.138	3.539	0.139	3.735	0.138	3.849	0.134	3.836
Max3-Min3	0.112	2.110	0.112	2.266	0.082	1.857	0.055	1.365	0.028	0.758	0.017	0.529	0.013	0.443	0.012	0.446	0.006	0.270

Table II (continued)

	<i>K=1</i>		<i>K=3</i>		<i>K=6</i>		<i>K=9</i>		<i>K=12</i>		<i>K=15</i>		<i>K=18</i>		<i>K=21</i>		<i>K=24</i>	
	Mean Return	t-ratio	Mean Return	t-ratio	mean return	t-ratio	mean return	t-ratio	Mean Return	t-ratio	Mean Return	t-ratio	mean return	t-ratio	Mean Return	t-ratio	mean return	t-ratio
<i>J=15</i>																		
Max1	0.113	1.636	0.112	1.824	0.159	2.892	0.152	2.900	0.140	2.799	0.136	2.845	0.135	2.960	0.131	2.964	0.120	2.824
Max1-Min1	-0.016	-0.199	-0.009	-0.118	0.042	0.668	0.032	0.565	0.017	0.321	-0.004	-0.075	-0.007	-0.149	-0.013	-0.314	-0.023	-0.594
Max3	0.149	2.807	0.159	3.380	0.144	3.231	0.137	3.280	0.136	3.377	0.137	3.570	0.141	3.840	0.140	3.969	0.136	3.940
Max3-Min3	0.052	0.966	0.051	1.056	0.043	0.998	0.030	0.769	0.016	0.440	0.009	0.292	0.010	0.330	0.008	0.286	0.004	0.180
<i>J=18</i>																		
Max1	0.122	1.718	0.168	2.847	0.164	2.955	0.154	2.826	0.142	2.737	0.140	2.841	0.136	2.877	0.124	2.740	0.115	2.628
Max1-Min1	-0.027	-0.341	0.056	0.825	0.044	0.712	0.040	0.670	0.008	0.142	0.001	0.013	-0.010	-0.202	-0.022	-0.487	-0.029	-0.676
Max3	0.140	2.650	0.150	3.356	0.141	3.377	0.135	3.354	0.133	3.396	0.134	3.585	0.135	3.767	0.135	3.888	0.130	3.845
Max3-Min3	0.030	0.573	0.037	0.827	0.033	0.816	0.018	0.467	0.005	0.129	0.001	0.023	-0.002	-0.054	-0.001	-0.044	-0.005	-0.200
<i>J=21</i>																		
Max1	0.149	2.279	0.164	2.743	0.147	2.588	0.139	2.518	0.135	2.559	0.121	2.447	0.111	2.367	0.106	2.371	0.101	2.315
Max1-Min1	0.045	0.564	0.051	0.733	0.050	0.760	0.033	0.522	0.017	0.289	-0.005	-0.089	-0.021	-0.415	-0.025	-0.509	-0.031	-0.667
Max3	0.145	3.116	0.155	3.659	0.140	3.475	0.136	3.469	0.139	3.607	0.134	3.641	0.138	3.854	0.133	3.850	0.127	3.777
Max3-Min3	0.013	0.276	0.036	0.854	0.030	0.763	0.017	0.451	0.007	0.210	-0.004	-0.134	-0.004	-0.130	-0.008	-0.290	-0.010	-0.406
<i>J=24</i>																		
Max1	0.154	2.419	0.149	2.505	0.134	2.335	0.125	2.266	0.121	2.288	0.102	2.081	0.099	2.124	0.099	2.205	0.099	2.278
Max1-Min1	0.029	0.379	0.032	0.445	0.011	0.171	-0.001	-0.009	-0.007	-0.110	-0.035	-0.620	-0.040	-0.743	-0.043	-0.848	-0.036	-0.733
Max3	0.142	3.177	0.144	3.534	0.128	3.188	0.128	3.273	0.125	3.260	0.122	3.304	0.128	3.586	0.125	3.636	0.120	3.554
Max3-Min3	0.028	0.628	0.021	0.513	0.002	0.062	-0.002	-0.067	-0.016	-0.459	-0.022	-0.694	-0.018	-0.621	-0.020	-0.735	-0.022	-0.843

**Table III Performance of Portfolio Switching Strategies: Pure Mean Reversion and Pure Random Walk Approaches**

This table reports the mean returns (annualized) of Max1, Max1-Min1, Max3 and Max3-Min3 portfolios. The portfolios are formed by assuming that either equity prices follow a pure random walk, or a pure mean reversion process.  $K$  represents the holding period.

	$K=1$		$K=3$		$K=6$		$K=9$		$K=12$		$K=15$		$K=18$		$K=21$		$K=24$	
	Mean Return	t-ratio	Mean Return	t-ratio	mean return	t-ratio	Mean Return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	Mean return	t-ratio	mean return	t-ratio
<i>Pure mean reversion</i>																		
Max1	0.198	3.983	0.209	4.490	0.211	4.442	0.202	4.179	0.194	4.115	0.187	4.103	0.182	4.097	0.172	3.943	0.166	3.830
Max1-Min1	0.085	1.248	0.086	1.434	0.111	1.946	0.110	2.008	0.106	2.034	0.103	2.104	0.092	1.966	0.083	1.820	0.075	1.729
Max3	0.153	3.945	0.158	4.211	0.155	4.259	0.157	4.322	0.160	4.450	0.168	4.679	0.168	4.672	0.166	4.613	0.166	4.698
Max3-Min3	0.034	0.902	0.035	0.996	0.043	1.297	0.048	1.522	0.050	1.641	0.056	1.913	0.048	1.666	0.040	1.455	0.042	1.576
<i>Pure random walk</i>																		
Max1	0.141	2.077	0.130	1.939	0.104	1.574	0.089	1.355	0.084	1.316	0.077	1.243	0.074	1.239	0.077	1.336	0.074	1.302
Max1-Min1	-0.043	-0.580	-0.064	-0.860	-0.088	-1.199	-0.091	-1.255	-0.088	-1.235	-0.093	-1.336	-0.094	-1.378	-0.089	-1.328	-0.092	-1.411
Max3	0.115	2.402	0.124	2.657	0.111	2.429	0.102	2.296	0.099	2.273	0.102	2.401	0.112	2.693	0.115	2.833	0.114	2.843
Max3-Min3	-0.028	-0.776	-0.022	-0.604	-0.029	-0.815	-0.033	-0.938	-0.036	-1.048	-0.035	-1.059	-0.029	-0.896	-0.027	-0.849	-0.028	-0.867



**Table IV Performance of Portfolio Switching Strategies: Momentum with Mean Reversion**

This table reports the mean returns (annualized) of Max1, Max1-Min1, Max3 and Max3-Min3 portfolios. The portfolios are formed by assuming that equity prices have both momentum and mean reversion effects. Shaded numbers signify that the current strategy beats the Jagadeesh-Titman pure momentum strategy.  $J$  represents sorting period and  $K$  represents holding period.

	$K=1$		$K=3$		$K=6$		$K=9$		$K=12$		$K=15$		$K=18$		$K=21$		$K=24$	
	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	Mean Return	t-ratio	mean return	t-ratio
$J=3$																		
Max1	0.233	4.637	0.201	4.239	0.190	3.892	0.183	3.982	0.179	3.987	0.171	3.867	0.167	3.849	0.169	4.005	0.164	3.979
Max1-Min1	0.094	1.464	0.074	1.305	0.103	1.917	0.109	2.202	0.117	2.493	0.098	2.211	0.088	2.024	0.083	2.026	0.073	1.861
Max3	0.187	4.662	0.181	4.697	0.179	4.636	0.180	4.735	0.185	4.754	0.175	4.528	0.170	4.474	0.170	4.593	0.168	4.615
Max3-Min3	0.079	2.165	0.066	1.993	0.080	2.497	0.090	2.885	0.087	2.797	0.070	2.361	0.058	2.016	0.055	2.029	0.048	1.797
$J=6$																		
Max1	0.162	2.868	0.185	3.347	0.169	3.319	0.170	3.431	0.161	3.341	0.153	3.242	0.153	3.367	0.153	3.499	0.156	3.633
Max1-Min1	0.061	0.945	0.079	1.310	0.095	1.743	0.108	2.130	0.096	1.996	0.084	1.790	0.074	1.681	0.073	1.766	0.074	1.891
Max3	0.176	4.366	0.177	4.405	0.180	4.510	0.186	4.622	0.175	4.383	0.170	4.310	0.170	4.403	0.168	4.513	0.168	4.622
Max3-Min3	0.062	1.726	0.067	1.927	0.094	2.730	0.097	2.847	0.075	2.284	0.061	1.950	0.056	1.875	0.048	1.674	0.048	1.734
$J=9$																		
Max1	0.179	3.244	0.165	3.203	0.161	3.200	0.152	3.092	0.139	2.877	0.125	2.725	0.129	2.899	0.140	3.241	0.158	3.758
Max1-Min1	0.168	2.562	0.143	2.363	0.146	2.660	0.124	2.367	0.089	1.747	0.068	1.403	0.051	1.083	0.053	1.175	0.063	1.487
Max3	0.195	4.671	0.201	4.854	0.201	4.792	0.183	4.429	0.170	4.219	0.163	4.158	0.164	4.344	0.166	4.515	0.165	4.592
Max3-Min3	0.101	2.707	0.113	3.021	0.121	3.325	0.092	2.639	0.067	2.026	0.054	1.676	0.049	1.605	0.049	1.681	0.047	1.678
$J=12$																		
Max1	0.180	3.401	0.177	3.450	0.159	3.187	0.153	3.091	0.143	3.095	0.128	2.859	0.134	3.108	0.150	3.533	0.152	3.655
Max1-Min1	0.167	2.449	0.156	2.540	0.130	2.278	0.106	1.890	0.093	1.789	0.066	1.310	0.062	1.256	0.077	1.649	0.074	1.649
Max3	0.203	4.528	0.216	4.958	0.190	4.545	0.173	4.240	0.163	4.072	0.155	4.033	0.161	4.313	0.163	4.494	0.160	4.490
Max3-Min3	0.119	2.964	0.121	3.152	0.102	2.797	0.079	2.288	0.063	1.906	0.048	1.478	0.047	1.530	0.047	1.565	0.042	1.469

Table IV (continued)

	<i>K=1</i>		<i>K=3</i>		<i>K=6</i>		<i>K=9</i>		<i>K=12</i>		<i>K=15</i>		<i>K=18</i>		<i>K=21</i>		<i>K=24</i>	
	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	mean return	t-ratio	Mean Return	t-ratio	mean return	t-ratio
<i>J=15</i>																		
Max1	0.166	3.197	0.164	3.206	0.150	2.949	0.148	3.001	0.146	3.064	0.136	2.911	0.157	3.417	0.150	3.329	0.166	3.678
Max1-Min1	0.083	1.423	0.074	1.362	0.087	1.620	0.093	1.856	0.094	1.952	0.077	1.640	0.100	2.179	0.087	1.947	0.099	2.250
Max3	0.217	5.359	0.203	5.255	0.183	4.741	0.174	4.553	0.166	4.433	0.162	4.382	0.168	4.666	0.167	4.781	0.160	4.628
Max3-Min3	0.111	3.070	0.082	2.449	0.069	2.045	0.064	1.951	0.052	1.610	0.047	1.510	0.051	1.708	0.048	1.679	0.040	1.415
<i>J=18</i>																		
Max1	0.157	2.970	0.159	3.065	0.154	3.125	0.154	3.218	0.151	3.215	0.154	3.355	0.154	3.430	0.157	3.520	0.160	3.628
Max1-Min1	0.052	0.876	0.074	1.297	0.081	1.519	0.083	1.617	0.080	1.656	0.086	1.829	0.087	1.872	0.084	1.885	0.089	2.056
Max3	0.184	4.602	0.186	4.845	0.178	4.705	0.173	4.629	0.170	4.551	0.172	4.740	0.174	4.835	0.171	4.817	0.165	4.690
Max3-Min3	0.061	1.784	0.062	1.891	0.064	2.058	0.062	2.007	0.059	1.939	0.064	2.151	0.063	2.135	0.056	1.938	0.048	1.718
<i>J=21</i>																		
Max1	0.158	2.989	0.157	3.122	0.157	3.292	0.153	3.259	0.155	3.358	0.151	3.352	0.155	3.478	0.158	3.581	0.162	3.706
Max1-Min1	0.069	1.166	0.063	1.140	0.063	1.174	0.068	1.335	0.079	1.615	0.082	1.740	0.088	1.898	0.093	2.066	0.101	2.299
Max3	0.197	4.853	0.193	5.047	0.178	4.822	0.172	4.689	0.174	4.762	0.172	4.758	0.171	4.812	0.167	4.729	0.163	4.670
Max3-Min3	0.080	2.301	0.061	1.847	0.057	1.811	0.059	1.886	0.066	2.137	0.061	2.022	0.057	1.952	0.051	1.770	0.046	1.652
<i>J=24</i>																		
Max1	0.156	2.941	0.160	3.246	0.157	3.345	0.165	3.591	0.156	3.478	0.157	3.535	0.159	3.605	0.159	3.660	0.166	3.829
Max1-Min1	0.047	0.770	0.048	0.866	0.065	1.232	0.080	1.563	0.075	1.529	0.084	1.795	0.086	1.887	0.090	2.014	0.102	2.327
Max3	0.192	4.812	0.193	5.076	0.186	5.025	0.179	4.883	0.178	4.912	0.179	4.945	0.175	4.898	0.168	4.784	0.166	4.740
Max3-Min3	0.078	2.152	0.066	1.921	0.067	2.044	0.073	2.296	0.069	2.217	0.072	2.434	0.062	2.168	0.052	1.866	0.047	1.709

**Table V Model Parameters and Variance Decomposition**

This table reports key parameter estimates of the baseline model and the implied variance decomposition. All notation follows that in the text.  $\mathbf{g}_{mrv,mom}$  is the correlation coefficient between the mean reversion and momentum components and  $R-square$  is the coefficient of determination from regression equation (5) in the text.

Moment	Estimate
$\delta$	0.979
$\rho$	0.026
$\mathbf{s}_R^2$	3.157 E-3
$\mathbf{s}_h^2$	3.103 E-3
$\mathbf{s}_{mrv}^2$	3.060 E-5
$\mathbf{s}_{mom}^2$	2.560 E-5
$\mathbf{g}_{mrv,mom}$	-0.211
$\mathbf{s}_h^2 / \mathbf{s}_R^2$ (percent)	98.5
$\mathbf{s}_{mrv}^2 / \mathbf{s}_R^2$ (percent)	1.19
$\mathbf{s}_{mom}^2 / \mathbf{s}_R^2$ (percent)	0.81
$R-square$ (percent)	2.07

**Table VI Comparison of Model Performance**

**Panel A.** 1. Baseline model where the mean reversion parameter is identical across countries, and the momentum parameter is identical across lags and countries; 2. Jegadeesh-Titman pure momentum; 3. Pure mean reversion; 4. Pure random walk; 5. Perfect foresight; 6. Baseline model with full-sample parameter estimates; 7. 24-month momentum with mean reversion. The 24 momentum lags are constrained with 3 Almon lags, but lag parameters as well as the mean reversion parameter are identical across countries; 8. Baseline model with forecast starting at ¼ of sample; and 9. Baseline model with forecast

Model	Portfolio	Mean Return	t-ratio	$\beta$ with World Portfolio	Expected Return	Percentage Switches in Portfolio
1	Max1	0.180	3.401	0.962	0.318	0.13
	Max1-Min1	0.167	2.449	-0.301	0.393	0.16
	Max3	0.203	4.528	0.984	0.260	0.10
	Max3-Min3	0.119	2.964	-0.064	0.367	0.10
2	Max1	0.184	2.583	1.284	0.212	0.35
	Max1-Min1	0.095	1.107	0.373	0.151	0.39
	Max3	0.177	3.374	0.154	0.191	0.25
	Max3-Min3	0.112	2.110	0.297	0.130	0.26
3	Max1	0.198	3.983	0.615	0.241	0.11
	Max1-Min1	0.085	1.248	-0.621	0.218	0.11
	Max3	0.153	3.945	0.837	0.212	0.10
	Max3-Min3	0.034	0.902	-0.245	0.198	0.09
4	Max1	0.141	2.077	1.284	0.238	0.03
	Max1-Min1	-0.043	-0.580	0.434	0.154	0.04
	Max3	0.115	2.402	1.177	0.216	0.05
	Max3-Min3	-0.028	-0.776	0.240	0.115	0.03
5	Max1	1.284	28.304	0.920	1.284	0.88
	Max1-Min1	2.275	45.572	-0.310	2.275	0.86
	Max3	0.979	25.356	0.924	0.979	0.78
	Max3-Min3	1.667	44.330	-0.201	1.667	0.79
6	Max1	0.277	4.991	1.134	0.263	0.20
	Max1-Min1	0.322	5.046	0.090	0.284	0.16
	Max3	0.230	4.816	1.078	0.232	0.12
	Max3-Min3	0.202	4.754	0.100	0.211	0.14
7	Max1	0.165	3.071	0.992	0.354	0.02
	Max1-Min1	0.105	1.638	-0.199	0.476	0.05
	Max3	0.218	5.268	0.917	0.275	0.06
	Max3-Min3	0.115	3.246	-0.117	0.355	0.06
8	Max1	0.212	4.164	0.934	0.318	0.14
	Max1-Min1	0.191	2.990	-0.292	0.389	0.17
	Max3	0.215	5.180	0.970	0.262	0.09
	Max3-Min3	0.132	3.448	-0.060	0.228	0.10
9	Max1	0.206	3.144	1.159	0.304	0.16
	Max1-Min1	0.130	1.704	-0.047	0.361	0.17
	Max3	0.230	4.183	1.069	0.260	0.11
	Max3-Min3	0.081	1.760	0.052	0.278	0.10

**Panel B.** 1. Baseline model where the mean reversion parameter is identical across countries, and the momentum parameter is identical across lags and countries; 2. The mean reversion parameter is identical across countries. The momentum parameter is identical across lags, but different across countries; 3. The mean reversion parameter is identical across countries. The 12 momentum parameters are different across lags but each lag parameter is identical across countries; 4. The mean reversion parameter is identical across countries. The 12 momentum parameters are different across lags and countries; 5. The mean reversion parameters are different across countries, and the momentum parameter is identical across lags and countries; 6. The mean reversion parameters are different across countries. The momentum parameter is identical across lags, but different across countries; 7. The mean reversion parameters are different across countries. The 12 momentum parameters are different across lags but each lag parameter is identical across countries; and 8. The mean reversion parameters are different across countries; and 9. Consensus forecast from models 1-8.

Model	Portfolio	Mean Return	t-ratio	$\beta$ with World Portfolio	Expected Return	Percentage Switches in Portfolio
1	Max1	0.180	3.401	0.962	0.318	0.13
	Max1-Min1	0.167	2.449	-0.301	0.393	0.16
	Max3	0.203	4.528	0.984	0.260	0.10
	Max3-Min3	0.119	2.964	-0.064	0.367	0.10
2	Max1	0.199	3.549	1.018	0.359	0.25
	Max1-Min1	0.157	2.228	-0.171	0.439	0.25
	Max3	0.219	5.017	0.964	0.282	0.14
	Max3-Min3	0.115	2.846	-0.090	0.320	0.15
3	Max1	0.219	4.465	0.715	0.335	0.47
	Max1-Min1	0.209	3.189	-0.326	0.433	0.53
	Max3	0.194	4.371	0.986	0.274	0.40
	Max3-Min3	0.102	2.626	-0.021	0.325	0.41
4	Max1	0.234	3.752	1.070	0.583	0.83
	Max1-Min1	0.203	2.791	0.212	0.828	0.86
	Max3	0.208	4.862	0.941	0.446	0.69
	Max3-Min3	0.143	3.952	-0.074	0.640	0.72
5	Max1	0.207	3.310	1.050	0.336	0.22
	Max1-Min1	0.178	2.283	-0.105	0.438	0.17
	Max3	0.223	4.629	1.063	0.296	0.13
	Max3-Min3	0.112	2.680	0.080	0.357	0.12
6	Max1	0.173	2.777	1.115	0.393	0.25
	Max1-Min1	0.117	1.551	-0.028	0.476	0.24
	Max3	0.203	4.081	1.106	0.325	0.15
	Max3-Min3	0.103	2.351	0.120	0.336	0.16
7	Max1	0.174	2.868	1.075	0.350	0.58
	Max1-Min1	0.110	1.425	-0.034	0.456	0.46
	Max3	0.200	4.253	1.050	0.304	0.35
	Max3-Min3	0.087	2.261	0.052	0.329	0.34
8	Max1	0.226	3.495	1.093	0.590	0.82
	Max1-Min1	0.153	1.955	0.117	0.862	0.80
	Max3	0.212	5.022	0.945	0.448	0.68
	Max3-Min3	0.135	3.717	0.010	0.589	0.69
9	Max1	0.265	4.428	0.977	0.353	0.59
	Max1-Min1	0.211	2.723	-0.102	0.434	0.50
	Max3	0.245	5.581	0.955	0.294	0.39
	Max3-Min3	0.155	3.750	-0.051	0.311	0.41

**Table VII Robustness Check on the Performance of Portfolio Switching Strategies**

**Panel A** reports the performance of various portfolio switching strategies with a 1 percent transactions cost filter. The models are: 1. Momentum with mean reversion without transaction cost; 2. Momentum with mean reversion with 1 percent transactions cost filter; 3. Momentum without mean reversion with 1 percent transactions cost filter; 4. Mean reversion without momentum with 1 percent transactions costs filter; and 5. Pure random walk with 1 percent transactions cost filter. **Panel B** presents the performance of the baseline model without transactions cost but portfolios are formed one month after ranking.

Model	Portfolio	Mean Return	t-ratio	$\beta$ with World Portfolio	Expected Return	Percentage Switches in Portfolio
<b>Panel A. Switching Strategies with a 1 percent Transactions Cost Filter</b>						
1	Max1	0.180	3.401	0.962	0.318	0.13
	Max1-Min1	0.167	2.449	-0.301	0.393	0.16
	Max3	0.203	4.528	0.984	0.260	0.10
	Max3-Min3	0.119	2.964	-0.064	0.367	0.10
2	Max1	0.179	3.313	1.042	0.301	0.01
	Max1-Min1	0.172	2.599	-0.079	0.357	0.03
	Max3	0.184	4.104	0.988	0.248	0.02
	Max3-Min3	0.108	2.734	-0.024	0.269	0.02
3	Max1	0.127	1.757	1.334	0.185	0.05
	Max1-Min1	-0.015	-0.189	0.360	0.110	0.05
	Max3	0.125	2.671	1.094	0.158	0.03
	Max3-Min3	0.010	0.227	0.198	0.055	0.03
4	Max1	0.157	2.539	1.096	0.219	0.00
	Max1-Min1	0.088	1.543	-0.060	0.170	0.01
	Max3	0.171	4.301	0.870	0.192	0.01
	Max3-Min3	0.081	2.424	-0.241	0.134	0.01
5	Max1	0.158	2.035	1.180	0.229	0.00
	Max1-Min1	0.014	0.172	0.285	0.142	0.00
	Max3	0.117	2.132	1.143	0.198	0.00
	Max3-Min3	-0.021	-0.474	0.175	0.096	0.00
<b>Panel B. Baseline Model with Portfolio Formed One Month after Ranking</b>						
6	Max1	0.163	3.101	0.952	0.318	0.13
	Max1-Min1	0.151	2.257	-0.259	0.393	0.16
	Max3	0.218	4.820	0.983	0.260	0.10
	Max3-Min3	0.133	3.250	-0.074	0.296	0.10

**Table VIII Percentage Overlap in the Max3 and Min3 Portfolios across Models**

The models are: 1. Baseline model; 2. Jegadeesh-Titman pure momentum; 3. Pure mean reversion; 4. Pure random walk; 5. Perfect foresight; 6. Baseline model with 1 percent transactions cost; 7. 24-month momentum with mean reversion. The 24 momentum lags are constrained with 3 Almon lags, but each lag parameter is identical across countries, and the mean reversion parameter is identical across countries; 8. The mean reversion parameter is identical across countries. The momentum parameter is identical across lags, but is different across countries; 9. The mean reversion parameter is identical across countries. The 12 momentum parameters are different across lags but identical across countries; 10. The mean reversion parameter is identical across countries. The 12 momentum parameters are different across lags and countries; 11. The mean reversion parameters are different across countries, and the momentum parameter is identical across lags and countries; 12. The mean reversion parameters are different across countries. The momentum parameter is identical across lags, but different across countries; 13. The mean reversion parameters are different across countries. The 12 momentum parameters are different across lags but identical across countries; and 14. The mean reversion parameters are different across countries. The 12 momentum parameters are different across lags and countries.

**Panel A: Percentage Overlap in the Max3 Portfolio**

Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	100													
2	28	100												
3	61	8	100											
4	5	30	7	100										
5	21	21	19	21	100									
6	74	28	54	7	20	100								
7	87	23	63	5	20	76	100							
8	79	31	53	5	21	70	74	100						
9	73	27	55	7	21	65	70	64	100					
10	41	26	32	11	22	41	40	43	44	100				
11	52	26	33	4	23	46	49	51	43	34	100			
12	51	33	31	5	22	48	47	54	44	39	78	100		
13	48	26	32	5	22	41	45	46	51	37	78	68	100	
14	37	25	28	10	23	34	34	37	39	78	44	48	45	100

**Panel B: Percentage Overlap in the Min3 Portfolio**

Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	100													
2	23	100												
3	61	5	100											
4	4	21	6	100										
5	19	26	17	21	100									
6	71	24	54	7	19	100								
7	85	18	67	5	17	68	100							
8	84	24	60	4	19	67	77	100						
9	73	23	54	6	19	62	69	67	100					
10	34	24	30	12	23	31	34	35	36	100				
11	54	21	41	6	20	45	51	53	48	28	100			
12	47	30	38	6	22	40	45	51	44	32	75	100		
13	50	24	40	7	20	42	48	49	53	31	79	71	100	
14	29	24	27	13	23	28	29	31	32	77	38	42	43	100

**Table IX Risk-Adjusted Excess Returns**

**Panel A.** This panel reports results from regressing monthly returns of Max1 and Max3 portfolios on the excess return on the MSCI world index and the excess return on an internationally diversified portfolio long on value and short on growth stocks:

$$r_{\max i,t} - r_{f,t} = \mathbf{a} + \mathbf{b}_{wld}(r_{wld,t} - r_{f,t}) + \mathbf{b}_{vmg}r_{vmg,t} + \mathbf{e}_t$$

and the results from regressing monthly returns of Max1-Min1 and Max3-Min3 portfolios on the same two factors:

$$r_{\max i,t} - r_{\min i,t} = \mathbf{a} + \mathbf{b}_{wld}(r_{wld,t} - r_{f,t}) + \mathbf{b}_{vmg}r_{vmg,t} + \mathbf{e}_t .$$

The U.S. T-bill rate is used as the risk-free rate. The  $\mathbf{a}$  values are annualized.

The models considered are: 1. Baseline model in which the mean reversion parameter is identical across countries, and the momentum parameter is identical across lags and countries; 2. Jegadeesh-Titman pure momentum  $J=12, K=1$ ; 3. Pure mean reversion; and 4. Jegadeesh-Titman pure momentum  $J=6, K=6$ .

Model	Portfolio	Mean return	t-ratio	$\mathbf{a}$	t-ratio	$\mathbf{b}_{wld}$	t-ratio	$\mathbf{b}_{vmg}$	t-ratio
1	Max1	0.180	3.401	0.031	0.699	0.993	11.262	0.323	1.568
	Min1	0.013	0.201	-0.156	-3.058	1.266	12.302	0.032	0.131
	Max1-Min1	0.167	2.449	0.186	2.702	-0.273	-1.959	0.291	0.896
	Max3	0.203	4.528	0.049	1.539	1.030	16.138	0.476	3.193
	Min3	0.083	1.938	-0.070	-2.545	1.063	19.011	0.162	1.244
	Max3-Min3	0.119	2.964	0.119	2.917	-0.032	-0.391	0.314	1.629
2	Max1	0.184	2.583	0.007	0.114	1.329	11.147	0.460	1.652
	Min1	0.089	1.381	-0.055	-0.944	0.936	7.874	0.258	0.931
	Max1-Min1	0.095	1.107	0.062	0.718	0.393	2.245	0.201	0.492
	Max3	0.177	3.374	0.012	0.318	1.188	15.636	0.350	1.975
	Min3	0.066	1.521	-0.075	-2.223	0.885	12.919	0.279	1.744
	Max3-Min3	0.112	2.110	0.087	1.642	0.304	2.826	0.071	0.285
3	Max1	0.198	3.983	0.069	1.519	0.683	7.403	0.697	3.234
	Min1	0.113	1.857	-0.053	-1.124	1.237	12.944	0.008	0.035
	Max1-Min1	0.085	1.248	0.122	1.858	-0.554	-4.156	0.689	2.214
	Max3	0.153	3.945	0.011	0.378	0.885	15.595	0.480	3.622
	Min3	0.120	2.758	-0.035	-1.320	1.087	20.191	0.050	0.402
	Max3-Min3	0.034	0.902	0.046	1.240	-0.203	-2.717	0.429	2.465
4	Max1	0.188	3.729	0.033	0.824	1.024	12.713	0.646	3.434
	Min1	0.104	2.149	-0.036	-0.875	0.856	10.286	0.401	2.062
	Max1-Min1	0.084	1.478	0.069	1.189	0.168	1.434	0.245	0.897
	Max3	0.195	4.629	0.039	1.444	1.045	19.085	0.513	4.014
	Min3	0.088	2.412	-0.049	-1.875	0.836	15.701	0.355	2.856
	Max3-Min3	0.106	2.864	0.088	2.374	0.208	2.767	0.158	0.897



**Panel B.** This panel reports results from regressing monthly returns of Max1 and Max3 portfolios on the excess return on the MSCI world index and the excess returns on the Fama-French SMB and HML factors:

$$r_{\max i,t} - r_{f,t} = \mathbf{a} + \mathbf{b}_{wld}(r_{wld,t} - r_{f,t}) + \mathbf{b}_{smb}r_{smb,t} + \mathbf{b}_{hml}r_{hml,t} + \mathbf{e}_t$$

and the results from regressing monthly returns of Max1-Min1 and Max3-Min3 portfolios on the same three factors:

$$r_{\max i,t} - r_{\min i,t} = \mathbf{a} + \mathbf{b}_{wld}(r_{wld,t} - r_{f,t}) + \mathbf{b}_{smb}r_{smb,t} + \mathbf{b}_{hml}r_{hml,t} + \mathbf{e}_t.$$

The U.S. T-bill rate is used as the risk-free rate. The  $\mathbf{a}$  values are annualized.

The models considered are: 1. Baseline model in which the mean reversion parameter identical across countries, and the momentum parameter is identical across lags and countries; 2. Jegadeesh-Titman pure momentum  $J=12, K=1$ ; 3. Pure mean reversion; and 4. Jegadeesh-Titman pure momentum  $J=6, K=6$ .

Model	Portfolio	Mean return	t-ratio	$\mathbf{a}$	t-ratio	$\mathbf{b}_{wld}$	t-ratio	$\mathbf{b}_{smb}$	t-ratio	$\mathbf{b}_{hml}$	t-ratio
1	Max1	0.180	3.401	0.032	0.733	0.992	10.662	0.263	1.863	0.180	1.323
	Min1	0.013	0.201	-0.158	-3.094	1.286	11.811	0.031	0.185	0.092	0.576
	Max1-Min1	0.167	2.449	0.190	2.749	-0.294	-1.996	0.233	1.039	0.088	0.410
	Max3	0.203	4.528	0.052	1.685	1.019	15.476	0.458	4.572	0.252	2.611
	Min3	0.083	1.938	-0.070	-2.516	1.064	17.985	0.086	0.957	0.087	1.002
	Max3-Min3	0.119	2.964	0.122	3.013	-0.045	-0.520	0.372	2.834	0.165	1.306
2	Max1	0.184	2.583	0.002	0.033	1.380	11.387	0.782	4.246	0.560	3.156
	Min1	0.089	1.381	-0.058	-0.982	0.960	7.640	-0.134	-0.699	0.145	0.790
	Max1-Min1	0.095	1.107	0.060	0.704	0.420	2.322	0.916	3.328	0.415	1.565
	Max3	0.177	3.374	0.012	0.332	1.199	15.518	0.542	4.611	0.310	2.736
	Min3	0.066	1.521	-0.072	-2.104	0.869	11.910	0.005	0.041	0.042	0.398
	Max3-Min3	0.112	2.110	0.084	1.611	0.331	2.973	0.537	3.176	0.267	1.640
3	Max1	0.198	3.983	0.074	1.585	0.668	6.733	0.118	0.782	0.227	1.563
	Min1	0.113	1.857	-0.057	-1.216	1.270	12.616	0.189	1.235	0.174	1.178
	Max1-Min1	0.085	1.248	0.131	1.964	-0.602	-4.223	-0.071	-0.328	0.054	0.257
	Max3	0.153	3.945	0.016	0.545	0.862	14.166	0.216	2.334	0.146	1.639
	Min3	0.120	2.758	-0.039	-1.488	1.117	20.100	0.264	3.129	0.196	2.406
	Max3-Min3	0.034	0.902	0.054	1.450	-0.255	-3.189	-0.048	-0.399	-0.050	-0.425
4	Max1	0.188	3.729	0.038	0.947	1.005	11.760	0.382	2.945	0.263	2.106
	Min1	0.104	2.149	-0.037	-0.899	0.875	9.913	-0.027	-0.198	0.208	1.609
	Max1-Min1	0.084	1.478	0.075	1.305	0.129	1.051	0.409	2.191	0.055	0.308
	Max3	0.195	4.629	0.043	1.560	1.034	17.791	0.295	3.341	0.223	2.620
	Min3	0.088	2.412	-0.046	-1.726	0.823	14.411	0.075	0.862	0.100	1.196
	Max3-Min3	0.106	2.864	0.089	2.387	0.211	2.657	0.220	1.827	0.123	1.059

**Table X Correlation of Country Characteristics**

This table reports correlation coefficients (in percent) of various characteristics of the 18 MSCI national equity indexes. The characteristics are: mean return, standard deviation of return, world market beta, number of firms, firm size, and excess return in January (mean return in January minus full sample mean return).

	Mean return	standard dev	Beta	no. of firms	firm size	Jan excess return
mean return	100.00					
standard dev	15.00	100.00				
Beta	35.44	62.71	100.00			
no. of firms	0.29	-27.34	19.39	100.00		
firm size	8.67	-52.05	4.12	66.82	100.00	
Jan excess return	15.78	66.23	63.27	-15.64	-27.67	100.00



Fig 1(1) Impulse Response Following a 10% Innovation in  $\eta_t$   
12-Month Momentum with Mean Reversion, One Parameter Case

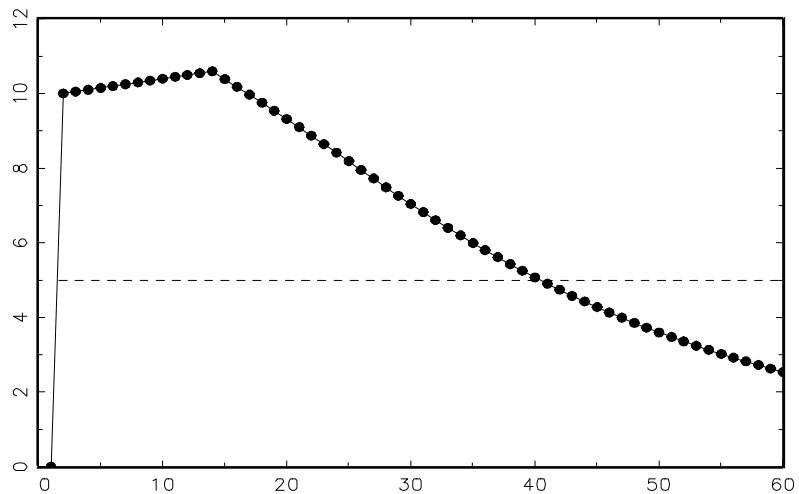


Fig 1(2) Impulse Response Following a 10% Innovation in  $\eta_t$   
Pure Momentum

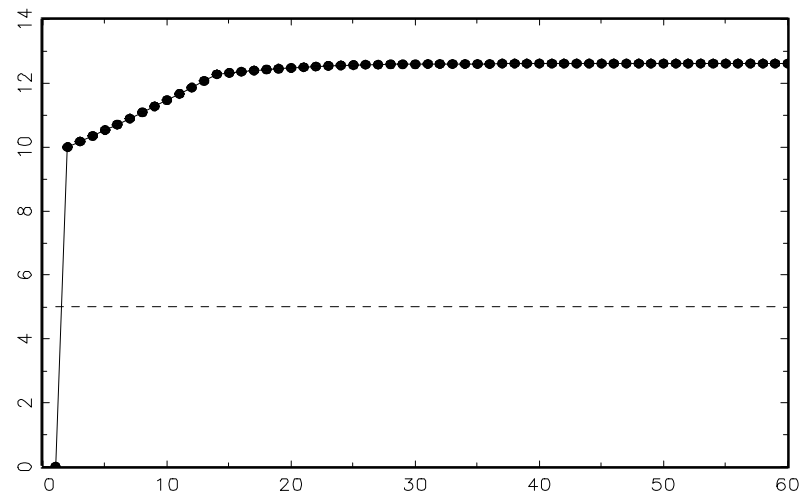


Fig 1(3) Impulse Response Following a 10% Innovation in  $\eta_t$   
Pure Mean Reversion

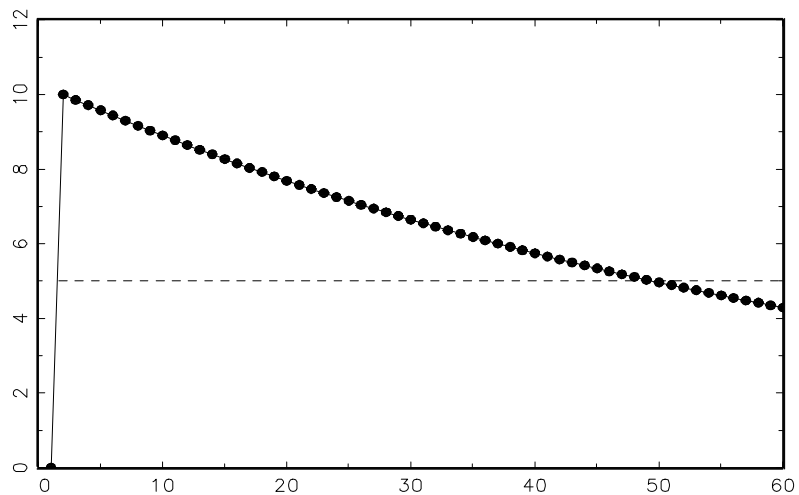


Fig 1(4) Impulse Response Following a 10% Innovation in  $\eta_t$   
24-Month Momentum with Mean Reversion, 3-Almon Lag Case

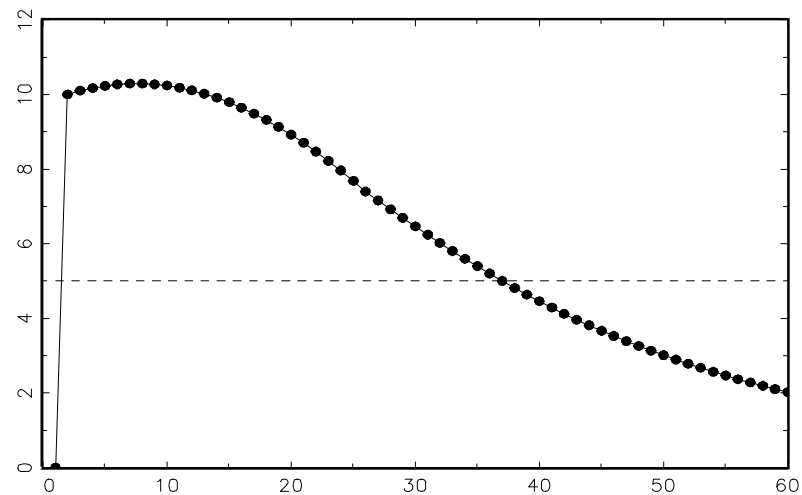


Fig 2(1) Mean Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags and countries: Baseline

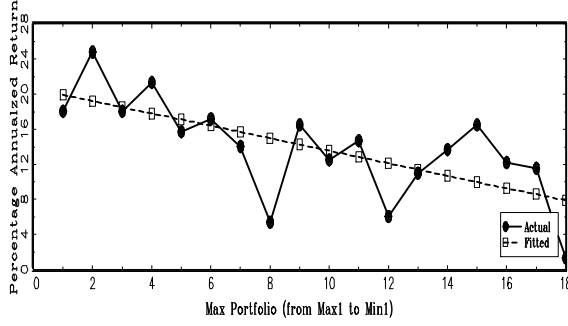


Fig 2(2) Mean Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags but diff for countries

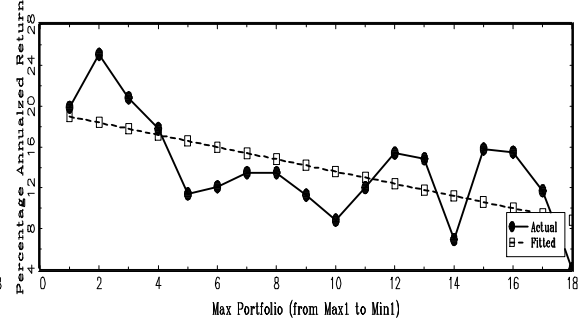


Fig 2(3) Mean Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for countries but diff for lags

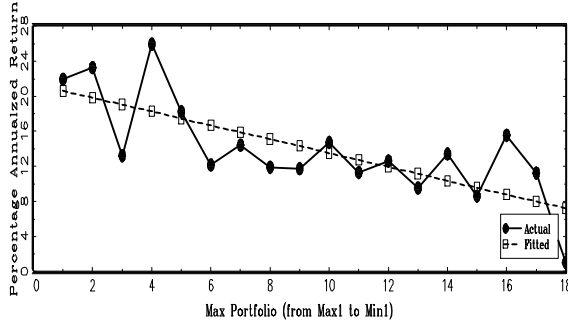


Fig 2(4) Mean Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  diff for lags and countries

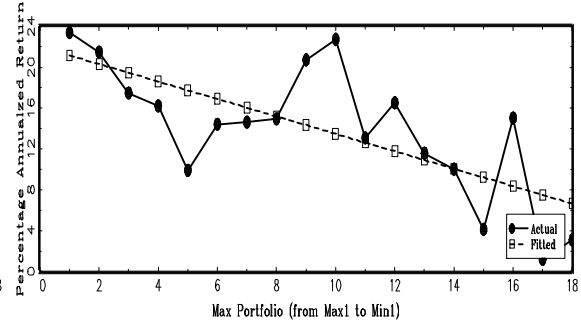


Fig 2(5) Mean Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags and countries

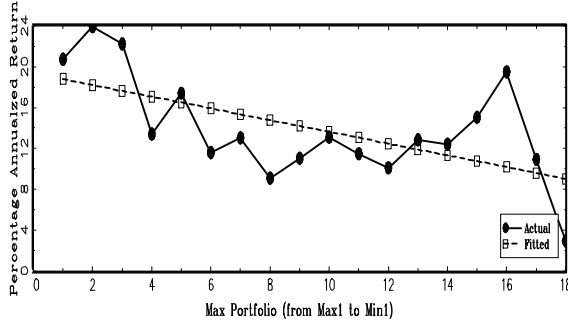


Fig 2(6) Mean Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags but diff for countries

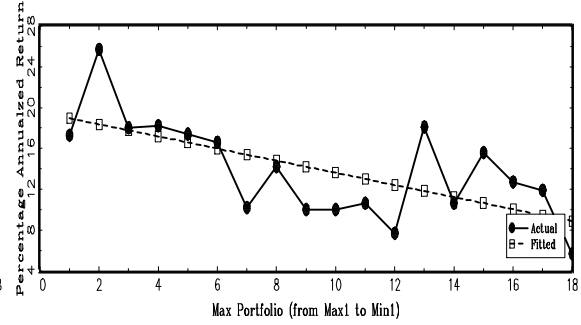


Fig 2(7) Mean Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for countries but diff for lags

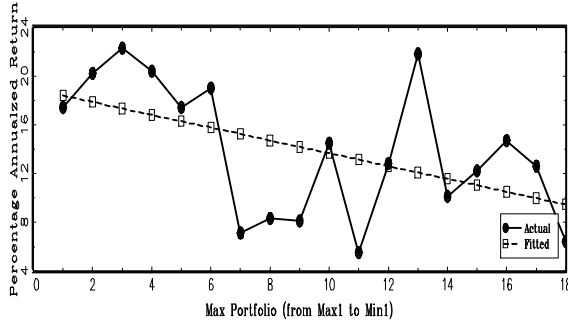


Fig 2(8) Mean Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  diff for lags and countries

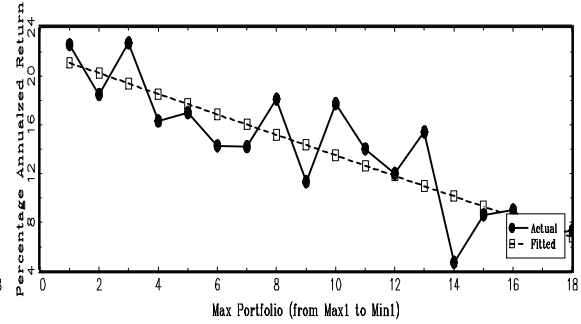


Fig 3(1) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags and countries: Baseline

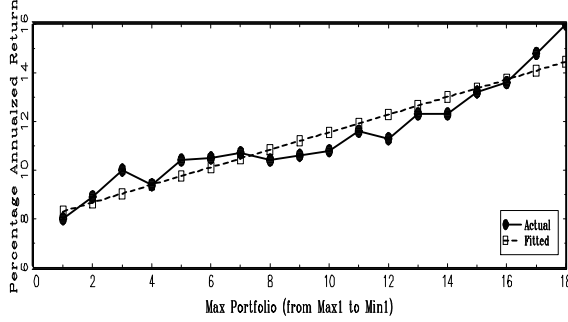


Fig 3(2) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags but diff for countries

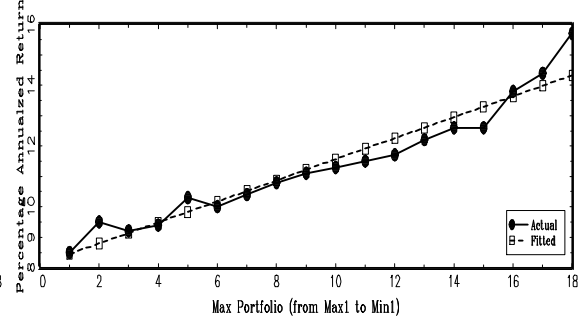


Fig 3(3) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for countries but diff for lags

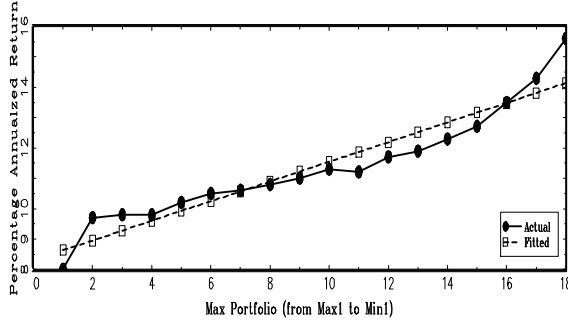


Fig 3(4) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  diff for lags and countries

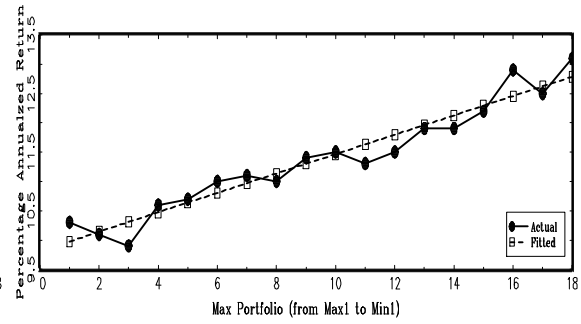


Fig 3(5) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags and countries

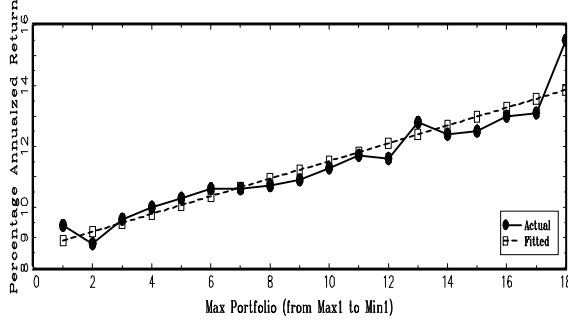


Fig 3(6) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags but diff for countries

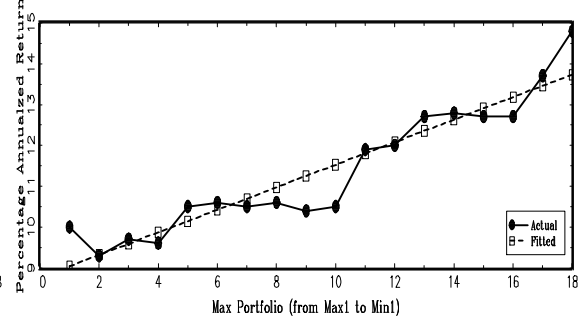


Fig 3(7) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for countries but diff for lags

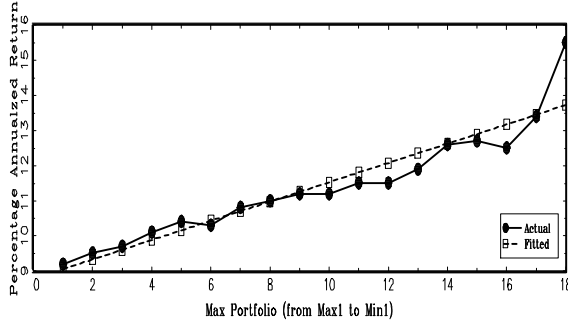


Fig 3(8) Conditional Return of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  diff for lags and countries

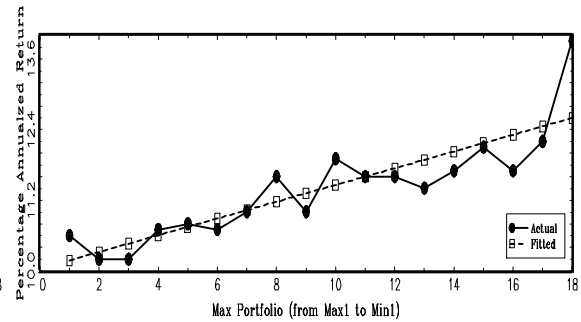


Fig 4(1) Betas of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags and countries: Baseline

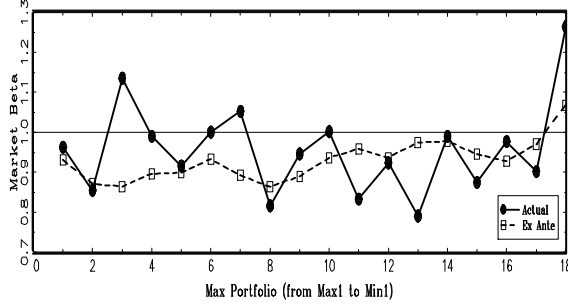


Fig 4(2) Betas of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags but diff for countries

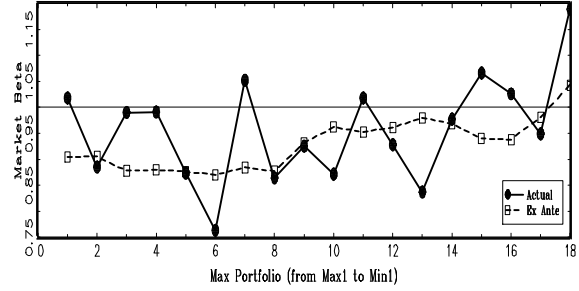


Fig 4(3) Betas of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for countries but diff for lags

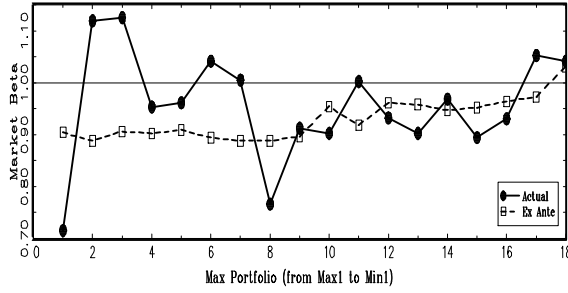


Fig 4(4) Betas of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  diff for lags and countries

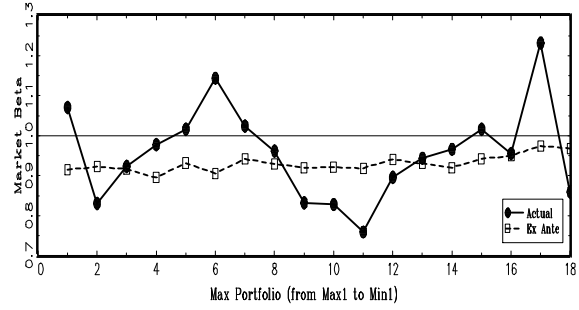


Fig 4(5) Betas of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags and countries

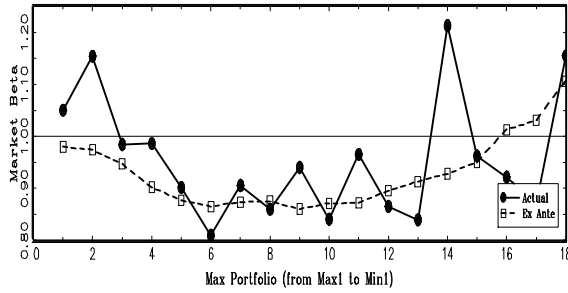


Fig 4(6) Betas of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags but diff for countries

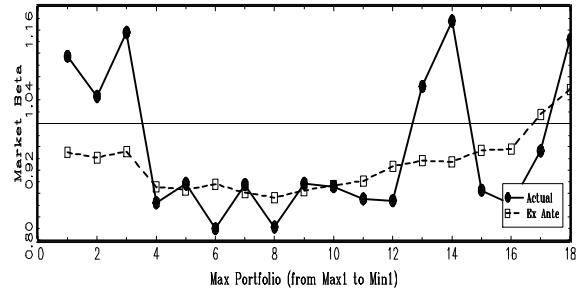


Fig 4(7) Betas of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for countries but diff for lags

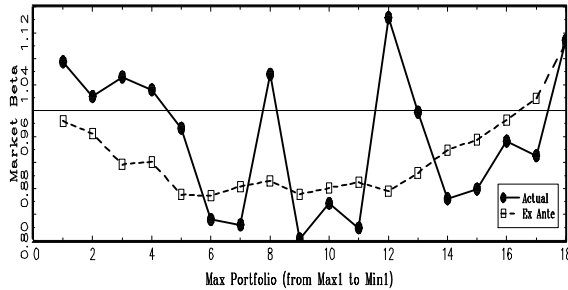


Fig 4(8) Betas of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  diff for lags and countries

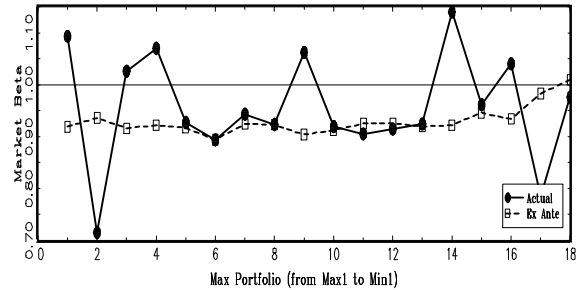


Fig 5(1) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags and countries: Baseline

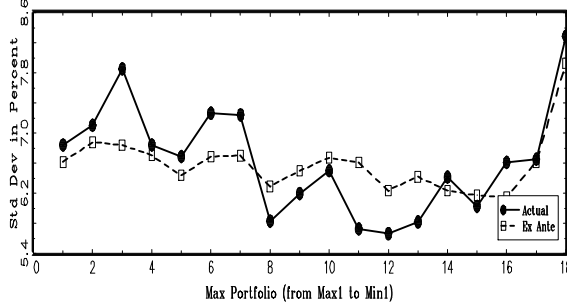


Fig 5(2) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags but diff for countries

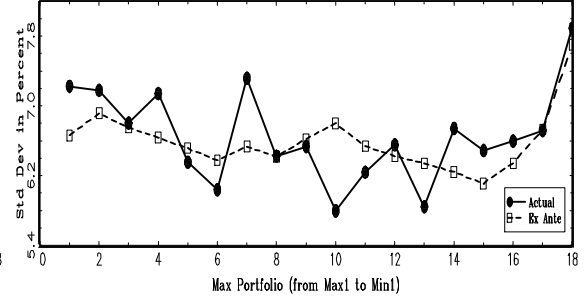


Fig 5(3) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for countries but diff for lags

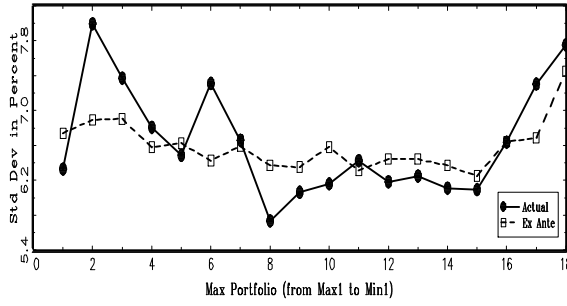


Fig 5(4) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  diff for lags and countries

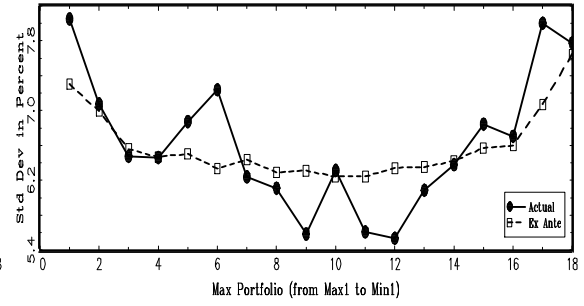


Fig 5(5) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags and countries

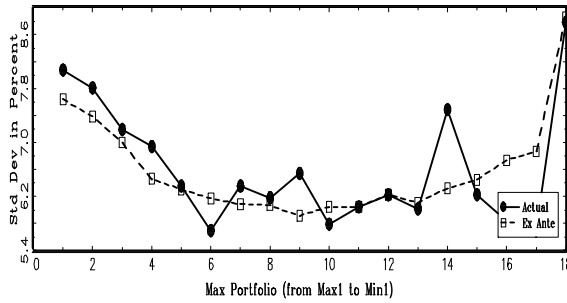


Fig 5(6) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags but diff for countries

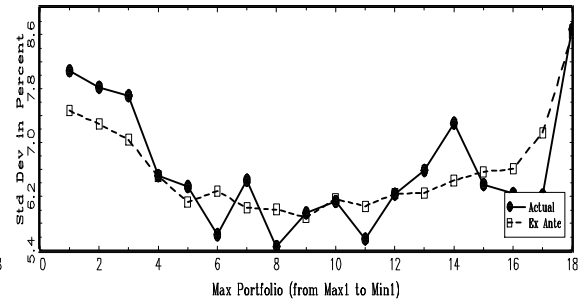


Fig 5(7) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for countries but diff for lags

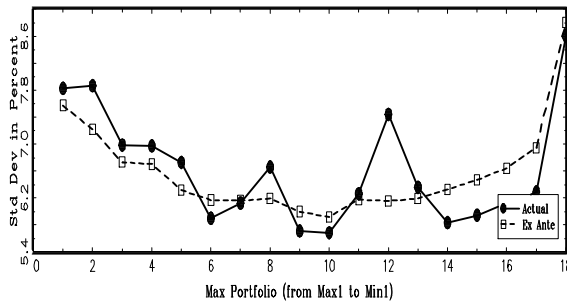


Fig 5(8) Standard Dev of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  diff for lags and countries

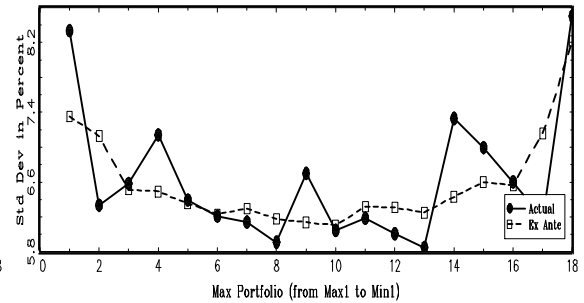




Fig 6(1) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags and countries: Baseline

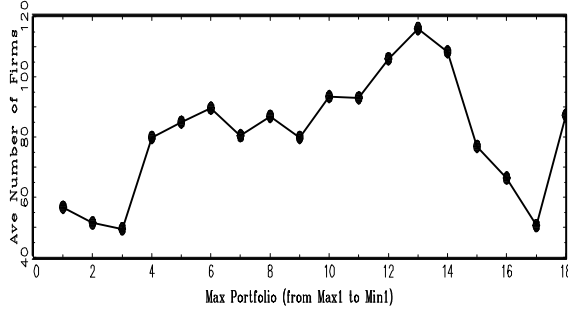


Fig 6(2) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags but diff for countries

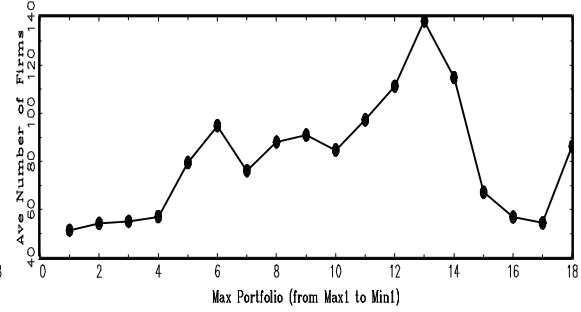


Fig 6(3) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for countries but diff for lags

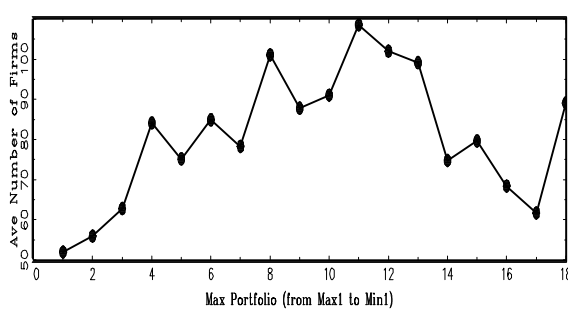


Fig 6(4) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  diff for lags and countries

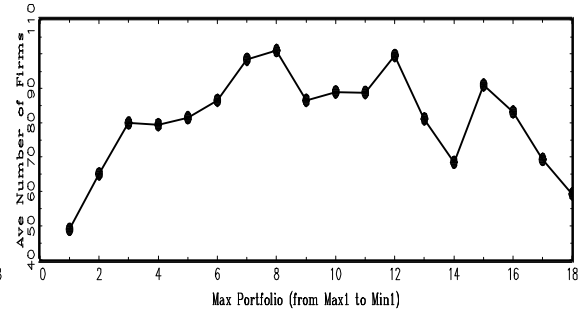


Fig 6(5) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags and countries

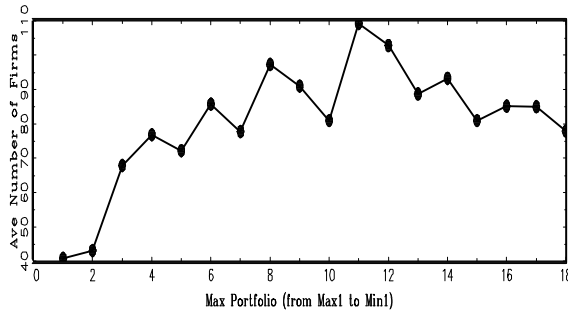


Fig 6(6) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags but diff for countries

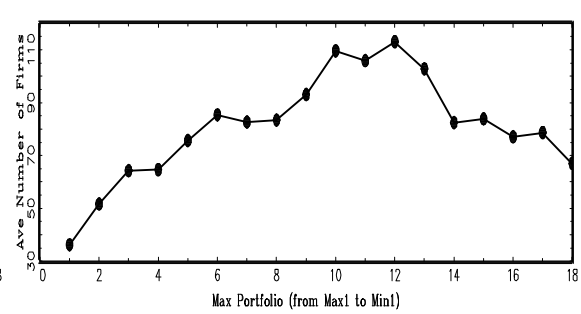


Fig 6(7) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for countries but diff for lags

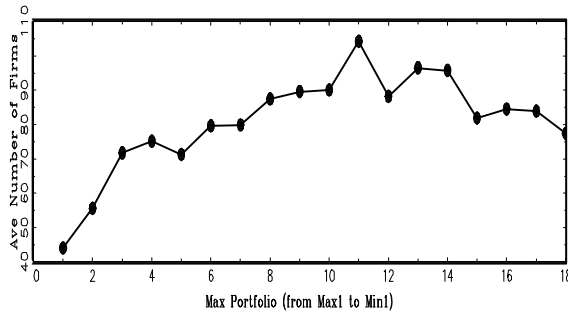


Fig 6(8) Ave Number of Firms of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  diff for lags and countries

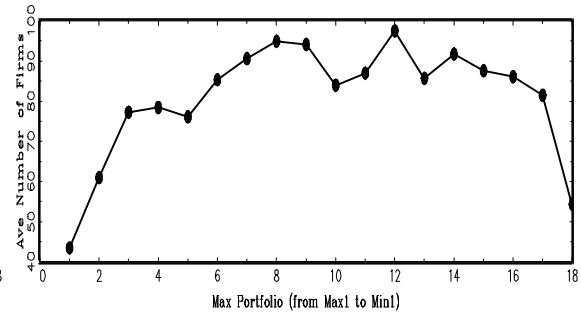


Fig 7(1) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags and countries: Baseline

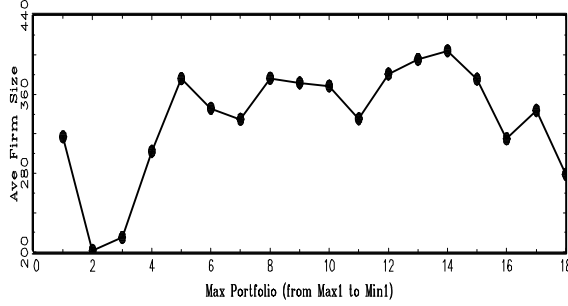


Fig 7(2) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for lags but diff for countries

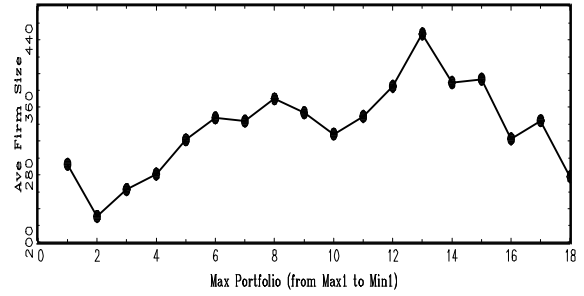


Fig 7(3) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  same for countries but diff for lags

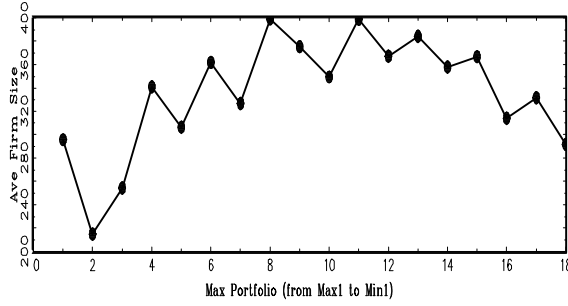


Fig 7(4) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  same,  $\rho$  diff for lags and countries

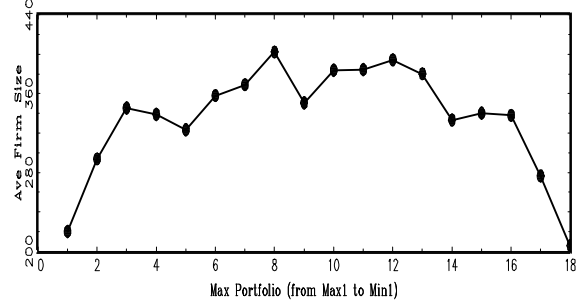


Fig 7(5) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags and countries

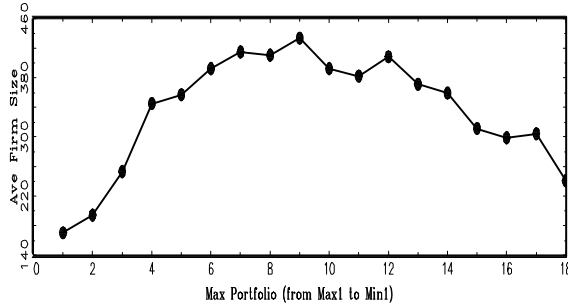


Fig 7(6) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for lags but diff for countries

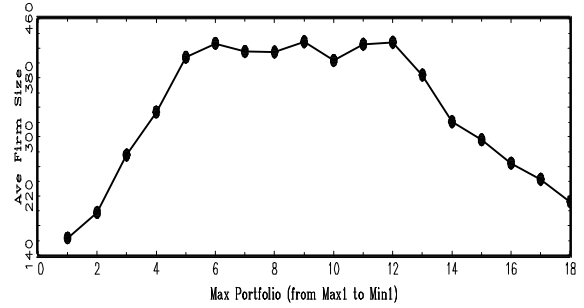


Fig 7(7) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  same for countries but diff for lags

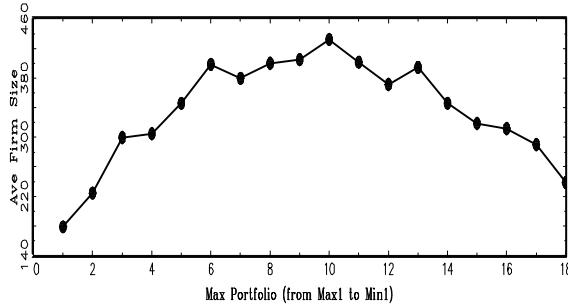


Fig 7(9) Ave Firm Size of Max1--Max18 Portfolios  
 $\delta$  diff,  $\rho$  diff for lags and countries

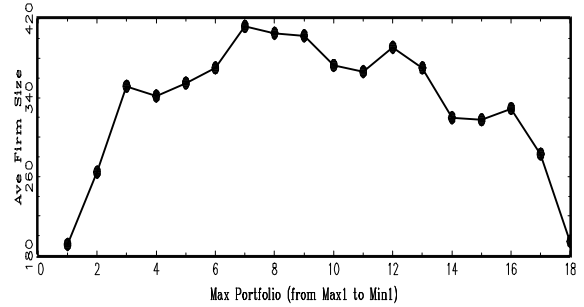


Fig 8(1) Seasonality of Max1: MRV with MOM, J=12, K=1

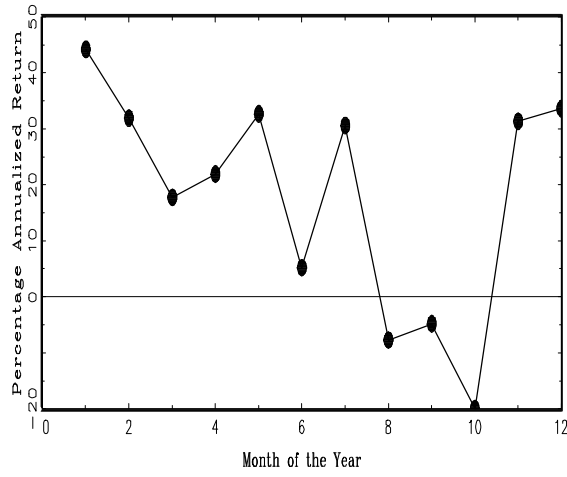


Fig 8(4) Seasonality of Max3: MRV with MOM, J=12, K=1

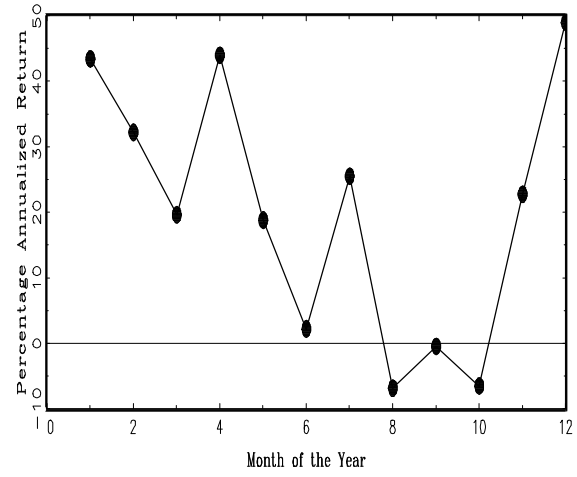


Fig 8(2) Seasonality of Min1: MRV with MOM, J=12, K=1

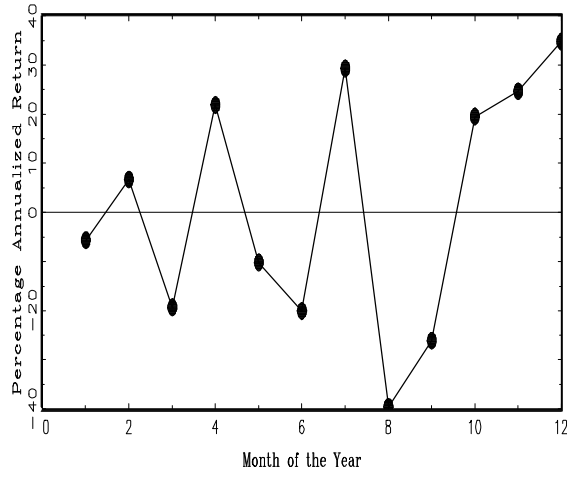


Fig 8(5) Seasonality of Min3: MRV with MOM, J=12, K=1

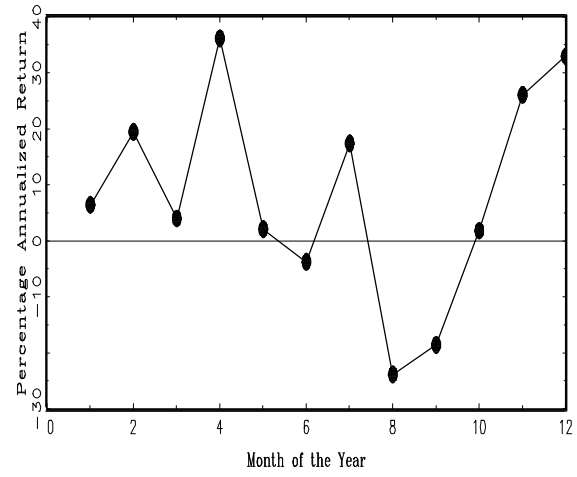


Fig 8(3) Seasonality of Max1-Min1: MRV with MOM, J=12, K=1

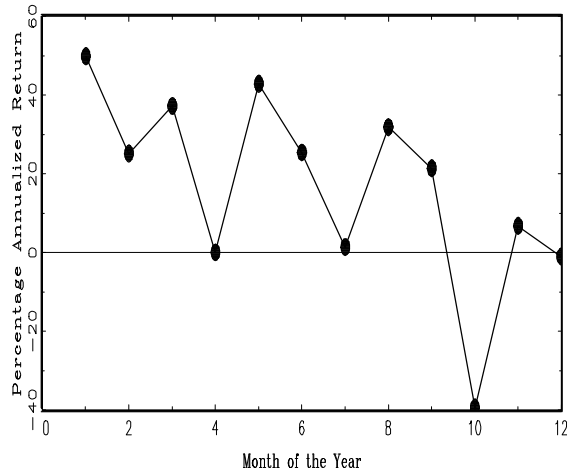


Fig 8(6) Seasonality of Max3-Min3: MRV with MOM, J=12, K=1

