Leading indicator information in UK equity prices: an assessment of economic tracking portfolios

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Abstract

An economic tracking portfolio (ETP) is a portfolio of financial assets whose returns are correlated with some macroeconomic variable of interest. Specifically, an ETP is designed to track revisions to investors' expectations about the target macroeconomic variable. My primary interest is in whether ETPs are a useful tool for conjunctural economic assessment, providing information about expectations of future macroeconomic outcomes. I estimate a set of ETPs using UK equity returns for three target variables: inflation, industrial production growth, and growth in the volume of retail sales. In sample, it is possible to track all three target variables with equity returns. But the out-of-sample results are poor. Although some ETPs retain significant explanatory power, most do not, and in all cases there is a substantial deterioration in the relationship between the ETPs and the target variables. Covariances between equity returns and macroeconomic variables appear to change substantially over time, and the consequent instability in portfolio weights significantly diminishes the usefulness of ETPs for conjunctural analysis.

Summary

Although movements in asset prices often seem to defy rational analysis, they do seem to respond to macroeconomic news in fairly predictable ways—see, for example, recent event studies such as Clare and Courtenay (2000). Clare and Courtenay relate asset prices only to the announcement of the most recent data point. But because equities are claims on cash flows over an indefinite time period, one might expect equity prices to respond to changes in expectations of macroeconomic events some way into the future. The question addressed in this paper is whether equity price movements can be used to infer changes in investors' expectations about particular macroeconomic variables over a variety of time horizons.

The approach taken is based on Lamont (1999), who constructs what he calls 'economic tracking portfolios' (ETPs). The returns on an ETP track how investors revise their expectations about the relevant macroeconomic variable period by period. To understand this relationship, note first that the level of asset prices is likely to incorporate forecasts of future macroeconomic outcomes. For example, equity prices are likely to reflect expectations of future dividends, interest rates and risk premia, all of which may be related to forecasts of a variety of macroeconomic variables. Changes in equity prices should therefore be related to **revisions** to investors' forecasts. An ETP is constructed so that the unexpected portion of the portfolio return has the maximum correlation with revisions to expectations of the target variable. In this paper I construct a set of ETPs using UK data, and assess their usefulness for macroeconomic forecasting.

When assessing the information content of equity prices, ETPs have a number of attractive features:

- One can, in principle, construct a tracking portfolio for any macroeconomic variable of interest over any forecast horizon.

- Previous studies have looked at the relation between capitalisation-weighted equity indices and macroeconomic variables. But it seems likely that the values of the largest companies are more dependent on macroeconomic factors outside the United Kingdom, and should therefore be given less weight than smaller firms' equity. The weights of an ETP are tailor-made to maximise the relationship with the target macroeconomic variable.

- Once the portfolio weights have been estimated, we can study the portfolio's performance at any frequency of interest. In this way, ETPs may provide a more timely indication of the economic state than the lower-frequency economic data on which they are based.

An important aspect of this study is that I focus on the out-of-sample properties of tracking portfolios. Many previous studies have found that, over a long sample, there is a significant relationship between equity prices and various macroeconomic variables. But if one were to use ETPs in real-time conjunctural assessment, what matters is the out-of-sample performance, which in turn depends on the stability of the relationship.

I construct ETPs for three target variables: inflation, industrial production growth, and growth in the volume of retail sales. I present results for forecast horizons of 0, 6, 12 and 24 months. The tracking portfolios are constructed using sectoral equity indices. In sample, practically all of the tracking portfolios are highly significant. But out of sample, the results are poor. There is a marked deterioration in the relationship between the target variables and the ETPs, such that the latter provide virtually no reliable information. This finding is apparent for all forecast horizons, and holds regardless of the frequency with which the portfolios are rebalanced or of the data window over which the weights are estimated.

This analysis suggests, therefore, that ETPs should be treated with some caution. One should certainly not automatically assume that an ETP will prove useful for out-of-sample analysis: a full statistical analysis needs to be conducted on a case-by-case basis to determine whether a given set of base assets can track a particular target variable over a particular horizon. The potential benefits of tapping into information that is not available from any other source need to be weighed against the danger of uncovering spurious relationships, which is a problem with any data-based approach to forecasting.

1 Introduction

Although equity price levels often seem to defy rational explanation, equity prices do change in response to macroeconomic news. For example, Clare and Courtenay (2000) present an event study analysis of the reaction of, *inter alia*, FTSE 100 futures prices to news about a large number of macroeconomic variables. Event studies relate asset price movements only to the announcement of the most recent data point. But because equity prices are the present value of an income stream over a long horizon, one might expect equity prices to respond to changes in expectations of macroeconomic events some way into the future. In this paper I address the question of whether equity price movements can be used to infer changes in investors' expectations about macroeconomic variables over a variety of time horizons, and so provide leading indicator information about macroeconomic outcomes.

The vehicle for this analysis is the 'economic tracking portfolio' (ETP) developed by Lamont (1999). An ETP is a portfolio of financial assets, the returns on which may be informative about future macroeconomic outcomes. Although financial asset returns have been used as leading indicators in the past, ETPs have the advantage that their returns have an economic interpretation: the unexpected ETP returns track how investors revise their expectations about the relevant macroeconomic variable period by period. To understand this relationship, note first that the level of asset prices is likely to incorporate forecasts of future macroeconomic outcomes. For example, if equities are priced according to the standard present-value formula, the current price incorporates expectations of future dividends, interest rates and risk premia. All three of these are likely to be related to forecasts of macroeconomic variables. Empirically, returns arise predominantly from unexpected price changes;(1) so returns must reflect revisions to investors' forecasts. This is genuinely new information, not available even in *ex post* historical macroeconomic data. An ETP is constructed so that its unexpected returns have the maximum correlation with revisions to expectations of the target variable of any possible combination of the assets from which the portfolio is formed. In this paper I construct a set of ETPs for UK data, and assess their usefulness for macroeconomic forecasting.

Previous work has put ETPs to a number of uses. Lamont (1999) uses ETPs to measure risk premia associated with particular macroeconomic variables, to estimate portfolio betas and to explain movements in bond prices. Lamont (1999) and Perez-Quiros and Timmermann (1998) use ETPs to investigate cyclical patterns in small-firm stock returns. For example, an ETP for output is used as an instrument for the unobservable changes in output expectations over the business cycle. My concentration on the leading indicator properties of ETPs leads me to focus more on the out-of-sample rather than the in-sample properties of these portfolios. This is important because although other studies have found significant roles for equity returns in forecasting macroeconomic variables (see Section 2 below), the out-of-sample properties of such equations are rarely tested, and it is the latter that are important for real-time economic assessment.

(1) In other words, regressions of financial asset return on lagged information variables have low R^2s. For example, Pesaran and Timmermann (1994) find that an assortment of variables can explain a maximum of 8.2% of the variation in monthly US equity returns.

The remainder of the paper is set out as follows. Past work on the leading indicator properties of equity prices and returns is reviewed in Section 2. The mechanics of the construction of ETPs, and the details of the statistical analysis, are set out in Section 3. Section 4 contains the data and analysis, and I present my conclusions in Section 5.

2 Previous work on leading indicators

Interest in leading indicators dates back at least as far as the work by Mitchell and Burns (1938) and Burns and Mitchell (1946).[2] Equity prices commonly appear in composite leading indices:[3] the US Department of Commerce leading index contains the S&P 500, and until recently the UK Office for National Statistics produced a shorter leading indicator that contained the FTSE All-Share index. But there are exceptions: the UK longer leading index did not contain equity prices, and Stock and Watson's (1989) leading index had no role for equity prices.

A separate strand of literature focuses at the forecasting ability of equity prices and returns. Fama (1990) finds that US equity returns forecast US industrial production growth (IPG). Many lagged equity returns forecast IPG in any one period, and each lagged equity return forecasts IPG for multiple future periods, consistent with equities being long-horizon assets. Canova and De Nicolo (1995) examine the relationship between output growth and equity returns for five different countries—the United States, the United Kingdom, Germany, France and Italy. Equity returns are found to have some leading indicator property for output growth for all countries except the United Kingdom. Canova and De Nicolo surmise that the UK equity market constitutes substantial claims on foreign assets, weakening the link between UK equity returns and UK output. More recently, Andreou, Osborn and Sensier (1998) have documented a number of statistical links between financial variables and real activity. In other relevant work, Barro (1990) finds that changes in equity prices have substantial explanatory power for investment growth, and Estrella and Mishkin (1998) develop a simple model containing just the term spread and the aggregate equity price that they use for out-of-sample prediction of US recessions.

Economic tracking portfolios have several attractive features for a study of the leading indicator properties of equity returns. Previous work on the leading indicator properties of equity prices has used aggregate equity portfolios—usually capitalisation-weighted—to forecast output. But there is no reason to expect capitalisation weights to be appropriate. For example, recalling Canova and De Nicolo's point about the weak forecasting power of UK equity returns for UK output, this link might be strengthened if the weight on large multinational companies is reduced and more weight given to companies with a high business exposure to the United Kingdom. In constructing an ETP, the portfolio weights are chosen to maximise the correlation of the portfolio returns to the target variable, and these weights may differ greatly from capitalisation weights. Indeed, Lamont (1999) finds that the US capitalisation-weighted portfolio accounts for only 32%

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(2) More recent studies of leading indicators include Camba-Mendez, Smith and Weale (1998), Artis, Bladen-Hovell, Osborn, Smith and Zhang (1995a, 1995b), Diebold and Rudebusch (1989, 1991a, 1991b), Kock and Rasche (1988), Lahiri and Moore (1991), Neftci (1979), Samuleson (1987), Stock and Watson (1989, 1992), Zarnowitz and Braun (1992).

(3) A composite leading index is a combination of individual leading indicators.

of the variation in his ETP for US industrial production. Another useful feature of ETPs is that once the portfolio weights have been estimated, the portfolio's performance can be monitored at any frequency of interest. In this way, ETPs may provide a more timely indication of the economic state than the lower-frequency economic data on which they are based.

3 Constructing ETPs

In this section I describe how the ETPs are estimated and their properties tested. But before doing this, it is useful to set out precisely what an ETP is designed to track.

A traditional leading indicator forecasts the level of some variable of interest. In contrast, an economic tracking portfolio is designed to track a shock. ETPs are constructed so that the **unexpected** ETP returns have the maximum correlation with **revisions to expectations** of the target variable. This gives ETPs a degree of interpretability that is absent in standard leading indicators.

Why focus on shocks? Consider Campbell's (1991) expression for the unexpected excess return on equity:

$$e_{t+1} - E_t e_{t+1} = (E_{t+1} - E_t)(\sum_{j=0}^{\infty} r^{j} \Delta d_{t+1+j} - \sum_{j=1}^{\infty} r^{j} r^{f}_{t+1+j} - \sum_{j=0}^{\infty} r^{j} e_{t+1+j}) \quad \textbf{(1)}$$

where e_t is the log excess return on equity, Δd_t is the change in log real dividend, r^f_t is the log real risk-free interest rate and r is a linearisation parameter, which is less than unity. Investors will enjoy a positive unexpected excess return if expected dividend growth is revised upwards, or if expected risk-free real interest rates and/or expected future excess equity returns are revised downwards. Revisions to these components of equity valuation are likely to be related to changes in expectations of macroeconomic variables of interest. That is, if Y_t denotes a vector of macroeconomic state variables, then

$$e_{t+1} - E_t e_{t+1} = f\left[(E_{t+1} - E_t)Y_{t+j}, j = 0,1,...,\infty\right] \quad \textbf{(2)}$$

where $f[.]$ denotes some mapping from revisions in expectations of macroeconomic variables to unexpected changes in equity prices. So when an unexpected equity return is observed, this may contain information on how investors have revised their expectations of the future macroeconomic state.

Note that rational valuation is not necessary for the construction of ETPs. For example, suppose that investors overreact to news. In particular, suppose that if investors revise their expectations of aggregate output upwards, they raise their dividend growth expectations 'too much', and when they revise their expectations of aggregate output downwards, they are 'too pessimistic' about the implications for dividends. Even though equity prices will not be consistent with rational valuation, unexpected equity returns will still be correlated with changes in expected output, and this will be captured by a tracking portfolio for output.

A simple decomposition of the target variable will illustrate which portion is being tracked. For any target variable y_t, the outturn at time $t+k$ can be written as the sum of the previous period's conditional expectation plus a one-period forecast error, e_{t+k}:

$$y_{t+k} = E_{t+k-1} y_{t+k} + e_{t+k} \tag{3}$$

where E_t denotes expectations formed at the end of time t. In the same way, we can rewrite the conditional expectation at $t+k$-1 as the sum of the conditional expectation at $t+k$-2 plus the change in the expectation between the two periods, which gives:

$$y_{t+k} = E_{t+k-2} y_{t+k} + \left(E_{t+k-1} - E_{t+k-2}\right) y_{t+k} + e_{t+k} \tag{4}$$

Backward recursion to time t-1 gives the following expression

$$y_{t+k} = E_{t-1} y_{t+k} + \sum_{j=0}^{k} \left(E_{t+k-j} - E_{t+k-j-1}\right) y_{t+k} \tag{5}$$

(Note that $E_{t+k}\, y_{t+k} = y_{t+k}$). The second term on the right-hand side of **(5)** is the sum of $k+1$ one-period expectations revisions. Since expectations are only revised in the light of news, assume that these are independently and identically distributed (iid) shocks.[4] An ETP for y_{t+k} is designed to track the first of these expectations revisions, ie $\left(E_t - E_{t-1}\right) y_{t+k}$. This component can be seen more clearly if **(5)** is rewritten as

$$y_{t+k} = E_{t-1} y_{t+k} + \left(E_t - E_{t-1}\right) y_{t+k} + x_{t,t+k} \tag{6}$$

where $x_{t,t+k} \equiv \sum_{j=1}^{k} e_{t+j}$ and $e_{t+j} \equiv \left(E_{t+j} - E_{t+j-1}\right) y_{t+k}$

The target variable is now the sum of the conditional expectation at time t-1, the revision to this expectation between t-1 and t, and the sum of k one-period future expectation revisions.

One can think of an ETP in terms of an equation that relates the change in expectations of y_{t+k} between time t-1 and t—the second term in equation **(6)**—to the unexpected returns on a portfolio of assets:

$$\left(E_t - E_{t-1}\right) y_{t+k} = w' \tilde{r}_t + e_t \tag{7}$$

where $\tilde{r}_t$ is a vector of unexpected (log) returns on N base assets, w is a Nx1 vector of portfolio weights, and e_t is a tracking error. The left-hand side of **(7)** is in general unobservable, and

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[4] Although the assumption that news arrival is iid is common, it may be at odds with reality. For example, Jones, Lamont and Lumsdaine (1998) suggest that serially correlated news arrival is a likely explanation for predictability in bond market volatility. However, the covariance matrix correction discussed below should be sufficient to take account of the statistical effects of any serial correlation arising from this source.

consequently—as explained below—the estimation and testing of the ETP weights is conducted in terms of the observable outcome y_{t+k}.

3.1 Estimation of ETP weights

An ETP is a particular kind of 'maximum correlation portfolio' (MCP) (see Breeden, Gibbons and Litzenberger (1989)). An MCP has returns that have the maximum correlation with the target variable of any portfolio of the base assets. Let x_t denote the target variable and r_t denote a vector of returns on N base assets. The objective is to estimate an Nx1 vector of portfolio weights, w, such that $r_t^{MCP} \equiv w' r_t$ is the return on the MCP.

The MCP weights can be estimated using the following simple OLS regression:

$$x_t = w' r_t + u_t \qquad \textbf{(8)}$$

It is a basic property of OLS that the estimated parameter vector $\hat{w}$ maximises the correlation between the fitted values and the left-hand side variable. Since the fitted values of equation **(8)** are exactly the portfolio returns, OLS produces the MCP weights.

An ETP uses unexpected asset returns to track the revision in expectations between periods t and $t+1$ of the target variable k periods ahead. By analogy to the MCP, the aim would be to perform OLS on equation **(7)**. But neither the left-hand side nor right-hand side variables are directly observable. Lamont (1999) derives an alternative regression that can be used to estimate the ETP weights. If equation **(7)** is substituted into equation **(6)**, this gives

$$y_{t+k} = E_{t-1} y_{t+k} + w' \tilde{r}_t + e_t + x_{t,t+k} \qquad \textbf{(9)}$$

Assume now that the expected return on the ith base asset can be written as a linear function of a vector of L control variables Z_t, ie $E_{t-1} r_{it} = b_i' Z_{t-1}$. The vector of unexpected returns on the base assets is then

$$\tilde{r}_t = r_t - b' Z_{t-1} \qquad \textbf{(10)}$$

where b is an LxN matrix. Equation **(10)** can be used to substitute out $\tilde{r}_t$ from equation **(9)**

$$y_{t+k} = E_{t-1} y_{t+k} + w' r_t - w' (b' Z_{t-1}) + e_t + x_{t,t+k} \qquad \textbf{(11)}$$

Lastly, write the projection of the conditional expectation of y_{t+k} on the control variables Z_{t-1} as follows:

$$E_{t-1} y_{t+k} = a' Z_{t-1} + v_{t-1} \qquad \textbf{(12)}$$

where a is Lx1. Substituting equation **(12)** into **(11)** gives

$$y_{t+k} = w' r_t + c' Z_{t-1} + e_{t,t+k} \qquad \textbf{(13)}$$

where $e_{t,t+k} \equiv v_{t-1} + e_t + x_{t,t+k}$

$$c' \equiv a' - w' b'$$

OLS applied to equation **(13)** produces the ETP weights as the parameter vector applied to the base asset returns r_t. The unexpected ETP returns are obtained by attaching the estimated weights from **(13)**, $\hat{w}$, to the vector of unexpected base asset returns from equation **(10)**.

The fact that the coefficient vector w in equation **(13)** will be the same as those on unexpected returns in equation **(7)** can be explained as follows. A property of OLS is that if y is regressed on x and z, the OLS parameter on x will be the same as the slope coefficient in the last of the three following regressions:

- regress y on z to obtain the residuals $\tilde{y}$
- regress x on z to obtain the residuals $\tilde{x}$
- regress $\tilde{y}$ on $\tilde{x}$

Because the control variables Z_{t-1} measure expected returns, the coefficients on the actual returns in equation **(13)** will be the same as if the unexpected returns were included while the control variables were excluded (as in equation **(7)**). (The reason for including the control variables separately is that if $E_{t-1}y_{t+k}$ is correlated with Z_{t-1}, the error variance in equation **(13)** will be reduced, leading to more precise estimates of the ETP weights.)

Given that regression **(13)** is equivalent to regressing y_{t+k} on $\tilde{r}_t$, it might not be immediately apparent that in estimating w only the correlation between $\tilde{r}_t$ and $(E_t-E_{t-1})y_{t+k}$, is being picked up, as equation **(7)** requires. But if investors' expectations are efficient, so that the expectation formed at time t-1 uses all known relevant information, $\tilde{r}_t$ must be orthogonal to all other components of y_{t+k}. The unexpected return between t-1 and t cannot be correlated with $E_{t-1}y_{t+k}$; neither can it be correlated with shocks to investors' expectations from t+1 onwards. Thus any correlation between y_{t+k} and $\tilde{r}_t$ can only arise because $\tilde{r}_t$ is tracking $(E_t-E_{t-1})y_{t+k}$.

3.2 Statistical inference

The regression error in **(13)** is the sum of three components: the ETP tracking error, e_t, from equation **(7)**; the k-step-ahead forecast error for y_{t+k}, $x_{t,t+k}$, from equation **(6)**; and the error between the time t-1 expectation of y_{t+k} and the projection using only the control variables, v_{t-1}. Although e_t is iid, it is likely that v_{t-1} will be serially correlated (since the control variables are chosen simply to forecast equity returns, they are likely to omit variables relevant to forecasting y_{t+k}). Also, a k-step-ahead forecast error such as $x_{t,t+k}$ gives rise to a moving average error of order k-1.

Although regression **(13)** is not interesting *per se*, it can be used for statistical inference on the portfolio weights. In particular, the joint significance of the portfolio weights is tested using a

Wald test with a Newey-West covariance matrix and a truncation lag of 24, which should be sufficient to account for the degree of serial correlation in these regressions.(5)

4 Data and results

All data are monthly, and the largest usable sample period after data transformations runs from February 1965 to February 2000 (421 observations). A full description of the data is given in the data appendix. I construct ETPs for three target variables: inflation, industrial production growth (IPG), and growth in the volume of retail sales (RSVG). All three variables are measured as annual percentage changes.

In constructing ETPs, one needs to choose the forecast horizon k. For each target variable I have estimated ETPs with k ranging from 0 to 24 months. For brevity, I only report results for k=0, 6, 12 and 24.

The choice of base assets presents a trade-off between explanatory power and the danger of overfitting. On the one hand, it seems sensible to choose a large number of base assets, as the resultant portfolio is likely to pick up a variety of sources of information about shocks to the target macroeconomic variable. In freely choosing a large number of portfolio weights, the data are given the best opportunity of revealing their information content. The flip-side is that one is more likely to uncover spurious relationships, with the consequence of poor out-of-sample performance. I therefore use two different sets of base assets. The first comprises 8 broad industry-based equity portfolios: the second set consists of 29 industry-based portfolios, which are a disaggregation of the first set.(6) In both cases I add the aggregate market index (which is not an exact linear combination of the industry portfolios), giving 9 and 30 base assets respectively. However, for brevity I present detailed estimates only for the smaller number of base assets. I use one-month log excess returns, where, in the absence of a one-month rate, the 3-month Treasury Bill yield is used as a proxy for the ‘risk-free’ interest rate. Excess returns measure the return on a zero-cost portfolio, with the long equity position being exactly offset by a short position in the risk-free asset. Since each ETP is a combination of zero-cost portfolios, no constraints need be put on the portfolio weights.

Control variables are needed to proxy for expected asset returns. I use four control variables (chosen on the basis of previous studies of expected equity returns):(7) the dividend yield on the total equity market; the three-month Treasury Bill yield; the change in the three-month Treasury Bill yield; and the yield on a consol. However, there is no consensus on which variables are best

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(5) In fact, the qualitative findings are unaffected when the truncation lag is varied between 12 and 24.

(6) The portfolios are taken from Datastream, and are the capitalisation-weighted Level 3 and Level 4 portfolios. Not all the Level 3 and Level 4 portfolios span the full sample period. For example, because utility companies were nationalised until the mid 1980s, the Datastream utilities index is reported only from December 1986. Because I want to use the longest possible sample period for the statistical tests, portfolios that do not span the full sample period are omitted from the set of base assets.

(7) See, *inter alia*, Campbell (1987), Fama and French (1988), Pesaran and Timmermann (1994), and Clare, Thomas and Wickens (1994).

able to capture time variation in expected equity returns, and so I also study the sensitivity of the ETP estimates to the choice of control variables.

4.1 Full-sample estimates

Table 1 shows summary statistics for ETPs for each of the three target variables estimated over the full sample using nine base assets. The estimated portfolio weights are presented together with two Wald statistics: ‘Wald 1’ tests the null hypothesis that the ETP weights are jointly zero while ‘Wald 2’ tests the hypothesis that all portfolio weights are zero except for that on the market return. The latter test therefore addresses the question of whether allowing the portfolio weights to differ from those of the market portfolio adds anything to the explanatory power of equity returns. The table also shows the mean of the ETP returns, which measures the *ex post* risk premium earned by the portfolios, together with the standard deviation of the ETP returns.

With the exception of contemporaneous inflation (k=0), the Wald 1 statistics indicate that the tracking portfolios are significant for all three target variables for all horizons at the 10% level of significance. At the 5% level, the one-year-ahead inflation portfolio and the two-year-ahead portfolio for IPG are insignificant. The Wald 2 statistics indicate that, with only one exception (IPG with k=12), the eight sectoral indices add significantly to the tracking portfolios’ explanatory power. In other words, there is some benefit to be had (in terms of explanatory power) from allowing portfolio weights to deviate from the capitalisation weights of the market portfolio.

Table 2 shows the same statistics for the case when no control variables are included in the ETP regression. The results are very similar to those reported by Lamont (1999) for US data. For one variable, industrial production growth, the omission of the control variables has a marked effect on the viability of ETPs, which generally become insignificant. But the omission of control variable has little impact on the significance of the ETPs for the other two variables (although a comparison of the Wald 2 statistics suggests that there is less evidence in support of allowing a deviation from capitalisation weights). That said, a comparison of Tables 1 and 2 indicates that the estimated portfolio weights may be substantially affected, not only in terms of their size but in some instances their sign. For example, the weight on the market portfolio of the inflation ETP for k=0 changes from 0.72 to -0.02 when the controls are omitted. So although the pattern of significance may be fairly insensitive to the choice of controls, it is possible that the tracking portfolios themselves are very different. Table 3 shows the correlation between the unexpected ETP returns including and excluding the control variables. In general, the correlation is around 0.9, suggesting a fairly high correspondence between the two. But for k=0, 6 and 12, the correlation between the two portfolios for inflation is closer to 0.5. The implication is that the choice of control variables potentially has a significant impact on the estimated portfolios. This may be problematic, given the arbitrariness of the choice of controls.

Table 1: Full sample estimates

k=	0	6	12	24
Inflation				
Portfolio weights				
Market	0.72	0.51	0.14	-0.50
Resources	-0.11	-0.01	0.04	0.13
Basic industries	-0.03	-0.02	-0.04	0.27
General industrials	0.04	-0.04	0.01	0.09
Cyc cons goods	-0.01	0.00	0.04	-0.10
Non-cyc cons goods	-0.19	-0.21	-0.18	-0.06
Cyc services	-0.16	-0.17	-0.12	0.03
Non-cyc services	-0.05	0.00	0.02	0.02
Financials	-0.21	-0.10	-0.01	0.09
Wald 1	13.48	18.97	15.58	17.13
p-value	0.14	0.03	0.08	0.05
Wald 2	13.46	17.70	13.34	17.13
p-value	0.10	0.02	0.10	0.03
Mean return (% per month)	-1.38	-1.12	-3.99	-5.94
Standard deviation	54.49	66.11	76.15	96.23
Industrial production growth				
Portfolio weights				
Market	-0.28	-0.09	-0.33	0.44
Resources	0.12	0.09	0.05	-0.09
Basic industries	0.00	0.11	0.13	-0.02
General industrials	-0.06	-0.14	0.07	-0.18
Cyc cons goods	0.03	0.06	-0.06	0.09
Non-cyc cons goods	-0.01	0.01	0.19	-0.08
Cyc services	0.15	0.04	-0.03	0.03
Non-cyc services	0.02	0.06	0.07	-0.07
Financials	0.02	-0.16	0.06	-0.10
Wald 1	16.63	37.53	25.43	14.75
p-value	0.05	0.00	0.00	0.10
Wald 2	16.59	33.48	10.05	14.13
p-value	0.30	0.00	0.26	0.08
Mean return (% per month)	0.03	-2.31	9.50	-4.65
Standard deviation	51.53	83.44	96.28	74.31
Retail sales volume growth				
Portfolio weights				
Market	0.23	-0.66	-0.12	0.49
Resources	0.00	0.11	-0.03	-0.07
Basic industries	0.05	0.07	0.08	-0.16
General industrials	-0.12	-0.03	0.01	-0.10
Cyc cons goods	-0.02	-0.01	-0.07	0.03
Non-cyc cons goods	-0.11	0.08	-0.01	-0.08
Cyc services	-0.03	0.17	0.14	0.09
Non-cyc services	0.01	0.10	0.00	-0.06
Financials	0.01	0.15	0.08	-0.12
Wald 1	34.32	22.45	42.79	15.11
p-value	0.00	0.01	0.00	0.09
Wald 2	22.56	21.45	24.60	14.75
p-value	0.00	0.01	0.00	0.06
Mean return (% per month)	2.24	2.10	3.44	1.96
Standard deviation	48.90	52.10	71.54	59.15

Table 2: Full sample estimates, no control variables

k=	0	6	12	24
Inflation				
Portfolio weights				
Market	-0.02	0.35	-0.49	-0.72
Resources	0.00	0.00	0.15	0.16
Basic industries	0.07	-0.02	0.07	0.31
General industrials	0.17	0.09	0.18	0.18
Cyc cons goods	-0.07	-0.05	-0.01	-0.13
Non-cyc cons goods	0.15	-0.02	0.02	-0.03
Cyc services	-0.03	-0.11	-0.03	0.13
Non-cyc services	-0.08	-0.03	0.01	-0.03
Financials	-0.16	-0.21	0.00	0.05
Wald 1	14.88	16.30	16.48	21.47
p-value	0.09	0.06	0.25	0.01
Wald 2	12.56	12.43	11.27	21.46
p-value	0.13	0.13	0.19	0.01
Mean return (% per month)	-3.01	0.02	-6.81	-12.63
Standard deviation	87.52	67.62	89.87	128.83
Industrial production growth				
Portfolio weights				
Market	-0.05	0.00	-0.26	0.22
Resources	0.08	0.06	0.02	-0.04
Basic industries	0.00	0.13	0.13	-0.05
General industrials	-0.09	-0.18	0.05	-0.13
Cyc cons goods	0.04	0.07	-0.05	0.10
Non-cyc cons goods	-0.11	-0.09	0.09	0.00
Cyc services	0.14	0.08	0.03	0.05
Non-cyc services	-0.01	0.01	0.01	-0.03
Financials	-0.02	-0.15	0.09	-0.05
Wald 1	11.53	25.38	9.03	11.03
p-value	0.24	0.00	0.43	0.27
Wald 2	10.31	23.24	6.91	7.50
p-value	0.24	0.00	0.55	0.48
Mean return (% per month)	-4.01	-8.88	3.57	0.47
Standard deviation	62.72	96.86	70.28	74.74
Retail sales volume growth				
Portfolio weights				
Market	0.48	-0.63	0.03	0.48
Resources	-0.04	0.10	-0.06	-0.07
Basic industries	0.03	0.08	0.06	-0.17
General industrials	-0.16	-0.06	-0.03	-0.10
Cyc cons goods	-0.01	0.01	-0.05	0.04
Non-cyc cons goods	-0.21	0.02	-0.09	-0.08
Cyc services	-0.06	0.18	0.15	0.09
Non-cyc services	0.00	0.08	-0.02	-0.05
Financials	-0.03	0.19	0.08	-0.10
Wald 1	59.05	39.05	31.80	16.53
p-value	0.00	0.00	0.00	0.06
Wald 2	44.96	38.07	21.95	15.72
p-value	0.00	0.00	0.01	0.05
Mean return (% per month)	0.79	-0.26	1.22	2.64
Standard deviation	61.58	58.63	71.28	62.07

Table 3: Correlation between ETPs including and excluding control variables

k=	0	6	12	24
Inflation	0.44	0.50	0.66	0.92
Industrial production growth	0.88	0.90	0.91	0.89
Retail sales volume growth	0.93	0.93	0.95	0.99

Full-sample results using the 30 base assets (not reported) are qualitatively very similar to those using 9 base assets, except that the ETPs are highly significant without exception, and there is even stronger support for allowing the portfolio weights to deviate from those of the market portfolio. This increased ability to track the target variables is not surprising, since the models with 30 base assets are to a large extent unrestricted versions of the models with 9 base assets, giving more scope for the equity price data to pick up variation in the target variables.

4.2 Out-of-sample forecasts

The fact that the in-sample ETPs generally explain a significant proportion of variation in the target variable may support their use as latent variable proxies, ie as an empirical measure of an unobservable expectations variable. But ETPs would be most useful for conjunctural policy analysis if they perform well in out-of-sample forecast tests. Ideally, one would like to monitor ETP returns on a frequent basis to see what the recent performance of the base assets implies for investors' expectations about future values of the target variable. For example, one might be interested in whether investors have revised their expectations of future industrial production growth upwards or downwards in response to some macroeconomic shock. To do this, one needs to be confident that the ETP weights estimated using currently available data are stable enough to track a significant portion of expectations revisions to future values of the target variables. This aim raises two further issues: how much past data should be used to estimate the ETP weights?; and how often do the weights need to be re-estimated, ie how often should the portfolio be rebalanced? This section addresses these questions.

With regard to the appropriate estimation window, finance practitioners commonly use the previous 60 months of data to estimate covariances. But Lamont (1999) suggests that this period may not be long enough to capture covariances across business cycles. He finds that using 20 years of past data is generally a more successful way of tracking variables out of sample. Let m denote the sample window used to estimate the ETP weights. I examine the out-of-sample performance of each ETP using m=60, 120, 180 and 240 months.

The issue of portfolio rebalancing is related to the explanatory power/overfitting trade-off. On the one hand, if the 'true' portfolio weights are highly variable, frequent rebalancing will pick this up. On the other hand, if the 'true' weights are fairly stable, frequent re-estimation may simply maximise the sensitivity of the weights to random variation in the data, with correspondingly poor out-of-sample performance. I present results for both monthly and quarterly portfolio rebalancing. The tests are conducted as follows. At the end of month t, the portfolio weights are estimated from equation **(13)** using m past observations of the target variables, controls and base asset returns. Denote the resultant weight estimates $\hat{w}_t$. In the case of monthly rebalancing, the weights estimated at time t are used to construct the ETP returns at

t+1, ie $r_{t+1}^{ETP} = \hat{w}_t \, r_{t+1}$. This process is repeated at t+1, t+2 and so on, producing a time series of ETP returns with monthly rebalancing.(8) To test the stability of the portfolio weights, the time series of ETP returns is used as a dependent variable in the following regression:

$$y_{t+k} = g r_t^{ETP} + d Z_{t-1}^{*} + h_{t,t+k} \qquad \textbf{(14)}$$

where $Z_{t-1}^{*} \equiv \hat{c}' Z_{t-1}$, and c is estimated using the same estimation window and the same re-estimation frequency and the portfolio weights. Each regression of the form in equation **(14)** is run over the same sample period, namely January 1985 to February 2000, so that a direct comparison can be made between different estimation windows for the ETP weights.(9)

If there were no deterioration in the ETP's performance out of sample then $\hat{g}$ should be close to unity. At the other extreme, if the ETP's explanatory power deteriorated fully out of sample then $\hat{g}$ will be close to zero. More generally, errors in the parameter estimation, and the possibility that the estimation procedure fails to pick up some variation in the true ETP weights means one may be content to use ETPs out of sample as long as g is significantly positive. The shortfall of g from unity could then be used to adjust the ETP forecasts to take account of the deterioration in out-of-sample performance.

Table 4 presents the estimates of g along with marginal probability values for the hypotheses that g=1 and g=0. Overall, the out-of-sample performance of the ETPs is poor. Looking first at the results with monthly portfolio rebalancing, the point estimates of g are generally low, rarely exceeding 0.3, and are significantly less than unity with only two exceptions (IPF with k=6 and RSVG with k=24). In fact, many of the point estimates are negative, indicating that these portfolios on average in the wrong direction out of sample. Of those portfolios producing a positive value for g, a number are significantly positive. But the overarching impression is that the ETPs are unlikely to be much use for out-of-sample forecasting. Table 4 also shows that there is little qualitative difference between the results from the portfolios rebalanced every month and those rebalanced on a quarterly basis.(10) Nor is there any perceivable benefit to lengthening the estimation window for the portfolio weights.

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(8) With quarterly rebalancing, the weights estimated at time t are applied to returns in periods t+1, t+2 and t+3. Data up to t+3 are then used to estimate weights for t+4, t+5 and t+6, and so on.

(9) Note that although this is the longest sample period afforded by the availability of UK data, Lamont (1999) is able to perform his analysis over a longer period using data for the United States, and obtains more positive out-of-sample results.

(10) The out-of-sample results using 30 base assets are, if anything, worse, suggesting that the stronger in-sample performance of using the greater number of base assets is the result of overfitting.

Table 4: Out-of-sample estimates

		Monthly rebalancing				Quarterly rebalancing			
	m=	60	120	180	240	60	120	180	240
k=0	**Inflation**								
	g	0.093	0.254	0.072	-0.094	0.052	0.240	-0.023	-0.189
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.313	0.024	0.361	0.379	0.393	0.047	0.454	0.278
	Industrial production growth								
	g	0.319	-0.007	-0.020	-0.126	0.287	-0.019	0.014	-0.106
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.031	0.478	0.439	0.261	0.080	0.440	0.458	0.305
	Retail sales volume growth								
	g	0.174	0.025	0.249	0.151	0.105	-0.024	0.215	0.088
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.191	0.440	0.096	0.263	0.291	0.446	0.165	0.363
k=6	**Inflation**								
	g	-0.004	0.328	0.134	-0.047	0.015	0.317	0.118	-0.033
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.494	0.000	0.173	0.409	0.473	0.000	0.190	0.437
	Industrial production growth								
	g	0.513	0.085	0.258	-0.047	0.223	0.016	0.181	-0.056
	p-val(1)	0.040	0.000	0.001	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.032	0.257	0.133	0.422	0.062	0.456	0.181	0.411
	Retail sales volume growth								
	g	0.303	0.113	0.301	-0.118	0.255	0.060	0.262	-0.174
	p-val(1)	0.000	0.000	0.005	0.008	0.000	0.000	0.009	0.000
	p-val(0)	0.048	0.306	0.130	0.398	0.112	0.411	0.201	0.163
k=12	**Inflation**								
	g	0.019	0.157	0.201	0.102	0.114	0.165	0.179	0.096
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.438	0.070	0.034	0.256	0.206	0.092	0.067	0.285
	Industrial production growth								
	g	-0.523	0.017	0.061	-0.136	-0.431	0.070	0.054	-0.129
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.000	0.448	0.379	0.112	0.004	0.304	0.394	0.123
	Retail sales volume growth								
	g	0.235	0.009	0.092	-0.037	0.156	0.053	0.061	-0.015
	p-val(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p-val(0)	0.110	0.477	0.299	0.431	0.174	0.370	0.362	0.473
k=24	**Inflation**								
	g	0.036	0.155	0.452	0.695	-0.048	0.170	0.449	0.694
	p-val(1)	0.000	0.000	0.000	0.085	0.000	0.000	0.000	0.091
	p-val(0)	0.343	0.068	0.000	0.001	0.328	0.075	0.000	0.001
	Industrial production growth								
	g	-0.201	-0.072	0.364	0.242	-0.146	0.003	0.401	0.198
	p-val(1)	0.000	0.000	0.019	0.000	0.000	0.000	0.029	0.000
	p-val(0)	0.083	0.265	0.118	0.138	0.145	0.491	0.101	0.199
	Retail sales volume growth								
	g	-0.183	-0.250	0.341	0.605	-0.184	-0.367	0.360	0.597
	p-val(1)	0.000	0.000	0.017	0.162	0.000	0.000	0.015	0.156
	p-val(0)	0.156	0.362	0.137	0.066	0.118	0.044	0.110	0.067

Table 5: Out-of-sample estimates using a restricted number of base assets, monthly rebalancing

	m=	60	120	180	240
k=0	**Inflation**				
	g	-0.062	0.084	0.080	-0.087
	p-val(1)	0.000	0.000	0.000	0.000
	p-val(0)	0.341	0.339	0.367	0.374
	Industrial production growth				
	g	0.012	-0.224	0.018	0.159
	p-val(1)	0.000	0.002	0.001	0.002
	p-val(0)	0.483	0.300	0.477	0.290
	Retail sales volume growth				
	g	0.270	0.082	-0.280	-0.480
	p-val(1)	0.029	0.001	0.000	0.003
	p-val(0)	0.241	0.390	0.146	0.184
k=6	**Inflation**				
	g	0.254	0.018	-0.326	-0.409
	p-val(1)	0.002	0.000	0.000	0.000
	p-val(0)	0.155	0.456	0.071	0.033
	Industrial production growth				
	g	0.321	-0.139	-0.064	0.013
	p-val(1)	0.023	0.000	0.000	0.000
	p-val(0)	0.171	0.217	0.358	0.477
	Retail sales volume growth				
	g	0.307	-0.060	-0.054	-0.001
	p-val(1)	0.000	0.000	0.000	0.005
	p-val(0)	0.043	0.407	0.426	0.499
k=12	**Inflation**				
	g	0.055	0.140	-0.036	-0.033
	p-val(1)	0.000	0.000	0.000	0.000
	p-val(0)	0.362	0.039	0.433	0.450
	Industrial production growth				
	g	-0.003	0.273	0.318	0.232
	p-val(1)	0.008	0.001	0.001	0.000
	p-val(0)	0.497	0.110	0.069	0.113
	Retail sales volume growth				
	g	0.352	0.019	0.131	0.100
	p-val(1)	0.004	0.000	0.000	0.000
	p-val(0)	0.073	0.443	0.294	0.347
k=24	**Inflation**				
	g	-0.071	-0.374	-0.009	-0.539
	p-val(1)	0.000	0.000	0.001	0.000
	p-val(0)	0.288	0.019	0.489	0.057
	Industrial production growth				
	g	-0.239	-0.293	0.064	0.121
	p-val(1)	0.000	0.000	0.001	0.002
	p-val(0)	0.218	0.154	0.417	0.344
	Retail sales volume growth				
	g	-0.168	-0.426	0.075	0.497
	p-val(1)	0.000	0.000	0.021	0.152
	p-val(0)	0.292	0.122	0.434	0.155

Note: Inflation portfolio includes market, resources, basic industries, general industrials, cyclical consumer goods and cyclical services indices. IPG portfolio includes market, resources, basic industries and general industrials indices. RSVG portfolio includes market, cyclical consumer goods, non-cyclical consumer goods, cyclical services and non-cyclical services indices.

One potential remedy for the poor out-of-sample performance of many of the ETPs is to reduce the number of base assets used to construct them. Although irrelevant information will be given a weight of zero on average—suggesting that nothing is lost by including more base assets—in practice, in any given sample, it may be more efficacious to reduce the set of base assets on *a priori* grounds. Table 5 presents the out-of-sample estimates of g and the corresponding test statistics when the set of base assets is restricted. Specifically, I have excluded the non-cyclical and financial indices from the set of base assets for the inflation ETP, leaving seven base assets; the ETP for industrial production growth includes just four indices—the market, resources, basic industries and general industrials; and the portfolio for retail sales growth is made up from five indices—the market, cyclical and non-cyclical consumer goods, and cyclical and non-cyclical services. The results in Table 5 indicate that there is no improvement in out-of-sample performance when the number of base assets is restricted in this way. The point estimates of g are of a similar range to those with a full set of base assets, although even fewer are significantly positive.

5 Conclusions

In this paper I present evidence of the in-sample and out-of-sample performance of ETPs constructed using UK equity returns data. In estimating the portfolio weights, ETPs give the returns data a better opportunity of displaying leading indicator properties than traditional capitalisation weights. The latter may be particularly unsuitable for economies whose equity market value is heavily weighted towards a small number of large multinational companies, such as the United Kingdom.

In sample, it is possible to construct ETPs that track a significant proportion of variation in all of the target variables. This suggests that ETPs may provide useful proxy measures for latent expectations variables in econometric models. But the out-of-sample performance is poor. There is significant deterioration in the relationship between the target variables and the ETPs for all horizons and estimation windows. Although some evidence of significant relationships remains, there is no clear pattern to this. The incipient instability in the portfolio weights is not overcome by less frequent portfolio rebalancing, nor by restricting the set of base assets on *a priori* grounds.

Any data-based approach to forecasting raises the danger of overfitting, and ETPs appear to be a case in point. More structural approaches to analysing asset price movements, which attempt a more direct mapping of asset price ‘fundamentals’ into macroeconomic variables, may prove to be more successful.

Data appendix

All data are monthly. The longest sample period after data transformations runs from February 1965 to December 1998.
Excess equity returns measured as change in log returns index minus log of (one plus) three-month Treasury Bill yield (re-scaled to a one-month rate).

Base assets

The main results reported in the paper are derived using the Datastream total market index plus Datastream Level 3 industry indices, namely resources, basic industries, general industrials, cyclical consumer goods, non-cyclical consumer goods, cyclical services, non-cyclical services and financials.

Results using 30 base assets replace the Datastream Level 3 industry indices with the Level 4 indices, namely extractive industries, oil integrated, construction, building materials and merchants, chemicals, diversified industrials, electronics and engineering, engineering, engineering vehicle components, paper and printing, alcoholic beverages, food producers, household goods and textiles, healthcare, pharmaceuticals, tobacco, distributors, leisure and hotels, media, food retailers, general retailers, telecommunications, breweries, pubs and restaurants, support services, transport, retail banks, insurance, life assurance, other financial, property and investment trusts.

Target variables

Target variables are measured as twelve-month log changes in respective indices.

Controls

Control variables are measured in logs, and comprise the Datastream total market index dividend yield, the three-month Treasury Bill yield, the change in the three-month Treasury Bill yield and the yield on a government consol.

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