ELSEVIER

Journal of Econometrics 105 (2001) 161–184

JOURNAL OF
Econometrics

www.elsevier.com/locate/econbase

Economic tracking portfolios

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Abstract

An economic tracking portfolio is a portfolio of assets with returns that track an economic variable. Monthly returns on stocks and bonds help forecast post-war US output, consumption, labor income, inflation, stock returns, bond returns, and Treasury bill returns. These forecasting relationships define portfolios that track market expectations about future economic variables. Out-of-sample results show that tracking portfolios, despite forecast deterioration, can be useful in forecasting macroeconomic variables. © 2001 Elsevier Science S.A. All rights reserved.

JEL classification: E17; E44; G11

Keywords: Forecasting; Factor models; Economic news; Portfolio theory

Changes in asset prices reflect, among other things, changing information about future economic conditions. Identifying the impact of different macroeconomic shocks on asset prices can reveal sources of economic fluctuations, measure risk premia, and help predict future economic fluctuations. Economic tracking portfolios connect asset prices with news about economic variables. An economic tracking portfolio is a portfolio of assets whose returns track an economic variable, such as expected output, inflation, or returns. The portfolios constructed here have unexpected returns with maximum correlation with news about future macroeconomic variables.

Empirical finance has a long tradition of explaining current returns with other current returns. A second tradition is to try to explain returns with

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PII: S0304-4076(01)00074-4

contemporaneous economic variables, or with future economic variables, or with both. Economic tracking portfolios represent a middle ground between these two alternatives. On the one hand, tracking portfolios are asset returns. On the other hand, they are returns with an interpretable economic content.

This paper builds on Breeden et al. (1989). They construct economic tracking portfolios (which they call "maximum correlation portfolios") for current consumption, in order to test the Consumption Capital Asset Pricing Model (CCAPM). This paper has several differences. First, and most importantly, it constructs tracking portfolios for future (not current) economic variables, since asset returns reflect information about future cash flows and discount rates. Second, as a consequence, it uses only the unexpected component of returns (not total returns) in constructing the tracking portfolios. Last, it constructs tracking portfolios for a variety of economic variables (not just consumption).

Tracking portfolios have several uses. One use is measuring risk premia. If tracking portfolios earn risk premia, then the signs of the risk premia and the identities of the premia-generating economic variables can reveal which state variables are important determinants of expected returns, and can help evaluate asset-pricing models. Tracking portfolios have (at least) two other uses that do not rely on the portfolios earning non-zero risk premia.

First, tracking portfolios can serve as hedging tools for individuals who wish to insure themselves against a particular economic risk. For example, individuals who wish to insure against inflation could take a position in the inflation tracking portfolio. Second, tracking portfolios forecast economic variables. Since asset returns are available on a daily basis, tracking portfolios can provide daily information about the market's expectations about future economic variables.

These uses are empirically testable, and do not depend on a particular asset pricing model. For example, suppose the CAPM is true. In that case, an economic tracking portfolio would have an expected return that is a linear function of covariance with the market, but its unexpected return would still reveal news about future economic variables. Alternatively, suppose that asset markets are inefficient, irrational sentiment affects market prices, and returns are partially predictable. In this case, as long as asset prices reflect *some* information about future economic variables, tracking portfolio returns will still be useful for hedging and forecasting.

This paper is organized as follows. Section 1 defines tracking portfolios, states their statistical properties, and introduces the notation. Section 2 discusses the relation of tracking portfolios to previous research. Section 3 describes the data. Section 4 shows the properties of the estimated tracking portfolios. Section 5 shows the out-of-sample tracking ability of the portfolios, and performs robustness tests. Section 6 summarizing the results and discusses possible applications.

1. Definitions and basic properties

1.1. Simple tracking portfolios

A tracking portfolio for any variable y can be obtained as the fitted value of a regression of y on a set of base asset returns. The portfolio weights for the economic tracking portfolio for y are identical to the coefficients of an OLS regression. If y happens to be a state variable for asset pricing, then a multi-factor model holds with one of the factors being y's tracking portfolio (Breeden, 1979). However, even if y is not a state variable for asset pricing, its tracking portfolio is still an interesting economic object, since it reveals changes in market expectations about y.

The following three statements are equivalent descriptions of an economic tracking portfolio. Out of all possible linear combinations of the base asset returns, the portfolio: (a) has the minimum variance out of all portfolios with a given beta (univariate regression coefficient) in a regression of portfolio return on y; (b) has returns with the maximum possible correlation with y; (c) has the highest R-squared in a univariate regression of y on returns. These properties come directly from the definition of an OLS regression (see Breeden et al., 1989).

1.2. Tracking portfolios for news

This paper constructs portfolios with unexpected returns that are maximally correlated with unexpected components of future y. Specifically, the target variable is "news" about y_{t+k}, where y_{t+k} is a macroeconomic variable such as the inflation rate in period $t+k$. News is innovations in expectations about y_{t+k} with notation $\Delta E_t[y_{t+k}] \equiv E_t[y_{t+k}] - E_{t-1}[y_{t+k}]$. For example, $\Delta E_t[y_{t+k}]$ might be the news that the market learns in July 1980 about the inflation rate between July 1980 and July 1981.

The tracking portfolio returns are $r_{t-1,t} = \mathbf{b}\mathbf{R}_{t-1,t}$, where $\mathbf{R}_{t-1,t}$ is a column vector of asset returns from the end of period $t-1$ to the end of period t and $\mathbf{b}$ is a row vector of portfolio weights. The tracking portfolio is constructed using unexpected returns on the base assets. Unexpected returns are actual returns minus expected returns, with notation $\tilde{\mathbf{R}}_{t-1,t} \equiv \mathbf{R}_{t-1,t} - E_{t-1}[\mathbf{R}_{t-1,t}]$. The portfolio weights are chosen so that $\tilde{r}_{t-1,t}$ is maximally correlated with $\Delta E_t[y_{t+k}]$.

Estimating tracking portfolios for news is only slightly more complicated than estimating simple tracking portfolios. One can always write a projection equation of news on unexpected returns. The key assumption in this paper is that innovations in returns reflect innovations in expectations about future variables, so that the vector $\mathbf{a}$ has non-zero elements in the projection equation:

$$\Delta \mathrm{E}_t[y_{t+k}] = \mathbf{a}\tilde{\mathbf{R}}_{t-1,t} + \eta_t, \tag{1}$$

where η_t is the component of news that is orthogonal to unexpected returns. Since unexpected asset returns reflect news about future cash flows and discount rates, **a** will generally be non-zero for any variable that is correlated with future cash flows and discount rates (there is no intercept in Eq. (1) because both the right- and left-hand side are mean zero expectational errors).

As Eq. (1) is written, it seems as if one needs to obtain $\Delta \mathrm{E}_t[y_{t+k}]$, the period t news, in order to run the regression. Fortunately, this daunting task is not necessary in order to construct a tracking portfolio for news. All that is needed is $\tilde{\mathbf{R}}_{t-1,t}$, unexpected returns.

The realization of y_{t+k} can be written as the sum of the expectation in period $t-1$, the innovation in expectations occurring in period t, and the innovation in expectations from period t to period $t+k$:

$$y_{t+k} = \mathrm{E}_t[y_{t+k}] + \mathrm{e}_{t,t+k} = \mathrm{E}_{t-1}[y_{t+k}] + \Delta \mathrm{E}_t[y_{t+k}] + \mathrm{e}_{t,t+k}. \tag{2}$$

The second assumption made here is that expected returns on the base assets in period t are linear functions of $\mathbf{Z}_{t-1}$, a vector of control variables known at period $t-1$:

$$\mathrm{E}_{t-1}[\mathbf{R}_{t-1,t}] = \mathbf{d}\mathbf{Z}_{t-1}. \tag{3}$$

While the assumption in Eq. (3) is a potential source of model misspecification, one might expect the empirical results to be relatively robust to this form of misspecification, since asset returns are largely unpredictable at short horizons.

Last, for notational convenience, define the projection equation of lagged expectations of y on the lagged control variables:

$$\mathrm{E}_{t-1}[y_{t+k}] = \mathbf{f}\mathbf{Z}_{t-1} + \mu_{t-1}. \tag{4}$$

Combining (1)–(4) results in the representation

$$y_{t+k} = \mathbf{b}\mathbf{R}_{t-1,t} + \mathbf{c}\mathbf{Z}_{t-1} + \varepsilon_{t,t+k}, \tag{5}$$

where $\mathbf{b} = \mathbf{a}$, $\mathbf{c} = \mathbf{f} - \mathbf{a}\mathrm{d}$, and $\varepsilon_{t,t+k} = \eta_t + \mu_{t-1} + \mathrm{e}_{t,t+k}$. Eq. (5) is a regression equation with realized future y on the left-hand side and period t returns and period $t-1$ control variables on the right-hand side. It is consistent because the three components of $\varepsilon_{t,t+k}$ are all by definition orthogonal to both $\mathbf{R}_{t-1,t}$ and $\mathbf{Z}_{t-1}$.

The OLS regression defined by Eq. (5) produces $\mathbf{b}\mathbf{R}_{t-1,t}$, the portfolio return having unexpected components maximally correlated with $\Delta \mathrm{E}_t[y_{t+k}]$. This paper estimates Eq. (5) and examines the properties of the resulting tracking portfolios. Eq. (5) is completely atheoretical and depends only on the assumptions that changes in expectations about future y are reflected in asset returns, and that expected asset returns are a function of the lagged control variables. The approach does not impose any particular model of asset prices or equilibrium economic relationship, unlike (for example) the Fisher equation approach to expected inflation in Fama (1975).

Here I make several comments on empirical implementation of Eq. (5). First, this paper uses zero cost portfolio returns for $\mathbf{R}_{t-1,t}$. Using zero cost portfolios means that there is no need to impose the restriction that the portfolio weights in $\mathbf{b}$ add to anything. The resulting tracking portfolio is zero cost because it is a linear combination of zero cost portfolios. Second, this paper uses monthly returns for the base assets. One should be careful using longer horizons for base assets (such as annual returns), since as horizons lengthen, return predictability rises (see Campbell, 1991), and the estimates might become more sensitive to violations of Eq. (3). Third, one wants to pick base asset returns that are informative about changes in expectations about future y. It is important that the different assets have different sensitivities to future y, so that the regression can pick the linear combination of returns that hedges out common sources of return variation that are unrelated to future y. Fourth, the main reason to include control variables is to model expected returns, so $\mathbf{Z}_{t-1}$ should include variables that forecast base asset returns. If asset returns were completely unpredictable, or if $\mathrm{E}_{t-1}[\mathbf{R}_{t-1,t}]$ were uncorrelated with $\mathrm{E}_{t-1}[y_{t+k}]$, then one would not need any control variables. A secondary role for the lagged control variables in Eq. (5) is to help explain future y. By including variables in $\mathbf{Z}_{t-1}$ that are correlated with $\mathrm{E}_{t-1}[y_{t+k}]$, one can decrease the variance of the residual in Eq. (5), and thus gain more precise estimates of b. Fifth, adding variables to $\mathbf{R}_{t-1,t}$ and $\mathbf{Z}_{t-1}$ is not costless, since more variables raise the problem of overfitting, poor out-of-sample performance, and spurious inferences.

2. Relation to previous research

One use of economic tracking portfolios is to hedge economic risk using existing assets. An alternative approach is to create entirely new assets indexed to economic variables. Shiller (1993), Shiller and Athanasoulis (1995), and Davis and Willen (1998) discuss the creation of these new assets and the resulting welfare gains. Economic tracking portfolios using existing liquid assets should make such financial innovation easier because tracking portfolios help the issuers of new securities partially hedge their exposure to economic risk.

A separate use of tracking portfolios is to estimate return premia associated with different economic risks and to identify sources of return variation.

Unlike Chen et al. (1986), Huberman et al. (1987) and Balduzzi and Robotti (1999), the goal of this paper is neither to estimate risk premia nor to test asset-pricing models with multiple sources of risk.

Rather, the goal of this paper is to use asset returns to learn about the markets' changing expectations of future economic variables and the connection between economic variables and asset prices. Previous research has drawn this connection in three ways: using current economic variables, using future economic variables, and using both via vector autoregression models.

The first approach involves regressing asset returns on contemporaneous economic variables. Examples of this approach include Chen et al. (1986) and numerous papers testing the CCAPM. Chen et al. (1986) find that covariance with industrial production growth, inflation, and bond market returns all lead to risk premia.

Unfortunately, attempts to identify factor mimicking portfolios for macroeconomic variables have been disappointing. Chan et al. (1998) construct portfolios by sorting stocks on monthly contemporaneous correlations over a five-year estimation period. They form portfolios based on inflation and industrial production. After examining these returns, they conclude that the macroeconomic factors are basically noise, and are not distinguishable from randomly generated portfolios.

The second approach involves regressing current returns on future realizations of economic variables. Examples of this approach include Fama (1981, 1990) and Schwert (1990), who seek to evaluate how much of the variance of returns on some test asset is due to news about future economic conditions. A previous version of this paper, Lamont (1999), shows that the economic tracking portfolios can be interpreted as an instrumental variables version of this approach. Using tracking portfolio returns as proxies for expected future economic variables substantially raises the estimated sensitivity of asset prices to news about future economic variables. Like other factors in asset-pricing, tracking portfolios can be used to explain asset returns, in a regression with candidate portfolio asset returns on the left-hand side and tracking portfolio returns on the right-hand side. Unlike less structured factor explanations of asset returns, in this regression the coefficients have an economic interpretation. Using tracking portfolios imposes discipline: asset returns are only allowed to go on the right-hand side of the regression if they contain information about economic variables.

The third approach uses vector autoregressions. Like the first approach, it uses innovations in contemporaneous variables to explain current asset returns. Like the second approach, it is interested in how changes in expectations about future economic variables affect asset returns. It uses the innovations from a vector autoregression (VAR) system to estimate changes in expected future variables, and uses the resulting estimated changes to explain asset returns. The VAR approach (Campbell, 1991, 1996; Campbell and Ammer, 1993; Campbell and Mei, 1993) uses a variety of current economic variables to explain asset returns. It uses both return and non-return forecasting variables (for target variables such as inflation, interest rates, labor income and future returns), and then tests whether innovations in these forecasting variables (from a VAR) are factors in asset returns.[1]

The VAR procedure for detecting loadings on the factors is mediated through a specific dynamic model of all the variables in the system. This requirement introduces a potential source of model misspecification. In contrast, the tracking portfolio approach lets the data choose loadings directly from regressions of future variables on returns, without having to rely on a complete description of the time series process generating the data.[2]

3. Data

3.1. Target variables and horizon

The targets (y_{t+k}) include seven macroeconomic variables suggested by theory and previous empirical work (such as Chen et al., 1986; Campbell and Ammer, 1993; Campbell, 1996; Jagannathan and Wang, 1996; Britten-Jones, 1999). The seven target variables are: industrial production growth, real consumption growth, real labor income growth, inflation, excess stock returns, excess bond returns, and Treasury bill returns.

Industrial production is the change in the log of total production, seasonally adjusted. Consumption is the change in the log of real consumption of services and nondurable goods, seasonally adjusted. Labor income is the change in the log of personal income from wages and salaries, seasonally adjusted, minus CPI inflation. Inflation is the change in the log of the Consumer Price Index, not seasonally adjusted. Excess stock returns are continuously compounded returns on the CRSP value weighted aggregate portfolio minus continuously compounded returns on Treasury bills. Excess bond returns are continuously compounded returns on a portfolio of long-term government bonds minus continuously compounded returns on Treasury bills. Nominal Treasury bill returns are continuously compounded returns on Treasury bills.[3]

[1] Both the VAR approach and this paper assume that the coefficients do not change over time. An alternative would be to allow for conditional coefficients, as in Ferson and Harvey (1991). McQueen and Roley (1993) find that stock price reaction to news depends on the state of the business cycle.

[2] A previous version of this paper, Lamont (1999), shows that VARs and tracking portfolios produce results that are empirically similar.

[3] Industrial production data are from the Federal Reserve, consumption and labor income are from DRI Basic Economics, and CPI and asset return data are from Ibbotson Associates.

I construct tracking portfolios for news about annual changes in variables, using monthly data on the target variables and tracking future 12-month ahead changes in these variables. In the terms of the notation, period t is a month and $k = 12$. For example, future 12-month inflation in month t is the inflation rate from the end of month t to the end of month $t + 12$. The forecasting regressions use monthly control variables and base asset returns from 1947:1 to 1994:12, and target variables from 1947:1 to 1995:12 (except for consumption, which starts in 1959:1).

3.2. Base assets

The 13 base assets, $\mathbf{R}_{t-1,t}$, consist of four bond portfolios, eight industry-sorted stock portfolios, and the market portfolio for the stock market. All asset returns are in excess of the T-bill return. The four bond market portfolios are a portfolio of long-term government bonds, a portfolio of intermediate-term government bonds, a portfolio of one-year government bonds, and a portfolio of low-grade corporate bonds. The eight value weighted industry portfolios consist of all stocks in CRSP sorted by SIC code: basic industries, capital goods, construction, consumer goods, energy, finance, transportation, and utilities. The industry definitions are from Sharpe (1982). Last, the market (RMRF) is the CRSP NYSE/AMEX/NASDAQ value-weighted portfolio.[4]

These 13 portfolio returns are likely to be informative about future economic conditions. Industry portfolios are potentially useful because of obvious variations across industry in cyclicality, and because of evidence (see Boudoukh et al., 1994) that this cyclicality is reflected in stock returns. Bond returns are likely to be useful since bond yields have also been shown to forecast future economic activity (see Stock and Watson, 1989). Last, the aggregate stock market has traditionally been used to forecast aggregate economic changes.

3.3. Control variables

The lagged control variables, $\mathbf{Z}_{t-1}$, include nine variables (plus a constant term). These nine variables are the Treasury bill return, a term premium for long-term government bonds (yield on long bonds minus Treasury bill yield), a term premium for one-year government notes (yield on one-year notes minus Treasury bill yield), a default premium for corporate bonds (BAA yield minus AAA yield), a default premium for commercial paper (commercial paper yield minus Treasury bill yield), the dividend yield on the CRSP value weight aggregate portfolio, and 12-month production growth, CPI inflation, and excess stock returns. It is important to note that the Treasury bill return

[4] The four bond portfolio returns are provided by Ibbotson Associates.

in month t is a control variable, not a base asset, since the Treasury bill return in month t is known as of month $t-1$.[5]

The lagged control variables include the standard variables known to forecast returns on stocks and bonds. As a side effect, these Z's should also help forecast the target variable as well since the same variables that forecast returns also forecast economic activity (that is, $\mathbf{Z}_{t-1}$ is correlated with $\mathrm{E}_{t-1}[y_{t+12}]$).

4. Properties of estimated tracking portfolios

Table 1 shows the forecasting regressions that define the economic tracking portfolios for the seven target variables. Table 1 reports coefficients from OLS regressions of the 12-month ahead macroeconomic variables (from month t to month $t+12$) on returns in month t and lagged variables in month $t-1$. The standard errors have been corrected for the overlapping dependent observations.[6] Since the 13 base assets have returns that are highly collinear, the portfolio weights are not easy to interpret and have no particular meaning. More meaningful are the properties of the tracking portfolios shown in Table 2. Table 2 contains hypothesis tests and summary statistics for the tracking portfolio returns defined by the regressions of Table 1.

4.1. Do the tracking portfolios track their target variables?

A crucial assumption for the use of tracking portfolios, in Eq. (1), is that returns reflect revisions in expectations about the target variable. Panel A of Table 2 reports p-values from tests of whether the returns forecast the target variable (the p-values are simply exclusion tests from the regressions presented in Table 1). The first row of Panel A reports tests of whether all 13 return series jointly forecast the target variables. The p-values reject the null of no forecasting ability, indicating that the returns are useful given the control variables in $\mathbf{Z}_{t-1}$. This result verifies that innovations in returns are correlated with innovations in expectations about future variables, so that it is feasible to track all seven target variables using the base assets.

[5] The long bond yield, one-year yield, and commercial paper yield are provided by Ibbotson Associates. The T-bill yield, BAA yield, and AAA yield are provided by DRI Basic Economics. The dividend yield is constructed using the total and capital gains-only returns on the CRSP value weight aggregate portfolio.

[6] The standard errors are calculated using Newey-West with 24 lags. The exact correction would be Hansen–Hodrick with 12 lags, but this covariance matrix was not convenient to use since it resulted in undefined test statistics for some of the tests performed in this paper.

Table 1

Monthly OLS regressions of the form $y_{t+12} = \mathbf{b}\mathbf{R}_{t-1,t} + \mathbf{c}\mathbf{Z}_{t-1} + \varepsilon_{t,t+12}$. y_{t+12} is a macroeconomic variable from month t to month $t+12$, $\mathbf{R}_{t-1,t}$ is a vector of monthly returns in month t, and $\mathbf{Z}_{t-1}$ is a vector of control variables observed in month $t-1$. The sample period is 1947:1–1994:12, except for consumption which is 1959:1–1994:12. Robust standard errors are calculated with Newey-West 24 month lags

		Production growth$_{t,t+12}$		Consumption growth$_{t,t+12}$		Labor income growth$_{t,t+12}$		Inflation$_{t,t+12}$		Excess stock returns$_{t,t+12}$		Excess bond returns$_{t,t+12}$		Nom. T-bill returns$_{t,t+12}$	
		Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
	RMRF$_{t-1,t}$ (market)	−0.38	0.33	0.11	0.11	0.20	0.16	−0.40	0.24	2.94	0.73	3.98	0.63	−0.30	0.07
	BASIC INDUSTRIES$_{t-1,t}$	0.03	0.09	−0.02	0.03	−0.08	0.05	0.17	0.07	−0.71	0.35	−0.66	0.15	0.06	0.02
	CAPITAL GOODS$_{t-1,t}$	−0.16	0.14	−0.02	0.04	−0.16	0.08	0.03	0.06	−0.85	0.29	−0.53	0.20	0.03	0.02
	CONSTRUCTION$_{t-1,t}$	0.02	0.08	−0.05	0.03	−0.04	0.04	0.05	0.05	0.14	0.22	−0.32	0.16	0.03	0.02
	CONSUMER GDS$_{t-1,t}$	0.20	0.12	0.02	0.04	0.06	0.07	0.00	0.07	−0.73	0.42	−0.93	0.26	0.08	0.03
	ENERGY$_{t-1,t}$	0.13	0.06	−0.04	0.02	−0.03	0.03	0.11	0.04	−0.42	0.16	−0.79	0.13	0.06	0.01
$\mathbf{R}_{t-1,t}$	FINANCE$_{t-1,t}$	0.14	0.08	0.01	0.04	0.08	0.05	0.04	0.04	−0.37	0.25	−0.35	0.12	0.03	0.01
	TRANSPORTATION$_{t-1,t}$	0.20	0.08	0.02	0.02	0.10	0.04	0.03	0.03	0.00	0.21	−0.36	0.12	0.03	0.02
	UTILITIES$_{t-1,t}$	−0.09	0.10	−0.04	0.05	−0.10	0.05	−0.01	0.07	−0.62	0.26	−0.32	0.19	0.02	0.02
	LONGBOND$_{t-1,t}$	−0.08	0.10	0.03	0.03	−0.06	0.05	−0.01	0.04	−0.19	0.26	−0.68	0.20	0.02	0.03
	INTRMDBOND$_{t-1,t}$	−0.15	0.14	−0.12	0.07	−0.09	0.08	0.13	0.07	0.58	0.64	0.16	0.47	−0.06	0.07
	ONEYRBOND$_{t-1,t}$	1.13	0.63	0.56	0.20	0.85	0.32	−1.10	0.44	4.15	2.11	2.28	1.27	−0.81	0.26
	JUNKBOND$_{t-1,t}$	0.11	0.12	−0.01	0.04	0.05	0.07	0.02	0.05	−0.38	0.28	0.07	0.16	0.00	0.03
	Constant	7.82	2.78	2.76	0.97	4.03	1.78	1.96	1.43	−11.95	6.61	−10.28	4.03	0.69	0.43
	RF$_{t-1,t}$	−11.20	2.95	−4.65	1.59	−6.05	1.76	4.59	1.80	−6.72	5.33	11.08	6.58	9.84	0.74
	TERMLONG$_{t-1}$	−0.05	0.50	−0.20	0.18	−0.12	0.34	−0.29	0.23	2.99	1.15	3.93	0.98	−0.01	0.10
	TERM1YR$_{t-1}$	1.95	0.86	0.29	0.28	0.82	0.48	0.89	0.41	−0.87	1.55	−2.51	1.59	0.62	0.22
$\mathbf{Z}_{t-1}$	DEFBOND$_{t-1}$	3.48	1.56	1.00	0.52	1.92	0.80	−0.98	0.98	−0.97	3.01	−1.04	3.34	0.15	0.43
	DEFCP$_{t-1}$	−1.82	0.86	−0.02	0.27	−0.53	0.45	−0.30	0.42	1.50	2.03	1.34	1.26	0.06	0.20
	DIVYIELD$_{t-1}$	−0.22	0.60	0.75	0.36	0.18	0.32	−0.15	0.40	6.64	1.38	1.38	0.79	−0.16	0.09
	Production growth$_{t-13,t-1}$	−0.30	0.09	−0.02	0.03	−0.06	0.05	0.05	0.03	−0.49	0.21	0.07	0.11	0.01	0.01
	Inflation$_{t-13,t-1}$	−0.32	0.25	−0.20	0.10	−0.29	0.10	0.41	0.14	−1.30	0.30	−0.64	0.31	0.07	0.05
	Excess stock returns$_{t-13,t-1}$	0.05	0.03	0.01	0.01	0.05	0.02	0.00	0.01	−0.22	0.10	−0.14	0.05	0.01	0.01
	R^2	0.45		0.38		0.48		0.54		0.45		0.35		0.91	

Table 2
Forecasting ability and descriptive statistics for tracking portfolios[a]

	Production growth	Consumption growth	Labor income growth	Inflation	Excess stock returns	Excess bond returns	Nom. T-bill returns
Panel A—P-values from exclusion tests on $\hat{b}$, in regression $y_{t+12} = \mathbf{bR}_{t-1,t} + \mathbf{cZ}_{t-1} + \varepsilon_{t,t+12}$							
All returns	0.00	0.00	0.00	0.00	0.00	0.00	0.00
All except RMRF	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Eight industries	0.00	0.42	0.00	0.00	0.00	0.00	0.00
Four bonds	0.24	0.00	0.05	0.01	0.00	0.00	0.00
Panel B—Partial R^2: R-squared from the regression of $y_{t+k} - \mathrm{E}[y_{t+k} \mid Z_{t-1}]$ on $\hat{\mathbf{b}}\mathbf{R}_{t-1,t} - \mathrm{E}[\hat{\mathbf{b}}\mathbf{R}_{t-1,t} \mid Z_{t-1}]$							
	0.05	0.04	0.06	0.10	0.08	0.12	0.23
Panel C—Summary statistics for portfolio returns: properties of $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$							
Mean	0.17	0.04	0.10	−0.04	−0.20	−0.13	−0.02
Std Dev	1.04	0.27	0.60	0.71	3.45	2.88	0.50
(t-stat)	(2.76)	(2.06)	(2.78)	(0.76)	(0.89)	(0.77)	(0.66)
Panel D—Market model regression: $\hat{\mathbf{b}}\mathbf{R}_{t-1,t} = \alpha + \beta(\mathrm{RMRF}_{t-1,t}) + \xi_{t-1,t}$							
α	0.09	0.04	0.06	−0.06	0.09	0.09	−0.05
(t-stat)	(1.30)	(2.32)	(1.40)	(1.50)	(0.47)	(0.59)	(1.46)
β	0.14	−0.00	0.06	0.05	−0.48	−0.36	0.04
(t-stat)	(3.24)	(0.10)	(2.25)	(1.89)	(5.45)	(3.76)	(3.09)
R^2	0.32	0.00	0.20	0.07	0.33	0.27	0.10
Panel E—Correlation matrix for tracking portfolio returns and base asset returns							
Consumption	0.14						
Labor income	0.82	0.59					
Inflation	0.29	−0.80	−0.23				
Excess stock	−0.26	0.54	0.10	−0.70			
Excess bond	−0.57	0.42	−0.10	−0.73	0.68		
Nom. T-bill	0.21	−0.68	−0.17	0.85	−0.80	−0.62	

Table 2 (*Continued*)

	Production growth	Consumption growth	Labor income growth	Inflation	Excess stock returns	Excess bond returns	Nom. T-bill returns
RMRF	0.57	−0.03	0.45	0.27	−0.58	−0.52	0.31
BASIC	0.56	−0.19	0.30	0.51	−0.67	−0.65	0.43
CAPITAL	0.39	−0.04	0.25	0.27	−0.63	−0.50	0.34
CONSTRUCT	0.56	−0.15	0.38	0.34	−0.52	−0.59	0.36
CONSUMER	0.54	0.09	0.49	0.16	−0.57	−0.48	0.31
ENERGY	0.56	−0.36	0.23	0.53	−0.52	−0.61	0.40
FINANCE	0.64	0.08	0.56	0.20	−0.53	−0.53	0.24
TRANSPORT	0.71	0.04	0.59	0.30	−0.48	−0.56	0.34
UTILITIES	0.37	0.03	0.37	−0.06	−0.37	−0.29	−0.02
LONGBOND	0.17	0.45	0.31	−0.41	0.26	−0.15	−0.55
INTRMDBOND	0.20	0.41	0.34	−0.44	0.38	−0.03	−0.69
ONEYRBOND	0.31	0.60	0.46	−0.54	0.45	0.06	−0.78
JUNKBOND	0.58	0.11	0.52	0.02	−0.24	−0.30	−0.12

[a]Notes: Shows the properties of the tracking portfolios defined by the regressions in Table 1, $y_{t+12} = \mathbf{b}\mathbf{R}_{t-1,t} + \mathbf{c}\mathbf{Z}_{t-1} + \varepsilon_{t,t+12}$. Shows additional information about the statistical significance of returns in the regressions in Table 1. For consumption, all statistics are calculated using data from 1959:1–1994:12. For the other series, the data are 1947:1–1994:12.

(A) P-values report tests of the hypothesis that different elements of $\mathbf{R}_{t-1,t}$ can be omitted from the regressions in Table 1. "all returns" tests whether all 13 base assets can be omitted from the regressions in Table 1. "all except RMRF" tests whether the 8 industry stock portfolios and 4 bond portfolios can be omitted from the regressions in Table 1. "eight industries" tests whether the 8 industry stock portfolios can be omitted from the regressions in Table 1. "four bonds" tests whether the 4 bond portfolios can be omitted from the regressions in Table 1. P-values are constructed using robust standard errors with Newey-West 24 month lags.

(B) shows R-squared in a regression where the left hand side is the residual from a regression of y_{t+12} on $\mathbf{Z}_{t-1}$, and the right hand side is the residual from a regression of $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$ on $\mathbf{Z}_{t-1}$. $\hat{\mathbf{b}}$ is derived from the regression in Table 1.

(C) Summary statistics show mean, standard deviation, and t-statistic for the monthly tracking portfolios, $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$. $\hat{\mathbf{b}}$ is derived from the regression in Table 1. The mean and standard deviation are simply the time series statistics for $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$. The t-statistic tests the hypothesis that $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$ is zero, using GMM standard errors. The GMM standard errors take into account the estimation error of $\hat{\mathbf{b}}$.

(D) Market model regressions show univariate regressions of tracking portfolio returns on the market excess return. $\hat{\mathbf{b}}$ is derived from the regression in Table 1. The t-statistics use GMM standard errors, which take into account the estimation error of $\hat{\mathbf{b}}$.

(E) The correlation matrix shows correlations of tracking portfolio returns $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$ with itself and with base asset returns $\mathbf{R}_{t-1,t}$, using monthly data. $\hat{\mathbf{b}}$ is derived from the regression in Table 1.

The other rows of Panel A test whether three subsets of returns forecast the target variable (given the other returns): the 12 returns excluding the market portfolio, the eight industry portfolios, and the four bond portfolios. For example, the second row shows that for all seven variables, forecasting power is not limited to just the aggregate stock market. In general, both bonds and stocks contribute tracking power.

4.2. Tracking ability

Panel A shows that the tracking portfolios do track. How *well* do the tracking portfolios track? They are designed to track news, so to evaluating the tracking power, one would like to examine the R-squared in a regression of news on unexpected returns ($\Delta \mathrm{E}_t[y_{t+k}]$ on $\tilde{r}_{t-1,t}$). Unfortunately, this measure is unknown, since one does not observe $\Delta \mathrm{E}_t[y_{t+k}]$.

One can calculate a partial R-squared that gives a lower bound on the fraction of news variance that is captured by tracking portfolio returns. Specifically, one runs a regression of $y_{t+k} - \mathrm{E}[y_{t+k}|\mathbf{Z}_{t-1}]$ on $\mathrm{b}\mathbf{R}_{t-1,t} - \mathrm{E}[\mathbf{bR}_{t-1,t}|\mathbf{Z}_{t-1}]$, which in the notation is the same as running a regression with $\mu_{t-1} + \Delta \mathrm{E}_t[y_{t+k}] + \mathrm{e}_{t,t+k}$ on the left hand side and $\tilde{r}_{t-1,t}$ on the right hand side. The R-squared in this regression is lower bound for the R-squared in a regression of $\Delta \mathrm{E}_t[y_{t+k}]$ on $\tilde{r}_{t-1,t}$. Panel B of Table 2 shows this partial R-squared. The lower bound ranges from 0.04 to 0.23.

4.3. Risk premia, CAPM, and correlations

Panel C of Table 2 shows mean excess returns for the tracking portfolios. The numerical magnitude of these risk premia show the price of one unit of exposure to $\Delta \mathrm{E}_t[y_{t+k}]$. Panel C also shows the standard deviation of these portfolio returns, and the t-test for the hypothesis that the mean return is zero. [7]

The production, consumption, and labor income portfolios have risk premia which are positive, while the inflation and T-bill portfolios have risk premia which are negative, similar to Chen et al. (1986). For future stock and bond returns, the theoretical sign is ambiguous and depends on risk aversion (see for example Campbell, 1996). Panel C shows that both future stock and bond

[7] The reported standard deviation is the usual time-series standard deviation, taken $\hat{b}$ as given (so that one can generate the in-sample Sharpe ratio by taking the ratio of the mean and standard deviation). The t-statistic, in contrast, is calculated using GMM, and takes into account the estimation error of $\hat{\mathbf{b}}$. The calculations use Hansen (1982) Generalized Method of Moments. See also example Hamilton (1994) and Ogaki (1993). As before, the covariance matrix is computed using Newey West with 24 month lags.

return portfolios earn negative returns, suggestive (loosely) of a coefficient of relative risk aversion that is less than one.

The market model regressions in Panel D of Table 2 evaluate the ability of the CAPM to explain the risk premia on tracking portfolios. Before discussing the results, a statistical fact: since the tracking portfolios are linear combinations of the base assets, the α's of the tracking portfolios are linear combination of the α's of the base assets. In other words, the CAPM can only misprice the tracking portfolio if it also misprices one or more of the 13 base assets.

Only the consumption portfolio has an α that is significantly different from zero. The primary reason for the consumption portfolio's mispricing by the CAPM is that the returns on one of the base assets (the one-year treasury bond portfolio) is also mispriced by the CAPM. Removal of this portfolio from the set of base assets results in an insignificant α for consumption.

Panel E shows correlations of the seven tracking portfolio returns with each other, as well as correlations of the tracking portfolios with the base assets. Economists often test hypotheses about the predictive power of aggregate stock returns for various economic variables. For example, Stock and Watson (1989) find that given other forecasting variables, aggregate stock returns do not help predict future economic activity. The correlation of aggregate stock returns (RMRF) with tracking portfolios in Panel E show how different the market portfolio is from the optimal portfolio for forecasting future economic activity. Tracking portfolios might perform better than aggregate stock returns because they hedge out portions of aggregate return variation that are unrelated to future production (such as changes in taxes, liquidity, or sentiment). For example, Panel E shows that the correlation of the production tracking portfolio and the market portfolio is 0.57, so that the market portfolio is far from being the optimal predictive portfolio for production.

4.4. Examining the implied forecasts

Fig. 1 show the time series of the cumulative innovations in returns on the production portfolio from 1947 to 1994. The figure cumulates unexpected returns on the tracking portfolio ($\tilde{r}_{t-1,t}$ from Eq. (9)). By cumulating, the intention is to approximately display $\mathrm{E}_t[y_{t+k}]$. Since the tracking portfolios have been chosen in-sample to forecast the 12-month ahead target variable, it is no surprise that one can see some of this forecasting ability in the figures. For example, Fig. 1 shows the recession of 1990–1991. The recession started in August 1990; the production tracking portfolio peaked 12 months earlier (as it should), in August 1989.

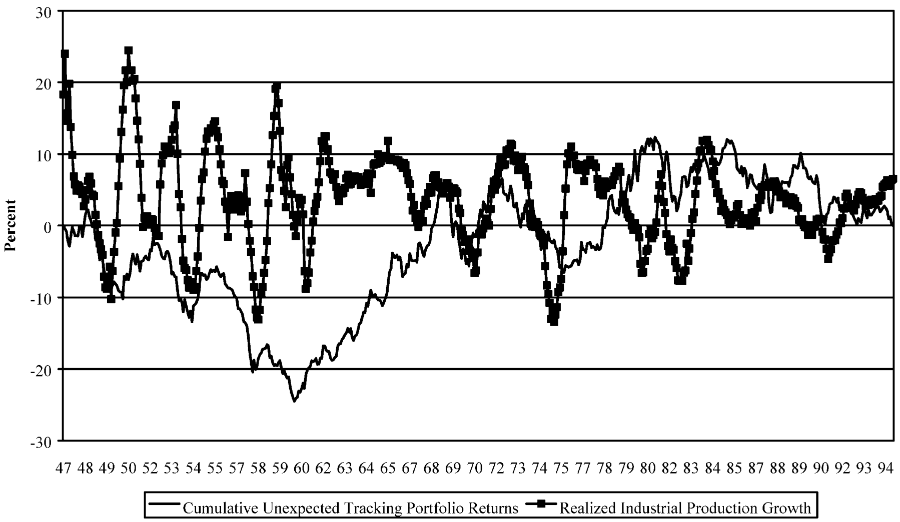

Fig. 1. The figure shows cumulative unexpected returns on the tracking portfolios, calculated as the residual, $\tilde{r}_{t-1,t}$, from the regression $\hat{\mathbf{b}}\mathbf{R}_{t-1,t} = \mathbf{a}Z_{t-1} + \tilde{r}_{t-1,t}$. $\tilde{r}_{t-1,t}$ is summed to make cumulative returns. Realized production growth is (in percentage points) the change in natural log of industrial production from month t to month $t+12$.

5. Robustness tests

5.1. Rolling regressions

Table 3 uses rolling regressions to examine the out-of-sample performance of tracking portfolios, using a 20-year estimation window. Every month, one runs the tracking portfolio regression using only historical data, up to and including this month's realization of the target variable. In month t, one estimates $\hat{\mathbf{b}}_t$ and $\hat{\mathbf{c}}_t$ using the past 20 years of monthly data. This procedure is repeated every month, and the result is two times series: $\hat{\mathbf{b}}_t\mathbf{R}_{t-1,t}$ and $\hat{\mathbf{c}}_t\mathbf{Z}_{t-1}$. $\hat{\mathbf{b}}_t\mathbf{R}_{t-1,t}$ is the return from a dynamic portfolio strategy following a well defined trading rule that is a function only of observable data.

Using these two forecast components, Table 3 reports regressions of y_{t+12} on $\hat{\mathbf{b}}_t\mathbf{R}_{t-1,t}$ and $\hat{\mathbf{c}}_t\mathbf{Z}_{t-1}$. The coefficient on $\hat{\mathbf{b}}_t\mathbf{R}_{t-1,t}$ in these OLS time-series regressions is a measure of how well the tracking portfolios tracks out-of-sample. If the tracking portfolio generated using the rolling procedure were perfect, then the coefficient would be one.[8] If the tracking portfolio were useless, the

[8] This test is standard for testing forecast optimality. See for example Diebold and Lopez (1996).

Table 3
Out-of sample results using 20-year rolling regressions[a]

	Production growth	Cons. Growth	Labor income growth	Inflation	Excess stock returns	Excess bond returns	Nom. T-bill returns
$y_{t+12} = \kappa + \lambda \hat{\mathbf{b}}_t \mathbf{R}_{t-1,t} + \pi \hat{\mathbf{c}}_t \mathbf{Z}_{t-1} + \xi_{t,t+12}$							
κ	0.69	1.01	0.44	2.63	2.25	0.21	0.44
(Standard error)	(0.68)	(0.35)	(0.45)	(0.64)	(2.75)	(2.07)	(0.64)
λ	0.40	0.45	0.56	0.56	0.37	0.73	0.66
(Standard error)	(0.18)	(0.12)	(0.10)	(0.13)	(0.14)	(0.22)	(0.16)
π	0.67	0.48	0.56	0.54	0.27	0.29	1.03
(Standard error)	(0.10)	(0.05)	(0.07)	(0.13)	(0.19)	(0.18)	(0.10)
R2	0.34	0.36	0.37	0.36	0.04	0.09	0.67
Rolling MSE	18.89	2.02	7.17	7.34	312.78	167.88	2.43
In-sample MSE	5.83	0.38	2.66	1.61	113.00	62.41	0.91
Variance	24.42	1.55	7.77	8.12	251.95	132.74	5.94
1-Rolling MSE/Variance	0.23	−0.30	0.08	0.10	−0.24	−0.26	0.59
In-sample R2	0.76	0.75	0.66	0.80	0.55	0.53	0.85

[a]Notes: Every month, for each target variable, the rolling regression procedure estimates the OLS regression $y_{t+12} = \mathbf{b}\mathbf{R}_{t-1,t} + \mathbf{c}\mathbf{Z}_{t-1} + \varepsilon_{t,t+12}$. This regression uses 240 months of past data (the target variable data is from month $t-241$ to t and the return data is from month $t-251$–$t-12$). Each month, this regression produces $\hat{\mathbf{b}}_t$ and $\hat{\mathbf{c}}_t$. After calculating a time series of $\hat{b}_t$ and $\hat{c}_t$, the table reports the results from the out-of sample regression $y_{t+12} = \kappa + \lambda \hat{\mathbf{b}}_t \mathbf{R}_{t-1,t} + \pi \hat{\mathbf{c}}_t \mathbf{Z}_{t-1} + \xi_{t,t+12}$. The sample period for the reported regression is 1967:12–1994:12 (1979:12–1994:12 for Consumption). The robust standard errors use Newey-West 24 month lags. Rolling MSE is the average of $(y_{t+12} - \hat{\mathbf{b}}_t \mathbf{R}_{t-1,t} - \hat{\mathbf{c}}_t \mathbf{Z}_{t-1})^2$. In-sample MSE and in-sample R^2 are from the full regression, estimated for 1967:12–1994:12 (1979:12–1994:12 for Consumption).

coefficient would be zero. In general, one would expect a coefficient of less than one because of error in coefficient estimates, and possibly because of changing true parameter values as well. The issue is similar to the shrinkage of CAPM β's.

Table 3 shows that tracking portfolios have the ability to track the target variable out-of-sample, since the coefficient is in all seven cases significantly different from zero. The coefficients range from 0.37 to 0.73. Forecasting deterioration is not limited to tracking portfolios. The coefficients on $\hat{\mathbf{c}}_t \mathbf{Z}_{t-1}$ range between 0.27 and 1.03, indicating that non-return variables also are not perfect out-of-sample.

The standard errors in Table 3 are calculated in the customary way. West and McCracken (1998) develop procedures for rolling regressions that adjust for estimation error. Their procedure, when regressing actual on forecasts, is to divide the t-statistic by an adjustment factor which depends on the number of observations in the out-of-sample period and the number used to obtain the forecast. Based on the out-of-sample period of 325 months (181 months for consumption) and the estimation period of 240 months, West and McCracken (1998) suggest that the t-statistics should be divided by 0.7 (0.9 for consumption). Thus the coefficients are even more statistically significant than shown by the standard errors in Table 3.

Table 3 also shows mean-squared error (MSE) for the out-of-sample period. The rolling MSE is the average of the squared value of $y_{t+12} - \hat{\mathbf{b}}_t \mathbf{R}_{t-1,t} - \hat{\mathbf{c}}_t \mathbf{Z}_{t-1}$. The in-sample MSE shows the properties of the residual from the full regression estimated over the same out-of-sample period, and the variance shows the properties of the target variable. The rolling MSE is naïve in the sense that it does not correct for the expected performance deterioration, and one can reduce forecast error by correcting for deterioration.

Table 3 shows the rolling MSE in an R^2-like measure by showing the percent of the variance explained out-of-sample (one minus the rolling MSE divided by the variance of the target variable). By this measure, it appears that the production and T-bill forecasts are fairly useful out-of-sample, the labor income and inflation forecasts are somewhat useful, and the consumption, stock, and bond return forecasts are not useful. Comparing this R^2-like measure with the actual R^2 of the regression with $\hat{\mathbf{b}}_t \mathbf{R}_{t-1,t}$ and $\hat{\mathbf{c}}_t \mathbf{Z}_{t-1}$ shows the importance of correcting for forecast deterioration. For example, for consumption, the R^2 of 0.36 when allowing for forecast deterioration, compared with the rolling MSE that 30% larger than the target variance (with an R^2-like measure of -0.30), shows that ignoring deterioration has large costs.

In summary, tracking portfolios do track out-of-sample, although imperfectly. Tracking portfolios are a feasible way for investors to hedge economic risk in real time, although investors should take into account the predictable out-of-sample deterioration.

5.2. Alternative horizons for target variables and base assets

Table 4 shows various alternative ways of constructing tracking portfolios. Panel A reprints relevant statistics from Table 2. Panels B–F each shows a different variation on the baseline specification of Table 1.

The table shows three sets of facts about the differently constructed tracking portfolio. First, it tests whether the tracking portfolios track: it shows p-values from exclusion tests in the forecasting regression, which evaluate whether the returns have forecasting ability. Second, it shows the partial R-squared of the target variable on tracking returns. Third, it shows the correlation of the baseline tracking portfolios with the tracking portfolio constructed using the various different methods.

Panel B shows results using a five-year target variable instead of one-year target variable. The first row shows that the tracking portfolios do track. The

Table 4
Tracking portfolios constructed using alternative methods[a]

	Production growth	Consumption growth	Labor income growth	Inflation	Excess stock returns	Excess bond returns	Nom. T-bill returns
Panel A—Baseline							
P-values from exclusion test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Partial R^2	0.05	0.04	0.06	0.10	0.08	0.12	0.23
Correlation with baseline portfolio	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel B—60 Month ahead target variable: $y_{t+60} = \mathbf{bR}_{t-1,t} + \mathbf{cZ}_{t-1} + \varepsilon_{t,t+60}$							
P-values from exclusion test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Partial R^2	0.04	0.03	0.03	0.03	0.08	0.07	0.08
Correlation with baseline portfolio	0.27	0.50	0.58	0.81	0.84	0.70	0.79
Panel C—3 Month base asset returns: $y_{t+12} = \mathbf{bR}_{t-3,t} + \mathbf{cZ}_{t-3} + \varepsilon_{t,t+12}$							
P-values from exclusion test	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Partial R^2	0.09	0.10	0.12	0.19	0.22	0.23	0.34
Correlation with baseline portfolio	0.91	0.92	0.96	0.97	0.95	0.97	0.94
Panel D—Stock only in base assets: $y_{t+12} = \mathbf{bR}_{t-1,t} + \mathbf{cZ}_{t-1} + \varepsilon_{t,t+12}$							
P-values from exclusion test	0.00	0.52	0.00	0.00	0.00	0.00	0.00
Partial R^2	0.04	0.02	0.05	0.08	0.06	0.11	0.11
Correlation with baseline portfolio	0.93	0.75	0.90	0.89	0.85	0.94	0.70
Panel E—Bonds only in base assets: $y_{t+12} = \mathbf{bR}_{t-1,t} + \mathbf{cZ}_{t-1} + \varepsilon_{t,t+12}$							
P-values from exclusion test	0.01	0.00	0.00	0.01	0.00	0.00	0.00
Partial R^2	0.02	0.02	0.02	0.04	0.04	0.02	0.15
Correlation with baseline portfolio	0.63	0.70	0.60	0.63	0.69	0.43	0.83

Panel F—No control variables: $y_{t+12} = \mathbf{b}\mathbf{R}_{t-1,t} + c + \varepsilon_{t,t+12}$							
P-values from exclusion test	0.00	0.00	0.00	0.27	0.00	0.00	0.01
Partial R^2	0.08	0.06	0.07	0.06	0.06	0.11	0.03
Correlation with baseline portfolio	0.77	0.66	0.75	0.63	0.63	0.89	0.09

[a]Table 4 shows results from different ways of estimating the regression $y_{t+k} = \mathbf{b}\mathbf{R}_{t-j,t} + \mathbf{c}\mathbf{Z}_{t-j} + \varepsilon_{t,t+j}$. The different ways of constructing tracking portfolios are choosing different values for k (target horizon), different values for j (base asset return period), and different compositions of $\mathbf{R}$ and $\mathbf{Z}$. "*P*-values from exclusion test" report tests of the hypothesis that $R_{t-j,t}$ can be omitted from the regression, and is constructed using robust standard errors with Newey-West 24 month lags (except in the case of 60-month ahead target variables, which use 120 month lags). "Partial R^2" is the R-squared from a regression of $y_{t+k} - \mathrm{E}[y_{t+k}|\mathbf{Z}_{t-j}]$ on $\hat{\mathbf{b}}\mathbf{R}_{t-1,t} - \mathrm{E}[\hat{\mathbf{b}}\mathbf{R}_{t-1,t}|\mathbf{Z}_{t-j}]$; in other words, the R-squared in a regression where the left-hand side is the residual from a regression of y_{t+k} on Z_{t-j}, and the right-hand side is the residual from a regression of $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$ on $\mathbf{Z}_{t-j}$. "Correlation with baseline portfolio" shows the correlation of the tracking portfolio for the given target variable with the baseline tracking portfolio for the same target variable. The baseline tracking portfolio, $\hat{\mathbf{b}}\mathbf{R}_{t-1,t}$ is derived from Table 1. For Panel B, the sample period is 1947:1–1990:12, except for consumption which is 1959:1–1990:12. For Panels A and C–F, the sample period is 1947:1–1994:12, except for consumption which is 1959:1–1994:12.

(A) Reprints information from Table 2.

(B) Uses 5-year ahead target variables.

(C) Uses 3 month excess returns for base assets. The correlation with baseline portfolio is $\mathrm{corr}(\hat{\mathbf{b}}^{\text{Table 9c}}\mathbf{R}_{t-1,t}, \hat{\mathbf{b}}^{\text{Table 2}}\mathbf{R}_{t-1,t})$. In other words, the portfolio weights are taken from the regression $y_{t+12} = \mathbf{b}\mathbf{R}_{t-3,t} + \mathbf{c}\mathbf{Z}_{t-3} + \varepsilon_{t,t+12}$ but the returns are monthly.

(D) The base asset return vector $\mathbf{R}_{t-1,t}$ includes only the nine stock market portfolio returns.

(E) The base asset return vector $\mathbf{R}_{t-1,t}$ includes only the four bond market portfolio returns.

(F) The control variable vector $\mathbf{Z}_{t-1}$ includes only a constant term. The partial R-squared's are now equivalent to simple R-squareds.

second row shows that the partial R-squared is generally lower than in Panel A. This fact is unsurprising since only a smaller percentage of news about the next five years is released in any given month. The last row shows that the correlations with the baseline tracking portfolios are moderately high, ranging from 0.27 to 0.84.

Panel C shows results using quarterly base asset returns instead of monthly base asset returns. These regressions continue to use monthly observations, but they use returns $\mathbf{R}_{t-3,t}$ and control variables $\mathbf{Z}_{t-3}$. Again, quarterly tracking portfolios do track. Not surprisingly, the partial R-squared's rise, since more information is released in three months than in one. The correlations with baseline portfolios are calculated using monthly returns, where the portfolio weights come from the regression using quarterly returns. The correlations are very high (0.91–0.97), indicating that it is essentially irrelevant whether one calculates portfolio weights using monthly or quarterly regressions.

5.3. Restricting the base assets

Panels D and E show tracking portfolio returns constructed with subsets of the 13 base assets, $\mathbf{R}_{t-1,t}$. Panel D uses only the nine stock portfolios, and Panel E uses only the four bond portfolios.

With the exception of the stock-only consumption tracking portfolio, the p-values in Panels D and E show that one can track the target variables with either bond returns or stock returns. Except for the nominal T-bill tracking portfolio, the correlations with baseline are higher for the stock-only tracking portfolios (0.70–0.94) than for the bond-only portfolios (0.43–0.83), indicating that the baseline portfolios are more influenced by stock returns than bond returns.

5.4. Restricting the control variables

Panel F shows results with no control variables, so that the right hand side of the regression contains a constant term and 13 base asset returns. These regressions are surely misspecified, but they give a sense of the importance of the control variables. With the exception of the inflation tracking portfolio, the tracking portfolios still track.

For the nominal T-bill return, the baseline portfolio correlation is near zero, suggesting that control variables are a very important ingredient in constructing its tracking portfolio. Nominal T-bill returns over the next year are very predictable (as shown by the R-squared of 0.91 in Table 1). Thus excluding lagged control variables, such as the lagged T-bill return, makes a dramatic difference in the properties of the tracking portfolio.

For the other six tracking portfolios, the baseline portfolio correlations are fairly high, ranging from 0.63 to 0.89. For these tracking portfolios, then, control variables are not important.

5.5. Summary of robustness results

In general, the results of this section suggest that the portfolios estimated in Table 1 are robust to different specifications. The baseline portfolios are not very different from portfolios constructed using alternative methods. Some changes (such as using 3-month returns on base assets or dropping all bonds from the base assets) make virtually no difference in most cases.

5.6. Subsequent work

Since this paper was first circulated as Lamont (1999), the tracking portfolio approach has been applied in other contexts. Hayes (1999) constructs tracking portfolios for UK macroeconomic variables using UK equity returns. His out-of-sample results are more mixed than the ones presented here, probably because his shorter sample period of 1965–1998 leaves only a small number of years with which to test the out-of-sample tracking ability.

Christoffersen and Slok (2000) apply the approach to transition economies in Eastern Europe. In their short sample of 1994–1999, they find that tracking portfolios forecast real economic activity, using stock prices, interest rates, and exchange rates.

One important issue not addressed here is historical data revisions (see, for example, Diebold and Rudebusch, 1991). Some of the macroeconomic variables have been revised and could not have been known in real-time. One slight benefit of using asset returns is that they are not subject to revision, unlike most macroeconomic variables. Christoffersen et al. (2000) study the impact of data revisions for constructing tracking portfolios.

One could imagine adding other interesting portfolios to the base assets such as gold, real estate, and international securities.[9] Vassalou (2000) constructs a tracking portfolio for future GDP using stock portfolios based on size and value. She finds that these base assets help track GDP (although she does not consider industry returns or bond returns). In contrast, Lamont (1999) examines three factors in stock returns: the value and size factors of Fama and Kenneth R. French (1993) and the momentum factor of Carhart (1997). Compared to the existing base assets used here, these three candi-

[9] Titman and Warga (1989) examine inflation expectations and real estate returns, while Becker et al. (2000) examine currency devaluation expectations and returns on importing and exporting firms.

date portfolios do not help track the target variables, and are not particularly highly correlated with any of the tracking portfolios.

6. Conclusions

Using post-war US data, it is possible to track expectations about future economic variables using stocks from different industries and bonds of different maturities and qualities. These tracking portfolios do not merely reflect the aggregate stock market or aggregate bond market, but instead combine the different returns optimally. Out-of-sample results suggest that going into the future, tracking portfolios may be useful in forecasting and hedging macroeconomic variables. Of course, as with any forecast, overfitting and changing parameter values can cause accuracy to deteriorate. Users of tracking portfolios need to take into account the deterioration of forecast accuracy out-of-sample.

One could also construct tracking portfolios using daily returns. This would allow one to estimate daily updates on what financial markets think about future inflation, economic activity, and expected returns, and to examine specific episodes. E.g., when the Fed announces it is tightening monetary policy, do the inflation and output forecasting portfolios fall? In this respect, tracking portfolios have an inherent advantage over monthly VAR's using non-return variables.

Acknowledgements

I thank Nichnolas Barberis, John Cochrane, Francis X. Diebold, Eugene Fama, Wayne Ferson, Larry Glosten, Simon Hayes, Ming Huang, Ken West, and the workshop participants at the Columbia Business School, International Monetary Fund, London School of Economics, MIT Sloan, NBER Asset Pricing Conference, Stanford University, Stockholm School of Economics, University of Chicago, University of Washington, Vanderbilt University, and the Yale School of Management, and anonymous referees for helpful comments. I am especially grateful for comments and collaboration from Christopher Polk. I thank Mark Carhart and Eugene Fama for providing data. I thank David Robinson and Kevin Qing Wang for research assistance. I gratefully acknowledge support from the Alfred P. Sloan Foundation, the Center for Research in Securities Prices at the University of Chicago Graduate School of Business, the FMC Faculty Research Fund, and the National Science Foundation.

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