Investor Expectations, Business Conditions, and the Pricing of Beta-Instability Risk*

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ABSTRACT

This paper examines the pricing implications of time-variation in assets' market betas over the business cycle in a conditional CAPM framework. We use a half century of real GDP growth expectations from economists' surveys to determine forecasted economic states. This approach largely avoids the confounding effects of econometric forecasting model error. The expectation measure forecasts the market return controlling for existing predictive variables. The loadings on the expectation measure explain a significant fraction of cross-sectional variation in stock returns. A fully tradable, ex ante mimicking portfolio generates positive risk-adjusted returns during good economic times over four decades.

The link between macroeconomic fundamentals and stock returns is an important yet unresolved issue in finance. There is a long strand of literature that examines the effect of expected business conditions on expected stock returns. The traditional approach has been to proxy expected business conditions by realized macroeconomic variables such as industrial production and the inflation rate (Chen, Roll, and Ross (1986), Chen (1991)), financial market instruments such as the dividend yield, the default and term premia, and the short rate (Campbell and Shiller (1988), Fama and French (1988, 1989), Ferson and Harvey (1991, 1999)), or combination thereof such as the aggregate consumption-wealth ratio (Lettau and Ludvigson (2001a, 2001b)). It has been more challenging to identify a direct measure of macroeconomic expectations for asset pricing tests. Most expectations data is not available in time series for periods long enough to draw inferences about asset return premia.

In addition, there is a more subtle issue. Expectations about macroeconomic factors are not formed mechanically, but instead created through a process of human reasoning that, at the very least relies upon current, observed conditions and past experience in ways that are difficult to simply proxy with a linear model and a handful of quantitative variables. While some economic forecasts are predictable given the model (one thinks of the Fair model, for instance), others may be based upon intuition, shifting inputs, or even on polling of corporate opinion. Equity market participants presumably rely on an extensive institutional network of professional economic forecasters in the public and private sector. Most major financial institutions have a chief economist. These forecasters publish outlooks, talk to the media, convey proprietary information to the firms that employ them, write newsletters and blogs – in short, economists are important agents in the development of a consensus (or lack thereof) about the direction of the economy. In any test of the relation between asset prices and macroeconomic expectations, it would be particularly useful to filter macro-economic data through the mind of the forecaster, and use this "processed" expectational information to test whether asset returns reflect macro-economic expectations. That is the objective of this paper.

We use a half-century of expectational survey data to examine whether the time-variation in assets' market betas over the business cycle, or the *beta-instability risk*, is priced in the cross section of stock returns. Jagannathan and Wang (1996, hereafter JW) observe that the conditional Capital Asset Pricing Model (CAPM) relation does not condition down to an unconditional CAPM in general, producing a covariance term between the market beta and the market premium.[1] This covariance term naturally leads to a projection of the market beta onto the market premium. The slope coefficient, or the beta-premium sensitivity, measures how an asset's market beta varies with the business cycle as reflected in the market premium. This produces a two-beta model in which an asset's expected return is proportional to the market beta and the beta with respect to the market premium (the premium beta).

We advance JW's analysis in two directions. First, we explicitly derive the relation between the market and premium betas as well as their premia. This helps us examine the various cross-sectional restrictions that the conditional CAPM imposes when it is conditioned down. Most importantly, we quantify the premium beta and the beta-instability risk premium. Lewellen and Nagel (2006) point out that many existing studies ignore cross-sectional restrictions on these and other quantities. Our result shows that it *is* difficult, if not impossible, to impose such restrictions in our two-beta framework and JW's, because the beta-instability risk premium is a nonlinear function of the market premium and its high-order moments. We address this issue by introducing a mimicking portfolio of an instrument predicting the market premium.

[1] Chan and Chen (1988) also condition down the conditional CAPM to an unconditional equation.

Second, we empirically extend JW's unconditional result to one conditional on economic states, across which can vary the market beta and the premium beta as well as the premia themselves. To determine the economic states, we employ a direct measure of investor expectations about the future prospect of the economy. The Livingston Survey publishes leading economists' forecasts about national output, prices, unemployment, and interest rates semiannually. Initiated by Joseph Livingston in 1946 and currently maintained by the Federal Reserve Bank (FRB) of Philadelphia, the survey provides more than half a century of direct investor expectations. Using this dataset, Campbell and Diebold (2005) recently construct a time series of the growth rate of the expected real Gross Domestic Product (GDP) and find that it negatively predicts the aggregate stock returns controlling for standard predictive instruments. This implies that expected returns rise when future business conditions are expected to be poor and vice versa. Importantly to our purpose, this result implies that the expected real GDP growth rate qualifies as a predictive instrument to determine the state of the real economy in JW's two-beta model and in our extension.

Our cross-sectional empirical results support this conjecture. We first examine how the expected real GDP growth rate captures beta-instability risk. Using the Fama-French 25 portfolios sorted by size and the book-to-market (B/M) ratio, we find that the covariance of returns with respect to the lagged expected real GDP growth rate is lower for value stocks than for growth stocks during bad times, which are defined as periods in which the lagged growth rate is lower than its ten-year moving average. Because the expected real GDP growth rate negatively predicts the future market return, this implies that the premium beta is higher for value stocks than growth stocks during bad times. This pattern is remarkably robust across the size quintiles. This cross-sectional relation, however, is reversed during good times. This is consistent with the hypothesis that value stocks are riskier not because their returns are always sensitive to changes in the market premium, and hence under some assumptions clarified below, to changes in the market return, but because they are so in bad times. This is related to the finding of Lettau and Ludvigson (2001b), who make a similar observation in a Consumption CAPM framework. We find that the ability of the expected real GDP growth rate to capture the cross-sectional difference in beta-instability risk is unsurpassed by other instruments such as the dividend yield, default spread, term spread, short rate, and the consumption-wealth ratio.

We then bring this finding to asset-pricing tests. In addition to the non-traded lagged expected real GDP growth rate, we test the pricing of its mimicking portfolio. Our mimicking portfolio is fully tradable, is conditional upon a current publicly available information set and behaves very well, with no extreme short position in any basis asset. Controlling for the market, size, value, and momentum factors, we find that the mimicking-portfolio premia are significant conditional on economic states. As the theory implies, the bad-time mimicking portfolio premium is lower than its good-time counterpart. Unfortunately, while their relative relation is right, their magnitude is not. Nevertheless, they do explain a considerable fraction of the cross-sectional variation in stock returns. Using the 25 size-B/M portfolios as test assets, while the adjusted R-squared from the regression of average realized returns on estimated betas is only -1% for the CAPM specification, it jumps up impressively to 71% when the lagged Livingston factor alone is added. We also measure the beta-instability risk directly using an extension of Petkova and Zhang (2005) conditional on economic states.

The existing asset-pricing study closest to ours is Vassalou (2003), who finds that news to future realized GDP growth is priced in the cross section of stock returns. Our approach differs from hers in two fundamental ways. First, we base our theoretical model on JW, which implies that the beta with respect to a *lagged* predictive instrument is useful in explaining the cross-sectional difference in stock returns. This differs from the implementation of most multi-factor asset pricing models such as those based on Merton's (1973) Intertemporal CAPM and Ross' (1976) Arbitrage Pricing Theory, in which *news* to economic series is extracted in some way to form factors (also see JW, p.10). Vassalou (2003) falls in this category. Second, she uses the component of the realized future GDP growth rate that is reflected on basis asset returns as a proxy for investors' expectations about future investment opportunities. In contrast, we use a contemporaneously observable measure of investor expectations that is generally recognized by market participants as potentially of value. This is important, because any factor model that relies upon the pervasive perception of risk factors and sensitivities must also address the issue of common observability.

The rest of the paper is organized as follows. The next section extends JW's unconditional model to one conditional on economic states, which will form the basis of the empirical analysis to follow. Section II explains the data and examines the predictive ability of the expected real GDP growth rate from the Livingston Survey. Section III conducts asset-pricing tests, constructs a mimicking portfolio, and measures the beta-instability risk directly. The final section concludes.

I. Conditional CAPM and Beta-Instability Risk

This section derives a two-beta model that will form the basis of the subsequent analysis. The derivation closely follows JW. Start with the conditional CAPM relation,

$$\mathbf{E}_{t-1}[r_{it}^e] = \gamma_{1t-1}\beta_{it-1}, \tag{1}$$

where $r^e_{it} \equiv r_{it} - \gamma_{0t-1}$ is the return on asset i in excess of the risk-free rate γ_{0t-1} (or the return on a zero-beta portfolio if a risk-free asset does not exist). γ_{1t-1} is the market premium (in excess of γ_{0t-1}) and β_{it-1} is asset i's market beta, both conditional on the information set at time $t-1$. The conditional market beta is defined as

$$\beta_{it-1} \equiv \frac{Cov_{t-1}(r^e_{it}, r^e_{mt})}{Var_{t-1}(r^e_{mt})}, \tag{2}$$

where $r^e_{mt} \equiv r_{mt} - \gamma_{0t-1}$ is the excess market return. JW take an unconditional expectation of equation (1) and observe that the conditional CAPM relation does not condition down to an unconditional CAPM in general, producing a covariance term between the premium and the beta. We also condition down to a coarser information set, but one that is not so coarse as the unconditional one. Specifically, define an information set $I_s \subseteq I_{t-1}$. I_s can represent an economic state, such as an expansion and a contraction in a business cycle. Then, taking expectation of equation (1) conditional on I_s yields

$$\mathbf{E}_s[r^e_{it}] = \gamma_{1s}\overline{\beta}_{is} + Cov_s(\gamma_{1t-1}, \beta_{it-1}), \tag{3}$$

where $\gamma_{1s} \equiv \mathbf{E}_s[\gamma_{1t-1}]$, and $\overline{\beta}_{is} \equiv \mathbf{E}_s[\beta_{it-1}]$. The last term is the covariance between the market premium and the beta conditional on an economic state s. This leads us to naturally define a sensitivity measure between these two variables. Following JW, we project β_{it-1} onto γ_{1t-1},

$$\beta_{it-1} = \overline{\beta}_{is} + \vartheta_{is}(\gamma_{1t-1} - \gamma_{1s}) + \eta_{it-1}, \tag{4}$$

where $\mathbf{E}_s[\eta_{it-1}] = 0$ and $\mathbf{E}_s[\eta_{it-1}\gamma_{1t-1}] = 0$. Here, the beta-premium sensitivity, ϑ_{is}, measures how an asset's market beta varies with the market premium within an economic state s. We call this variation the *beta-instability risk*. Substituting equation (4) into (3) gives

$$\mathbf{E}_s[r^e_{it}] = \gamma_{1s}\overline{\beta}_{is} + Var_s(\gamma_{1t-1})\vartheta_{is}. \tag{5}$$

Define the market beta, β_{is}, and the premium beta, β^{γ}_{is}, as the coefficients in a multiple regression of asset i's excess return (r^e_{it}) on the excess market return (r^e_{mt}) and the market premium (γ_{1t-1}), respectively, conditional on information set $I_s \subseteq I_{t-1}$. Also define the conditional variance of the residual excess market return, $\varepsilon_{mt} \equiv r^e_{mt} - \gamma_{1t-1}$, as $\sigma^2_{\varepsilon mt-1} \equiv Var_{t-1}(\varepsilon_{mt})$ and $\sigma^2_{\varepsilon ms} \equiv Var_s(\varepsilon_{mt})$, and similarly the premium variance as $\sigma^2_{\gamma 1s} \equiv Var_s(\gamma_{1t-1})$. The following proposition rewrites $\overline{\beta}_{is}$ and ϑ_{is} in the above equation by β_{is} and β^{γ}_{is} and derives a cross-sectional restriction:

PROPOSITION 1 *(Two-beta CAPM): Under additional assumptions described in the appendix, the expected return on asset i conditional on economic state s is given by*

$$\mathbf{E}_s[r^e_{it}] = \gamma_{1s}\beta_{is} + \gamma_{2s}\beta^{\gamma}_{is}, \tag{6}$$

where

$$\beta_{is} = \overline{\beta}_{is} + \vartheta_{is} Cov_s(\gamma_{1t-1}, \sigma^2_{\varepsilon mt-1})/\sigma^2_{\varepsilon ms}, \tag{7}$$

$$\beta^{\gamma}_{is} = \vartheta_{is} b_s, \tag{8}$$

$$\gamma_{2s} = [\sigma^2_{\gamma 1s} - \gamma_{1s} Cov_s(\gamma_{1t-1}, \sigma^2_{\varepsilon mt-1})/\sigma^2_{\varepsilon ms}]/b_s, \tag{9}$$

$$b_s \equiv \gamma_{1s} + Skew_s(\gamma_{1t-1})/\sigma^2_{\gamma 1s} - Cov_s(\gamma_{1t-1}, \sigma^2_{\varepsilon mt-1})/\sigma^2_{\varepsilon ms}, \tag{10}$$

$Skew_s(\cdot)$ *is the skewness of the argument conditional on information set* I_s *and we have assumed that* $b_s \neq 0$*.*

Proof. All proofs can be found in the appendix. ■

As in JW, the conditional CAPM produces a two-beta expression on a coarser information set. Our result extends JW in three dimensions. First, our market and premium betas are defined (and measured later empirically) as multiple regression coefficients, rather than simple regression coefficients as in JW. We believe that this is more in accord with the empirical practice of controlling for known factors simultaneously in asset pricing tests. Moreover, it turns out that multiple regression betas are mathematically less involved than simple regression betas. The proof in the appendix demonstrates this point.

Second and more importantly, these betas and the premia are conditional on an economic state, s. Mathematically, aside from the above distinction between multiple and simple regression betas, this is as easily accomplished as putting subscript s to JW's unconditional result; one can simply change the conditioning information set from the unconditional one to I_s. Economically, however, this has an important implication. In particular, as equations (8) and (9) indicate, both the premium beta, β^{γ}_{is}, and the beta instability-risk premium, γ_{2s}, can vary across distinct economic states. For example, assume for simplicity that the high-order moments in the second and third terms of b_s in (10) are negligible or cancel out. Then from equation (8),

$$\beta_{is}^{\gamma} \approx \vartheta_{is}\gamma_{1s}. \tag{11}$$

This says that the premium betas as well as the market betas of stocks with positive (negative) beta-premium sensitivities rise (fall) during bad times as the market premium rises. We will find evidence consistent with this hypothesis in Section III.C.

Finally, unlike JW, we fully identify the parameters in the two-beta expression (6). The analysis in the preceding paragraph is one application that takes advantage of it. We additionally observe the following two points. First, the market premium on the market beta is still γ_{1s}; somewhat surprisingly, conditioning down does not set us free from the bedeviled CAPM relation as long as we measure betas by a multiple regression. Note that it does change the market beta in equation (7), in the sense that it differs from the expected conditional beta, $\overline{\beta}_{is} = \mathbf{E}_s[\beta_{it-1}]$, or the state s beta, $\frac{Cov_s(r_{it}^e, r_{mt}^e)}{Var_s(r_{mt}^e)}$. Lewellen and Nagel (2006) discuss the relationship between these two betas in an unconditional context. It follows that our market beta also differs from theirs. This point is demonstrated in the proof in the appendix.[2] Second, identifying γ_{2s} allows us to potentially impose the cross-sectional restriction that equation (6) implies. Lewellen and Nagel (2006) point out that many existing studies ignore such a restriction. That is, not only is γ_{2s} theoretically unidentified, but also treated as a free parameter in empirical estimation. However, equation (9) does reveal that imposing such a restriction *is* difficult, since it is a nonlinear function of high order moments of the premium and the residual

[2] We thank Ravi Jagannathan for comments that led us to examine this point in detail.

excess market return. In fact, without knowledge about these moments, we cannot even sign γ_{2s}.

Fortunately, we can address this issue by employing a mimicking portfolio of a variable predicting the market premium. To this end, we first rewrite Proposition 1 in terms of a (possibly nontraded) predictive variable. Let z_{t-1} be such an instrument that

$$r^e_{mt} = \delta_{0s} + \delta_{1s} z_{t-1} + \varepsilon_{mt}, \tag{12}$$

or

$$\gamma_{1t-1} = \delta_{0s} + \delta_{1s} z_{t-1}. \tag{13}$$

Define β_{is} and β^z_{is} as the slope coefficients in a multiple regression of r^e_{it} on the excess market return and the predictive instrument, respectively. We call β^z_{is} the *instrument beta*. The following corollary first rewrites Proposition 1 in terms of β_{is} and β^z_{is}, and then shows that, if z^e_{t-1} is additionally an excess return on a traded asset, the beta-instability risk premium must equal the asset's excess return conditional on economic state s:

COROLLARY 1 *(Two-beta CAPM by an instrument): If z_{t-1} is a predictive instrument such that equation (13) holds, then*

$$\mathbf{E}_s[r^e_{it}] = \gamma_{1s}\beta_{is} + \gamma_{3s}\beta^z_{is}, \tag{14}$$

where β_{is} is given by equation (7) and

$$\beta^z_{is} = \delta_{1s}\beta^\gamma_{is}, \quad \gamma_{3s} = \gamma_{2s}/\delta_{1s}.$$

If z_{t-1}^e is additionally an excess return on a traded asset, then

$$\mathbf{E}_s[r_{it}^e] = \gamma_{1s}\beta_{is} + z_s^e \beta_{is}^z, \tag{15}$$

where $z_s^e \equiv \mathbf{E}_s[z_{t-1}^e]$.

Equation (15) is readily testable. Equipped with these results, we now turn to our empirical analysis.

II. GDP Growth Forecast as a Predictive Instrument

This section examines if a measure of investors' expectation about future business conditions, constructed from publicly available surveys predicts future market return, which is the qualification that Corollary 1 calls for. We then examine whether it indeed captures the beta-instability risk.

A. Data and the Construction of the Expected GDP Growth Measure

Our measure of expected GDP growth comes from the Livingston Survey, which summarizes the forecasts of approximately 50 economists from industry, government, banking, and academia. Started in 1946 by a financial columnist Joseph Livingston and later taken over by the Philadelphia FRB in 1990, it is the oldest continuous survey of economists' expectations. The survey is conducted twice a year in June and December and currently consists of the forecasts of 18 different variables describing national output, prices, unemployment, and interest rates.[3] The results of the forecasts are released by the Philadelphia FRB during the two survey

[3]See Croushore (1997) and the Federal Reserve Bank of Philadelphia (2005) for details of the survey.

months, and are often reported in major newspapers and Internet newswires.[4]

Following Campbell and Diebold (2005), we construct a measure of expected real GDP growth ($EGDP$) from the median forecasts of the nominal GDP level ($GDPX$) and the CPI level (CPI). The six- and twelve-month-ahead forecasts of these variables are continuously available from the second half of 1951 through the second half of 2006. This allows us to create a directly observable measure of the two-step-ahead log expected real GDP growth rate semiannually,

$$EGDP_t^{t+1,t+2} = \ln \frac{GDPX_t^{t+2}}{CPI_t^{t+2}} - \ln \frac{GDPX_t^{t+1}}{CPI_t^{t+1}}.$$

The Livingston Survey did not request the respondents to provide their forecasts on the nominal GDP and CPI levels at the end of each forecast month until June 1992. Hence, we are unable to create a one-step-ahead forecast of real GDP growth for the majority of our sample period. Since it is essential to ensure accurate timing of investor expectations for our purpose, we use the two-step-ahead forecast defined above.

The first two rows of Table 1 reports the summary statistics of $EGDP$ and the realized real GDP growth rate ($RGDP$), computed from data publicly available from the St. Louis FRB. The mean expected real semi-annual GDP growth rate is 1.3%, which is close to the realized growth rate of 1.5%. Figure 1 plots $RGDP$ and the second lag of $EGDP$, denoted by $LEGDP$, which matches the forecasting period to the measurement period of $RGDP$. Henceforth we put a prefix "L" to denote a lagged series without a time subscript. We observe that $LEGDP$ is much smoother than $RGDP$, which is a property of optimal expectations as noted by Campbell and Diebold (2005). The figure also shows the NBER business cycle. Each narrow band represents a

[4]Much of the existing research using the Livingston Survey focuses on inflation forecasts (see, e.g., Ang, Bekaert, and Wei (2006), Fama and Gibbons (1984), and Gultekin (1983)).

recession, starting with a peak and ending with a trough. If economists make "good" forecasts, LEGDP should start declining at the beginning of each narrow band and be lowest at its end. We see that this is perfectly true for the first three recessions, somewhat true for the next two, and mixed for the last four.

B. Relation between Expected GDP Growth and Predictive Instruments

This subsection investigates the link between $EGDP$ and instruments that are known to forecast aggregate returns. This allows us to examine if $EGDP$ provides additional information that existing predictive instruments do not. We employ the following five variables typically used in the predictability literature; the dividend yield (DY), default spread (DEF), term spread ($TERM$), risk-free rate (RF), and the consumption-wealth ratio (CAY).[5]

DY is the sum of dividends accruing to the Center for Research in Securities Prices (CRSP) value-weighted market portfolio over the previous 12 months divided by the level of the market index. DEF is the yield spread between Moody's Baa and Aaa corporate bonds, and $TERM$ is the yield spread between the ten-year Treasury bond and the three-month Treasury bill. The relevant series are from the St. Louis FRB. RF is the one-month Treasury bill rate downloaded from Kenneth French's web page. CAY is available on Martin Lettau's and Sydney Ludvigson's web pages.[6] The third row and below of Table 1 report the summary statistics along with the CRSP value-weighted excess market return (MKT) to be predicted. Not surprisingly, MKT is much more volatile than these predictive instruments.

Column 1 of Table 2 reports the results of the following contemporaneous regression of

[5]See, e.g., Fama and French (1988) for DY, Keim and Stambaugh (1986) for DEF, Fama and French (1989) for $TERM$, Fama (1981) for RF, and Lettau and Ludvigson (2001a, 2001b) for CAY.

[6]We thank these researchers for making their data available.

$EGDP$ on other predictive instruments,

$$EGDP_t^{t+1,t+2} = a + b_{DY}DY_t + b_{DEF}DEF_t + b_{TERM}TERM_t + b_{RF}RF_t + b_{CAY}CAY_t + e_t.$$

Following Campbell and Diebold (2005), all the regressors are standardized with mean zero and variance one for this regression only. Like them, we find that DY has a significant negative effect, implying that strong future growth expectations tend to be associated with lower discount rates and higher current prices, which in turn depress dividend yields. We also see a counterintuitive positive effect of DEF, which may suggest that it captures business conditions over a longer horizon than that captured by $EGDP$ (Fama and French (1989)).

Liew and Vassalou (2000) and Vassalou (2003) find that the size and value premia contain information about future GDP growth, supporting a risk-based explanation of these premia.[7] According to them, the significant positive relationship between these premia and future GDP growth arises because small value firms can become more profitable when high economic growth is expected in the future. This implies that the size (SMB) and value (HML) factors are contemporaneously related to the measure of investor expectations about the real economy. To examine this point, we run the following regression:

$$EGDP_t^{t+1,t+2} = a + b_{SMB}SMB_t + b_{HML}HML_t + e_t.$$

[7] Aretz, Bartram, and Pope (2007) find that B/M, and therefore HML, captures risk exposures to innovations in economic growth expectations, although the relation can change sign.

Column 2 of Table 2 shows that there is indeed a significant positive relationship between $EGDP$ and SMB as well as HML.

Importantly, while $EGDP$ is contemporaneously related to the predictive instruments and the known priced factors, the R-square of the regression is low in both of these two columns (at most 27%). That is, $EGDP$ may contain information that is not present in existing instruments and factors. We now investigate this point with a particular focus on the information about the future excess aggregate return.

C. Predictive Regressions

This subsection tests the ability of $EGDP$ to forecast the future excess market return, which is the qualification that Corollary 1 calls for. We run the following predictive regression for the commonly available sample period (the first half of 1953 through the second half of 2005),

$$\begin{aligned} MKT_t = {} & \delta_0 + \delta_{EGDP} EGDP_{t-2}^{t-1,t} + \delta_{DY} DY_{t-1} + \delta_{DEF} DEF_{t-1} \\ & + \delta_{TERM} TERM_{t-1} + \delta_{RF} RF_{t-1} + \delta_{CAY} CAY_{t-1} + e_t, \end{aligned} \tag{16}$$

where MKT is the CRSP value-weighted market return less the one-month treasury bill rate. Note that we use the second lag of $EGDP$ to match its forecasting horizon to the holding period of the market return. All other instruments are lagged by one period.

Table 3 shows that $LEGDP$ has a significant predictive ability, controlling for other predictive instruments, many of which are also significant. Again, the prefix "L" signifies a lagged series, where the lag order is 2 for $EGDP$ and 1 for all other instruments. The negative coefficient on $LEGDP$ captures the counter-cyclical pattern in expected excess returns; a large equity premium arises when the economic outlook is poor and hence the perceived risk is high. This indicates that $EGDP$ is a useful new addition to the set of predictive instruments traditionally used in the literature. We now examine if it indeed captures time variation in premium betas, namely, the beta-instability risk.

D. *Instrument Betas for Value and Growth Stocks*

Motivated by Corollary 1, we estimate the following CAPM regression augmented by a conditional lagged instrument,

$$r_{it}^{e} = \alpha_i + \beta_i MKT_t + \beta_{is}^{z} D_s z_{t-l} + \varepsilon_{it}, \tag{17}$$

where r_{it}^{e} is the excess return on asset i, D_s is a dummy variable for an economic state s defined below, and z_{t-l} is a lagged instrument with l representing the lag order appropriate for the instrument ($l = 2$ for $EGDP$ and 1 for all others). We define "low times" ("high times") as periods in which the value of the lagged instrument is lower (higher) than its past 20-period (ten-year) moving average ($\overline{z}_{t-l}$), and set the low-time (high-time) dummy variable $D_s = 1$ if $z_{t-l} \leq \overline{z}_{t-l}$ ($z_{t-l} > \overline{z}_{t-l}$) and 0 otherwise. While the corollary implies that the market beta can also vary across economic states, we do not condition it on state s because we did not find the associated conditional premium significant in unreported cross-sectional asset pricing tests; that is, the premium for the conditional market risk $D_s MKT_t$ was insignificant when it replaced MKT_t in equation (17) (D_s is determined from $LEGDP$, which is our final specification to be presented below).[8] An advantage of this approach is that we can view equation (17) as a straightforward extension of the market model. According to Corollary 1, β^z_{is} will have the same sign as (opposite sign from) the premium beta β^γ_{is} if the instrument positively (negatively) predicts the future market return.

Figure 2 plots estimated β^z_{is} on various predictive instruments for B/M quintile portfolios in selected size groups. The top row shows the conditional instrument beta for $LEGDP$. Since $EGDP$ negatively predicts future market return, the "low time" instrument betas shown by circles are those for periods with high-premium, or bad economic times. We see that value stocks have a smaller lagged Livingston beta (β^z_{is}), and hence a larger premium beta (β^γ_{is}), than growth stocks in bad times across the three size-quintile portfolios. This cross-sectional relation, however, is reversed in "high times," or good economic times; during such times value stocks have a larger lagged Livingston beta (marked by crosses in the figure), and hence a smaller premium beta, than growth stocks. This is consistent with a hypothesis that value stocks are riskier not because their returns are always sensitive to changes in the market premium, but because they are so in *bad* times. In other words, they tend to deliver higher returns forward as business conditions deteriorate and the expected aggregate return rises in bad states of the economy; this is accomplished by lower current prices of value stocks as aggregate prices fall. This is similar to the finding of Lettau and Ludvigson (2001b), who make a similar observation in a Consumption CAPM framework.[9] What makes our finding striking is the fact that we do not model β^z_{is} by any instrument; it is just a constant given an economic state s (see equation

[8]This already indicates a mixed result for the cross-sectional restriction imposed by Corollary 1; the premium on D_sMKT_t should equal the expected market return in the given economic state. While the sample mean of the excess market return is insignificant at 1.5% ($t = 1.1$) in the good state, it was significantly positive at 6.0% ($t = 3.5$) in the bad state as shown in Panel A of Table 5.

[9]Also see Chan and Chen (1988, footnote 6) and Petkova and Zhang (2005). Chen and Zhang (1998) find that value premium is large in established markets such as the U.S. and Japan but not in the fast-growing markets of Taiwan and Thailand because the spread of risk between value and growth stocks is small.

(17)). In contrast, Lettau and Ludvigson's (2001b) consumption betas are functions of CAY, a variable that varies across good and bad economic times.

The ability of $LEGDP$ to capture the cross-sectional difference in beta-instability risk is unsurpassed by other instruments. The rest of the figure shows β^z_{is} for other predictive instruments, lagged dividend yield (LDY), default spread ($LDEF$), term spread ($LTERM$), short rate (LRF), and the consumption-wealth ratio ($LCAY$). Compared to these instruments, $LEGDP$ is the only variable whose beta varies almost monotonically with the level of B/M consistently across the three size quintiles, and flips the cross-sectional relation between good and bad times. Given this result, we focus on the analysis using $LEGDP$ in the rest of the paper.

This observation suggests that betas vary substantially over the business cycle. The challenge in measurement of these variations is the selection of the appropriate windows and instruments. For example, Lewellen and Nagel (2006), using daily, weekly, and monthly data in relatively short estimation windows ranging from a month to a year, argue that betas and equity premium must vary enormously over time to account for known anomalies. Chan, Hameed, and Lau (2003), using daily data in annual windows, find that the location of trade affects assets' betas due to a difference in investor clientele. For our purposes, however, such short-window regressions are unlikely to capture variations in betas related to the business cycle which has a multi-year horizon. In fact, the sensitivity of estimated betas to the horizon of measurement is the subject of recent research. Hoberg and Welch (2007) show that the market beta computed using daily returns during the most recent one-year period is negatively related to the future stock return, while the beta computed using daily returns from one to ten years ago is positively related. They further propose that the long-term beta captures the standard hedging motive. Given these findings, the instrument betas depicted in Figure 2, computed using all observations within an economic state determined from long ten-year windows, are more likely to reflect changes in economic conditions than short-window betas. Needless to say, it is exactly such changes that are relevant in the conditional CAPM relation.[10]

These results demonstrate the potential gain to advancing JW's unconditional framework to one conditional on the business cycle. An empirical model that estimates unconditional instrument betas (or unconditional premium betas) may be seriously misspecified. In particular, the opposing behavior of value and growth instrument betas found above suggests that conditioning on economic states can increase the power of asset pricing tests. We examine this point in the next section.

III. Pricing of Beta-Instability Risk

A. Asset-Pricing Tests for Expected Real GDP Growth

This section evaluates the premium for bearing beta-instability risk. We employ the Fama-MacBeth (1973) two-pass procedure to conduct the cross-sectional asset pricing tests. To account for the possible errors-in-variable problem, we employ the Shanken (1992) correction for standard errors. The test assets are the Fama-French size-B/M 25 portfolios here, and will be later extended to individual stocks. The first column in Panel A of Table 4 shows the estimated premia for the CAPM specification. The insignificant market (MKT) premium and the significantly positive intercept confirm the well known fact that the CAPM cannot explain the cross-sectional variation in stock returns. The adjusted R-squared in the cross-sectional regres-

[10]We thank Ravi Jagannathan for his insights on this issue.

sion of the average realized excess returns on estimated betas ("Adj R^2") is only -1%. The second column introduces the lagged Livingston expected real-GDP growth rate ($LEGDP$) to the CAPM specification. While $LEGDP$ has a significantly positive premium, it is unclear whether it is consistent with γ_{3s} in equation (14) as we do not know its magnitude. Therefore, we defer the examination of the cross-sectional restriction until we construct a mimicking portfolio of $LEGDP$. Notably however, the adjusted R-squared jumps impressively from -1% to 71% by simply adding $LEGDP$ to the CAPM. By comparison, the next column shows the estimated premia for the four-factor model comprised of the market, size (SMB), value (HML), and momentum (MOM) factors. The adjusted R-squared is 77%, demonstrating the ability of this model to capture the cross-sectional variation in the size-B/M sorted portfolios. These points are visually demonstrated in Figure 3, which plots the fitted returns from the three models against average realized returns. The dashed line represents a 45 degree line, on which the fitted returns will fall if the model perfectly explains the cross-sectional variation in average returns. We see that the flat relation for the CAPM gets more aligned along the 45 degree line in the Livingston model and the four-factor model.

Back to Table 4, column 4 introduces $LEGDP$ to the four-factor model. The 77% R-squared is unchanged from the four-factor model. This suggests that the lagged Livingston factor and the set of four factors have similar explanatory power in the cross section of stock returns. While the $LEGDP$ premium becomes insignificant in this specification, this is again little informative about the validity of the cross-sectional model. A conditional model, however, is likely to be better specified given the result in the previous section; we know that the premium betas vary in such a manner that their cross-sectional differences tend to cancel out over good and bad economic times (see the top row of Figure 2). To accommodate this point, Column 5

(6) replaces $LEGDP$ with its bad- (good-) time counterpart, $LEGDPB$ ($LEGDPG$), which equals $LEGDP$ during periods in which its level is lower (higher) than its past twenty-period moving average and zero otherwise. This is the model in (17) with $LEGDP$ as the lagged instrument (z_{t-l}), additionally controlled for the size, value, and momentum factors. We see that the bad-time premium for $LEGDPB$ in column 5 is significant at 10%. By comparison, the good-time premium for $LEGDPG$ is also significant but positive. Note, however, that in addition to the beta-instability risk premium, this positive premium may partially reflect the growth expectation of the U.S. economy. To see this, consider an asset that is positively correlated with $LEGDP$, whose extreme example is its mimicking portfolio. It will earn high returns during good times if it is indeed a good tradable proxy for $LEGDP$. In fact, $LEGDP$ has a positive mean ($EGDP$ has a mean of 1.3% in Table 1), suggesting that economists have expected the U.S. economy to grow on average over the last half century. Then its mimicking portfolio must earn high returns in some periods, which occurs exactly during good times.

Panel B of Table 4 uses individual stocks on NYSE, AMEX, and NASDAQ as test assets. Since betas of individual stocks are expected to be noisy, we follow Fama and French (1992) and assign betas of the Fama-French 25 portfolios to their member stocks. We find that the signs of the $LEGDP$ premium and its conditional versions in columns 2, 4, 5, and 6 are consistent with Panel A. The magnitude of the premia, however, is generally much larger here. This may be due to the assignment of identical betas of a single size-B/M portfolio to all of its component stocks that may actually have different loadings on non-size or non-B/M factors; in fact, the momentum premium is also very large and carries a wrong sign at around -20% across columns 3 through 6. The market premium has also changed especially in columns 1 and 2. Not surprisingly, the adjusted R-squared is much lower for individual stocks.[11]

B. Economic Significance of Beta-Instability Risk

B.1. Construction of the Mimicking Portfolio

To see the economic significance of the beta-instability risk premium, we construct a mimicking portfolio of $LEGDP$. Starting in June 1967, we regress the second lag of $EGDP$ on returns of basis assets ($\boldsymbol{R}_\tau$) without an intercept using the past 30 observations (15 years):

$$EGDP_{\tau-2}^{\tau-1,\tau} = \boldsymbol{b}_{t-1}'\boldsymbol{R}_\tau + \varepsilon_\tau, \quad t-30 \leq \tau \leq t-1 \tag{18}$$

where $\boldsymbol{b}_{t-1}$ is a conforming vector of loadings. The length of the rolling window balances the desire to increase statistical power using enough number of observations and yet to capture most recent, presumably relevant, economic conditions. The return on the mimicking portfolio, $LGDPM$, in period t is then given by

$$LGDPM_t = \frac{\boldsymbol{b}_{t-1}'\boldsymbol{R}_t}{|\boldsymbol{b}_{t-1}'\boldsymbol{1}|},$$

where $\boldsymbol{1}$ is a vector of ones. The division by $|\boldsymbol{b}_{t-1}'\boldsymbol{1}|$ simply normalizes the loadings so that they have a weight interpretation. We use returns of only four portfolios, MKT, SMB, HML, and MOM, as components of $\boldsymbol{R}_\tau$. This avoids multicollinearity issues typically associated with the use of a finer partition of traded assets; we also tried using the Fama-French size-B/M 25 and 6

[11] Since the size-B/M portfolio to which an individual stock belongs can change over time, the average return is computed within each stock-beta pair. Consequently, the cross-sectional regressions in Panel B of Table 4 have 77,969 observations for 18,027 stocks in columns 1 and 3 and 77,816 observations for 18,021 stocks in other columns.

portfolios as $\boldsymbol{R}_\tau$, but in both cases the procedure resulted in practically unreasonable weights such as short positions in excess of 200% in some portfolios. Since all of our four basis assets are returns on zero-investment portfolios, so is $LGDPM$. Because weights are constructed by rolling regressions using information up to time $t-1$, $LGDPM$ is the return on a fully tradable portfolio. The average R^2 of the rolling regressions (18) was 52% (unreported in a table).

Our approach to constructing the mimicking portfolio in equation (18) fundamentally differs from the one proposed by Lamont (2001) and its application to the realized GDP growth rate by Vassalou (2003). These authors place a lead, rather than lag, on the economic series in the left hand side of the mimicking regression and additionally include lagged instruments that predict basis-asset returns in the right hand side. Their objective is to extract the *news* component contained in the economic series that is relevant to the pricing of traded assets and that is hence reflected on basis asset returns. In contrast, our goal is to construct a traded portfolio that captures beta-instability risk inherent in the conditional CAPM rather than news as in, for example, ICAPM. As JW (1996, p.10) note, the lagged premium (γ_{1t-1}) in equation (3) with respect to which the beta-instability risk is measured is "a predetermined variable and is not a factor in the sense commonly understood."[12]

B.2. Properties of the Mimicking Portfolio

Table 5 shows the return properties of the mimicking portfolio and the basis assets used in its construction. $LGDPM$ has a semiannual mean of 3.5% with a 5.1% standard deviation, which yields the highest mean-standard deviation ratio, 0.68 (in the column labeled "Mn/Std"), of all the factors examined here. By comparison, while the mean excess market return (MKT)

[12]Ferson and Harvey (1999) also use lagged predictive variables, specifically the conditional expected return fitted by them, to explain the cross section of stock returns.

is slightly higher at 3.7%, it is twice as volatile as $LGDPM$ with a standard deviation of 12%. These two series are plotted in Figure 4. It is visually clear that $LGDPM$ hovers above zero most of the time and yet is much less volatile than MKT. As noted earlier, the positive unconditional mean of $LGDPM$ may partially reflect the growth expectation of the U.S. economy over the last half century, in addition to the beta-instability risk premium.

The pairwise correlations in Panel B indicate that $LGDPM$ does a modest job of tracking $LEGDP$, to which it is correlated at 0.31. $LGDPM$ is also correlated to HML and MOM at 0.40 and 0.56, respectively.

Another way to demonstrate how well our mimicking portfolio behaves is to check its weights, which are depicted in Figure 5. Clearly, no extreme position is taken in any basis asset. The mimicking portfolio takes a small position in SMB or even goes short on it in most of the '90s, a period known for a weakening of the size effect. Generally, the SMB weight moves in the mirror image of MKT throughout the sample period. Interestingly, the four weights appear to have converged in recent years so that the mimicking portfolio currently holds MKT, SMB, HML, and MOM with approximately equal weights.

Ultimately for our purpose, it is important that the mimicking portfolio capture the beta-instability risk. We can examine this point by the last row of Figure 2, which depicts the conditional beta with respect to $LGDPM$. The mimicking portfolio appears to do a modest job of capturing the cross-sectional difference in instrument betas between value and growth stocks except for the largest size quintile during low (bad) times. We now test the pricing of the mimicking portfolio when it is used as a tradable predictive instrument in Corollary 1.

B.3. Pricing of the Mimicking Portfolio

Panel A of Table 6 shows the result of the asset-pricing tests using the mimicking portfolio. The test assets are the Fama-French size-B/M 25 portfolios in this panel. $LGDPM$ has a significantly positive 5.7% premium in column 1 where MKT is the only other non-constant factor. Corollary 1 requires that this premium equal the unconditional mean of $LGDPM$, which is 3.5% in Table 5.[13] However, the entire premium almost disappears when the three factors are included in column 2. This suggests that the unconditionally positive mean return of $LGDPM$ more reflects the average growth expectation of the U.S. economy than the beta-instability risk premium per se.

However, when the instrument beta is conditioned on economic states, a different story emerges. We construct a conditional version of the mimicking portfolio during bad- (good-) times, $LGDPMB$ ($LGDPMG$), which equals $LGDPM$ in periods when $LEGDP$ is lower (higher) than its past twenty-period moving average and zero otherwise. Corollary 1 again imposes a restriction that their premia must equal the expected excess (or zero-investment) mimicking portfolio return in the states they are conditioned on. Since $LGDPM$ proxies the expected real GDP growth rate, we expect that the $LGDPMB$ premium will be lower than the $LGDPMG$ premium. The result in columns 3 and 4 is consistent with this expectation; the estimated $LGDPMB$ and $LGDPMG$ premia are -2.9% and 3.7%, respectively, both of which are statistically significant controlling for the size, value, and momentum factors. However, while the relative relation between the $LGDPMB$ and $LGDPMG$ premia is right, their magnitude appears not. From Panel A of Table 5, the average returns on $LGDPM$ during

[13] z^e_{t-1} in Corollary 1 can be a return on a zero-investment portfolio such as $LGDPM$ rather than an excess return over a risk-free asset. Since we use excess returns as test assets, the intercept should be zero if the model is correct. z^e_{t-1} can still price itself because it can price the excess return on each of the long and short positions in its construction.

bad and good times are 2.2% and 5.1%, respectively, the former of which is particularly off the above negative cross-sectional premium. Moreover, the other two cross-sectional restrictions are also violated. Equation (15) demands that the intercept be zero and that the MKT premium equal the conditional market premium (in excess of the risk-free rate) in state s. However, the intercept and the MKT premium are significantly positive and negative, respectively, across columns 2 through 4. Panel A of Table 5 shows that the mean MKT return is 3.7% unconditionally, 6.0% conditionally on bad states, and 1.5% conditionally on good states, and that the first two of these three numbers are significantly positive. Therefore, our empirical asset pricing models do not satisfy the cross-sectional restrictions that theory imposes.

This result is consistent with the findings of recent studies that the conditional CAPM does not fully explain the cross-sectional variation in stock returns (see, e.g., Petkova and Zhang (2005) and Lewellen and Nagel (2006)). However, we wish to emphasize *how much* cross-sectional variation it can explain if an appropriate instrument is employed. The adjusted R-squared of the conditional mimicking-portfolio models in columns 3 and 4 is 88% and 85%, respectively. Thus, the conditional factors improve the fraction of cross-sectional variation in average realized returns by 8% to 11% over the four-factor model (see column 3 of Table 4, Panel A). While these levels of R-squared seem impressive, Lewellen, Nagel, and Shanken (2006) cast a doubt on asset pricing tests that use only size-B/M-sorted portfolios. These test assets are known to possess a strong factor structure, and therefore a factor that is only weakly correlated with the size and B/M factors may exhibit a high explanatory power. To address this issue, we follow their advice and use individual stocks on NYSE, AMEX, and NASDAQ in Panel B. As expected, none of the models shown there satisfy all the three cross-sectional restrictions discussed above. However, the bottom line is that the estimated premia using individual stocks carry the same signs as those using portfolios when they are statistically significant.

C. Measuring the Beta-Instability Risk Directly

This section gets back to the basics and directly estimates the deep parameters representing the beta-instability risk, namely, the beta-premium sensitivity ϑ_{is}. We start with the specification proposed by Petkova and Zhang (2005). Let $\boldsymbol{Z}_{t-1}$ be the $k+1$ vector of lagged instruments with 1 as the first element, where k is the number of predictive instruments. Our conditional CAPM framework is described by the following three equations (see Petkova and Zhang's (2005) equations (1), (3), and (6)):

$$\text{Predictive regression: } r^e_{mt} = \boldsymbol{\delta}'\boldsymbol{Z}_{t-1} + \varepsilon_{Mt}, \tag{19}$$

$$\text{Market regression: } r^e_{it} = \alpha_i + \boldsymbol{b}'_i\boldsymbol{Z}_{t-1}r^e_{mt} + \varepsilon_{it}, \tag{20}$$

$$\text{Beta-premium regression: } \boldsymbol{b}'_i\boldsymbol{Z}_{t-1} = \overline{\beta}_i + \vartheta_i\boldsymbol{\delta}'\boldsymbol{Z}_{t-1} + \eta_{it-1}, \tag{21}$$

where $\boldsymbol{\delta}$ and $\boldsymbol{b}_i$ are both $k+1$-vectors, and α_i, $\overline{\beta}_i$, and ϑ_i are scalars. The first equation corresponds to earlier equation (12) and represents the predictive regression in which the excess market return, r^e_{mt}, is regressed on lagged instruments, $\boldsymbol{Z}_{t-1}$. We take MKT as r^e_{mt} and a vector comprised of $LEGDP$, LDY, $LDEF$, $LTERM$, LRF, and $LCAY$ as $\boldsymbol{Z}_{t-1}$, which makes the predictive regression in equation (16). The second equation is the CAPM regression in which asset i's excess return, r^e_{it}, is regressed on the excess market return, r^e_{mt}, with the time variation in market beta modeled by lagged instruments, $\boldsymbol{Z}_{t-1}$ (see equation (A1) in the appendix). The last equation is the beta-premium regression corresponding to an unconditional version of equation (4). The beta-premium sensitivity, ϑ_i, captures how asset i's market beta changes over the business cycle measured by $\boldsymbol{\delta}'\boldsymbol{Z}_{t-1}$, the fitted market premium from equation (19). These three equations specify a time-series model, as opposed to cross-sectional models that have been estimated in preceding sections.

We estimate the system in equations (19)-(21) for each asset by GMM. The corresponding moment conditions are:

$$\mathbf{E}[(r^e_{mt+1} - \boldsymbol{\delta}'\boldsymbol{Z}_t)\boldsymbol{Z}_t] = 0 \quad (k+1 \text{ equations}), \tag{22}$$

$$\mathbf{E}[(r^e_{it+1} - \alpha_i - \boldsymbol{b}_i'\boldsymbol{Z}_t r^e_{mt+1})[\begin{array}{cc} 1 & \boldsymbol{Z}_t r^e_{mt+1} \end{array}]'] = 0 \quad (k+2 \text{ equations}), \tag{23}$$

$$\mathbf{E}[(\boldsymbol{b}_i'\boldsymbol{Z}_t - c_i - \vartheta_i\boldsymbol{\delta}'\boldsymbol{Z}_t)[\begin{array}{cc} 1 & \boldsymbol{\delta}'\boldsymbol{Z}_t \end{array}]'] = 0 \quad (2 \text{ equations}). \tag{24}$$

There are $2k+5$ equations for $2k+5$ parameters. So the system is exactly identified.

For parsimony, Panel A of Table 7 only reports the parameters of interest, α_i and ϑ_i, estimated using size-controlled B/M quintile portfolios. Each of these portfolio returns is computed as the equally weighted average of the returns on the five size portfolios that belong to a given B/M quintile using the Fama-French 25 portfolios. We see that ϑ_i is monotonically increasing with B/M, and the highest B/M portfolio has a positive ϑ_i that is significantly different from zero at 10%. Consistent with Petkova and Zhang (2005), however, we find that the beta-instability risk cannot explain the value premium. The intercept, α_i, monotonically increases with the level of B/M and becomes significantly positive for the medium to high B/M portfolios.

Our presumption in equation (4), however, is that the beta-premium sensitivity can also depend on an economic state. To accommodate this point, we modify equation (21) as

$$\boldsymbol{b}_i'\boldsymbol{Z}_{t-1} = \overline{\beta}_i + \vartheta_{1i}[\boldsymbol{\delta}'\boldsymbol{Z}_{t-1}]_+ + \vartheta_{2i}[\boldsymbol{\delta}'\boldsymbol{Z}_{t-1}]_- + \eta_{it-1},$$

where $[\boldsymbol{\delta}'\boldsymbol{Z}_{t-1}]_+$ ($[\boldsymbol{\delta}'\boldsymbol{Z}_{t-1}]_-$) equals $\boldsymbol{\delta}'\boldsymbol{Z}_{t-1}$ if it is higher (lower) than its past 20 period moving average, and 0 otherwise. Here, to avoid parameter proliferation we allow only the beta-premium sensitivity (and not $\overline{\beta}_i$) to vary across economic states. Because the expected market premium is higher (lower) during bad (good) times, ϑ_{1i} and ϑ_{2i} can be interpreted as bad- and good-time beta-premium sensitivities, respectively. Panel B of Table 7 report the estimates of these conditional beta-premium sensitivities. We observe that, while the bad-time beta-premium sensitivity, ϑ_{1i}, is increasing in the level of B/M across the quintiles, none of the estimates is significantly different from zero. An examination of the residuals from the first equation in (24) reveals that the fitted premium, $\boldsymbol{\delta}'\boldsymbol{Z}_t$, has a higher dispersion during bad times than good times (not shown), and this appears to reduce the statistical significance of ϑ_{1i}. In contrast, the good-time sensitivity, ϑ_{2i}, shows a strong dispersion across the B/M quintiles. Starting with a significantly negative estimate for the lowest B/M quintile, it increases monotonically as B/M rises, until it becomes significantly positive for the highest B/M quintile. Because of this strong dispersion, ϑ_{2i} for the zero-investment portfolio that goes long the highest and short the lowest B/M portfolios is 7.45 (in the bottom row labeled "5 − 1"), which is significant at 5%.[14]

Let us link this finding to our theory. The positive beta-premium sensitivity of value stocks implies that their market betas rise as the market premium does during bad times. Recall the discussion on equation (11). It says that, under the assumption stated there, the premium betas as well as the market betas of value (growth) stocks rise (fall) during bad times as the market premium rises. This is exactly what we find in the top row of Figure 2, which shows that value (growth) stocks' Livingston betas fall (rise) during bad times with low expected real

[14]The estimated α_i's in the two panels are identical because not only is the whole system exactly identified, but also each of equations (22) and (23) is exactly identified.

GDP growth. The premium betas move in the opposite direction since the expected real GDP growth rate negatively predicts the market return.

IV. Conclusion

This paper finds that the time-variation in assets' market betas over the business cycle, or the beta-instability risk, is priced in the cross section of stock returns. We build on JW's insight that the conditional CAPM relation does not condition down to an unconditional CAPM in general, producing a covariance term between the market beta and the market premium. We derive explicit relations between the market and instrument betas as well as their premia. This helps us examine the cross-sectional restrictions that the conditional CAPM imposes on a coarser information set. We further extend JW's framework to one conditional on economic states, which, unlike most existing studies, are determined from more than half a century of real GDP growth expectations from economists' surveys. The expected real GDP growth rate constructed from the Livingston Survey forecasts the future aggregate return, controlling for existing instruments such as the dividend yield, default spread, term spread, short rate, and the consumption-wealth ratio. The ability of the expected real GDP growth rate to capture the cross-sectional difference in beta-instability risk is unsurpassed by these existing instruments.

We find that stocks whose returns are positively correlated with the lagged expected real GDP growth rate during bad (good) times earn a negative (positive) premium. To examine the conditional CAPM restriction, we construct a mimicking portfolio of the lagged expected real GDP growth rate. Our mimicking portfolio is fully tradable and behaves very well in terms of both the basis-asset weights and the first two moments of the return. While the conditional mimicking-portfolio premium is significant controlling for the market, size, value, and momentum factors, the models cannot satisfy all the cross-sectional restrictions that theory imposes. However, they can explain a considerable fraction of the cross-sectional variation in size-B/M portfolio returns. We also measure the beta-instability risk directly by the sensitivity of the market beta with respect to the market premium.

Our analysis leaves some unresolved issues. Along with Campbell and Diebold (2005), our results demonstrate that the Livingston-Survey expected real GDP growth rate is a useful new addition to the set of existing predictive instruments. If so, however, it qualifies not only as a predictive instrument in JW's two-beta model, but also as an economic series whose news component can serve as a factor in the multi-factor asset pricing models of Merton (1973) and Ross (1976). As Cochrane (2005, p.445) puts it, "[t]hough Merton's (1971, 1973) theory says that variables which predict market returns should show up as factors which explain cross-sectional variation in average returns, surprisingly few papers have actually tried to see whether this is true."Asset pricing models based on priced systematic risk factors rely fundamentally on a widespread perception of risks. Although latent variable methods and ex post variable realizations are useful for identifying factor structure in asset returns, ultimately researchers must look for priced factors in the public flow of economic information. For surely if people care a lot about a few factors they will seek news about them, and the public demand will be met in a free information marketplace.

Appendix: Proofs

Proof of Proposition 1: From the definition of γ_{0t-1}, γ_{1t-1}, and ε_{mt}, the excess market return is written as

$$r_{mt}^e \equiv r_{mt} - \gamma_{0t-1} = \gamma_{1t-1} + \varepsilon_{mt}, \quad \mathbf{E}_{t-1}[\varepsilon_{mt}] = 0.$$

The conditional CAPM gives the excess return on asset i as

$$r_{it}^e \equiv r_{it} - \gamma_{0t-1} = \beta_{it-1} r_{mt}^e + \varepsilon_{it}, \tag{A1}$$

$$\mathbf{E}_{t-1}[\varepsilon_{it}] = \mathbf{E}_{t-1}[\varepsilon_{it}\varepsilon_{mt}] = 0, \tag{A2}$$

which yields equations (1) and (2). Define the vector of regressors,

$$\boldsymbol{f}_t \equiv \begin{pmatrix} r_{mt}^e \\ \gamma_{1t-1} \end{pmatrix} = \begin{pmatrix} \gamma_{1t-1} + \varepsilon_{mt} \\ \gamma_{1t-1} \end{pmatrix}. \tag{A3}$$

Before proceeding, note that the covariance between a time $t-1$ quantity and a time t mean-zero shock is zero, which we will implicitly use below. For example,

$$Cov_s(\gamma_{1t-1}, \varepsilon_{mt}) = Cov_s(\gamma_{1t-1}, \mathbf{E}_{t-1}[\varepsilon_{mt}]) = 0,$$

where we have invoked the law of iterated expectations. Then,

$$Var_s(\boldsymbol{f}_t) = \begin{pmatrix} \sigma_{\gamma 1s}^2 + \sigma_{\varepsilon ms}^2 & \sigma_{\gamma 1s}^2 \\ \sigma_{\gamma 1s}^2 & \sigma_{\gamma 1s}^2 \end{pmatrix}. \tag{A4}$$

Next, using equations (A1) and (A3),

$$\begin{aligned}
Cov_s(\boldsymbol{f}_t, r^e_{it}) &= Cov_s(\boldsymbol{f}_t, \beta_{it-1} r^e_{mt}) \\
&= Cov_s\left[\begin{pmatrix}\gamma_{1t-1}+\varepsilon_{mt} \\ \gamma_{1t-1}\end{pmatrix}, \beta_{it-1}(\gamma_{1t-1}+\varepsilon_{mt})\right] \equiv \begin{pmatrix}\kappa_1+\kappa_2 \\ \kappa_1\end{pmatrix},
\end{aligned} \tag{A5}$$

where we have used $Cov_s(\boldsymbol{f}_t, \varepsilon_{it}) = \mathbf{0}$, which follows from equation (A2). The second element in the above expression is

$$\begin{aligned}
\kappa_1 &\equiv Cov_s(\gamma_{1t-1}, \beta_{it-1}(\gamma_{1t-1}+\varepsilon_{mt})) \\
&= Cov_s(\gamma_{1t-1}-\gamma_{1s}, \beta_{it-1}\gamma_{1t-1}) \\
&= Cov_s(\gamma_{1t-1}-\gamma_{1s}, \overline{\beta}_{is}(\gamma_{1t-1}-\gamma_{1s}) + \beta_{it-1}\gamma_{1s} + (\beta_{it-1}-\overline{\beta}_{is})(\gamma_{1t-1}-\gamma_{1s})) \\
&= \overline{\beta}_{is}\sigma^2_{\gamma 1s} + \gamma_{1s} Cov_s(\beta_{it-1}, \gamma_{1t-1}) + Cov_s(\beta_{it-1}, (\gamma_{1t-1}-\gamma_{1s})^2)
\end{aligned}$$

and the first element additionally has

$$\begin{aligned}
\kappa_2 &\equiv Cov_s(\varepsilon_{mt}, \beta_{it-1}(\gamma_{1t-1}+\varepsilon_{mt})) \\
&= Cov_s(\varepsilon_{mt}, \beta_{it-1}\varepsilon_{mt}) \\
&= Cov_s(\varepsilon_{mt}, \overline{\beta}_{is}\varepsilon_{mt} + (\beta_{it-1}-\overline{\beta}_{is})\varepsilon_{mt}) \\
&= \overline{\beta}_{is}\sigma^2_{\varepsilon ms} + Cov_s(\beta_{it-1}-\overline{\beta}_{is}, \varepsilon^2_{mt}) \\
&= \overline{\beta}_{is}\sigma^2_{\varepsilon ms} + Cov_s(\beta_{it-1}, \sigma^2_{\varepsilon mt-1}).
\end{aligned}$$

Now we can compute multiple-regression betas. Taking the inverse of $Var_s(\boldsymbol{f}_t)$ in (A4),

$$\boldsymbol{\beta}_{is} \equiv Var_s^{-1}(\boldsymbol{f}_t)Cov_s(\boldsymbol{f}_t, r_{it}^e) = \frac{1}{\sigma_{\gamma 1s}^2 \sigma_{\varepsilon ms}^2} \begin{pmatrix} \sigma_{\gamma 1s}^2 & -\sigma_{\gamma 1s}^2 \\ -\sigma_{\gamma 1s}^2 & \sigma_{\gamma 1s}^2 + \sigma_{\varepsilon ms}^2 \end{pmatrix} \begin{pmatrix} \kappa_1 + \kappa_2 \\ \kappa_1 \end{pmatrix} = \begin{pmatrix} \kappa_2/\sigma_{\varepsilon ms}^2 \\ -\kappa_2/\sigma_{\varepsilon ms}^2 + \kappa_1/\sigma_{\gamma 1s}^2 \end{pmatrix}$$
$$= \begin{pmatrix} \overline{\beta}_{is} + Cov_s(\beta_{it-1}, \sigma_{\varepsilon mt-1}^2)/\sigma_{\varepsilon ms}^2 \\ -Cov_s(\beta_{it-1}, \sigma_{\varepsilon mt-1}^2)/\sigma_{\varepsilon ms}^2 + \{\gamma_{1s} Cov_s(\beta_{it-1}, \gamma_{1t-1}) + Cov_s(\beta_{it-1}, (\gamma_{1t-1} - \gamma_{1s})^2)\}/\sigma_{\gamma 1s}^2 \end{pmatrix}.$$

This is a general expression with no assumption about the dynamics of β_{it-1}.

To prove the proposition, consider substituting equation (4) for β_{it-1} in the above expression, which will yield covariance terms between η_{it-1} and $\sigma_{\varepsilon mt-1}^2$ as well as γ_{1t-1}^2. Following JW, we assume that these covariances are zero, i.e., that the residual individual beta is uncorrelated with the market quantities, $\sigma_{\varepsilon mt-1}^2$ and γ_{1t-1}^2. This can be ensured by the following conditions similar to their Assumption 3:

ASSUMPTION 1 *For each asset i, the residual beta η_{it-1} satisfies*

$$\mathbf{E}_s[\eta_{it-1}\gamma_{1t-1}^2] = 0,$$
$$\mathbf{E}_s[\eta_{it-1}\sigma_{\varepsilon mt-1}^2] = 0.$$

Under this assumption, the preceding equation for $\boldsymbol{\beta}_{is}$ becomes

$$\boldsymbol{\beta}_{is} \equiv \begin{pmatrix} \beta_{is} \\ \beta_{is}^{\gamma} \end{pmatrix} = \begin{pmatrix} 1 & Cov_s(\gamma_{1t-1}, \sigma_{\varepsilon mt-1}^2)/\sigma_{\varepsilon ms}^2 \\ 0 & b_s \end{pmatrix} \begin{pmatrix} \overline{\beta}_{is} \\ \vartheta_{is} \end{pmatrix} \equiv \boldsymbol{B}_s \boldsymbol{\theta}_{is},$$

where b_s is given in equation (10). This proves equations (7) and (8). Assuming $b_s \neq 0$, the above equation can be inverted. This shows that both $\overline{\beta}_{is}$ and ϑ_{is} are linear functions of the multiple regression betas, β_{is} and β_{is}^{γ}. Finally, rewrite equation (5) in a vector form and substitute for $\boldsymbol{\theta}_{is}$ to get

$$
\begin{aligned}
\mathbf{E}_s[r^e_{it}] &= [\gamma_{1s} \quad Var_s(\gamma_{1t-1})]\boldsymbol{\theta}_{is} \\
&= [\gamma_{1s} \quad \sigma^2_{\gamma 1s}]\boldsymbol{B}_s^{-1}\boldsymbol{\beta}_{is} \\
&= [\gamma_{1s} \quad \sigma^2_{\gamma 1s}]\begin{pmatrix} 1 & -Cov_s(\gamma_{1t-1}, \sigma^2_{\varepsilon mt-1})/(\sigma^2_{\varepsilon ms} b_s) \\ 0 & 1/b_s \end{pmatrix}\boldsymbol{\beta}_{is} \\
&= [\gamma_{1s} \quad \{-\gamma_{1s} Cov_s(\gamma_{1t-1}, \sigma^2_{\varepsilon mt-1})/\sigma^2_{\varepsilon ms} + \sigma^2_{\gamma 1s}\}/b_s]\boldsymbol{\beta}_{is} \\
&\equiv \gamma_{1s}\beta_{is} + \gamma_{2s}\beta^{\gamma}_{is}, \qquad \text{(A6)}
\end{aligned}
$$

which gives γ_{2s} in equation (9).

JW's result can be obtained as simple-regression betas. Premultiplying the inverse diagonal matrix of regressor variances to $Cov_s(\boldsymbol{f}_t, r^e_{it})$ in equation (A5) gives

$$
\begin{aligned}
\boldsymbol{\beta}_{is} &= \begin{pmatrix} 1/(\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}) & 0 \\ 0 & 1/\sigma^2_{\gamma 1s} \end{pmatrix}\begin{pmatrix} \kappa_1 + \kappa_2 \\ \kappa_1 \end{pmatrix} = \begin{pmatrix} (\kappa_1 + \kappa_2)/(\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}) \\ \kappa_1/\sigma^2_{\gamma 1s} \end{pmatrix} \qquad \text{(A7)} \\
&= \begin{pmatrix} \overline{\beta}_{is} + [\gamma_{1s} Cov_s(\beta_{it-1}, \gamma_{1t-1}) + Cov_s(\beta_{it-1}, (\gamma_{1t-1} - \gamma_{1s})^2) + Cov_s(\beta_{it-1}, \sigma^2_{\varepsilon mt-1})]/(\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}) \\ \overline{\beta}_{is} + [\gamma_{1s} Cov_s(\beta_{it-1}, \gamma_{1t-1}) + Cov_s(\beta_{it-1}, (\gamma_{1t-1} - \gamma_{1s})^2)]/\sigma^2_{\gamma 1s} \end{pmatrix}.
\end{aligned}
$$

Substituting equation (4) for β_{it-1} yields

$$
\boldsymbol{\beta}_{is} = \begin{pmatrix} 1 & [\gamma_{1s}\sigma^2_{\gamma 1s} + Skew_s(\gamma_{1t-1}) + Cov_s(\gamma_{it-1}, \sigma^2_{\varepsilon mt-1})]/(\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}) \\ 1 & \gamma_{1s} + Skew_s(\gamma_{1t-1})/\sigma^2_{\gamma 1s} \end{pmatrix}\begin{pmatrix} \overline{\beta}_{is} \\ \vartheta_{is} \end{pmatrix} \equiv \boldsymbol{B}^{JW}_s \boldsymbol{\theta}_{is}.
$$

Starting with the second line of equation (A6),

$$
\begin{aligned}
&\mathbf{E}_s[r^e_{it}] \\
&= [\gamma_{1s} \quad \sigma^2_{\gamma 1s}](\boldsymbol{B}^{JW}_s)^{-1}\boldsymbol{\beta}_{is} \\
&= [\gamma_{1s} \quad \sigma^2_{\gamma 1s}]|\boldsymbol{B}^{JW}_s|^{-1}\cdot \\
&\begin{pmatrix} \gamma_{1s} + Skew_s(\gamma_{1t-1})/\sigma^2_{\gamma 1s} & -[\gamma_{1s}\sigma^2_{\gamma 1s} + Skew_s(\gamma_{1t-1}) + Cov_s(\gamma_{it-1}, \sigma^2_{\varepsilon mt-1})]/(\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}) \\ -1 & 1 \end{pmatrix} \boldsymbol{\beta}_{is} \\
&\equiv \gamma^{JW}_{1s}\beta_{is} + \gamma^{JW}_{2s}\beta^{\gamma}_{is},
\end{aligned}
$$

where

$$
\begin{aligned}
\gamma^{JW}_{1s} &= |\boldsymbol{B}^{JW}_s|^{-1}\left(\frac{\gamma_{1s}Skew_s(\gamma_{1t-1})}{\sigma^2_{\gamma 1s}} + \gamma^2_{1s} - \sigma^2_{\gamma 1s}\right), \\
\gamma^{JW}_{2s} &= |\boldsymbol{B}^{JW}_s|^{-1}\left(\frac{-\gamma_{1s}[Skew_s(\gamma_{1t-1}) + \gamma_{1s}\sigma^2_{\gamma 1s} + Cov_s(\gamma_{1t-1}, \sigma^2_{\varepsilon mt-1})]}{\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}} + \sigma^2_{\gamma 1s}\right)
\end{aligned}
$$

and we have assumed that

$$
|\boldsymbol{B}^{JW}_s| = \gamma_{1s} + \frac{Skew_s(\gamma_{1t-1})}{\sigma^2_{\gamma 1s}} - \frac{\gamma_{1s}\sigma^2_{\gamma 1s} + Skew_s(\gamma_{1t-1}) + Cov_s(\gamma_{it-1}, \sigma^2_{\varepsilon mt-1})}{\sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}} \neq 0.
$$

Finally, the first element in the line following equation (A7) is the unconditional beta in Lewellen and Nagel (2006). Define $\sigma^2_{ms} \equiv \sigma^2_{\gamma 1s} + \sigma^2_{\varepsilon ms}$ and rewrite the expression as

$$
\beta_{is} = \overline{\beta}_{is} + \frac{\gamma_{1s}}{\sigma^2_{ms}}Cov_s(\beta_{it-1}, \gamma_{1t-1}) + \frac{1}{\sigma^2_{ms}}Cov_s(\beta_{it-1}, (\gamma_{1t-1} - \gamma_{1s})^2) + \frac{1}{\sigma^2_{ms}}Cov_s(\beta_{it-1}, \sigma^2_{\varepsilon mt-1}).
$$

Dropping the s subscript gives their equation (2) on p.293. Q.E.D.

Proof of Corollary 1: The linearity assumption in equation (13) implies that equation (6) holds with $\beta^{\gamma}_{is} = \beta^{z}_{is}/\delta_{1s}$. Defining $\gamma_{3s} = \gamma_{2s}/\delta_{1s}$, we obtain equation (14).

If z^e_{t-1} is additionally an excess return on a traded asset proxying the premium (e.g., a mimicking portfolio of a predictive instrument), it will load fully on itself in its regression on

$$\boldsymbol{f}_t = \begin{pmatrix} r^e_{mt} \\ z^e_{t-1} \end{pmatrix} = \begin{pmatrix} \delta_{0s} + \delta_{1s} z^e_{t-1} + \varepsilon_{mt} \\ z^e_{t-1} \end{pmatrix}.$$

Formally,

$$\boldsymbol{\beta}_{is} = Var_s^{-1}(\boldsymbol{f}_t) Cov_s(\boldsymbol{f}_t, z^e_{t-1}) = \frac{1}{\sigma^2_{zs}\sigma^2_{\varepsilon ms}} \begin{pmatrix} \sigma^2_{zs} & -\delta_{1s}\sigma^2_{zs} \\ -\delta_{1s}\sigma^2_{zs} & \delta^2_{1s}\sigma^2_{zs} + \sigma^2_{\varepsilon ms} \end{pmatrix} \begin{pmatrix} \delta_{1s}\sigma^2_{zs} \\ \sigma^2_{zs} \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix},$$

where $\sigma^2_{zs} \equiv Var_s(z^e_{t-1})$. That is, $\beta_{is} = 0$ and $\beta^z_{is} = 1$. Equation (14) must still price this asset:

$$\mathbf{E}_s[z^e_{t-1}] = \gamma_{3s} \cdot 1.$$

But by definition the left hand side must equal z^e_s, which requires that

$$\gamma_{3s} \equiv z^e_s.$$

Substituting this for γ_{3s} in equation (14) produces equation (15). Q.E.D.

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Table 1: **Summary statistics**

	Mean	Stdev	N	Start	End
$EGDP$	0.0128	0.0074	111	1951S2	2006S2
$RGDP$	0.0147	0.0170	111	1951S2	2006S2
DY	0.0322	0.0113	111	1951S2	2006S2
DEF	0.0008	0.0004	111	1951S2	2006S2
$TERM$	0.0011	0.0010	108	1953S1	2006S2
RF	0.0041	0.0024	111	1951S2	2006S2
CAY	-0.0004	0.0120	109	1951S2	2005S2
MKT	0.0371	0.1156	111	1951S2	2006S2

Summary statistics. This table shows the mean, standard deviation (Stdev), number of observations (N), starting and ending semiannual periods of selected variables. $EGDP$ is the Livingston-Survey expected real GDP growth rate. $RGDP$ is the realized GDP growth rate. DY is the dividend yield. DEF is the default spread. $TERM$ is the term spread. RF is the one-month Treasury bill rate. CAY is the consumption-wealth ratio. MKT is the excess return on the CRSP value-weighted portfolio.

Table 2: **Regressions of the expected real GDP growth rate on other predictive instruments**

	1	2
Const	1.292***(20.93)	1.239***(17.23)
DY	-0.229***(-3.07)	
DEF	0.352***(3.49)	
$TERM$	0.076 (0.86)	
RF	-0.036 (-0.34)	
CAY	-0.048 (-0.70)	
SMB		2.427***(2.81)
HML		1.541** (1.99)
R^2	0.270	0.090

Regressions of the expected real GDP growth rate on other predictive instruments. This table shows estimated coefficients from the semiannual regression of the Livingston-Survey expected real GDP growth rate ($EGDP$) with t-statistics in parentheses. DY is the dividend yield. DEF is the default spread. $TERM$ is the term spread. RF is the one-month Treasury bill rate. CAY is the consumption-wealth ratio. SMB and HML are the size and value factors, respectively. All the regressors in column 1 are standardized with mean zero and variance one. *, **, and *** represent significance at 10, 5, and 1%, respectively.

Table 3: **Predictive return regressions**

	1		2	
Const	-0.02	(-0.39)	0.01	(0.33)
$LEGDP$	-3.81**	(-2.40)	-3.34**	(-2.14)
LDY	3.06***	(2.64)	2.22*	(1.87)
$LDEF$	62.50	(1.34)	99.94**	(2.08)
$LTERM$	11.51	(0.84)	-3.20	(-0.22)
LRF	-13.87*	(-1.93)	-19.44**	(-2.63)
$LCAY$			2.35**	(2.40)
R^2	0.20		0.24	

Predictive return regressions. This table shows estimated coefficients of the semiannual predictive return regressions with t-statistics in parentheses. The excess return on the CRSP value-weighted portfolio (MKT) is regressed on the lags of the following instruments (denoted by prefix 'L'): the Livingston-Survey expected real GDP growth rate ($EGDP$), dividend yield (DY), default spread (DEF), term spread ($TERM$), one-month Treasury bill rate (RF), and the consumption-wealth ratio (CAY). The lag order is 2 for $EGDP$ and 1 for all others. *, **, and *** represent significance at 10, 5, and 1%, respectively.

Table 4: **Estimated premia**

Panel A: FF25 portfolios as test assets

	1		2		3		4		5		6	
Const	0.067***	(3.08)	0.082*	(1.84)	0.088***	(3.43)	0.095***	(3.16)	0.081***	(2.91)	0.090***	(2.79)
MKT	-0.014	(-0.52)	-0.039	(-0.81)	-0.050	(-1.66)	-0.057*	(-1.67)	-0.043	(-1.34)	-0.051	(-1.41)
SMB					0.012	(0.99)	0.012	(0.98)	0.014	(1.09)	0.013	(0.99)
HML					0.028**	(2.17)	0.028**	(2.02)	0.029**	(2.04)	0.029*	(1.91)
MOM					0.012	(0.50)	0.016	(0.65)	0.024	(0.96)	0.023	(0.84)
$LEGDP$			0.012**	(2.02)			0.004	(1.40)				
$LEGDPB$									-0.0035*	(-1.91)		
$LEGDPG$											0.0085**	(2.14)
Adj R^2	-0.01		0.71		0.77		0.77		0.78		0.79	

Panel B: Individual stocks as test assets

	1		2		3		4		5		6	
Const	0.231***	(6.07)	0.233***	(5.19)	0.042	(0.71)	0.086	(0.92)	0.014	(0.20)	0.056	(0.54)
MKT	-0.141***	(-3.47)	-0.150***	(-3.21)	0.044	(0.73)	0.005	(0.06)	0.073	(1.02)	0.036	(0.34)
SMB					-0.044	(-1.47)	-0.042	(-0.97)	-0.039	(-1.14)	-0.036	(-0.74)
HML					0.034	(1.06)	0.036	(0.75)	0.030	(0.79)	0.028	(0.53)
MOM					-0.244**	(-2.50)	-0.217	(-1.60)	-0.221**	(-2.02)	-0.207	(-1.34)
$LEGDP$			0.008	(0.97)			0.025**	(2.31)				
$LEGDPB$									-0.012	(-1.64)		
$LEGDPG$											0.038*	(1.89)
Adj R^2	0.03		0.03		0.04		0.04		0.04		0.04	

Estimated premia. Panel A uses the Fama-French (FF) size-B/M 25 portfolios as test assets, while Panel B uses individual stocks. Betas of an individual stock are estimated as those of the FF 25 portfolio to which it belongs. MKT is the excess return on the CRSP value-weighted portfolio; SMB, HML, and MOM are the size, book-to-market, and momentum factors, respectively. $LEGDP$ is the lagged expected real GDP growth rate constructed from the Livingston Survey. $LEGDPB$ ($LEGDPG$) takes the value of $LEGDP$ during bad (good) times and zero otherwise, where bad (good) times are defined as periods in which $LEGDP$ is lower (higher) than its past twenty-period moving average. Adj R^2 is the adjusted R-squared in the cross-sectional regression of average excess returns on estimated betas. In Panel B, an individual stock is assigned the beta of the size-B/M 25 portfolio that it belongs to at a given time. The individual stock's average excess return is computed by the periods during which it belongs to a particular portfolio. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and t-statistics in parentheses. *, **, and *** represent significance at 10, 5, and 1%, respectively.

Table 5: **Properties of the mimicking portfolio and its basis assets**

Panel A: Summary statistics

	Mean	Stdev	Mn/Std	N	Start	End	MeanB	MeanG
LGDPM	0.0350***(6.07)	0.0512	0.683	79	1967S2	2006S2	0.0216***(3.82)	0.0509***(5.02)
MKT	0.0371***(3.38)	0.1156	0.321	111	1951S2	2006S2	0.0599***(3.45)	0.0149 (1.08)
SMB	0.0109 (1.46)	0.0786	0.139	111	1951S2	2006S2	0.0139 (1.21)	0.0099 (0.97)
HML	0.0264***(3.19)	0.0873	0.303	111	1951S2	2006S2	-0.0001 (-0.01)	0.0494***(4.15)
MOM	0.0514***(5.87)	0.0922	0.557	111	1951S2	2006S2	0.0608***(4.39)	0.0426***(3.72)

Panel B: Pairwise correlations

	LEGDP	*LGDPM*	*MKT*	*SMB*	*HML*	*MOM*
LEGDP	1					
LGDPM	0.31	1				
MKT	-0.21	-0.05	1			
SMB	0.06	-0.16	0.37	1		
HML	0.17	0.40	-0.30	-0.17	1	
MOM	-0.02	0.56	-0.14	-0.13	-0.24	1

Properties of the mimicking portfolio and its basis assets. Panel A shows the mean with its t-statistic in parentheses, the standard deviation (Stdev), the ratio of the mean to the standard deviation (Mn/Std), the number of observations (N), and the starting and ending semiannual periods of the mimicking portfolio return and other factors used in the asset pricing tests. Panel B shows their pairwise correlations. $LEGDP$ is the lagged Livingston-Survey expected real GDP growth rate. $LGDPM$ is its mimicking portfolio. MKT is the excess return on the CRSP value-weighted portfolio. SMB, HML, and MOM are the size, value, and momentum factors, respectively. MeanB (MeanG) is the mean during bad (good) times, defined as periods in which $LEGDP$ is lower (higher) than its past twenty-period moving average. *, **, and *** represent significance at 10, 5, and 1%, respectively.

Table 6: **Estimated premia using the mimicking portfolio**

Panel A: FF25 portfolios as test assets

	1		2		3		4	
Const	-0.020	(-0.42)	0.090***	(3.27)	0.112***	(3.04)	0.116***	(2.98)
MKT	0.054	(1.00)	-0.059*	(-1.72)	-0.080*	(-1.80)	-0.082*	(-1.80)
SMB			0.013	(0.87)	0.014	(0.78)	0.013	(0.71)
HML			0.032*	(1.81)	0.031	(1.48)	0.029	(1.40)
MOM			0.005	(0.18)	0.007	(0.21)	0.015	(0.43)
$LGDPM$	0.057*	(1.89)	0.001	(0.05)				
$LGDPMB$					-0.029**	(-2.28)		
$LGDPMG$							0.037*	(1.90)
Adj R^2	0.46		0.77		0.88		0.85	

Panel B: Individual stocks as test assets

	1		2		3		4	
Const	0.181***	(3.01)	-0.138	(-1.48)	-0.079	(-0.85)	0.031	(0.31)
MKT	-0.100	(-1.58)	0.216*	(1.90)	0.155	(1.41)	0.059	(0.55)
SMB			-0.049	(-1.11)	-0.035	(-0.63)	-0.046	(-0.92)
HML			0.045	(0.89)	0.028	(0.46)	0.020	(0.36)
MOM			-0.251**	(-2.20)	-0.134	(-1.08)	-0.182	(-1.50)
$LGDPM$	0.034	(0.87)	-0.058	(-0.87)				
$LGDPMB$					-0.095**	(-2.21)		
$LGDPMG$							0.064	(1.03)
Adj R^2	0.03		0.04		0.05		0.05	

Estimated premia using the mimicking portfolio. Panel A uses the Fama-French (FF) size-B/M 25 portfolios as test assets, while Panel B uses individual stocks. Betas of an individual stock are estimated as those of the FF 25 portfolio to which it belongs. $LGDPM$ is the mimicking portfolio of the lagged expected real GDP growth rate ($LEGDP$) constructed from the Livingston Survey. $LGDPMB$ ($LGDPMG$) takes the value of $LGDPM$ during bad (good) times and zero otherwise, where bad (good) times are defined as periods in which $LEGDP$ is lower (higher) than its past twenty-period moving average. MKT is the excess return on the CRSP value-weighted portfolio. SMB, HML, and MOM are the size, book-to-market, and momentum factors, respectively. Adj R^2 is the adjusted R-squared in the cross-sectional regression of average excess returns on estimated betas. In Panel B, an individual stock is assigned the beta of the size-B/M 25 portfolio that it belongs to at a given time. The individual stock's average excess return is computed by the periods during which it belongs to a particular portfolio. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and t-statistics in parentheses. *, **, and *** represent significance at 10, 5, and 1%, respectively.

Table 7: **Estimated beta-premium sensitivities**

Panel A: Unconditional beta-premium regression

B/M quintile	α_i		ϑ_i	
1	-0.0107	(-1.30)	-0.80	(-0.66)
2	0.0038	(0.55)	1.17	(1.00)
3	0.0131*	(1.81)	1.72	(1.25)
4	0.0178**	(2.38)	2.52	(1.41)
5	0.0189**	(2.12)	2.74*	(1.75)
$5-1$	0.0297***	(2.85)	3.54	(1.57)

Panel B: Conditional beta-premium regression

B/M quintile	α_i		ϑ_{i1}		ϑ_{i2}	
1	-0.0107	(-1.30)	0.08	(0.07)	-2.79**	(-2.10)
2	0.0038	(0.55)	1.25	(1.19)	0.98	(0.57)
3	0.0131*	(1.81)	1.47	(1.22)	2.28	(1.12)
4	0.0178**	(2.38)	1.83	(1.20)	4.07	(1.53)
5	0.0189**	(2.12)	1.89	(1.35)	4.66*	(1.87)
$5-1$	0.0297***	(2.85)	1.81	(0.90)	7.45**	(2.39)

Estimated beta-premium sensitivities. This table shows the estimated beta-premium sensitivities (ϑ_i) by size-controlled B/M quintiles. $5-1$ is the zero-investment portfolio that goes long the highest and short the lowest B/M portfolios. The estimation is by GMM. ϑ_{i1} (ϑ_{i2}) is the bad- (good-) time beta-premium sensitivity. t-statistics are shown in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

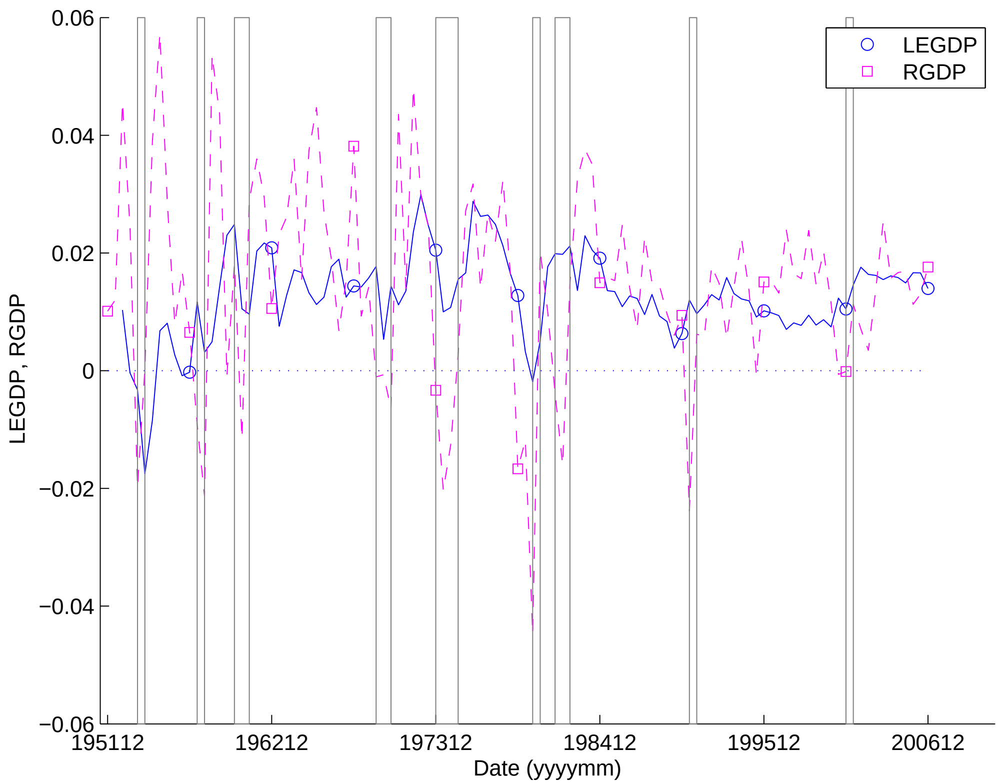

Figure 1: The lagged Livingston-Survey expected real GDP growth rate ($LEGDP$) and the realized GDP growth rate ($RGDP$). Each narrow band represents a recession period as defined by NBER, starting with a peak and ending with a trough.

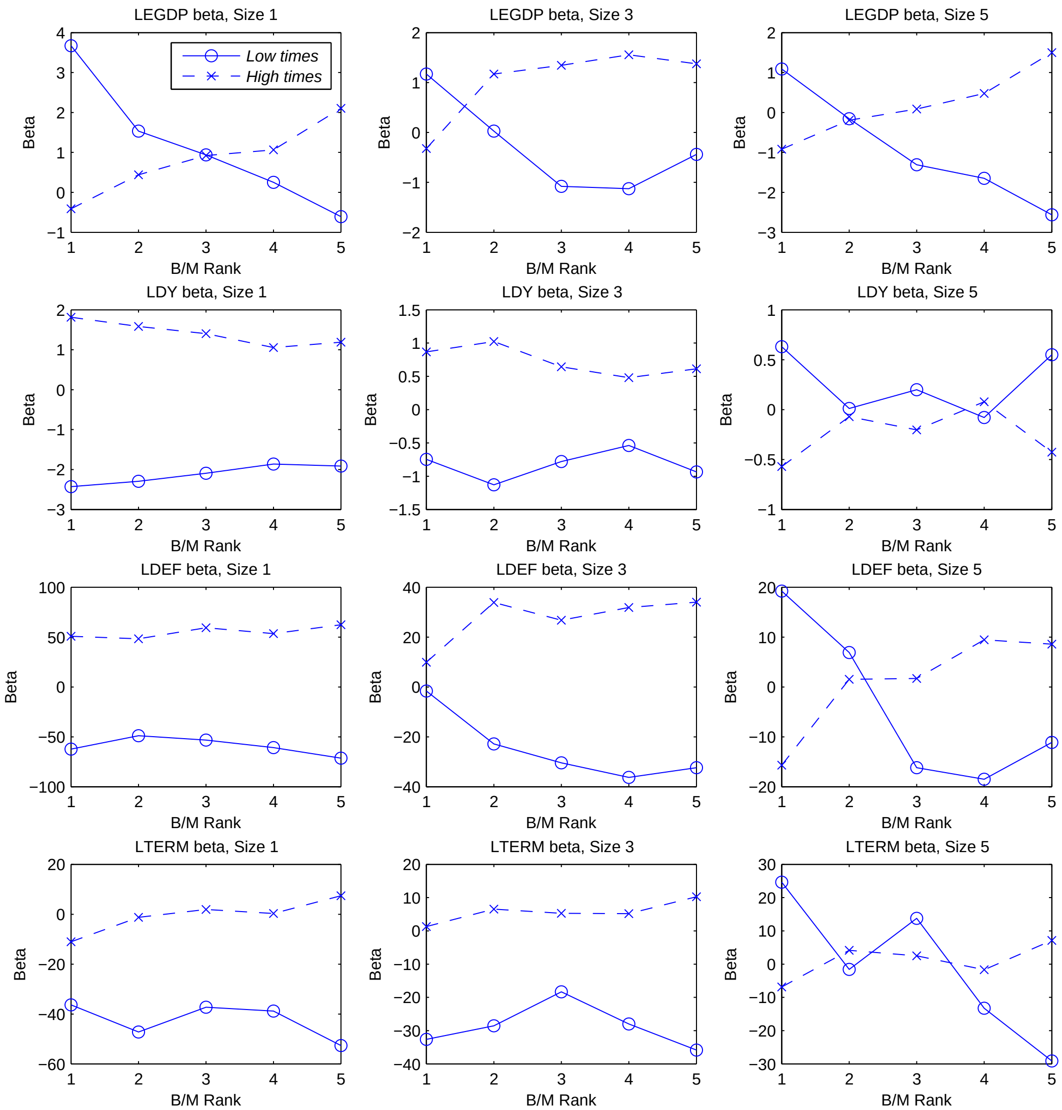

Figure 2: Conditional instrument betas (β_{is}^{z}) with respect to various predictive instruments by B/M and selected size quintiles. This figure plots estimated β_{is}^{z} in the regression, $r_{it}^{e} = \alpha + \beta_i MKT_t + \beta_{is}^{z} D_s z_{t-l} + \varepsilon_{it}$, where r_{it}^{e} is the excess return on asset i, D_s is a dummy variable for an economic state s defined below, and z_{t-l} is a lagged instrument with l representing the lag order appropriate for the instrument ($l = 2$ for $EGDP$ and 1 for all others). We define "low times" ("high times") as periods in which the value of the lagged instrument is lower (higher) than its past twenty-period (ten-year) moving average ($\overline{z}_{t-l}$), and set the low-time (high-time) dummy variable $D_s = 1$ if $z_{t-l} \leq \overline{z}_{t-l}$ ($z_{t-l} > \overline{z}_{t-l}$) and 0 otherwise.

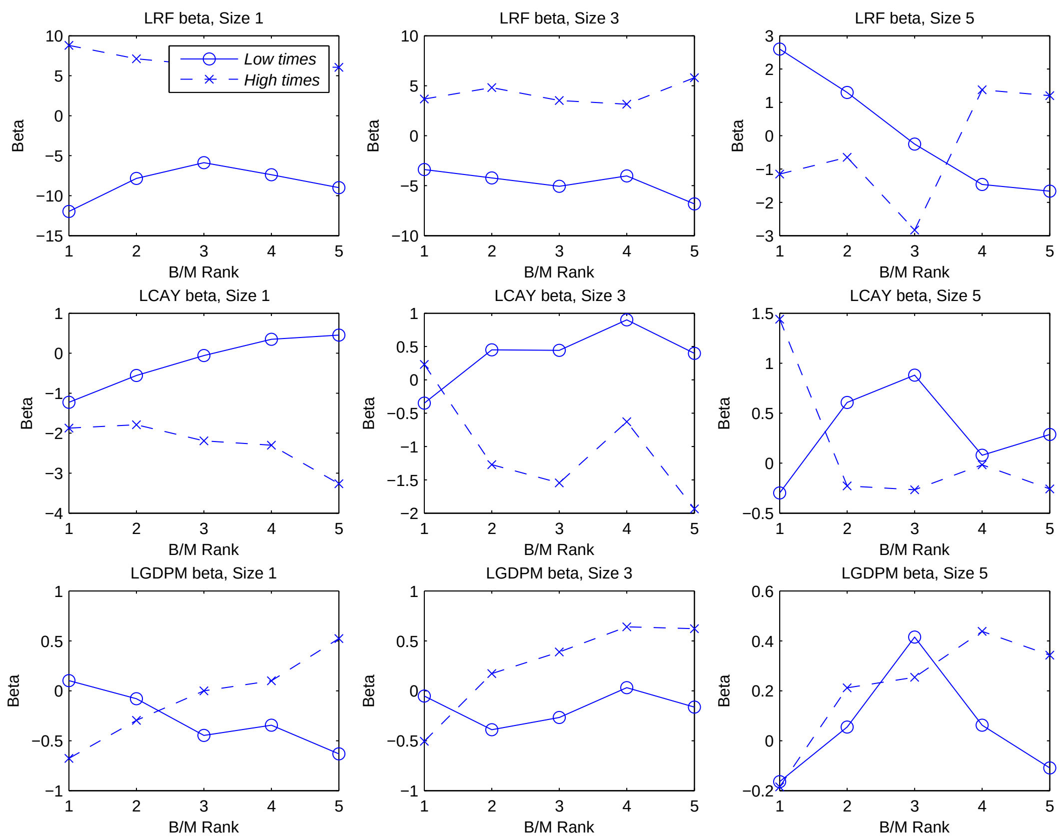

Figure 2: Continued

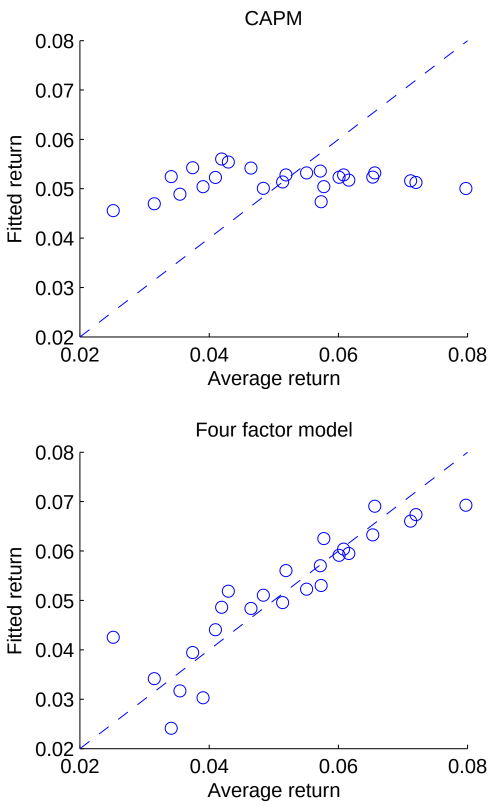

Figure 3: Fitted returns plotted against average realized returns. Fitted returns are the fitted values from the regression of average excess size-B/M 25 portfolio returns on a constant and the estimated loadings on the following factors: the excess market return (MKT) in CAPM; MKT and the lagged Livingston-Survey expected real GDP growth rate ($LEGDP$) in "Livingston"; MKT and the size (SMB), book-to-market (HML) and momentum (MOM) factors in the four-factor model.

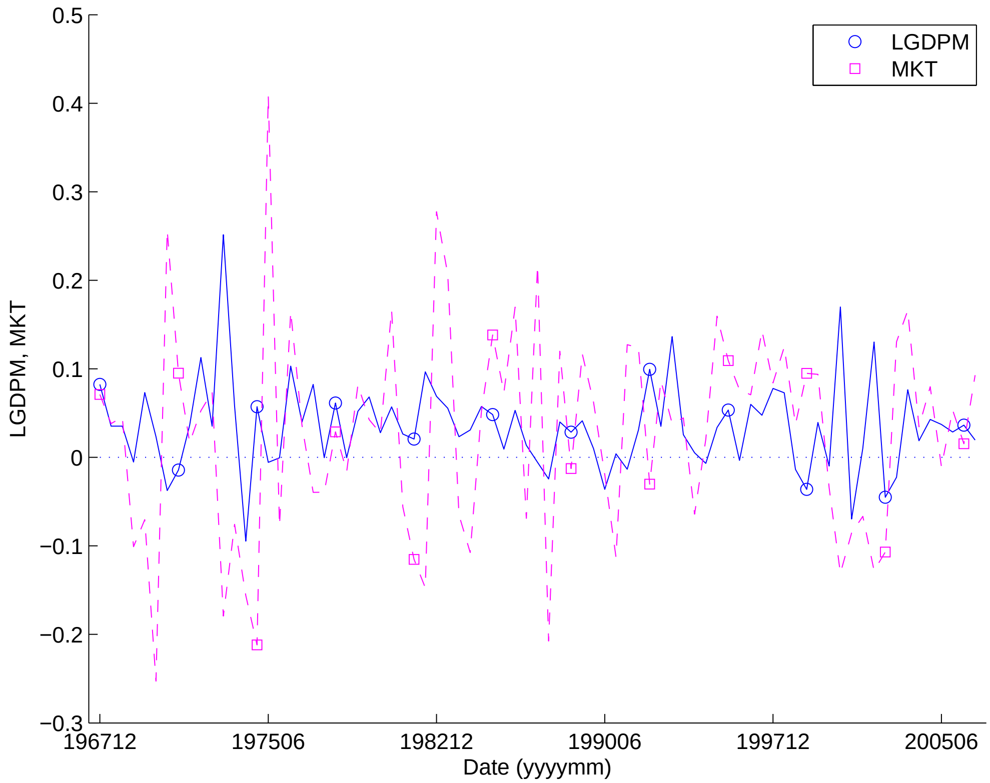

Figure 4: Return on the mimicking portfolio ($LGDPM$) of the lagged Livingston-Survey expected real GDP growth rate and the excess market return (MKT).

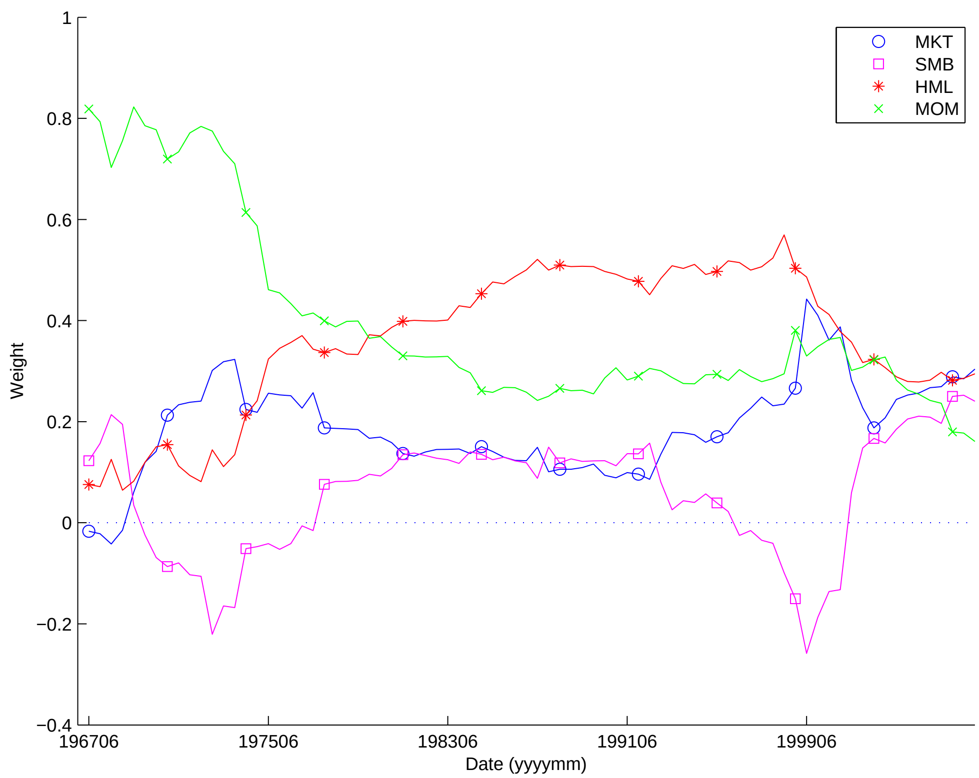

Figure 5: Weights in the mimicking portfolio ($LGDPM$) of the lagged Livingston-Survey expected real GDP growth rate. Starting in December 1966, we regress $LEGDP$ on MKT, SMB, HML, and MOM without an intercept using past 30 observations (15 years). The weights in the mimicking portfolio are the four coefficient estimates normalized to add up to 1. The return is measured over the next semiannual period.