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Another Look at the Cross-section and Time-series of Stock Returns: 1951 to 2011

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1. Introduction

Asset pricing models are of crucial importance to both financial economists and investment practitioners. Despite its theoretical appeal, the CAPM of Sharpe (1964) and Lintner (1965) fails to explain the cross-section of stock returns. Motivated by the CAPM anomalies of the size effect of Banz (1981) and the value-growth effect of Stattman (1980), Fama and French (1993) propose a three-factor model (FF) that augments the CAPM with the size and book-to-market-equity factors. Fama and French (1996) find that the FF model is unable to capture momentum effects of Jegadeesh and Titman (1993). Subsequently, Carhart (1997) proposes a four-factor model (FFC), which enhances the FF model with a momentum factor. Fama and French (1998) show that different measures of the value-growth effect contain similar information, which suggests that these value-based factors may proxy for the same underlying state variables.[1]

Hou, Karolyi, and Kho (2011) find that a three-factor model (HKK) which enhances the CAPM with the momentum and cash flow-to-price factors outperforms the FF model and an alternative version of the FFC model in explaining time-series of global stock returns. Specifically, in time-series regressions, the global HKK model is only rejected by global size portfolios, where the global FF model and an alternative version of the global FFC model (which does not include the size factor) are rejected by not only global size portfolios but also global portfolios formed on industry, cash flow-to-price, earnings yield and dividend yield. Hou, Karolyi, and Kho (2011) also find that different measures of value-growth characteristics (cash flow-to-price versus book-to-market-equity) contain different information.

Both findings of Hou, Karolyi, and Kho (2011) challenge the status quo in empirical asset-pricing literature and have important implications. First, if the HKK model is a better empirical asset-pricing model relative to the FF and the FFC models, it will call into question the usefulness of a large number of extant studies based on the FF and the FFC models (e.g. portfolio performance evaluation studies of Carhart, 1997; Kosowski, Timmermann, and Wermers, 2006; and Fama and French, 2010 among others). Second, if different measures of value-growth characteristics contain different information, it will make it more difficult to understand what state variables these value-based measures proxy for.

The important implications of Hou, Karolyi, and Kho (2011) warrant a re-examination of these competing asset-pricing models (i.e. FF, HKK and FFC). The most robust one is an out-of-sample test. Hou, Karolyi, and Kho (2011) examine all publicly traded companies in the global stock market for the post-1981 period. Thus, the only possible out-of-sample test may be to investigate a sample period beyond their specific sample period as in Davis, Fama, and French's (2000) examination of the robustness of Daniel and Titman (1997).[2] Because global financial data are not easily available for the sample period before 1980, we focus on the US stock market, which allows us to go back to 1951.

There is another important reason for us to focus on the US market. Griffin (2002) and Fama and French (2012) suggest that global stock markets are not integrated. Therefore, "global" asset pricing models in Hou, Karolyi, and Kho (2011) may be mis-specified, and "global" stock portfolios may not be appropriate test assets. A cleaner test may be to compare the "local" versions of these competing asset-pricing models with "local" stock portfolios as test assets. We focus on the US stock market because it is the largest stock market and accounts for about 40% of the global market (see Hou, Karolyi, and Kho,

[1] Fama and French (1996) argue that "the empirical successes of (1) (the FF model) suggest that it is an equilibrium pricing model, a three-factor version of Merton's (1973) intertemporal CAPM (ICAPM) or Ross's (1976) arbitrage pricing theory (APT). In this view, SMB and HML mimic combinations of two underlying risk factors or state variables of special hedging concern to investors." (p.57).

[2] Daniel and Titman (1997) reject the Fama-French "covariance risk" factor model in favor of the characteristics model using US stock returns between 1973 and 1993. Davis, Fama, and French (2000), in turn, extend the investigation back to 1925 to show that Daniel and Titman's findings are specific to the 1973 to 1993 period.

2011). In this regard, the first contribution of the paper is to provide a cleaner out-of-sample test of the competing asset-pricing models.

Hou, Karolyi, and Kho (2011) as well as Fama and French (2012) mainly use the time-series regression approach of Fama and French (1996). How the competing asset-pricing models perform in cross-sectional regressions is not thoroughly studied. Thus, our second contribution to the literature is to provide a comprehensive examination about the performance of these competing models in not only time-series but also cross-section regressions. For cross-sectional regressions, we use the Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) two-pass methodology with refinements of Shanken (1992), Shanken and Zhou (2007), and Lewellen, Nagel and Shanken (2010).

Empirically, in both time-series and cross-sectional tests, the FFC model does not underperform the HKK model, and adding the cash flow-to-price factor to the FFC model in general does not reduce the pricing error or increase the explanatory power for the whole sample period as well as for three subsample periods. Our results thus suggest that the cash flow-to-price factor does not have incremental information and that different measures of the value-growth effect (i.e. cash flow-to-price versus book-to-market-equity) contain similar information. We also find that the models with the momentum factor (i.e. HKK and FFC) in general outperform the models without this factor (i.e. FF) for a wide variety of test assets, which implies that momentum is a pervasive factor of stock returns.

The empirical success of the value and momentum factors calls for more research on what state variables these factors proxy for. Until recently, researchers generally study these factors in isolation, and there is no unifying risk-based explanation. However, Garlappi and Yan (2011) propose a theoretical model, which implies that both value and momentum effects may be driven by common macro factors. Aretz, Bartram, and Pope (2010) empirically find that six common macro factors help explain about 16% of the value effect and 13% of the momentum effect.

Motivated by Garlappi and Yan (2011) and Aretz, Bartram, and Pope (2010), we extend the literature by utilizing two aggregate macroeconomic and financial condition indexes. These indexes not only cover much broader sets of macroeconomic and financial variables but also focus on their common movements. Empirically, we find that innovations in macroeconomic conditions do help explain the value and momentum factors. Specifically, the news about future growth and inflation explains at least 41% of the value effect and 37% of the momentum effect. Therefore, the third contribution of the paper is that we provide stronger evidence for a unifying risk-based explanation for the value and momentum effects.

The remainder of the paper is organized as follows: Section 2 provides a cleaner and comprehensive out-of-sample test of three competing asset-pricing models. Section 3 investigates what state variables the value and momentum factors proxy for. Section 4 concludes the manuscript.

2. Comparing the competing asset-pricing models

2.1 Data

We construct the cash flow-to-price (CFP) factor-mimicking portfolio in the same spirit of Hou, Karolyi and Kho (2011). Our cash flow-to-price mimicking portfolio returns are calculated as the highest-CFP-quintile returns minus the lowest-CFP-quintile returns, where the monthly cash flow-to-price portfolio returns are from Kenneth French's website.[3] Other relevant monthly factors data including the risk-free rate (RF), the excess market return (MKT), the momentum factor (WML), the size factor (SMB), and the book-to-market-equity factor (HML) are also from Kenneth French's website. Our sample period is from July 1951 to July 2011. The start of the sample period coincides with the initial availability of the cash flow-to-price portfolio returns from Kenneth French's website. Table 1 reports summary statistics for these factors. As we can see, the risk premiums on the candidate risk factors are generally significant except for the size factor, which is consistent with the literature (e.g. Fama and French, 2012).

[3] We thank Fama and French for making these data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Table 1. Summary statistics of factors, July 1951-July 2011

Panel A: Returns distributions of Factors	Mean (%)	t-statistic	Var	
MKT	0.56	3.45	18.87	
SMB	0.20	1.80	8.56	
HML	0.36	3.55	7.51	
CFP	0.46	3.69	11.15	
WML	0.77	5.13	16.06	
Panel B: Correlations of factors				
	MKT	SMB	HML	CFP	WML

Panel B: Correlations of factors	MKT	SMB	HML	CFP	WML
MKT	1.00				
SMB	0.27	1.00			
HML	-0.26	-0.21	1.00		
CFP	-0.18	-0.04	0.75	1.00	
WML	-0.12	-0.03	-0.18	-0.08	1.00

Table 1 reports summary statistics for these factors.

Furthermore, there is a strong correlation between the book-to-market-equity factor (HML) and the cash flow-to-price factor (CFP), which may indicate that they contain similar information.

In terms of test assets, we first focus on the 25 size and book-to-market (BM) portfolios and 25 size and momentum portfolios, which are commonly used in the literature (e.g. Fama and French, 2012). However, Lewellen, Nagel and Shanken (2010) show that any (spurious) factor can seem to be relevant if it is correlated with the size (or value) factor and the test assets have a strong factor structure. One suggestion that Lewellen, Nagel and Shanken (2010) offer is to expand the set of test assets beyond size and BM portfolios to "relax the tight factor structure of size-B/M portfolios" (p. 182). Therefore, we increase our test assets to include 10 portfolios formed on earnings-to-price, 10 portfolios formed on dividend yield, 10 Portfolios formed on short-term reversal, 10 Portfolios formed on long-term reversal, and 30 industry portfolios. All the monthly portfolio returns data are from Kenneth French's website. The details of the construction of these portfolios are also available at Kenneth French's website.

2.2 Empirical methodology

We focus on the following four asset-pricing models in this paper. The first model is the FF model:

$$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + \varepsilon_{it} \tag{1}$$

where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The second model is the HKK model of Hou, Karolyi, and Kho (2011):

$$r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it} \tag{2}$$

where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio.

The FF model is well-known to be unable to account for stock momentum of Jegadeesh and Titman (1993), while the HKK model is augmented with the momentum factor. Therefore, it is important to evaluate the HKK model relative to the FFC model.

$$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it} \quad (3)$$

The fourth model is a five-factor model (Five-factor) that includes all the candidate factors.

$$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it} \quad (4)$$

If different measures of the value-growth effect (i.e. cash flow-to-price versus book-to-market-equity) contain similar information, we expect that the FFC model will not underperform the HKK model, and the Five-factor model that includes the cash flow-to-price factor will not outperform the FFC model. If momentum is a pervasive factor of stock returns, we expect that the models with the momentum factor (i.e. HKK and FFC) will outperform the models without this factor (i.e. FF).

To evaluate these candidate asset-pricing models, we carry out two complementary sets of tests. The first set focuses on the time-series of stock returns with the time-series regression approach of Fama and French (1993, 1996). Essentially, Eqs. (1) through (4) are estimated for each test asset with monthly data. Following relevant literature (e.g. Hou, Karolyi, and Kho, 2011; Fama and French 2012), we evaluate each model based on the magnitude of pricing errors (the average absolute value of the intercepts and the average of the standard errors of the intercepts), the explanatory power (the average adjusted R^2), and the Gibbons, Ross, and Shanken (1989) (GRS) F-test statistic for the hypothesis that the intercepts are jointly equal to zero for all test assets.

The second set of tests focuses on the cross-section of stock returns with the Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) two-pass methodology – estimating factor loadings in the first pass, and using those to obtain risk premium in the second pass – with standard refinements: the Shanken (1992) correction to obtain errors-in-variables (EIV) robust standard errors, accounting for the fact that factor sensitivities are estimated, and the Shanken and Zhou (2007) correction to generate misspecification (MIS) robust standard errors. We also take into consideration the prescriptions that Lewellen, Nagel and Shanken (2010) suggest regarding cross-sectional asset pricing tests: (1) we expand the set of test assets beyond portfolios formed on size and book-to-market-equity; (2) we report not only the OLS results but also the GLS results; (3) we "take the magnitude of the cross-sectional slopes seriously" by including the competing factors (i.e. the cash flow-to-price factor and the book-to-market-equity factor) as test assets with GLS regressions. We evaluate each model based on the Adjusted R^2 (i.e. the pricing error).

2.3 Empirical results

We first report the results based on 25 size and book-to-market and 25 size and momentum portfolios. Then, following the suggestion of Lewellen, Nagel and Shanken (2010), we present the results with the expanded set of test assets which, besides 25 size-BM and 25 size-momentum portfolios, also includes 10 portfolios formed on earnings-to-price, 10 portfolios formed on dividend yield, 10 Portfolios formed on short-term reversal, 10 Portfolios formed on long-term reversal, and 30 industry portfolios. The total number of test assets thus increases from 50 to 120 with the expansion.

2.3.1 Test results for 50 size-BM and size-momentum portfolios

Time-series tests

Tables 2 and 3 summarize time-series regressions to explain monthly excess returns on 25 size-BM and 25 size-momentum portfolios. Table 2 shows the average absolute value of the intercepts ($|\alpha|$), the average of the standard errors of the intercepts ($s(\alpha)$), the average adjusted R^2 (R^2), and the GRS F-test

Table 2. Summary statistics for time-series regressions, July 1951-July 2011

Sample	Test assets	FF				HKK				FFC				Five-factor			
		|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS
1951-2011	Size-BM	0.09	0.07	0.91	3.10*	0.17	0.10	0.78	3.27*	0.09	0.06	0.91	2.48*	0.09	0.06	0.91	2.80*
	Size-Momentum	0.35	0.08	0.84	5.40*	0.19	0.10	0.81	3.73*	0.13	0.07	0.91	3.56*	0.13	0.07	0.91	3.56*
	50 test assets	0.22	0.07	0.88	4.23*	0.18	0.10	0.80	3.71*	0.11	0.07	0.91	3.23*	0.11	0.07	0.91	3.44*
1951-1971	Size-BM	0.13	0.10	0.90	1.61*	0.19	0.15	0.78	1.66*	0.12	0.10	0.90	1.31	0.12	0.09	0.90	1.50
	Size-Momentum	0.37	0.10	0.87	4.12*	0.21	0.14	0.81	2.94*	0.13	0.09	0.91	2.71*	0.13	0.09	0.91	2.70*
	50 test assets	0.25	0.10	0.89	2.65*	0.20	0.14	0.79	2.11*	0.12	0.09	0.91	1.92*	0.12	0.09	0.91	1.98*
1971-1991	Size-BM	0.10	0.09	0.94	1.36	0.22	0.16	0.84	1.96*	0.12	0.09	0.94	1.66*	0.11	0.09	0.94	1.65*
	Size-Momentum	0.37	0.12	0.89	5.03*	0.26	0.17	0.86	4.34*	0.20	0.10	0.94	4.04*	0.20	0.10	0.94	4.00*
	50 test assets	0.23	0.11	0.91	3.05*	0.24	0.17	0.85	2.79*	0.16	0.10	0.94	2.55*	0.15	0.10	0.94	2.56*
1991-2011	Size-BM	0.15	0.13	0.89	3.41*	0.21	0.19	0.73	3.42*	0.14	0.12	0.89	3.04*	0.14	0.12	0.89	3.23*
	Size-Momentum	0.32	0.18	0.80	1.92*	0.23	0.20	0.78	1.75*	0.14	0.14	0.89	1.64*	0.14	0.14	0.89	1.69*
	50 test assets	0.24	0.15	0.85	2.63*	0.22	0.19	0.76	2.71*	0.14	0.13	0.89	2.52*	0.14	0.13	0.89	2.68*

The Fama-French three-factor model (FF) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + \varepsilon_{it}$, where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The HKK model of Hou, Karolyi, and Kho (2010) is: $r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$. The five-factor model (Five-factor) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. Table 2 shows the average absolute value of the intercepts (|α|), and the average of the standard errors of the intercepts (s(α)), the average adjusted R^2 (R^2), and the GRS F-test statistic (GRS).

Table 3. Intercepts from time-series regressions, July 1951-July 2011

		FF				HKK				FFC				Five-factor			
		Size-BM		Size-Momentum		Size-BM		Size-Momentum		Size-BM		Size-Momentum		Size-BM		Size-Momentum	
		α	t(α)	α	t(α)	α	t(α)	α	t(α)	α	t(α)	α	t(α)	α	t(α)	α	t(α)
Small	Low	-0.52	-4.32	-0.98	-8.26	-0.43	-2.31	-0.18	-1.03	-0.45	-4.00	-0.30	-2.71	-0.46	-4.05	-0.31	-2.82
	2	-0.02	-0.20	-0.22	-2.96	0.09	0.59	0.22	1.80	-0.02	-0.28	0.04	0.64	-0.02	-0.32	0.04	0.65
	3	0.00	-0.03	0.14	1.94	0.17	1.25	0.40	3.18	0.00	-0.06	0.22	3.21	0.00	-0.03	0.22	3.21
	4	0.15	2.57	0.31	4.47	0.34	2.62	0.40	2.92	0.13	2.35	0.23	2.99	0.13	2.39	0.23	3.00
	High	0.11	2.03	0.61	6.04	0.41	3.17	0.44	2.68	0.14	2.53	0.31	3.25	0.14	2.60	0.31	3.22
2	Low	-0.21	-3.20	-0.88	-8.08	-0.20	-1.50	-0.08	-0.55	-0.17	-2.84	-0.18	-1.81	-0.18	-2.83	-0.18	-1.81
	2	-0.03	-0.46	-0.22	-2.93	0.10	0.90	0.22	2.13	0.01	0.23	0.09	1.53	0.01	0.19	0.09	1.53
	3	0.11	2.01	0.02	0.28	0.27	2.62	0.23	2.33	0.12	2.40	0.08	1.27	0.12	2.38	0.08	1.30
	4	0.06	1.09	0.26	5.06	0.24	2.49	0.30	2.87	0.05	1.02	0.16	2.72	0.05	1.02	0.16	2.73
	High	-0.01	-0.11	0.53	5.98	0.28	2.44	0.25	2.12	0.00	0.02	0.17	2.41	0.01	0.09	0.16	2.35
3	Low	-0.03	-0.71	-0.71	-5.81	-0.04	-0.42	0.07	0.61	0.00	0.08	0.03	0.33	0.00	0.05	0.03	0.31
	2	0.06	1.01	-0.24	-3.10	0.15	1.72	0.18	2.17	0.08	1.41	0.08	1.25	0.08	1.36	0.08	1.26
	3	0.03	0.45	-0.05	-0.63	0.18	2.12	0.22	2.60	0.06	0.92	0.09	1.38	0.06	0.91	0.09	1.39
	4	0.06	0.85	0.11	1.76	0.24	2.83	0.13	1.51	0.07	1.04	0.01	0.10	0.07	1.04	0.01	0.12
	High	0.05	0.54	0.57	6.60	0.32	2.62	0.22	2.22	0.09	1.02	0.16	2.65	0.09	1.05	0.16	2.58
4	Low	0.10	1.47	-0.67	-5.10	0.03	0.41	0.10	1.00	0.09	1.49	0.10	1.08	0.09	1.48	0.09	1.03
	2	-0.06	-0.82	-0.22	-2.72	0.03	0.37	0.22	3.27	-0.02	-0.33	0.15	2.45	-0.02	-0.36	0.16	2.47
	3	0.02	0.29	-0.03	-0.35	0.16	2.08	0.20	2.59	0.07	1.05	0.11	1.55	0.06	1.00	0.11	1.56
	4	0.04	0.59	0.18	2.94	0.19	2.58	0.16	2.39	0.05	0.89	0.09	1.51	0.05	0.87	0.09	1.51
	High	-0.12	-1.85	0.53	6.48	0.14	1.63	0.11	1.57	-0.06	-0.98	0.08	1.23	-0.06	-0.96	0.08	1.20
Big	Low	0.14	2.91	-0.60	-3.95	0.11	2.53	0.10	0.80	0.15	3.24	0.13	0.98	0.16	4.01	0.13	0.98
	2	0.02	0.43	-0.16	-1.77	-0.02	-0.31	0.27	3.72	0.02	0.31	0.26	3.67	0.01	0.22	0.26	3.74
	3	0.01	0.23	-0.08	-1.42	0.00	0.00	0.02	0.34	0.02	0.25	0.02	0.28	0.01	0.12	0.02	0.29
	4	-0.14	-2.77	0.12	2.03	-0.04	-0.64	-0.04	-0.69	-0.11	-2.24	-0.05	-0.88	-0.12	-2.41	-0.05	-0.85
	High	-0.19	-2.19	0.41	5.04	-0.02	-0.17	-0.09	-1.45	-0.16	-2.00	-0.06	-1.05	-0.16	-2.03	-0.06	-1.08

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$r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is:
$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$. The five-factor model (Five-factor) is:
$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. Table 3 shows matrices of the intercepts and their t-statistics for selected models. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12.

statistic (GRS). Table 3 shows matrices of the intercepts and their t-statistics for selected models. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12.[4]

As we can see from Table 2, for the whole sample period from July 1951 to July 2011, the intersection of "FF" and "Size-BM" reports the summary statistics for the FF regressions (i.e. Eq. 1) for 25 size-BM portfolios. The average absolute value of the intercepts from 25 time-series regressions based on the FF model is 0.09 with an average standard error of 0.07. The average adjusted R^2 is 0.91. But the GRS statistic of 3.10 still rejects the FF model at the 5% significance level. From the column headed by "FF"/"Size-BM" in Table 3, we can see that the rejection is due to the inability of the FF model to explain the excess returns of eight extreme portfolios. Our results are in general consistent with previous studies (e.g. Fama and French, 2012).

The intersection of "HKK" and "Size-BM" in Table 2 reports the results for the HKK regressions (i.e. Eq. 2) for 25 size-BM portfolios. The pricing error measured by the average absolute value of the intercepts is 0.17 with an average standard error of 0.10. The average adjusted R^2 is 0.78. The GRS statistic of 3.27 implies a rejection for the hypothesis that the intercepts are jointly equal to zero for all test assets. From the column headed by "HKK"/"Size-BM" in Table 3, we can see that the rejection is due to that the HKK model fails to explain the excess returns of twelve portfolios throughout the entire spectrum of size.

The intersection of "FFC" and "Size-BM" in Table 2 presents the results for the FFC four-factor regressions (i.e. Eq. 3) for 25 size-BM portfolios. As we can see, the FFC model (which is also enhanced with the momentum factor) does not underperform the HKK model. The average absolute value of the intercepts is 0.09; the average R^2 is 0.91; and the GRS statistic is 2.48. Corresponding results in the column headed by "FFC"/"Size-BM" in Table 3 show that the FFC model performs similarly as the FF model, which is not surprising given that the test assets are the size-BM portfolios.

The intersection of "Five-factor" and "Size-BM" in Table 2 presents the results for the Five-factor model regressions (i.e. Eq. 4) for 25 size-BM portfolios. Relative to the FFC model, the Five-factor model that includes the cash flow-to-price factor does not reduce the pricing errors or increase the explanatory power; the GRS statistic of this model is also similar to that of the FFC model. Corresponding results in the column headed by "Five-factor"/"Size-BM" in Table 3 further confirms that the Five-factor model performs similarly as the FFC model.

Next, we evaluate the four candidate models with the 25 size-momentum portfolios as test assets. Given that the FF three-factor model is well-known to be unable to account for momentum effects of Jegadeesh and Titman (1993), we expect the HKK model will substantially outperform the FF model. However, the key question is whether the HKK model will also outperform the FFC model (which is also enhanced with the momentum factor). The answer to this question will shed light on whether different measures of the value-growth effect contain similar information.

The results for 25 size-momentum portfolios are reported in the same fashion as those for the size-BM portfolios in Tables 2 and 3. From Table 2, we can see that the FF model has greater pricing errors compared to the HKK model. The average absolute value of the intercepts is 0.35 for the FF model, but 0.19 for the HKK model. The GRS statistic of the HKK model is 3.73, substantially smaller than that of the FF model which is 5.40. Again, this is expected since the HKK model includes the momentum factor, while the FF model does not. Therefore, we focus on the comparison between the HKK model and the FFC model. Consistent with previous results, the FFC model does not underperform the HKK model in explaining the excess returns of 25 size-momentum portfolios. The average absolute value of the intercepts is 0.13; the average adjusted R^2 is 0.91; and the GRS statistic is 3.56. Furthermore, consistent with previous results, the Five-factor model that includes the cash flow-to-price factor does not outperform the FFC model: the pricing error, the explanatory power, and the GRS statistic are all similar as those of the FFC model.

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[4] Detailed regression results are available on request.

We also report the summary statistics for regressions based on all 50 test assets (i.e. 25 size-BM portfolios and 25 size-momentum portfolios) in Table 2. In this case, the GRS F-test is for the hypothesis that all intercepts are jointly equal to zero for all 50 test assets. The results show that, when 50 test assets are considered simultaneously, the FFC model does not underperform the HKK model, the Five-factor model does not outperform the FFC model, and the models with the momentum factor (i.e. HKK and FFC) outperform the models without the this factor (i.e. FF). Therefore, the evidence suggests that different measures of the value-growth effect contain similar information, and that momentum is a pervasive factor of stock returns.

For robustness, we also look at three equal-length sub-sample periods: July 1951 to June 1971, July 1971 to June 1991, and July 1991 to July 2011. The summary statistics for regressions based on the same test assets are reported in Table 2 in the same fashion. Although there is some time variation in the summary statistics, the overall picture is consistent with the whole-sample results. That is, the FFC model does not underperform the HKK model; the Five-factor model does not outperform the FFC model; and the models with the momentum factor outperform the models without the momentum factor. Thus, the evidence again suggests that different measures of the value-growth effect contain similar information, and that momentum is a pervasive factor of stock returns.

Cross-sectional tests

Table 4 reports the Fama and MacBeth (1973) two-pass OLS regressions with 50 size-BM and size-momentum portfolios as the test assets. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R^2.

We first focus on the whole sample period from July 1951 to July 2011. The column headed by "FF" presents the results for the FF three-factor model. The FF model fails to explain the expected returns of 50 test assets: the intercept (Alpha) is significantly different from zero; none of three factors has significantly positive risk premium; the cross-sectional R^2 is only 0.38.[5] The column headed by "HKK" presents the results for the HKK model. As we can see, the HKK model noticeably outperforms the FF model: the intercept is indifferent from zero; both the cash flow-to price and momentum factors have significantly positive risk premiums; and the cross-sectional R^2 increases to 0.74.

Again, the underperformance of the FF model is expected given that 25 out of 50 test assets are size-momentum portfolios and the FF model is well-known to be unable to capture momentum effects. Therefore, we next evaluate the FFC and the Five-factor models. The column headed by "FFC" presents the results for the FFC model. Consistent with the time-series regression results in Table 2, the FFC model (which is augmented with the momentum factor) does not underperform the HKK model in explaining the expected returns of 50 test assets. Although the intercept is larger, the cross-sectional R^2 is also slighter higher. Furthermore, both the book-to-market-equity and momentum factors carry significantly positive risk premiums. The column headed by "Five-factor" presents the results for the Five-factor model. As we can see, adding the cash flow-to-price factor does not result in noticeable improvement. Furthermore, the cash flow-to-price factor is insignificant when the book-to-market-equity factor is present. Taken together, the evidence suggests that the cash flow-to-price factor does not seem to have incremental information relative to the value factor. Put differently, different measures of the value-growth effect contain similar information.

It is important to note that the models with the momentum factor (i.e. HKK and FFC) again outperform the models without this factor (i.e. FF) in terms of the cross-sectional R^2. Furthermore, the momentum factor is always significant regardless of whether we look at the HKK model, the FFC model,

[5] Lewellen, Nagel and Shanken (2010) show that "a sample adjusted R^2 might need to be as high as 44% to be statistically significant in models with one factor, 62% in models with three factors, and 69% in models with five factors." (p. 176)

Table 4. Two-pass OLS regressions with 50 test assets, July 1951-July 2011

		FF			HKK			FFC			Five-Factor		
		γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}
1951	Alpha	2.49	6.99	7.18	0.36	1.02	1.02	0.63	2.81	2.62	0.42	1.78	1.68
-	MKT	-1.81	-4.72	-4.83	0.31	0.79	0.79	0.01	0.03	0.03	0.22	0.76	0.74
2011	SMB	0.16	1.38	1.37				0.16	1.41	1.41	0.17	1.47	1.46
	HML	0.09	0.81	0.79				0.36	3.42	3.41	0.35	3.31	3.30
	WML				0.83	5.45	5.45	0.81	5.38	5.37	0.82	5.39	5.39
	CFP				0.81	4.32	4.34				-0.28	-1.47	-1.27
	R^2	0.38			0.74			0.82			0.84		
1951	Alpha	1.89	6.64	3.14	0.47	0.95	0.94	1.40	4.79	4.65	1.46	4.98	4.89
-	MKT	-1.05	-2.82	-1.62	0.43	0.75	0.74	-0.60	-1.58	-1.55	-0.65	-1.74	-1.72
1971	SMB	0.14	0.88	0.87				0.14	0.88	0.88	0.14	0.90	0.90
	HML	-0.08	-0.54	-0.49				0.26	2.00	1.99	0.26	2.00	1.99
	WML				0.87	4.88	4.75	0.93	5.20	5.20	0.92	5.19	5.19
	CFP				0.94	3.24	3.23				0.05	0.18	0.17
	R^2	0.05			0.69			0.88			0.88		
1971	Alpha	1.43	3.37	1.30	0.60	1.09	1.07	0.57	1.47	1.14	0.50	1.19	1.06
-	MKT	-0.92	-1.73	-0.83	-0.07	-0.11	-0.11	-0.06	-0.13	-0.11	0.05	0.10	0.09
1991	SMB	0.00	0.00	0.00				0.02	0.10	0.10	0.04	0.19	0.19
	HML	0.22	1.17	1.04				0.42	2.35	2.31	0.34	1.90	1.89
	WML				0.86	3.64	3.62	0.89	3.77	3.75	0.92	3.86	3.85
	CFP				0.76	2.16	2.16				-0.46	-1.50	-1.44
	R^2	0.02			0.55			0.63			0.73		
1991	Alpha	1.49	3.15	3.17	0.37	0.97	0.94	0.56	1.90	1.83	0.49	1.66	1.52
-	MKT	-0.87	-1.58	-1.59	0.34	0.65	0.65	0.05	0.12	0.12	0.14	0.34	0.32
2011	SMB	0.26	1.10	1.10				0.25	1.08	1.08	0.24	1.06	1.06
	HML	0.20	0.86	0.85				0.37	1.61	1.60	0.38	1.71	1.70
	WML				0.64	1.83	1.83	0.58	1.68	1.68	0.58	1.70	1.70
	CFP				0.53	1.80	1.72				0.14	0.37	0.34
	R^2	0.50			0.50			0.65			0.64		

The Fama-French three-factor model (FF) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + \varepsilon_{it}$, where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The HKK model of Hou, Karolyi, and Kho (2010) is: $r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$. The five-factor model (Five-factor) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. Table 4 reports the Fama and MacBeth (1973) two-pass OLS regressions with 50 size-BM and size-momentum portfolios as the test assets. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional R^2.

or the Five-factor model, suggesting that the momentum factor provides incremental information relative to the Fama-French factors in explaining the cross-section of stock returns.

For robustness, we also look at three equal-length sub-sample periods: July 1951 to June 1971, July 1971 to June 1991, and July 1991 to July 2011. The results for OLS cross-sectional regressions based on the same test assets are reported in Table 4 in the same fashion. Although there is some time variation in the results, the overall pattern is consistent with the whole-sample results. That is, the FFC model does not underperform the HKK model; the Five-factor model does not outperform the FFC model; and the models with the momentum factor outperform the models without this factor. Thus, the evidence again suggests that different measures of the value-growth effect contain similar information, and that momentum is a pervasive factor of stock returns.

2.3.2 Test results for the expanded set of test assets

Time-series tests

To "relax the tight factor structure of size-B/M portfolios" (Lewellen, Nagel and Shanken 2010, p. 182), we expand our set of test assets to 120 portfolios formed on size-BM, size-momentum, earnings-to-price, dividend yield, short-term reversal, long-term reversal, and industry. Table 5 summarizes time-series regressions in the same fashion as Table 2. We report summary regression statistics for the portfolios formed on individual characteristics (e.g. earnings-to-price) as well as those for all 120 assets.

Again, we first focus on the results for the whole sample period from July 1951 to July 2011. Regardless of whether we look at the portfolios formed on individual characteristics or all 120 portfolios, the same pattern emerges: the FFC model does not underperform the HKK model; the Five-factor model does not outperform the FFC model; and the models with the momentum factor tend to outperform the models without this factor. Consider the summary statistics for regressions with 120 portfolios as test assets. The average absolute value of the intercepts from 120 time-series regressions is 0.17 for the FF model, 0.16 for the HKK model, 0.11 for the FFC model, and 0.11 for the Five-factor model, respectively. For these models, the average adjusted R^2s are 0.80, 0.76, 0.82 and 0.82, respectively; and the GRS statistics are 3.05, 2.70, 2.59 and 2.60, respectively. The evidence thus again confirms that different measures of the value-growth effect contain similar information, and that momentum is a pervasive factor to drive stock returns.

For robustness, we again look at three equal-length sub-sample periods. The summary statistics for regressions for the same 120 test assets are also reported in Table 5. Although there is some time variation in the summary statistics, the overall pattern is consistent with the whole-sample results, and suggests that the cash flow-to-price factor does not provide incremental information relative to the book-to-market-equity factor, and that momentum is a pervasive factor to drive stock returns.

Cross-sectional tests

Table 6 reports the Fama and MacBeth (1973) two-pass OLS regressions with 120 portfolios as the test assets in the same fashion as Table 4. The results for the whole sample period as well as for the three subs-ample periods are, in general, consistent with those in Table 4. For instance, for the whole sample period from July 1951 to July 2011, the FF model fails to explain the expected returns of 120 test assets: the intercept is significantly different from zero; none of three factors has significantly positive risk premium; and the cross-sectional R^2 is only 0.17. The HKK model outperforms the FF model: the intercept is insignificantly different from zero; both the cash flow-to price and momentum factors have significantly positive risk premiums; and the cross-sectional R^2 increases to 0.49. However, as soon as the momentum factor is taken into account, the FFC model does not underperform the HKK model in explaining the expected returns of these test assets. Furthermore, the cash flow-to-price factor is insignificant when the book-to-market-equity factor is present in the Five-factor model. Taken together, the evidence confirms that the cash flow-to-price factor does not have incremental information relative to the value factor.

Again, it is important to note that the models with the momentum factor (i.e. HKK and FFC) outperform the models without this factor (i.e. FF). Furthermore, the momentum factor is in general significant regardless of which model we use or which sample period we look at. The evidence thus confirms that the momentum factor provides incremental information.

Table 5. Summary statistics for time-series regressions, July 1951-July 2011

Sample	Test assets	FF				HKK				FFC				Five-factor			
		|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS
1951-2011	Earnings/Price	0.08	0.07	0.86	1.53	0.10	0.07	0.86	2.00*	0.08	0.07	0.86	1.36	0.08	0.06	0.87	1.36
	Dividend Yield	0.06	0.08	0.83	1.16	0.09	0.08	0.81	1.50	0.06	0.07	0.83	1.20	0.06	0.07	0.83	1.18
	Short-Term Reversal	0.12	0.07	0.86	2.82*	0.17	0.08	0.85	3.18*	0.15	0.08	0.86	2.85*	0.15	0.08	0.86	2.93*
	Long-Term Reversal	0.05	0.07	0.85	0.77	0.10	0.08	0.82	1.01	0.04	0.07	0.85	0.44	0.04	0.07	0.85	0.45
	Industry	0.21	0.15	0.62	2.90*	0.17	0.14	0.61	2.46*	0.17	0.14	0.63	2.71*	0.17	0.13	0.64	2.79*
	120 portfolios	0.17	0.09	0.80	3.05*	0.16	0.10	0.76	2.70*	0.11	0.09	0.82	2.59*	0.11	0.09	0.82	2.60*
1951-1971	Earnings/Price	0.16	0.11	0.85	4.18*	0.12	0.10	0.87	3.13*	0.12	0.11	0.86	2.61*	0.11	0.10	0.87	2.74*
	Dividend Yield	0.06	0.10	0.87	0.91	0.11	0.10	0.86	1.20	0.07	0.10	0.87	0.79	0.07	0.10	0.88	0.79
	Short-Term Reversal	0.15	0.10	0.87	2.42*	0.22	0.10	0.87	3.56*	0.22	0.10	0.87	3.63*	0.22	0.10	0.87	3.67*
	Long-Term Reversal	0.08	0.10	0.86	1.54	0.10	0.11	0.85	1.19	0.09	0.10	0.86	1.20	0.09	0.10	0.86	1.19
	Industry	0.23	0.21	0.68	2.46*	0.23	0.21	0.64	2.67*	0.25	0.20	0.68	2.38*	0.25	0.19	0.69	2.69*
	120 portfolios	0.20	0.13	0.83	2.39*	0.19	0.15	0.78	2.06*	0.15	0.12	0.84	1.98*	0.15	0.12	0.84	1.97*
1971-1991	Earnings/Price	0.10	0.10	0.91	1.16	0.08	0.09	0.92	0.94	0.10	0.10	0.91	1.29	0.10	0.09	0.92	1.24
	Dividend Yield	0.13	0.11	0.89	2.86*	0.12	0.11	0.89	1.98*	0.10	0.10	0.90	1.97*	0.10	0.10	0.90	2.10*
	Short-Term Reversal	0.11	0.12	0.90	1.20	0.26	0.13	0.90	2.89*	0.25	0.12	0.91	2.66*	0.24	0.12	0.91	2.61*
	Long-Term Reversal	0.11	0.12	0.89	0.97	0.12	0.14	0.88	1.07	0.06	0.12	0.90	0.77	0.07	0.12	0.90	0.82
	Industry	0.20	0.22	0.73	1.69*	0.23	0.22	0.71	1.88*	0.20	0.21	0.73	1.73*	0.19	0.20	0.74	1.70*
	120 portfolios	0.18	0.14	0.86	2.76*	0.21	0.16	0.83	2.72*	0.16	0.13	0.87	2.49*	0.16	0.13	0.88	2.58*
1991-2011	Earnings/Price	0.10	0.13	0.83	0.89	0.13	0.12	0.81	0.88	0.11	0.12	0.83	0.75	0.11	0.11	0.84	0.75
	Dividend Yield	0.11	0.15	0.78	0.62	0.14	0.15	0.70	0.65	0.11	0.14	0.78	0.63	0.11	0.14	0.78	0.62
	Short-Term Reversal	0.18	0.14	0.82	1.94*	0.16	0.14	0.81	1.16	0.15	0.14	0.82	1.40	0.15	0.14	0.82	1.43
	Long-Term Reversal	0.16	0.13	0.82	1.36	0.20	0.14	0.77	1.50	0.15	0.13	0.82	1.19	0.14	0.13	0.82	1.18
	Industry	0.30	0.25	0.55	1.49	0.24	0.25	0.54	1.07	0.26	0.24	0.56	1.39	0.26	0.24	0.58	1.38
	120 portfolios	0.22	0.17	0.76	1.80*	0.20	0.19	0.71	1.77*	0.17	0.16	0.78	1.75*	0.17	0.16	0.79	1.74*

The Fama-French three-factor model (FF) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + \varepsilon_{it}$, where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The HKK model of Hou, Karolyi, and Kho (2010) is: $r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$. The five-factor model (Five-factor) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. Table 5 shows the average absolute value of the intercepts (|α|), and the average of the standard errors of the intercepts (s(α)), the average adjusted R^2 (R^2), and the GRS F-test statistic (GRS).

Table 6. Two-pass OLS regressions with 120 portfolios as test assets, July 1951-July 2011

		FF			HKK			FFC			Five-Factor		
		γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}
1951	Alpha	1.24	6.17	5.80	0.38	1.53	1.53	0.56	2.82	2.74	0.53	2.78	2.68
-	MKT	-0.61	-2.39	-2.30	0.29	0.98	0.97	0.07	0.28	0.27	0.09	0.38	0.37
2011	SMB	0.18	1.65	1.64				0.18	1.65	1.64	0.18	1.64	1.64
	HML	0.10	0.93	0.92				0.27	2.47	2.46	0.29	2.63	2.61
	WML				0.71	4.59	4.53	0.77	4.97	4.95	0.78	5.06	5.04
	CFP				0.50	3.30	3.27				0.24	1.47	1.46
	R^2	0.17			0.49			0.61			0.61		
1951	Alpha	0.74	3.35	2.80	0.44	1.42	1.39	0.82	3.46	3.36	0.82	3.41	3.31
-	MKT	0.06	0.20	0.18	0.44	1.08	1.07	-0.02	-0.06	-0.06	-0.02	-0.06	-0.06
1971	SMB	0.15	0.95	0.94				0.14	0.92	0.92	0.14	0.91	0.90
	HML	-0.02	-0.12	-0.12				0.17	1.24	1.23	0.18	1.32	1.29
	WML				0.73	3.73	3.46	0.90	4.96	4.89	0.90	4.95	4.89
	CFP				0.47	2.25	2.18				0.27	1.34	1.31
	R^2	0.04			0.36			0.53			0.52		
1971	Alpha	0.86	2.66	1.97	0.48	1.18	1.16	0.54	1.64	1.35	0.45	1.33	1.17
-	MKT	-0.39	-0.87	-0.73	0.02	0.04	0.04	-0.06	-0.13	-0.12	0.03	0.07	0.06
1991	SMB	0.04	0.21	0.20				0.06	0.30	0.30	0.05	0.27	0.27
	HML	0.20	1.08	1.05				0.34	1.83	1.79	0.44	2.40	2.37
	WML				0.58	2.33	2.26	0.68	2.80	2.74	0.75	3.10	3.05
	CFP				0.48	1.71	1.69				0.15	0.55	0.55
	R^2	0.06			0.27			0.38			0.46		
1991	Alpha	0.99	3.49	3.41	0.35	1.04	1.04	0.49	1.77	1.73	0.55	2.16	2.10
-	MKT	-0.36	-0.90	-0.89	0.33	0.72	0.72	0.15	0.39	0.38	0.09	0.25	0.24
2011	SMB	0.28	1.23	1.22				0.26	1.12	1.12	0.26	1.14	1.14
	HML	0.10	0.43	0.43				0.23	0.98	0.97	0.19	0.83	0.83
	WML				0.66	1.84	1.84	0.68	1.93	1.93	0.65	1.88	1.88
	CFP				0.36	1.35	1.33				0.35	1.18	1.17
	R^2	0.22			0.38			0.45			0.46		

The Fama-French three-factor model (FF) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + \varepsilon_{it}$, where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The HKK model of Hou, Karolyi, and Kho (2010) is: $r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$. The five-factor model (Five-factor) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. Table 5 reports the Fama and MacBeth (1973) two-pass OLS regressions with 120 portfolios as the test assets. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional R^2.

Table 7. Two-pass GLS regressions, July 1951-July 2011

Panel A Unrestricted GLS regressions									
	HKK			FFC			Five-factor		
	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}
Alpha	0.59	5.45	4.16	0.58	5.18	3.94	0.58	5.17	3.94
MKT	0.01	0.05	0.04	0.02	0.10	0.09	0.02	0.10	0.09
SMB				0.20	1.87	1.86	0.20	1.87	1.86
HML				0.31	3.05	3.03	0.32	3.05	3.03
WML	0.77	5.14	5.12	0.78	5.16	5.14	0.78	5.16	5.14
CFP	0.41	3.16	3.09				0.37	2.84	2.76
R^2	0.26			0.59			0.59		
Panel B Restricted GLS regressions									
	HKK			FFC			Five-factor		
	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}	γ	t_{EIV}	t_{MIS}
Alpha	-0.25	-6.53	-5.08	-0.35	-18.95	-15.17	-0.30	-12.75	-10.06
MKT	0.84	5.07	4.98	0.94	5.76	5.73	0.89	5.46	5.43
SMB				0.21	1.90	1.89	0.20	1.84	1.83
HML				0.32	3.09	3.07	0.33	3.20	3.17
WML	0.78	5.19	5.17	0.78	5.20	5.17	0.78	5.21	5.19
CFP	0.32	2.46	2.39				0.31	2.37	2.30
R^2	0.23			0.48			0.53		

The HKK model of Hou, Karolyi, and Kho (2010) is: $r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$, where SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The five-factor model (Five-factor) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. Table 7 reports the Fama and MacBeth (1973) two-pass GLS regressions. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the GLS cross-sectional R^2. Panel A presents the results for 120 portfolios over the sample period from 1951 to 2011. Panel B reports the results when proposed factor portfolios are included as test assets. For the HKK model, we include the cash flow-to-price factor as a test asset in additional to the 120 portfolios used in previous tests. For the FFC model, we include the value factor as an additional test asset. For the Five-factor model, we include both the cash flow-to-price and the value factors as additional test assets.

Lewellen, Nagel and Shanken (2010) suggest researchers report not only the OLS results but also the GLS results, especially the GLS cross-sectional R^2.[6] We thus report the GLS results for the three competing models (i.e. HKK, FFC and Five-factor) in Panel A of Table 7 for 120 portfolios over the sample period from 1951 to 2011. The results are, in principle, consistent with the OLS results in Table 6. In terms of the GLS cross-sectional R^2, the FFC model does not underperform the HKK model, and the Five-factor model does not outperform the FFC model. Thus, our evidence again does not support the notion that the cash flow-to-price factor has incremental information. Furthermore, the models with the

[6] As they point out, "The broader point is that, while the OLS R2 might be relevant for some questions—for example, asking whether a model's predictions of expected returns are accurate for a given set of assets (subject to the limitations discussed in Section 2)—the GLS R2 is probably more relevant for other questions—for example, asking how well a model explains the risk-return opportunities available in the market." (p. 184).

momentum factor typically outperform the models without this factor, and the momentum factor carries a significant positive risk premium in all three models. Taken together, the evidence again suggests that momentum provides incremental information.

Lewellen, Nagel and Shanken (2010) also suggest researchers "take the magnitude of the cross-sectional slopes seriously" by including the proposed factors as test assets with GLS regressions.[7] For the HKK model, we include the cash flow-to-price factor as a test asset in additional to the 120 portfolios used in previous tests. For the FFC model, we include the book-to-market-equity factor as an additional test asset. For the Five-factor model, we include both the cash flow-to-price and book-to-market-equity factors as additional test assets. The results for the sample period from July 1951 to July 2011 are presented in Panel B of Table 7. The results again are consistent with the previous OLS and GLS results. In terms of the GLS cross-sectional R^2, the FFC model does not underperform the HKK model, and the Five-factor model does not outperform the FFC model. Thus, our evidence again suggests that different measures of value-growth characteristics contain similar information. Momentum again is significant in all three models, suggesting that momentum is a pervasive factor to drive stock returns.

2.3.3 Additional evidence

We have found that the models including the value-growth and momentum effects (i.e. HKK, FFC and Five-factor) perform similarly in the standard time-series and cross-sectional regressions, which suggests that different measures of value-growth characteristics contain similar information and momentum is a pervasive factor of stock returns. In this section, we provide additional evidence that these models yield similar out-of-sample forecast errors.

We rank the competing models based on the model confidence set (MCS) methodology of Hansen, Lunde, and Nason (2011). "A MCS is a set of models that is constructed so that it will contain the best model with a given level of confidence. The MCS is in this sense analogous to a confidence interval for a parameter." (Hansen, Lunde, and Nason, 2011, 453) The MCS procedure thus helps determine the "best" model(s) from a collection of competing models, where "best" is defined by a user-specified criterion. In this paper, we focus on (absolute) forecast errors (as in Griffin, 2002) to construct the MCS. That is, the loss function for Model i (i.e. FF, FFC, HKK, or Five-factor) in month t is defined as $L_{i,t} = \sum_{k=1}^{K} | r_{k,t} - \hat{r}_{k,t,i} |$ for K test assets, where $r_{k,t}$ is the actual return of asset k in month t, and $\hat{r}_{k,t,i}$ is the corresponding expected return based on Model i. We follow Griffin (2002) to estimate expected returns of our test assets. Specifically, every month beginning in June 1956, we estimate the competing models (without intercept terms) for each asset with the most recent five-year monthly data to obtain expected factor loadings. Then we use the average factor returns over the entire period prior to the forecast as expected factor returns. Finally, we multiply the expected factor loadings with the expected factor returns to calculate expected returns of our test assets for the next month.

With the loss variables $L_{i,t}$ for our competing models, we then follow Hansen, Lunde, and Nason (2011) to construct the MCS.[8] We focus on the Max t statistic to determine MCS p-values for our competing models. If the MCS p-value for a model is less than α, the model is not in the MCS with a confidence level of 1-α. We use α = 10%. The number of bootstrap resamples, B, is set to be 10000. The block length, d, is set to be 12 or 24, for robustness. If different measures of value-growth characteristics contain similar information and momentum is a pervasive factor of stock returns, we expect that the FFC,

[7] "When a factor portfolio is included as a left-hand-side asset, GLS forces the regression to price the asset perfectly: the risk premium on the factor exactly equals the factor's average return in excess of the estimated zero-beta rate (in essence, the asset is given infinite weight in the regression). Thus, a GLS cross-sectional regression, when a traded factor is included as a test asset, is similar to the time-series approach of Black, Jensen, and Scholes (1972) and Gibbons, Ross, and Shanken (1989)." (p. 184-185)

[8] The MCS is estimated with the MULCOM package written by Peter Reinhard Hansen and Asger Lunde.

the HKK and the Five-factor models perform similarly in terms of forecast errors and all end up in the MCS, but the FF model may not (since it is not augmented with the momentum factor). If the cash flow-to-price factor is more informative, we expect that only the HKK and the Five-factor models end up in the MCS.

The results are reported in Table 8. The column headed by "Mean Absolute Forecast Error" presents the mean absolute monthly forecast errors for the competing models for the portfolios formed on individual characteristics as well as for all 120 assets. As we can see, based on the MCS p-values, the HKK, the FFC and the Five-factor models always end up in the MCS (i.e. their MCS p-values > 10%), while the FF model is excluded from the MCS in two cases (i.e. its MCS p-values < 10% for 25 size and momentum portfolios and all 120 portfolios). Therefore, the results confirm that different measures of value-growth characteristics contain similar information, and that momentum is a pervasive factor of stock returns.

3. Explaining the value and momentum effects

3.1 Prior literature and motivation

The empirical success of the value (HML) and momentum (WML) effects in Section 2 calls for more research on what state variables HML and WML proxy for. This is an important question. If we do not thoroughly understand the relationship between these factors and the state variables that describe the investment/consumption opportunity set, we will not be able to confidently refute the notion that these factors simply capture behavioral biases as suggested by Daniel and Titman (1997) or they are a chance result as argued by MacKinlay (1995). Our finding that different measures of the value-growth effect contain similar information makes it easier for financial economists to undertake this task.

Until recently, researchers generally study HML and WML in isolation, and there is no unifying risk-based explanation for HML and WML.[9] HML has been explained by future GDP growth (Vassalou, 2003), the aggregate consumption-to-wealth ratio (Lettau and Ludvigson, 2001), the housing collateral ratio (Lustig and Van Nieuwerburgh, 2004), durable-consumption (Yogo, 2006), sector investment growth (Li, Vassalou, and Xing, 2006), the labor income-to-consumption ratio (Santos and Veronesi, 2006), and default risk and the term structure (Vassalou, and Xing, 2004; Hahn and Lee, 2006; Petkova, 2006, Kapadia, 2011).[10] WML has been explained by business cycles (Chordia and Shivakumar, 2002; Avramov and Chordia, 2006; Liu and Zhang, 2006; Avramov, Chordia, Jostova, and Philipov, 2007), liquidity risk (Pastor and Stambaugh, 2003), consumption risk (Bansal, Dittmar, and Lundblad, 2005), investment (Chen and Zhang, 2008), and technology prospects (Hsu and Huang, 2010).

A recent study by Garlappi and Yan (2011), however, suggests that both HML and WML may be driven by common macro shocks. In their model, for low levels of default probability shocks to stock prices can generate the value effect between two firms, while for high levels of default probability shocks to stock prices can result in the momentum effect between two firms. Clearly, the market-wide value and momentum effects require that shocks to stock prices be systematic or macro. Therefore, their model implies that it may be some common macro factors that explain the value and momentum effects, which is also suggested by previous studies on HML and WML.

To the best of our knowledge, there are few studies that examine if common macro risk can explain both HML and WML. Liew and Vassalou (2000) find that future GDP growth explains HML but not WML. More recently, Aretz, Bartram, and Pope (2010) consider a broader set of macro variables and find evidence that both HML and WML are driven by six common macro factors. Their success is partly due to their use of a larger set of macro variables. However, the explanatory power of their macro factors

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[9] Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) provide behavioral-based explanation.

[10] See also Ang and Chen (2007), Simpson and Ramchander (2008), Lewellen, Nagel and Shanken (2010), and Cooper and Gubellini (2011).

Table 8. Out-of-sample forecast errors, July 1951-July 2011

Test assets	Model	Mean Absolute Forecast Error	MCS p-value (B=10000) d=12	d=24
Size-BM	FF	4.124	0.81	0.82
	HKK	4.132	0.19	0.16
	FFC	4.124	1.00	1.00
	Five-factor	4.124	0.60	0.60
Size-Momentum	**FF**	**4.238**	**0.00**	**0.00**
	HKK	4.227	0.23	0.20
	FFC	4.219	1.00	1.00
	Five-factor	4.219	0.55	0.55
Earnings/Price	FF	3.556	0.96	0.97
	HKK	3.555	0.97	0.97
	FFC	3.555	1.00	1.00
	Five-factor	3.555	0.97	0.97
Dividend Yield	FF	3.486	0.24	0.26
	HKK	3.486	0.14	0.16
	FFC	3.484	1.00	1.00
	Five-factor	3.485	0.24	0.26
Short-Term Reversal	FF	3.753	1.00	1.00
	HKK	3.758	0.25	0.25
	FFC	3.756	0.25	0.25
	Five-factor	3.756	0.25	0.25
Long-Term Reversal	FF	3.662	1.00	1.00
	HKK	3.664	0.73	0.72
	FFC	3.663	0.71	0.71
	Five-factor	3.663	0.73	0.72
Industry	FF	4.473	0.58	0.58
	HKK	4.476	0.40	0.40
	FFC	4.472	1.00	1.00
	Five-factor	4.473	0.58	0.58
120 portfolios	**FF**	**4.065**	**0.03**	**0.02**
	HKK	4.066	0.20	0.18
	FFC	4.061	1.00	1.00
	Five-factor	4.061	0.31	0.34

The Fama-French three-factor model (FF) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + \varepsilon_{it}$, where r_{it} is the excess return on asset *i* in period *t*, MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The HKK model of Hou, Karolyi, and Kho (2010) is: $r_{it} = \alpha_i + b_i MKT_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$, where WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year, and CFP_t is the return of the cash flow-to-price factor-mimicking portfolio. The Carhart (1997) four-factor model (FFC) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it}$. The five-factor model (Five-factor) is: $r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i CFP_t + \varepsilon_{it}$. We follow Griffin (2002) to estimate out-of-sample forecast errors for each model. Specifically, every month beginning in June 1956, we estimate the model (without intercept terms) for each asset with the most recent five-year monthly data to obtain expected factor loadings. Then we use the average factor returns over the entire period prior to the forecast as expected factor returns. Next, we multiply the expected factor loadings with the expected factor returns to calculate expected returns of our test assets for the next month. Finally, for each asset, out-of-sample forecast errors are estimated as the differences between next month's actual return and the expected return obtained previously. The column headed by "Mean Absolute Forecast Error" presents the mean absolute monthly forecast errors for the competition models for the portfolios formed on individual characteristics as well as for all 120 assets. We also report MCS p-values based on Hansen, Lunde, and Nason (2011). If MCS p-value < α, the model is not in the model confidence set with a confidence level of 1-α. B is the number of bootstrap resamples, and d is the block length.

is still limited. For instance, their macro variables can only explain 16.1% and 12.8% of HML and WML, respectively, in terms of the time-series regression adjusted R^2.

We extend the literature along the same line as Aretz, Bartram, and Pope (2010) by utilizing two broad macro condition indexes from the Federal Reserve Bank of Chicago, the Chicago Fed National Activity Index (CFNAI) and the National Financial Conditions Index (NFCI). Our use of these indexes is motivated by the following two observations. First, these two indexes cover much larger sets of macroeconomic and financial variables. While Aretz, Bartram, and Pope (2010) take into account six macro variables, the CFNAI covers 85 macroeconomic variables (drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories) to gauge growth and inflation, and the NFCI covers 100 financial variables to measure financial conditions in money markets, debt and equity markets, and the traditional and "shadow" banking systems. Second, the CFNAI and the NFCI are more relevant to asset pricing compared to individual macroeconomic and financial variables used in previous studies, since as the first principal components of the underlying macro variables these indexes capture the common movements in these variables (which define the state of economy).

3.2 Data

The CFNAI was originally proposed by Stock and Watson (1999). Boyd, Jagannathan, and Hu (2005) use the Stock and Watson activity index to identify the state of economy. We focus on the three-month moving average of CFNAI (CFNAI-MA3), because it better captures the persistent rather than transitory component of the index. The NFCI is based on Stock and Watson (2002) and Aruoba, Diebold, and Scotti (2009). We use the adjusted NFCI (ANFCI), because it is constructed to be orthogonal to the CFNAI-MA3. Thus, the CFNAI-MA3 and the ANFCI gauge two distinct dimensions of macro economy, namely, growth and inflation versus pure financial conditions. The CFNAI-MA3/ANFCI has a mean value of zero and a standard deviation of one, with a reading of zero corresponding to trend growing/average financial conditions. [11]

The monthly CFNAI-MA3 is available from May 1967 to July 2012. The weekly ANFCI is available from January 1973 to July 2012. Following the relevant literature (e.g. Kapadia, 2011), we use monthly data in empirical tests. The monthly ANFCI is constructed as averages of weekly data. Since we use both the CFNAI-MA3 and the ANFCI, we focus on the common sample period from January 1973 to July 2012. Figure 1 depicts the CFNAI-MA3 and the ANFCI with the shaded areas corresponding to recession periods dated by the NBER. In general, the CFNAI-MA3 tracks the US aggregate economic activity well. The contemporaneous correlation between the CFNAI-MA3 and the ANFCI is -0.04 in our sample, suggesting that they are orthogonal.

3.3 Empirical methodology

Empirically, we follow recent studies (e.g. Aretz, Bartram, and Pope, 2010; Kapadia, 2011) and use the tracking portfolio approach of Lamont (2001) to estimate the news about future macroeconomic and financial conditions. As Lamont (2001) shows, the tracking portfolio can be constructed by the following regression:

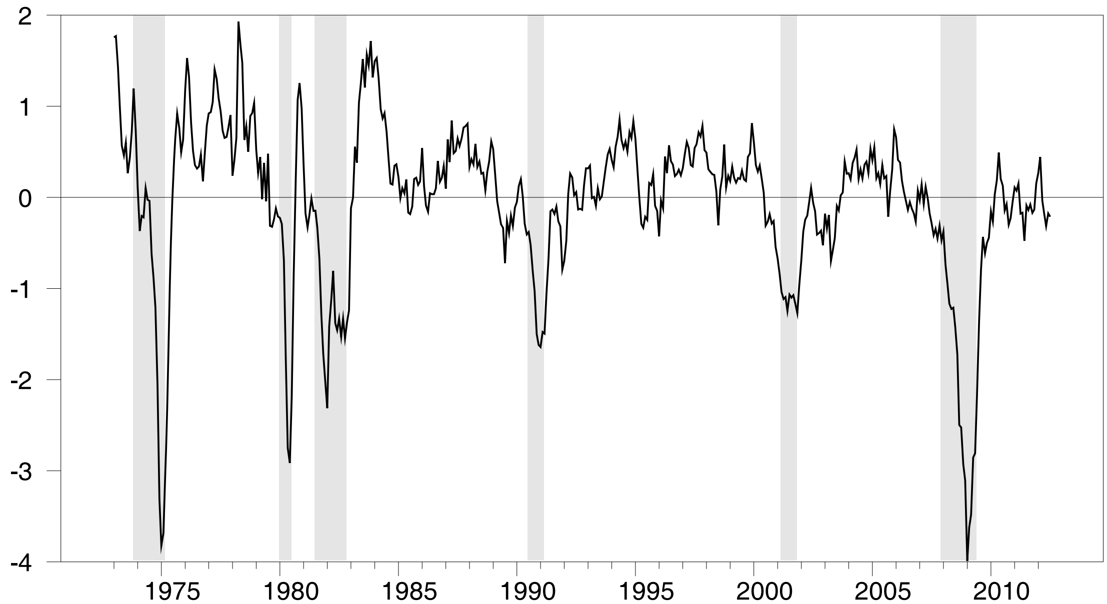
$$y_{t+12} = bR_t + cZ_{t-1} + dZ'_{t-1} + e_{t+12} \quad (5)$$

where y_{t+12} is the future annual change in the CFNAI-MA3 or the ANFCI (i.e. $\frac{1}{12}(\sum_{k=1}^{12} CFNAI-MA3_{t+k} - \sum_{k=1}^{12} CFNAI-MA3_{t-12+k})$ or $\frac{1}{12}(\sum_{k=1}^{12} ANFCI_{t+k} - \sum_{k=1}^{12} ANFCI_{t-12+k})$), R_t is a

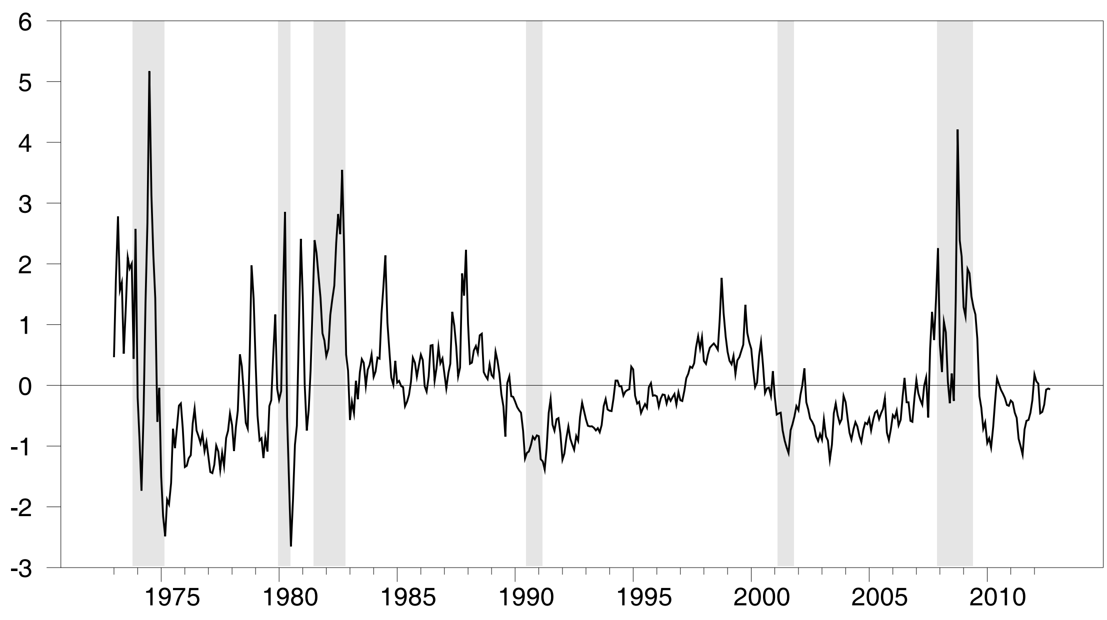
[11] For more information, please refer to Background on the Chicago Fed National Activity Index (2011) and Brave and Butters (2011).

Figure 1. CFNAI-MA3 and ANFCI: January 1973 to July2012

Panel A: CFNAI-MA3



Panel B: ANFCI



vector of excess returns of base assets in month t, Z_{t-1} is a vector of conditioning variables known at period t-1 that may help predict base asset returns, and $Z_{t-1}^{'}$ is a vector of conditioning variables known at period t-1 that may help predict y_{t+12}. The tracking portfolio is a linear combination of base asset returns with the portfolio weights b estimated by Eq. (5). That is,

$$TRACK_t = \hat{b} R_t \tag{6}$$

Garlappi and Yan (2011) imply that macro shocks can result in both the value and momentum effects, depending on probability of default as well as shareholder recovery. To capture differential effects of macro shocks, we construct two sets of tracking portfolios, TRACK1 and TRACK2. TRACK1 is to capture the effects of macro shocks on low default-probability stocks (i.e. the value effect), while TRACK2 is to capture their effects on high default-probability stocks (i.e. the momentum effect). Kapadia (2011) suggests that researchers use the based assets that are informative about the effects the tracking portfolio attempts to capture. Therefore, following Kapadia (2011), we use the market, the size, and the value factors as the base assets to construct TRACK1. In the same spirit, we construct TRACK2 with the market, the momentum loser (MOM1), and the momentum winner (MOM10) as base assets. The 10 momentum portfolio returns are downloaded from Kenneth French's web site.

As for conditioning variables – the Z_{t-1} in equation (5), we again largely follow Kapadia (2011) and use macro variables which are known to predict equity returns. They are the risk-free rate (RF), the term premium (TERM) (the rate difference between the 10-year and the 1-year government bonds from the Federal Reserve Bank - St. Louis), and the default premium (DEF) (the yield difference between BAA and AAA bonds from the Federal Reserve Bank - St. Louis). We use the lagged annual change in the CFNAI-MA3 or the ANFCI (i.e. y_{t-1}) as the only conditioning variable in Z'. All the results are for 1975:2 - 2011:7 (note that we lose the first two years because we need y_{t-1}; we also lose the last year as we need it for the final sample point of y_{t+12}).

If the value and momentum effects are driven by changes in future macroeconomic or financial conditions, we expect that our base assets returns (which capture the value or momentum effects) have significant correlation with future changes in the CFNAI-MA3 or the ANFCI. That is, (1) the coefficients on our base assets returns in Eq. (5) should not be jointly zero, and (2) innovations in our base assets returns should track innovations in future changes in the CFNAI-MA3 or the ANFCI. We therefore focus on two statistics. One is the chi-square test p-value which tests the hypothesis that the coefficients on the base assets are jointly zero, and the other is the lower-bound adjusted R^2 which provides a lower bound for the tracking ability of our base assets.

To supplement our findings from the tracking portfolio regressions, we also follow Aretz, Bartram, and Pope (2010) and Kapadia (2011) and directly examine if TRACK1/TRACK2 can help explain HML/WML. Essentially, we run two sets of time-series regressions:

$$HML_t = \alpha + \beta MKT_t + e_t \tag{7a}$$

$$HML_t = \alpha + \beta MKT_t + \gamma TRACK1_t + e_t \tag{7b}$$

and

$$WML_t = \alpha + \beta MKT_t + e_t \tag{8a}$$

$$WML_t = \alpha + \beta MKT_t + \gamma TRACK2_t + e_t \tag{8b}$$

If TRACK1/TRACK2 helps explain HML/WML, we expect that the Alpha will decrease and the adjusted R^2 will increase when TRACK1/TRACK2 is added.

3.4 Empirical results

3.4.1 Main results

Panel A of Table 9 presents the construction and diagnostic tests of the tracking portfolio regressions based on Eq. (5). The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12. TRACK1 is constructed to study the value effect. The column headed by "CFNAI-MA3" looks at if the news about future growth and inflation (i.e. CFNAI-MA3) drives the value effect captured in the market, the value, and the size factors. The chi-square test rejects the hypothesis that the coefficients on the base assets are jointly zero at the 5% level, indicating that the base assets returns

Table 9. Explaining HML and WML, February 1975 – July 2011

Panel A: Tracking portfolio regressions

	TRACK1					TRACK2			
	CFNAI-MA3		ANFCI			CFNAI-MA3		ANFCI	
	Estimate	t-ratio	Estimate	t-ratio		Estimate	t-ratio	Estimate	t-ratio
MKT_t	0.033	2.89	-0.017	-1.98	MKT_t	0.002	0.14	-0.034	-1.70
SMB_t	0.003	0.36	0.007	0.61	$MOM1_t$	0.016	1.58	0.003	0.30
HML_t	0.019	1.90	-0.008	-0.47	$MOM10_t$	0.004	0.53	0.013	1.29
Constant	-0.809	-2.44	0.296	1.00	Constant	-0.807	-2.46	0.286	0.97
RF_t	0.018	0.03	0.340	0.84	RF_t	0.112	0.17	0.325	0.80
DEF_{t-1}	0.355	1.54	-0.348	-2.25	DEF_{t-1}	0.321	1.28	-0.336	-2.14
$TERM_{t-1}$	0.343	3.12	-0.040	-0.50	$TERM_{t-1}$	0.357	3.20	-0.042	-0.54
y_{t-1}	-0.346	-3.59	-0.068	-0.70	y_{t-1}	-0.347	-3.61	-0.069	-0.71
Adj-R^2	0.44		0.11		Adj-R^2	0.44		0.11	
χ^2 p-value	0.02		0.27		χ^2 p-value	0.03		0.07	
Lower bound	0.03		0.00		Lower bound	0.03		0.00	

Panel B: Explaining HML and WML

		CAPM		Two-factor	
		Estimate	t-value	Estimate	t-value
HML	Constant	0.48	3.08	-0.04	-1.23
	MKT	-0.21	-2.11	-1.77	-42.67
	TRACK1			52.85	39.33
	Adj-R^2	0.10		0.97	
WML	Constant	0.72	4.29	0.22	1.46
	MKT	-0.11	-0.87	1.17	11.42
	TRACK2			-43.15	-16.80
	Adj-R^2	0.01		0.52	

The results for the regression of Eq. (5), $y_{t+12} = bR_t + cZ_{t-1} + e_{t+12}$, are in Panel A, where y_{t+12} is the future annual change in the CFNAI-MA3 or the ANFCI, R_t = (MKT_t, SMB_t, HML_t)' and (MKT_t, $MOM1_t$, $MOM10_t$)' represents excess returns: the three Fama-French factors, and the excess returns of the market, the momentum loser and the momentum winner. Z_{t-1} = (RF_{t-1}, DEF_{t-1},$TERM_{t-1}$, y_{t-1})', represents, respectively, the lagged one-month T-Bill rate, the lagged default risk premium, the lagged term premium, and the lagged annual change in the CFNAI-MA3 or the ANFCI. The tracking portfolio (TRACK1/TRACK2) is a linear combination of base asset returns with the portfolio weights b estimated by Eq. (5). That is, $TRACK_t = \hat{b}R_t$. Panel 2 presents the results of time series regressions of HML and WML on the CAPM and a two-factor model. The two factors are the market factor and the CFNAI-MA3 tacking portfolio (TRACK1/TRACK2) constructed in Panel A. All the t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12.

are driven by such news. The lower-bound adjusted R^2 is 3%, which is compatible to those in Aretz, Bartram, and Pope (2010) and confirms the tacking ability of the base assets. However, the results in the column headed by “ANFCI” suggest that the value effect captured in the base assets returns is not related to future changes in pure financial conditions (i.e. ANFCI). For instance, the chi-square test cannot reject the hypothesis that the coefficients on the base assets are jointly zero at the 5% level; and the lower-bound adjusted R^2 is 0%. Taken together, the evidence suggests that news about future growth and inflation (i.e. CFNAI-MA3) is more relevant for the value effect.

TRACK2 is constructed to study the momentum effect. The column headed by “CFNAI-MA3” examines if the news about future growth and inflation (i.e. CFNAI-MA3) drives the momentum effect captured in the market, the momentum loser (MOM1) and the momentum winner (MOM10). The column headed by “ANFCI” examines if the momentum effect instead is driven by the news about future pure financial conditions (i.e. ANFCI). Panel A of Table 9 shows that the momentum effect is driven by the news about future growth and inflation not by the news about future pure financial conditions. For instance, the lower-bound adjusted R^2 is 3% for the CFNAI-MA3 regression, but 0% for the ANFCI regression. Therefore, the evidence suggests that it is the news about future growth and inflation that matters for explaining the value and momentum effects. Consequently, we construct TRACK1 and TRACK2 with the future change in the CFNAI-MA3 as the dependent variable.

To directly examine if TRACK1 and TRACK2 help explain HML and WML, we estimate Eqs. (7a) to (8b). The results are reported in Panel B of Table 9. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12. Consistent with our conjecture, TRACK1 helps explain HML in that including TRACK1 reduces the Alpha from 0.48 (t = 3.08) to -0.04 (t = -1.23) and increases the adjusted R^2 from 0.10 to 0.97; TRACK2 also helps explain WML in that including TRACK2 reduces the Alpha from 0.72 (t = 4.29) to 0.22 (t = 1.46) and increases the adjusted R^2 from 0.01 to 0.52. Thus, the evidence confirms that HML and WML may be in part driven by the news about future growth and inflation.

3.4.2 Robustness

For robustness, we also consider a number of alternative tracking portfolio specifications. Following Aretz, Bartram, and Pope (2010), Alternative 1 is to add the one-month lagged base asset returns as the conditioning variables in Z to construct the tracking portfolios. The results are reported in the section headed by "Alternative 1" in Table 10. The dependent variable is the future annual change in the CFNAI-MA3. Panel A shows that the base assets returns that capture the value effect (i.e. the market, the size and the value factors) are still driven by the news about future change in the CFNAI-MA3 (the chi-square test is significant at the 5% level); Panel B shows that adding TRACK1 based on the tracking portfolio regression in Panel A can reduce the Alpha of HML from 0.48 (in Table 9) to 0.23 (t = 2.83) and increase the adjusted R^2 from 0.10 (in Table 9) to 0.80.

Similarly, Panel A also shows that the base assets that capture the momentum effect (i.e. the market, the momentum loser and the momentum winner) are still related to the news about future change in the CFNAI-MA3 (the chi-square test is significant at the 5% level); Panel B also shows that adding TRACK2 based on the tracking portfolio regression in Panel A can reduce the Alpha of WML from 0.72 (in Table 9) to 0.18 (t = 1.28) and increase the adjusted R^2 from 0.01 (in Table 9) to 0.56.

Following Kapadia (2011), Alternative 2 is to use a broader set of base assets to construct the tracking portfolios, which as Kapadia (2011) points out can introduce noise. Specifically, we follow Vassalou (2003) and use six Fama-French size and BM portfolios as the base assets to construct TRACK1. In the same spirit, we use six momentum portfolios (i.e. MOM1, MOM2, MOM5, MOM6, MOM9, and MOM10) as the base assets to construct TRACK2. Overall, as expected, the results are weaker yet qualitatively similar. Panel A shows that the value and momentum effects are driven by the news about future changes in the CFNAI-MA3 (the lower-bound adjusted R^2 is 3% for both regressions); Panel B shows that adding TRACK1/TRACK2 helps reduce the Alpha of HML/WML and increase the adjusted R^2.

Since Table 9 shows that pure financial conditions (ANFCI) do not affect HML and WML, we can focus on the CFNAI-MA3, which allows us to extend our sample back to 1967. Therefore, we redo our tests by using the entire sample of the CFNAI-MA3. The results are reported in Table 11 and are qualitatively similar: Panel A shows that the momentum and value effects are related to the news about future changes in CFNAI-MA3 (the chi-square test is significant at the 1% level for both tracking portfolio regressions); Panel B shows that adding TRACK1/TRACK2 helps reduce the Alpha of HML/WML and increase the adjusted R^2.

In brief, the evidence in Tables 9 to 11 suggests that HML and WML may be in part driven by the news about future growth and inflation. In the weakest case (Alternative 2 in Table 10), the news about future CFNAI-MA3 explains 41% of HML and 37% of WML in terms of the time-series regression adjusted R^2. In comparison, the macro variables in Aretz, Bartram, and Pope (2010) explain about 16% of HML and 13% of WML. Thus, we provide stronger evidence for a unifying risk-based explanation for HML and WML.

Table 10. Alternative specifications, February 1975 – July 2011

Panel A: Tracking portfolio regressions

Alternative 1

	TRACK1 Estimate	t-ratio		TRACK2 Estimate	t-ratio
MKT_t	0.031	3.14	MKT_t	0.007	0.47
SMB_t	-0.006	-0.56	$MOM1_t$	0.011	1.33
HML_t	0.010	1.21	$MOM10_t$	0.002	0.29
Constant	-0.821	-2.52	Constant	-0.806	-2.54
RF_t	0.007	0.01	RF_t	0.136	0.21
DEF_{t-1}	0.364	1.77	DEF_{t-1}	0.309	1.30
$TERM_{t-1}$	0.335	3.16	$TERM_{t-1}$	0.352	3.30
y_{t-1}	-0.337	-3.57	y_{t-1}	-0.339	-3.64
MKT_{t-1}	0.028	2.75	MKT_{t-1}	0.001	0.10
SMB_{t-1}	-0.001	-0.06	$MOM1_{t-1}$	0.014	1.89
HML_{t-1}	0.012	1.50	$MOM10_{t-1}$	0.004	0.49
Adj-R^2	0.46		Adj-R^2	0.46	
χ^2 p-value	0.01		χ^2 p-value	0.01	
Lower bound	0.03		Lower bound	0.03	

Alternative 2

	TRACK1 Estimate	t-ratio		TRACK2 Estimate	t-ratio
$SB1_t$	0.010	0.66	$MOM1_t$	0.016	1.59
$SB2_t$	-0.051	-1.72	$MOM2_t$	0.006	0.43
$SB3_t$	0.046	1.71	$MOM5_t$	-0.024	-1.47
$SB4_t$	-0.011	-0.57	$MOM6_t$	0.011	0.63
$SB5_t$	0.052	1.37	$MOM9_t$	0.012	0.68
$SB6_t$	-0.018	-0.72	$MOM10_t$	0.000	0.01
Constant	-0.818	-2.44	Constant	-0.801	-2.47
RF_t	0.040	0.06	RF_t	0.092	0.14
DEF_{t-1}	0.360	1.58	DEF_{t-1}	0.325	1.32
$TERM_{t-1}$	0.342	3.07	$TERM_{t-1}$	0.354	3.21
y_{t-1}	-0.348	-3.63	y_{t-1}	-0.342	-3.51
Adj-R^2	0.44		Adj-R^2	0.44	
χ^2 p-value	0.05		χ^2 p-value	0.10	
Lower bound	0.03		Lower bound	0.03	

Panel B: Explaining HML and WML

Alternative 1

		Estimate	t-value
HML	Constant	0.23	2.83
	MKT	-2.11	-16.67
	TRACK1	68.58	14.19
	Adj-R^2	0.80	
WML	Constant	0.18	1.28
	MKT	1.48	12.89
	TRACK2	-60.00	-17.87
	Adj-R^2	0.56	

Alternative 2

		Estimate	t-value
HML	Constant	0.36	2.74
	MKT	-0.76	-9.37
	TRACK1	19.51	7.54
	Adj-R^2	0.41	
WML	Constant	0.38	1.95
	MKT	0.82	9.10
	TRACK2	-31.71	-11.42
	Adj-R^2	0.37	

The results for the regression of Eq. (5), $y_{t+12} = bR_t + cZ_{t-1} + e_{t+12}$, are in Panel A, where y_{t+12} is the future annual change in the CFNAI-MA3. Alternative 1 is to add the lagged base asset returns as the conditioning variables. Alternative 2 is to use a broader set of base assets. Specifically, $R_t = (SL_t, SM_t, SH_t, BL_t, BM_t, BH_t)'$ and $(MOM1_t, MOM2_t, MOM5_t, MOM6_t, MOM9_t, MOM10_t)'$ represents excess returns: the Fama-French six size-BM portfolios net of the one-month T-Bill rate, and six momentum portfolios net of the one-month T-Bill rate. The tracking portfolio (TRACK1/TRACK2) is a linear combination of base asset returns with the portfolio weights b estimated by Eq. (5). That is, $TRACK_t = \hat{b}R_t$. Panel 2 presents the results of time series regressions of HML and WML on a two-factor model. The two factors are the market factor and the CFNAI-MA3 tacking portfolio (TRACK1/TRACK2) constructed in Panel A. All the t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12

Table 11. Alternative sample, June 1969 – July 2011

Panel A: Tracking portfolio regressions					
	TRACK1			TRACK2	
	Estimate	t-ratio		Estimate	t-ratio
MKT_t	0.035	3.36	MKT_t	0.015	0.93
SMB_t	-0.004	-0.47	$MOM1_t$	0.009	1.01
HML_t	0.012	1.35	$MOM10_t$	0.003	0.40
Constant	-0.874	-2.77	Constant	-0.869	-2.78
RF_t	-0.107	-0.17	RF_t	-0.049	-0.07
DEF_{t-1}	0.456	1.84	DEF_{t-1}	0.432	1.64
$TERM_{t-1}$	0.361	3.48	$TERM_{t-1}$	0.369	3.52
y_{t-1}	-0.285	-3.18	y_{t-1}	-0.284	-3.17
Adj-R^2	0.46		Adj-R^2	0.46	
χ^2 p-value	0.01		χ^2 p-value	0.00	
Lower bound	0.03		Lower bound	0.03	

Panel B: Explaining HML and WML					
		CAPM		Two-factor	
		Estimate	t-value	Estimate	t-value
HML	Constant	0.48	3.51	0.10	1.98
	MKT	-0.21	-2.35	-2.46	-26.00
	TRACK1			70.12	23.39
	Adj-R^2	0.10		0.92	
WML	Constant	0.75	4.99	0.23	1.64
	MKT	-0.14	-1.20	2.11	14.07
	TRACK2			-69.79	-16.44
	Adj-R^2	0.02		0.48	

The results for the regression of Eq. (5), $y_{t+12} = bR_t + cZ_{t-1} + e_{t+12}$, are in Panel A, where y_{t+12} is the future annual change in the CFNAI-MA3, R_t = (MKT_t, SMB_t, HML_t)' and (MKT_t, $MOM1_t$, $MOM10_t$)' represents excess returns: the three Fama-French factors, and the excess returns of the market, the momentum loser and the momentum winner. Z_{t-1} = (RF_{t-1}, DEF_{t-1},$TERM_{t-1}$, y_{t-1})', represents, respectively, the lagged one-month T-Bill rate, the lagged default risk premium, the lagged term premium, and the lagged annual change in the CFNAI-MA3. The tracking portfolio (TRACK1/TRACK2) is a linear combination of base asset returns with the portfolio weights b estimated by Eq. (5). That is, $TRACK_t = \hat{b}R_t$. Panel 2 presents the results of time series regressions of HML and WML on the CAPM and a two-factor model. The two factors are the market factor and the CFNAI-MA3 tacking portfolio (TRACK1/TRACK2) constructed in Panel A. All the t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12.

4. Conclusion

Asset pricing models are of crucial importance to both financial economists and investment practitioners. We first provide a comprehensive examination of three competing asset-pricing models. Our results suggest that the value and momentum factors have pervasive pricing power. The empirical success of the value and momentum factors motivates us to examine what state variables these factors proxy for. Using two broad aggregate indexes and the tracking portfolio methodology, we find that both value and momentum effects are in part explained by the news about future growth and inflation, which suggests a unifying risk-based explanation for the value and momentum effects.

Our findings also have important practical implications. For instance, our findings support the use of the Carhart (1997) four-factor model in applications such as portfolio performance evaluation. In this regard, the finding of Fama and French (2010) that "few funds produce benchmark-adjusted expected returns sufficient to cover their costs" has significant implications to investors (p. 1915). Furthermore, because the momentum factor provides incremental information, a two-way portfolio classification system based on size and value/growth characteristics (such as the one used by Morningstar) may not be sufficient, and a three-way system that takes into account momentum may be more informative.

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