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Are Characteristics Covariances or Characteristics?

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Abstract

In this article, we shed more light on the covariances versus characteristics debate by investigating the explanatory power of the instrumented principal component analysis (IPCA), recently proposed by Kelly et al. (2019). They conclude that characteristics are covariances because there is no residual return predictability from characteristics above and beyond that in factor loadings. Our findings indicate that there is no residual return predictability from factor loadings above and beyond that in characteristics either. In particular, we find that stock returns are best explained by characteristics (characteristics are characteristics) and that a one-factor IPCA model is sufficient to explain stock risk (characteristics are covariances). We therefore conclude that characteristics are covariances or characteristics, depending on whether the goal is to explain stock returns or risk.

JEL-Codes: C230, G110, G120.

Keywords: cross-section of stock returns, covariances, characteristics, IPCA.

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1 Introduction

Recently, Kelly et al. (2019) introduced the instrumented principal component analysis (IPCA), a powerful method that provides a formal statistical bridge between characteristics and expected returns. The IPCA follows the equilibrium asset pricing principle in describing returns by a factor model. The novelty of this approach is that observable asset characteristics serve as instrumental variables for latent conditional factor loadings, allowing the consistent recovery of factor loadings and factors from asset characteristics.

The IPCA helps determine the characteristics that provide independent information about average stocks returns. Among others, McLean and Pontiff (2016), Harvey et al. (2016) and Green et al. (2017) provide an overview of hundreds of characteristics appearing in the literature to explain the cross-section of stock returns. Given the high dimensionality, Cochrane (2011) asks which characteristics really provide independent information about average returns and which characteristics are subsumed by others. By choosing a few linear combinations of characteristics that are the most informative about average returns, the IPCA builds a dimension reduction directly into the model and therefore contributes to one of the most important challenges in empirical asset pricing. Kelly et al. (2019) find that ten of 36 stock characteristics are statistically significant at the 1% level in their sample.

Moreover, another research area at the heart of modern empirical asset pricing to which the IPCA contributes is the covariances versus characteristics debate. This research area, initiated by Daniel and Titman (1997) and Davis et al. (2000), directly compares stock characteristics and factor loadings in terms of their ability to explain differences in average returns. According to Lin and Zhang (2013), the majority of empirical studies in the covariances versus characteristics literature have shown that characteristic models dominate risk models in horse races. However, this finding might be due to the unobservability of factors and factor loadings, which means that they must be estimated while stock characteristics can be observed. A common approach taken by Fama and French (1993), Carhart (1997) and Fama and French (2015), among others, is to pre-specify factors empirically. Another approach is to use factor analytic techniques and simultaneously estimate factors and static factor loadings (Chamberlain and Rothschild (1983) and Connor and Korajczyk (1986)). By mapping between observable characteristics and factor loadings, the IPCA bypasses many of the shortcomings of the noted approaches and offers a new framework to disentangle risk

from mispricing.

In addition to describing returns by a factor model, the IPCA allows considering an intercept or alpha that accounts for a characteristic-based return phenomenon unrelated to risk. This specification is called an unrestricted IPCA model, while the model accounting for return compensation related to risk only is called a restricted IPCA model. Comparing the performance of the unrestricted and restricted IPCA models allows disentangling risk from mispricing. Kelly et al. (2019) find that the unrestricted IPCA model is not able to outperform the restricted IPCA model and therefore conclude that there is no residual return predictability from characteristics above and beyond that in factor loadings.

In this paper, we show that some of the conclusions derived from the IPCA in Kelly et al. (2019) might be premature. We introduce a second restricted IPCA model that allows only for a characteristic-based return phenomenon unrelated to risk. We find that all three IPCA models, the unrestricted and the two restricted IPCA models, exhibit the same performance. We argue that this is because the restricted IPCA model allowing only for risk-based compensation is not fully capable of eliminating a possible non-risk-based compensation, and *vice versa*. The only model capable of disentangling a risk-based from a non-risk-based return compensation is the unrestricted IPCA model. Therefore, we sort stocks on the expected returns from the three IPCA models, and in the case of the unrestricted IPCA model, we also sort stocks on expected returns resulting from both a risk-based and a non-risk-based compensation. Our results reveal that most, if not all, of the explanatory power of the unrestricted IPCA model is driven by a return phenomenon that is unrelated to risk. In terms of the covariances versus characteristics debate, we conclude that characteristics are characteristics, not covariances. While characteristics are sufficient to explain the cross-section of average stock returns, we also show that a one-factor IPCA model is sufficient to explain the average risk in stock returns. Therefore, characteristics act as characteristics in describing returns, and characteristics act as covariances in describing risk.

Another notable finding of our analyses is that the IPCA models are capable of producing a large spread in risk and return. With regard to returns, the monthly spread produced by the IPCA models is approximately 1.5% larger than the largest spread reported by Lewellen (2015) using cross-sectional regressions and approximately 0.8% larger than the largest spread reported by Gu et al. (2020) using machine learning models. Compared with cross-sectional regressions or machine learning models, the unrestricted IPCA is also able to disentangle risk and returns or, in other

words, to identify stocks that promise high returns (high non-risk-based compensation) and low risk (low risk-based compensation).

The remainder of this paper is structured as follows. In the next section, we outline our data and IPCA models. In Section 3, we report our empirical findings; Section 4 concludes.

2 Data and Method

2.1 Data

To allow for a comparison of our results, we use the same data as Kelly et al. (2019). Kelly et al. (2019) use stock returns and characteristics provided by Freyberger et al. (2017). More specific, they use 36 characteristics from 12,813 unique stocks on NYSE, Amex, and Nasdaq between July 1962 and May 2014. The data come from the Center for Research in Security Prices (CRSP) and the Standard and Poor’s Compustat database. The 36 characteristics are market beta (Frazzini and Pedersen (2014)), assets-to-market (Bhandari (1988)), total assets (Gandhi and Lustig (2015)), sales-to-assets (Soliman (2008)), book-to-market (Rosenberg et al. (1985)), cash-to-short-term-investment (Palazzo (2012)), capital turnover (Haugen and Baker (1996)), capital intensity (Gorodnichenko and Weber (2016)), ratio of change in property, plants and equipment to change in total assets (Lyandres et al. (2008)), earnings-to-price (Basu (1983)), fixed costs-to-sales (D’Acunto et al. (2018)), cash flow-to-book (Hou et al. (2011)), idiosyncratic volatility with respect to the Fama and French (1993) three-factor model (Ang et al. (2006)), investment (Cooper et al. (2008)), leverage (Lewellen (2015)), market capitalization (Fama and French (1992)), turnover (Datar et al. (1998)), net operating assets (Hirshleifer et al. (2004)), operating accruals (Sloan (1996)), operating leverage (Novy-Marx (2011)), price-to-cost margin (Bustamante and Donangelo (2017)), profit margin (Soliman (2008)), gross profitability (Ball et al. (2015)), Tobin’s Q (Freyberger et al. (2017)), price relative to its 52-week high (George and Hwang (2004)), return on net operating assets (Soliman (2008)), return on assets (Balakrishnan et al. (2010)), return on equity (Haugen and Baker (1996)), momentum (Fama and French (1996)), intermediate momentum (Novy-Marx (2012)), short-term reversal (Jegadeesh (1990)), long-term reversal (de Bondt and Thaler (1985)), sales-to-price (Lewellen (2015)), the ratio of sales and general administrative costs to sales (Freyberger et al. (2017)), bid-ask spread (Chung and Zhang (2014)), and unexplained volume (Garfinkel

(2009)). Stock i is only included in month t if all characteristics are available. Freyberger et al. (2017) provide further details and summary statistics on the data.

2.2 Method

The restricted IPCA specification as introduced by Kelly et al. (2019) is

$$r_{i,t+1} = \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}^*, \quad (1)$$

$$\beta_{i,t} = z'_{i,t} \Gamma_{\beta} + v_{\beta,i,t},$$

where $\beta_{i,t}$ is the factor loadings of stock i at time t on a K -vector of latent factors, f_{t+1} . Central to the IPCA is that the factor loadings are described by linear combinations of firm characteristics. The term Γ_{β} defines the mapping of firm characteristics $z'_{i,t}$ to factor exposures $\beta_{i,t}$. In the restricted IPCA model, stock returns $r_{i,t+1}$ are only allowed to compensate for exposure to latent risk factors. In addition to compensating for exposure to latent risk factors, the unrestricted IPCA specification allows for a residual return from characteristics above and beyond that in factor loadings. The unrestricted IPCA specification is

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}, \quad (2)$$

$$\alpha_{i,t} = z'_{i,t} \Gamma_{\alpha} + v_{\alpha,i,t}, \quad \beta_{i,t} = z'_{i,t} \Gamma_{\beta} + v_{\beta,i,t},$$

where $\beta_{i,t} f_{t+1}$ is compensation for exposure to latent risk factors and $\alpha_{i,t}$ is return from characteristics above and beyond that in factor loadings. Comparing the performance of the restricted and the unrestricted IPCA model allows testing whether a characteristic- or behavioral-based return phenomenon beyond a risk- or rational-based return phenomenon exists. In case the unrestricted IPCA model does not outperform the restricted IPCA model, there is no residual return predictability from characteristics above and beyond that in factor loadings. In addition to the aforementioned IPCA models considered in Kelly et al. (2019), we incorporate another restricted IPCA specification that allows only for a characteristic-based return phenomenon unrelated to risk. Our second restricted IPCA specification is

$$r_{i,t+1} = \alpha_{i,t} + \epsilon_{i,t+1}^{**}, \quad (3)$$

$$\alpha_{i,t} = z'_{i,t} \Gamma_{\alpha} + v_{\alpha,i,t}.$$

In this IPCA specification, stock returns are only allowed to be a compensation unrelated to risk. Therefore, in comparison with the unrestricted IPCA specification, the restricted IPCA specification allows us to test whether there is any return predictability from factor loadings above and beyond a characteristics- or behavioral-based return phenomenon unrelated to risk. In the following, we denote the restricted IPCA model only allowing for a risk-based explanation by $\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}$, the restricted IPCA model only allowing for a non-risk-based explanation by $\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}$, and the unrestricted IPCA model by $\Gamma_{\alpha \neq 0}, \Gamma_{\beta \neq 0}$.

Daniel and Titman (1997), Brennan et al. (1998), Davis et al. (2000) and Daniel et al. (2001) directly compare stock characteristics (behavioral-based explanation) with factor loadings (covariances, rational-based explanation) on their ability to explain differences in average returns. According to Kelly et al. (2019), the behavioral-based explanation and the rational-based explanation can also be disentangled by comparing the performance of the IPCA models. To make the IPCA models comparable, the estimation of Γ_{α} , Γ_{β} , and f_{t+1} must rely on information that is available at time t . Therefore, in every month $t \geq 120$, we use all data through t to estimate the IPCA models and denote the resulting backward-looking parameter estimates $\hat{\Gamma}_{\alpha,t}$ and $\hat{\Gamma}_{\beta,t}$. To determine f_{t+1} without any information beyond time t , we use the factor mean through t , denoted by $\hat{\lambda}_t$. The “predictive R^2 ’s [sic]” of the three IPCA models are

$$R_{\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}}^2 = 1 - \frac{\sum_{i,t} (r_{i,t+1} - z'_{i,t} \hat{\Gamma}_{\beta,t} \hat{\lambda}_t)^2}{\sum_{i,t} r_{i,t+1}^2}, \quad (4)$$

$$R_{\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}}^2 = 1 - \frac{\sum_{i,t} (r_{i,t+1} - z'_{i,t} \hat{\Gamma}_{\alpha,t})^2}{\sum_{i,t} r_{i,t+1}^2}, \quad (5)$$

and

$$R_{\Gamma_{\alpha \neq 0}, \Gamma_{\beta \neq 0}}^2 = 1 - \frac{\sum_{i,t} (r_{i,t+1} - z'_{i,t} (\hat{\Gamma}_{\alpha,t} + \hat{\Gamma}_{\beta,t} \hat{\lambda}_t))^2}{\sum_{i,t} r_{i,t+1}^2}. \quad (6)$$

The R^2 ’s provide information about the fraction of volatility explained by the IPCA models and represent statistical measures on the explanatory power of the models. For a more economical perspective on the explanatory power of the expected returns from the IPCA models, we compare the expected and realized returns using expected-return-sorted portfolios. Furthermore, in the case of the unrestricted IPCA specification, we can decompose the models’ total explanatory power ($z'_{i,t} (\hat{\Gamma}_{\alpha,t} + \hat{\Gamma}_{\beta,t} \hat{\lambda}_t)$) into a behavioral pricing component ($z'_{i,t} \hat{\Gamma}_{\alpha,t}$) and a rational pricing component ($z'_{i,t} \hat{\Gamma}_{\beta,t} \hat{\lambda}_t$) and analyze them separately.

Moving beyond the analysis of Kelly et al. (2019), we test the models' ability to explain risk. Specifically, for the unrestricted IPCA specification and the restricted IPCA specification allowing for factor loadings only, we estimate the variance-covariance matrix of returns as

$$\sum_{r,t} = (z_t' \hat{\Gamma}_{\beta,t}) \sum_{f,t} (z_t' \hat{\Gamma}_{\beta,t}), \quad (7)$$

where $\sum_{r,t}$ is the $N \times N$ variance-covariance matrix between the returns on assets i and j at time t , $z_t' \hat{\Gamma}_{\beta,t}$ is an $N \times K$ matrix of factor loadings, and $\sum_{f,t}$ is the $K \times K$ variance-covariance matrix between the returns on the K factors. To determine $\sum_{f,t}$ without any information beyond time t , we use the factor covariances through t . In the subsequent section, we analyze the three IPCA models in terms of their ability to explain differences in average returns and risks.

3 Results

3.1 Characteristics Explain Returns

We begin our analyses by replicating some of the results reported in Kelly et al. (2019). Kelly et al. (2019) report out-of-sample total R^2 s and predictive R^2 s of the restricted IPCA models with respect to individual stocks and characteristic-managed portfolios for $K = 1, \dots, 6$ factors.¹ The first row of Table 1 replicates the out-of-sample predictive R^2 s of the restricted IPCA models with respect to individual stocks. We obtain the same results as Kelly et al. (2019).

We extend the results reported in Kelly et al. (2019) in row two of Table 1 and report the out-of-sample predictive R^2 s of the unrestricted IPCA models. We find that for lower numbers of factors, unrestricted models outperform restricted models. As the number of factors increases, the gap between restricted and unrestricted models shrinks. These results are similar to the in-sample results Kelly et al. (2019) report in their Table 1.² They conclude that five IPCA factors and the restricted IPCA specification are sufficient to explain the cross-section of average stock returns. This means that there is no residual return predictability from characteristics above and beyond that in factor loadings and that characteristics are in fact covariances.

¹See Table 5 in Kelly et al. (2019).

²Their out-of-sample analysis takes only the restricted IPCA specification into consideration. This is because they find small and statistically nonsignificant characteristic-associated anomaly intercepts in their in-sample analysis. They therefore reject the unrestricted models in favor of the restricted models.

-Table 1 around here-

To shed more light on this question, we perform additional analyses. In addition to the unrestricted IPCA specification ($\Gamma_{\alpha \neq 0}$ and $\Gamma_{\beta \neq 0}$) and the restricted IPCA specification ($\Gamma_{\alpha=0}$ and $\Gamma_{\beta \neq 0}$) considered in Kelly et al. (2019), our analysis incorporates a second restricted IPCA specification ($\Gamma_{\alpha \neq 0}$ and $\Gamma_{\beta=0}$), which does not allow compensating for exposure to latent risk factors. Rather, it only allows for a characteristic-based return phenomenon without risk. We determine the predictive R^2 of this specification and compare it with the other IPCA specifications. As Table 1 shows, the restricted IPCA specification in Kelly et al. (2019) that allows for “covariances-compensation” only is not able to outperform a restricted IPCA specification that allows for “characteristics-compensation” only ($K = 0$).³ A conclusion that there is no residual return predictability from characteristics above and beyond that in factor loadings might therefore be premature. Given our results, it could also be argued that there is no residual return predictability from factor loadings above and beyond that in characteristics.

In the following analysis, we compare the expected and actual returns based on expected-return-sorted portfolios from the three IPCA specifications. Panel A of Table 2 reports the results of sorts on the expected returns from the restricted IPCA specification allowing for alpha but not for factor loadings. We find that the average realized value-weighted portfolio returns (column “Avg”) align well with the predicted returns (column (“Pred”)) and that the spread of 3.36% per month is impressively high and left unexplained by the Fama and French (2015)’s five-factor model (column “Alpha” and row “pVal(H-L)”). Furthermore, we find a U-shaped relation between realized returns and volatility (column “Std”).

Panel B of Table 2 reports the results of sorts on the expected returns from the unrestricted IPCA specification. We find that the results are similar to those reported in Panel A, which implies that when alpha (characteristics-compensation) is considered in the IPCA model, there is little improvement by taking factor loadings (covariances-compensation) into consideration. By contrast, an increasing number of IPCA factors seem to slowly decrease the spread in portfolio returns, meaning that the explanatory power of the model decreases. This can also be observed in out-of-sample predictive R^2 s reported in Table 1 or in the in-sample predictive R^2 s reported in Table 1 in Kelly et al. (2019).

³In unreported estimations, this finding also holds in in-sample analyses. The results are available on request.

Panel C of Table 2 reports the results of sorts on the expected returns from the restricted IPCA specification allowing for factor loadings but not for alpha. We find that the spread in portfolio returns increases with an increasing number of IPCA factors but remains below the return spreads reported in Panels A or B. Again, this can also be observed in the out-of-sample predictive R^2 s reported in Table 1 or in the in-sample predictive R^2 s reported in Table 1 in Kelly et al. (2019).

The in-sample R^2 s reported in Table 1 in Kelly et al. (2019), the out-of-sample R^2 s reported in our Table 1, and our expected-return-sorted portfolios in Table 2 all show that increasing the number of IPCA factors increases the explanatory power of the restricted IPCA specification allowing for factor loadings only and decreases the explanatory power of the unrestricted IPCA specification. These developments seem to converge to a similar explanatory power of both specifications when five IPCA factors or more are incorporated. Therefore, abandoning the characteristics-based story in favor of a factor loadings-based story seems to be invalid. Moreover, it is noteworthy to point out the astonishing predictive power of the IPCA models. All three models are able to produce a spread of more than 3% in average portfolio returns. This is approximately 1.5% larger than the largest spread reported by Lewellen (2015) using linear models and 0.8% larger than the largest spread reported by Gu et al. (2020) using machine learning models.

-Table 2 around here-

To further compare the performance of the characteristics-based story with the factor loadings-based story, we cross-sectionally orthogonalize the expected returns from the unrestricted IPCA specification and from the restricted IPCA specification allowing for factor loadings but not for alpha by the expected returns from the restricted IPCA specification allowing for alpha only. Panel A of Table 3 reports average portfolio returns from the sorts on the orthogonalized expected returns of the two models. We find that no specification produces a non-zero spread in portfolio returns, which is statistically significant. This means that there is no explanatory power in these IPCA specifications above and beyond a characteristics-based return phenomenon unrelated to risk. In addition, we orthogonalize the expected returns from all three IPCA specifications by the expected returns from the restricted IPCA specification with six factors allowing for factor loadings only. Panel B of Table 3 reports average portfolio returns from sorts on the orthogonalized expected returns of the three models. We find that the restricted IPCA specifications allowing for factor loadings only are not able to produce a non-zero spread in average portfolio returns. However, the

unrestricted IPCA specifications and the restricted IPCA specification allowing for alpha only still produce a spread in average portfolio returns, which is statistically significantly different from zero. This means that the IPCA specifications allowing for alpha can compensate the explanatory power of the IPCA specifications allowing for factor loadings only, but not *vice versa*.

-Table 3 around here-

So far, our results have shown that the restricted IPCA specification allowing for alpha only exhibits the highest explanatory power. However, it could be argued that when no factor loadings are taken into consideration, the alpha accounts for both a characteristic-based return phenomenon unrelated to risk and a characteristic-based return phenomenon related to risk because the model is not able to distinguish between these explanations. This also holds for the restricted IPCA specification allowing for no alpha. We therefore further examine the unrestricted IPCA models and disentangle the characteristics-compensation and the covariances-compensation.

The expected return from the unrestricted IPCA model at time t is $z'_{i,t}(\hat{\Gamma}_{\alpha,t} + \hat{\Gamma}_{\beta,t}\hat{\lambda}_t)$ and can be decomposed into the expected return from characteristics without any relation to risk ($z'_{i,t}\hat{\Gamma}_{\alpha,t}$) and into the expected return from covariances ($z'_{i,t}\hat{\Gamma}_{\beta,t}\hat{\lambda}_t$). We compare the expected and actual returns based on expected-return-sorted portfolios from the unrestricted IPCA models and differentiate between the characteristics-compensation and the covariances-compensation. Table 4 reports the results of this analysis and reveals that the spread produced in portfolio returns from characteristics-compensation is two to three times the spread produced by covariances-compensation (depending on K). The return spread produced from the characteristics-compensation is almost similar to the return spread produced by the entire unrestricted IPCA model reported in Table 2. This means that taking factor loadings into consideration does not improve the models' performance, or in other words, the characteristics do not seem to be covariances but characteristics instead. We have shown that when the IPCA model is able to distinguish between characteristics and covariances, the characteristics-compensation is far more important than the covariances-compensation. It could also be argued that there is no covariances-compensation above and beyond the characteristics-compensation. Kelly et al. (2019) find that five IPCA factors without an intercept explain the cross-section of average stock returns because the explanatory power of the unrestricted IPCA specification decreases by increasing the number of IPCA factors. Furthermore, the more factors are taken into consideration, the more the restricted IPCA specification allowing for factor loadings

only behaves like a cross-sectional regression of stock returns on aggregated characteristics. It follows that the more IPCA factors are considered in the restricted IPCA specification not allowing for alpha, the more it behaves like a restricted IPCA specification only allowing for alpha.

-Table 4 around here-

3.2 Covariances Explain Risk

The previous analyses show that a restricted IPCA specification only allowing for alpha is sufficient to explain the cross-sectional dispersion in average stock returns. This means that stocks realize a return premium that is unrelated to the underlying covariance structure and that risk and return are not described by a unified model. The remaining question is, which model is best suited to describe risk? To answer this question, we sort stocks on the expected variances from the unrestricted IPCA specifications and the restricted IPCA specifications allowing for factor loadings only. Specifically, we are interested in (1) whether there are any differences between the unrestricted and restricted specifications and (2) how many factors are required to describe the variance in returns. Table 5 reports the standard deviations of ten portfolios formed on the expected variances from the two IPCA specifications varying the number of IPCA factors between one and six. The results in Table 5 show that all models produce a similar spread in the standard deviations of portfolio returns. We therefore conclude that one factor is sufficient to describe the risk in returns. In summary, our results reveal that returns are best explained by characteristics while risk is best explained by covariances. However, because characteristics serve as instrumental variables for covariances, characteristics are both covariances and characteristics.

-Table 5 around here-

4 Conclusion

The IPCA introduced by Kelly et al. (2019) might become one of the most important approaches in empirical asset pricing. Among other things, it contributes to the use of empirical factor models such as those proposed by Fama and French (1993), Carhart (1997) and Fama and French (2015); it contributes to dimension reduction purposes in the “zoo of anomalies” as it was called by Cochrane (2011); it contributes to the cross-sectional return predictability literature covered by Lewellen

(2015) and Gu et al. (2020); and it contributes to the covariances versus characteristics debate initiated by Daniel and Titman (1997) and Davis et al. (2000). In our study, we focus on the last two research areas. We find that the average stock returns are best explained by a return phenomenon unrelated to risk. In this sense, characteristics are characteristics, not covariances. Furthermore, we find that a one-factor IPCA model is sufficient to explain stock risk. In this sense, characteristics are covariances. Thus, our empirical evidence supports the characteristic-based pricing model proposed by Daniel and Titman (1997). Another important finding is that the spread produced by the IPCA models in stock returns and stock risk is large. For example, the return spread produced by the IPCA models is larger than that in the forecasting approaches taken by Lewellen (2015) or Gu et al. (2020). We therefore recommend the use of IPCA models as benchmark models in forecasting studies. Our findings also provide important insights for portfolio management purposes, as we are able to provide a recommendation on how returns and risk should be estimated.

References

- Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1):259–299.
- Balakrishnan, K., Bartov, E., and Faurel, L. (2010). Post loss/profit announcement drift. *Journal of Accounting and Economics*, 50(1):20–41.
- Ball, R., Gerakos, J., Linnainmaa, J. T., and Nikolaev, V. V. (2015). Deflating profitability. *Journal of Financial Economics*, 117(2):225–248.
- Basu, S. (1983). The relationship between earnings’ yield, market value and return for nyse common stocks. *Journal of Financial Economics*, 12(1):129–156.
- Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance*, 43(2):507.
- Brennan, M. J., Chordia, T., and Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, 49(3):345–373.
- Bustamante, M. C. and Donangelo, A. (2017). Product market competition and industry returns. *Review of Financial Studies*, 30(12):4216–4266.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82.
- Chamberlain, G. and Rothschild, M. (1983). Arbitrage, factor structure, and mean-variance analysis on large asset markets. *Econometrica*, 51(5):1281.
- Chung, K. H. and Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, 17:94–120.
- Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance*, 66(4):1047–1108.
- Connor, G. and Korajczyk, R. A. (1986). Performance measurement with the arbitrage pricing theory. *Journal of Financial Economics*, 15(3):373–394.

- Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *The Journal of Finance*, 63(4):1609–1651.
- D’Acunto, F., Liu, R., Pflueger, C., and Weber, M. (2018). Flexible prices and leverage. *Journal of Financial Economics*, 129(1):46–68.
- Daniel, K. and Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *The Journal of Finance*, 52(1):1–33.
- Daniel, K., Titman, S., and Wei, K. J. (2001). Explaining the cross-section of stock returns in japan: Factors or characteristics? *The Journal of Finance*, 56(2):743–766.
- Datar, V. T., Y. Naik, N., and Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1(2):203–219.
- Davis, J. L., Fama, E. F., and French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance*, 55(1):389–406.
- de Bondt, W. F. M. and Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3):793.
- Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2):427–465.
- Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.
- Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1):55–84.
- Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.
- Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1):1–25.
- Freyberger, J., Neuhierl, A., and Weber, M. (2017). Dissecting characteristics nonparametrically. Technical report, National Bureau of Economic Research.

- Gandhi, P. and Lustig, H. (2015). Size anomalies in u.s. bank stock returns. *The Journal of Finance*, 70(2):733–768.
- Garfinkel, J. A. (2009). Measuring investors’ opinion divergence. *Journal of Accounting Research*, 47(5):1317–1348.
- George, T. J. and Hwang, C.-Y. (2004). The 52-week high and momentum investing. *The Journal of Finance*, 59(5):2145–2176.
- Gorodnichenko, Y. and Weber, M. (2016). Are sticky prices costly? evidence from the stock market. *The American Economic Review*, 106(1):165–199.
- Green, J., Hand, J. R. M., and Zhang, X. F. (2017). The characteristics that provide independent information about average u.s. monthly stock returns. *Review of Financial Studies*, 30(12):4389–4436.
- Gu, S., Kelly, B., and Xiu, D. (2020). Empirical asset pricing via machine learning. *Forthcoming in the Review of Financial Studies*.
- Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.
- Haugen, R. A. and Baker, N. L. (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics*, 41(3):401–439.
- Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38:297–331.
- Hou, K., Karolyi, G. A., and Kho, B.-C. (2011). What factors drive global stock returns? *Review of Financial Studies*, 24(8):2527–2574.
- Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance*, 45(3):881.
- Kelly, B. T., Pruitt, S., and Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics*, 134(3):501–524.
- Lewellen, J. (2015). The cross-section of expected stock returns. *Critical Finance Review*, 4(1):1–44.

- Lin, X. and Zhang, L. (2013). The investment manifesto. *Journal of Monetary Economics*, 60(3):351–366.
- Lyandres, E., Le Sun, and Zhang, L. (2008). The new issues puzzle: Testing the investment-based explanation. *Review of Financial Studies*, 21(6):2825–2855.
- McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *The Journal of Finance*, 71(1):5–32.
- Novy-Marx, R. (2011). Operating leverage. *Review of Finance*, 15(1):103–134.
- Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, 103(3):429–453.
- Palazzo, B. (2012). Cash holdings, risk, and expected returns. *Journal of Financial Economics*, 104(1):162–185.
- Patton, A. J. and Timmermann, A. (2010). Monotonicity in asset returns: New tests with applications to the term structure, the capm, and portfolio sorts. *Journal of Financial Economics*, 98(3):605–625.
- Rosenberg, B., Reid, K., and Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, 11(3):9–16.
- Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.
- Soliman, M. T. (2008). The use of dupont analysis by market participants. *The Accounting Review*, 83(3):823–853.

Tables

Table 1: IPCA model performance

The table reports the predictive R^2 s in percentages for the unrestricted ($\Gamma_{\alpha \neq 0}$ and $\Gamma_{\beta \neq 0}$) and the two restricted (restricted to covariances-compensation ($\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}$) and restricted to characteristics-compensation ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}$)) IPCA models. K represents the number of IPCA factors considered in the unrestricted and the restricted to covariances-compensation IPCA models. No IPCA factors are considered in the restricted to characteristics-compensation IPCA specification. The predictive R^2 s are calculated out-of-sample with respect to 12,813 unique stocks for which 36 lagged characteristics and excess returns are nonmissing in month t between July 1962 and May 2014.

| | K | | | | | | |
|--------------------------|------|------|------|------|------|------|------|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| $\Gamma_{\alpha=0}$ | | 0.34 | 0.33 | 0.55 | 0.61 | 0.60 | 0.60 |
| $\Gamma_{\alpha \neq 0}$ | 0.62 | 0.67 | 0.67 | 0.65 | 0.64 | 0.64 | 0.62 |

Table 2: Expected-return-sorted portfolios from IPCA models

The table reports characteristics of decile portfolios formed from monthly sorts of CRSP/Compustat stocks on expected returns from three IPCA specifications. Panel A reports the results of sorts on the expected returns from the restricted IPCA specification allowing for alpha but not for factor loadings ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}$). Panel B reports the results of sorts on the expected returns from the unrestricted IPCA specification ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta \neq 0}$). Panel C reports the results of sorts on the expected returns from the restricted IPCA specification allowing for factor loadings but not for alpha ($\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}$). In Panels B and C, a maximum of six IPCA factors (K) are considered. The ten portfolios are defined as follows. For each month from July 1962 to May 2014, we assign all stocks to ten portfolios using decile breakpoints from the cross-section of the estimated returns from the three IPCA specifications and calculate the value-weighted monthly percentage excess returns for the next month. To analyze the aggregate effect of a certain model on stock returns, we take a long position in portfolio 10 (High) and a short position in portfolio 1 (Low). For each portfolio, we estimate a Fama and French (2015) five-factor model (i.e. Mkt-Rf, SMB, HML, RMW, and CMW) for the value-weighted returns (in excess of the T-bill rate) of the ten single-sorted portfolios as well as the value-weighted returns of the High minus Low portfolio. Mkt-Rf is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio in excess of the T-bill rate. SMB, HML, RMW, and CMW are factor-mimicking portfolios associated with the size effect, the book-to-market effect, the operating profitability effect, and the investment effect, respectively. We retrieve the data from Kenneth French's website. Avg (Std, Shp) is the average (standard deviation, sharpe ratio) of the value-weighted returns formed from sorts of stocks on expected returns from the IPCA models. Pred is the average expected portfolio return of a model and Alpha is regression alpha from the Fama and French (2015) five-factor model. pVal(H-L) reports the p-value from a t-test against the null hypothesis of zero average return (column Avg) or zero alpha (column Alpha) for the H-L portfolio.

Panel A: Expected-return sorted portfolios, $\Gamma_{\alpha \neq 0}$ and $\Gamma_{\beta=0}$.

| | $\Gamma_{\alpha \neq 0}$ and $\Gamma_{\beta=0}$ | | | | |
|-----------|---|------|-------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.75 | 6.25 | -0.12 | -1.48 | -1.37 |
| 2 | -0.04 | 5.80 | -0.01 | -0.63 | -0.74 |
| 3 | 0.25 | 5.75 | 0.04 | -0.17 | -0.46 |
| 4 | 0.52 | 5.66 | 0.09 | 0.20 | -0.23 |
| 5 | 0.70 | 5.64 | 0.12 | 0.53 | -0.09 |
| 6 | 0.92 | 5.80 | 0.16 | 0.85 | 0.14 |
| 7 | 1.14 | 5.86 | 0.19 | 1.19 | 0.38 |
| 8 | 1.44 | 6.11 | 0.24 | 1.56 | 0.69 |
| 9 | 1.74 | 6.50 | 0.27 | 2.03 | 0.95 |
| High (H) | 2.61 | 7.49 | 0.35 | 2.88 | 1.87 |
| H-L | 3.36 | 4.49 | 0.75 | 4.37 | 3.24 |
| pVal(H-L) | 0.00 | | | | 0.00 |

Panel B: Expected-return sorted portfolios, $\Gamma_{\alpha \neq 0}$ and $\Gamma_{\beta \neq 0}$.

| $\Gamma_{\alpha \neq 0}$ and $K = 1$ | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 2$ | | | | | |
|--------------------------------------|-------|------|-------|-------|-------|--------------------------------------|-------|------|-------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.76 | 6.14 | -0.12 | -1.35 | -1.37 | Low (L) | -0.75 | 6.15 | -0.12 | -1.28 | -1.36 |
| 2 | -0.03 | 5.72 | -0.01 | -0.52 | -0.73 | 2 | 0.01 | 5.71 | 0.00 | -0.49 | -0.67 |
| 3 | 0.31 | 5.68 | 0.05 | -0.07 | -0.40 | 3 | 0.33 | 5.63 | 0.06 | -0.06 | -0.37 |
| 4 | 0.46 | 5.59 | 0.08 | 0.29 | -0.27 | 4 | 0.52 | 5.55 | 0.09 | 0.30 | -0.20 |
| 5 | 0.69 | 5.62 | 0.12 | 0.62 | -0.08 | 5 | 0.74 | 5.61 | 0.13 | 0.62 | -0.04 |
| 6 | 0.93 | 5.78 | 0.16 | 0.94 | 0.15 | 6 | 0.88 | 5.73 | 0.15 | 0.95 | 0.10 |
| 7 | 1.14 | 5.89 | 0.19 | 1.28 | 0.36 | 7 | 1.16 | 5.94 | 0.19 | 1.28 | 0.37 |
| 8 | 1.41 | 6.22 | 0.23 | 1.66 | 0.65 | 8 | 1.37 | 6.29 | 0.22 | 1.65 | 0.59 |
| 9 | 1.77 | 6.65 | 0.27 | 2.13 | 0.97 | 9 | 1.72 | 6.69 | 0.26 | 2.11 | 0.94 |
| High (H) | 2.62 | 7.70 | 0.34 | 2.96 | 1.87 | High (H) | 2.62 | 7.88 | 0.33 | 2.90 | 1.86 |
| H-L | 3.38 | 4.64 | 0.73 | 4.31 | 3.24 | H-L | 3.37 | 4.94 | 0.68 | 4.18 | 3.22 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.00 | | | | 0.00 |

| $\Gamma_{\alpha \neq 0}$ and $K = 3$ | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 4$ | | | | | |
|--------------------------------------|-------|------|-------|-------|-------|--------------------------------------|-------|------|-------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.76 | 6.22 | -0.12 | -1.28 | -1.34 | Low (L) | -0.74 | 6.31 | -0.12 | -1.28 | -1.29 |
| 2 | 0.06 | 5.73 | 0.01 | -0.50 | -0.62 | 2 | 0.08 | 5.83 | 0.01 | -0.50 | -0.59 |
| 3 | 0.34 | 5.68 | 0.06 | -0.07 | -0.35 | 3 | 0.33 | 5.62 | 0.06 | -0.07 | -0.35 |
| 4 | 0.55 | 5.53 | 0.10 | 0.28 | -0.18 | 4 | 0.59 | 5.61 | 0.10 | 0.29 | -0.14 |
| 5 | 0.71 | 5.60 | 0.13 | 0.61 | -0.06 | 5 | 0.71 | 5.59 | 0.13 | 0.62 | -0.07 |
| 6 | 0.92 | 5.75 | 0.16 | 0.94 | 0.13 | 6 | 0.95 | 5.73 | 0.16 | 0.94 | 0.16 |
| 7 | 1.15 | 5.96 | 0.19 | 1.28 | 0.37 | 7 | 1.08 | 5.98 | 0.18 | 1.28 | 0.28 |
| 8 | 1.35 | 6.29 | 0.22 | 1.65 | 0.55 | 8 | 1.36 | 6.21 | 0.22 | 1.65 | 0.56 |
| 9 | 1.74 | 6.66 | 0.26 | 2.10 | 0.94 | 9 | 1.75 | 6.65 | 0.26 | 2.10 | 0.93 |
| High (H) | 2.56 | 7.74 | 0.33 | 2.88 | 1.79 | High (H) | 2.54 | 7.58 | 0.33 | 2.86 | 1.74 |
| H-L | 3.32 | 4.76 | 0.70 | 4.16 | 3.13 | H-L | 3.28 | 4.68 | 0.70 | 4.14 | 3.03 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.00 | | | | 0.00 |

| $\Gamma_{\alpha \neq 0}$ and $K = 5$ | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 6$ | | | | | |
|--------------------------------------|-------|------|-------|-------|-------|--------------------------------------|-------|------|-------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.71 | 6.29 | -0.11 | -1.27 | -1.26 | Low (L) | -0.64 | 6.26 | -0.10 | -1.27 | -1.20 |
| 2 | 0.08 | 5.75 | 0.01 | -0.50 | -0.58 | 2 | 0.08 | 5.80 | 0.01 | -0.51 | -0.58 |
| 3 | 0.35 | 5.64 | 0.06 | -0.07 | -0.34 | 3 | 0.38 | 5.63 | 0.07 | -0.09 | -0.32 |
| 4 | 0.57 | 5.57 | 0.10 | 0.28 | -0.15 | 4 | 0.54 | 5.57 | 0.10 | 0.27 | -0.17 |
| 5 | 0.72 | 5.61 | 0.13 | 0.61 | -0.05 | 5 | 0.72 | 5.61 | 0.13 | 0.61 | -0.04 |
| 6 | 0.94 | 5.82 | 0.16 | 0.94 | 0.13 | 6 | 0.93 | 5.84 | 0.16 | 0.94 | 0.11 |
| 7 | 1.02 | 5.91 | 0.17 | 1.28 | 0.22 | 7 | 1.02 | 5.92 | 0.17 | 1.28 | 0.22 |
| 8 | 1.40 | 6.30 | 0.22 | 1.65 | 0.59 | 8 | 1.37 | 6.30 | 0.22 | 1.66 | 0.57 |
| 9 | 1.72 | 6.63 | 0.26 | 2.10 | 0.92 | 9 | 1.70 | 6.64 | 0.26 | 2.11 | 0.90 |
| High (H) | 2.59 | 7.67 | 0.34 | 2.86 | 1.79 | High (H) | 2.61 | 7.70 | 0.34 | 2.87 | 1.82 |
| H-L | 3.30 | 4.72 | 0.70 | 4.12 | 3.05 | H-L | 3.25 | 4.86 | 0.67 | 4.13 | 3.02 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.00 | | | | 0.00 |

Panel C: Expected-return sorted portfolios, $\Gamma_{\alpha=0}$ and $\Gamma_{\beta \neq 0}$.

| $\Gamma_{\alpha=0}$ and $K = 1$ | | | | | | $\Gamma_{\alpha=0}$ and $K = 2$ | | | | | |
|---------------------------------|------|-------|------|------|-------|---------------------------------|------|-------|------|------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | 0.41 | 3.64 | 0.11 | 0.36 | -0.26 | Low (L) | 0.53 | 4.28 | 0.12 | 0.09 | -0.19 |
| 2 | 0.57 | 4.25 | 0.13 | 0.51 | -0.21 | 2 | 0.63 | 4.72 | 0.13 | 0.29 | -0.16 |
| 3 | 0.71 | 4.74 | 0.15 | 0.60 | -0.11 | 3 | 0.73 | 5.12 | 0.14 | 0.42 | -0.11 |
| 4 | 0.76 | 5.17 | 0.15 | 0.69 | -0.12 | 4 | 0.83 | 5.54 | 0.15 | 0.55 | -0.06 |
| 5 | 0.81 | 5.59 | 0.14 | 0.77 | -0.05 | 5 | 0.78 | 5.86 | 0.13 | 0.68 | -0.06 |
| 6 | 0.82 | 6.14 | 0.13 | 0.86 | -0.02 | 6 | 0.71 | 6.26 | 0.11 | 0.81 | -0.10 |
| 7 | 0.83 | 6.87 | 0.12 | 0.94 | 0.05 | 7 | 0.75 | 6.81 | 0.11 | 0.96 | 0.02 |
| 8 | 0.79 | 7.64 | 0.10 | 1.04 | 0.07 | 8 | 0.74 | 7.50 | 0.10 | 1.12 | 0.04 |
| 9 | 0.91 | 8.98 | 0.10 | 1.16 | 0.27 | 9 | 0.86 | 8.59 | 0.10 | 1.31 | 0.23 |
| High (H) | 1.63 | 11.14 | 0.15 | 1.36 | 1.09 | High (H) | 1.83 | 11.23 | 0.16 | 1.64 | 1.36 |
| H-L | 1.22 | 9.38 | 0.13 | 1.00 | 1.36 | H-L | 1.31 | 9.88 | 0.13 | 1.55 | 1.55 |
| pVal(H-L) | 0.28 | | | | 0.00 | pVal(H-L) | 0.23 | | | | 0.00 |

| $\Gamma_{\alpha=0}$ and $K = 3$ | | | | | | $\Gamma_{\alpha=0}$ and $K = 4$ | | | | | |
|---------------------------------|-------|------|-------|-------|-------|---------------------------------|-------|------|-------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.16 | 6.17 | -0.03 | -0.62 | -0.59 | Low (L) | -0.54 | 5.98 | -0.09 | -0.86 | -1.15 |
| 2 | 0.22 | 5.36 | 0.04 | -0.08 | -0.42 | 2 | 0.10 | 5.54 | 0.02 | -0.23 | -0.57 |
| 3 | 0.41 | 5.39 | 0.08 | 0.22 | -0.31 | 3 | 0.39 | 5.53 | 0.07 | 0.11 | -0.34 |
| 4 | 0.52 | 5.57 | 0.09 | 0.46 | -0.27 | 4 | 0.58 | 5.60 | 0.10 | 0.39 | -0.18 |
| 5 | 0.71 | 5.71 | 0.13 | 0.69 | -0.11 | 5 | 0.72 | 5.63 | 0.13 | 0.66 | -0.07 |
| 6 | 0.76 | 5.93 | 0.13 | 0.91 | -0.07 | 6 | 0.88 | 5.79 | 0.15 | 0.92 | 0.06 |
| 7 | 0.99 | 6.22 | 0.16 | 1.15 | 0.15 | 7 | 1.08 | 6.06 | 0.18 | 1.19 | 0.30 |
| 8 | 1.29 | 6.56 | 0.20 | 1.41 | 0.44 | 8 | 1.38 | 6.47 | 0.21 | 1.50 | 0.57 |
| 9 | 1.55 | 7.18 | 0.22 | 1.73 | 0.76 | 9 | 1.64 | 6.96 | 0.24 | 1.87 | 0.88 |
| High (H) | 2.35 | 8.83 | 0.27 | 2.29 | 1.57 | High (H) | 2.47 | 8.55 | 0.29 | 2.52 | 1.79 |
| H-L | 2.52 | 6.48 | 0.39 | 2.91 | 2.16 | H-L | 3.01 | 5.92 | 0.51 | 3.38 | 2.94 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.00 | | | | 0.00 |

| $\Gamma_{\alpha=0}$ and $K = 5$ | | | | | | $\Gamma_{\alpha=0}$ and $K = 6$ | | | | | |
|---------------------------------|-------|------|-------|-------|-------|---------------------------------|-------|------|-------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.63 | 6.32 | -0.10 | -1.13 | -1.19 | Low (L) | -0.64 | 6.32 | -0.10 | -1.16 | -1.20 |
| 2 | 0.12 | 5.80 | 0.02 | -0.43 | -0.56 | 2 | 0.14 | 5.78 | 0.02 | -0.46 | -0.53 |
| 3 | 0.37 | 5.56 | 0.07 | -0.03 | -0.31 | 3 | 0.37 | 5.53 | 0.07 | -0.05 | -0.31 |
| 4 | 0.60 | 5.60 | 0.11 | 0.30 | -0.14 | 4 | 0.61 | 5.60 | 0.11 | 0.29 | -0.14 |
| 5 | 0.68 | 5.63 | 0.12 | 0.62 | -0.08 | 5 | 0.71 | 5.63 | 0.13 | 0.61 | -0.05 |
| 6 | 0.92 | 5.74 | 0.16 | 0.93 | 0.14 | 6 | 0.89 | 5.76 | 0.16 | 0.93 | 0.10 |
| 7 | 1.08 | 5.93 | 0.18 | 1.25 | 0.28 | 7 | 1.02 | 5.96 | 0.17 | 1.26 | 0.20 |
| 8 | 1.34 | 6.26 | 0.21 | 1.61 | 0.53 | 8 | 1.35 | 6.28 | 0.22 | 1.62 | 0.55 |
| 9 | 1.70 | 6.80 | 0.25 | 2.03 | 0.88 | 9 | 1.70 | 6.77 | 0.25 | 2.05 | 0.89 |
| High (H) | 2.45 | 7.65 | 0.32 | 2.75 | 1.67 | High (H) | 2.52 | 7.71 | 0.33 | 2.77 | 1.74 |
| H-L | 3.08 | 4.86 | 0.63 | 3.88 | 2.86 | H-L | 3.16 | 4.88 | 0.65 | 3.93 | 2.94 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.00 | | | | 0.00 |

Table 3: Expected-return-sorted portfolios from orthogonalized IPCA models

The table reports characteristics of decile portfolios formed from monthly sorts of CRSP/Compustat stocks on orthogonalized expected returns from three IPCA specifications. Panel A reports the results of sorts on the expected returns from the unrestricted IPCA specification ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta \neq 0}$) and on the expected returns from the restricted IPCA specification allowing for factor loadings but not for alpha ($\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}$), both orthogonalized by the expected returns from the restricted IPCA specification allowing for alpha but not for factor loadings ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}$). Panel B reports the results of sorts on the expected returns from the restricted IPCA specification allowing for alpha but not for factor loadings ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}, K=0$), on the expected returns from the unrestricted IPCA specification ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta \neq 0}$), and on the expected returns from the restricted IPCA specification (up to five IPCA factors) allowing for factor loadings but not for alpha ($\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}$), all orthogonalized by the expected returns from the restricted IPCA specification with six factors allowing for factor loadings but not for alpha ($\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}, K=6$). The ten portfolios are defined as follows. For each month from July 1962 to May 2014, we assign all stocks to ten portfolios using decile breakpoints from the cross-section of the estimated returns from the three IPCA specifications and calculate the value-weighted monthly percentage excess returns for the next month. To analyze the aggregate effect of a certain model on stock returns, we take a long position in portfolio 10 (High) and a short position in portfolio 1 (Low). The numbers in the table represent the average of the value-weighted returns formed from sorts of stocks on orthogonalized expected returns from the IPCA models. pVal(H-L) reports the p-value from a t-test against the null hypothesis of zero average return (column Avg) for the H-L portfolio.

Panel A: Expected-return sorted portfolios, orthogonalized by the restricted IPCA specification $\Gamma_{\alpha \neq 0}, \Gamma_{\beta=0}$.

| | $\Gamma_{\alpha \neq 0}$ | | | | | | | $\Gamma_{\alpha=0}$ | | | | | |
|-----------|--------------------------|-------|-------|-------|-------|-------|-----------|---------------------|-------|-------|-------|-------|-------|
| | 1 | 2 | 3 | 4 | 5 | 6 | | 1 | 2 | 3 | 4 | 5 | 6 |
| Low (L) | 0.68 | 0.70 | 0.76 | 0.80 | 0.83 | 0.89 | Low (L) | 0.65 | 0.83 | 1.00 | 0.84 | 0.96 | 0.95 |
| 2 | 0.71 | 0.82 | 0.83 | 0.83 | 0.77 | 0.84 | 2 | 0.73 | 0.80 | 0.91 | 0.88 | 0.89 | 0.90 |
| 3 | 0.77 | 0.80 | 0.86 | 0.91 | 0.81 | 0.81 | 3 | 0.80 | 0.82 | 0.87 | 0.84 | 0.91 | 0.83 |
| 4 | 0.75 | 0.83 | 0.85 | 0.76 | 0.83 | 0.81 | 4 | 0.83 | 0.84 | 0.77 | 0.86 | 0.88 | 0.84 |
| 5 | 0.79 | 0.78 | 0.79 | 0.81 | 0.82 | 0.81 | 5 | 0.85 | 0.78 | 0.78 | 0.79 | 0.76 | 0.86 |
| 6 | 0.76 | 0.81 | 0.76 | 0.80 | 0.78 | 0.81 | 6 | 0.93 | 0.79 | 0.73 | 0.74 | 0.74 | 0.71 |
| 7 | 0.85 | 0.77 | 0.76 | 0.77 | 0.81 | 0.76 | 7 | 0.78 | 0.68 | 0.65 | 0.69 | 0.70 | 0.70 |
| 8 | 0.83 | 0.74 | 0.71 | 0.68 | 0.74 | 0.70 | 8 | 0.81 | 0.69 | 0.67 | 0.73 | 0.64 | 0.64 |
| 9 | 0.86 | 0.74 | 0.76 | 0.72 | 0.71 | 0.66 | 9 | 0.71 | 0.66 | 0.72 | 0.77 | 0.61 | 0.67 |
| High (H) | 0.96 | 0.94 | 0.78 | 0.81 | 0.80 | 0.80 | High (H) | 0.85 | 0.99 | 0.78 | 0.74 | 0.72 | 0.75 |
| H-L | 0.28 | 0.24 | 0.02 | 0.01 | -0.03 | -0.09 | H-L | 0.20 | 0.17 | -0.22 | -0.09 | -0.24 | -0.20 |
| pVal(H-L) | 16.92 | 24.36 | 94.25 | 96.94 | 89.66 | 65.40 | pVal(H-L) | 59.82 | 67.13 | 41.07 | 71.20 | 23.34 | 32.85 |

Panel B: Expected-return sorted portfolios, orthogonalized by the restricted IPCA specification $\Gamma_{\alpha=0}$, $\Gamma_{\beta \neq 0}$, $K = 6$.

| | $\Gamma_{\alpha \neq 0}$ | | | | | | | | $\Gamma_{\alpha=0}$ | | | | |
|-----------|--------------------------|------|------|------|------|------|------|-----------|---------------------|-------|-------|-------|-------|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | | 1 | 2 | 3 | 4 | 5 |
| Low (L) | 0.14 | 0.06 | 0.12 | 0.14 | 0.07 | 0.09 | 0.32 | Low (L) | 0.64 | 0.87 | 0.76 | 0.62 | 0.64 |
| 2 | 0.27 | 0.28 | 0.37 | 0.36 | 0.41 | 0.39 | 0.42 | 2 | 0.74 | 0.84 | 0.90 | 0.67 | 0.76 |
| 3 | 0.45 | 0.38 | 0.48 | 0.52 | 0.52 | 0.45 | 0.57 | 3 | 0.82 | 0.84 | 0.83 | 0.79 | 0.83 |
| 4 | 0.61 | 0.53 | 0.56 | 0.61 | 0.66 | 0.67 | 0.67 | 4 | 0.85 | 0.82 | 0.84 | 0.78 | 0.81 |
| 5 | 0.72 | 0.71 | 0.73 | 0.72 | 0.78 | 0.77 | 0.79 | 5 | 0.86 | 0.76 | 0.79 | 0.82 | 0.83 |
| 6 | 0.81 | 0.80 | 0.79 | 0.83 | 0.87 | 0.82 | 0.83 | 6 | 0.91 | 0.84 | 0.79 | 0.82 | 0.82 |
| 7 | 0.94 | 0.93 | 0.86 | 0.87 | 0.91 | 0.98 | 0.95 | 7 | 0.82 | 0.64 | 0.77 | 0.79 | 0.77 |
| 8 | 1.02 | 1.09 | 1.04 | 1.04 | 1.06 | 1.10 | 1.03 | 8 | 0.86 | 0.79 | 0.70 | 0.86 | 0.84 |
| 9 | 1.28 | 1.28 | 1.21 | 1.16 | 1.11 | 1.16 | 1.13 | 9 | 0.75 | 0.71 | 0.73 | 0.86 | 0.79 |
| High (H) | 1.50 | 1.57 | 1.54 | 1.50 | 1.36 | 1.34 | 1.18 | High (H) | 0.67 | 0.68 | 0.79 | 1.02 | 0.83 |
| H-L | 1.36 | 1.51 | 1.42 | 1.36 | 1.29 | 1.25 | 0.87 | H-L | 0.03 | -0.19 | 0.03 | 0.40 | 0.18 |
| pVal(H-L) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | pVal(H-L) | 93.46 | 62.50 | 90.21 | 15.83 | 34.69 |

Table 4: Expected-return-sorted portfolios from unrestricted IPCA models

The table reports characteristics of decile portfolios formed from monthly sorts of CRSP/Compustat stocks on expected returns from the components of the unrestricted IPCA specification. The expected return from the unrestricted IPCA model at time t is $z'_{i,t}(\hat{\Gamma}_{\alpha,t} + \hat{\Gamma}_{\beta,t}\hat{\lambda}_t)$ and can be decomposed into the expected return from characteristics without any relation to risk (characteristics-compensation, $z'_{i,t}\hat{\Gamma}_{\alpha,t}$) and into the expected return from covariances (covariances-compensation, $z'_{i,t}\hat{\Gamma}_{\beta,t}\hat{\lambda}_t$). A maximum of six IPCA factors (K) is considered. The ten portfolios are defined as follows. For each month from July 1962 to May 2014, we assign all stocks to ten portfolios using decile breakpoints from the cross-section of the estimated returns from the unrestricted IPCA specifications and calculate the value-weighted monthly percentage excess returns for the next month. To analyze the aggregate effect of a certain model on stock returns, we take a long position in portfolio 10 (High) and a short position in portfolio 1 (Low). For each portfolio, we estimate a Fama and French (2015) five-factor model (i.e. Mkt-Rf, SMB, HML, RMW, and CMW) for the value-weighted returns (in excess of the T-bill rate) of the ten single-sorted portfolios as well as the value-weighted returns of the High minus Low portfolio. Mkt-Rf is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio in excess of the T-bill rate. SMB, HML, RMW, and CMW are factor-mimicking portfolios associated with the size effect, the book-to-market effect, the operating profitability effect, and the investment effect, respectively. We retrieve the data from Kenneth French's website. Avg (Std, Shp) is the average (standard deviation, sharpe ratio) of the value-weighted returns formed from sorts of stocks on expected returns from the IPCA models. Pred is the average expected portfolio return of a model, and Alpha is regression alpha from the Fama and French (2015) five-factor model. pVal(H-L) reports the p-value from a t-test against the null hypothesis of zero average return (column Avg) or zero alpha (column Alpha) for the H-L portfolio.

| $\Gamma_{\alpha \neq 0}$ and $K = 1$, characteristics-compensation | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 1$, covariance-compensation | | | | | |
|---|-------|------|-------|-------|-------|--|------|-------|------|------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.97 | 7.64 | -0.13 | -3.29 | -1.55 | Low (L) | 0.49 | 3.62 | 0.13 | 0.75 | -0.19 |
| 2 | 0.11 | 6.70 | 0.02 | -2.31 | -0.57 | 2 | 0.60 | 4.22 | 0.14 | 1.06 | -0.18 |
| 3 | 0.34 | 6.35 | 0.05 | -1.80 | -0.38 | 3 | 0.73 | 4.71 | 0.16 | 1.27 | -0.09 |
| 4 | 0.60 | 6.10 | 0.10 | -1.41 | -0.13 | 4 | 0.78 | 5.15 | 0.15 | 1.45 | -0.09 |
| 5 | 0.81 | 5.87 | 0.14 | -1.06 | 0.02 | 5 | 0.82 | 5.57 | 0.15 | 1.62 | -0.03 |
| 6 | 0.94 | 5.65 | 0.17 | -0.73 | 0.17 | 6 | 0.86 | 6.16 | 0.14 | 1.80 | 0.01 |
| 7 | 1.13 | 5.66 | 0.20 | -0.40 | 0.33 | 7 | 0.81 | 6.83 | 0.12 | 1.98 | 0.02 |
| 8 | 1.38 | 5.60 | 0.25 | -0.03 | 0.58 | 8 | 0.81 | 7.69 | 0.11 | 2.19 | 0.09 |
| 9 | 1.58 | 5.55 | 0.29 | 0.40 | 0.80 | 9 | 0.86 | 8.97 | 0.10 | 2.44 | 0.21 |
| High (H) | 2.15 | 5.85 | 0.37 | 1.16 | 1.41 | High (H) | 1.39 | 11.17 | 0.12 | 2.86 | 0.87 |
| H-L | 3.12 | 5.02 | 0.62 | 4.45 | 2.96 | H-L | 0.90 | 9.42 | 0.10 | 2.11 | 1.06 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 2.73 | | | | 0.00 |

| $\Gamma_{\alpha \neq 0}$ and $K = 2$, characteristics-compensation | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 2$, covariance-compensation | | | | | |
|---|-------|------|-------|-------|-------|--|------|-------|------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -1.00 | 7.41 | -0.13 | -2.48 | -1.60 | Low (L) | 0.66 | 4.59 | 0.14 | -0.34 | -0.03 |
| 2 | 0.06 | 6.56 | 0.01 | -1.44 | -0.58 | 2 | 0.73 | 5.03 | 0.14 | -0.01 | -0.04 |
| 3 | 0.39 | 6.29 | 0.06 | -0.90 | -0.30 | 3 | 0.75 | 5.33 | 0.14 | 0.22 | -0.05 |
| 4 | 0.69 | 6.02 | 0.11 | -0.48 | -0.03 | 4 | 0.77 | 5.66 | 0.14 | 0.43 | -0.04 |
| 5 | 0.85 | 5.84 | 0.15 | -0.13 | 0.10 | 5 | 0.81 | 5.91 | 0.14 | 0.65 | 0.03 |
| 6 | 0.97 | 5.75 | 0.17 | 0.20 | 0.20 | 6 | 0.73 | 6.28 | 0.12 | 0.88 | -0.06 |
| 7 | 1.07 | 5.73 | 0.19 | 0.53 | 0.28 | 7 | 0.69 | 6.73 | 0.10 | 1.13 | -0.09 |
| 8 | 1.24 | 5.72 | 0.22 | 0.89 | 0.44 | 8 | 0.73 | 7.32 | 0.10 | 1.41 | -0.01 |
| 9 | 1.47 | 5.82 | 0.25 | 1.31 | 0.68 | 9 | 0.83 | 8.27 | 0.10 | 1.75 | 0.14 |
| High (H) | 1.86 | 6.17 | 0.30 | 2.05 | 1.06 | High (H) | 1.65 | 10.63 | 0.16 | 2.34 | 1.14 |
| H-L | 2.86 | 4.83 | 0.59 | 4.53 | 2.66 | H-L | 0.99 | 9.05 | 0.11 | 2.68 | 1.17 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 1.15 | | | | 0.01 |

| $\Gamma_{\alpha \neq 0}$ and $K = 3$, characteristics-compensation | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 3$, covariance-compensation | | | | | |
|---|-------|------|-------|-------|-------|--|------|-------|------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.96 | 7.40 | -0.13 | -2.31 | -1.47 | Low (L) | 0.62 | 4.82 | 0.13 | -0.23 | -0.11 |
| 2 | 0.12 | 6.63 | 0.02 | -1.35 | -0.47 | 2 | 0.66 | 5.09 | 0.13 | 0.07 | -0.11 |
| 3 | 0.37 | 6.24 | 0.06 | -0.85 | -0.31 | 3 | 0.71 | 5.38 | 0.13 | 0.27 | -0.08 |
| 4 | 0.66 | 6.02 | 0.11 | -0.46 | -0.04 | 4 | 0.71 | 5.64 | 0.13 | 0.46 | -0.07 |
| 5 | 0.84 | 5.83 | 0.14 | -0.12 | 0.11 | 5 | 0.76 | 5.94 | 0.13 | 0.65 | -0.00 |
| 6 | 0.90 | 5.76 | 0.16 | 0.19 | 0.11 | 6 | 0.73 | 6.23 | 0.12 | 0.85 | -0.03 |
| 7 | 1.12 | 5.74 | 0.20 | 0.51 | 0.34 | 7 | 0.74 | 6.61 | 0.11 | 1.06 | -0.03 |
| 8 | 1.28 | 5.68 | 0.23 | 0.86 | 0.44 | 8 | 0.81 | 7.08 | 0.12 | 1.30 | 0.08 |
| 9 | 1.50 | 5.82 | 0.26 | 1.27 | 0.64 | 9 | 0.91 | 8.05 | 0.11 | 1.60 | 0.26 |
| High (H) | 1.89 | 6.13 | 0.31 | 2.00 | 1.01 | High (H) | 1.75 | 10.54 | 0.17 | 2.14 | 1.21 |
| H-L | 2.85 | 4.82 | 0.59 | 4.30 | 2.48 | H-L | 1.13 | 8.90 | 0.13 | 2.37 | 1.32 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.33 | | | | 0.00 |

| $\Gamma_{\alpha \neq 0}$ and $K = 4$, characteristics-compensation | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 4$, covariance-compensation | | | | | |
|---|-------|------|-------|-------|-------|--|------|-------|------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.92 | 7.69 | -0.12 | -2.12 | -1.38 | Low (L) | 0.62 | 4.68 | 0.13 | -0.33 | -0.18 |
| 2 | 0.07 | 6.63 | 0.01 | -1.18 | -0.49 | 2 | 0.65 | 4.87 | 0.13 | -0.03 | -0.17 |
| 3 | 0.44 | 6.31 | 0.07 | -0.69 | -0.17 | 3 | 0.74 | 5.11 | 0.14 | 0.16 | -0.11 |
| 4 | 0.60 | 6.05 | 0.10 | -0.30 | -0.09 | 4 | 0.78 | 5.43 | 0.14 | 0.33 | -0.07 |
| 5 | 0.82 | 5.81 | 0.14 | 0.04 | 0.09 | 5 | 0.72 | 5.71 | 0.13 | 0.50 | -0.09 |
| 6 | 0.85 | 5.69 | 0.15 | 0.35 | 0.07 | 6 | 0.73 | 6.08 | 0.12 | 0.68 | -0.04 |
| 7 | 1.13 | 5.67 | 0.20 | 0.67 | 0.30 | 7 | 0.76 | 6.53 | 0.12 | 0.87 | 0.07 |
| 8 | 1.32 | 5.59 | 0.24 | 1.02 | 0.44 | 8 | 0.72 | 7.29 | 0.10 | 1.10 | 0.04 |
| 9 | 1.54 | 5.75 | 0.27 | 1.42 | 0.63 | 9 | 0.93 | 8.25 | 0.11 | 1.38 | 0.38 |
| High (H) | 2.05 | 5.91 | 0.35 | 2.13 | 1.09 | High (H) | 1.60 | 10.92 | 0.15 | 1.89 | 1.14 |
| H-L | 2.97 | 5.14 | 0.58 | 4.25 | 2.47 | H-L | 0.98 | 9.33 | 0.11 | 2.22 | 1.32 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 1.50 | | | | 0.01 |

| $\Gamma_{\alpha \neq 0}$ and $K = 5$, characteristics-compensation | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 5$, covariance-compensation | | | | | |
|---|-------|------|-------|-------|-------|--|------|-------|------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.95 | 7.60 | -0.13 | -2.03 | -1.39 | Low (L) | 0.62 | 4.66 | 0.13 | -0.32 | -0.16 |
| 2 | 0.13 | 6.72 | 0.02 | -1.13 | -0.45 | 2 | 0.71 | 4.86 | 0.15 | -0.02 | -0.13 |
| 3 | 0.39 | 6.29 | 0.06 | -0.65 | -0.22 | 3 | 0.76 | 5.13 | 0.15 | 0.16 | -0.08 |
| 4 | 0.63 | 6.02 | 0.10 | -0.27 | -0.06 | 4 | 0.81 | 5.37 | 0.15 | 0.33 | -0.04 |
| 5 | 0.78 | 5.88 | 0.13 | 0.06 | 0.04 | 5 | 0.72 | 5.67 | 0.13 | 0.49 | -0.09 |
| 6 | 0.89 | 5.68 | 0.16 | 0.37 | 0.10 | 6 | 0.78 | 6.15 | 0.13 | 0.65 | -0.02 |
| 7 | 1.16 | 5.64 | 0.21 | 0.68 | 0.34 | 7 | 0.71 | 6.58 | 0.11 | 0.84 | 0.00 |
| 8 | 1.33 | 5.68 | 0.23 | 1.02 | 0.43 | 8 | 0.73 | 7.26 | 0.10 | 1.05 | 0.07 |
| 9 | 1.60 | 5.69 | 0.28 | 1.42 | 0.68 | 9 | 0.88 | 8.16 | 0.11 | 1.33 | 0.33 |
| High (H) | 2.09 | 5.94 | 0.35 | 2.09 | 1.14 | High (H) | 1.55 | 10.86 | 0.14 | 1.82 | 1.08 |
| H-L | 3.05 | 5.16 | 0.59 | 4.13 | 2.53 | H-L | 0.92 | 9.20 | 0.10 | 2.14 | 1.24 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 2.01 | | | | 0.01 |

| $\Gamma_{\alpha \neq 0}$ and $K = 6$, characteristics-compensation | | | | | | $\Gamma_{\alpha \neq 0}$ and $K = 6$, covariance-compensation | | | | | |
|---|-------|------|-------|-------|-------|--|------|------|------|-------|-------|
| | Avg | Std | Shp | Pred | Alpha | | Avg | Std | Shp | Pred | Alpha |
| Low (L) | -0.88 | 7.52 | -0.12 | -1.74 | -1.30 | Low (L) | 0.42 | 5.07 | 0.08 | -0.50 | -0.31 |
| 2 | 0.07 | 6.71 | 0.01 | -0.97 | -0.47 | 2 | 0.58 | 5.18 | 0.11 | -0.13 | -0.21 |
| 3 | 0.42 | 6.25 | 0.07 | -0.56 | -0.23 | 3 | 0.61 | 5.36 | 0.11 | 0.10 | -0.19 |
| 4 | 0.63 | 6.01 | 0.10 | -0.24 | -0.06 | 4 | 0.69 | 5.48 | 0.13 | 0.30 | -0.13 |
| 5 | 0.75 | 5.76 | 0.13 | 0.05 | -0.01 | 5 | 0.74 | 5.75 | 0.13 | 0.50 | -0.07 |
| 6 | 0.93 | 5.71 | 0.16 | 0.31 | 0.12 | 6 | 0.83 | 6.01 | 0.14 | 0.70 | 0.03 |
| 7 | 1.12 | 5.71 | 0.20 | 0.58 | 0.30 | 7 | 0.82 | 6.36 | 0.13 | 0.91 | 0.04 |
| 8 | 1.32 | 5.69 | 0.23 | 0.86 | 0.44 | 8 | 0.95 | 6.90 | 0.14 | 1.16 | 0.23 |
| 9 | 1.47 | 5.68 | 0.26 | 1.20 | 0.58 | 9 | 1.09 | 7.67 | 0.14 | 1.48 | 0.45 |
| High (H) | 2.08 | 6.13 | 0.34 | 1.79 | 1.13 | High (H) | 1.83 | 9.80 | 0.19 | 2.06 | 1.41 |
| H-L | 2.96 | 4.94 | 0.60 | 3.53 | 2.42 | H-L | 1.41 | 7.80 | 0.18 | 2.55 | 1.71 |
| pVal(H-L) | 0.00 | | | | 0.00 | pVal(H-L) | 0.00 | | | | 0.00 |

Table 5: Expected-variance-sorted portfolios from IPCA models

The table reports characteristics of decile portfolios formed from monthly sorts of CRSP/Compustat stocks on expected variances from the IPCA specifications accounting for factor loadings. The left-hand side reports the results of sorts on the expected variances from the unrestricted IPCA specification ($\Gamma_{\alpha \neq 0}, \Gamma_{\beta \neq 0}$). The right-hand side reports the results from sorts on the expected variances from the restricted IPCA specification allowing for factor loadings but not for alpha ($\Gamma_{\alpha=0}, \Gamma_{\beta \neq 0}$). The ten portfolios are defined as follows. For each month from July 1962 to May 2014, we assign all stocks to ten portfolios using decile breakpoints from the cross-section of the estimated variances from the two IPCA models and calculate the value-weighted monthly percentage excess returns for the next month. To analyze the aggregate effect of a certain model on stock returns, we take a long position in portfolio 10 (High) and a short position in portfolio 1 (Low). The numbers in the table represent the standard deviations of the value-weighted returns formed from sorts of stocks on expected variances from the IPCA models. pVal(MR) reports the p-value from a Patton and Timmermann (2010)-like monotonic relationship test against the null hypothesis of a decreasing or no monotonic relationship from portfolio one through ten.

| | $\Gamma_{\alpha \neq 0}$ | | | | | | | $\Gamma_{\alpha=0}$ | | | | | |
|----------|--------------------------|-------|-------|-------|-------|-------|----------|---------------------|-------|-------|-------|-------|-------|
| | 1 | 2 | 3 | 4 | 5 | 6 | | 1 | 2 | 3 | 4 | 5 | 6 |
| Low (L) | 3.62 | 3.70 | 3.72 | 3.75 | 3.78 | 3.80 | Low (L) | 3.64 | 3.71 | 3.70 | 3.75 | 3.77 | 3.79 |
| 2 | 4.22 | 4.23 | 4.25 | 4.30 | 4.31 | 4.30 | 2 | 4.25 | 4.26 | 4.23 | 4.26 | 4.28 | 4.29 |
| 3 | 4.71 | 4.62 | 4.67 | 4.65 | 4.67 | 4.67 | 3 | 4.74 | 4.64 | 4.65 | 4.71 | 4.68 | 4.69 |
| 4 | 5.15 | 5.05 | 5.05 | 5.11 | 5.12 | 5.11 | 4 | 5.17 | 5.06 | 5.06 | 5.06 | 5.12 | 5.13 |
| 5 | 5.57 | 5.51 | 5.52 | 5.55 | 5.54 | 5.54 | 5 | 5.59 | 5.49 | 5.53 | 5.57 | 5.54 | 5.53 |
| 6 | 6.16 | 6.09 | 6.06 | 6.07 | 6.07 | 6.06 | 6 | 6.14 | 6.11 | 6.09 | 6.07 | 6.06 | 6.06 |
| 7 | 6.83 | 6.75 | 6.77 | 6.80 | 6.79 | 6.77 | 7 | 6.87 | 6.75 | 6.81 | 6.81 | 6.81 | 6.79 |
| 8 | 7.69 | 7.69 | 7.68 | 7.71 | 7.70 | 7.74 | 8 | 7.64 | 7.68 | 7.65 | 7.73 | 7.72 | 7.71 |
| 9 | 8.97 | 8.83 | 8.92 | 8.93 | 8.91 | 8.89 | 9 | 8.98 | 8.84 | 8.87 | 8.86 | 8.89 | 8.88 |
| High (H) | 11.17 | 11.35 | 11.43 | 11.36 | 11.36 | 11.36 | High (H) | 11.14 | 11.36 | 11.46 | 11.35 | 11.35 | 11.36 |
| H-L | 9.42 | 9.45 | 9.52 | 9.48 | 9.50 | 9.47 | H-L | 9.38 | 9.44 | 9.55 | 9.43 | 9.46 | 9.48 |
| pVal(MR) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | pVal(MR) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |