



Do the production-based factors capture the time-varying patterns in stock returns? ☆



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ABSTRACT

As a summarization of previously suggested production-based approaches, [Chen et al. \(2010\)](#) propose two production-based factors. We examine whether the proposed factors explain the time-varying patterns in stock returns, captured by the common conditioning variables. With a variety of test portfolios, we find that the fitted conditional expected return (*fit*) is always statistically significant in the presence of the production-based factors. Moreover, when the *fit* is included in the analysis, the magnitude of the production-based factors becomes consistently smaller and the *fit* drives out the significance of the production-based factors. Our empirical results cast some doubt on the validity of the production-based model as a conditional benchmark for risk adjustment.

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1. Introduction

Understanding the risk and return in stock markets is one of the most fundamental questions in financial economics. In the empirical asset-pricing literature, the Fama–French three-factor model (1993) has served as a benchmark for risk adjustment. However, the empirical performance of the Fama–French model has weakened over the last two decades. For example, it does not capture the momentum effect, and financial distress anomaly.¹

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¹ The fact that stocks with high (low) returns over the preceding several months tend to have high (low) future returns is referred as momentum effect ([Jegadeesh and Titman, 1993](#)). Financial distress anomaly means negative relation between average stock returns and financial distress measured by bankruptcy risk ([Campbell et al., 2008](#)).

Given the failure of the Fama–French three-factor model, researchers have proposed many alternative models. One prominent area of research is the production-based model. From the producer's first order conditions, the production-based model implies that investment should be high when expected returns are low. Since the pioneer work of [Cochrane \(1991\)](#), there is extensive literature investigating the impact of production-based models on expected stock returns ([Cochrane, 1996](#); [Lamont, 2000](#); [Kogan, 2004](#); [Lyandres et al., 2008](#); [Xing, 2008](#); [Liu et al., 2009](#), [Liu and Zhang, 2011](#)). In addition, there have been numerous works on the relation between stock returns and profitability. Prominent examples include [Ball \(1978\)](#), [Basu \(1983\)](#), [Zhang \(2005\)](#), [Fama and French \(2006\)](#), and [Novy-Marx \(in press\)](#). These studies are also linked to the production-based approaches because profitability measures such as earning-to-price ratio, and return on equity can be interpreted as firm characteristics from the production side of economy.

Based on the empirical success of the production-based models, [Chen et al. \(2010, hereafter CNZ\)](#) propose a new three-factor model by summarizing these two strands of previous studies on the production-based approaches. The three factors are (1) market excess return (MKT), (2) investment factor (INV), the difference between the returns on low and high investment-to-asset portfolios, and (3) return-on-assets factor (ROA), the difference between the returns on high and low return-on-asset portfolios. The INV and ROA are production-based factors since they are motivated from production side of economy, while the MKT is from the consumption side of economy.

In the empirical asset-pricing literature, the CNZ model is very important with at least three reasons. First, the CNZ model explains many cross-sectional patterns of average stock returns that the famous Fama–French three-factor model fails to account for, including the momentum effect and the financial distress anomaly. Given the dominance of the Fama–French model in empirical studies, an appearance of a new model which is comparable to the Fama–French model draws much attention. Second, as an analogy to the Fama–French three-factor model, it is a factor pricing model which means that the proposed model is practical due to the availability of high-quality monthly returns data. In other words, the new model can be used for risk adjustment such as calculating costs of equity, and evaluating mutual fund performance. Finally, the CNZ model well summarizes previously suggested successful works on the production-based asset pricing approaches. Therefore, investigating the CNZ model is crucial given the importance of the production-based models as one promising area of research.

The development of a new asset pricing model always triggers further investigation of the proposed model. For example, there is still an ongoing debate surrounding the validity of the widely used Fama–French three-factor model.² Similarly, given the striking empirical performance of the alternative three-factor model, we believe that it is equally interesting to study whether the model indeed performs well.³ In addition, our investigation has one big implication: although we investigate mainly the CNZ model, our work reviews the extensive literature on the production-based models since the factors in the CNZ model well summarizes previous studies in this line of approaches.

There are many empirical methodologies to test the performance of the proposed model. One concrete study is conducted by [Ferson and Harvey \(1999\)](#), who investigate the empirical performance of the Fama–French three-factor model. In this paper, we revisit [Ferson and Harvey \(1999\)](#)'s experiment with the production-based factors. One reason that we choose the Ferson and Harvey's approach is that [CNZ \(2010\)](#) advertise that their model is an alternative of the Fama–French model, and [Ferson and Harvey \(1999\)](#)'s work is one of the most elegant studies which carefully tests the performance of the Fama–French three-factor model. Therefore, the adoption of the Ferson and Harvey's approach fits into our purpose.

Moreover, the Ferson and Harvey's experiment has at least two advantages. First, it enables us to test whether the CNZ model is a good candidate for a conditional model.⁴ Specifically, by adding the fitted conditional expected return (*fit*) predicted by common conditioning variables in the cross-sectional

² [Barry et al. \(2002\)](#) find that the value premium exists in 35 emerging markets. Using the data on North African countries, [Hearn \(2011\)](#) finds that while firm size is a priced factor in Morocco, the empirical results for other North African countries are mixed. [Lischewski and Voronkova \(2012\)](#) document that size and value factors are priced in Polish markets.

³ For example, [Walkshäusl and Lobe \(in press\)](#) investigate the performance of the CNZ model using 40 non-US stock markets. They document that the CNZ model underperforms the Fama–French three-factor model.

⁴ Recent papers in the literature propose empirical methodologies in evaluating conditional asset pricing models. For example, a recent paper by [Nagel and Singleton \(2011\)](#) suggests a methodology when the stochastic discount factor is a conditionally affine function of a set of priced factors. [Ang and Kristensen \(2012\)](#) develop a way to estimate time-varying alphas and betas using nonparametric techniques.

regressions, we test whether the production-based factors capture the time-varying patterns in stock returns. Since [CNZ \(2010\)](#) argue that their model well captures the dynamic patterns in returns, such as the momentum effect, such a test is essentially needed. Second, it provides the specification test of an asset pricing model documented by [Jagannathan and Wang \(1998\)](#). In the asset-pricing literature, whenever a new model is proposed, the specification test is always conducted ([Lettau and Ludvigson, 2001](#); [Petkova, 2006](#)). To the best of our knowledge, we are the first to perform the specification test on the CNZ model.

The central findings are summarized as follows. First, we find that the *fit* is always statistically significant in the presence of the production-based factors. The results are robust to a variety of test portfolios, which indicates that the CNZ model does not capture time-varying patterns in stock returns. Second, when the *fit* is included in the analysis, the magnitude of the production-based factors becomes consistently smaller and the *fit* drives out the significance of the production-based factors. This means that the substantial information content of the production-based factors is subsumed by the *fit*. Finally, among the conditioning variables considered, default spread and term spread play important roles in explaining the cross-section of expected stock returns. Our empirical results cast some doubt on the validity of the CNZ model as a conditional benchmark for risk adjustment. Further, it appears that the production-based asset pricing models do not capture the time-varying patterns in stock returns to the extent that the CNZ model serves as a summarization of the previously proposed production-based models.

The studies closely related to our approach include the work of [Ferson and Harvey \(1999\)](#), [Petkova \(2006\)](#). [Ferson and Harvey \(1999\)](#) argue that the Fama–French three-factor model does not capture the time-varying patterns in equity returns by documenting that the slope on the *fit* is statistically significant when added to the Fama–French factors in the cross-sectional regressions. Conducting similar experiment, [Petkova \(2006\)](#) shows that her model better captures time-varying patterns in returns than the Fama–French three-factor model does. Whereas their main questions are to investigate whether the Fama–French three-factor model captures the time-varying patterns in equity returns, our study attempts to understand the performance of the production-based approaches. Therefore, this paper contributes to the extensive literature on testing the validity of the asset pricing models by providing empirical evidence on the performance of the production-based models.

The remainder of this paper is organized as follows. [Section 2](#) introduces related literature. [Section 3](#) describes the data and empirical methodology. [Section 4](#) presents empirical evidence and [Section 5](#) discusses the robustness of the results. [Section 6](#) summarizes and presents our conclusions.

2. Related literature

In terms of the empirical approach, our paper is motivated by [Ferson and Harvey \(1999\)](#), who investigate whether the Fama–French three-factor model captures the time-varying patterns in stock returns. While applying Ferson and Harvey's methodology, we innovate by focusing on the production-based models. Launched by [Cochrane \(1991\)](#) as an analogy to the consumption-based asset pricing model, the production-based approaches have drawn much attention in the asset-pricing literature ([Cochrane, 1996](#); [Lamont, 2000](#); [Kogan, 2004](#); [Lyandres et al., 2008](#); [Xing, 2008](#); [Liu et al., 2009](#), [Liu and Zhang, 2011](#)). One reason is that the production-based models explain anomalous return patterns which the CAPM, Fama–French three-factor model, and consumption-based models cannot explain.⁵ For example, [Lyandres et al. \(2008\)](#) document that adding a production-based factor into the CAPM and Fama–French three-factor model helps to account for the underperformance following the initial public offerings, and seasoned equity offerings. In addition, [Liu et al. \(2009\)](#) provide the empirical evidence that a production-based model describes portfolios sorted on earnings surprises, book-to-market ratio, and capital investment. Despite the striking empirical success of the production-based models, a specification test on these models has not been conducted. Since the CNZ model serves as a summarization of the previously proposed production-based models, our analysis of the CNZ model is meaningful in that we test empirical performance of the production-based model as an asset pricing model.

⁵ Despite the striking performance, the production-based models have some shortcomings. For example, although [Liu and Zhang \(2011\)](#) show that production-based models explain momentum profits and return reversals, they create counter-cyclical momentum profits. However, a large number of studies show that momentum profits are strongly pro-cyclical ([Cooper et al. 2004](#)). As a result, while these models are promising, they do not explain all anomalies.

Our work is also related to the conditional asset pricing models. Theoretically, using the linear factor models such as the Fama–French three-factor model and the CNZ model is equivalent to assuming that the stochastic discount factor is a linear function of factors. However, since the foundation of a linear factor model is based on the conditional Euler equation, factor loadings can vary as the information set changes over time. Therefore, incorporating the conditioning information into such a model is important. One simple way is to model betas of factors as linear functions of lagged conditioning variables (Shanken, 1990; Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001; Petkova and Zhang, 2005; Avramov and Chordia, 2006). Following this line of research, we implement a conditional version of the CNZ model, and investigate whether it may serve as a conditional asset pricing model.

3. Data and empirical methodology

3.1. Data

We use monthly data from January 1972 to June 2009. We obtain monthly returns on the production-based factors from Long Chen. The construction of INV and ROA is very similar to that of SMB and HML in Fama and French (1993). Specifically, at the end of June in each year, all stocks listed on NYSE, AMEX, and NASDAQ are sorted into two size groups using the median NYSE market equity and three investment-to-asset groups (30%, 40%, 30%).⁶ Then, INV is the simple average of the differences between the value-weighted returns on low and high investment-to-assets portfolios in each size. Construction of ROA factor is identical to the construction of INV except that the portfolios are rebalanced monthly. The market excess return (MKT) and one-month Treasury bill rate data are from Kenneth French's website.

For test assets, we use 25 size and momentum sorted portfolios, and 25 size and book-to-market sorted portfolios.⁷ We study these portfolios because CNZ (2010) emphasize the empirical success in explaining the momentum effect, and 25 size and book-to-market sorted portfolios have been a standard playground for evaluating asset pricing models over the last two decades. Our choice of various test portfolios is also consistent with the suggestion in Lewellen et al. (2010).

Following Petkova and Zhang (2005), and other time-series predictability literature, we use lagged dividend yield (DIV), term spread (TERM), default spread (DEF), and one-month Treasury bill rate (RF) as conditioning variables.⁸ DIV is defined as the sum of dividends of CRSP value-weighted portfolio over 12 months relative to the level of the index. TERM is the difference between the yields of a 10-year and a 1-year government bonds. DEF is the difference between the yields on Moody's Baa and Aaa corporate bonds. Bond yield data are from FRED® database of the Federal Reserve Bank of St. Louis.

Panel A of Table 1 presents the correlations between the production-based factors and the traditional common factors. The high correlation of 0.45 between INV and HML is observed, and ROA has a strong negative correlation of -0.43 with SMB. In Panel B, the average returns of the new factors are positive and statistically significant; the average returns of INV and ROA are 0.28% (t -statistic of 3.21) and 0.76% (t -statistic of 3.84) per month, respectively.

3.2. Empirical methodology

3.2.1. Time-varying beta tests

Our goal is to investigate whether the lagged conditioning variables have explanatory power in the presence of the production-based factors. Although we find empirical evidence for this, one may argue that additional variables proxy for time-variation in the production-based factor betas (Ferson and Harvey,

⁶ Following CNZ (2010), investment-to-assets is defined as the annual change in gross property, plant, and equipment plus the annual change in inventories divided by the lagged book value of assets.

⁷ These data are from Kenneth French's website. For momentum portfolios, following Fama and French (1996), we use the "11/1/1" convention. Specifically, at the beginning of each month t , stocks are sorted by their prior returns from month $t-2$ to $t-11$. Skipping month $t-1$, portfolio returns are evaluated in month t . We also employ the "6/1/6" convention, and using "6/1/6" convention does not alter the empirical results.

⁸ We use the most widely used conditioning variables for forecasting the future returns. See, for example, Fama and French (1988) for the dividend yield, Fama and French (1989) for the term spread, Keim and Stambaugh (1986) for the default spread, and Ferson (1989) for the short-term interest rate.

Table 1

Summary statistics. Panel A presents the correlation coefficients between the CNZ factors and the traditional common factors. Panel B shows the monthly percentage mean returns of the factors and *t*-values. MKT is the realized market excess returns on the CRSP value-weighted index; INV is the difference between the returns on low-investment portfolios and high-investment portfolios; ROA is the difference between the returns on high-returns-on-asset portfolios and low-returns-on-asset portfolios; SMB is the difference between the returns of small stock portfolios and large stock portfolios; HML is the difference between the returns of value stock portfolios and growth stock portfolios; WML is the return difference between high-past-return portfolios and low-past-return portfolios. The sample period is from January 1972 to June 2009.

	MKT	INV	ROA	SMB	HML	WML
<i>Panel A: Correlation matrix</i>						
MKT	1.00	−0.26	−0.26	−0.26	−0.36	−0.14
INV		1.00	−0.03	0.00	0.45	0.04
ROA			1.00	−0.43	0.20	0.30
SMB				1.00	−0.26	−0.01
HML					1.00	−0.15
WML						1.00
<i>Panel B: Monthly percentage mean returns</i>						
Mean return	0.39	0.28	0.76	0.19	0.42	0.78
<i>t</i> -value	1.79	3.21	3.84	1.25	2.90	3.58

1999). Therefore, in addition to unconditional models, we test our hypothesis with conditional models in which the factor loadings are time-varying.

The unconditional equation is given by

$$r_t^i - r_t^f = \alpha^i + \beta_{\text{MKT}}^i \text{MKT}_t + \beta_{\text{INV}}^i \text{INV}_t + \beta_{\text{ROA}}^i \text{ROA}_t + \epsilon_t^i \quad (1)$$

For conditional models, we assume that betas are linear functions of lagged conditioning variables (Lettau and Ludvigson, 2001; Shanken, 1990).

$$\beta_{j,t}^i = b_{0,j}^i + b_{1,j}^i \text{DIV}_{t-1} + b_{2,j}^i \text{TERM}_{t-1} + b_{3,j}^i \text{DEF}_{t-1} + b_{4,j}^i \text{RF}_{t-1} = b_{0,j}^i + (b_j^i)' Z_{t-1} \quad (2)$$

where $Z_{t-1} = \begin{bmatrix} \text{DIV}_{t-1} \\ \text{TERM}_{t-1} \\ \text{DEF}_{t-1} \\ \text{RF}_{t-1} \end{bmatrix}$, b_j^i is a 4×1 coefficient matrix. We further assume that the alphas are time-varying

(Ferson et al., 2008; Jagannathan and Wang, 1996).

$$\alpha_t^i = a_0^i + a_1^i \text{DIV}_{t-1} + a_2^i \text{TERM}_{t-1} + a_3^i \text{DEF}_{t-1} + a_4^i \text{RF}_{t-1} = a_0^i + (a^i)' Z_{t-1} \quad (3)$$

Substituting Eqs. (2) and (3) into Eq. (1), we have following conditional equation:

$$r_t^i - r_t^f = a_0^i + (a^i)' Z_{t-1} + (b_{0,\text{MKT}}^i + b_{\text{MKT}}^{i'} Z_{t-1}) \text{MKT}_t + (b_{0,\text{INV}}^i + b_{\text{INV}}^{i'} Z_{t-1}) \text{INV}_t + (b_{0,\text{ROA}}^i + b_{\text{ROA}}^{i'} Z_{t-1}) \text{ROA}_t + \epsilon_t^i \quad (4)$$

Comparing this conditional version of the CNZ model with the unconditional Eq. (1), the unconditional one is a restricted version of the Eq. (4), with the restrictions $a^i = 0, b_j^i = 0$.

By performing specification test with these restrictions, we can determine whether the factor loadings are time-varying.

3.2.2. Cross-sectional tests

To test whether the expected returns captured by the common conditioning variables have additional explanatory power in the presence of the production-based factors, we run the cross-sectional regressions.

Following Ferson and Harvey (1999), we construct the *fit* variable, which is the conditional expected return of each test portfolio using the information at time $t-1$. Specifically, we regress portfolio excess returns on a constant and four lagged instrumental variables (DIV, TERM, DEF, RF). Then, the *fit* variable for portfolio i at time t is defined as the fitted value of the regression,

$$r_t^i - r_t^f = c_{0t} + c_{1t} \text{DIV}_{t-1} + c_{2t} \text{TERM}_{t-1} + c_{3t} \text{DEF}_{t-1} + c_{4t} \text{RF}_{t-1} + e_t^i \quad (5)$$

where c_0 and c_t are the estimated coefficients from time-series regression. We construct the *fit* variable using data up to time $t-1$ for the lagged instruments. For the first 60 months, we use c_t from the 60-month time-series predictive regression. After the first 60-month periods, following Ferson and Harvey (1999), we obtain the *fit* variable with expanding sample method, which is described below.

We estimate betas from the time-series regressions in two different ways, namely, expanding sample and 60-month rolling sample methodology. For the first 60-month periods, we use the first 60 samples to compute betas in both methods. In the expanding sample method, we use data from time 1 to time t to

Table 2

Time-series regressions. This table displays the time-series alphas and their t -values of the following time-series regressions. Newey–West HAC covariance matrices with 5 lags are used for the calculation of t -values.

$$r_{it} - r_{ft} = \alpha_i + \beta_{\text{MKT},i} \text{MKT}_t + \beta_{\text{INV},i} \text{INV}_t + \beta_{\text{ROA},i} \text{ROA}_t + \epsilon_{it}$$

Panel A shows the time-series alphas and their t -values of 25 size and momentum portfolios, and Panel B depicts the time-series alphas and their t -values of 25 size and book-to-market portfolios. Gibbons, Ross, and Shanken (1989) F-statistics (FGRS), and their p -values (pGRS) are in the parentheses. W-L stands for the Winner-minus-Loser portfolio, which is the difference between the highest and the lowest short-term prior return portfolios. V-G is the Value-minus-Growth portfolio, which is the difference between the highest and the lowest book-to-market portfolios. The sample period is from January 1972 to June 2009.

Panel A: Size and momentum sorted portfolios													
		Loser	2	3	4	Winner	W-L	Loser	2	3	4	Winner	W-L
		Alpha						t -value ($F_{\text{GRS}} = 3.09$, $p_{\text{GRS}} = 0.00$)					
CNZ model	Small	−0.14	0.19	0.36	0.56	1.00	1.14	−0.49	1.05	2.20	3.17	3.74	3.28
	2	−0.13	0.12	0.25	0.41	0.73	0.86	−0.56	0.70	1.93	2.88	3.15	2.49
	3	0.01	−0.06	0.05	0.11	0.65	0.64	0.03	−0.39	0.37	1.02	3.12	1.72
	4	−0.13	−0.06	−0.07	0.08	0.42	0.55	−0.48	−0.40	−0.58	0.80	2.13	1.31
	Big	−0.33	−0.12	−0.27	−0.12	0.14	0.48	−1.23	−0.76	−2.84	−1.66	1.02	1.25
		Alpha						t -value ($F_{\text{GRS}} = 4.40$, $p_{\text{GRS}} = 0.00$)					
FF model	Small	−1.10	−0.28	0.03	0.28	0.71	1.81	−6.26	−3.03	0.43	3.31	5.27	7.43
	2	−0.90	−0.27	0.06	0.24	0.56	1.46	−5.38	−2.53	0.72	3.27	5.17	6.07
	3	−0.63	−0.31	−0.11	0.08	0.59	1.21	−3.43	−2.76	−1.14	0.96	5.48	4.71
	4	−0.71	−0.20	−0.10	0.15	0.47	1.18	−3.49	−1.70	−0.95	1.66	3.98	4.22
	Big	−0.58	−0.12	−0.16	0.13	0.39	0.98	−2.71	−0.94	−2.05	1.62	3.22	3.30
Panel B: Size and B/M sorted portfolios													
		Growth	2	3	4	Value	V-G	Growth	2	3	4	Value	V-G
		Alpha						t -value ($F_{\text{GRS}} = 2.77$, $p_{\text{GRS}} = 0.00$)					
CNZ model	Small	0.01	0.59	0.43	0.55	0.61	0.60	0.03	2.27	2.24	2.90	3.18	2.26
	2	0.11	0.22	0.34	0.37	0.36	0.25	0.51	1.48	2.49	2.47	1.92	1.02
	3	0.15	0.16	0.18	0.19	0.40	0.25	0.92	1.36	1.47	1.34	2.26	1.02
	4	0.18	−0.07	0.03	0.18	0.08	−0.10	1.03	−0.68	0.28	1.56	0.52	−0.37
	Big	−0.09	−0.06	−0.10	−0.09	0.08	0.17	−0.96	−0.74	−0.92	−0.61	0.53	0.81
		Alpha						t -value ($F_{\text{GRS}} = 2.92$, $p_{\text{GRS}} = 0.00$)					
FF model	Small	−0.53	0.06	0.06	0.18	0.12	0.64	−4.42	0.73	0.96	2.44	1.58	4.74
	2	−0.19	−0.04	0.09	0.08	−0.05	0.14	−2.53	−0.56	1.38	1.08	−0.66	1.41
	3	−0.04	0.01	0.02	−0.01	0.13	0.16	−0.57	0.14	0.22	−0.08	1.12	1.20
	4	0.12	−0.09	−0.07	0.00	−0.10	−0.22	1.47	−0.91	−0.73	0.03	−1.19	−2.03
	Big	0.16	0.11	−0.05	−0.14	−0.14	−0.30	2.57	1.34	−0.56	−2.05	−1.26	−2.24

obtain the beta at time t . In the rolling window method, we use data from time $t - 59$ to time t to compute the beta at time t . Finally, with betas and the fit variables, we run the following cross-sectional regressions.

$$r_t^i - r_t^f = \gamma_0 + \gamma_{MKT} \beta_{MKT,t}^i + \gamma_{INV} \beta_{INV,t}^i + \gamma_{ROA} \beta_{ROA,t}^i + \gamma_{fit} fit_t^i + \nu_t^i, t = 1, 2, \dots, T \tag{6}$$

We report time-series averages of γ s from the cross-sectional regressions in each period. Following the spirit of Fama and MacBeth (1973), we estimate t -values on betas and the fit variable by dividing the estimates with their standard errors. It allows us to examine whether the CNZ model is missing some important information about the patterns in the cross-section of the conditional expected returns captured by common conditioning variables.

4. Empirical evidence

4.1. Performance of the production-based model

Table 2 illustrates the time-series regression results of the CNZ model and the Fama–French model. In each panel, we report the time-series alphas, their t -values, and Gibbons, Ross, and Shanken (1989, hereafter GRS) F -statistics. Panel A shows the results when the dependent variables are the 25 size and momentum sorted portfolios. W-L stands for the Winner-minus-Loser portfolio, which is the difference between the highest and the lowest short-term prior return portfolios. Several features of the empirical

Table 3
Time-varying beta tests for the 25 size and momentum portfolios. This table shows the results of time-varying beta tests with 25 size and momentum sorted portfolios. Each row represents the result of different portfolio. The first digit represents the size quintiles of the portfolios (1 indicating the smallest and 5 the largest), while the second digit refers to the past return quintiles of the portfolios (1 indicating the lowest and 5 the highest). Panel A reports the results with constant alphas, and Panel B displays the results with time-varying alphas. In the first and second columns of each panel, the adjusted R -squares of constant-beta and time-varying beta models are presented. In the third column of each panel, the p -values of F -test to examine whether the constant-beta model restrictions are valid are reported. The sample period is from January 1972 to June 2009.

Portfolio	Panel A: Constant alphas			Panel B: Time-varying alphas		
	R^2 constant betas	R^2 time-varying betas	F -test (p-value)	R^2 constant betas	R^2 time-varying betas	F -test (p-value)
11	0.697	0.736	0.000	0.687	0.733	0.000
12	0.673	0.731	0.000	0.670	0.730	0.000
13	0.679	0.724	0.000	0.676	0.722	0.000
14	0.687	0.727	0.000	0.684	0.726	0.000
15	0.668	0.714	0.000	0.670	0.715	0.000
21	0.744	0.795	0.000	0.737	0.792	0.000
22	0.719	0.766	0.000	0.714	0.765	0.000
23	0.755	0.790	0.000	0.754	0.791	0.000
24	0.759	0.786	0.000	0.758	0.786	0.000
25	0.722	0.757	0.000	0.724	0.759	0.000
31	0.728	0.776	0.000	0.723	0.773	0.000
32	0.778	0.822	0.000	0.775	0.820	0.000
33	0.795	0.841	0.000	0.790	0.838	0.000
34	0.815	0.835	0.000	0.815	0.834	0.000
35	0.745	0.775	0.000	0.745	0.775	0.000
41	0.696	0.766	0.000	0.697	0.764	0.000
42	0.783	0.839	0.000	0.780	0.838	0.000
43	0.838	0.882	0.000	0.833	0.879	0.000
44	0.875	0.893	0.000	0.874	0.892	0.000
45	0.754	0.789	0.000	0.755	0.788	0.000
51	0.646	0.699	0.000	0.646	0.698	0.000
52	0.710	0.760	0.000	0.710	0.758	0.000
53	0.841	0.850	0.000	0.842	0.851	0.000
54	0.867	0.872	0.003	0.867	0.873	0.003
55	0.770	0.802	0.000	0.767	0.800	0.000

findings are worth highlighting. First, while the alphas of any W-L portfolios are positively significant in the Fama–French model, the alphas of the three largest W-L portfolios are not statistically significant in the CNZ model. In addition, after controlling for the production-based factors, the alpha of the smallest W-L portfolio is reduced by 37% compared to the Fama–French model, though it is statistically significant. Explaining the dynamic patterns in returns such as momentum profit is an important innovation of the production-based model. Second, although the CNZ model does a better job in explaining the momentum effect than the Fama–French model, the GRS F -statistic ($F = 3.09$ and p -value = 0.00) rejects the hypothesis that alphas are jointly zero.

In Panel B, we use 25 size and book-to-market sorted portfolios. While the performance is comparable to the Fama–French model, the CNZ model does a good job in explaining the return behavior of the small-growth portfolio. Since a linear asset pricing model, such as the Fama–French model, does not explain the small-growth stocks, a low alpha in small-growth portfolio is a performance gain for the production-based model.

In sum, the CNZ model performs better than the Fama–French three-factor model in explaining the momentum effect, and its performance is comparable to the Fama–French model in capturing the size and book-to-market effects. Given the striking empirical performance combined with the fact that the model effectively summarizes previously proposed production-based approaches, it is worthwhile to investigate empirical performance of the CNZ model as an asset pricing model.

4.2. Necessity of conditional model

In the next subsection, we examine whether the lagged predictive variables have explanatory power in the presence of the production-based factors. Although we document empirical evidence for this, one may argue that these variables proxy for time-variation in the CNZ factor betas. Therefore, in addition to unconditional models, we test our hypothesis with conditional models in which the factor loadings are time-varying.

To investigate whether the factor loadings are time-varying, we conduct the time-varying beta tests discussed in Section 3. Table 3 shows the results with 25 size and momentum sorted portfolios, and we align the result of each portfolio in each row. The first digit represents the size quintiles of the portfolios (1 indicating the smallest and 5 the largest), while the second digit refers to the past return quintiles of the portfolios (1 indicating the lowest and 5 the highest). Panel A reports the results with constant alphas, and Panel B displays the results with time-varying alphas. In the first and second columns of each panel, the adjusted R -squares of constant-beta and time-varying beta models are presented. In the third column of each panel, we report the p -values of F -test to examine whether the constant-beta model restrictions are valid. The results indicate that the constant-beta restrictions are rejected regardless of portfolio considered.

We perform time-varying beta tests with 25 size and book-to-market sorted portfolios, and the empirical results are identical. We also test other anomalous portfolios discussed in CNZ (2010), such as Campbell et al. (2008) failure probability sorted portfolios, Ohlson (1980) O-score sorted portfolios, and standard unexpected earnings (SUE) portfolios. Although the results are not reported for the sake of brevity, the specification test for detecting time-varying betas strongly rejects the unconditional CNZ model regardless of the anomalous portfolios considered. Therefore, to investigate whether the lagged conditioning variables indeed have explanatory power in the presence of the production-based factors, we need to examine the conditional models as well.⁹

4.3. Evidence from cross-sectional regressions

In this subsection, we perform the cross-sectional regressions of Eq. (6) with the *fit* variable. The purpose of the cross-sectional regressions is twofold. First, the results allow us to investigate whether the

⁹ We also investigate whether the incorporation of time-varying betas improves the performance of the CNZ model by looking at the alphas. The empirical results show that the alphas under the time-varying beta specifications are not jointly zero. Thus, a conditional version of the CNZ model is also rejected, which is consistent with the results in Section 4. However, we do not display the results of time-varying alpha tests since our goal is not to improve the performance of the CNZ model.

Table 4

Cross sectional regressions. This table shows the results of the following cross-sectional regressions.

$$r_t^i - r_t^f = \gamma_0 + \gamma_{\text{MKT}} \beta_{\text{MKT},t}^i + \gamma_{\text{INV}} \beta_{\text{INV},t}^i + \gamma_{\text{ROA}} \beta_{\text{ROA},t}^i + \gamma_{\text{fit}} \text{fit}_t^i + v_t^i, t = 1, 2, \dots, T$$

Each column identifies different test assets. In each column and each panel, we report time-series averages of coefficients, and their Fama and MacBeth *t*-ratios are revealed in the second row. Panel A shows estimates with expanding sample betas; Panel B reports results with 60-month rolling sample betas; Panel C displays results of expanding samples with conditional betas; Panel D reports estimates of 60-month rolling samples with conditional betas. *fit* is the conditional expected return of each test portfolio using the information at time $t-1$. The sample period is from January 1972 to June 2009.

Column 1: 25 Size and momentum sorted portfolios						Column 2: 25 Size and B/M sorted portfolios				
	Intercept	MKT	INV	ROA	<i>fit</i>	Intercept	MKT	INV	ROA	<i>fit</i>
<i>Panel A: With expanding sample betas</i>										
Estimate	0.22	0.20	1.60	0.14		0.64	−0.21	0.87	−0.03	
<i>t</i> -value	0.35	0.34	4.74	0.47		1.91	−0.56	3.88	−0.11	
Estimate	0.12				0.85	0.03				0.66
<i>t</i> -value	0.45				8.26	0.11				6.55
Estimate	−0.41	0.43	0.07	−0.01	1.02	−0.09	0.06	0.02	0.08	0.78
<i>t</i> -value	−0.83	0.86	0.22	−0.03	9.37	−0.27	0.17	0.10	0.29	10.83
<i>Panel B: With 60-period rolling sample betas</i>										
Estimate	0.87	−0.39	0.61	0.21		1.32	−0.88	0.46	0.07	
<i>t</i> -value	3.08	−1.09	3.15	0.82		4.79	−2.55	3.22	0.32	
Estimate	0.12				0.85	0.03				0.66
<i>t</i> -value	0.45				8.26	0.11				6.55
Estimate	0.48	−0.44	−0.29	−0.01	1.06	0.63	−0.67	−0.34	0.06	0.81
<i>t</i> -value	1.66	−1.26	−1.64	−0.06	12.93	2.20	−2.04	−2.22	0.24	10.50
<i>Panel C: With expanding sample conditional betas</i>										
Estimate	0.64	−0.07	0.52	0.42		1.34	−0.84	0.42	0.28	
<i>t</i> -value	2.48	−0.22	2.83	1.68		5.60	−2.71	3.60	1.27	
Estimate	0.12				0.85	0.03				0.66
<i>t</i> -value	0.45				8.26	0.11				6.55
Estimate	0.09	0.16	−0.22	0.16	0.90	0.36	−0.33	−0.10	−0.02	0.71
<i>t</i> -value	0.35	0.49	−1.31	0.67	10.40	1.44	−1.06	−0.86	−0.07	10.44
<i>Panel D: With 60-period rolling sample conditional betas</i>										
Estimate	0.26	0.30	0.17	0.48		0.63	−0.16	0.35	0.28	
<i>t</i> -value	2.02	1.22	1.52	2.10		4.82	−0.66	3.37	1.30	
Estimate	0.12				0.85	0.03				0.66
<i>t</i> -value	0.45				8.26	0.11				6.55
Estimate	0.09	0.30	0.05	0.28	0.70	0.22	0.01	0.13	0.29	0.53
<i>t</i> -value	0.62	1.25	0.53	1.26	11.28	1.48	0.04	1.25	1.33	9.81

expected returns predicted by the conditioning variables have additional explanatory power in the presence of the CNZ factors. Specifically, if the coefficient on the *fit* in Eq. (6) is zero, the production-based factor betas explain the cross-section of stock returns. On the other hand, if the slope on the *fit* in Eq. (6) is statistically significant, the production-based factors do not capture the conditional expected returns forecasted by the predictive variables. Second, as documented by Petkova (2006), the experiment provides the specification test of an asset pricing model (Jagannathan and Wang, 1998).¹⁰

Table 4 displays the results of the cross-sectional regressions. For robustness, we estimate betas with different ways. Specifically, Panel A shows estimates with expanding sample betas; Panel B reports results with 60-month rolling sample betas; Panel C displays results of expanding samples with conditional betas; Panel D reports estimates of 60-month rolling samples with conditional betas. In each column and panel, time-series averages of coefficients are reported in the first row, and their Fama and MacBeth (1973) *t*-ratios are revealed in the second row. We perform three versions of cross-sectional regressions. First,

¹⁰ Jagannathan and Wang (1998) show that if an asset pricing model is mis-specified, the estimated coefficients in cross-sectional regressions are biased. Thus, if we add another variable (e.g., portfolio characteristics such as size, or book-to-market) into the regressions and its coefficient is significant, it indicates that the model is mis-specified.

we only use the CNZ factors (MKT, INV, and ROA). Second, we employ the *fit* variable alone as the independent variable. Finally, the CNZ factors and the *fit* variable are used as independent variables together.

In the first specification, the coefficients of INV are positive and statistically significant in seven out of eight cases showing that the INV has explanatory power to describe the cross-sectional variation of average stock returns. This finding confirms the empirical success of the previously suggested production-based approaches. However, coefficient on ROA is not statistically significant in most cases.

In the second specification, the coefficient on the *fit* has a range of 0.66–0.85 and is always significant. Therefore, the expected stock returns captured by the common conditioning variables have a strong power to explain the cross-section of stock returns. If the *fit* serves as a perfect proxy for the expected return, the estimate on the *fit* variable should be one. However, we employ only the subset of available information, the results seem natural.

We now examine the explanatory power of the *fit* in the presence of the production-based factors. The hypothesis that the production-based model accounts for the cross-section of expected stock return means that the estimate on the *fit* is zero. The results show that the coefficient on the *fit* in any consideration is positive and highly significant with *t*-ratios over 9, which indicates a strong rejection of the production-based model. That is, the production-based factors do not capture the conditional expected returns forecasted by common predictive variables. More importantly, when the *fit* is included, the magnitude of the production-based factors tends to be smaller and the *fit* drives out the significance of the production-based factors. For example, for seven out of eight cases, the coefficient on INV is not statistically significant in the presence of the *fit* variable.¹¹ Thus, empirical results in Table 4 strongly reject the production-based model, indicating that the production-based model is missing some important information about the patterns in the cross-section of the conditional expected returns captured by common conditioning variables. In addition, the explanatory power of conditioning variables to explain the cross-section of stock returns provides a strong rejection of the production-based model as a conditional asset pricing model.

5. Robustness test

5.1. Evidence from individual conditioning variable

Given the strong rejection of the production-based model, we investigate relative importance of each conditioning variable in this subsection. To this end, we rerun the cross-sectional regressions except that we put the factor loading of each conditioning variable in the place of the *fit* variable.

$$r_t^i - r_t^f = \gamma_0 + \gamma_{\text{MKT}} \beta_{\text{MKT},t}^i + \gamma_{\text{INV}} \beta_{\text{INV},t}^i + \gamma_{\text{ROA}} \beta_{\text{ROA},t}^i + \gamma_{\delta} \delta_{\text{CV},t}^i + \varepsilon_t^i, t = 1, 2, \dots, T \quad (7)$$

where $\delta_{\text{CV},t}^i$ is the loading from the time-series regression $r_t^i - r_t^f = \alpha^i + \delta_{\text{CV},t}^i \text{CV}_{t-1} + \eta_b^i$ and CV_{t-1} is one of the four conditioning variables at time $t-1$.

Table 5 reports the empirical results. Panel A and B show the results with 25 size and momentum, and 25 size and book-to-market portfolios, respectively. In each panel, we estimate betas with different ways. Specifically, model 1 shows estimates with expanding sample betas; model 2 reports results with 60-month rolling sample betas; model 3 displays results of expanding samples with conditional betas; model 4 reports estimates of 60-month rolling samples with conditional betas. In each panel and model, the first row shows the time-series averages of coefficients, and their Fama and MacBeth (1973) *t*-ratios are in the second row.

Table 5 shows that some of the estimates on conditioning variable are statistically significant, and the significance is especially pronounced when we use the conditional betas. For default spread (DEF), 5 out of 8 estimated coefficients on CV are significant at the 5% significant level in the presence of the production-

¹¹ Following Ferson and Harvey (1999), the *fit* variable is constructed from expanding sample regressions. However, one may argue that rolling window analysis is more adequate to the “conditional” sense. We perform the above analyses with 60-month rolling window regressions. The results with rolling window analysis show that the *fit* is still highly significant and the magnitude of estimated coefficients and *t*-values are even higher than the results in Table 4. At the same time, the significance of the cross-sectional coefficients of ROA and INV is driven out. Thus, our results are robust to the construction method of the *fit* variable.

Table 5

Cross-sectional regressions with individual conditioning variables. This table displays the results of the following cross-sectional regressions.

$$r_t^i - r_t^f = \gamma_0 + \gamma_{\text{MKT}} \beta_{\text{MKT},t}^i + \gamma_{\text{INV}} \beta_{\text{INV},t}^i + \gamma_{\text{ROA}} \beta_{\text{ROA},t}^i + \gamma_6 \delta_{\text{CV},t}^i + \varepsilon_t^i, t = 1, 2, \dots, T$$

where $\delta_{\text{CV},t}^i$ is the loading from the time-series regression $r_t^i - r_t^f = \alpha^i + \delta_{\text{CV},t}^i \text{CV}_{t-1} + \eta_t^i$, and CV_{t-1} is one of the four conditioning variables at time $t-1$.

Panel A shows the results with 25 size and momentum, and Panel B presents the results with 25 size and book-to-market portfolios. In each panel, betas are estimated with different ways. Specifically, model 1 shows estimates with expanding sample betas; model 2 reports results with 60-month rolling sample betas; model 3 displays results of expanding samples with conditional betas; model 4 reports estimates of 60-month rolling samples with conditional betas. In each panel and model, the first row shows the time-series average of coefficients, and their [Fama and MacBeth \(1973\)](#) t -ratios are in the second row. The sample period is from January 1972 to June 2009.

		DIV					DEF					RF					TERM				
		Intercept	MKT	INV	ROA	CV	Intercept	MKT	INV	ROA	CV	Intercept	MKT	INV	ROA	CV	Intercept	MKT	INV	ROA	CV
<i>Panel A: 25 size and momentum sorted portfolios</i>																					
Model 1	Estimate	0.11	0.43	1.90	0.06	−0.72	0.04	0.12	1.54	0.19	0.16	0.29	0.10	1.47	0.33	−0.06	−0.16	0.40	1.29	0.42	0.66
	t -value	0.18	0.68	5.23	0.20	−2.12	0.07	0.19	3.48	0.67	1.02	0.44	0.17	4.24	1.11	−0.72	−0.29	0.75	3.57	1.38	1.56
Model 2	Estimate	1.29	−0.91	0.50	0.41	−0.06	0.77	−0.46	0.51	0.30	0.15	0.96	−0.39	0.55	0.36	0.06	1.13	−0.46	0.62	0.30	−0.18
	t -value	4.81	−2.53	2.60	1.66	−0.24	2.48	−1.29	2.57	1.21	1.56	3.43	−1.08	2.84	1.37	0.90	2.94	−1.25	3.14	1.20	−0.48
Model 3	Estimate	0.81	−0.32	0.41	0.62	0.08	0.47	−0.11	0.55	0.49	0.19	0.49	0.10	0.56	0.44	−0.02	0.56	0.00	0.50	0.51	0.19
	t -value	3.20	−0.98	2.22	2.47	0.30	1.77	−0.34	2.84	1.98	2.05	1.90	0.30	2.94	1.66	−0.36	1.64	0.01	2.87	2.06	0.53
Model 4	Estimate	0.22	0.17	0.22	0.52	0.14	0.11	0.13	0.23	0.56	0.23	0.29	0.30	0.15	0.50	0.01	0.33	0.24	0.21	0.53	0.22
	t -value	1.58	0.66	2.00	2.33	0.75	0.65	0.53	2.13	2.49	3.03	2.21	1.21	1.31	2.10	0.18	1.63	0.98	1.87	2.32	0.84
<i>Panel B: 25 size and book-to-market sorted portfolios</i>																					
Model 1	Estimate	0.33	0.20	0.85	−0.23	−0.37	0.76	−0.63	0.73	0.08	0.20	0.68	−0.26	0.78	−0.03	−0.01	0.61	−0.54	0.81	0.11	0.80
	t -value	1.11	0.55	3.99	−0.77	−1.81	2.50	−1.71	3.38	0.28	2.14	2.01	−0.71	3.54	−0.12	−0.28	1.69	−1.49	3.62	0.39	3.03
Model 2	Estimate	1.66	−1.05	0.29	−0.11	−0.31	1.39	−0.99	0.32	0.02	0.05	1.57	−1.14	0.35	0.15	0.00	0.88	−0.78	0.59	0.21	0.78
	t -value	7.41	−3.36	2.04	−0.49	−1.47	4.99	−3.08	2.27	0.07	0.56	5.81	−3.39	2.40	0.65	0.07	2.66	−2.30	4.10	0.88	2.81
Model 3	Estimate	1.23	−0.66	0.28	0.05	−0.19	0.76	−0.72	0.45	0.31	0.27	1.36	−0.86	0.33	0.17	0.05	0.64	−0.61	0.46	0.24	1.09
	t -value	5.60	−2.24	2.27	0.22	−0.94	2.95	−2.50	3.79	1.40	2.97	5.80	−2.84	2.80	0.77	0.93	2.32	−2.05	4.01	1.10	4.21
Model 4	Estimate	0.67	−0.19	0.28	0.20	−0.15	0.32	−0.29	0.31	0.33	0.22	0.60	−0.16	0.33	0.27	0.01	0.05	−0.20	0.35	0.29	1.30
	t -value	5.78	−0.80	2.85	0.95	−1.20	2.02	−1.20	3.14	1.55	3.35	4.31	−0.66	3.27	1.24	0.34	0.28	−0.82	3.46	1.37	5.93

based factors. Also, 4 out of 8 estimated slopes on CV are significant for the term spread (TERM). In particular, every estimated coefficient on TERM betas is significant on 25 size and book-to-market sorted portfolios. Thus, it appears that default spread and term spread play important roles in explaining the cross-section of expected returns. This is consistent with [Hahn and Lee \(2006\)](#), who document that changes in default spread and changes in term spread help to capture the systematic differences in average stock returns. In sum, these

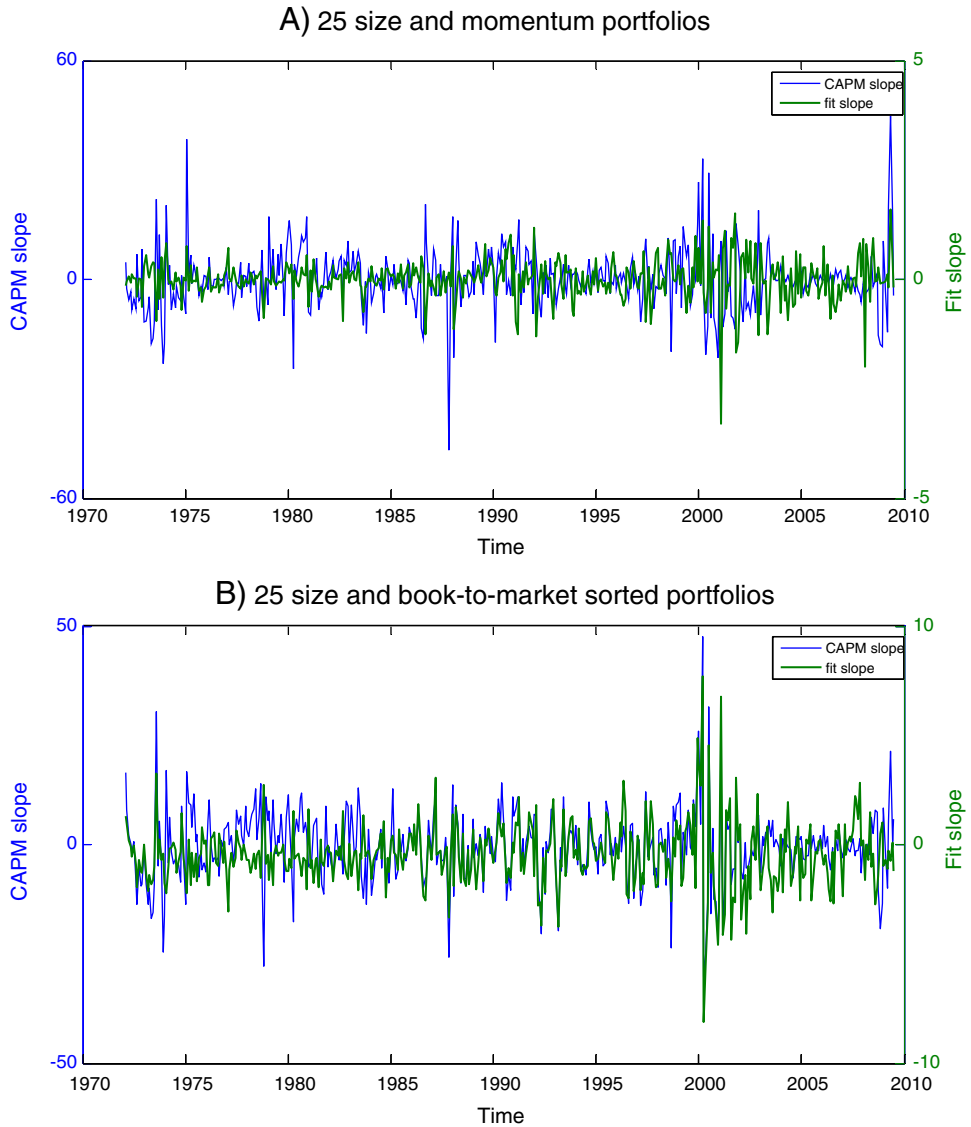


Fig. 1. The time-series of slopes on CAPM betas and *fit* values. This figure displays the time-series of slopes on CAPM betas and *fit* values. Panel A shows the results with 25 size and momentum portfolios, and Panel B illustrates the results with 25 size and book-to-market sorted portfolios. The CAPM slope (left scale) is the cross-sectional regression coefficient of portfolio returns on market betas. Fit slope (right scale) is the cross-sectional regression coefficient of portfolio returns on *fit* values. Expanding sample method is used to obtain *fit* values, and the rolling window method is employed to compute the market betas. The *fit* slopes are scaled to have the same mean as the CAPM slopes. The sample period is January 1972 to June 2009.

results again indicate that the production-based model fails to capture the time-varying patterns of expected returns.

5.2. Test on useless factor

Kan and Zhang (1999) document that the risk premium on the beta risk can be statistically different from zero in the cross-sectional regressions although a useless factor is used in the analysis. In their paper, a factor is useless if the suggested factor is independent of all the stock returns used in the test. Although we find the *fit* is statistically significant in the presence of the production-based factors, one may argue that the *fit* is a useless factor since the construction of the *fit* variable is empirically motivated from the time-series predictability literature. As one possible way to detect a useless factor, Kan and Zhang (1999) suggest investigating the cross-sectional slopes since the cross-sectional estimates are stable for a true factor, but unstable for a useless factor. Since it is well-known that the market factor is not useless in time-series regressions, we compare the stability of the coefficients on the *fit* with the slopes on CAPM betas.

Fig. 1 displays the time-series of slopes on CAPM betas and the *fit* values. Panel A shows the results with 25 size and momentum portfolios, and Panel B illustrates the results with 25 size and book-to-market sorted portfolios. The CAPM slope (left scale) is the cross-sectional regression coefficient of portfolio returns on market betas, and the *fit* slope (right scale) is the cross-sectional regression coefficient of portfolio returns on the *fit* values. Expanding sample method is used to obtain the *fit* values, and the rolling window method is employed to compute the market betas. Since the units of regressors are different, we multiply the slopes on the *fit* by the ratio of the time-series mean of the slopes on the CAPM betas to that on the *fit* values.

Since we use different scales for the two variables, the results should be interpreted with some caution. Scaled to the same means, Fig. 1 indicates that the volatility of slopes on the CAPM betas is substantially higher than that on the *fit* values. The fact that the coefficients on the *fit* values are much more stable than those for the CAPM betas implies that the *fit* is not a useless factor.

6. Conclusion

Since the pioneer work of Cochrane (1991), there is extensive literature investigating the impact of production-based models on expected stock returns. Summarizing the previous studies on the production-based approaches, CNZ (2010) propose a new three-factor model. Given the striking empirical performance combined with the fact that the CNZ model effectively summarizes previously proposed production-based approaches, we investigate empirical performance of the CNZ model as an asset pricing model.

Employing Ferson and Harvey's approach, we find that the *fit* is always statistically significant in the presence of the production-based factors, which indicates that the proposed three-factor model does not capture time-varying patterns in stock returns. Moreover, when the *fit* is included in the analysis, the magnitude of the CNZ factors is consistently smaller and the *fit* drives out the significance of the CNZ factors. We interpret the empirical evidence as strong rejection of the CNZ model as a conditional model.

As documented in CNZ (2010), the empirical success of the production-based factors in explaining various anomalous patterns in stock returns justifies the use of the CNZ model in many applications—for example, calculating costs of equity, evaluating mutual fund performance, and measuring abnormal returns in event studies. This paper provides empirical evidence in favor of the adoption of a conditional production-based model in place of the unconditional one. However, even a conditional version of the CNZ model is rejected in this paper. Our empirical results cast some doubt on the validity of the CNZ model as a conditional benchmark for risk adjustment. Therefore, given the empirical evidence suggested in our study, we remain skeptical about relying on the production-based models to estimate a risk-adjusted return in practice.

In the asset-pricing literature, there are numerous methodologies to investigate the validity of a proposed model. As one possible way, in this paper, we test whether the CNZ model explains time-varying patterns in stock returns, captured by common conditioning variables. This approach also allows us to perform a specification test documented in Jagannathan and Wang (1998). Given the importance of the

conditional asset pricing models combined with the popularity of the specification test, we believe that our work contributes to the literature. However, we should mention that the empirical test performed in our paper is not the only criterion to judge whether an asset pricing model is successful or not. Future research should employ different methodologies to test the validity of the production-based models.

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