Prospective book-to-market ratio and expected stock returns

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We propose a novel stock return predictor, the "*prospective* book-to-market", defined as the present value of expected future demeaned book-to-market ratios. We find that the aggregate prospective book-to-market ratio can significantly predict market returns, with an adjusted R-squared between 3.8% and 4.2% out-of-sample. Additionally, a high-minus-low investment strategy based on the prospective book-to-market ratio generates a significant monthly alpha ranging from 12.1 to 19.0 basis points across various factor models. Furthermore, the return spread is also shown to be non-redundant as an alternative value factor in pricing the cross-section of stock returns.

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JEL Classification: G12, F31

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1 Introduction

In this paper, we propose a new stock return predictor, through decomposing the book-to-market ratio into permanent and transitory components. Our decomposition relates the present value of demeaned stock return to the transitory component of the book-to-market ratio, the present value of demeaned book-to-market, and the present value of demeaned return on equity. When expected return moves with each or all of these three terms, future stock return can be predictable when the investor observes new information about book-to-market ratio. Specifically, we focus on the "*prospective* book-to-market",[1] defined as the expected sum of all future book-to-market ratios around their long-run trend. When this expected sum exceeds the long-run trend, it indicates that either the expected return is above its long-run trend or the market value is temporarily underpriced relative to the book value, with an expectation to rise in the future. Indeed, our findings suggest that the prospective book-to-market is particularly useful in predicting next-period returns.

Empirically, we model the prospective book-to-market by assuming a simple autoregressive form of the book-to-market ratio and then estimate its infinite sum while accounting for the historical average. Similar to van Binsbergen and Koijen (2010) who utilize the variation of persistence in state variables to better predict stock returns, the superior predictive power of the prospective book-to-market in our setup depends on both the persistence of the book-to-market ratio and its current level relative to the long-run trend.

We present the predictability tests on three portfolio levels: market, industry, and the cross-section of individual firms. In our out-of-sample tests, we use only currently available information to ensure there is no look-ahead bias. For all three portfolio levels, we use the historical sample average of the book-to-market ratio as a proxy for the long-run trend. However, the estimation of its persistence deserves further elaboration. For both market and industry portfolios, we rely on autoregression from not only the simple OLS but also a robust regression to minimize the effects of outliers. For the cross-section of individual stocks, we assign their industry-level persistence estimates to them to alleviate noise from a limited time-series.[2]

[1] The naming of this term is analogous to Engel (2011), although in a different setting.

[2] In the meantime, we are aware that we will encounter the well-known "Hurwicz bias", which occurs when a

We find that our prospective book-to-market ratio is a significant return predictor at the market, industry, and individual-stock levels. At the market level, the prospective book-to-market ratio yields an out-of-sample adjusted R-squared between 3.8% and 4.2%. This contrasts with the conclusion by Goyal and Welch (2008) that market returns can not be reliably predicted out of sample. Moreover, as shown in Campbell and Thompson (2008), these out-of-sample R-squared values imply substantial economic gains for investors.

In industry-level time-series tests, we demonstrate that the prospective book-to-market ratio predicts returns for the Fama-French 48-industry portfolios. Moreover, employing a zero-cost long-short strategy, the industry prospective book-to-market ratio is shown to generate a significant annual spread of between 2.3% and 2.8% in risk-adjusted returns across industries. In contrast, the original book-to-market ratio fails to produce similar results, which is consistent with the findings of Asness, Porter, and Stevens (2000).

At the individual-firm level, because the persistence in the book-to-market ratio could be noisy when estimated firm-by-firm within a short time period, we use a straightforward pooled OLS regression across all firms within an industry, assigning the persistence values to individual stocks that belong to that industry. We observe substantial cross-industry variations in the persistence parameter. These variations create additional degrees of heterogeneity and lead to a highly profitable investment strategy as we sort firms into portfolios. To demonstrate the forecasting power of our new predictor, we take long positions in firms whose expected sum of future book-to-market ratios is higher than its historical average, and short positions when it is lower, after controlling for firm size. This strategy generates significant monthly alphas ranging from 12.1 to 19.0 basis points, under both the 4-factor q model and the augmented 3- and 5-factor Fama-French models with an additional momentum factor.

We provide time-series spanning tests by regressing the returns of two traditional HML factors on our prospective book-to-market factor. One HML factor follows the methodology of Fama and French (1992) and uses the end-of-December market value, while the other follows Asness and Frazzini (2013) and uses the end-of-June market value. We find that both versions of the HML

sample size is small, especially at the early stage of the out-of-sample period. This bias presents another difficulty: our point estimates will be imprecise in the early sample period, thereby contaminating the return predictability results. To address this issue, we also employ other econometric tools, such as the recursive mean least squares.

factors show an insignificant alpha when regressed on our prospective book-to-market factor, but not vice versa. Finally, we contribute to the debate on whether HML is a redundant factor in existing factor models. Although these two annually formed HML factors display redundancy under the Fama-French 5-factor model, the prospective book-to-market factor remains useful in pricing the cross-section of stock returns.

Our study contributes to the existing literature in at least two significant ways. Methodologically, we extend the model presented in Engel (2011) by decomposing the book-to-market ratio into transitory and permanent components. Our model derives the transitory component of the book-to-market ratio, implying the return predictability of a multi-period sum of expected book-to-market ratios, which we term the "prospective book-to-market ratio". This innovation is similar to the "prospective interest rate differentials" found in Engel (2011) and Dong, Goto, Hou, Xu, and Zhang (2024), which has been shown to predict currency excess returns.

Our work also contributes to the literature on the value premium. Recent studies have focused on decomposing the book-to-market ratio and examining the return predictive power of each component. For example, Asness, Porter, and Stevens (2000) demonstrate that most of the return predictability of book-to-market comes from the within-industry components. Daniel and Titman (2006), and Fama and French (2008) have also examined the components of the book-to-market ratio. Gerakos and Linnainmaa (2014) propose the use of a "priced" component of the book-to-market, which outperforms the raw-value component. In contrast, we study the transitory component of the book-to-market ratio as a starting point to improve the predictive power of the raw value of book-to-market.

The paper is organized as follows: Section 2 details our present-value model and presents the decomposition into permanent and transitory components. In section 3, we introduce the data, report the estimation of model parameters, present predictive regressions of expected returns, and compare out-of-sample portfolio performance. We also explore various variations of our proposed predictor and conduct robustness checks. Section 4 concludes the paper.

2 Model

We start from the definition of stock return

$$\frac{P_{t+1}}{P_t}\left(1+\frac{D_{t+1}}{P_{t+1}}\right)=R_{t+1},$$

where P_t, D_t, R_t denote the stock price, dividend, and returns, separately. We use the lower-case letters to denote the logarithm of these variables. Let δ_t be the log dividend-price ratio $\delta_t = \log\left(1+\exp\left(dp_t\right)\right)$, and if we take log on both sides

$$p_{t+1}-p_t+\delta_{t+1}=r_{t+1}.$$

Taking expectations at time t and iterating forward, we have

$$\begin{aligned}
E_t p_{t+1}-p_t+E_t\delta_{t+1} &= E_t r_{t+1},\\
E_t p_{t+2}-E_t p_{t+1}+E_t\delta_{t+2} &= E_t r_{t+2},\\
&\quad ...,\\
E_t p_{t+j}-E_t p_{t+j-1}+E_t\delta_{t+j} &= E_t r_{t+j}.
\end{aligned}$$

Summing up, we have

$$E_t p_{t+j}-p_t+\sum_{j=1}^{k}E_t\delta_{t+j}=\sum_{j=1}^{k}E_t r_{t+j}.$$

We then write the expected return $E_t r_{t+1}$ as the sum of risk-free rate i_t and risk premium μ_t, and specify the dynamics of i_t, μ_t and δ_t as

$$\begin{aligned}
i_t-\bar{i} &= \phi\left(i_{t-1}-\bar{i}\right)+\varepsilon_{i,t},\\
\mu_t-\bar{\mu} &= \gamma\left(\mu_{t-1}-\bar{\mu}\right)+\varepsilon_{\mu,t},\\
\delta_t-\bar{\delta} &= \beta\left(\delta_{t-1}-\bar{\delta}\right)+\varepsilon_{\delta,t}.
\end{aligned}$$

In other words, we assume these three variables each follow simple first-order autoregressive processes, with AR(1) coefficients ϕ, γ, and β, and their long-run trends $\bar{i}$, $\bar{\mu}$, and $\bar{\delta}$, respectively. Similar to Pastor and Stambaugh (2009), van Binsbergen and Koijen (2010), and Lacerda and Santa-Clara (2011), this approach eliminates the need to specify a utility function and derive the dynamics for expected returns. Additionally, since our methodology does not rely on the Campbell and Shiller's approximate identity on the dividend-price ratio, it is also noteworthy that we only require estimating β, without having to impose any of cross-equation restrictions on the AR(1) coefficients, unlike the approaches seen in Cochrane (1992), Cochrane (2008), and Cochrane (2011).

We then let $\tau = \bar{\mu} + \bar{i} - \bar{\delta}$, $k \to \infty$ and thus have

$$\lim_{j\to\infty} E_t p_{t+j} - p_t - j\tau + \sum_{j=1}^{\infty} E_t\left[\delta_{t+j} - \bar{\delta}\right] = \sum_{j=1}^{\infty} E_t\left(\mu_{t+j} - \bar{\mu}\right) + \sum_{j=1}^{\infty} E_t\left[i_{t+j} - \bar{i}\right]. \tag{1}$$

The modeling methodology follows Engel (2011), which focuses on the sum of deviations of expected future interest rates from their long-run trend. Dong, Goto, Hou, Xu, and Zhang (2024) develop an empirical proxy for this "prospective interest rate differential" and demonstrate that it predicts currency returns beyond the conventional carry trade. According to the Beveridge and Nelson (1981) decomposition, $\lim_{j\to\infty} E_t p_{t+j} - j\tau$ can be viewed as the permanent component of the stock price p_t^P. Once we eliminate the permanent component, both sides of the equation become stationary.

The above equation is reminiscent of the well-known Campbell and Shiller's approximate identity, which relates log dividend-price to the present value of returns and cash flows. It also appears similar to Vuolteenaho's approximate identity, which relates book-to-market to the present value of returns and cash flows, as discussed in Vuolteenaho (2002) and Cohen, Gompers, and Vuolteenaho (2002). However, there are several important conceptual differences. Our decomposition focuses on an unobservable term, specifically, the transitory component of the book-to-market ratio, and our equation holds as an identity rather than an approximation. Additionally, the return decomposition by Cohen, Gompers, and Vuolteenaho (2002) and Campbell (1991) is related to the Beveridge and Nelson (1981) decomposition in the time-series literature. This is motivated by the intuition that news about cash flow and expected returns each correspond to shocks to the random-walk and stationary components of the log stock price, respectively. In contrast, our decomposition is motivated by the present-value relationship.

We then simplify the permanent-transitory components decomposition as

$$p_t^P - p_t + \beta \frac{\delta_t - \bar{\delta}}{1-\beta} = \frac{\mu_t - \bar{\mu}}{1-\gamma} + \frac{i_t - \bar{\imath}}{1-\phi}. \tag{2}$$

Next, we apply the same approach to the log book equity $b_t = \log(B_t)$. Define the log dividend-book equity as $\psi_t = \ln(1+\exp(db_t))$, and then we also have

$$b_t^P - b_t + \beta \frac{\psi_t - \bar{\psi}}{1-\beta} = \frac{g_t - \bar{g}}{1-\xi} + \frac{i_t - \bar{\imath}}{1-\phi}, \tag{3}$$

where the expected excess returns on equity g_t also follows a simple first order autoregressive process, with AR(1) coefficient ξ and long-run trend $\bar{g}$:

$$g_t = E_t[roe_{t+1}] - i_t; \text{ and } g_t - \bar{g} = \xi.(g_{t-1} - \bar{g}) + e_t.$$

Now define the book-to-market ratio as

$$\theta_t \equiv \log(B_t/P_t) = b_t - p_t.$$

By subtracting equation (3) from equation (2), we obtain

$$-\left(\theta_t^P - \theta_t\right) - \beta\left[\frac{\psi_t - \bar{\psi}}{1-\beta} - \frac{\delta_t - \bar{\delta}}{1-\beta}\right] = \frac{\mu_t - \bar{\mu}}{1-\gamma} - \frac{g_t - \bar{g}}{1-\xi}.$$

Next, we conduct the log-linearization (Campbell and Shiller (1988)) and assume that, as in Vuolteenaho (2002), the historical dividend-price and dividend-book equity are equivalent in the steady state:

$$\rho = 1/\left[1 + \frac{\overline{D}}{P}\right] = 1/\left[1 + \frac{\overline{D}}{B}\right].$$

Then for both the log dividend-price ratio and log dividend-book equity ratio, we obtain

$$\delta_t = \ln\left(1 + \exp\left(dp_t\right)\right) \approx (1-\rho) \times \left(dp_t - dp\right) + \kappa_t,$$

$$\psi_t = \ln\left(1 + \exp\left(db_t\right)\right) \approx (1-\rho) \times \left(db_t - db\right) + \kappa_t.$$

We emphasize that, in line with the convention in this literature, we assume that the historical dividend-price and dividend-book equity ratios are known to the investor. This is in contrast to Lacerda and Santa-Clara (2011), who estimate the sample mean at each time t. Then it follows

$$\left(\theta_t - \theta_t^P\right) \approx \frac{\mu_t - \bar{\mu}}{1-\gamma} - \frac{g_t - \bar{g}}{1-\xi} - (1-\rho)\frac{\beta\left(\theta_t - \bar{\theta}\right)}{1-\beta}. \tag{4}$$

This equation decomposes the transitory component of the book-to-market ratio into the infinite sum of three terms: the future demeaned expected return, the expected demeaned return on equity, and the demeaned log book-to-market ratio. Therefore, if the book-to-market ratio is temporarily high, it may indicate that investors expect a persistently above-average future discount rate (i.e., the first term), or persistently below-average future cash flows (i.e., the second term). If there is no time variation in these first two terms, then the current change in the book-to-market ratio will purely reflect the time variation in future book-to-market values (i.e., the third term).

Now we rewrite equation (4) as

$$\frac{\mu_t - \bar{\mu}}{1-\gamma} \approx \left(\theta_t - \theta_t^P\right) + \frac{g_t - \bar{g}}{1-\xi} + (1-\rho)\frac{\beta\left(\theta_t - \bar{\theta}\right)}{1-\beta}.$$

If an investor expects no time variation in cash flow, and if the book-to-market ratio is independent of its own history, then returns can be predicted using the conventional regression where the lagged book-to-market is the predictor. However, an investor updates her beliefs whenever she receives new information about the cash flow or the book-to-market ratio, thus both are expected to fluctuate around their own averages. Therefore, instead of running the conventional predictive regression, we find from this equation that the three variables on the right-hand side could separately or jointly predict future returns. We label the third term, $(1-\rho)\frac{\beta\left(\theta_t - \bar{\theta}\right)}{1-\beta}$, as the "prospective book-to-market," and this is the novel predictor we develop in this paper. By considering the persistence and long-run trend of the book-to-market ratio, the prospective book-to-market ratio is less persistent and more volatile than the original book-to-market..

In the empirical analysis, we focus on β and θ, and treat the AR(1) coefficient of return process ρ as constant, thus it plays no role in the time series predictive regression. We set ρ to be 0.96 per year, following previous literature (e.g., Campbell and Shiller (1988) and Campbell and Shiller (1991)). Without considering its variation, we still achieve superior performance in return predictability. Additionally, we do not address the transitory component of the book-to-market ratio, $\theta_t - \theta_t^P$, as its estimation requires more time series modeling and would defeat our purpose of developing a parsimonious new return predictor. Finally, we also leave the term involving returns on equity, $\frac{g_t - \bar{g}}{1-\xi}$, for separate research.[3]

3 Data and empirical results

3.1 Predicting market returns

We first estimate the prospective book-to-market ratio at the market level and examine its predictive power for market returns. For the aggregate market data, we rely on the dataset from Goyal and Welch (2008), which is available on Amit Goyal's website. The book values are sourced from Value Line and Dow Jones. The annual book-to-market ratio is calculated as the ratio of the book value at the end of the previous year to the market value at the end of the current year, specifically for the Dow Jones Industrial Average. This dataset starts in 1921 and the market returns data from Kenneth French's website begins in 1926, with both datasets ending in 2022.

[3] In a companion paper, we propose a slightly different empirical approach that better accommodates the much weaker persistence of return on equity, demonstrating that this framework also allows the prospective ROE to predict returns. In fact, we introduce a much larger array of accounting variables to enhance their return predictive power, applicable both to the U.S. equity market and international markets, all within the same framework.

3.1.1 Parameter estimation

To construct the prospective book-to-market, we use the sample historical mean, $\bar{\theta}$, and the sample first-order autoregression coefficient, β, as the proxies for the long-run trend and the persistence of the log book-to-market ratios, respectively. To facilitate a fair comparison with the benchmark log book-to-market ratio, these parameters are re-estimated annually using only the data available at the time of estimation. Specifically, we start with the first 10 observations to obtain their initial estimates. Each subsequent year, we add one more observation and re-estimate both parameters.[4]

Table 1 Panel A presents the summary statistics of the long-run trend and persistence parameters. The mean of the long-run trend is -0.548, slightly higher than the full sample average -0.740 shown in Panel B. The average persistence is 0.786, confirming that the log book-to-market ratio is a slow-moving random variable.

Our baseline prospective book-to-market is constructed as follows,

$$\pi = \frac{\beta(\theta - \bar{\theta})}{1 - \beta},$$

in which the persistence parameter, β, is the simple OLS estimate. Both the historical mean and persistence parameters are updated annually. We emphasize that each observation is constructed using only the information available at that point in time, ensuring there is no look-ahead bias in obtaining the π variable. Our main results are based on π, and we will also examine alternative specifications in the robustness-check section.

Table 1 about here.

Table 1 Panel B presents the summary statistics for market excess return, log book-to-market ratio, and our main predictor, the prospective log book-to-market ratio (π). Given the extensive study of market returns in prior literature, our focus is on comparing the latter two variables. Notably, compared with the original book-to-market, the mean of π is slightly smaller in magnitude (-1.258 vs. -0.740) but exhibits a much higher standard deviation (14.178 vs. 0.520).

[4]Our main results depend on the choice of the initial year used in the estimation process.

This amplified variability is due to several outliers where π becomes exceptionally large as its β approaches one. For instance, π's maximum (123.092) and minimum (-33.076) values occur in 1933 and 2001, where β is 0.992 and 0.959, respectively. We further address this issue in the robustness section by utilizing an alternative regression method. Moreover, π is much less persistent than the original variable (0.175 vs. 0.902), which is expected since it removes the persistence inherent in the original book-to-market ratio. Panel C shows the pairwise correlations among the market excess return, log book-to-market ratio, and π. The correlation between the original variable and π is 0.524, indicating that despite their differences, the two variables still share common information.

3.1.2 Predictive regressions

Our primary objective in this paper is to compare the predictive power of the prospective ratio with that of the original variable. We begin by examining the predictability of the market risk premium in a time-series setting, with results reported in Table 2.

Table 2 about here.

Panel A presents the in-sample (IS) predictive regression results. "In-sample" refers to the regression being conducted using the full sample period, ensuring there is no look-ahead bias in our prospective variable. Initially, we find that the original book-to-market ratio marginally predicts the market risk premium, with a moderate t-statistics of 1.55.[5]. More importantly, when we use π as the predictor, its coefficient is 0.004 and highly significant, with a t-statistic of 5.44 and an adjusted R^2 of 7%. The economic significance is also notable; a one-standard-deviation increase in π predicts a positive excess return of 5.67% (computed as 0.004×14.178) in the following year.

Many known return predictors have failed in the post-oil shock sample (Goyal and Welch (2008)). In response, we examine the performance of predictors from 1975 to 2022 in Panel B. As indicated, the log book-to-market itself completely loses its predictive power for market returns

[5]Because our sample period covers the 2009 financial crisis and the 2022 Pandemic, this result is generally consistent with, albeit different from, those in Goyal and Welch (2008) and Kothari and Shanken (1997)

during this period, with a t-statistic of 0.59 and an R^2 of -0.01. In contrast, the coefficient of prospective book-to-market, proxied by π, remains highly significant. The point estimate, 0.008, is about twice as large as that in the full sample and is statistically significant, with a t-statistic of 2.61 and an adjusted R^2 of 9%.

To minimize the effect of outliers, we first winsorize the 1933 observation—the largest value of π—and replace it with the next largest value. This adjustment reduces the power of π to a t-statistic of 2.32 and an adjusted R^2 of 3%, as shown in Panel C. Additionally, we winsorize the top and bottom 5% extreme observations of the π variable, with the results presented in Panel D. The slope coefficient, 0.007, is marginally significant with a t-statistic of 1.81. It is important to note that in both winsorized samples, the log book-to-market ratio itself becomes insignificant at the 10% level.

Goyal and Welch (2008) caution that in-sample predictability often fails to translate into out-of-sample (OOS) predictability. To address this concern, we examine the out-of-sample predictive power in Table 3. The metrics we use include adjusted R^2, root-mean-square deviation ($\Delta RMSE$), and a statistic that tests for equal mean-squared error between the unconditional forecast and the conditional forecast (MSE-F), as advocated by Goyal and Welch (2008).[6]

Table 3 about here.

Panel A presents the out-of-sample predictive test results using the first 15 observations to initialize the regression, also known as the burn-in period.[7] As documented in the extant literature, the original book-to-market ratio shows negative values across all three metrics we examine. This suggests that the original book-to-market fails to outperform a simple historical moving average estimate.

In contrast, the prospective book-to-market ratio, π, exhibits strong out-of-sample performance across all three measures we use. The adjusted out-of-sample R^2 is 3.8% with a p-value

[6] We provide the formulas for these measures in the appendix. These statistics are used to examine the relative performance of a predictor against the historical mean.

[7] Because we require an additional 10 observations to begin estimating the prospective book-to-market ratio, the first 25 observations are excluded from evaluating model performance. Our results are not sensitive to the choice of the out-of-sample period.

of 0.01, significantly outperforming the naïve model that uses simple moving average. Previous literature also indicates that commonly used predictors perform even worse in the modern sample starting from 1975, following the Oil Crisis. To investigate whether our proposed predictor suffers from this reduced predictive power in the later period, we conduct the out-of-sample test using the first 45 observations to initialize the estimate and report the results in Panel B. We find that the original book-to-market ratio completely loses its predictive power during this period, with p-values almost equal to 1.00. In stark contrast, the prospective book-to-market ratio still achieves a significant R^2 at 5.2% with a p-value of 0.01. Collectively, the results in Tables 2 and 3 underscore the robust predictive power of our prospective ratio, both in-sample and out-of-sample, across different periods.

3.1.3 Robustness

We have demonstrated strong return predictability using empirical proxies for the long-run trend and persistence in the model. To further investigate the robustness of these results, we explore several alternative constructs.[8] As the prospective book-to-market ratio critically depends on the estimate of β, its time variation can also be sensitive to outliers in the original book-to-market ratio. Consequently, we consider a robust estimator (π') using iteratively reweighted least squares (RLS, Green (1984)), assigns lower weights to poorly fitting points. Specifically, the weights for each iteration are calculated by applying the bi-square function to the residuals from the previous iteration. RLS estimates are known to be less sensitive to outliers in the data compared to OLS estimates. With this alternative measure of persistence, we construct

$$\pi' = \frac{\beta_{RLS}(\theta - \bar{\theta})}{1 - \beta_{RLS}}.$$

Table 1 Panel A presents the summary statistics for the alternative measure β_{RLS}. In general, β_{RLS} is similar to β with a linear correlation of 0.890 (Panel C). Panel A of Table 2 confirms

[8]Our primary concern relates to the large values of π resulting from uncertainty in the estimation of β. Additionally, β tends to have a downward bias in estimation, especially when the sample size is small. To address this issue, we experiment with recursive mean least squares for the market level, industry portfolios, and cross-section of stock returns. The results are consistent, and we omit them here to save space. Adjusting the estimate of β upwards may, of course, increase the time variation of π.

the in-sample predictive power of this alternative measures, with a t-statistic of 4.69 and an adjusted R^2 of 8%. In the post-oil-shock sample and winsorized samples (Panel B, C, and D), π' consistently shows statistical significance at the 10% level, with t-statistics of 2.91, 2.46, and 1.91, respectively. Interestingly, the point estimates of π' are almost identical across all four Panels at 0.007. This consistency is due to the measure's robustness to outliers by design. The significance of π' is also confirmed in the out-of-sample performance reported in Table 3. The OOS R^2 is 4.2% in the full sample and 5.1% in the post-oil-shock sample, with p-values of 0.01 and 0.02, respectively. Given that the OLS AR(1) coefficient is potentially sensitive to outliers, it is not surprising that this alternative measure sometimes outperforms our baseline prospective book-to-market ratio, further corroborating our main findings.

3.2 Predicting industry portfolio returns

Lewellen (1999) finds that the book-to-market ratio predicts returns both for the market and for industry portfolios in a time-series setting. In this section, we also investigate whether the prospective book-to-market ratios at industry level can predict industry returns. Our industry classification, returns, book values, and market values are all from Kenneth French's data library. We focus on the 48 industry portfolios and compute the end-of-year industry book-to-market ratio by dividing the book value at the end of the previous year by the market value at the end of the current year. The sample period for our industry portfolio data spans from 1926 to 2022.

3.2.1 Parameter estimation

We estimate the long-run trend and persistence parameters for each industry using the same method employed for the market book-to-market ratios. Table 4 presents the summary statistics of the excess returns and log book-to-market ratios for each industry.

Table 4 about here.

Variations in excess returns and book-to-market ratios across industries are considerable. For instance, the highest average excess return is approximately 19% per year in the Aircraft industry (Aero), while the lowest is 8% in both Banking (Banks) and Real Estate (RlEst). The Transportation industry (Trans) reports the highest log book-to-market ratio at 0.172, whereas the Pharmaceutical Products industry (Drugs) has the lowest at -1.292. Additionally, the AR(1) coefficients for excess returns are predominantly negative across all industries, while those for log book-to-market ratios are consistently very high.

Table 5 about here.

The cross-industry difference in persistence leads to a distinction between book-to-market ratios (bm) and prospective book-to-market ratios (π). Table 5 presents the summary statistics of π of each industry. The Banking industry (Banks) records the highest π at -0.142, while the Transportation industry (Trans) exhibits the most negative π at -10.638.

Table 6 about here.

Table 6 further displays the cross-industry average of summary statistics after pooling all industry estimates. Panel A presents the estimated parameters, revealing that, similar to the market-level estimates from the previous section, the sample mean of average persistence across 48 industry portfolios is 0.737. This suggests that log book-to-market ratios also exhibit persistence at the industry level. Panel B provides the summary statistics of industry returns, industry book-to-market ratios, and industry prospective book-to-market ratios (π). Compared to the original book-to-market ratios, the prospective ratios exhibit higher volatility (4.207 vs. 0.561) and lower persistence (0.776 vs. 0.841). These characteristics align with the construction of the variables, as discussed in the previous section. Panel C shows the correlations among the variables of interest, where the cross-industry correlation between the original and prospective book-to-market ratios is notably high at 0.894.

3.2.2 Predictive regressions and industry portfolio sorts

We next examine whether the prospective book-to-market ratio aids in predicting industry portfolio returns. Table 7 presents the in-sample predictive regressions of annual returns for 48 industries on lagged industry book-to-market ratios bm, π, and π'.[9] All time-series predictive regressions are adjusted for Newey-West correction with 3 lags. For the sake of brevity, we only display the coefficients, t-statistics of the predictors, and the adjusted R^2 for each predictive regression.

Table 7 about here.

Out of 48 industries, bm, π, and π' each generates 15, 16, and 15 coefficients, respectively, with p-values less than 5%. The magnitude of the average R-squared are also similar among the three measures across industries. Overall, the three predictors demonstrate comparable predictive power in the sample.

Table 8 about here.

To examine the out-of-sample predictive power of our variables, Tables 8 and 9 present the results at the industry level.[10] For consistency with the OOS test on market returns, we applied the same time-series out-of-sample method across all industries and counted the number of industries where the p-value of the adjusted R^2 is less than 5% and 10%.[11] Out of 48 industries, bm and π each shows a p-value lower than 5% for 5 industries (Textiles (Txtls), Aircraft (Aero), Petroleum and Natural Gas (Oil), Real Estate (RlEst), and Other) and 3 industries (Construction (Cnstr), Real Estate (RlEst), and Trading (Fin)), respectively. For a p-value lower than 10%, bm indicate significance in four additional industries (Healthcare (Hlth), Construction (Cnstr), Precious Metals (Gold), and Other), while π achieves none.

Table 9 about here.

We also examine the alternative measure, π', with its OOS results presented in Table 10. For π', the number of industry portfolio OOS R^2 values that are significant at 5% and 10% level are 4 and 5, respectively. Overall, the original book-to-market ratio appears to perform more favorably than the prospective ratios.

[9]For robustness, we also present results of these tests for 12 industry portfolios and 38 industry portfolios in the Appendix.
[10]We use the first 15 observations to initialize the estimate.
[11]Using p-values of the other two metrics yield identical results.

Table 10 about here.

The industry portfolios naturally provide us with a cross-section to enhance the power of our test. Each year-end, we sort the 48 industries into 5 quintiles based on the available book-to-market ratio. The highest and lowest quintiles each include 10 industry portfolios. We then examine the mean returns of these 5 quintiles, as well as the zero-cost high-minus-low industry portfolios, which are presented in 11 Panel A.

Table 11 about here.

Industry portfolio excess returns increase with both bm and π. While the bm strategy generates a cross-industry return spread of 3.3% per year, the pi strategy yields a slightly higher spread of 4.0% per year. However, the risk-adjusted returns show a great difference between these two strategies. Panel B displays the α under the Fama-French 3-factor model. The high-minus-low α for the book-to-market ratio is -0.4% per year with a t-statistic of -0.43, while that for the prospective book-to-market ratio is significantly higher at 2.8% per year with a t-statistic of 3.23. For robustness, we also examine the portfolios formed by the alternative measure, π'. The mean return spread is 3.6% with a t-statistic of 3.67, and α is 2.3% per year with a t-statistic 2.64. These results are quantitatively similar with those generated by π. Therefore, the industry prospective book-to-market ratio generates a significant spread in risk-adjusted returns across industries, whereas the original book-to-market ratio does not, consistent with the findings in Asness, Porter, and Stevens (2000).

Moreover, we also examine the predictability of bm and π using seemingly unrelated regressions (SUR). Table 12 presents the in-sample SUR results. The average SUR coefficient for bm is 0.106 with a t-statistic of 11.17. For π, the average SUR coefficient is 0.041 with a t-statistic of 7.609. The alternative measure, π', shows similarly significant predictive power in the SUR test, with a t-statistic of 7.615. The statistical significance of bm is stronger than that reported in Lewellen (1999), which we attribute to examining a larger number of industry portfolios. When using 12 Fama-French industry portfolios, we obtain results that are similar to those reported by Lewellen (1999).[12]

[12] The results are available upon request.

Table 12 about here.

3.3 Cross-section of returns

The evidence from the stock market and industry portfolios indicates that the prospective book-to-market ratio performs favorably in predicting next period returns compared to the log book-to-market value. In this section, we turn to the cross-section of individual stocks to examine whether this predictability can translate into profitable investment strategies.

We collected data on stock returns from CRSP and accounting information from Compustat, starting with all common shares (share codes 10 or 11) traded on the NYSE, Amex, and Nasdaq. For these firms, we calculate the book value of equity at the end of June each year. This calculation includes shareholder equity, balance sheet deferred taxes, and balance sheet investment tax credits, and subtracts the value of preferred stock. For deferred taxes and investment tax credits, we set missing values to zero. Preferred stock is valued at the redemption value if available, otherwise at the liquidation value or the carrying value. Our main sample comprises individual firms from July 1959 through December 2022 and includes stock returns, firms' SIC codes, and accounting information.

3.3.1 Parameter estimation

To avoid look-ahead bias, we conduct all our tests on return predictability during the out-of-sample (OOS) period. However, estimating the first-order autocorrelation coefficient and long-run trend poses a significant challenge in the cross-section of individual stocks due to the large dimension of the cross-section and the smaller time series dimension. Unlike the industry portfolios data, which has a broader historical range, the CRSP-Compustat data starts only from 1959. Running first-order autoregressions on a firm-by-firm basis would likely result in noisy estimates. To mitigate potential estimation errors, we pool individual firms into groups and focus on estimating parameters from these groups, subsequently assigning these group values to individual firms. Consistent with our industry portfolio results, we assume that all firms within the same industry share the same AR(1) coefficient and long-run trend. Additionally, we report results that primarily rely on estimating individual firms' AR(1) coefficients and long-run trends. This is supplemented by group estimations when individual data from a short history prove unreliable. This robustness check still yields similar results.

Our out-of-sample (OOS) period extends from July 1962 to December 2022. At the beginning of July 1962, we categorize firms according to their Standard Industrial Classification (SIC) codes at that time. We then conduct a pooled ordinary least squares (OLS) regression on this panel, using the log book-to-market values from 1959 to 1962 to generate an initial estimate of β. We calculate each firm's past annual book-to-market ratios and estimate a value-weighted average as the long-run trend $\bar{\theta}$. For each subsequent year, we expand our estimation window to generate a new set of estimates. Based on these estimates, we compute the prospective book-to-market ratio and assign it to each firm within that industry.[13]

Table 13 about here.

Table 13 reports the estimates and standard deviations of $\hat{\beta}$ and $\bar{\theta}$ for each of the 48 industries during the sample period. There are large variations across different industries. For example, the Coal industry log book-to-market ratio has an AR(1) coefficient of 1.334, as the largest estimate compared to the rest of industries. The Entertainment (Fun) industry on the other hand has the smallest AR(1) coefficient estimate of 0.673 only. The Steel Works (Steel) industry provides a very stable estimate with the standard deviation of 0.022 only, while the Coal industry contains the most volatile estimate with a very large standard deviation of 3.985. Across all the firms, the average firm's β is estimated to be 0.806, which is higher than the aggregate market or average industry estimates.

Turning to the estimate of the long-run trend, we find that the Smoke industry once again has the highest estimate at 0.382, while the Drugs industry has the lowest at -1.228. The Health industry's estimate shows the largest standard deviation, at 0.539, whereas the Agriculture (Agric)

[13] We have also employed various regression methods, including firm-specific fixed-effect regression, two-way fixed-effect regression, and random-effect regression (GLS), all of which yield similar results. Additionally, using an equal-weighted industry book-to-market ratio as the long-run trend also produces comparable outcomes.

industry has the smallest, at only 0.079. On average, the long-run trend for U.S. firms stands at -0.328.

3.3.2 The prospective factor

We examine whether the return predictability of the prospective book-to-market, defined as $\pi = \frac{\beta(\theta_t - \bar{\theta})}{1-\beta}$, can translate into profitable portfolio performances. The original book-to-market ratio is well-known for producing the value anomaly across stock returns. However, Fama and French (2015) found that their HML factor did not produce a significant alpha when regressed against the other four factors, suggesting its redundancy in explaining cross-sectional returns. Conversely, Asness and Frazzini (2013) demonstrated that the HML factor, when constructed using either the June-end market value or the current-month market value for calculating the book-to-market ratio, could generate significant alphas exceeding those of the original HML. Therefore, our objective in this section is to determine whether our proposed prospective book-to-market ratio provides a more effective measure in pricing the cross-section of stock returns, compared to the existing three HML factors.

Following the methodology of Fama and French (1992) and Fama and French (1993), we construct the prospective factor using six value-weighted portfolios formed based on size and the prospective book-to-market ratio. At the end of June each year, stocks are independently sorted into two size-based portfolios determined by the NYSE market-cap median and into three portfolios based on the 30% and 70% NYSE breakpoints for prospective book-to-market ratios, using the most recent data. We value-weight these portfolios and update the breakpoints annually in June. The prospective factor is derived from the high-minus-low return, calculated as the difference between the average returns of the top two portfolios within the highest 30% of prospective book-to-market ratios and the bottom two portfolios within the lowest 30%.

Table 14 about here.

Panel A of Table 14 provides the summary statistics for the prospective book-to-market ratio factor, including the mean, standard deviation, maximum, minimum, and Sharpe ratio. Over our sample period, the factor achieved a mean return of 29.9 basis points per month, corresponding to an annualized Sharpe ratio of 0.464.

Panel B of Table 14 presents the time-series regression results of the prospective book-to-market factor against various factor asset pricing models. In accordance with the literature, we consider the following models: the q-factor model by Hou, Xue, and Zhang (2015), which includes MKT, ME, IA, and ROE; and the Fama-French models, which include the 3-factor (MKT, SMB, HML) model from Fama and French (1993) and the 5-factor (adding RMW and CMA) model from Fama and French (2015), supplemented by a momentum factor (MOM). The t-statistics, adjusted for 6-lag Newey-West standard errors, are reported in parentheses. While the q-factors are available starting from January 1967, all other factors commence from July 1963.

Our initial task is to determine whether the proposed prospective book-to-market ratio factor is encompassed by any existing risk factors. Our findings indicate that the α for every regression is significantly different from zero, suggesting that it is not spanned by these factors. Among all models tested, the q-factor model yields the largest alpha at 19.0 basis points per month (t=2.384), while the Fama-French 5-factor model leaves the smallest alpha with 13.2 basis points per month (t=2.385). Overall, we observe that the prospective factor is weakly negatively correlated with the market portfolio and the MOM factor, negatively correlated with the RMW factor, and strongly positively correlated with the size factor, CMA factor, and the q-factors related to investment and profitability.

In Table 15, we further assess whether our proposed prospective factor can encompass various versions of the HML factor. We analyze three HML factors: the standard version following Fama and French (1992), constructed using the December market cap (HML^{A,L}), and two alternative versions from Asness and Frazzini (2013)-one using the June market cap (HML^{A,C}) and the other using the monthly updated market cap (HML^{M,C}). Unlike HML^{A,L} and HML^{A,C}, which are constructed annually, HML^{M,C} is estimated monthly. Given that HML factors are not part of the q-factors, our examination focuses solely on the Fama-French three- and 5-factor models, both with and without the suppliment of the momentum factor. In each regression, we replace the standard HML factor on the right-hand-side with our prospective factor (π HML). Additionally, we specifically investigate whether the two non-standard versions of HML can be spanned by our prospective factor.

Table 15 about here.

Panel A presents regression results with the standard HML factor as the dependent variable, where π HML is our prospective factor. All the models demonstrate that the standard HML is spanned by π HML, evidenced by either an insignificant or a significantly negative alpha, ranging from -0.157 to 0.032 (t-stats from -1.991 to 0.393). Notably, three out of five alphas are negative. Starting with a simple regression, $\text{HML}^{A,L}$ is approximately 1.071 times π HML. Adding more factors reveals that MKT and SMB do not capture the residual returns of $\text{HML}^{A,L}$ beyond the π HML. Consistent with Asness and Frazzini (2013), $\text{HML}^{A,L}$ proves to be an inefficient method for incorporating momentum into a portfolio. Particularly in the presence of π HML, there is a negative correlation between $\text{HML}^{A,L}$ and the MOM factor.

Panel B presents the regression results with the $\text{HML}^{A,C}$ factor as the dependent variable. Again, all the models indicate that $\text{HML}^{A,C}$ is spanned by π HML, showing either an insignificant or a significantly negative alpha, ranging from -0.192 to 0.128 (t-stat from -2.065 to 1.454). This time, four out of five alphas are negative, except when the MOM factor is added to the Fama-French 3-factor model. In terms of alpha magnitudes, the results are consistent with Asness and Frazzini (2013) that $\text{HML}^{A,L}$ is somewhat inferior to $\text{HML}^{A,C}$. Starting with a simple regression, $\text{HML}^{A,C}$ is about 1.123 times π HML. Adding more factors reveals that SMB barely accounts for the residual returns of the $\text{HML}^{A,C}$, while MKT only significantly and negatively explains the residual return in the 3-factor model. Similar to the findings in Panel A, MOM also loads negatively, but its coefficients become more significant.

Finally, Finally, we address the debate regarding whether HML is a redundant factor in the presence of other factors. Fama and French (2015) find HML can be completely described by the other four factors in the 5-factor model, resulting in an insignificant alpha, thus concluding HML is redundant in measuring abnormal returns. Asness (2014) conducts similar regressions and find that $\text{HML}^{A,L}$ still fails to demonstrate significance in time-series regressions even after incorporating the MOM factor. They further show that the monthly updated book-to-market ratio, HML^{M,C}, does generate a significant alpha due to its heavily negative loading on momentum. Therefore, having demonstrated that the prospective HML, instead of being spanned by HML^{A,L} or HML^{A,C}, actually spans these two factors in the presence of other factors, our next goal is to examine whether the prospective factor can be a useful component in asset pricing models.

Table 16 about here.

In panel A of Table 16, we focus on the q-factors while analyzing four different versions of HML as dependent variables. The first model confirms the results from Table 14, showing that π HML has a significant monthly alpha of 0.190% (t=2.384). The subsequent models show that q-factors adequately explain both the standard HML and the HML^{A,C}, consistent with Hou, Xue, and Zhang (2015). Lastly, consistent with Asness (2014), the model with HML^{M,C} as the dependent variable also exhibits a significant alpha of 0.303% (t=2.037).

In panel B, we analyze the FF 5-factor model, excluding HML. The result indicates that all versions of HML are highly positively correlated with CMA and do not yield any significant alpha. However, a closer examination reveals that our π HML produces the largest and only positive alpha, at 0.089%, although the t-value of 1.108 is insignificant. This statistic is notably largest among all, compared to -0.708%, -0.943% and -0.436% for the others.

Finally, following Asness (2014), we incorporate the momentum factor into the model. The results show that π HML generates a marginally significant alpha of 0.157% (t=1.945), which is smaller and statistically weaker than that from HML^{M,C} (0.315%, t=3.424). Notably, π HML has the smallest loading on CMA, with the regression coefficient of 0.684 (t=9.767), in contrast to the higher coefficient of 1.030 for HML^{A,C}. Additionally, π HML also shows the smallest loading on MOM, with a regression coefficient of -0.095 (t=-3.105), which is notably less negative than -0.530 for HML^{M,C}.

Overall, these regression results indicate that our prospective HML is the best performing and least redundant among all three annually-refreshed HML factors, although it does not perform as strongly as the monthly updated version. Additionally, it avoids heavy loading on the momentum factor, a characteristic that is prominent in HML^{M,C}.

4 Conclusion

We model the transitory components of the book-to-market ratio as the sum of the present value of three demeaned terms: stock return, return on equity, and prospective book-to-market. We introduce an empirical proxy for the last term as a novel predictor of stock returns. This new variable requires estimates of the long-run trend and persistence of the book-to-market ratio and exhibits greater variations compared to its original form.

ur empirical tests, which encompass the market portfolio, industry portfolios, and the cross-section of individual firms, reveal that the prospective book-to-market ratio can significantly predict market returns, achieving an adjusted R-squared between 3.8% and 4.2% out-of-sample. It also generates a cross-industry risk-adjusted annual return spread of 2.8%. Additionally, a high-minus-low strategy based on this ratio produces significant monthly alphas ranging from 12.1 to 19.0 basis points across various workhorse factor models. As the prospective book-to-market factor spans, rather than of being spanned by, the standard HML factor, it proves to be a useful alternative value factor in factor models.

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Table 1: Summary Statistics

This table reports the summary statistics of the aggregate stock market from 1921 to 2022 and the sample frequency is annual. Panel A reports the moving average ($\bar{\theta}$), the AR(1) coefficient (β) of market level log book-to-market bm along with an alternative measure of the autoregressive coefficient, β_{RLS}. Panel B reports the summary statistics of market excess returns (r_e), market level log book-to-market (bm), prospective log book-to-market (π), and the alternative measure of the prospective log book-to-market (π'). Panel C shows the linear correlations of market excess returns, market level log book-to-market, and both measures of the prospective log book-to-market.

Panel A: Parameter estimates

	$\bar{\theta}$	β	β_{RLS}
$Mean$	-0.548	0.786	0.782
Std	0.093	0.098	0.108
min	-0.842	0.346	0.350
max	-0.434	0.992	0.979
$AR(1)$	0.908	0.715	0.751
Obs	93	93	93

Panel B: Excess returns, log book-to-market and prospective log book-to-market ratios

	r_e	bm	π	π'
$Mean$	0.085	-0.740	-1.258	-2.474
Std	0.201	0.520	14.178	8.330
min	-0.465	-2.031	-33.706	-39.816
max	0.529	0.366	123.092	48.389
$AR(1)$	0.012	0.902	0.175	0.514
Obs	97	102	93	93

Panel C: Correlations

	r_e	bm	π	π'
r_e	1.000	-0.163	-0.092	-0.057
bm	-0.163	1.000	0.524	0.765
π	-0.092	0.524	1.000	0.890
π	-0.057	0.765	0.890	1.000

Table 2: Predicting Market Returns

This table reports predictive regression results of $r_{e,t+1} - r_{f,t+1} = a + bx_t + \varepsilon_{t+1}$, where $r_{e,t+1}$ is the annual CRSP value-weighted market return and $r_{f,t+1}$ is the annual risk-free rate. Panel A reports the full sample results. Panel B reports the results from 1975 to 2022 (post oil shock). Panel C reports the results with the 1933 observation winsorized. Panel D reports the results with 5% observations of the independent variables winsorized.

Panel A: Full sample results

	bm	π	π'
a	0.130	0.091	0.103
	(3.83)	(4.71)	(5.23)
b	0.062	0.004	0.007
	(1.55)	(5.44)	(4.69)
Adj R^2	0.02	0.07	0.08

Panel B: Post oil shocks (1975 to 2022)

	bm	π	π'
a	0.112	0.125	0.126
	(2.72)	(5.01)	(5.12)
b	0.028	0.008	0.007
	(0.59)	(2.61)	(2.91)
Adj R^2	-0.01	0.09	0.09

Panel C: 1933 Winsorized

	bm	π	π'
a	0.128	0.103	0.104
	(3.75)	(4.82)	(4.86)
b	0.059	0.007	0.006
	(1.46)	(2.32)	(2.46)
Adj R^2	0.01	0.03	0.03

Panel D: 5% Winsorized

	bm	π	π'
a	0.128	0.103	0.104
	(3.71)	(4.71)	(4.73)
b	0.058	0.007	0.006
	(1.43)	(1.81)	(1.91)
Adj R^2	0.01	0.02	0.02

Table 3: Out-of-sample Tests

This table reports results of out-of-sample (OOS) tests of the predictive regressions. Panel A reports the out-of-sample results of the full sample (the first 15 observations are used to initialize the estimation). Panel B reports out-of-sample results for the post oil-shock sample (the first 45 observations are used to initialize the estimation).

Panel A: Full sample results

	bm	π	π'
Adj R^2	-0.079	0.038	0.042
	(0.80)	(0.01)	(0.01)
$\Delta RMSE$	-0.007	0.003	0.004
	(0.77)	(0.01)	(0.01)
$MSE-F$	-5.737	3.045	3.420
	(0.80)	(0.01)	(0.01)

Panel B: Post oil-shock sample (1975 to 2022)

	bm	π	π'
Adj R^2	-0.236	0.052	0.051
	(1.00)	(0.01)	(0.02)
$\Delta RMSE$	-0.020	0.005	0.005
	(1.00)	(0.02)	(0.02)
$MSE-F$	-10.116	2.887	2.875
	(1.00)	(0.01)	(0.02)

Table 4: Excess Returns and Log Book-to-market Ratios of 48 Industry Portfolios

This table reports the summary statistics of 48 industry portfolios' excess returns and log book-to-market ratios from 1926 to 2022.

	r_e			bm		
Industry	*Mean*	*Std*	*AR(1)*	*Mean*	*Std*	*AR(1)*
Agric	0.114	0.490	-0.119	-0.553	0.547	0.769
Food	0.095	0.225	-0.117	-0.637	0.426	0.882
Soda	0.101	0.282	-0.108	-0.808	0.831	0.901
Beer	0.131	0.421	-0.103	-0.712	0.949	0.930
Smoke	0.131	0.238	-0.127	-0.845	0.815	0.907
Toys	0.141	0.537	-0.225	-0.461	0.790	0.886
Fun	0.165	0.363	-0.078	-0.421	0.753	0.849
Books	0.153	0.440	-0.054	-0.478	0.667	0.817
Hshld	0.121	0.248	-0.241	-1.039	0.546	0.904
Clths	0.121	0.272	-0.216	-0.481	0.589	0.886
Hlth	0.142	0.360	-0.189	-0.458	0.605	0.820
MedEq	0.148	0.266	-0.004	-0.945	0.557	0.875
Drugs	0.146	0.260	-0.089	-1.292	0.440	0.867
Chems	0.146	0.334	-0.170	-0.795	0.385	0.812
Rubbr	0.165	0.393	-0.228	-0.423	0.617	0.886
Txtls	0.129	0.372	-0.174	0.046	0.545	0.815
BldMt	0.137	0.352	-0.212	-0.507	0.451	0.816
Cnstr	0.144	0.394	-0.238	-0.248	0.509	0.687
Steel	0.131	0.387	-0.206	-0.016	0.524	0.812
FabPr	0.118	0.328	-0.228	-0.234	0.428	0.732
Mach	0.148	0.359	-0.261	-0.494	0.522	0.839
ElcEq	0.153	0.346	-0.215	-0.793	0.439	0.798
Autos	0.159	0.436	-0.173	-0.469	0.489	0.737
Aero	0.192	0.512	-0.110	-0.580	0.620	0.855
Ships	0.124	0.416	-0.190	-0.205	0.541	0.847
Guns	0.135	0.300	-0.233	-0.530	0.924	0.890
Gold	0.105	0.389	-0.234	-0.501	0.565	0.886
Mines	0.128	0.346	-0.167	-0.522	0.434	0.742
Coal	0.162	0.535	-0.125	0.015	0.908	0.900
Oil	0.113	0.259	-0.115	-0.284	0.436	0.870
Util	0.088	0.239	-0.185	-0.219	0.432	0.874
Telcm	0.086	0.212	-0.053	-0.346	0.432	0.895
PerSv	0.114	0.401	-0.144	-0.495	0.699	0.864
BusSv	0.111	0.299	-0.075	-0.645	0.820	0.920
Comps	0.148	0.344	-0.093	-1.066	0.511	0.795
Chips	0.153	0.383	0.037	-0.803	0.599	0.828
LabEq	0.125	0.284	-0.164	-0.965	0.359	0.733
Paper	0.177	0.985	-0.168	-0.558	0.718	0.861
Boxes	0.104	0.300	-0.172	-0.616	0.445	0.837
Trans	0.097	0.396	-0.282	0.172	0.885	0.942
Whlsl	0.093	0.449	-0.192	-0.309	0.648	0.838
Rtail	0.094	0.276	-0.207	-0.757	0.532	0.867
Meals	0.091	0.295	-0.132	-0.555	0.829	0.927
Banks	0.083	0.350	-0.067	-0.327	0.374	0.762
Insur	0.088	0.313	-0.199	-0.215	0.311	0.783
RlEst	0.083	0.411	-0.146	-0.150	0.777	0.846
Fin	0.100	0.359	-0.196	-0.194	0.551	0.819
Other	0.020	0.308	-0.084	-0.446	0.568	0.841

Table 5: Alternative Prospective Book-to-market Estimates of 48 Industry Portfolios

This table reports the summary statistics of the two alternative prospective book-to-market estimates of 48 industry portfolios. The sample period is 1926 to 2022.

	π			π'		
Industry	*Mean*	*Std*	*AR*(1)	*Mean*	*Std*	*AR*(1)
Agric	-0.663	1.336	0.743	-0.739	1.552	0.737
Food	-1.754	3.303	0.831	-1.765	3.301	0.833
Soda	-8.746	13.495	0.825	-11.667	17.547	0.812
Beer	-7.489	10.742	0.960	-13.034	22.329	0.930
Smoke	-7.313	17.045	0.494	-16.072	34.167	0.819
Toys	-4.447	4.599	0.700	-4.054	4.375	0.678
Fun	-2.448	2.742	0.779	-2.792	3.248	0.790
Books	-1.549	1.696	0.848	-1.792	1.997	0.848
Hshld	-3.066	4.947	0.862	-3.238	5.233	0.862
Clths	-2.196	4.595	0.897	-2.274	4.849	0.896
Hlth	-1.528	1.942	0.723	-1.268	1.760	0.559
MedEq	-1.532	3.521	0.848	-1.587	3.328	0.843
Drugs	-1.262	2.236	0.896	-1.341	2.389	0.894
Chems	-0.208	1.418	0.857	-0.208	1.558	0.856
Rubbr	-2.394	3.794	0.884	-2.676	4.379	0.876
Txtls	-1.056	1.604	0.778	-1.113	1.676	0.766
BldMt	-0.790	1.282	0.831	-0.813	1.322	0.831
Cnstr	-0.356	1.523	0.185	-0.523	0.691	0.394
Steel	-1.123	1.719	0.674	-1.131	1.729	0.691
FabPr	-0.718	0.950	0.543	-0.711	0.945	0.546
Mach	-1.240	1.957	0.848	-1.231	2.006	0.851
ElcEq	-0.691	1.158	0.758	-0.726	1.214	0.757
Autos	-0.188	1.209	0.751	-0.234	1.342	0.740
Aero	-1.068	2.429	0.908	-1.244	2.741	0.901
Ships	-1.293	1.744	0.885	-1.439	1.992	0.888
Guns	-8.980	22.763	0.513	-9.005	22.218	0.518
Gold	-2.792	3.890	0.829	-2.603	3.570	0.828
Mines	-0.434	0.815	0.792	-0.408	0.770	0.792
Coal	-9.113	10.125	0.699	-8.783	9.319	0.729
Oil	-1.605	2.104	0.863	-1.664	2.204	0.864
Util	-0.812	2.404	0.875	-0.820	2.433	0.875
Telcm	-2.226	5.257	0.694	-2.198	5.128	0.697
PerSv	-2.832	2.642	0.779	-2.736	2.549	0.775
BusSv	-6.004	8.830	0.730	-7.153	10.626	0.731
Comps	-0.811	2.599	0.727	-0.880	2.821	0.712
Chips	-1.424	2.362	0.790	-1.334	2.452	0.786
LabEq	-0.503	1.927	0.677	-0.485	1.820	0.664
Paper	-2.027	3.700	0.777	-3.681	9.063	0.831
Boxes	-1.148	1.582	0.776	-1.213	1.677	0.775
Trans	-10.638	16.912	0.901	-10.099	15.930	0.903
Whlsl	-1.611	1.627	0.889	-1.881	2.138	0.897
Rtail	-1.453	2.860	0.858	-1.553	3.138	0.852
Meals	-6.508	8.328	0.849	-6.908	9.070	0.878
Banks	-0.142	0.883	0.833	-0.146	0.905	0.836
Insur	-0.215	1.172	0.753	-0.229	1.163	0.752
RlEst	-2.155	2.345	0.796	-2.511	3.253	0.761
Fin	-1.248	1.736	0.719	-1.364	1.868	0.730
Other	-1.251	2.106	0.841	-1.548	2.566	0.824

Table 6: Summary Statistics: 48 Industry Portfolios

This table reports the summary statistics of the 48 industry portfolios from 1926 to 2022 and the sample frequency is annual. All statistics are first computed at industry level and averaged across all industries. Panel A reports the historical mean ($\bar{\theta}$) and 2 alternative AR(1) coefficient estimates (β and β_{RLS}) of 48 industry portfolios' log book-to-market bm. Panel B reports the summary statistics of market excess returns (r_e), market level log book-to-market (bm), and 2 alternative prospective log book-to-market ratios (π, π'). Panel C shows the linear correlations of r_e, bm, π, and π'. All statistics are first computed at industry level and averaged across industries.

Panel A: Parameter estimates

	$\bar{\theta}$	β	β_{RLS}
$Mean$	-0.249	0.737	0.737
Std	0.184	0.099	0.108
$Skew$	0.011	-0.337	-0.588
$Kurt$	-0.609	0.919	2.614
min	-0.557	0.534	0.497
max	0.085	0.888	0.895
$AR(1)$	0.961	0.923	0.897
Obs	89	89	89

Panel B: Excess returns, log book-to-market and prospective log book-to-market ratios

	r_e	bm	π	π'
$Mean$	0.118	-0.554	-2.522	-2.977
Std	0.270	0.561	4.207	5.091
$Skew$	0.708	-0.033	-1.385	-1.607
$Kurt$	1.675	-0.171	5.643	4.883
min	-0.463	-1.844	-21.369	-25.269
max	1.059	0.683	3.097	2.914
$AR(1)$	-0.092	0.841	0.776	0.783
Obs	88	89	89	89

Panel C: Correlations

	r_e	bm	π	π'
r_e	1.000	-0.003	-0.012	-0.011
bm	-0.003	1.000	0.894	0.883
π	-0.012	0.894	1.000	0.988
π	-0.011	0.883	0.988	1.000

Table 7: Predicting Industry Portfolio Returns: 48 Industries

This table presents the annual industry portfolios regression results of $r_{e,i,t+1} = a_i + b_i x_{i,t} + \varepsilon_{i,t+1}$, with Newey-West corrected standard errors (3 lags).

	bm			π			π'		
Industry	b	t-stat	Adj R^2	b	t-stat	Adj R^2	b	t-stat	Adj R^2
Agric	0.100	1.905	0.035	0.037	2.180	0.031	0.033	2.255	0.034
Food	0.050	1.238	0.004	0.006	1.404	0.002	0.006	1.387	0.002
Soda	0.016	0.594	-0.009	0.002	0.848	-0.002	0.001	0.878	-0.002
Beer	0.047	1.839	0.021	0.004	2.722	0.026	0.002	3.578	0.032
Smoke	0.001	0.039	-0.012	-0.000	-0.358	-0.011	-0.000	-0.541	-0.009
Toys	0.109	2.543	0.031	0.014	2.293	0.021	0.015	2.497	0.020
Fun	0.030	0.570	-0.008	0.003	0.215	-0.011	0.003	0.290	-0.011
Books	0.147	1.340	0.041	0.027	1.031	0.003	0.021	0.948	-0.000
Hshld	0.068	2.275	0.026	0.008	2.507	0.025	0.007	2.552	0.024
Clths	0.040	1.284	-0.005	0.005	1.530	-0.006	0.005	1.515	-0.006
Hlth	0.065	0.961	0.002	0.023	0.968	0.007	0.011	0.360	-0.008
MedEq	0.102	1.816	0.038	0.017	1.782	0.046	0.018	1.790	0.044
Drugs	0.146	3.055	0.069	0.024	3.285	0.053	0.022	3.288	0.052
Chems	0.103	2.105	0.023	0.028	2.346	0.025	0.026	2.367	0.025
Rubbr	0.052	1.702	0.002	0.006	1.351	-0.006	0.005	1.306	-0.006
Txtls	0.100	1.905	0.019	0.029	1.674	0.013	0.029	1.778	0.016
BldMt	0.099	2.351	0.021	0.029	1.950	0.013	0.027	1.892	0.012
Cnstr	0.030	0.341	-0.010	-0.007	-0.593	-0.011	0.017	0.372	-0.010
Steel	0.066	0.982	0.001	0.023	1.263	0.008	0.024	1.305	0.009
FabPr	0.019	0.269	-0.011	0.013	0.479	-0.010	0.014	0.496	-0.010
Mach	0.013	0.353	-0.011	0.001	0.120	-0.012	0.000	0.009	-0.012
ElcEq	0.094	1.869	0.013	0.038	2.249	0.019	0.036	2.243	0.018
Autos	0.054	1.432	-0.005	0.016	1.007	-0.009	0.014	0.952	-0.009
Aero	0.083	2.198	0.022	0.018	2.001	0.014	0.016	1.976	0.013
Ships	0.008	0.190	-0.011	0.001	0.111	-0.012	0.001	0.102	-0.012
Guns	0.007	0.323	-0.011	-0.001	-1.266	-0.009	-0.000	-1.006	-0.010
Gold	0.091	1.992	0.006	0.012	2.039	0.006	0.013	1.991	0.006
Mines	0.093	1.531	0.008	0.057	1.780	0.013	0.059	1.745	0.012
Coal	-0.012	-0.246	-0.011	-0.005	-0.862	-0.001	-0.003	-0.577	-0.007
Oil	0.107	2.129	0.022	0.018	1.906	0.016	0.018	1.925	0.016
Util	0.061	1.411	0.010	0.014	2.270	0.022	0.014	2.290	0.022
Telcm	0.083	1.278	0.026	0.006	0.837	0.021	0.007	0.912	0.024
PerSv	0.182	2.700	0.100	0.040	2.819	0.078	0.040	2.793	0.075
BusSv	0.013	0.295	-0.010	0.005	1.378	0.017	0.004	1.472	0.019
Comps	0.035	0.459	-0.008	0.008	0.539	-0.005	0.008	0.545	-0.005
Chips	0.087	1.083	0.006	0.018	0.873	0.002	0.016	0.713	-0.001
LabEq	0.083	1.172	0.001	0.015	1.550	0.002	0.016	1.502	0.003
Paper	0.128	3.349	0.073	0.020	4.621	0.069	0.006	3.510	0.040
Boxes	0.114	2.562	0.042	0.020	1.495	0.012	0.019	1.492	0.012
Trans	0.012	0.465	-0.010	0.000	0.309	-0.011	0.000	0.324	-0.011
Whlsl	0.064	1.007	0.006	0.019	1.213	-0.000	0.013	1.184	-0.002
Rtail	0.061	1.498	0.008	0.010	1.249	-0.001	0.009	1.230	-0.002
Meals	0.025	0.750	-0.006	0.001	0.225	-0.011	0.001	0.285	-0.011
Banks	0.131	2.645	0.029	0.053	2.466	0.030	0.052	2.443	0.030
Insur	0.061	0.821	-0.003	0.017	0.821	-0.003	0.018	0.862	-0.002
RlEst	0.122	3.036	0.056	0.038	2.944	0.056	0.021	1.917	0.027
Fin	0.104	2.073	0.030	0.035	2.784	0.040	0.034	2.851	0.043
Other	0.101	2.528	0.035	0.028	2.760	0.047	0.025	3.108	0.055

Table 8: Out-of-sample Predictability of 48 Industry Portfolios by bm

This table reports results of out-of-sample (OOS) predictability tests of using industry bm as the predictor. The reported statistics are calculated as: $r_t = a_{1\to t-1} + b_{1\to t-1}x_{t-1} + \varepsilon_t$; $R^2 = 1 - \frac{\sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}{\sum_{j=20}^{T}\left(r_j - \bar{r}_{1\to j-1}\right)^2}$; $\bar{r}_{1\to j-1} = \sum_{t=1}^{j-1} r_t$;$\acute{r}^2 = 1 - \left(1 - R^2\right) \times \frac{T-1}{T-2}$; $\Delta RMSE = \sqrt{\frac{1}{T-t}\sum_{j=t}^{T}\left(r_j - \bar{r}_{1\to T}\right)^2} - \sqrt{\frac{1}{T-t}\sum_{j=t}^{T}\left(r_j - \hat{\alpha}_{1\to j-1} - \hat{\rho}_{1\to j-1}x_{j-1}\right)^2}$; $MSEF = (T-t+1) \times \frac{\sum_{j=t}^{T}\left(r_j - \bar{r}_{1\to j-1}\right)^2 - \sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}{\sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}$.

	Adj R^2	p-value	$\Delta RMSE$	p-value	$MSE-F$	p-value
Agric	-0.057	0.758	-0.007	0.766	-4.027	0.758
Food	-0.086	0.886	-0.007	0.886	-5.911	0.886
Soda	-0.076	0.825	-0.008	0.823	-5.303	0.825
Beer	-0.271	0.992	-0.024	0.981	-15.990	0.992
Smoke	-0.101	0.905	-0.011	0.917	-6.871	0.905
Toys	-0.030	0.403	-0.006	0.409	-2.218	0.403
Fun	-0.085	0.899	-0.013	0.870	-5.853	0.899
Books	-0.327	0.993	-0.042	0.986	-18.490	0.993
Hshld	-0.091	0.887	-0.008	0.891	-6.269	0.887
Clths	-0.034	0.367	-0.005	0.389	-2.491	0.367
Hlth	0.006	0.063	0.001	0.062	0.415	0.063
MedEq	-0.136	0.962	-0.015	0.947	-8.996	0.962
Drugs	-0.036	0.400	-0.004	0.379	-2.607	0.400
Chems	-0.062	0.774	-0.007	0.779	-4.348	0.774
Rubbr	-0.078	0.844	-0.009	0.805	-5.399	0.844
Txtls	0.020	0.032	0.003	0.032	1.519	0.032
BldMt	-0.072	0.857	-0.008	0.836	-5.021	0.857
Cnstr	0.007	0.070	0.001	0.076	0.532	0.070
Steel	-0.066	0.823	-0.010	0.819	-4.666	0.823
FabPr	-0.018	0.259	-0.003	0.273	-1.326	0.259
Mach	-0.156	0.983	-0.017	0.979	-10.115	0.983
ElcEq	-0.120	0.970	-0.015	0.968	-8.030	0.970
Autos	-0.120	0.957	-0.018	0.954	-8.020	0.957
Aero	0.039	0.012	0.006	0.013	3.066	0.012
Ships	-0.152	0.984	-0.018	0.984	-9.915	0.984
Guns	-0.064	0.697	-0.008	0.709	-4.501	0.697
Gold	0.002	0.076	0.000	0.075	0.148	0.076
Mines	-0.092	0.932	-0.013	0.942	-6.309	0.932
Coal	-0.029	0.335	-0.007	0.357	-2.109	0.335
Oil	0.017	0.030	0.002	0.032	1.313	0.030
Util	-0.289	0.999	-0.020	0.997	-16.820	0.999
Telcm	-0.155	0.986	-0.014	0.987	-10.073	0.986
PerSv	0.007	0.057	0.001	0.062	0.506	0.057
BusSv	-0.059	0.684	-0.007	0.606	-4.198	0.684
Comps	-0.084	0.905	-0.012	0.911	-5.840	0.905
Chips	-0.183	0.994	-0.027	0.993	-11.598	0.994
LabEq	-0.057	0.767	-0.007	0.793	-4.016	0.767
Paper	-0.051	0.638	-0.006	0.567	-3.663	0.638
Boxes	-0.027	0.305	-0.003	0.314	-1.948	0.305
Trans	-0.095	0.880	-0.011	0.865	-6.532	0.880
Whlsl	-0.019	0.197	-0.002	0.176	-1.392	0.197
Rtail	-0.072	0.810	-0.008	0.806	-5.020	0.810
Meals	-0.116	0.941	-0.014	0.926	-7.805	0.941
Banks	-0.051	0.707	-0.006	0.693	-3.665	0.707
Insur	-0.043	0.560	-0.004	0.586	-3.093	0.560
RlEst	0.037	0.011	0.006	0.014	2.897	0.011
Fin	-0.074	0.874	-0.009	0.820	-5.194	0.874
Other	0.009	0.050	0.001	0.049	0.717	0.050

Table 9: Out-of-sample Predictability of 48 Industry Portfolios by π

This table reports results of out-of-sample (OOS) predictability tests of using industry π as the predictor. The reported statistics are calculated as: $r_t = a_{1\to t-1} + b_{1\to t-1}x_{t-1} + \varepsilon_t$; $R^2 = 1 - \frac{\sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}{\sum_{j=20}^{T}\left(r_j - \bar{r}_{1\to j-1}\right)^2}$; $\bar{r}_{1\to j-1} = \sum_{t=1}^{j-1} r_t$;$\bar{r}^2 = 1 - \left(1 - R^2\right) \times \frac{T-1}{T-2}$; $\Delta RMSE = \sqrt{\frac{1}{T-t}\sum_{j=t}^{T}\left(r_j - \bar{r}_{1\to T}\right)^2} - \sqrt{\frac{1}{T-t}\sum_{j=t}^{T}\left(r_j - \hat{\alpha}_{1\to j-1} - \hat{\rho}_{1\to j-1}x_{j-1}\right)^2}$; $MSEF = (T-t+1) \times \frac{\sum_{j=t}^{T}\left(r_j - \bar{r}_{1\to j-1}\right)^2 - \sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}{\sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}$.

	Adj R^2	p-value	$\Delta RMSE$	p-value	$MSE-F$	p-value
Agric	-0.097	0.896	-0.012	0.901	-6.645	0.896
Food	-0.153	0.945	-0.013	0.946	-9.971	0.945
Soda	-0.214	0.977	-0.023	0.979	-13.231	0.977
Beer	-0.425	0.997	-0.036	0.994	-22.378	0.997
Smoke	-0.140	0.868	-0.016	0.876	-9.194	0.868
Toys	-0.167	0.979	-0.030	0.981	-10.758	0.979
Fun	-0.100	0.933	-0.015	0.915	-6.796	0.933
Books	-0.502	0.998	-0.062	0.996	-25.057	0.998
Hshld	-0.152	0.979	-0.014	0.981	-9.890	0.979
Clths	-0.177	0.926	-0.023	0.935	-11.258	0.926
Hlth	-0.026	0.367	-0.004	0.388	-1.927	0.367
MedEq	-0.144	0.970	-0.016	0.961	-9.468	0.970
Drugs	-0.109	0.915	-0.011	0.906	-7.342	0.915
Chems	-0.101	0.939	-0.011	0.942	-6.909	0.939
Rubbr	-0.126	0.925	-0.014	0.906	-8.366	0.925
Txtls	-0.059	0.756	-0.008	0.741	-4.195	0.756
BldMt	-0.107	0.950	-0.012	0.944	-7.252	0.950
Cnstr	0.064	0.005	0.009	0.008	5.110	0.005
Steel	-0.090	0.881	-0.013	0.881	-6.174	0.881
FabPr	-0.026	0.440	-0.004	0.460	-1.922	0.440
Mach	-0.182	0.980	-0.020	0.977	-11.560	0.980
ElcEq	-0.157	0.984	-0.019	0.983	-10.192	0.984
Autos	-0.154	0.971	-0.023	0.970	-10.034	0.971
Aero	-0.010	0.109	-0.001	0.108	-0.707	0.109
Ships	-0.197	0.986	-0.023	0.983	-12.321	0.986
Guns	-0.208	0.879	-0.025	0.884	-12.926	0.879
Gold	-0.018	0.240	-0.003	0.264	-1.343	0.240
Mines	-0.125	0.962	-0.017	0.969	-8.313	0.962
Coal	-0.056	0.750	-0.013	0.766	-3.984	0.750
Oil	-0.022	0.223	-0.002	0.218	-1.595	0.223
Util	-0.052	0.650	-0.004	0.528	-3.736	0.650
Telcm	-0.224	0.963	-0.020	0.963	-13.746	0.963
PerSv	-0.225	0.995	-0.031	0.991	-13.754	0.995
BusSv	-0.190	0.940	-0.022	0.924	-11.949	0.940
Comps	-0.166	0.981	-0.023	0.984	-10.703	0.981
Chips	-0.210	0.993	-0.031	0.992	-13.020	0.993
LabEq	-0.146	0.892	-0.019	0.902	-9.537	0.892
Paper	-0.010	0.131	-0.001	0.124	-0.728	0.131
Boxes	-0.073	0.854	-0.008	0.861	-5.087	0.854
Trans	-0.135	0.902	-0.016	0.891	-8.937	0.902
Whlsl	-0.090	0.869	-0.011	0.828	-6.224	0.869
Rtail	-0.134	0.907	-0.014	0.907	-8.881	0.907
Meals	-0.142	0.977	-0.017	0.970	-9.300	0.977
Banks	-0.119	0.967	-0.013	0.966	-7.953	0.967
Insur	-0.056	0.673	-0.005	0.700	-3.990	0.673
RlEst	0.031	0.020	0.005	0.024	2.437	0.020
Fin	0.025	0.022	0.003	0.026	1.952	0.022
Other	-0.038	0.444	-0.005	0.457	-2.775	0.444

Table 10: Out-of-sample Predictability of 48 Industry Portfolios by π'

This table reports results of out-of-sample (OOS) predictability tests of using industry π' as the predictor. The reported statistics are calculated as: $r_t = a_{1\to t-1} + b_{1\to t-1}x_{t-1} + \varepsilon_t$; $R^2 = 1 - \frac{\sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}{\sum_{j=20}^{T}\left(r_j - \bar{r}_{1\to j-1}\right)^2}$; $\bar{r}_{1\to j-1} = \sum_{t=1}^{j-1} r_t$;$\acute{r}^2 = 1 - \left(1 - R^2\right) \times \frac{T-1}{T-2}$; $\Delta RMSE = \sqrt{\frac{1}{T-t}\sum_{j=t}^{T}\left(r_j - \bar{r}_{1\to T}\right)^2} - \sqrt{\frac{1}{T-t}\sum_{j=t}^{T}\left(r_j - \hat{\alpha}_{1\to j-1} - \hat{\rho}_{1\to j-1}x_{j-1}\right)^2}$; $MSEF = (T-t+1) \times \frac{\sum_{j=t}^{T}\left(r_j - \bar{r}_{1\to j-1}\right)^2 - \sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}{\sum_{j=t}^{T}\left(r_j - \hat{a}_{1\to j-1} - \hat{b}_{1\to j-1}x_{j-1}\right)^2}$.

	Adj R^2	p-value	$\Delta RMSE$	p-value	$MSE-F$	p-value
Agric	-0.108	0.920	-0.013	0.923	-7.302	0.920
Food	-0.158	0.949	-0.013	0.948	-10.220	0.949
Soda	-0.211	0.980	-0.023	0.980	-13.083	0.980
Beer	-0.490	0.992	-0.041	0.987	-24.669	0.992
Smoke	-0.237	0.969	-0.026	0.972	-14.375	0.969
Toys	-0.183	0.976	-0.032	0.979	-11.586	0.976
Fun	-0.106	0.945	-0.016	0.926	-7.201	0.945
Books	-0.483	0.998	-0.060	0.996	-24.443	0.998
Hshld	-0.158	0.982	-0.014	0.983	-10.213	0.982
Clths	-0.178	0.923	-0.023	0.931	-11.315	0.923
Hlth	0.073	0.002	0.013	0.002	5.928	0.002
MedEq	-0.180	0.985	-0.020	0.980	-11.452	0.985
Drugs	-0.107	0.912	-0.011	0.902	-7.255	0.912
Chems	-0.107	0.947	-0.011	0.952	-7.254	0.947
Rubbr	-0.125	0.924	-0.014	0.905	-8.348	0.924
Txtls	-0.049	0.670	-0.007	0.655	-3.504	0.670
BldMt	-0.109	0.951	-0.012	0.946	-7.356	0.951
Cnstr	0.025	0.027	0.004	0.033	1.916	0.027
Steel	-0.098	0.906	-0.014	0.905	-6.724	0.906
FabPr	-0.027	0.458	-0.004	0.485	-2.006	0.458
Mach	-0.189	0.980	-0.021	0.977	-11.916	0.980
ElcEq	-0.160	0.981	-0.019	0.981	-10.330	0.981
Autos	-0.159	0.972	-0.023	0.971	-10.294	0.972
Aero	-0.010	0.119	-0.001	0.119	-0.733	0.119
Ships	-0.201	0.987	-0.024	0.986	-12.541	0.987
Guns	-0.197	0.866	-0.024	0.870	-12.328	0.866
Gold	-0.018	0.238	-0.003	0.260	-1.305	0.238
Mines	-0.126	0.965	-0.017	0.971	-8.408	0.965
Coal	-0.049	0.695	-0.011	0.714	-3.484	0.695
Oil	-0.023	0.242	-0.003	0.237	-1.696	0.242
Util	-0.044	0.537	-0.003	0.419	-3.148	0.537
Telcm	-0.214	0.965	-0.019	0.965	-13.223	0.965
PerSv	-0.235	0.998	-0.032	0.995	-14.257	0.998
BusSv	-0.189	0.940	-0.022	0.923	-11.896	0.940
Comps	-0.179	0.984	-0.025	0.985	-11.384	0.984
Chips	-0.257	0.994	-0.037	0.993	-15.311	0.994
LabEq	-0.159	0.933	-0.020	0.942	-10.271	0.933
Paper	-0.009	0.107	-0.001	0.102	-0.635	0.107
Boxes	-0.073	0.857	-0.008	0.864	-5.111	0.857
Trans	-0.133	0.911	-0.016	0.901	-8.795	0.911
Whlsl	-0.171	0.967	-0.020	0.957	-10.940	0.967
Rtail	-0.148	0.918	-0.015	0.919	-9.652	0.918
Meals	-0.170	0.986	-0.021	0.982	-10.891	0.986
Banks	-0.125	0.973	-0.014	0.973	-8.352	0.973
Insur	-0.056	0.683	-0.005	0.708	-3.986	0.683
RlEst	0.016	0.037	0.002	0.041	1.203	0.037
Fin	0.001	0.082	0.000	0.082	0.043	0.082
Other	0.010	0.044	0.001	0.043	0.779	0.044

Table 11: Cross-industry Portfolio Returns: 48 Industries

This table presents the cross-industry predictability of industry portfolios. Panel A reports the mean excess returns of quintile portfolios and return spreads sorted by industry portfolios' bm, π, and π'. Panel B reports the 3-factor αs of quintile industry portfolios and return spreads sorted by industry portfolios' bm, π, and π'. The αs are estimated using monthly time-series regressions with Newey-West corrected standard errors (3 lags).

Panel A: Mean Excess Returns

	bm	π	π'
Low	0.081	0.080	0.083
	(4.30)	(4.04)	(4.18)
2	0.080	0.086	0.085
	(4.10)	(4.48)	(4.38)
3	0.089	0.077	0.077
	(4.62)	(3.95)	(3.93)
4	0.098	0.098	0.097
	(5.09)	(5.04)	(5.05)
High	0.113	0.120	0.118
	(5.30)	(6.17)	(6.09)
HML	0.033	0.040	0.036
	(2.67)	(4.12)	(3.67)

Panel B: 3-factor α

	bm	π	π'
Low	0.006	-0.005	-0.002
	(0.87)	(-0.74)	(-0.28)
2	-0.003	-0.001	-0.004
	(-0.49)	(-0.24)	(-0.67)
3	-0.002	-0.013	-0.014
	(-0.38)	(-2.27)	(-2.37)
4	0.004	0.005	0.006
	(0.69)	(0.77)	(0.95)
High	0.002	0.023	0.021
	(0.35)	(3.78)	(3.55)
HML	-0.004	0.028	0.023
	(-0.43)	(3.23)	(2.64)

Table 12: 48 Industry Portfolios SUR

This table reports the Seemingly Unrelated Regression (SUR) predictive regression of 48 industry portfolios from 1926 to 2022.

	bm			π			π'		
Industry	b	t-stat	Adj R^2	b	t-stat	Adj R^2	b	t-stat	Adj R^2
Agric	0.049	1.922	-0.013	0.014	1.394	-0.003	0.012	1.475	-0.003
Food	0.055	3.033	0.015	0.005	2.190	0.002	0.005	2.498	0.003
Soda	0.016	0.975	-0.002	0.002	2.263	0.011	0.002	2.505	0.014
Beer	0.021	1.566	0.013	0.001	1.302	0.007	0.001	2.029	0.015
Smoke	0.000	0.021	-0.011	0.000	0.167	-0.011	-0.000	-0.851	-0.012
Toys	0.152	6.095	0.088	0.020	6.840	0.094	0.019	6.161	0.089
Fun	0.068	2.869	0.026	0.022	3.904	0.030	0.017	3.778	0.028
Books	0.159	6.599	0.040	0.029	3.777	0.004	0.024	3.743	0.002
Hshld	0.049	3.409	0.030	0.005	3.445	0.026	0.004	3.346	0.025
Clths	0.062	3.627	0.021	0.005	2.410	-0.006	0.005	2.366	-0.006
Hlth	0.127	4.899	0.054	0.039	5.511	0.054	0.041	5.219	0.083
MedEq	0.049	2.346	0.027	0.007	2.540	0.024	0.006	1.981	0.017
Drugs	0.058	2.348	0.037	0.008	1.744	0.018	0.007	1.826	0.019
Chems	0.086	5.005	0.033	0.017	3.659	0.019	0.015	3.703	0.019
Rubbr	0.064	4.026	0.016	0.006	2.344	-0.002	0.005	2.502	-0.002
Txtls	0.113	4.682	0.065	0.025	3.415	0.034	0.025	3.652	0.039
BldMt	0.089	5.548	0.038	0.018	3.621	0.010	0.015	3.169	0.007
Cnstr	0.217	7.845	0.118	0.099	14.781	0.219	0.054	3.345	0.021
Steel	0.106	4.925	0.037	0.025	4.565	0.031	0.025	4.601	0.030
FabPr	0.098	2.984	0.012	0.039	3.100	0.013	0.035	2.726	0.012
Mach	0.050	3.180	0.011	0.008	1.905	-0.007	0.006	1.603	-0.009
ElcEq	0.095	3.854	0.017	0.022	2.639	0.000	0.020	2.441	-0.001
Autos	0.067	2.361	0.007	0.009	0.757	-0.006	0.009	0.898	-0.006
Aero	0.098	4.740	0.055	0.021	4.046	0.033	0.019	4.197	0.033
Ships	0.022	0.823	-0.004	-0.004	-0.494	-0.016	-0.005	-0.737	-0.018
Guns	0.027	2.145	-0.000	-0.000	-0.891	-0.010	-0.000	-0.492	-0.012
Gold	0.134	3.317	0.029	0.019	3.632	0.029	0.020	3.481	0.029
Mines	0.036	1.327	-0.011	0.019	1.404	-0.013	0.019	1.316	-0.013
Coal	0.006	0.184	-0.012	-0.000	-0.054	-0.012	0.001	0.261	-0.011
Oil	0.100	3.832	0.036	0.014	3.042	0.021	0.013	2.880	0.019
Util	0.082	3.585	0.070	0.009	2.324	0.035	0.008	2.176	0.032
Telcm	0.083	3.811	0.021	0.006	3.497	-0.004	0.006	3.913	-0.003
PerSv	0.200	9.014	0.165	0.040	7.976	0.116	0.038	7.160	0.107
BusSv	0.013	1.031	-0.008	0.002	1.851	-0.001	0.002	2.378	0.003
Comps	0.030	1.329	-0.003	0.004	1.099	-0.005	0.005	1.307	-0.004
Chips	0.084	3.398	0.017	0.009	1.659	-0.002	0.006	1.167	-0.006
LabEq	0.056	1.968	0.014	0.004	0.913	-0.002	0.008	1.498	0.005
Paper	0.080	3.730	0.061	0.007	2.206	0.032	-0.000	-0.318	-0.015
Boxes	0.098	4.275	0.041	0.017	2.994	0.021	0.017	3.270	0.022
Trans	0.036	3.057	0.006	0.001	1.443	-0.006	0.001	1.486	-0.005
Whlsl	0.070	3.954	0.016	0.016	2.786	0.007	0.010	2.284	0.003
Rtail	0.035	1.848	0.012	0.001	0.316	-0.010	0.001	0.243	-0.010
Meals	0.053	3.671	0.031	0.005	3.782	0.030	0.004	2.988	0.016
Banks	0.142	5.949	0.065	0.040	4.047	0.034	0.036	3.675	0.032
Insur	0.079	3.044	0.005	0.021	2.897	0.009	0.020	2.823	0.009
RlEst	0.065	3.204	0.030	0.021	3.698	0.036	0.005	1.352	0.004
Fin	0.118	7.797	0.096	0.024	5.361	0.062	0.022	5.217	0.063
Other	0.142	7.516	0.098	0.030	7.100	0.081	0.025	7.080	0.089

Table 13: Summary statistics of each industry's estimation

Code	Industry	β		$\bar{\theta}$	
		Mean	Std	Mean	Std
1	Agric	0.828	0.100	-0.048	0.079
2	Food	0.799	0.058	-0.225	0.114
3	Soda	0.863	0.057	-0.587	0.204
4	Beer	0.918	0.065	-0.085	0.169
5	Smoke	0.944	0.075	0.382	0.261
6	Toys	0.845	0.063	-0.267	0.267
7	Fun	0.673	0.161	-0.495	0.154
8	Books	0.833	0.083	-0.502	0.247
9	Hshld	0.902	0.031	-0.353	0.157
10	Clths	0.772	0.074	-0.068	0.182
11	Hlth	0.700	0.143	-0.695	0.539
12	MedEq	0.761	0.058	-1.050	0.094
13	Drugs	0.815	0.062	-1.228	0.183
14	Chems	0.861	0.026	-0.365	0.104
15	Rubbr	0.764	0.041	-0.270	0.166
16	Txtls	0.870	0.031	0.288	0.129
17	BldMt	0.793	0.033	-0.178	0.119
18	Cnstr	0.705	0.154	-0.070	0.134
19	Steel	0.849	0.022	0.077	0.124
20	FabPr	0.812	0.089	-0.055	0.139
21	Mach	0.786	0.034	-0.272	0.100
22	ElcEq	0.750	0.055	-0.515	0.131
23	Autos	0.838	0.060	-0.113	0.106
24	Aero	0.698	0.052	-0.342	0.116
25	Ships	0.707	0.088	-0.040	0.120
26	Guns	0.703	0.099	-0.396	0.168
27	Gold	0.823	0.051	-0.685	0.223
28	Mines	0.869	0.034	-0.328	0.126
29	Coal	1.334	3.985	-0.279	0.267
30	Oil	0.790	0.063	-0.448	0.105
31	Util	0.860	0.032	-0.209	0.296
32	Telcm	0.828	0.078	-0.504	0.158
33	PerSv	0.749	0.046	-0.383	0.240
34	BusSv	0.754	0.063	-0.700	0.192
35	Comps	0.729	0.061	-0.879	0.152
36	Chips	0.760	0.042	-0.599	0.172
37	LabEq	0.703	0.069	-0.567	0.164
38	Paper	0.860	0.028	-0.167	0.131
39	Boxes	0.815	0.083	-0.110	0.226
40	Trans	0.820	0.041	-0.072	0.120
41	Whlsl	0.739	0.058	-0.276	0.154
42	Rtail	0.804	0.045	-0.272	0.142
43	Meals	0.698	0.046	-0.355	0.164
44	Banks	0.783	0.083	-0.161	0.253
45	Insur	0.778	0.075	-0.215	0.129
46	RlEst	0.770	0.167	-0.006	0.277
47	Fin	0.856	0.063	-0.214	0.237
48	Other	0.757	0.357	-0.827	0.140
Average		0.806	0.154	−0.328	0.174

This table reports the summary statistics of estimation of β and $\bar{\theta}$ of each of the 48 industries. The sample period is July 1962∼December 2022. For each industry, we report the mean and std. dev. of the two estimates. In the last row, we report the mean and std. dev. of β and $\bar{\theta}$ of the whole sample.

Table 14: Asset pricing tests

	Panel A: π high-minus-low Portfolio characteristics (%)				
	Mean	Std	Min	Max	Sharpe ratio
	0.299	2.232	-11.344	12.017	0.464
	Panel B: Time series regression				
MKT	-0.032	-0.020	-0.025	-0.009	-0.013
	(-1.370)	(-0.927)	(-1.209)	(-0.469)	(-0.679)
ME	0.106***				
	(2.875)				
IA	0.651***				
	(9.560)				
ROE	-0.233***				
	(-4.033)				
SMB		0.103***	0.102***	0.075**	0.076***
		(3.102)	(2.957)	(2.570)	(2.622)
HML		0.592***	0.584***	0.529***	0.516***
		(17.098)	(15.388)	(14.651)	(13.151)
MOM			-0.024		-0.026
			(-0.791)		(-1.010)
RMW				-0.125**	-0.120**
				(-2.215)	(-2.177)
CMA				0.155***	0.164***
				(2.652)	(2.891)
α	0.190**	0.121**	0.140**	0.132**	0.150**
	(2.384)	(2.134)	(2.433)	(2.385)	(2.499)
Obs	683	725	725	725	725

This table reports the portfolio characteristics of the prospective book-to-market ratio factor. At the end of June of year t, stocks are assigned to two size-sorted portfolios with median NYSE market equity as breakpoint, and three prospective book-to-market sorted portfolios with 30% and 70% NYSE firms breakpoints independently. We value-weight these portfolios then refresh the break points every June. The prospective factor's high-minus-low return is the average return on the two portfolios with the highest 30% prospective book-to-market ratios minus the average return on the two portfolios with the lowest 30% prospective book-to-market ratios. In Panel A, we present the mean, std dev, max, min, and Sharpe ratio. Panel B reports the results of the time series regressions. We consider the following risk factors: the q-factors MKT, ME, IA and ROE as in Hou, Xue, and Zhang (2015), Fama-French three factors MKT, SMB, and HML as in Fama and French (1993), the three factors augmented with momentum factor (UMD), and Fama-French five factors MKT, SMB, HML, RMW, and CMA as in Fama and French (2015). The *alpha*s are expressed in percentage points. The t-statistics are based on 6 lags Newey-West standard errors and reported in parentheses. Except that the q-factors are available from 1967:01, all the factors start from July 1963. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 15: Asset pricing with π factor

		Panel A: Regressing $HML^{A,L}$ on π HML			
π HML	1.071***	1.075***	1.059***	0.847***	0.816***
	(26.629)	(22.250)	(24.040)	(16.080)	(16.706)
MKT		-0.032	-0.039	0.027	0.017
		(-1.100)	(-1.427)	(0.955)	(0.663)
SMB		-0.093	-0.093	-0.017	-0.014
		(-1.481)	(-1.555)	(-0.414)	(-0.355)
MOM			-0.037		-0.056**
			(-1.011)		(-2.072)
RMW				0.206***	0.210***
				(2.735)	(3.040)
CMA				0.436***	0.450***
				(8.785)	(8.754)
α	-0.035	0.001	0.032	-0.157**	-0.114
	(-0.470)	(0.009)	(0.393)	(-1.991)	(-1.483)
Obs	725	725	725	725	725
		Panel B: Regressing $HML^{A,C}$ on π HML			
π HML	1.123***	1.123***	1.039***	0.884***	0.763***
	(21.428)	(18.145)	(13.809)	(13.180)	(11.964)
MKT		-0.045	-0.084***	0.015	-0.022
		(-1.178)	(-2.586)	(0.399)	(-0.728)
SMB		-0.092	-0.087*	-0.017	-0.005
		(-1.405)	(-1.821)	(-0.398)	(-0.142)
MOM			-0.194***		-0.214***
			(-4.095)		(-6.005)
RMW				0.194**	0.210***
				(2.429)	(4.271)
CMA				0.455***	0.508***
				(7.138)	(9.986)
α	-0.064	-0.035	0.128	-0.192**	-0.026
	(-0.801)	(-0.417)	(1.454)	(-2.065)	(-0.301)
Obs	737	725	725	725	725

This table tests whether our proposed prospective factor adds value to the conventional factors in explaining away different versions of HML: the standard version using the ME at the end-of-December year t in calculation of ME/BE which we denote as $HML^{A,L}$ following Fama and French (1992), the annually updated version using the ME at June 30 of year $t+1$ ($HML^{A,C}$) following Asness and Frazzini (2013). Panel A presents results with the standard HML factor as the dependent variable, where the π HML is our prospective factor. Panel B presents results with the $HML^{A,C}$ factor as the dependent variable. The sample period is July 1963∼December 2022. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 16: Redundancy test

	π HML	HML^{A,L}	HML^{A,C}	HML^{M,C}
MKT	-0.032	-0.016	-0.038	0.027
	(-1.370)	(-0.468)	(-0.954)	(0.576)
ME	0.106***	0.054	0.014	-0.055
	(2.875)	(0.789)	(0.196)	(-0.511)
IA	0.651***	1.007***	1.043***	0.939***
	(9.560)	(14.180)	(10.190)	(9.346)
ROE	-0.233***	-0.169**	-0.309***	-0.644***
	(-4.033)	(-2.482)	(-3.688)	(-6.839)
α	0.190**	0.008	0.073	0.303**
	(2.384)	(0.071)	(0.572)	(2.037)
Obs	683	684	683	684
MKT	0.009	0.035	0.023	0.101*
	(0.344)	(0.956)	(0.486)	(1.737)
SMB	0.119***	0.086	0.088	0.089
	(2.766)	(1.443)	(1.417)	(0.977)
RMW	-0.029	0.180*	0.168	0.038
	(-0.366)	(1.717)	(1.372)	(0.217)
CMA	0.698***	1.029***	1.072***	0.981***
	(10.852)	(19.628)	(14.927)	(11.761)
α	0.089	-0.078	-0.114	-0.065
	(1.108)	(-0.708)	(-0.943)	(-0.436)
Obs	725	726	725	726
MKT	-0.008	0.011	-0.027	0.008
	(-0.331)	(0.369)	(-0.832)	(0.270)
SMB	0.118***	0.085	0.085*	0.082
	(2.931)	(1.539)	(1.785)	(1.398)
RMW	-0.021	0.192**	0.194**	0.087
	(-0.284)	(2.189)	(2.384)	(1.045)
CMA	0.684***	1.009***	1.030***	0.901***
	(9.767)	(17.947)	(13.229)	(18.311)
MOM	-0.095***	-0.134***	-0.287***	-0.530***
	(-3.105)	(-3.957)	(-6.013)	(-13.138)
α	0.157*	0.018	0.094	0.315***
	(1.945)	(0.177)	(0.829)	(3.424)
Obs	725	726	725	726

This table examines whether prospective factor can be useful in asset pricing models. We consider four different version of HML: our prospective π HML, the standard version using the ME at the end-of-December year t in calculation of ME/BE which we denote as $\mathrm{HML}^{A,L}$ following Fama and French (1992), the annually updated version using the ME at June 30 of year t+1 ($\mathrm{HML}^{A,C}$) following Asness and Frazzini (2013), and the monthly updated book-to-market ratio $\mathrm{HML}^{M,C}$. The sample period is from July 1962 to December 2022. The t-statistics are based on Newey-West standard errors and reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.