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COMPARING ANOMALIES USING LIQUIDITY AND EARNINGS

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We compare three factor models and their ability to explain a set of portfolio anomalies. Two of these models are based on market capitalization which most of the industry currently uses to characterize stocks. We replace this line of thinking by utilizing both earnings and liquidity to construct a competing model, which is intuitive to practitioners. Partitioning and characterizing stock returns in this way enables us to dispel some of the most challenging asset pricing anomalies. Historically, investors have concerned themselves with our proposed stock descriptors for far longer than they have with value and size characteristics.

The goal of this paper is to create an intuitive model for the cross section of stock returns and then to test the performance of that model by comparing it with two of the current *state of the art* models in asset pricing theory. Our model adds to the market factor, factors for earnings and liquidity. There is a long history of both practitioner and economist's interest in earnings and liquidity as important macro variables, some of which are reviewed below. Snigaroff and Wroblewski (2018, 2020) provide a fuller theory and a more expansive literature review. In this work we test the ability of earnings and liquidity to describe stock returns. Liquidity-based weighting is an intuitive weighting scheme as the ability to establish positions may well be a different portfolio than one that is value weighted. Can a liquidity-based weighting scheme add value in modeling? We show these to very much the case, as they outperform benchmark models in describing well-known anomalies.

The methods that we utilize to gauge model performance would also be of interest to investment practitioners. One way to compare the models is by their ability to explain portfolio anomalies. We demonstrate that a newly constructed five-factor model outperforms its competitors

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with respect to explaining the cross-sectional variance in returns. If a factor model can better explain portfolio anomalies relative to a competing model, it implies that this factor model is a better basis for characterizing stock returns. Currently, stock investment styles are predominantly characterized by size or market capitalization and by the notion of a value or growth measure for a company which generally corresponds to relating the book value of a company relative to its market value against its peers. We propose a factor model based on characteristics pertaining to earnings and the liquidity or the dollar trading volume of stocks. These factors, the income stream of the investment and investors' ability to buy and sell that stream, are immediately recognizable by practitioners. Indeed, these have been important investment factors for a very long time. A cursory review of *New York Times* and *Wall Street Journal* business pages from the 1800s reveals daily reporting of stock volume and contains frequent stories concerning company earnings. Investors certainly desire to be able to sell their positions when they would like without negatively impacting the price. We show these two characteristics, which are also used in the model proposed by Snigaroff and Wroblewski (2018), are fundamental in the explanation of stock price movements. To show that this framework is a *better* basis than the small versus large and value versus growth return characterization of stocks, we compare our proposed framework with that of the current benchmark factor models proposed by Fama and French (2015; FF5), as well as Hou *et al.* (2015; HXZ4). While there are numerous ways to compare factor models, we focus our attention in this paper on the ability of these factor models to explain ten portfolio anomalies.

We focus on ten very common sets of anomaly deciles and obtain the data for these returns from Kenneth French's website.[1] To create anomaly portfolios, one may sort a universe of stocks by a characteristic at the security level and then create sets of decile portfolios. By creating ten test portfolio time series of returns based on these deciles we then have the test portfolios of the return space that we can use to test the asset pricing ability of these models via their ability to span the return space. Since numerous existing models have had much trouble explaining these sets of returns as linear combinations of their factors, they are called pricing anomalies. We demonstrate that by using this relatively simple and intuitive earnings and liquidity framework we can explain the test portfolios more robustly than the FF5 and the HXZ4 models. This further implies that these earnings and liquidity factors are important factors in describing the long-run behavior of stock returns.

We generate three competing annually constructed factor models over the sample period from July 1969 to October 2017. For each anomaly we regress all the decile returns onto the factors of three models in separate time-series regressions. Our main statistical measure used to quantify the factor models' spanning performance relative to these anomalies is the GRS-statistic of Gibbons *et al.* (1989). We perform this hypothesis test on the full sample period and on a rolling window time frame. We also compute the maximum squared Sharpe ratio for the intercepts as described in Fama and French (2017), as well as a measure based on the size of the intercepts (the average over their absolute values). As a final robustness test we perform the two-pass cross-sectional R-squared test of Kan *et al.* (2013). All these tests are useful in that they allow one to test the overall picture of a model's ability to span the return space.

The main findings of these tests are as follows: The full sample analysis of the GRS statistic shows that the earnings and liquidity-based model outperforms both other models in seven out of ten anomalies. The dynamic analysis of the 20-year rolling windows further confirms this finding. The results also show that the full sample analysis by the maximum squared Sharpe ratio for the intercepts resembles the results of the full sample GRS test as does the Sharpe rolling window computations. These again demonstrate that our model explains the return space better on a rolling window as well as on a full sample basis than the competitors. Another finding is that the smaller average absolute values of the intercepts also suggest that our model is once again a better basis for the anomaly return space. Lastly, the cross-sectional differences in *R*-squared statistic tests show that our model outperforms the HXZ4 model but only matches the performance against that of the FF5. These robust statistical test results support a macro idea that earnings and liquidity are fundamental in constructing portfolios and in characterizing exposures.

1 Previous studies and empirical underpinnings

There have been many studies regarding portfolio strategies that can explain or encompass anomaly returns; e.g., Fama and French (2008, 2016) and Hou *et al.* (2015) both use factor models to explain anomalies—as we do here. It is a difficult task for a four-factor or a five-factor model to explain the decile returns associated with numerous types of anomalies. One of our contributions towards this task is to move away from market capitalization as the proxy for the *size* of a company. We instead measure the weight of a company relative to the entire market based on its *liquidity.* For an example of a theoretical argument that views liquidity in such equilibrium framework see Snigaroff and Wroblewski (2020). We use as our measure of liquidity a simple-yet useful representation: the dollar trading volume of a company. Carpenter and Upton (1981) find that trading volume affects beta estimates, and the stock price relation to trading volume is also studied in Stoll (1978), Lakonishok and Smidt (1989), Admati and Pfleiderer (1988), Snigaroff and Wroblewski (2011), and others.

Many empirical studies find evidence of an illiquidity premium. Amihud (2002) and Brennan and Subrahmanyam (1996) find that required rates of return should be higher for securities that are relatively illiquid. Indeed, the liquidity literature has become vast. Recently, some authors, e.g., Ben-Rephael *et al.* (2015), have found liquidity to be inconsequential except for the smallest stocks. We demonstrate in this study, however, a model including a simple liquidity measure has strong descriptive power across all stocks.

The other dimension in our model is based on company earnings. This characteristic is a fundamental component in stocks' valuation and has been extensively used by investors. Earnings have a long history of explaining returns in the literature extending back to at least Ball and Brown (1968), who study annual net income. Beaver (1968) discusses the relationship of earnings and information while Ball (1992) explores how current earnings and future earnings predict future returns. This literature is also extensive with notable contributions germane to this study including Basu (1975), Jacobs and Levy's (1988) research of earnings yield and returns, and Sadka and Sadka's (2009) examination of prices and earnings growth. While others have used factors from 'higher up' on the income statement, utilizing the firm's *net income* is hard to criticize as data mining.

We additionally incorporate the growth in earnings and the growth in liquidity into our model to capture trend influence on prices. These may be viewed as second-order effects of our underlying liquidity and earnings motivators.[2] Hence, after the market risk premium, we essentially have two base factors, earnings and liquidity driving our model—very simple yet economically intuitive motivations for our factors.

2 Factor model construction

We construct the earnings liquidity market five-factor model (ELM5), as well as the FF5 and the HXZ4 over a sample period of 580 months from July 1969 to October 2017. Note that for best comparison, we completely reconstruct FF5 and HXZ4 with a common universe and time frame and do not merely rely on their factor data. We also use a common annual rebalance for all models.

The ELM5 model is dollar volume based and inspired by accounting earnings. We use independent sorts of NYSE stocks as breakpoints, but the sample consists of all NYSE, AMEX, and NASDAQ stocks within the Compustat database accessed via the Research Insight platform. We first apportion stocks to two groups, Illiquid (I) and Liquid (L) by the NYSE median dollar volume at the end of June for each year: these are the Liquidity groups. We divide stocks into three groups, High (*HY*), Neutral (*NY*), and Low (*LY*) by the NYSE 30th and 70th percentile earnings yield (*EYD*) which is defined as the one-year earnings per share (Compustat code epsfi; which is the earnings per share including extraordinary items) divided by the calendar-year-end stock price. The intersection of these two sorts results in six portfolios: *IHY*, *INY*, *ILY*, *LHY*, *LNY*, and *LLY*. In the similar manner, we allocate stocks to two additional sets of three groups by earnings growth (*EGR*) and the liquidity growth (*LQGR*), respectively. *EGR* is defined as a change in the one-year earnings per share all divided by the calendar-year ending price. *LQGR* is defined as the change in June dollar volume divided by the calendar-year ending market capitalization. There are High (*HG*), Neutral (*NG*), and Low (*LG*) for *EGR* while the three *LQGR* groups are High (*HQ*), Neutral (*NQ*) and Low (*LQ*). The intersections of both sorts with the Liquidity groups (I, or L) leads to two sets of six portfolios. One set from the *EGR* intersections, which we denote by *IHG*, *ING*, *ILG*, *LHG*, *LNG*, and *LLG*; and the other from the *LQGR* intersections which has the labeling scheme; *IHQ*, *INQ*, *ILQ*, *LHQ*, *LNQ*, and *LLQ*. We point out that the partitions that we use coincide with the original partitions defined in Fama and French (2015).

Our base liquidity factor (*LIQ*) is defined as the difference between the average portfolio return of low-liquid stocks and the average portfolio return of high-liquid stocks. As we can compute such difference in three ways depending on which matching pre-intersection sort we are using, we define the simple average of these as *LIQ*.[3] Similarly, we construct three differences in average returns to construct three other factors. The first is Earnings-to-Price (E/P), which is defined as the difference between the average portfolio returns of high earnings-yield stocks and the average portfolio returns of low earnings-yield stocks. The next factor represents a second-order effect in the E/P factor and is the Earnings-Growth-to-Price (EG/P) factor. This is defined as the difference between the average portfolio returns of high earnings-growth-to-price stocks and the average portfolio returns of low earnings-growth-to-price stocks. We also construct a second-order liquidity effect factor based on Liquidity Growth (*LIQG*) which is defined as the difference between the average portfolio returns of high liquidity-growth relative to cap stocks and the average portfolio returns of low liquidity-growth relative to cap stocks. The final factor used in the ELM5 model is a market factor, which we compute using a dollar volume-weighted market portfolio. This portfolio's returns in excess of the T-Bill rate (R_F) are denoted by *MKTv*. We summarize the construction of these factors in Table 1.

Table 1 Factor construction.

Breakpoints	Factors
ELM five factors	
Liquidity: NYSE median	$LIQ_{EYD} = (IHY + INY + ILY)/3 - (LHY + LNY + LLY)/3$
	$LIQ_{EGR} = (IHG + ING + ILG)/3 - (LHG + LNG + LLG)/3$
	$LIQ_{LQGR} = (IHQ + INQ + ILQ)/3 - (LHQ + LNQ + LLQ)/3$
	$LIQ = (LIQ_{EYD} + LIQ_{EGR} + LIQ_{LQGR})/3$
EYD: 30th & 70th NYSE percentiles	$E/P = (IHY + LHY)/2 - (ILY + LLY)/2$
EGR: 30th & 70th NYSE percentiles	$EG/P = (IHG + LHG)/2 - (ILG + LLG)/2$
LQGR: 30th & 70th NYSE percentiles	$LIQG = (IHQ + LHQ)/2 - (ILQ + LLQ)/2$
FF five factors & HXZ four factors	
Size: NYSE median	$SMB_{B/M} = (SH + SN + SL)/3 - (BH + BN + BL)/3$
	$SMB_{OP} = (SR + SN + SW)/3 - (BR + BN + BW)/3$
	$SMB_{INV} = (SC + SN + SA)/3 - (BC + BN + BA)/3$
	$SMB_{ROE} = (SHR + SNR + SLR)/3 - (BHR + BNR + BLR)/3$
	$SMB = (SMB_{B/M} + SMB_{OP} + SMB_{INV})/3$
	$ME = (SMB_{INV} + SMB_{ROE})/2$
B/M: 30th & 70th NYSE percentiles	$HML = (SH + BH)/2 - (SL + BL)/2$
OP: 30th & 70th NYSE percentiles	$RMW = (SR + BR)/2 - (SW + BW)/2$
INV: 30th & 70th NYSE percentiles	$CMA = (SC + BC)/2 - (SA + BA)/2$
	$I/A = (SC + BC)/2 - (SA + BA)/2$
ROE: 30th & 70th NYSE percentiles	$ROE = (SHR + BHR)/2 - (SLR + BLR)/2$

This table shows the construction of three sets of factors by using three 2×3 sorts of portfolios. To construct the Earnings Liquidity Market five factors (ELM5), we first split stocks into Illiquid (*I*) and Liquid (*L*) based on the NYSE median dollar volume (Liquidity). We also divide stocks into three groups by the earnings yield (*EYD*), the earnings growth (*EGR*), and the liquidity growth (*LQGR*): High (*HY*, *HG*, and *HQ*), Neutral (*NY*, *NG*, and *NQ*), and Low (*LY*, *LG*, and *LQ*). *EYD* is defined as the earnings-per-share (Compustat, epsfi) divided by the calendar-year-ending stock price. Similarly, *EGR* is defined as a change in earnings-per-share all divided by the calendar-year-ending stock price. *LQGR* is defined as a change in June dollar volume divided by the calendar-year ending market capitalization. The intersections of 2×3 sorts result in three sets of portfolios on *Liquidity-EYD*, *Liquidity-ENG*, or *Liquidity-LQGR*. Then, we generate factors as the difference between the average portfolio returns. They are *LIQ* (Liquidity Return), E/P (Earnings-to-Price), EG/P (Earnings-Growth-to-Price), *LIQG* (Liquidity Growth). We also generate the Fama–French five factors (FF5) and the Hou, Xue, and Zhang four factors (HXZ4) in the similar manner. The breakpoints generate two groups based on market cap (*size*) (Small and Big), three groups of B/M (High, Neutral, and Low), operating profitability (Robust, Neutral, and Weak), investment (Conservative, Neutral, Aggressive), and return on equity (High, Neutral, and Low or *HR*, *NR*, and *LR*). The Fama and French factors are *SMB* (Small minus Big), *HML* (High minus Low), *RMW* (Robust minus Weak), and *CMA* (Conservative minus Aggressive). The Hou, Xue, and Zhang factors are *ME* (size), I/A (investment) and *ROE* (profitability).

Using these five-factors we define the ELM5 model for excess portfolio returns by:

$$R_{it} - R_{Ft} = \alpha_i + \beta_i MKTv_t + l_i LIQ_t + p_i E/P_t + g_i EG/P_t + q_i LIQG_t + \varepsilon_{it}. \quad (1)$$

We also compare our ELM5 model with two well-known factor models, which we replicate by using our dataset in the following way. First the FF5, the details of which may be found in Fama and French (2015), is constructed very similarly to the ELM5 model except for some different naming conventions. We construct breakpoints to generate two groups (Small and Big) based on market capitalization. We also use the three sorting variables based on each of the following separately: B/M (High, Neutral, and Low), operating profitability (Robust, Neutral, and Weak), and investment (Conservative, Neutral, and Aggressive). These sorts then lead to intersections with the Small and Big groups to produce a size effect factor as measured by *SMB*, the difference between portfolio returns of small firms and big firms, a value effect factor as measured by *HML*, the difference between portfolio returns of high book-to-market (B/M) firms and low B/M firms. Using a similar construction, *RMW* explains the profitability effect as the difference between portfolio returns of firms with high and low profitability whereas *CMA* reflects the investment effect with the difference in portfolio returns between low investment firms and high investment firms. These four factors along with a market risk premium factor (*MKTc*) lead to the FF5 model:

$$R_{it} - R_{Ft} = a_i + b_i MKTc_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \tau_{it}. \quad (2)$$

The second model that we replicate for comparison to the ELM5 is the HXZ4 model. This is a four-factor model proposed by Hou *et al.* (2015). Their model again sorts on market cap to create *size* groups (Small and Big), but also separately sorts on investment (Conservative, Neutral, and Aggressive), and return on equity (High, Neutral, and Low). Upon intersecting these partitions and averaging as in the FF5 and ELM5 cases the HXZ4 model contains the factors, *ME* (size), I/A (investment), *ROE* (profitability) and *MKTc* (market):

$$R_{it} - R_{Ft} = \delta_i + \lambda_i MKTc_t + m_i ME_t + v_i I/A_t + o_i ROE_t + \eta_{it}. \quad (3)$$

Except for *MKTc*, we keep the same factor variable reference as the original authors. We add "c" to refer to capitalization weighting, to differentiate from the dollar volume weighting we use in our model.

In summary the FF5 factors are *SMB* (Small minus Big), *HML* (High minus Low), *RMW* (Robust minus Weak), and *CMA* (Conservative minus Aggressive) and the market factor. The HXZ4 factors are the market factor, a size factor (*ME*), an investment factor (I/A), and their profitability factor (*ROE)*. The ELM5 is given by a market factor, an earnings factor along with its growth, and a liquidity factor along with its growth. We will show that by using the liquidity and earnings variables rather than market capitalization and the other factors in the FF5 and HXZ4 that we can better explain stock returns and therefore provide a better way to partition stocks.

3 Statistical properties of the factors

We report descriptive statistics of the factors by model in Table 2. The average return of the market portfolio return by dollar-volume weighting is almost the same as the market portfolio return with market-capitalization weighting (0.55% vs. 0.56%), but the former has a larger volatility measure (5.48% vs. 4.44%). The mean return of the liquidity growth factor (*LIQG*) is negative. The size factors are positively correlated with the market-capitalization based market risk factor, but the liquidity factor is negatively correlated with the dollar-volume based market risk factor. Besides this, the size and liquidity factors are for the most part negatively correlated with other factors. The three profitability factors are negatively correlated with the investment factors in Panels B and C, while the earnings growth factor is positively correlated with the liquidity growth factor. In all three-factor models excess returns relative to these factors are persistent.

Table 2 Descriptive statistics of the factors.

	Mean	St. dev.	95% Conf. interval		Correlation (* significant at 5%)			
Panel A. Earnings Liquidity Market five factors (ELM5)								
MKTv	0.0055	0.0548	0.0010	0.0100	MKTv	LIQ	E/P	EG/P
LIQ	0.0023	0.0277	0.0000	0.0045	−0.1637*			
E/P	0.0036	0.0340	0.0008	0.0064	−0.5396*	0.0045		
EG/P	0.0011	0.0173	−0.0003	0.0025	−0.0310	−0.1102*	0.2634*	
LIQG	−0.0005	0.0245	−0.0025	0.0015	0.0303	−0.1264*	0.0117	0.1659*
Panel B. Fama and French five factors (FF5)								
MKTc	0.0056	0.0444	0.0020	0.0092	MKTc	SMB	HML	RMW
SMB	0.0026	0.0283	0.0003	0.0049	0.1669*			
HML	0.0031	0.0286	0.0008	0.0055	−0.3339*	−0.0448		
RMW	0.0017	0.0232	−0.0002	0.0036	−0.0551	−0.1738*	0.0326	
CMA	0.0027	0.0207	0.0010	0.0044	−0.4602*	−0.099*	0.6978*	−0.0752
Panel C. Hou–Xue–Zhang four factors (HXZ4)								
MKTc	0.0056	0.0444	0.0020	0.0092	MKTc	ME	I/A	
ME	0.0029	0.0287	0.0005	0.0052	0.1562*			
I/A	0.0027	0.0207	0.0010	0.0044	−0.4602*	−0.0806		
ROE	0.0018	0.0230	−0.0001	0.0036	−0.1643*	−0.3604*	−0.2165*	

This table reports some descriptive statistics relating to the factor models used in this study. In the ELM5 model the *LIQ* (Liquidity Return) factor is the simple average of three differences between a portfolio return of low-liquid stocks and a portfolio return of high-liquid stocks. Similarly, E/P (Earnings-to-Price), *EG/P* (Earnings-Growth-to-Price), and *LIQG* (Liquidity Growth) are, respectively, the difference in portfolio returns between high and low earnings yield stocks, between high and low earnings growth stocks, and between high and low liquidity growth stocks. We also generate Fama–French five factors (Fama and French, 2015) and Hou–Xue–Zhang four factors (Hou *et al.*, 2015). The market excess return is a market portfolio return less the U.S. T-bill rate with the market portfolio weighted by liquidity or market capitalization (*MKTv* or *MKTc*). The sample consists of 580 monthly observations from July 1969 to October 2017. Each panel shows the mean, standard deviation, 95% confidence interval for the mean, and the correlation coefficients for the factors.

4 Decile returns and average intercepts

Our sample includes the 580 months from July 1969 to October 2017. We use the decile portfolio return series for the anomalies. These are available from French's webpage. They serve as the dependent variables when we compare the three-factor models' ability to explain the well-known anomalies. They are listed as Size, B/M, Operating Profitability, Investment, Earnings/Price, Cash flow/Price, Dividends/Price, Momentum, Short-term Reversal and Long-term Reversal. Appendix 1 summarizes Fama and French's ten decile portfolio definitions and their rebalancing schemes. While these ten sets of decile returns are by no means exhaustive of the other anomalies in the literature today, these are important factors and are a good baseline for comparison.

We regress these deciles return series on the three competing models which are described in the previous sections. For example, each of ten decile portfolio returns with Size as a sort is used on the left-hand side of Equations (1), (2), and (3). Then we calculate the average of the absolute values of those ten intercepts to see which factor model has the smallest value of this measure. One may interpret this as the residual value

Table 3 Decile portfolio returns. Full sample analysis of average intercepts.

Panel A. Absolute average value of intercepts by decile return regression (unit: %)

	ELM5 factors		FF5 factors		HXZ4 factors	
	Average	Ave. R^2	Average	Ave. R^2	Average	Ave. R^2
Size	0.092	94.7	0.122	95.5	0.119	95.3
B/M	0.076	82.9	0.105	88.6	0.090	84.8
Op. Profitability	0.117	87.2	0.143	90.2	0.129	89.7
Investment	0.085	86.1	0.081	90.4	0.090	90.1
Earnings/Price	0.060	81.6	0.055	87.0	0.063	82.9
CF/Price	0.061	80.7	0.061	86.5	0.094	82.9
Dividends/P	0.102	76.2	0.106	82.2	0.126	79.1
Momentum	0.310	79.8	0.312	79.7	0.270	78.6
ST Reversal	0.107	83.0	0.096	85.1	0.101	84.8
LT Reversal	0.041	81.1	0.093	86.0	0.076	84.8

Panel B. Intercepts by high decile minus low decile portfolio return regression (unit: %)

	ELM5 factors			FF5 factors			HXZ4 factors		
	Intercept	t-Value	R^2	Intercept	t-Value	R^2	Intercept	t-Value	R^2
Size	0.088	0.92	79.9	0.244	3.11	84.9	0.185	2.31	84.7
B/M	−0.014	−0.08	35.0	−0.216	−1.86	67.9	−0.031	−0.19	41.8
Op. Profitability	0.293	2.30	49.3	0.405	3.53	59.9	0.241	1.99	53.4
Investment	−0.435	−3.56	24.7	−0.124	−1.23	50.6	−0.122	−1.15	50.0
Earnings/Price	−0.055	−0.39	42.8	−0.037	−0.30	58.3	0.058	0.35	20.9
CF/Price	0.043	0.28	32.4	−0.000	−0.00	54.1	0.128	0.75	20.5
Dividends/P	0.114	0.65	48.5	0.073	−0.42	49.5	0.092	0.46	40.6
Momentum	1.523	5.84	31.1	1.585	4.97	6.9	1.318	3.83	6.0
ST Reversal	0.077	0.35	15.5	0.022	0.09	12.5	−0.047	−0.19	11.7
LT Reversal	−0.070	−0.39	31.9	0.339	2.06	47.2	0.202	1.15	46.6

This table compares the ability of the factor models to explain anomaly returns. Decile portfolio returns are regressed on three sets of factors: ELM5, FF5, and HXZ4. ELM5 consists of *MKTv*, *LIQ*, *E/P*, *EG/P*, and *LIQG*. FF5 includes *MKTc*, *SMB*, *HML*, *RMW*, and *CMA*. HXZ4 is composed of *MKTc*, *ME*, *I/A*, and *ROE*. Decile portfolios are: Size, B/M, Operating profitability, Investment, Earnings/Price, Cash flow/Price, Dividends/Price, Momentum, Short-term reversal, and Long-term reversal. The sample consists of 580 monthly observations from July 1969 to October 2017. Panel A shows the arithmetic mean of the absolute value of the intercept given in the decile portfolio regressions and the average R-squared statistic. Panel B reports the intercept and the R-squared statistic from the high decile minus low decile portfolio return regressed on the above three sets of factors. Heteroscedasticity-consistent robust errors are used in all regressions.

not explained by the factors of each model. We report these averages over the absolute values of the intercepts in Table 3 Panel A. For the Size anomaly, ELM5 has the smallest value of 0.092%. FF5 has the smallest value (at the seventh decimal place) for Cash flow/Price. Overall, ELM5 outperforms FF5 by the number of the smallest averages over the absolute values (six to four). All

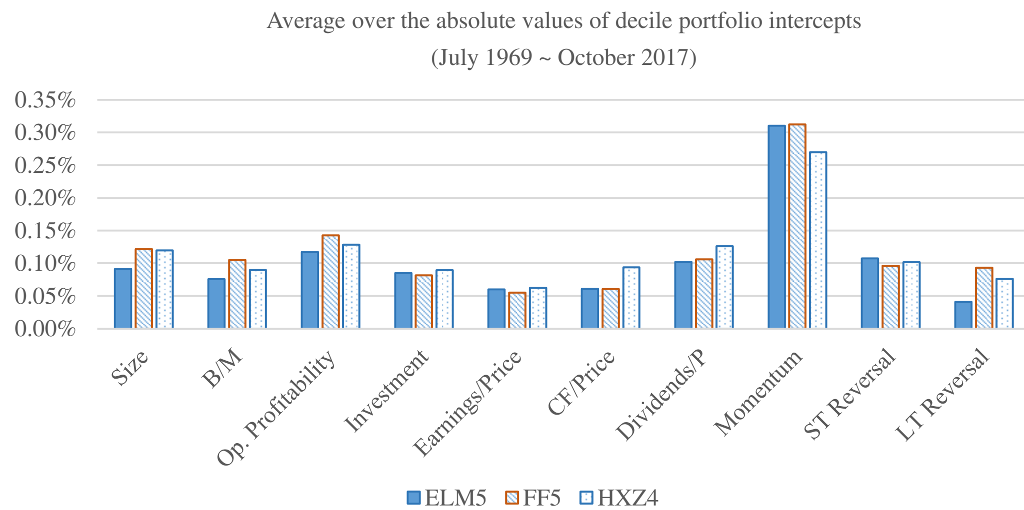

Figure 1 Decile portfolio regression intercept average magnitude.

Figure 1 graphically displays the magnitude of the average of the absolute values corresponding to each of the anomaly decile regressions. Lower means the model better describes the return space.

three-factor models are relatively poor at explaining Momentum in which HXZ4 outperforms the other two. Figure 1 shows each model's average absolute intercept by decile portfolio category. In Panel B, we use the difference in portfolio return between the highest decile and the lowest decile as the dependent variable for the same equations. In this case, the three models are fairly even in terms of the smallest absolute value of the intercept. ELM5 and FF5 have three counts each, whereas HXZ4 has four. Table 3 implies that ELM5 is at least as good as FF5 in explaining the decile portfolio returns with HXZ4 trailing both models.

Table 4 Asset pricing measures. Goodness of fit.

Panel A. GRS statistics and Sharpe for intercepts (full sample)

	ELM5 factors			FF5 factors			HXZ4 factors		
	GRS	*p*-Value	Sharpe	GRS	*p*-Value	Sharpe	GRS	*p*-Value	Sharpe
Size	**2.39**	0.01	**0.04**	4.32	0.00	0.08	3.60	0.00	0.07
B/*M*	**1.05**	0.40	**0.02**	1.83	0.05	0.04	1.28	0.24	0.03
Op. Profitability	**2.46**	0.01	**0.05**	3.43	0.00	0.07	2.46	0.01	0.05
Investment	2.51	0.01	0.05	**1.67**	0.08	**0.03**	1.82	0.05	0.04
Earnings/Price	**0.65**	0.77	**0.01**	0.70	0.72	0.01	0.95	0.49	0.02
CF/Price	**0.75**	0.68	**0.01**	0.93	0.50	0.02	1.50	0.14	0.03
Dividends/P	**1.39**	0.18	**0.03**	1.47	0.15	0.03	1.81	0.06	0.04
Momentum	4.48	0.00	0.08	4.38	0.00	0.08	**3.14**	0.00	**0.06**
ST Reversal	2.82	0.00	0.05	2.10	0.02	0.04	**1.98**	0.03	**0.04**
LT Reversal	**0.56**	0.84	**0.01**	1.06	0.39	0.02	0.71	0.71	0.01

Table 4 (*Continued*)
Panel B. GRS statistics (20-year rolling window)

	ELM5 factors		FF5 factors		HXZ4 factors	
	Average	St. dev.	Average	St. dev.	Average	St. dev.
Size	**2.26**	0.56	3.23	1.21	2.68	1.35
B/*M*	**1.02**	0.35	1.52	0.71	1.51	0.33
Op. Profitability	2.52	0.82	1.70	0.45	**1.44**	0.35
Investment	1.97	0.92	**1.25**	0.55	1.29	0.41
Earnings/Price	1.21	0.70	**1.15**	0.44	1.43	0.37
CF/Price	**0.74**	0.42	1.13	0.43	1.24	0.29
Dividends/P	**0.85**	0.46	1.14	0.46	1.15	0.24
Momentum	4.16	1.97	3.81	1.80	**3.37**	1.53
ST Reversal	2.04	0.79	1.59	0.47	**1.52**	0.39
LT Reversal	**0.72**	0.31	0.81	0.37	1.04	0.35

Panel C. Sharpe for intercepts (20-year rolling window)

	ELM5 factors		FF5 factors		HXZ4 factors	
	Average	St. dev.	Average	St. dev.	Average	St. dev.
Size	**0.11**	0.02	0.16	0.06	0.14	0.07
B/*M*	**0.05**	0.02	0.08	0.04	0.08	0.02
Op. Profitability	0.12	0.04	0.09	0.02	**0.07**	0.02
Investment	0.09	0.04	**0.06**	0.03	0.07	0.02
Earnings/Price	0.06	0.04	**0.06**	0.02	0.07	0.02
CF/Price	**0.04**	0.02	0.06	0.02	0.06	0.01
Dividends/P	**0.04**	0.02	0.06	0.02	0.06	0.01
Momentum	0.20	0.10	0.19	0.09	**0.17**	0.08
ST Reversal	0.10	0.03	0.08	0.02	**0.08**	0.02
LT Reversal	**0.04**	0.02	0.04	0.02	0.05	0.02

We show two measures of asset pricing, the GRS-statistic and the maximum squared Sharpe ratio for the intercepts. Each of which is calculated from ten decile portfolio return series and one of the three-factor models: ELM5, FF5 and HXZ4. Panel A includes the GRS statistics and their p-values and the maximum squared Sharpe ratio for intercepts for the full sample period. The sample consists of 580 monthly observations from July of 1967 to October 2017. Panel B and Panel C post the time series average and standard deviation of the GRS statistics and the Sharpe ratio for intercepts, respectively, for the rolling sample window of 20 years beginning with the first window of July 1967 through June 1989. The smallest values of each decile category are highlighted in bold.

5 Statistical inferences and test statistics

To examine the effectiveness of the three-factor models of our study we compute the GRS statistic proposed by Gibbons *et al.* (1989) and perform the associated hypothesis test. The null hypothesis is that simultaneously all the intercepts in the ten separate deciles return time series regressions are zero:

$$H_0 : a_i = 0; \quad i = 1, 2, \ldots, 10. \tag{4}$$

In this test we do not want to reject the null hypothesis. If we do not have evidence to overturn the intercepts simultaneously being zero, then the tested factor model is a statistically significant basis for the return space. When the intercepts are near zero, the better is the asset pricing model's representation of each security perfectly as a linear combination of a given set of factors. We also report the p-values associated with our test. We also note that the GRS statistic is based on the F-distribution.

Another similar measure to the GRS-statistic is suggested in Fama and French (2017). This measure is the maximum squared Sharpe ratio for the *intercepts* and is defined as:

$$Sh^2(a_i) = a_i^T \Sigma_i^{-1} a_i, \tag{5}$$

where the vector, a_i, is calculated by computing a vector of intercepts formed from the ten test portfolio regressions against factor model i. Also $\sum_i$ is the ten by ten covariance matrix for the residuals from the same regressions. This number represents how close the model is spanning the entire space of returns with a given factor model, and thus lower is better due to less error from the models' factors in spanning the return space.

Comparative statistics for the asset pricing models based on the ten different anomaly partitions are shown in Table 4 for the full sample period. The leftmost column displays the model used to simultaneously describe the ten-decile portfolio returns given by each panel. We report the GRS-statistic and the corresponding p-value. This statistic may be thought of as a measure of the pricing error for the model: the smaller the statistic is, the smaller the pricing error becomes. When comparing the GRS statistics, ceteris paribus, we compare the models based on the magnitude of the GRS-statistic in each anomaly case. In 70% of the anomalies the ELM5 has a smaller GRS-statistic (i.e. less pricing error) than each of the other models simultaneously. This makes a compelling argument for the ELM5 as a basis for the return space. In general, it is a tall order to ask of a four- or five-factor model to not reject the null of no pricing error in every anomaly case. When we compare the GRS-statistics, for example, with the size anomaly all three models have the significant GRS-statistics and thus pricing error still exists. However, the ELM5 has the smallest value of 2.39. With B/M both ELM5 and HXZ4 have statistically insignificant statistics whereas the FF5 rejects the zero-intercept assumption with statistical significance. When we compare these first two models, the ELM5 has a smaller value than the HXZ4 (1.05 vs. 1.28) for this B/M anomaly, and thus ELM5 has less pricing error for this case. We see that the ELM5 model has the least amount of pricing error relative to size and the value deciles, which is a promising result. We highlight by bold the best performing model for each given set of decile returns in Table 4. The anomalies in which the ELM5 does particularly well at explaining the decile returns are the seven corresponding to Size, B/M, Operating Profitability, Earnings/Price, Cash flow/Price, Dividends/Price, and Long-term Reversal. FF5 is the best of the three only on the Investments deciles while HXZ4 does best relative to ELM5 and FF5 on Momentum, and Short-term Reversal. We note that none of the factor models fail to reject the zero-intercept null hypothesis in all cases and that the momentum anomaly is a particularly difficult set of returns to explain for all three models, confirming the result of Table 3.

We additionally present the full sample maximum squared Sharpe ratio for the intercept's calculation. The results are consistent with those given by the GRS-statistic as this measure is also based on the intercepts. The results in Panel A suggest that the ELM5 model again performs very well relative to the FF5 and the HXZ4 models.

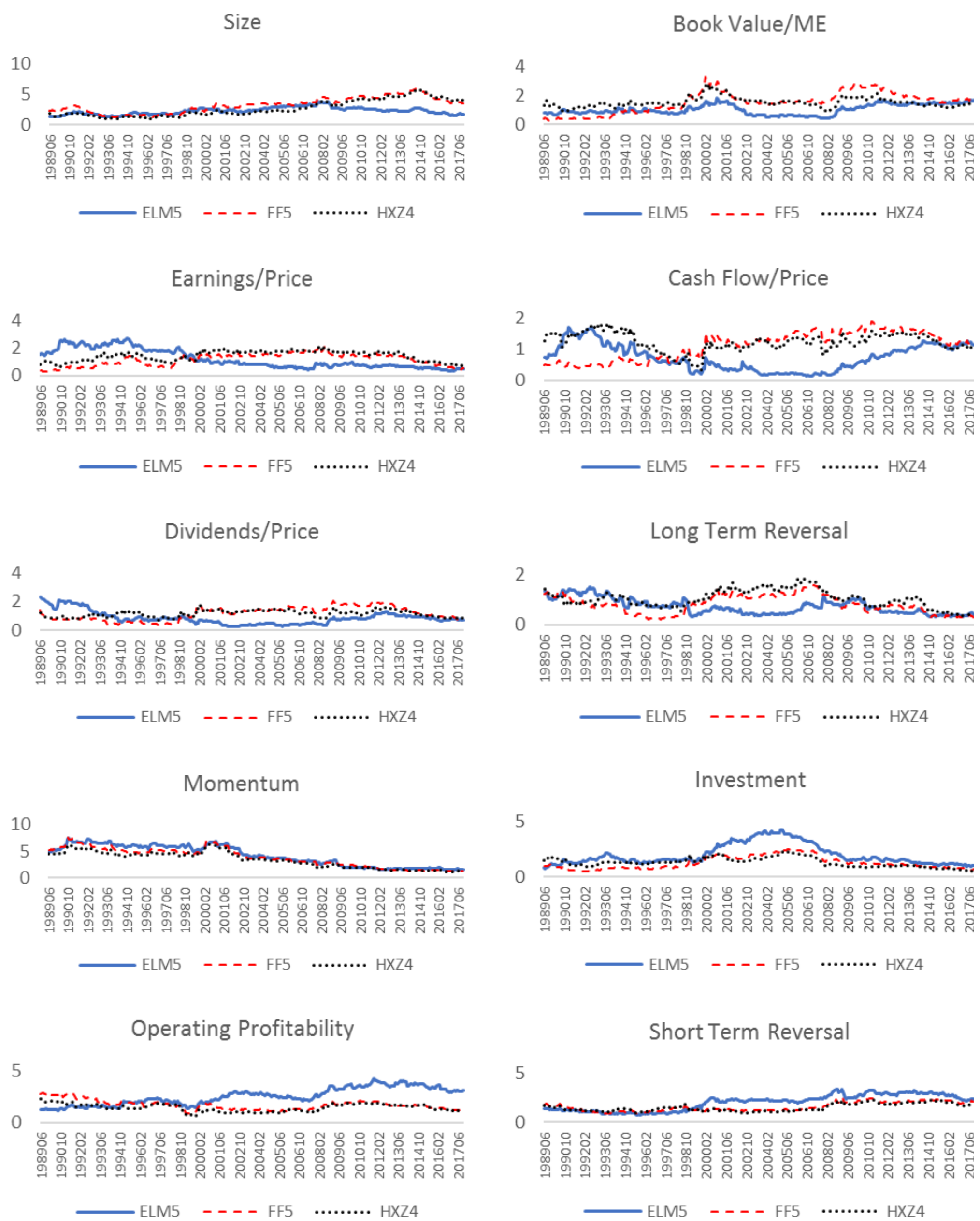

Figure 2 Ability to span the return space and the rolling GRS-statistic.

This figure displays the GRS-statistics corresponding to the spanning of the ten anomalies decile portfolio returns for ELM5, FF5, and HXZ4 models with a rolling window of 20 years. A lower value is preferred.

We find that the ELM5 model does well at spanning the return space of the decile anomaly portfolios returns when considering the entire sample period. To study this effect through time we now construct a time series of GRS statistics by using the trailing 20 years of data each month, beginning with the window from July 1969 to June 1989 and plotting the results in Figure 2.

Panel B of Table 4 shows the average GRS-statistic and its standard deviation from this rolling sample window for each anomaly. When we compare three models' average GRS statistics, ELM5 has the smallest value in five anomalies whereas the rest are split between FF5 and HXZ4. Figure 2 shows this graphically. Though in general it is difficult for a four- or five-factor model to span the return space, we suggest that the ELM5 model is highly competitive relative to the FF5 and HXZ4 models. We see that for the first six anomalies listed in Figure 2, namely—Size, Book Value to Market Equity, Earnings to Price, Cash Flow to Price, Dividends to Price, and Long-term Reversal there are in fact substantial periods of time in which the ELM5 outperforms the FF5 and the HXZ4 models in terms of this GRS-measure. With respect to the Momentum deciles all three models are closely clustered implying similar explanatory power. In the other three decile returns, Investment, Operating Profitability, and Short-term Reversal, ELM5 clearly appears to be outperformed by FF5 or HXZ4. In Table 4 Panel C we show the results of the Sharpe ratio for intercepts based on the same 20-year rolling window. The results of Panel C confirm those reported in Panel B. All in all, the GRS and Sharpe tests significantly indicate that ELM5 appears more effective in explaining stock returns than FF5 and HXZ4.

As a further robustness test we utilize the hypothesis test presented in Kan *et al.* (2013). We reproduce parts of that paper's Table IV in the context of the ELM5, FF5, and the HXZ4 models. A more detailed summary of these tests may be found in Appendix 2. We present Generalized Least Squares (*GLS*) version of the difference in cross-sectional R-squared statistics along with their p-values based on the hypothesis test:

$$\begin{aligned} H_0 &: \rho_i^2 = \rho_j^2 \\ H_1 &: \rho_i^2 \neq \rho_j^2. \end{aligned} \tag{6}$$

The p-values are provided under the assumption that the model may be mis-specified and by using the sequential tests for their computation. For the test portfolios we use the ten decile sets of returns along with five industry portfolios return series analogous to the aforementioned paper. Although we do not find strong statistical significance to show that the difference in cross-sectional R-squared statistics are different from zero for these test portfolios we do see that the ELM5 model has a higher cross-sectional R-squared statistic in seven out of the ten anomalies relative to the HXZ4 model and in five out of the ten anomalies relative to the FF5 model. These statistics are displayed in Table 5. This robustness check once again confirms the notion of the ELM5 being a very competitive factor model in terms of explaining the cross-sectional return space relative to the spanning abilities of the FF5 and the HXZ4 factor models.

6 Conclusion

Much of the industry today partitions and characterizes stocks based on market capitalization and value and growth measures. We construct a cross-sectional model based on earnings and liquidity. We weight on dollar volume, a liquidity measure. Unlike pure ad hoc weighting schemes, liquidity weighting is theory based. Investors who adjust weights by free float already act according to the belief that market cap weighting should be adjusted by investors' ability to freely trade their positions.

Also, we demonstrate evidence of investors in a Merton (1973) framework who desire to hedge their own earnings and liquidity state risk along with Sharpe's (1964) market risk. Fama and French (1995) discuss their use of *HML* and *SMB* as noisy proxies for an earnings state variable. We use a direct earnings variable to model and name the state risk. When we replace size with a proxy for the classical state variable of liquidity, we obtain a model that is highly effective as evidenced by its ability to better subsume difficult anomalies.

Table 5 Cross-sectional spanning of anomaly returns comparison.

	ELM5 vs. FF5		ELM5 vs. HXZ4	
	Difference in sample R-squared statistics	p-Values	Difference in sample R-squared statistics	p-Values
Cross-sectional R-squared statistics – Generalized least squares (GLS)				
Size	**0.043**	0.930	**0.151**	0.957
B/M	−0.021	0.279	**0.125**	0.262
Op. profitability	−0.117	0.815	−0.037	0.693
Investment	−0.150	0.327	−0.044	0.223
Earnings/Price	−0.217	0.806	−0.136	0.766
CF/Price	**0.106**	0.684	**0.130**	0.579
Dividends/P	**0.042**	0.948	**0.191**	0.940
Momentum	**0.076**	0.453	**0.039**	0.373
ST Reversal	−0.113	0.768	**0.223**	0.789
LT Reversal	**0.133**	0.821	**0.084**	0.665

This table displays the difference in cross-sectional R-squared statistics between the ELM5 factor model and both the FF5 and the HXZ4 models. In each case the test statistic uses the cross-sectional R-squared statistic for the ELM5 minus the cross-sectional R-squared statistic for the competing model (FF5 or HXZ4). Column 1 represents the anomaly being tested and represents the test portfolios used. We also add five industry portfolios into the set of test portfolios in each anomaly case. Columns 2 and 3 represent the comparisons with the FF5 while columns 4 and 5 show the comparisons with the HXZ4 model. We use generalized least squares, a sequential hypothesis test, and we compute the p-values under the assumption that the models may be mis-specified. The sample consists of 580 monthly observations from July 1969 to October 2017.

In the cross-sectional asset pricing literature, a standard method of testing models is to gauge their relative ability to subsume anomalies. We utilize numerous econometric tests to examine the validity of our model vis-à-vis two bellwether asset pricing factor models of Fama and French (2015) and Hou *et al.* (2015). Our test sample spans over 580 months from July 1969 to October 2017. We constructed annually rebalanced versions of these two benchmark factor models along with our model. Using the decile portfolio returns by anomaly we compare the three-factor models in terms of GRS-statistics, cross-sectional R-squared statistics, and the maximum squared Sharpe ratio for the intercept's statistic, as well as the average over the absolute values of the intercepts. Our test results imply that our model tends to have higher explanatory power relative to anomaly stock returns than these two models. In other words, our model better describes asset returns than this industry-wide status quo. Not only does this have far reaching applications in terms of a better way to allocate assets, but it can also allow practitioners to gain insight into what drives stock prices.

Appendix 1: Anomaly decile portfolio construction

Brief definitions of the decile portfolios, the returns of which are from French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The market value of equity (*ME*) is the price times the number of shares outstanding. Breakpoints are calculated with NYSE stocks. Stocks are rebalanced at the end of June of t for July of year t to June of $t+1$ or monthly.

Deciles	Rebalancing	Definition
Size	June-end annually	Market value of equity.
B/M	June-end annually	Book value of equity (BE) for the last fiscal year end in $t-1$; ME at December-end in $t-1$; for all stocks also to have ME for December.
Operating Profitability	June-end annually	(Sales – COGS – Interest expense – S,G & A expenses)/BE for the last fiscal year end in $t-1$.
Investments	June-end annually	(Total assets (TA) in $t-1$ minus TA in $t-2$)/TA in $t-2$.
Earnings/Price	June-end annually	Total earnings before extraordinary items for the last fiscal year end in $t-1$/ME at December-end in $t-1$.
Cash flow/Price	June-end annually	Cash flow = total earnings before extraordinary items + equity's share of depreciation + deferred taxes for the last fiscal year end in $t-1$; Price = ME at December-end in $t-1$.
Dividends/Price	June-end annually	Total dividends paid from July of $t-1$ to June of t per dollar of equity in June of t given minimum 7 monthly returns from July of $t-1$ to June of t.
Momentum	At the end of month $t-1$ monthly	Monthly NYSE prior (2–12) return decile breakpoints; all stocks having prior return data with a price at $t-13$ month-end and a good return for $t-2$; ME for $t-1$ month-end.
Short Term Reversal	At the end of month $t-1$ monthly	Monthly NYSE prior (1–1) return decile breakpoints; all stocks having prior return data with a price at $t-2$ month-end and a good return for $t-1$; ME for $t-1$ month end.
Long Term Reversal	At the end of month $t-1$ monthly	Monthly NYSE prior (13–60) return decile breakpoints; all stocks having prior return data with a price at $t-61$ month-end and a good return for $t-13$. ME for $t-1$ month end.

Appendix 2: Cross-sectional Goodness of fit tests

Let R the matrix of test portfolio returns and denote by F the matrix of factor returns and define the covariance matrix for the factor returns and the test portfolio returns, along with the covariance matrix of the factors alone by V_{RF}, V_F respectively. We describe and construct the cross-sectional R-squared statistics. The construction begins with a pricing model given by:

$$\mu_R = X\eta, \tag{7}$$

where μ_R denotes the mean of the test portfolio returns and the matrix X contains a vector of ones and the betas from a time series regression of the test portfolios onto the factors:

$$R_t = \alpha + \hat{\beta} \cdot F_t + \xi_t, \quad t = 1, 2, 3, \ldots T. \tag{8}$$

This gives a vector of betas for each test portfolio. The second pass of the regression is to use the matrix $X = \left[\vec{1}_N \mid \hat{\beta}\right]$ with $\vec{1}_N$ being a vector of ones with length N, the number of test portfolios. Since the betas are given by a multivariate regression one may use $\hat{\beta} = \hat{V}_{RF} \cdot \hat{V}_F^{-1}$, see the internet appendix[4] of Kan, Robotti, and Shaken (2013) for more details. Secondly we use a symmetric weighting matrix $W = V_R^{-1}$. When we use (7) as a pricing model and this two-pass methodology in order to estimate η we obtain the asset pricing error of our test assets:

$$\begin{aligned} \varepsilon_W &= \mu_R - X\hat{\eta} \\ &= (I_N - X(X'WX)^{-1}X'W)\mu_R. \end{aligned} \tag{9}$$

Following the paper of Kandel and Stambaugh (1995) then defines the sample cross-sectional R-squared measure as:

$$\rho_W^2 = 1 - \frac{\varepsilon_W' W \varepsilon_W}{\varepsilon_0' W \varepsilon_0}, \tag{10}$$

where $\varepsilon_0 = \left(I_N - \vec{1}_N\left(\vec{1}_N' W \vec{1}_N\right)^{-1} \vec{1}'_N W\right)\mu_{R,}$ which represents the deviations of the mean returns from their cross-sectional average. Since W is symmetric we can also factor part of this expression to obtain:

$$\begin{aligned} \varepsilon_W' W \varepsilon_W &= \mu_R'(I_N - W'X(X'WX)'^{-1}X') \\ &\quad \times W(I_N - X(X'WX)^{-1}X'W)\mu_R \\ &= \mu_R' W \mu_R - \mu_R' W' X(X'WX)^{-1} \\ &\quad \times X'W\mu_R. \end{aligned} \tag{11}$$

Kan, Robotti, and Shaken (2013), state the fact that one obtains the exact same pricing errors, ε_W, as they would by estimating in the way as described above by using $\tilde{X} = \left[\vec{1}_N \mid \hat{V}_{RF}\right]$, in place of the prior matrix $X = \left[\vec{1}_N \mid \hat{V}_{RF} \cdot \hat{V}_F^{-1}\right]$. This may be seen by defining the invertible matrix $C = \begin{pmatrix} 1 & \vec{0}_{K'} \\ \vec{0}_K & V_F^{-1} \end{pmatrix}$, and noticing that $\tilde{X}C = X$. Therefore any solution $\hat{\eta}$, of (7), is also a solution of the analogous equation involving $\tilde{X}$ by using $C\hat{\eta}$.

Similarly since C is invertible any $\hat{\lambda}$ solution corresponding to $\mu_R = \tilde{X}\lambda$ is also a solution of (7) with $\widehat{\eta} = C^{-1}\hat{\lambda}$. The final hypothesis test in which we consider both the nested models and the non-nested models cases and use the difference in the sample cross-sectional R-squared statistics given in (10) to consider:

$$\begin{aligned} H_0 &: \rho_i^2 = \rho_j^2 \\ H_1 &: \rho_i^2 \neq \rho_j^2, \end{aligned} \tag{12}$$

to test the differences between model i and model j. Fortunately, the asymptotic distribution for the difference in sample $\hat{\rho}_W^2$ statistics and the other test statistics have been computed for us in Kan, Robotti, and Shaken (2013). For the non-nested model cases a sequential test is used based on first testing if the normalized *SDF*s are equal which uses a *chi-squared* test. If we are not able to reject the equality of the normalized *SDF*'s test, then we may use that *p-value* for our hypothesis in Equation (12) since equal *SDFs* would imply equal R-squared statistics. If reject the equal *SDF*'s case, then we test for both model's equality of R-squared statistics along with proper specification for both models. If that test is not rejected, we may then use this *p-value* from the properly specified model *chi-squared* test in order to interpret Equation (12). If both tests are rejected, then we evaluate our null hypothesis under a normal distribution assumption for the difference in R-squared test statistic.

Notes

1 The ten decile portfolio's return series are available on French's web page address: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

2 Fama and French (1995, p. 147) use changes in earnings yield (earnings to book-equity) as "a crude proxy for shocks to expected net cash flows."

3 The *SMB* factor of Fama and French (2015) is constructed in a similar way.

4 Appendix: http://www-2.rotman.utoronto.ca/~kan/research.htm.

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