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Abstract

We show that much of the profitability in equity option return strategies, which try to capture option mispricing by taking exposure to underlying volatility, can be explained by an IPCA model. The alpha reduction, relative to competing static factor models, is between 50% and 75% depending on the computing model and the type of option position.

Keywords: Option returns, IPCA, Alpha

JEL Classification: G11, G12, G13

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1 Introduction

There is an extensive literature on factor models for stocks (see, for example, Fama and French, 1993, Fama and French, 2015, Hou, Xue, and Zhang, 2015, and Hou, Mo, Xue, and Zhang, 2021) and a growing literature on factor models for corporate bonds (see, for example, Bai, Bali, and Wen, 2019, Bali, Subrahmanyam, and Wen, 2021, Chung, Wang, and Wu, 2019, and Lin, Wang, and Wu, 2011). However, despite the proliferation of studies that document portfolio trading strategies in options that seem to generate abnormal profits (we discuss these studies later in this section), literature on factor models for equity options is relatively sparse and largely unsuccessful at explaining such abnormal returns.

In this paper, we propose an option factor model that can explain a substantial portion of realized returns for most option trading strategies. Expected returns from our model are very close to their realized counterparts. Accordingly, the most commonly studied option trading strategies display little abnormal profitability.

Our factor model is inspired by the instrumented principal component analysis (IPCA) of Kelly, Pruitt, and Su (2019). IPCA is ideally suited for our analysis as it helps in reducing the dimension of the many characteristics that are related to option returns, and allows a parsimonious, yet intuitive, way to model time varying betas. These betas are allowed to be functions of stock, option, and contract characteristics. IPCA eschews the need to construct portfolios on an ad-hoc basis and, instead, performs a dimension reduction of many individual assets into a few latent factors. Therefore, IPCA can be used to extract factors from individual option returns potentially including multiple option contracts on the same underlying stock.

IPCA provides a very different alternative to existing attempts to risk-adjust option returns. Option trading studies typically use stock factors to calculate alphas of the their trading strategies (occasionally with the inclusion of the aggregate volatility factor of Coval and Shumway, 2001). The use of stock factors is justifiable because options are derivatives on the underlying stocks. Nevertheless, it is well-understood that options are not redundant securities. For example, Bakshi and Kapadia (2003) show that delta-hedged returns contain variance risk premium that is not captured by stock factors. Some recent papers, such as Bali, Cao, Song, and Zhan (2022) and Horenstein, Vasquez, and Xiao (2020), make headway in resolving this issue by constructing option factors directly from option portfolio returns and using the methods commonly used to construct the stock returns factors.

These factor models have a few limitations. First, the factors are constructed only at the portfolio level and, as such, miss information that is present at the firm level and potentially even at the option contract level. Second, the models are typically static, in the sense that betas are not allowed to be time-varying. However, option returns, by their very nature, have dynamic betas that can depend on firm and option characteristics such as option Greeks even in the simplest of settings where CAPM holds period by period (Black and Scholes, 1973). Third, we show that even these factor models leave substantial alphas for many option trading strategies. In contrast, as mentioned at the beginning, our IPCA factor model is largely able to explain realized returns of these strategies.

In our empirical analysis, we construct a library of predictor variables for option returns over the sample period of 1996 to 2020. Our characteristics come from previous studies such as An, Ang, Bali, and Cakici (2014), Boyer and Vorkink (2014), Bali and Murray (2013), Cao and Han (2013), Christoffersen, Goyenko, Jacobs, and Karoui (2018), Goyal and Saretto (2009), Hu and Jacobs (2020), Vasquez (2017), and Zhan, Han, Cao, and Tong (2022), and can be classified into four categories: (i) Contract characteristics such as maturity, open interest, option Greeks, etc.; (ii) Descriptors of risk-neutral return distribution such as model free implied volatility, skewness, and kurtosis at the stock level; (iii) Measures of physical return distribution such as volatility, skewness, kurtosis, and autocorrelation at the stock level; and (iv) Firm level characteristics such as size, price, book-to-market. In total, we use 44 characteristics as predictors of option returns and as conditioning variables in IPCA.

As a preliminary step, we show that many predictors generate statistically significant average returns. A few predictors produce extremely significant average returns with t-statistics larger than 10. For example, the average monthly return from sorts on the Goyal and Saretto (2009) realized minus implied volatility variables is 3.5% with a t-statistic of 20. These high average returns are not explained by factor models. For example, even after controlling for multiple hypothesis testing (MHT; see Harvey, Liu, and Saretto, 2020), we find that 30 characteristics have statistically significant alphas after controlling for factors from Bali, Cao, Song, and Zhan (2022). Even the factor model of Horenstein, Vasquez, and Xiao (2020) produces 14 statistically significant alphas. Thus, the first pass suggests that option markets exhibit huge inefficiencies.

Our contention is that this conclusion is premature and most likely a function of the factor models. While the joint hypothesis problem afflicts all empirical studies, it is possible that the extant factor models in options exacerbate this issue because option returns are highly nonlinear and have dynamic factor loadings. Our IPCA factor model is designed to ameliorate these problems by extracting latent factors with dynamic betas from individual option returns.

We conduct IPCA analysis by varying the number of factors from one to six but find that four factors are sufficient to explain delta-hedged call option returns, while five factors required for delta-hedged puts and straddles. For example, our baseline four-factor IPCA model produces time-series R^2 (cross-sectional average of time-series R^2 for each stock) of 10.7% and cross-sectional R^2 (time-series average of the cross-sectional R^2 for each month) of 7.5%. Given the very high volatility of delta-hedged returns, these R^2 numbers are non-trivial and compare favorably with similar numbers reported for stocks (Kelly, Pruitt, and Su, 2019), corporate bonds (Kelly, Palhares, and Pruitt, 2022), and cryptocurrencies (Bianchi and Babiak, 2022). When we consider the pricing performance of managed portfolios constructed on the same 44 characteristics that we use in our IPCA, these R^2s are in the range of 75%-80%.

One concern with IPCA models is that the factors and model parameters are estimated using full-sample. While unconditional betas (or parameters of conditional betas) are estimated using full sample in most empirical studies, the extraction of latent factors could raise doubts about data over-fitting. To allay these concerns, we also perform an out-of-sample analysis. In this analysis, we estimate latent factors and model parameters on an expanding window basis and use these estimates to make real-time forecasts for the subsequent month. We find only a modest decrease in out-of-sample R^2s to their in-sample counterparts. For example, for the case of four factor, the cross-section R^2 for managed portfolios is 79.8% in-sample and 74.4% out-of-sample. As in Kelly, Palhares, and Pruitt (2022), the reason for this modest deterioration in performance is the relatively few parameters that are estimated in IPCA.

We have mentioned that traditionally constructed option factor models with static betas do not explain option returns well. It is possible that dynamic betas (modeled the same way as in IPCA) level the playing field a bit and improve the pricing performance of these factor models. We do find that model performance improves with dynamic betas. However, the IPCA model still beats these alternative option factor models with higher R^2 and lower pricing error. The closest competitor to IPCA is the Horenstein, Vasquez, and Xiao (2020) model; nevertheless, IPCA has substantially lower pricing errors: 0.3% versus 7.8% in explaining managed portfolio returns, for example.

Because the factors extracted from IPCA are latent, they must be thoroughly investigated. All factors have positive averages by construction. The average return of the first factor is 8.5% per month, while the remaining three factors have average returns of around 0.5%. The pairwise correlation of the last three factors are all close to zero but all these three factors are negatively correlated to the first factor. The annualized Sharpe ratio of the mean-variance tangency portfolio constructed from the four factors is 5.7 in-sample, and 4.9, out-of-sample.

We try to uncover what kind of risks IPCA factors are pricing by first comparing them to existing factors that have been used to price options. We regress them on the factors from Bali, Cao, Song, and Zhan (2022), Büchner and Kelly (2022), and Horenstein, Vasquez, and Xiao (2020). We find that the first factor (F1) is mostly related to the realized minus implied volatility spread factor and stock idiosyncratic volatility factor. Thus, F1 captures the fundamental components of option returns related to the most profitable trading strategies. The second factor (F2) is related to option liquidity and market capitalization of the firm. The third factor (F3) is mostly related to the option market portfolio. Finally, the fourth factor (F4) is negatively related to the option market portfolio and positively related to S&P500 delta-hedged returns, signaling that this factor picks up aggregate trends that are not driven by firm specific expectations about stock volatilities.

Second, we focus our attention on how the factors relate to the state of aggregate economy. We study how the factors' realized returns behave in periods of particular stress in the market, proxied by large negative directional movements in prices, changes in aggregate volatility, or high values of the tail risk indicator of Kelly and Jiang (2014) which they relate to higher moments of the return distribution. Following Kelly and Jiang (2014), we consider large differences between implied and realized skewness and kurtosis on the S&P500 index, that are meant to proxy for the return on skewness and kurtosis swaps (see, for example, Bakshi and Kapadia, 2003, Carr and Wu, 2009, and Kozhan, Neuberger, and Schneider, 2013), and thus capture high-order risk premia. We find that F1 and and F4 price uncertainty related to tail risk events; their returns are lower at times when risk-neutral skewness is particularly negative relative to its realized counterpart and risk-neutral kurtosis is particularly greater than its realized equivalent, both of which indicate large conditional risk premia. On the other hand, F2 and F3 mainly function as hedges against movements in the first two moments of the aggregate distribution (returns and changes in volatility). The fact that most of the premium in delta-hedged returns (which is related to F1) comes from uncertainty in higher moments of the aggregate return distribution is not too surprising, considering that the base assets (i.e., delta-hedged returns) are constructed to be neutral relative to movements in the underlying and are increasing in volatility. The risk undertaking these strategies is, thus, related to the possibility of extreme changes in market conditions

We finally turn back to the main objective of the paper, namely to understand whether returns to option trading strategies are compensation for risk. We find that of the 29 (out of 44) strategies with statistically significant returns after accounting for multiple hypothesis testing (MHT), only five (nine at conventional levels) still have a statistically significant IPCA alphas. Even the strategies that still produce statistically significant alpha, the magnitude of the alpha is much lower compared to the magnitude of raw returns. For example, the alpha of the Goyal and Saretto (2009) realized minus implied volatility strategy is only 1.0% (compared to the raw return of 3.6%) with a t-statistic of 9.4 (compared to the raw return t-statistic of 20.1). The IPCA does much better for signal-weighted portfolios. Only two of the 23 strategies with statistically significant returns have statistically significant alpha. We conclude that the extant evidence on option trading strategies presents no significant challenges to market efficiency.

We conduct a few robustness checks to explore variations on our baseline scenario. First, we explore the importance of liquidity for our results. Christoffersen, Goyenko, Jacobs, and Karoui (2018) and Muravyev (2016) show that liquidity is an important characteristic for option returns. We consider options with low/high open interest and low/high option bid-ask spread. We estimate separate IPCA models for each of these sub-samples and explore how the extracted IPCA factors price portfolios constructed within the same sub-sample. As expected, we find that IPCA fit (measured by R^2, relative pricing error, average absolute alpha, number of statistically significant alphas) is worse for the sub-sample of illiquid options vis-à-vis liquid options. Nevertheless, even for illiquid options, IPCA leaves no more than 2 statistically significant alphas. In contrast, competing factor models have a much harder time pricing portfolios of illiquid options. For example, the Horenstein, Vasquez, and Xiao (2020) model produces 29 statistically significant alphas for signal-weighted portfolios. Second, Karakaya (2013) and Büchner and Kelly (2022) show that equity and index option returns vary with the initial moneyness of the contracts. Thus, we explore variations across the moneyness range. We find that IPCA model does a better job of pricing in=the=money (ITM) options than it does for out-of-the-money (OTM) options but, even for OTM options, the number of statistically significant alphas is small. Third, the extant literature does not uniquely focus on call delta-hedged returns. Hence, we explore alternative option positions such as delta-hedged puts as in Ramachandran and Tayal, 2021 and straddles as in Vasquez, 2017. The biggest model that we estimate is a joint estimation in which we pool delta-hedged calls, delta-hedged puts, and straddle returns. Straddles returns are very volatile and thus pose unique pricing challenges to all factor models. Our IPCA model is not immune to these difficulties. Nevertheless, even for the straddle returns, the IPCA fit is relatively good an we find only 6 statistically significant alphas for signal-weighted portfolios. The joint estimation does not compound the problems generated by the much more volatile straddle returns, but delivers intermediate results. For example the number of strategies that have significant alphas is about the same as the sum of the unexplained strategies in the stand alone estimation of the three individual components of delta-hedged calls, delta-hedged puts, and straddles. Especially noteworthy is the fact that, for the joint estimation, signal-weighted portfolios have 12, 93, and 57 statistically significant alphas from the IPCA, Bali, Cao, Song, and Zhan (2022), and Horenstein, Vasquez, and Xiao (2020) models. We conclude that IPCA is a relatively flexible instrument, and can account for substantial differences in the data being explained.

1.1 Related literature

Although viewed as redundant assets by seminal papers (Black and Scholes, 1973 and Merton, 1973), later literature suggests that equity options inject additional information to the equity market (see, for example, Chakravarty, Gulen, and Mayhew, 2004, Chiras and Manaster, 1978, and Easley, O'Hara, and Srinivas, 1998). Trading by informed investors in the options market can, thus, help predict underlying stock returns. Many studies use information extracted from options to predict stock returns (see, for an incomplete list, Amin and Lee, 1997, An, Ang, Bali, and Cakici, 2014, Bali and Hovakimian, 2009, Cao, Chen, and Griffin, 2005, Cremers and Weinbaum, 2010, Easley, O'Hara, and Srinivas, 1998, Johnson and So, 2012, Pan and Poteshman, 2006, and Xing, Zhang, and Zhao, 2010). A related stream of literature analyzes the lead-lag relationship between option and stock returns. Chakravarty, Gulen, and Mayhew (2004) find that options markets contribute 17% to the price discovery process. There is also evidence that information extracted from options can predict corporate bond returns (see Cao, Goyal, Xiao, and Zhan, 2022).

More relevant to us is the literature on predicting option returns. One can classify option return predictors as broadly related to signals coming from the underlying stocks (or firms) or those coming from options themselves. Regarding stock predictors of option returns, Cao and Han (2013) show that delta-hedged option returns decrease with the stock idiosyncratic volatility. Galai and Masulis (1976) and Hu and Jacobs (2020) show, both theoretically and empirically, that the expected returns of calls (puts) decrease (increase) with underlying stock volatility. Aretz, Lin, and Poon (2022) show that it is important to distinguish the effect of idiosyncratic and systematic volatility in studying these relations. An, Ang, Bali, and Cakici (2014) show that implied volatility increases for options on stocks with high past returns. Ramachandran and Tayal (2021) report a monotonic relation between various measures of short-sales constraints and delta-hedged put returns on overpriced stocks. Zhan, Han, Cao, and Tong (2022) show that many stock characteristics (such as profit margin, firm profitability, cash holding, and shares issuance) have a strong predictive power for delta-hedged option returns.

There are also many studies that use option characteristics to predict option returns. Boyer and Vorkink (2014) find that ex-ante option implied skewness predicts option returns negatively. Relatedly, Bali and Murray (2013) find a negative relation between risk-neutral stock skewness and the returns of skewness assets constructed from options. Byun and Kim (2016) report that call options written on the most lottery-like stocks underperform otherwise similar call options written on the least lottery-like stocks. Christoffersen, Goyenko, Jacobs, and Karoui (2018) find a positive risk-adjusted return spread for illiquid over liquid equity options. Goyal and Saretto (2009) find that the difference between historical volatility and implied volatility predicts delta-hedged and straddle returns. Heston, Jones, Khorram, Li, and Mo (2022) find that momentum works in option markets too. Muravyev (2016) documents that option market order-flow imbalance significantly predicts daily option returns. Ruan (2020) finds that volatility-of-volatility has predictive power for option returns. Vasquez (2017) shows that difference in long-term and short-term implied volatility has predictive power for delta-hedged option returns. Bali, Beckmeyer, Moerke, and Weigert (2021) and Shafaati, Chance, and Brooks (2021) apply machine learning techniques to uncover which characteristics are important for explaining the cross-section of option returns (see also Goyenko and Zhang, 2022 for using machine learning to predict the joint cross-section of stock and option returns).

The literature on factor models for option returns is small. Coval and Shumway (2001) propose a factor constructed from zero-beta straddles to explain S&P500 index option returns. Büchner and Kelly (2022) apply IPCA techniques to construct factors for index options. Karakaya (2013) identifies three factors based on level, slope, and value in individual raw option returns. Broadie, Chernov, and Johannes (2009) warn against applying linear benchmarks to raw option returns and suggest that straddles or delta-hedged option returns are more immune to sampling problems. More recently, there is a resurgence in option factor models to explain delta-hedged option returns or returns on straddles. Bali, Cao, Song, and Zhan (2022) and Horenstein, Vasquez, and Xiao (2020) construct option factors by sorting on either stock or option characteristics. As we show later, even these recent factor models constructed from individual option returns leave high alphas for option portfolios. In contrast, our IPCA factor model does remarkably well in explaining the cross-section of option returns.

The rest of the paper proceeds as follows. Section 2 presents the data and descriptive statistics on the basic option portfolio strategies. We provide a brief overview of the IPCA method in Section 3. The main results of the paper are discussed in Section 4. Section 5 concludes.

2 Data

2.1 Sample and variable construction

Options data are from OptionMetrics and cover the period from January 1996 through November 2020. We impose two sets of filters. The first type of filter applies to all observations and is aimed at eliminating contracts that are non-standard or prices that violate basic no-arbitrage bounds or market minimum specifications. We eliminate contracts (i) for which the underlying is not a share code 10 or 11 stock, or (ii) that have non-standard settlements (i.e., not the closing of the expiration day), or (iii) that have non-standard expiration (i.e., weeklies), or (iv) that settle for a number of underlying shares different from 100, or (v) for which one of the bid or ask quotes is missing, or (v) for which the ask is lower than the bid, or the ask is $5 above the bid, or (vi) the bid-ask spread is lower than the minimum tick size (i.e., 5 cents for option prices below $3 and 10 cents for option prices above $3), or (vii) for which the mid-point price is below or $100 above the current exercise payoff, or (viii) option delta is less than equal to zero for calls, or greater than equal to zero for puts.

The second set of filters only applies to prices that are used to construct the first leg of the return. In general, we study one-month returns defined as the percentage change between an option position from month end to month end, where the option contract at the initiation of the position has residual maturity of around 50 days. For example, for calculation of return from the end of February to the end of March, we apply these filters only to the prices at the end of February. The filters are as follows. We consider options (i) that are closest to ATM with moneyness (defined as the ratio of strike to underlying price) between 0.8 and 1.2, and (ii) that have positive volume or positive open interest, and (iii) for which the mid-point price is higher than 25 cents.

We consider three types of option positions: delta-hedged calls, delta-hedged puts, and straddles. Following Cao and Han (2013) and Zhan, Han, Cao, and Tong (2022), we define returns to buying a delta-hedged call as:

$$\Delta \text{Call} = \frac{(C_{t+1} - \Delta_t S_{t+1}) - (C_t - \Delta_t S_t)}{\Delta_t S_t - C_t},$$

where we scale the delta-hedged gains by $(\Delta_t S_t - C_t) > 0$. Therefore, our returns can be thought of as the negative of the return to writing a delta-hedged call. The return to a long position in a delta-hedged put is defined as:

$$\Delta \text{Put} = \frac{(P_{t+1} - \Delta_t S_{t+1}) - (P_t - \Delta_t S_t)}{P_t - \Delta_t S_t}.$$

The straddle return is defined as:

$$\text{Straddle} = \frac{(C_{t+1} + P_{t+1}) - (C_t + P_t)}{C_t + P_t},$$

where calls and puts involved have the same strike (and maturity).

Stock level information is obtained from CRSP/Compustat data, which are matched and aligned in time with OptionMetrics information so that no look ahead biased is introduced. All accounting information is assumed to be available six months after the fiscal year end. For each stock-month return position we construct monthly characteristics that can generally be divided into four categories:

1. Contract characteristics such as moneyness, bid-ask spread, open interest, volume, option price, option delta, and implied volatility.

2. Measures of risk-neutral distribution. These are constructed using options with the same moneyness and the same maturity such as model-free implied volatility, model-free implied skewness, model-free implied kurtosis; using options with the same moneyness and approximate maturity but from different days such as the volatility of implied volatility. We also construct variables using the implied volatility surface: the ATM level for approximate maturity of 30 days; the slope of the 30 days curve, as the difference between moneyness of 0.8 and moneyness of 1.0; the ATM term, as the difference between the implied volatility value for 30 days minus the corresponding value for 360 days maturity.

3. Measures of the physical distribution of returns such as the stock returns, volatility, autocorrelation, skewness, kurtosis, cumulative return of the previous eleven months, largest absolute return in the past 10 days, turnover and idiosyncratic volatility.

4. Stock returns predictors that have been found to predict also option returns such as the book-to-market, profitability, RSI, etc.

We refer to Appendix A for detailed descriptions about variables constructions and their source references.

2.2 Empirical regularities

We construct portfolios of delta-hedged call positions by sorting stocks into deciles based on the firm-level characteristics detailed in the previous section. We consider month-end to month end returns and sort stocks based on the the last trading day of the month (i.e., we do not skip a day between portfolio formation and trading inception). For each sorting variable Table 1 reports average return, alphas from linear factor models, and related t-statistic of $10-1$ (long-short) portfolios.

We examine alphas from three factor models. The first factor model (FF+) is from Büchner and Kelly (2022), and includes the five factors from Fama and French (2015), the momentum factor of Carhart (1997), the embedded leverage factor of Frazzini and Pedersen (2021), and the zero-beta straddle factor of Coval and Shumway (2001). The second factor model (BCSZ) refers to the factor model of Bali, Cao, Song, and Zhan (2022). This factor model includes five factors constructed from delta-hedged call returns. The first four factors are obtained by sorting stocks based on the option bid-ask spread, the option price, the model free implied kurtosis, and the difference between realized and implied volatilities. The fifth factor is a dollar open interest weighted average of all delta-hedged call returns. The third factor model (HVX) is from Horenstein, Vasquez, and Xiao (2020). This factor model includes the S&P500 delta-hedged call return and three delta-hedge call return factors constructed by sorting stocks based on idiosyncratic volatility, equity market capitalization, and the difference between realized and idiosyncratic volatility. We refer the reader to the original papers for more details on the construction of these factors. To caution against the interpretation of single test statistical significance we provide multiple hypothesis thresholds based on the 5% FDR of Benjamini and Hochberg (1995) (see Harvey, Liu, and Saretto, 2020, for a review of multiple hypothesis methods).

Table 1 shows that many characteristics are strong predictors of delta-hedged call returns. Of the 44 predictors that we consider, 29 have statistically significant average returns. A few predictors produce extremely significant average returns with t-statistics larger than 10. For example, the average monthly return resulting from sorts on RV$-$IV and IV term is 3.6% and 2.4%, respectively, with t-statistics of around 20. Alphas from the FF+ and the BCSZ model (factor models that include stock market factors) provide limited risk-adjustment to option portfolios. For example, 34 (30) characteristics have statistically significant alphas after adjusting for FF+ (BCSZ) model even after after adjusting for multiple hypothesis testing. The HVX factor model that is based on option returns constructed to price the option anomalies (but has constant betas) does explain more of the anomaly returns. Nevertheless, even this model produces 14 out of 41 (after removing three portfolios which are also factors) statistically significant alphas. Note that if we use conventional statistical significance, the HVX model produces an additional 8 more significant alphas for a total of 22 statistically significant alphas. We conclude that the extant option return factor models suggest massive inefficiency in the option market.

Table 1: Long-short delta-hedged call portfolios

The table shows performance measures for long-short portfolios constructed by sorting stocks into decile characteristics, buying options positions in portfolio 10 and writing option positions in portfolio 1. We report average return and alphas from three linear factor model regressions as well as their relative t-statistics, in parentheses. The three factor models from Büchner and Kelly (2022) (FF+), Bali, Cao, Song, and Zhan (2022) (BCSZ), and Horenstein, Vasquez, and Xiao (2020) (HVX). t-statistics larger than the Benjamini and Hochberg (1995) 5% FDR adjusted threshold (i.e., 2.60 for mean return, and 2.08, 2.16, 2.43 for FF+, BCSZ, and HVX alpha, respectively) are reported in bold. Data spans the period between January 1996 and November 2020.

	Return		Alpha					
			FF+		BCSZ		HVX	
Moneyness	**0.47**	**(3.11)**	**0.84**	**(6.18)**	**0.73**	**(4.31)**	0.39	(1.85)
Bid-Ask	**1.05**	**(6.19)**	**1.16**	**(6.50)**	**1.34**	**(7.16)**	**0.61**	**(2.82)**
Open interest	**−0.76**	**(−7.57)**	**−0.87**	**(−8.30)**	**−0.90**	**(−7.16)**	**−0.59**	**(−4.47)**
Delta	**−1.06**	**(−8.19)**	**−1.43**	**(−11.50)**	**−1.01**	**(−6.45)**	−0.44	(−2.32)
Volume	−0.23	(−2.09)	**−0.27**	**(−2.24)**	**−0.44**	**(−3.25)**	0.08	(0.59)
Option price	**0.51**	**(3.16)**	**0.36**	**(2.25)**	0.16	(1.16)	0.20	(1.18)
IV ATM	**−2.36**	**(−10.69)**	**−2.19**	**(−9.53)**	**−1.60**	**(−7.74)**	−0.33	(−2.14)
IV slope	**−1.94**	**(−14.82)**	**−1.74**	**(−11.71)**	**−1.14**	**(−7.22)**	−0.28	(−1.67)
IV term	**−2.40**	**(−19.74)**	**−2.32**	**(−16.85)**	**−2.19**	**(−14.34)**	**−1.56**	**(−9.20)**
IV vol	**−0.64**	**(−3.71)**	**−0.47**	**(−2.76)**	−0.14	(−0.81)	**0.51**	**(3.07)**
MF vol	−0.40	(−1.56)	−0.41	(−1.48)	**−0.66**	**(−2.80)**	−0.09	(−0.34)
MF skew	**−0.34**	**(−2.78)**	−0.29	(−2.08)	−0.22	(−1.41)	−0.21	(−1.08)
MF kurt	**0.45**	**(2.60)**	**0.59**	**(3.07)**	**0.59**	**(3.46)**	0.49	(2.07)
Stock price	**0.54**	**(2.80)**	**0.44**	**(2.36)**	0.16	(0.83)	0.26	(1.40)
Stock return	0.07	(0.45)	0.19	(1.09)	−0.18	(−0.85)	−0.21	(−0.81)
Stock return11	**−0.54**	**(−2.62)**	**−0.60**	**(−2.98)**	**−0.77**	**(−3.27)**	**−1.08**	**(−3.74)**
Realized vol	**−0.66**	**(−2.98)**	**−0.63**	**(−2.79)**	**−0.72**	**(−3.82)**	−0.30	(−2.07)
Realized skew	−0.16	(−1.65)	**−0.27**	**(−2.59)**	−0.17	(−1.34)	−0.31	(−2.05)
Realized kurt	**−0.46**	**(−4.58)**	**−0.34**	**(−2.96)**	**−0.37**	**(−2.80)**	−0.33	(−2.07)
Idiosyn. vol	**−0.92**	**(−5.31)**	**−0.94**	**(−5.23)**	**−0.75**	**(−4.71)**	—	—
Max10	**−0.72**	**(−3.38)**	**−0.68**	**(−3.13)**	**−0.68**	**(−3.56)**	0.07	(0.51)
Market cap	0.16	(1.00)	0.05	(0.31)	−0.22	(−1.25)	—	—
Autocorrelation	**0.28**	**(2.91)**	0.21	(1.95)	**0.50**	**(4.17)**	**0.62**	**(4.40)**
Turnover	**−0.66**	**(−3.72)**	**−0.77**	**(−3.95)**	**−0.70**	**(−4.26)**	−0.13	(−0.79)
RV−IV	**3.56**	**(20.05)**	**3.42**	**(16.87)**	**1.69**	**(10.79)**	—	—
RV−MFvol	−0.34	(−1.90)	−0.22	(−1.17)	−0.40	(−2.17)	**−0.39**	**(−2.69)**
Rskew−MFskew	−0.14	(−1.53)	**−0.24**	**(−2.36)**	−0.17	(−1.38)	−0.29	(−1.98)
Rkurt−MFkurt	**−0.50**	**(−5.69)**	**−0.39**	**(−3.98)**	**−0.36**	**(−3.18)**	−0.30	(−2.24)
BM	**0.86**	**(4.96)**	**0.99**	**(5.41)**	**1.17**	**(5.96)**	**0.90**	**(3.77)**
Profits	**0.56**	**(3.77)**	**0.45**	**(2.92)**	0.35	(1.89)	0.29	(1.31)
Inst own	0.17	(1.52)	0.11	(0.89)	0.17	(1.16)	0.01	(0.07)
RSI	0.09	(0.85)	−0.10	(−0.88)	0.14	(0.99)	0.25	(1.54)
Assets	**0.75**	**(4.80)**	**0.79**	**(4.51)**	**0.68**	**(3.64)**	**0.50**	**(2.75)**
Financial debt	0.25	(1.94)	**0.32**	**(2.22)**	**0.42**	**(2.84)**	0.26	(1.71)
Leverage	0.23	(2.02)	**0.27**	**(2.19)**	**0.66**	**(4.88)**	**0.49**	**(3.00)**
Cash flow var	0.26	(1.76)	**0.35**	**(2.22)**	**0.72**	**(4.58)**	**0.74**	**(4.30)**
Cash to asset	**−0.92**	**(−5.07)**	**−0.99**	**(−5.08)**	**−1.14**	**(−5.24)**	**−0.62**	**(−2.69)**
Analyst disp	**0.38**	**(3.29)**	**0.37**	**(2.90)**	**0.54**	**(3.53)**	0.29	(1.63)
1 yr new iss	**−0.44**	**(−3.44)**	**−0.49**	**(−3.83)**	**−0.37**	**(−2.62)**	−0.10	(−0.67)
5 yr new iss	**−0.58**	**(−4.92)**	**−0.52**	**(−4.14)**	−0.28	(−2.02)	−0.18	(−1.10)
Profit margin	**0.70**	**(4.14)**	**0.81**	**(4.44)**	**0.99**	**(4.90)**	**0.65**	**(2.98)**
Profitability	0.28	(2.05)	**0.30**	**(2.10)**	**0.38**	**(2.45)**	**0.42**	**(2.44)**
External fin	−0.23	(−1.50)	−0.22	(−1.45)	−0.34	(−2.02)	−0.21	(−1.10)
Z score	0.03	(0.18)	−0.09	(−0.50)	**−0.44**	**(−2.44)**	−0.21	(−0.98)

Table 2: Multivariate regressions

The table presents regression results of monthly delta hedged call returns on predicting variables measured as of the end of the previous month. We report results of a Fama-McBeth regression, a time fixed effects panel regression with standard errors clustered at the firm level, and a lasso selection model. Data spans the period between January 1996 and November 2020.

	FM		Panel		Lasso
Moneyness	−4.37	(−10.60)	−4.90	(−12.62)	−4.79
Bid-Ask	0.01	(0.08)	0.06	(0.66)	0.06
Open interest	−0.32	(−4.67)	−0.55	(−8.98)	−0.55
Delta	−4.54	(−11.47)	−5.03	(−13.59)	−4.93
Volume	0.22	(3.18)	0.28	(4.67)	0.26
Option price	0.31	(2.18)	0.40	(3.09)	0.40
IV ATM	−0.79	(−2.41)	−0.78	(−3.30)	−0.78
IV slope	−0.17	(−1.97)	0.12	(1.69)	0.12
IV term	−0.95	(−10.92)	−1.11	(−12.90)	−1.10
IV vol	−0.12	(−1.25)	−0.07	(−1.01)	−0.06
MF vol	1.22	(4.46)	0.95	(5.59)	0.88
MF skew	0.12	(0.70)	0.00	(0.01)	−0.05
MF kurt	0.07	(0.42)	−0.04	(−0.26)	−0.02
Stock price	−0.06	(−0.33)	0.15	(1.17)	0.13
Stock return	−0.44	(−4.01)	−0.38	(−5.69)	−0.37
Stock return11	−0.92	(−6.40)	−0.95	(−13.51)	−0.94
Realized Vol	−2.13	(−4.84)	−1.19	(−3.44)	−1.06
Realized Skew	−0.24	(−0.83)	−0.21	(−0.81)	−
Realized Kurt	−0.28	(−0.79)	−0.48	(−2.17)	−0.43
Idiosyn. vol	−0.17	(−1.47)	−0.15	(−1.76)	−0.14
Max10	0.90	(5.19)	0.89	(7.22)	0.84
Market cap	−1.18	(−6.81)	−0.87	(−6.15)	−0.81
Autocorrelation	0.56	(8.13)	0.53	(10.09)	0.52
Turnover	−0.13	(−1.08)	−0.15	(−1.76)	−0.14
RV−IV	3.11	(18.27)	2.82	(24.39)	2.81
RV−MFvol	0.36	(1.19)	0.24	(1.08)	0.16
Rskew−MFskew	0.41	(1.34)	0.32	(1.16)	0.10
Rkurt−MFkurt	−0.55	(−1.54)	−0.57	(−2.54)	−0.62
BM	0.18	(1.61)	0.23	(2.46)	0.24
Profits	0.61	(5.04)	0.55	(6.95)	0.54
Inst own	−0.07	(−1.08)	0.02	(0.41)	0.02
RSI	0.28	(3.40)	−0.01	(−0.20)	−0.00
Assets	0.28	(0.97)	0.33	(1.58)	0.21
Financial debt	−0.32	(−1.47)	−0.48	(−2.95)	−0.37
Leverage	0.21	(1.48)	0.31	(2.90)	0.27
Cash flow Var	0.58	(7.55)	0.68	(9.42)	0.67
Cash to asset	−0.04	(−0.44)	−0.01	(−0.16)	−0.02
Analyst disp	0.08	(0.99)	0.04	(0.65)	0.04
1 yr new iss	0.12	(1.65)	0.23	(3.43)	0.22
5 yr new iss	−0.22	(−2.83)	−0.30	(−4.27)	−0.29
Profit margin	−0.22	(−2.32)	−0.14	(−2.07)	−0.13
Profitability	−0.26	(−2.98)	−0.33	(−4.23)	−0.32
External fin	0.21	(2.72)	0.13	(1.90)	0.12
Z score	−0.17	(−1.38)	−0.06	(−0.57)	−0.06

We also run Fama and MacBeth (1973) regressions and panel regressions in which the dependent variable is the delta-hedged call return and the independent variables is the kitchen sink of all the variables. To guard against over-fitting, we also run a LASSO selection model. The results of these regressions are reported in Table 2. We find again that many characteristics being economically and statistically important predictors of option returns. By and large, the characteristics that are important for portfolio returns are also important in cross-sectional regressions, with very large overlap and only a few that are picked up by one method rather than the other.

3 IPCA

In this section, we give a brief overview of the IPCA method. Readers are referred to Kelly, Pruitt, and Su (2019) for further details. Returns on N assets over time period $t = 1, \ldots, T$ are assumed to be generated by the model:

$$\begin{aligned} R_{it+1} &= \alpha_{it} + \beta_{it}' F_{t+1} + E_{it+1} \\ &= (Z_{it}' \Gamma_\alpha) + (Z_{it}' \Gamma_\beta) F_{t+1} + E_{it+1}, \end{aligned} \tag{1}$$

where F's are K latent factors. α_{it} and β_{it} are asset specific time-varying intercept and factor loadings that are both assumed to be linearly related to L observable characteristics summarized in Z_{it} (including a constant). The $L \times 1$ vector Γ_α and the $L \times K$ matrix Γ_β define the mapping from a potentially large number of characteristics to the mispricing and a small number of risk factor exposures. The parameters Γ are global in the sense that are assumed to be constant across all stocks and all time periods.

Kelly, Pruitt, and Su (2019) emphasize that the estimation of Γ_β amounts to finding a few linear combinations of candidate characteristics that best describe the latent factor loading structure. Thus, IPCA eschews the need to construct portfolios on an ad-hoc basis and instead performs a dimension reduction of many individual assets into a few latent factors.

Denote R_{t+1} as $N_{t+1} \times 1$ vector, Z_t as a $N_{t+1} \times L$ matrix, α_t as a $N_{t+1} \times 1$ vector, β_t as a $N_{t+1} \times K$ matrix. Here N_{t+1} is the number of stocks with a valid return at time $t+1$ and all observable characteristics at time t. Then, we can rewrite the mode in matrix form as:

$$R_{t+1} = \alpha_t + \beta_t F_{t+1} + E_{t+1} = (Z_t \Gamma_\alpha) + (Z_t \Gamma_\beta) F_{t+1} + E_{t+1}. \tag{2}$$

It will be useful to define a $L \times L$ matrix $W_t = Z_t' Z_t / N_{t+1}$ and a $L \times 1$ vector $X_{t+1} = Z_t' R_{t+1} / N_{t+1}$. We can interpret X_{t+1} as the $t+1$ returns on a set of L managed portfolios.

The return on the lth portfolio is a weighted average of stock returns with weights determined by the value of lth characteristic for each stock at time t (normalized by the number of non-missing stock observations each month, N_{t+1}).

The first order conditions for the estimation of the system are given by:

$$\begin{aligned}\hat{F}_{t+1} &= \left(\hat{\Gamma}_\beta' W_t \hat{\Gamma}_\beta\right)^{-1} \hat{\Gamma}_\beta'(X_{t+1} - W_t\hat{\Gamma}_\alpha) \\ \text{vec}\left(\hat{\Gamma}'\right) &= \left(\sum_{t=1}^{T-1} W_t \otimes \hat{\tilde{F}}_{t+1}\hat{\tilde{F}}_{t+1}'\right)^{-1} \sum_{t=1}^{T-1} X_{t+1} \otimes \hat{\tilde{F}}_{t+1}, \end{aligned} \tag{3}$$

where $\tilde{F}_{t+1} = [F_{t+1} : 1]'$, and $\Gamma = [\Gamma_\beta : \Gamma_\alpha]$. As Kelly, Pruitt, and Su (2019) show, the first order conditions involve OLS regressions only and, therefore, the estimation proceeds very quickly. As is evident from equation (3), the estimation requires only the L-dimensional objects W_t and X_{t+1} rather than original N-dimensional asset returns. A further advantage of this method, thus, is the ease with which missing data are handled. Further details on estimation (including initial conditions and orthogonalization) are provided in Kelly, Pruitt, and Su (2019).

We can also estimate a restricted IPCA model where $\Gamma_\alpha = 0$ to test whether risk compensation in returns solely arises from exposure to systematic factors, or whether returns partially line up with characteristics directly, hence constituting compensation without risk.

3.1 Pre-specified factors

The model is sufficiently general to also allow for pre-specified factors G_t where the loadings on these factors are also allowed to be a function of the same set of observable characteristics Z. Let there be M pre-specified factors. Define $L \times M$ matrix Γ_δ to be the mapping from characteristics to risk factor exposures to these factors. Thus, the return generating process is assumed to be:

$$R_{it+1} = (Z_{it}'\Gamma_\beta)\, F_{t+1} + (Z_{it}'\Gamma_\delta)\, G_{t+1} + E_{it+1}, \tag{4}$$

where $\delta_{it} = Z_{it}'\Gamma_\delta$ is the time-varying loading on the pre-specified factors.

The first order conditions change to:

$$\begin{aligned}\hat{F}_{t+1} &= \left(\hat{\Gamma}_\beta' W_t \hat{\Gamma}_\beta\right)^{-1} \hat{\Gamma}_\beta'(X_{t+1} - W_t\hat{\Gamma}_\delta G_{t+1}) \\ \text{vec}\left(\hat{\Gamma}'\right) &= \left(\sum_{t=1}^{T-1} W_t \otimes \hat{\tilde{F}}_{t+1}\hat{\tilde{F}}_{t+1}'\right)^{-1} \sum_{t=1}^{T-1} X_{t+1} \otimes \hat{\tilde{F}}_{t+1}, \end{aligned} \tag{5}$$

where $\tilde{F}_{t+1} = [F_{t+1} : G_{t+1}]'$, and $\Gamma = [\Gamma_\beta : \Gamma_\delta]$. The rest of the procedure remains the same.

3.2 Statistical inference via bootstrap

Statistical inference is carried out via a bootstrap. We illustrate the procedure for inference on parameters Γ_α. We first estimate the unrestricted model to obtain parameters $\hat{\Gamma}_\alpha$ and $\hat{\Gamma}_\beta$ and the time-series of the latent factors $\hat{F}_t$. Note that equation (2) and the definitions of W_t and X_{t+1} imply that:

$$X_{t+1} = W_t \Gamma_\alpha + W_t \Gamma_\beta F_{t+1} + Z_t' E_{t+1}/N_{t+1}. \tag{6}$$

Define the residuals of managed portfolio returns as $U_{t+1} \equiv Z_t' E_{t+1}/N_{t+1}$ and their fitted values as $\hat{U}_{t+1} = X_{t+1} - W_t \hat{\Gamma}_\alpha - W_t \hat{\Gamma}_\beta \hat{F}_{t+1}$. The returns on managed portfolio for the bth bootstrap are generated by:

$$X_{t+1}^b = W_t \hat{\Gamma}_\beta \hat{F}_{t+1} + q_{t+1}^b \hat{U}_{t+1}^b, \tag{7}$$

by imposing the null of zero alpha. In equation (7), $\hat{U}_{t+1}^b$ is the estimated residual from a random time period drawn uniformly from the set of all possible dates and q_{t+1}^b is a Student-t random variable with unit variance and five degrees of freedom. Using the bootstrapped sample, we reestimate the unrestricted IPCA model and record the estimated parameter $\hat{\Gamma}_\alpha^b$. Recall that since the estimation of IPCA model requires only W and X matrices, we do not need to bootstrap the asset returns themselves. Finally, we calculate Wald statistics $W_\alpha = \hat{\Gamma}_\alpha' \hat{\Gamma}_\alpha$ in the data and $W_\alpha^b = \hat{\Gamma}_\alpha^{b\prime} \hat{\Gamma}_\alpha^b$ in the bth bootstrap. Inferences are drawn by calculating a p-value as the fraction of bootstrapped W_α^b statistics that exceed the value of W_α from the actual data. We use $B = 1{,}000$ repetitions in the bootstrap.

We modify the procedure slightly for testing significance of individual characteristic. Define $\Gamma_\beta = (\gamma_{\beta,1}, \ldots \gamma_{\beta,L})'$. We can test for the significance of the lth characteristic by defining $\hat{\Gamma}_\beta^l = (\hat{\gamma}_{\beta,1}, \ldots, \hat{\gamma}_{\beta,l-1}, 0_{K\times 1}, \hat{\gamma}_{\beta,l+1}, \ldots \hat{\gamma}_{\beta,L})'$ and then bootstrapping managed portfolio returns as

$$X_{t+1}^b = W_t \hat{\Gamma}_\beta^l \hat{F}_{t+1} + q_{t+1}^b \hat{U}_{t+1}^b. \tag{8}$$

We calculate Wald statistics $W_{\beta,l} = \hat{\gamma}_{\beta,l}' \hat{\gamma}_{\beta,l}$ in the data and $W_{\beta,l}^b = \hat{\gamma}_{\beta,l}^{b\prime} \hat{\gamma}_{\beta,l}^b$ in the bth bootstrap. Inferences are drawn by calculating a p-value as the fraction of bootstrapped $W_{\beta,l}^b$ statistics that exceed the value of $W_{\beta,l}$ from the actual data.

3.3 Pricing performance

We calculate the pricing performance of the model by calculating a variety of R^2's and pricing error, following Kelly, Palhares, and Pruitt (2022) as follows:

$$\begin{aligned}
\text{Total } R^2 &= 1 - \frac{\sum_{it}\left(R_{it+1} - Z_{it}'\hat{\Gamma}_\beta \hat{F}_{t+1}\right)^2}{\sum_{it} R_{it+1}^2} \\
\text{Time Series } R^2 &= \frac{1}{\sum_i T_i}\sum_i T_i R_i^2;\text{ where } R_i^2 = 1 - \frac{\sum_t \left(R_{it+1} - Z_{it}'\hat{\Gamma}_\beta \hat{F}_{t+1}\right)^2}{\sum_i R_{it+1}^2} \\
\text{Cross Section } R^2 &= \frac{1}{T}\sum_t R_t^2;\text{ where } R_t^2 = 1 - \frac{\sum_i \left(R_{it+1} - Z_{it}'\hat{\Gamma}_\beta \hat{F}_{t+1}\right)^2}{\sum_i R_{it+1}^2} \\
\text{Relative Pricing Error} &= \frac{\sum_i \alpha_i^2}{\sum_i \bar{R}_i^2};\text{ where } \alpha_i = \frac{1}{T_i}\sum_t \left(R_{it+1} - Z_{it}'\hat{\Gamma}_\beta \hat{F}_{t+1}\right). \qquad (9)
\end{aligned}$$

Note that the denominator is sum of squared returns without demeaning following Gu, Kelly, and Xiu (2020). Total R^2 describes how well the model describes the realized returns in a panel context. Time Series R^2 summarizes pricing performance as the cross-sectional average of performance for each test asset i (we weight each asset's performance by the number of time-series observations for that asset, T_i). Cross Section R^2 quantifies the cross-sectional predictive performance as in a Fama-MacBeth context. Relative Pricing Error analyzes IPCA's ability to price average return. In contrast to R^2 measures, lower value of pricing error indicates better performance.

We calculate similar measures even when pre-specified factors are included. For instance, we calculate Total R^2 in the presence of latent factors F and pre-specified factors G as:

$$\text{Total } R^2 = 1 - \frac{\sum_{it}\left(R_{it+1} - Z_{it}'\hat{\Gamma}_\beta \hat{F}_{t+1} - Z_{it}'\hat{\Gamma}_\delta G_{t+1}\right)^2}{\sum_{it} R_{it+1}^2}. \qquad (10)$$

The equation is also adapted in an obvious way to the case of only pre-specified factors G. Note that we can calculate all the measures in equation (9) for either individual assets, R, or for managed portfolios, X.

We also calculate these measures in an out-of-sample context, following Kelly, Pruitt, and Su (2019). The exact procedure is as follows. In every month t during the out-of-sample period, we first estimate IPCA using expanding window using data through t. Denote the resulting parameter estimates as $\hat{\Gamma}_{\beta,t}$. Then, we calculate the out-of-sample factor return at time $t+1$ as $\hat{F}_{t+1,t} = \left(\hat{\Gamma}_{\beta,t}' Z_t' Z_t \hat{\Gamma}_{\beta,t}\right)^{-1} \hat{\Gamma}_{\beta,t}' X_{t+1}$. In this way, IPCA factor return at time $t+1$

uses portfolio weights observable at time t only. The out-of-sample measures in equation (9) are then calculated by replacing $\hat{\Gamma}_\beta$ with $\hat{\Gamma}_{\beta,t}$ and $\hat{F}_{t+1}$ with $\hat{F}_{t+1,t}$.

4 Empirical results

We include all the stock and option level characteristics described in Section 2.1 in our baseline results. As is standard in IPCA analysis, we convert all characteristics to cross-sectional ranks and then rescale then to a -0.5 to 0.5 interval.

4.1 IPCA factors

4.1.1 In-sample performance

We start our analysis with a constrained IPCA where we force the alpha to be zero ($\Gamma_\alpha = 0$). Since theory provides little guidance on the number of factors, we perform the IPCA analysis for up to six latent factors. Table 3 tabulates total, time-series and cross-sectional R^2s as well as relative pricing errors from equation (9) for this specification. We report the statistics for individual equity option position as well as for the characteristics managed portfolios.

As is typical of other IPCA applications (see, for example, Kelly, Palhares, and Pruitt, 2022), we find that increasing the number of factors monotonically improves performance measures in-sample. The total R^2 for individual option positions increases from about 6% to about 10% when going from one to six latent factors. The time-series and cross-section R^2 are of roughly the same magnitude as that for the total R^2. As is usually the case, we also find that the performance measures are higher for managed portfolios than those for individual options. This result obtains partly because the managed portfolios have much lower cross-sectional and time-series dispersion in returns than individual option returns. For example, the total R^2 for managed portfolios is 85% for one factor and increases to 97% for six factor IPCA.

The relative pricing error is around 95% for individual option positions and remains relatively high even when we increase the number of factors. The relative pricing error is high at 63% for managed portfolios for the case of one latent factor but declines to about 0.3% when the number of latent factors is bigger than two. Overall, we conclude that IPCA is able to explain about 6-10% of the variability in stock level option returns and about 85-95% of the variation in managed portfolios returns in-sample.

The IPCA option return performance measures compare well with similar estimates for stocks (Kelly, Pruitt, and Su, 2019), corporate bonds (Kelly, Palhares, and Pruitt, 2022),

Table 3: IPCA performance

The table presents performance measures of IPCA models for delta-hedged call returns. We report Total, Time Series, and Cross Section R^2, as well as the Relative Pricing Error from equation (9) for individual stock option positions and managed portfolios for the constrained ($\Gamma_\alpha = 0$), as well as p-values on the bootstrap Wald test of no alpha (i.e., $\Gamma_\alpha = 0$), which is obtained by comparing the models fit to their unconstrained equivalents ($\Gamma_\alpha \neq 0$). In the middle panel we report out-of-sample performance measures, obtained by splitting the sample in half and using the first half to estimate the model. We then use estimated factors and conditional betas to produce a one month out-of-sample forecast. We then roll the estimation procedure forward one month at a time, until the end of the sample. Results are reported for IPCA models with up to six factors. Conditional betas are estimated for each of the characteristics used in Table 1 and Table 2. Data spans the period between January 1996 and November 2020.

	Number of factors					
	1	2	3	4	5	6
	In-sample					
Stock Level Option Positions:						
Total R^2	6.11	7.77	8.73	9.29	9.61	9.88
Time Series R^2	8.45	9.48	10.44	10.94	11.14	11.38
Cross Section R^2	4.78	6.43	7.05	7.45	7.76	8.01
Relative Pricing Error	98.59	97.94	97.29	96.83	96.01	95.24
Managed Portfolios:						
Total R^2	85.04	88.53	92.82	95.14	96.24	96.85
Time Series R^2	39.38	51.96	66.10	72.71	77.08	79.78
Cross Section R^2	61.30	68.72	74.56	79.78	84.44	86.55
Relative Pricing Error	63.03	4.41	0.29	0.27	0.29	0.29
	Out-of-sample					
Stock Level Option Positions:						
Total R^2	5.66	7.13	8.12	8.50	8.73	9.00
Time Series R^2	9.01	9.53	10.07	10.64	10.49	10.47
Cross Section R^2	4.17	5.46	6.09	6.41	6.62	6.88
Relative Pricing Error	98.66	97.93	96.86	96.95	96.66	96.29
Managed Portfolios:						
Total R^2	84.57	88.26	91.67	93.96	95.00	95.75
Time Series R^2	19.99	34.21	50.95	59.98	64.92	69.36
Cross Section R^2	58.77	64.23	69.61	74.41	79.95	81.86
Relative Pricing Error	106.72	28.00	4.00	2.76	2.49	3.14
Bootstrap test:						
W_α p-value	0.00	0.00	4.10	80.00	34.70	8.20

and index equity options (Büchner and Kelly, 2022). Our measures are a bit lower (lower R^2s and higher relative pricing error) than those in these studies but that is to be expected given the higher volatility of delta-hedged option returns. Our measures are very similar to the respective measures extracted by applying IPCA to cryptocurrencies, which are among the most volatile assets (Bianchi and Babiak, 2022).

Although we tabulate results only for the constrained version, we also estimate an unconstrained IPCA model where we place no restriction on alpha. Following the procedure described in Section 3.2, we calculate a Wald test and its bootstrapped p-value and report this in the last row of Table 3. We find that the p-values are lower than 0.05 for up to three latent factors. The p-value becomes 0.8 for the case of four latent factors indicating that four factors are sufficient to describe the variation in returns with only the time-varying loadings on factors without an intercept. In the rest of the paper, therefore, we adopt the $K = 4$ specification as our baseline specification.

4.1.2 Out-of-sample performance

The results so far are based on in-sample estimation where we estimate both the factors and the model parameters using the entire sample. This is the usual practice in asset pricing studies where unconditional betas (or parameters of conditional betas in conditional models) are estimated using the full sample. Nevertheless, given that our latent factors are also extracted using full-sample estimation, this could raise doubts about data over-fitting. Accordingly, we also consider how the IPCA model perform out-of-sample.

We calculate the statistics from equation (9) in an out-of-sample fashion as described in Section 3.3. The out-of-sample period is the second half of our sample, from 2008 to 2020. The results are tabulated in the middle panel of Table 3. We find only a modest decrease in out-of-sample R^2s to their in-sample counterparts. For example, for $K = 4$, the cross-section R^2 for managed portfolios is 79.8% in-sample and 74.4% out-of-sample. One notable exception is the Time-series R^2 that presents greater differences in in-sample and out-of-sample estimates. For example, taking the $K = 4$ case again, IPCA can explain 72.7% and 59.9% of the average time-series variation of managed portfolios, in-sample and out-of-sample, respectively. Pricing errors for individual option positions also change only by modest amount in the out-of-sample test. Although the relative increase is more substantial for managed portfolios, out-of-sample pricing errors for portfolios remain low. For example, with four latent factors, pricing errors are 0.3% to 2.7%, in-sample and out-of-sample, respectively.

It may seem surprising that we do not see much deterioration in out-of-sample performance relative to in-sample performance. As Kelly, Palhares, and Pruitt (2022) argue, this is explained by the relatively few parameters that are estimated in IPCA. With 45 characteristics (including a constant), our four factor model requires 180 parameters while a standard static beta model would require more than 100,000 parameter estimates for thousands of stock options.

4.2 Pre-specified factors

The evidence presented in Table 1 suggests that traditionally specified factors, without conditional betas, have varying degrees of success at explaining the returns of option trading strategies. Even the factor model proposed by Horenstein, Vasquez, and Xiao (2020), which is designed to explain the most profitable trading strategies (based on the difference between realized and implied volatility), cannot eliminate all alphas.

Table 4: Pre-specified factors' performance with unconditional betas

The table compares performance measures for three pre-specified factor models. We consider the same three factor models as in Table 1, which are recomputed as in Büchner and Kelly (2022) (FF+), Bali, Cao, Song, and Zhan (2022) (BCSZ), and Horenstein, Vasquez, and Xiao (2020) (HVX). We consider characteristic managed portfolios as test assets, and run time-series regressions for each portfolio against each of the three models, plus a constant. We report Total, Time Series, and Cross Section R^2, as well as the Relative Pricing Error from equation (9). Data spans the period between January 1996 and November 2020.

	FF+	BCSZ	HVX
Total R^2	41.44	70.06	66.51
Time Series R^2	20.03	38.38	49.09
Cross Section R^2	−49.57	9.05	9.51
Relative Pricing Error	115.21	86.90	53.83

We can compute the same measures of performance as those in equation (9), and that we compute for IPCA factors, also for pre-specified factors (PSF). We do this by regressing each time-series of characteristic managed portfolio on the PSF (including a constant) and then constructing R^2s and relative pricing errors. We consider the same three models (FF+, BCSZ, and HVX) as those in Section 2.2 and show the results for characteristic managed portfolios in Table 4. Of the three models, the FF+ model has the weakest performance (the lowest R^2 and the highest relative pricing error). The BCSZ model has the highest total R^2 of 70% but its relative pricing error is also high at 87%. The HVX model has the highest time-series and cross-sectional R^2, and the lowest relative pricing error of only 54%. These results largely confirm the visual impression from Table 1. Of particular importance to us, the performance of no PSF model approaches that of the four factor IPCA model in Table 3. For example, the relative pricing error of the IPCA model at 0.3% is an order of magnitude lower than that of the comparable numbers for the three PSF models. Particularly noteworthy is the fact that even the out-of-sample performance of the IPCA model is significantly better than the in-sample performance of PSF models.

One limitation of the preceding evidence is that betas are not allowed to change over time. Thus, while the beta vary vary across test assets, they do not vary based on conditioning information. Do dynamic conditional betas improve the performance of these traditional PSF models? While it is infeasible to estimate a model with conditional betas for each individual option, as discussed in Section 3.1, we can easily adapt the IPCA methodology to use PSF instead of latent factors. By allowing betas to depend on characteristics, we put the PSF on equal footing with IPCA factors.

We report results in Table 5, where we compare performance measures for the four factor IPCA model to FF+, BCSZ, and HVX. Comparing PSF model fits in Tables 4 and 5, we find that the model performance improves with dynamic betas. For example, the total R^2 for the BCSZ model is 70% (74.3%) with static (dynamic) betas. The relative pricing error for the BCSZ model declines from 86.9% with static betas to only 23.7% with dynamic betas. However, the IPCA model still beats the PSF models with better R^2 and lower pricing error. The closest competitor to IPCA is the HVX model; the latter, nevertheless, has pricing error of 7.8%.

The bottom panel of Table 5 shows the out-of-sample performance. As already noted, the deterioration in out-of-sample performance is modest relative to the in-sample performance for the IPCA model. We observe the same phenomenon for the HVX model but not so for the FF+ and the BCSZ model. For the latter two models, the out-of-sample performance with dynamic betas in Table 5 is worse than that with in-sample performance with static betas in Table 4. Once again, for our purposes, the IPCA model emerges as the clear winner.

4.2.1 Tangency portfolio

We next consider the performance of a tangency portfolio of IPCA factors and the PSF. The tangency portfolio combines the factors optimally in a Sharpe ratio sense. Therefore, the tangency portfolio provides another perspective on the ability of different factor models to price assets. As is well-known, factors that can price all the assets with zero alpha are also the factors that can be combined to obtain the maximum Sharpe ratio (Gibbons, Ross, and Shanken, 1989).

We calculate Sharpe ratios of tangency portfolios both in-sample and out-of-sample. The in-sample tangency portfolio calculation uses the sample average and the sample covariance matrix for portfolio weights. The out-of-sample calculation follows the same procedure as described in Section 3.3. In every month t during the out-of-sample period, we calculate the

Table 5: Pre-specified factors' performance with dynamic betas

The table compares performance measures of the 4-factor IPCA model for delta-hedged call returns to three pre-specified factor models. We consider the same three factor models as in Table 1, which are recomputed as in Büchner and Kelly (2022) (FF+), Bali, Cao, Song, and Zhan (2022) (BCSZ), and Horenstein, Vasquez, and Xiao (2020) (HVX). All models are estimated with dynamic betas where the betas are modeled as function of characteristics. We report Total, Time Series, and Cross Section R^2, as well as the Relative Pricing Error from equation (9) for individual stock option positions and managed portfolios. Data spans the period between January 1996 and November 2020.

	IPCA	FF+	BCSZ	HVX
	In-sample			
Stock Level Option Positions:				
Total R^2	9.29	3.98	6.64	6.70
Time Series R^2	10.75	5.55	8.09	7.28
Cross Section R^2	7.45	2.80	5.22	5.49
Relative Pricing Error	96.83	99.41	97.89	95.79
Managed Portfolios:				
Total R^2	95.14	45.92	74.35	69.59
Time Series R^2	72.71	30.99	51.17	56.64
Cross Section R^2	79.78	−32.35	24.57	19.76
Relative Pricing Error	0.27	66.06	23.73	7.85
Tangency Portfolio SR	5.72	1.96	3.13	4.47
	Out-of-sample			
Stock Level Option Positions:				
Total R^2	8.50	1.78	5.43	5.81
Time Series R^2	10.64	1.97	7.34	6.09
Cross Section R^2	6.41	1.47	4.01	4.58
Relative Pricing Error	96.95	100.53	98.94	95.96
Managed Portfolios:				
Total R^2	93.96	32.54	67.04	65.32
Time Series R^2	59.98	4.23	30.73	43.22
Cross Section R^2	74.41	−82.20	8.20	15.79
Relative Pricing Error	2.76	239.43	138.88	13.26
Tangency Portfolio SR	4.98	1.06	2.17	4.07

portfolio weights, w_t, using sample moments calculated using data through t. The tangency portfolio return at time $t+1$ is then given by weights w_t and out-of-sample IPCA factor return, $\hat{F}_{t+1,t}$. For PSF, we use the realization of factor return itself, F_{t+1} and, therefore, the out-of-sample tangency portfolio differs from its in-sample counterpart only in the use of changing portfolio weights.

Before discussing the results, it is important to note that Sharpe Ratios are dependent on how the factors are constructed. This is especially true for some of the PSF models that we consider. For example, both the BCSZ and HVX contain a factor constructed by sorting stocks on the difference between realized and implied volatility.[1] Table 1 shows that sorts on this characteristic produce the highest average returns and the highest associated t-statistic. Therefore, we expect the Sharpe ratios of the BCSZ and the HXZ models to be high by construction.

We report the annualized Sharpe ratios of the various models in the last row of each panel in Table 5. As expected, the Sharpe ratios of the BCSZ and the HVX models are higher than those of the FF+ model. For example, the in-sample Sharpe ratio of the HVX model at 4.4 is more than twice that of FF+ model at 1.9. The IPCA model extracts factors that seek of explain a broad set of characteristic managed portfolio returns. As such, they are not expected to put more weight on any particular variable. Despite this 'disadvantage' relative to the PSF, we find that the IPCA latent factors produce the largest Sharpe ratios both in-sample and out-of-sample. The IPCA tangency portfolio Sharpe ratio is 5.7 in-sample and only slightly lower at 4.9 out-of-sample. For comparison, the annualized Sharpe ratio of the market portfolio, weighted by dollar open interest, is only 0.7 in our sample period. Therefore these results provide further evidence on the pricing ability of IPCA factors relative to PSF even when we consider dynamic beta versions of PSF models.

4.3 Interpreting IPCA factors

While our analysis so far shows that IPCA factors with dynamic conditional betas do well in explaining option returns, one limitation is that these factors are latent. In this section, we seek to understand what these factors might represent.

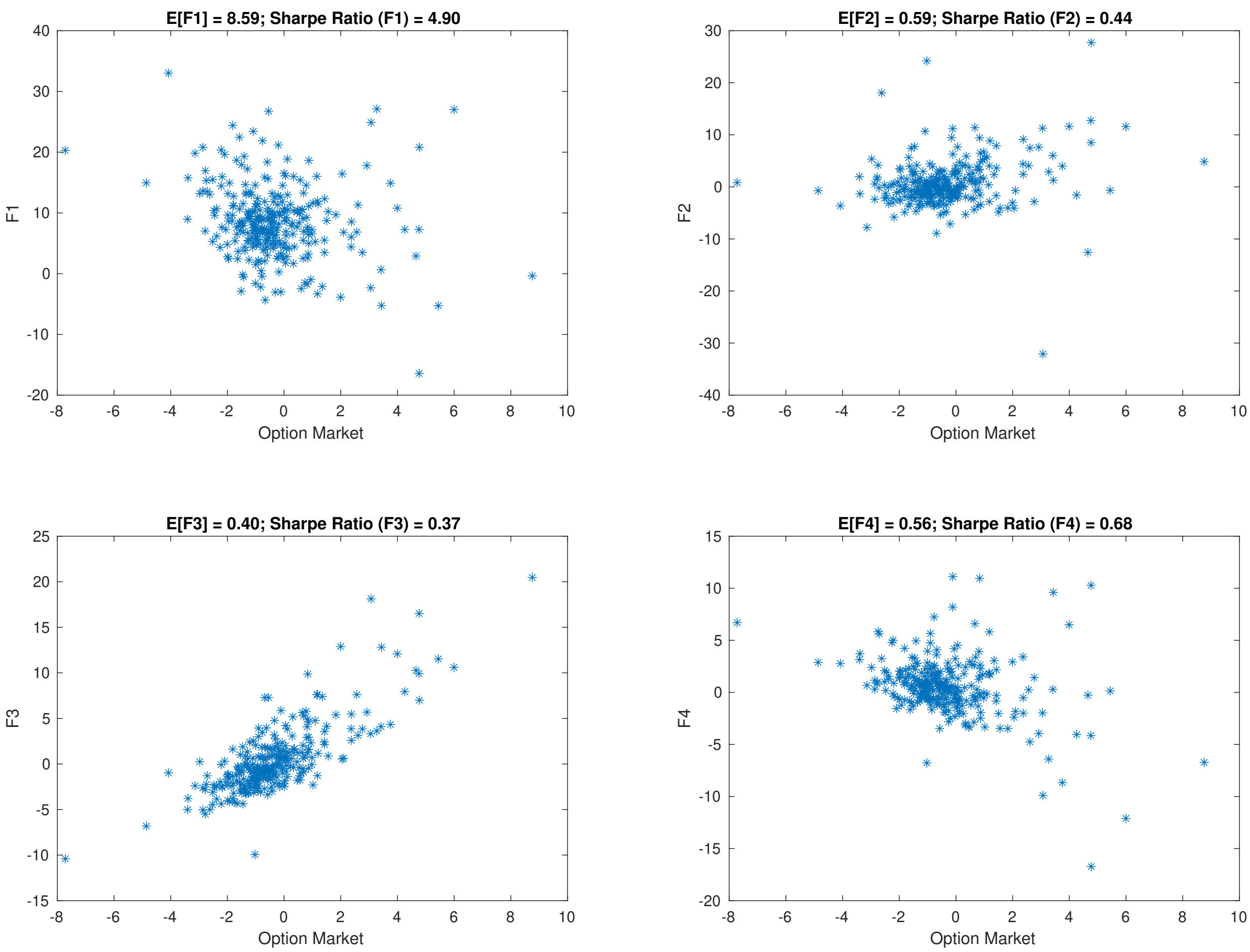
We start with some descriptive statistics on our benchmark four-factor IPCA model. We order the factors in descending order of realized volatility so that F4 is the least volatile. All factors have positive averages by construction. The average return of F1 is 8.5% per month, while the remaining three factors have average returns of around 0.5%. The volatility of the

[1] BCSZ model forms the factor in the traditional Fama-French style by forming tercile portfolios. HVX model forms factors by considering the top and bottom deciles.

factors goes from 6.1% for F1 to 2.8% for F2. Thus, the Sharpe ratio of the first factor is the highest at 4.9. The pairwise correlation of F2, F2, and F3 are all relatively close to zero but all three factors are negatively correlated to F1. As already noted in the previous Section 4.2.1, the annualized Sharpe ratio of the mean-variance tangency portfolio constructed from the four factors is 5.7 in-sample, and 4.9, out-of-sample. Thus, the IPCA factors span a wide region of the risk-return space.

Figure 1: IPCA factors

The figure plots realizations of the 4 IPCA against return realizations of the dollar open interest weighted option market portfolio (i.e., the weighted value of long delta-hedged call returns). Data spans the period between January 1996 and November 2020.



For a visual inspection, we plot a scatter diagram of the four factors versus the option market factor, which is calculated as dollar open interest weighted portfolio of delta-hedge call returns. Figure 1 shows that the IPCA factor returns are quite dispersed and can have extreme realizations corresponding to both very positive or very negative market return. The correlation between the market factor and the factors F1, F2, and F4 does not seem very high but F3 appears related to the option market return.

We next run regressions of each IPCA factor against the three PSF models introduced in Section 2.2 and whose pricing performance is analyzed in Section 4.2. To ease interpretation, we standardize all left-hand side variables, so that the slope coefficient magnitude is directly related to how much that PSF helps explain the IPCA factor. Table 6 shows the results for regressions of each IPCA factor against each of the three modes. The fourth regression for each IPCA factor is against a kitchen sink PSF model that combines the 7 FF+ factors, 5 BCSZ factors, and 4 HVX factors. Because two different version of the same factor appear in BCSZ and HVX, the last regression considers only the version of RV−IV factor of HVX. We multiple all coefficients by 100. Coefficients that are statistically significant at the 95% level are starred. We also boldface the coefficient with the highest absolute value in each regression. Finally, we decompose each factor's contribution in explaining the IPCA factor by computing the Shapley-Owen R^2 (see Büchner and Kelly, 2022), which compare the explanatory power of a model with a particular regressor to the explanatory power of all other models that do not include it (i.e., all possible combinations of the other variables).

Considering the FF+ model first, we find that F1 is not related to any of the FF+ factors—the R^2 of the regression is low and none of the slope coefficients are statistically significant. F2 is related to UMD and F3 is related to ZBStrad. F4 has the highest slope coefficient on RMW but the highest Shapley-Owen R^2 is for the UMD factor. The R^2 of the regressions for F2-F4 factors are around 30%. Therefore, we conclude while F1 is unrelated to traditional stock market and option market factors, the other three factors have some modest relation to these PSF. Turning to the BCSZ model, we find that the F1 factor is related to RV−IV, F2 to option liquidity, F3 to option market portfolio, and F4 to negative of the option market portfolio. F1, F2, and F4 have R^2s of around 30% but F3 is very strongly related to the option market portfolio with even the Shapley-Owen R^2 of 47%. Finally, regarding the HVX model, we find that the F1 factor is related to idiosyncratic volatility factor and the RV−IV factor with each contributing around 25% of Shapley-Owen R^2. F2 is related to stock market cap factor, F3 to idiosyncratic volatility, and F4 to SP500 DHCall.

The kitchen sink model provides a comprehensive view of the relation between the IPCA factors and the PSFs. We find that F1 is mostly related to the RV−IV and the stock idiosyncratic volatility factors: both coefficients and Shapely-Owen R^2 are significantly higher relative to all other factors, and are in line with the results from the specification that only contains HVX factors. The evidence thus confirms our intuition that F1 captures the fundamental components of option returns related to the most profitable trading strategies. F2 is mostly related to cross-sectional differences in delta-hedge returns due to liquidity of the op-

Table 6: IPCA factors and PSF

The table presents regressions of the 4 IPCA factors extracted in Table 3 against two sets of pre-specified factors. We regress each IPCA factors on the three sets of factors used in Table 5. All left hand side variables are standardized to make regression coefficient comparable. Besides regression coefficients (multiplied by 100), heteroskedasticity and adjusted R^2, we also report Shapley-Owen R^2 decompositions. Statistical significance is indicated with a star for regressors which t-statistics are larger than 1.96. Data spans the period between January 1996 and November 2020.

	FF+	BCSZ	HVX	All	FF+	BCSZ	HVX	All
	F1				F2			
Stock Market	0.04			0.06	−0.91*			−0.33
SMB	0.14			0.44	−0.39			−0.25
HML	−0.53			−0.28	−1.56*			−0.70
RMW	**−0.87**			−0.51	1.21*			1.05*
CMA	−0.45			0.22	0.49			−0.03
UMD	0.02			−0.34	**−2.21***			−1.33*
BAB	−0.24			−0.02	0.96*			0.95*
ZBstrad	−0.20			−0.04	1.07*			0.05
Option Market		−0.69		0.61		0.34		−0.13
Option Price		0.78		0.95*		0.15		−0.34
Liquidity		1.36*		0.81*		**−2.45***		−1.35*
MF Kurtosis		1.38*		0.19		0.48		−0.03
RV−IV		**2.19***				0.01		
Market cap			1.02*	0.88*			**2.65***	**1.75***
Idiosyn. Vol			**4.00***	**3.70***			0.37	0.74
RV−IV			3.32*	3.33*			−0.04	−0.04
SP500 DHCall			0.41	0.35			0.89*	1.20*
Adjusted R^2	0.04	0.22	0.52	0.55	0.34	0.30	0.33	0.54
Shapely-Owen R^2:								
Stock Market	0.00			0.00	0.03			0.01
SMB	0.00			0.00	0.03			0.02
HML	0.02			0.01	0.02			0.01
RMW	**0.02**			0.02	0.05			0.04
CMA	0.01			0.00	0.00			0.00
UMD	−0.00			−0.00	**0.14**			0.08
BAB	−0.00			−0.00	0.02			0.02
ZBstrad	−0.00			0.00	0.03			0.01
Option Market		0.02		0.01		0.02		0.01
Option Price		0.01		0.01		0.02		0.01
Liquidity		0.05		0.02		**0.25**		0.14
MF Kurtosis		0.05		0.02		0.00		0.00
RV−IV		**0.10**				−0.00		
Market cap			0.02	0.01			**0.26**	**0.15**
Idiosyn. Vol			**0.25**	0.17			0.03	0.02
RV−IV			0.24	**0.25**			−0.00	−0.00
SP500 DHCall			0.01	0.00			0.04	0.02

	FF+	BCSZ	HVX	All	FF+	BCSZ	HVX	All
	F3				F4			
Stock Market	−0.86*			−0.16	0.59*			0.24
SMB	0.06			−0.13	0.19			−0.09
HML	−0.07			0.11	0.31			0.20
RMW	−0.26			−0.26	**0.91***			0.65*
CMA	0.58			0.10	0.04			−0.05
UMD	0.63*			0.31	−0.08			−0.17
BAB	0.18			−0.20	0.58*			0.24
ZBstrad	**1.55***			0.03	−0.62*			0.73*
Option Market		**2.57***		**2.11***		**−1.65***		−1.17*
Option Price		0.36*		0.23		−0.62*		−0.54*
Liquidity		0.27		0.39*		−0.50*		−0.39*
MF Kurtosis		−0.82*		−0.27		−0.76*		−0.22
RV−IV		1.05*				0.90*		
Market cap			−0.11	−0.03			−0.81*	−0.63*
Idiosyn. Vol			**−2.12***	−1.24*			−1.08*	−1.07*
RV−IV			1.40*	1.16*			0.70*	0.74*
SP500 DHCall			1.23*	−0.20			**−1.39***	**−1.29***
Adjusted R^2	0.31	0.75	0.68	0.83	0.26	0.37	0.37	0.55
Shapely-Owen R^2:								
Stock Market	0.08			0.03	0.03			0.01
SMB	−0.00			0.00	0.00			0.00
HML	0.00			0.00	0.03			0.02
RMW	0.00			0.00	0.05			0.05
CMA	0.04			0.01	0.00			0.00
UMD	0.04			0.02	0.00			0.01
BAB	0.02			0.01	**0.08**			0.04
ZBstrad	**0.14**			0.05	0.07			0.04
Option Market		**0.47**		**0.25**		**0.19**		0.08
Option Price		0.00		0.00		0.03		0.03
Liquidity		0.02		0.01		0.01		0.00
MF Kurtosis		0.13		0.08		0.05		0.02
RV−IV		0.13				0.09		
Market cap			0.04	0.02			0.04	0.02
Idiosyn. Vol			**0.34**	0.17			0.05	0.05
RV−IV			0.16	0.12			0.09	0.09
SP500 DHCall			0.15	0.05			**0.20**	**0.09**

tion and market capitalization of the firm. F2 also correlates (negatively) with UMD, which measures the relative performance of looser stocks, which usually have very high realized and implied volatility. As Figure 1 already indicates, F3 is mostly related to the option market portfolio. F4 is negatively related to the option market portfolio and positively related to S&P500 delta-hedged returns, signaling that this factor picks up aggregate trends that are not driven by firm specific expectations about stock volatilities. In summary, the four IPCA factors capture different risks in option returns. We note, however, that the observable PSFs explain only about 50% of the variation in IPCA returns (F3 is an exception with an R^2 of 80%). Thus, despite the fact that IPCA factors share some characteristics with observable factors, it remains the case that the IPCA factors have components orthogonal to the PSFs that are nevertheless important for explaining option returns.

Finally, we consider how the IPCA factors relate to negative macroeconomic shocks, as proposed by Karakaya (2013) and Büchner and Kelly (2022). Based on the analysis presented in Table 6 we already know that, with some exceptions, the IPCA factors overall have a negative relation with the aggregate stock market returns and a positive relation to changes in aggregate market volatility (proxied by the return of an ATM call delta-hedge position in the S&P500).

We consider months in which the market portfolio return is lower than the 33rd percentile of the sample distribution (Low Market Return), or the economy is in a recession according to the NBER (Recession), or the change in the VIX index from the previous month is larger than the 66th percentile of the sample distribution (Large VIX Change). Table 7 reports number of observations, average and standard deviation of factor returns in each of the scenarios mentioned above, as well as for the entire sample. We also report the t-statistic for the difference in mean in the factor return in the months defined by the event relative to the rest of the sample.

The first factor return does not vary much across the specified events, and as a result all difference in means tests are insignificant. The second and the third factors appear to behave as hedges against these negative shocks, although F3 does not respond to recessions. The last factor has negative average returns when the market is down or when VIX is up, although only the last one is significant.

The fact that it is hard to relate the IPCA factors to traditional sources of risk is not completely surprising once one takes into account that these factors are constructed from payoffs that are ex-ante neutral relative to movements in the underlying stocks, and instead are positively related to increases in total stock volatility. One might expect that when there is a lot of uncertainty about the entire shape of the return distribution, the returns from delta-hedged positions, and consequently the factor returns, would also be more uncertain.

Table 7: IPCA factors and macro shocks

The table presents sample statistics (mean, standard deviation, and Sharpe ratio) for the estimated IPCA factors under different scenarios that represent substantial macroeconomic shocks. We consider months in which the market portfolio return is lower than the 33rd percentile of the sample distribution (Low Market Return), the economy is in a recession according to the NBER (Recession), the change in the VIX index from the previous month is larger than the 66th percentile of the sample distribution (Large VIX Change), the level of the tail risk measure of Kelly and Jiang (2014) is higher than the 66th percentile (High Tail Risk), the difference between the beginning of the month level of the S&P500 risk-neutral skewness extracted from approximately 51 days to maturity and the future realized skewness over the same 51 trading days is lower (more negative) than the 33rd percentile (High Skewness Risk), and the difference between the beginning of the month level of the risk-neutral kurtosis extracted from approximately 51 days to maturity and the future realized skewness over the same 51 trading days is higher than the 66th percentile (High Skewness Risk). We also report the t-statistic for the difference in mean in the factor return in the months defined by the event relative to the rest of the sample. Data spans the period between January 1996 and November 2020.

	Obs	Mean	StDev	t-stat	Mean	StDev	t-stat
		F1			F2		
Full sample	297	8.59	6.07		0.59	4.63	
Low Market Return	98	7.87	7.54	−1.19	1.78	4.88	3.12
Recession	30	10.62	8.34	1.24	4.18	7.67	2.59
Large VIX Change	98	8.13	6.98	−0.91	1.50	4.86	2.27
High Tail Risk	98	7.53	4.77	−2.18	0.80	2.87	0.60
High Skewness Risk	98	7.14	5.74	−2.92	0.54	2.97	−0.16
High Kurtosis Risk	98	7.21	5.20	−2.84	0.42	2.54	−0.49
		F3			F4		
Full sample	297	0.40	3.76		0.56	2.84	
Low Market Return	98	2.19	4.32	5.20	0.39	3.72	−0.52
Recession	30	0.10	5.57	−0.30	0.34	5.12	−0.33
Large VIX Change	98	2.22	4.27	5.56	0.08	3.70	−1.59
High Tail Risk	98	−0.07	2.46	−1.67	0.00	2.18	−2.77
High Skewness Risk	98	0.02	3.04	−1.32	0.27	2.36	−1.43
High Kurtosis Risk	98	−0.10	2.37	−1.78	−0.31	1.84	−4.63

Thus, a more fruitful exercise in trying to understand what kind of aggregate risks investors face is to relate the factor returns to proxies that measure changes in the tails of the aggregate distribution. We take inspiration from Kelly and Jiang (2014), who construct a measure of tail risk from stock market data and relate it to higher moments of the risk-neutral distribution (i.e., skewness and kurtosis). We study how our IPCA factors are linked to the tail risk measure, and to differences between risk-neutral (model free) skewness and kurtosis extracted from S&P500 options with approximately one month to maturity (i.e., 52 days average similar to the maturity of stock options from which the factor are constructed), measured at the beginning of the month, and their corresponding realized future counterparts. Risk-neutral higher order moments are constructed as in Bakshi, Kapadia, and Madan (2003) following the procedure described in Hansis, Schlag, and Vilkov (2010). The differences between implied and realized moments, thus, capture the return on skewness and kurtosis swaps, à la Carr and Wu (2009) and Kozhan, Neuberger, and Schneider (2013), and proxy for conditional risk premia of the higher moments of the return distribution.

As before we consider terciles: tail risk measure higher than the 66th percentile (High Tail Risk), implied-realized skewness difference lower (more negative) than the 33rd percentile (High Skewness Risk), and implied-realized kurtosis difference higher than the 66th percentile (High Kurtosis Risk). Most of the factors have lower returns during these periods of high uncertainty relative to extreme realizations of possibly very negative states of the world. Prominently, F1 and F4 exhibit large negative and statistically significant differences in the periods during which aggregate higher-moments distribution uncertainty is large. F2 and F3, also exhibit negative performance during this periods, although not in a statistically significant way.

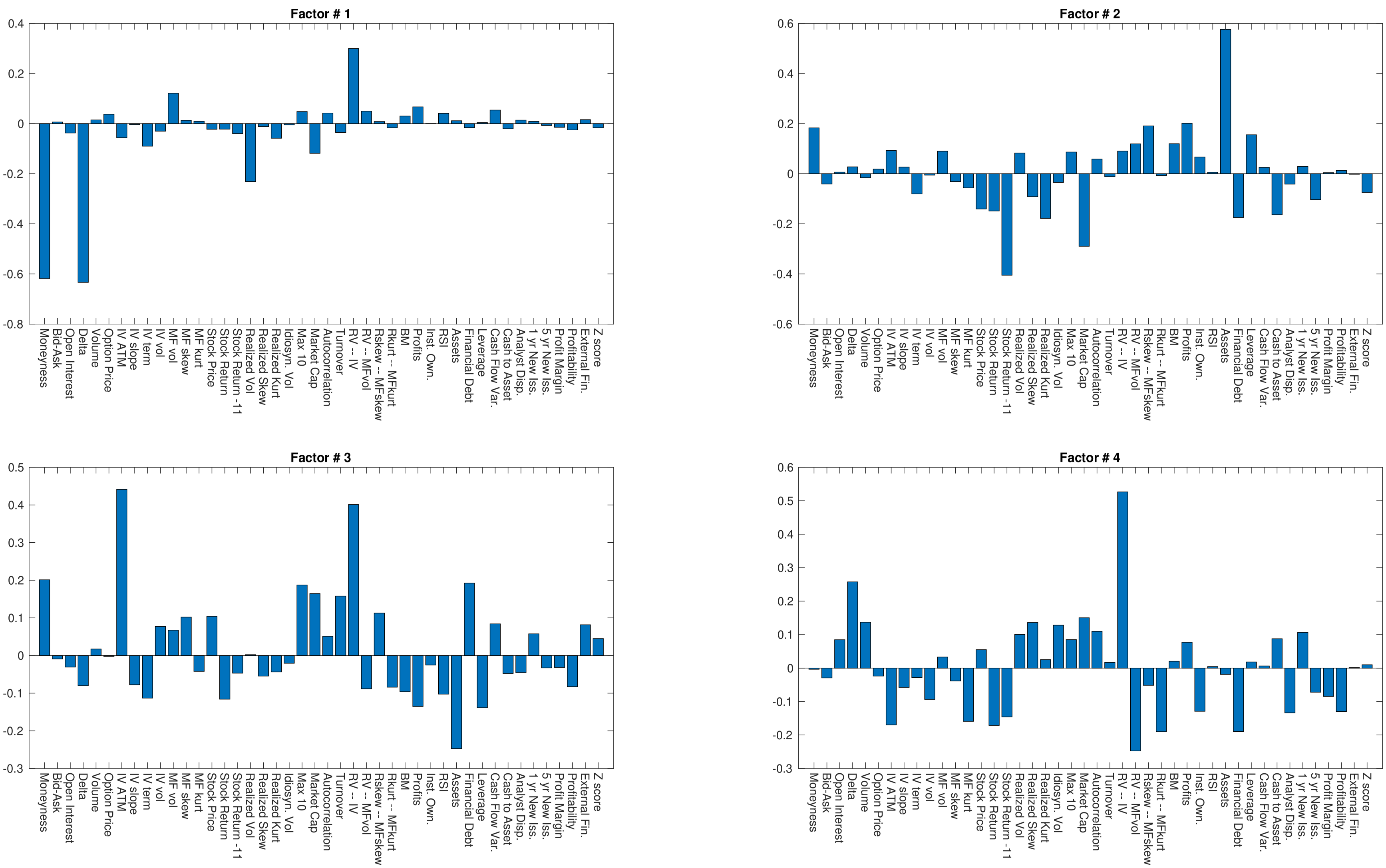
Overall, factors F1 and F4 appear to price uncertainty related to tail risk events, while factors F2 and F3 mainly functions as hedges against movements in the first two moments of the aggregate distribution, as their returns are more positive during times in which the market return is negative or changes in VIX are positive.

4.4 Characteristics importance

One advantage of IPCA is that it allows conditional betas to be a linear function of observable characteristics. This is summarized by the matrix of coefficients Γ_β. For example, $\gamma_{\beta,l,k}$ reflects the influence of the lth characteristic in determining the beta of an option position with respect to the kth factor. Figure 2 plots these $\gamma_{\beta,l,k}$s for each factor in separate panels. A quick look by singling out the absolute largest coefficient in each panel suggests a large role for the option delta, the difference between IV and RV, and the total assets of the firm.

Figure 2: IPCA gammas

The figure shows IPCA gammas for each of the four factors in the IPCA model from Table 3. Data spans the period between January 1996 and November 2020.



We can characterize the impact of each characteristic as the square-root of the sum of squares for the $l$the characteristic as $\sqrt{\sum_k \gamma^2_{\beta,l,k}}$. The statistical significance is computed using a bootstrap procedure of Kelly, Pruitt, and Su (2019) that we describe in Section 3.2. We report the impact and its p-value in Table 8. The table entries are organized in descending order of the impact metric.

Table 8: Characteristics importance

The table presents measures of importance for each characteristic used in the IPCA estimation of Table 3 with 4 factors. Variables are sorted by the square root of the sum of squared Γs (i.e., four for each variable corresponding to the four factors). We also report the p-value of the bootstrap test for each $\Gamma_\beta = 0$. p-values smaller than the Benjamini and Hochberg (1995) 5% FDR adjusted threshold of 0.0005, which corresponds to a t-statistic of 3.29, are reported in bold. Data spans the period between January 1996 and November 2020.

RV−IV	**0.73** (**0.00**)	IV term	0.17 (0.03)
Delta	0.69 (0.01)	Turnover	0.16 (0.24)
Moneyness	0.68 (0.01)	BM	0.16 (0.07)
Assets	**0.63** (**0.00**)	Profitability	0.16 (0.02)
IV ATM	0.49 (0.08)	Analyst disp	0.15 (0.04)
Stock return11	**0.44** (**0.00**)	Inst own	0.15 (0.01)
Market cap	**0.38** (**0.00**)	Autocorrelation	0.14 (0.05)
Financial debt	0.32 (0.07)	Volume	0.14 (0.02)
RV−MFvol	0.29 (0.22)	Idiosyn. vol	0.13 (0.19)
Realized Vol	0.27 (0.59)	5 yr new iss	0.13 (0.04)
Profits	0.26 (0.01)	1 yr new iss	0.13 (0.05)
Stock return	0.26 (0.03)	IV vol	0.13 (0.13)
Max10	0.23 (0.09)	MF skew	0.11 (0.38)
Rskew−MFskew	0.23 (0.27)	RSI	0.11 (0.21)
Leverage	0.21 (0.08)	Cash flow var	0.10 (0.09)
Rkurt−MFkurt	0.21 (0.38)	IV slope	0.10 (0.18)
Realized kurt	0.19 (0.48)	Open interest	0.10 (0.11)
Cash to asset	0.19 (0.03)	Profit margin	0.09 (0.33)
Stock price	0.18 (0.14)	Z score	0.09 (0.45)
MF kurt	0.17 (0.11)	External fin	0.08 (0.14)
Realized Skew	0.17 (0.43)	Bid-Ask	0.05 (0.78)
MF vol	0.17 (0.46)	Option price	0.05 (0.85)

In general, characteristic with larger impact metric are also more statistically significant, although this correlation is not perfect. The characteristics with the larger impact metric that are also statistically significant are RV−IV, Assets, Market cap, and the previous 11 month stock return (Stock return11). Some of those were also visible in Figure 2, others, like for example Market cap, would have not been easily spotted.

4.5 Portfolio alphas redux

We now return to the strategies presented in Table 1. We showed in Section 2.2 that alphas from standard PSF models are high for a vast majority of these strategies. The variables underlying these strategies are the conditioning variables in IPCA and we have also shown that IPCA prices option returns well. In this section, we complete the circle and discuss how expected option returns extracted from the four factor IPCA model are useful at risk-adjusting performance of these strategies.

We present returns for the 10−1 portfolios from Table 1 and for signal weighted portfolios. These portfolios are constructed using the characteristics ranks as portfolio weights. Differently from the description in Section 3, the weights are rescaled so that they add up to one on both the long side (positive weight/rank) and the short side (negative weight/rank), as opposed to simply net out to zero. We do this to facilitate comparison of the average return to those of 10−1 portfolios. We calculate the raw average returns and the difference between the strategy return and the IPCA expected return (i.e., the IPCA alpha). The expected return of the portfolio is constructed by aggregating the expected return of the individual option positions, at the stock level. For example, if the long leg is composed of 30 stocks in a particular month, then the expected return for that month is the average of the IPCA expected returns of those 30 stocks for the same month. Thus,

$$\hat{\alpha}_p = \frac{1}{T}\sum_{t=1}^{T}\left(R_{pt+1} - Z_{pt}'\hat{\Gamma}_\beta\hat{F}_{t+1}\right), \tag{11}$$

where Z_{pt} is the $L \times 1$ vector of the portfolio p's characteristics at time t. Note, however, that one cannot calculate the standard error of the alpha estimate by simply taking the time-series standard deviation of abnormal returns. Equation (11) shows that that the alpha depends on estimated parameters $\hat{\Gamma}_\beta$, and estimated factors $\hat{F}$. Therefore, one needs to account for the estimation error in these model parameters to properly calculate the standard error of alpha estimates. We provide details on the exact procedure we follow in Appendix B.

Table 9 shows that, of the 29 (out of 32) strategies with statistically significant returns after accounting for MHT, only five (nine at conventional levels) still have a statistically significant IPCA alpha: IV ATM, IV slope, IV term, RV−IV, and BM. IPCA does much better at pricing signal weighted portfolios, which are much closer to managed portfolios: only one of 23 strategies with statistically significant returns have statistically significant alpha. One signal weighted portfolio (constructed on model-free implied skewness) has a statistically significant alpha but not statistically significant average return (the average return does not cross the MHT threshold for significance).

We plot the 10−1 portfolio alphas against their raw returns in Figure 3. This figure has four panels corresponding to the factor models IPCA, FF+, BCSZ, and HVX. While the portfolio alphas are the same as those from Table 1 and from Table 9, the figure provides a

Table 9: IPCA alphas

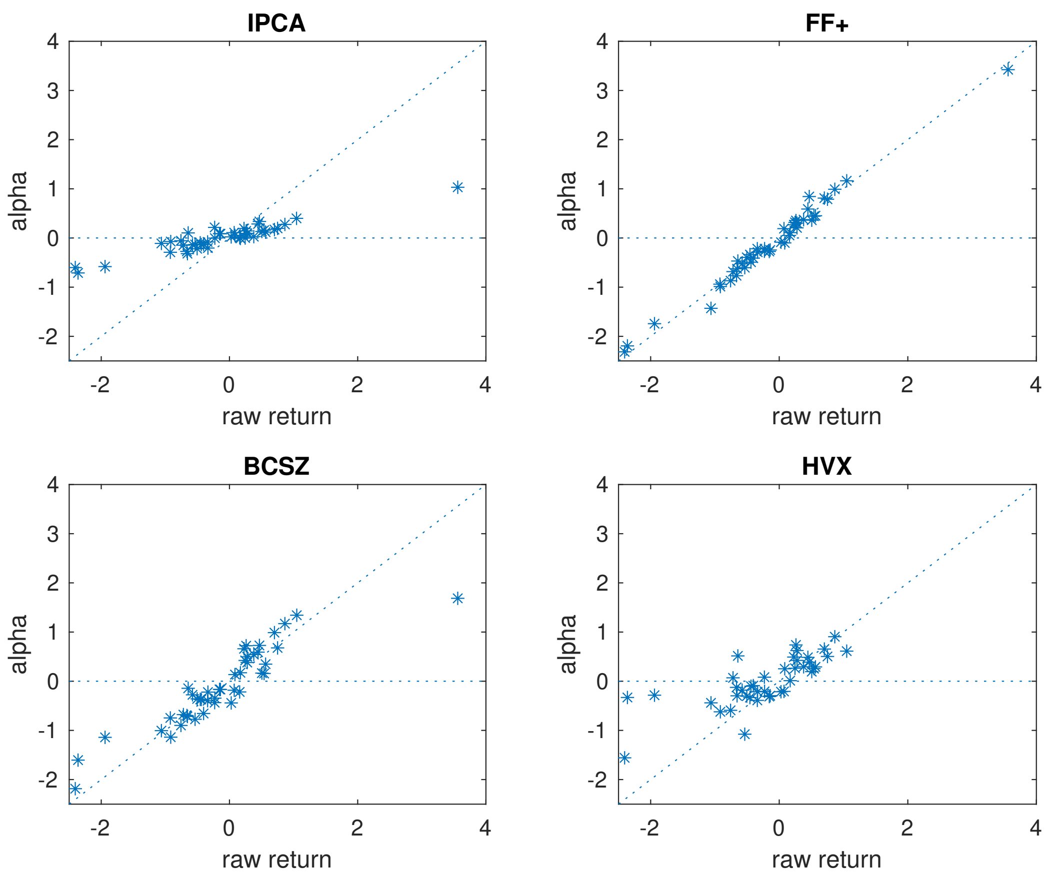
The table presents IPCA alphas for 10−1 and signal weighted portfolios of delta-hedged call returns. The IPCA model has 4 factors. *t*-statistics larger than the Benjamini and Hochberg (1995) 5% FDR adjusted threshold (i.e., 2.60 and 2.25 for mean return of 10−1 and signal weighted portfolios, 3.18 and 1.82 for IPCA alphas of 10−1 and signal weighted portfolios, respectively) are reported in bold. Data spans the period between January 1996 and November 2020.

	10−1				Signal weighted			
	Return		Alpha		Return		Alpha	
Moneyness	**0.47**	**(3.11)**	0.34	(2.32)	**0.26**	**(3.28)**	0.01	(0.12)
Bid-Ask	**1.05**	**(6.17)**	0.40	(2.62)	**0.40**	**(4.38)**	0.00	(0.08)
Open Interest	**−0.76**	**(−7.56)**	−0.06	(−0.59)	**−0.50**	**(−7.44)**	−0.01	(−0.17)
Delta	**−1.06**	**(−8.19)**	−0.11	(−0.84)	**−0.62**	**(−8.33)**	0.02	(0.41)
Volume	−0.23	(−2.09)	0.22	(2.16)	**−0.25**	**(−3.28)**	0.08	(1.53)
Option Price	**0.51**	**(3.16)**	0.13	(0.91)	0.18	(1.75)	0.04	(0.78)
IV ATM	**−2.36**	**(−10.69)**	**−0.71**	**(−4.27)**	**−0.97**	**(−6.77)**	−0.03	(−0.86)
IV slope	**−1.94**	**(−14.82)**	**−0.58**	**(−6.00)**	**−0.94**	**(−12.39)**	−0.03	(−0.75)
IV term	**−2.40**	**(−19.74)**	**−0.60**	**(−5.53)**	**−1.31**	**(−17.11)**	**−0.10**	**(−2.37)**
IV vol	**−0.64**	**(−3.71)**	0.10	(0.75)	**−0.44**	**(−3.99)**	0.05	(1.23)
MF vol	−0.40	(−1.56)	−0.13	(−0.63)	−0.13	(−0.83)	−0.11	(−1.96)
MF skew	**−0.34**	**(−2.78)**	−0.20	(−1.51)	−0.15	(−2.26)	−0.10	(−1.77)
MF kurt	**0.45**	**(2.60)**	0.28	(1.81)	0.20	(2.12)	**0.16**	**(2.67)**
Stock Price	**0.54**	**(2.80)**	0.16	(1.04)	0.14	(1.24)	0.02	(0.43)
Stock Return	0.07	(0.45)	0.11	(0.90)	−0.07	(−0.73)	0.01	(0.19)
Stock Return -11	**−0.54**	**(−2.62)**	−0.13	(−1.13)	**−0.38**	**(−3.05)**	−0.03	(−0.79)
Realized Vol	**−0.66**	**(−2.98)**	−0.32	(−1.80)	−0.27	(−1.88)	−0.02	(−0.41)
Realized Skew	−0.16	(−1.65)	0.09	(0.74)	**−0.13**	**(−2.51)**	−0.02	(−0.51)
Realized Kurt	**−0.46**	**(−4.58)**	−0.10	(−0.69)	**−0.31**	**(−5.69)**	0.02	(0.42)
Idiosyn. Vol	**−0.92**	**(−5.31)**	−0.29	(−1.99)	**−0.42**	**(−3.40)**	−0.03	(−0.75)
Max 10	**−0.72**	**(−3.38)**	−0.15	(−0.91)	**−0.34**	**(−2.42)**	−0.00	(−0.08)
Market Cap	0.16	(1.00)	0.01	(0.03)	−0.00	(−0.01)	−0.01	(−0.17)
Autocorrelation	**0.28**	**(2.91)**	0.10	(0.99)	**0.21**	**(3.46)**	0.03	(0.75)
Turnover	**−0.66**	**(−3.72)**	−0.27	(−2.01)	**−0.33**	**(−2.87)**	−0.04	(−0.74)
RV − IV	**3.56**	**(20.05)**	**1.03**	**(9.42)**	**1.83**	**(18.37)**	0.01	(0.45)
RV − MFvol	−0.34	(−1.90)	−0.08	(−0.49)	−0.11	(−0.96)	0.00	(0.06)
Rskew − MFskew	−0.14	(−1.53)	0.09	(0.73)	−0.10	(−1.94)	−0.01	(−0.16)
Rkurt − MFkurt	**−0.50**	**(−5.69)**	−0.22	(−1.57)	**−0.32**	**(−6.18)**	0.00	(0.06)
BM	**0.86**	**(4.96)**	**0.28**	**(2.83)**	**0.48**	**(4.30)**	−0.03	(−0.79)
Profits	**0.56**	**(3.77)**	0.12	(0.91)	0.13	(1.84)	−0.01	(−0.13)
Inst. Own.	0.17	(1.52)	−0.01	(−0.09)	0.06	(0.84)	−0.03	(−0.56)
RSI	0.09	(0.85)	0.05	(0.47)	−0.06	(−0.90)	0.00	(0.03)
Assets	**0.75**	**(4.80)**	0.20	(1.20)	**0.25**	**(2.27)**	−0.01	(−0.12)
Financial Debt	0.25	(1.94)	−0.00	(−0.01)	0.19	(1.84)	0.01	(0.27)
Leverage	0.23	(2.02)	0.19	(1.92)	0.15	(1.85)	0.06	(1.23)
Cash Flow Var.	0.26	(1.76)	0.14	(1.15)	0.13	(1.55)	0.02	(0.64)
Cash to Asset	**−0.92**	**(−5.07)**	−0.07	(−0.59)	**−0.46**	**(−3.82)**	0.05	(1.13)
Analyst Disp.	**0.38**	**(3.29)**	0.03	(0.26)	**0.27**	**(3.86)**	0.02	(0.40)
1 yr New Iss.	**−0.44**	**(−3.44)**	−0.13	(−1.40)	−0.19	(−2.01)	−0.00	(−0.11)
5 yr New Iss.	**−0.58**	**(−4.92)**	−0.14	(−1.27)	**−0.28**	**(−3.98)**	−0.01	(−0.25)
Profit Margin	**0.70**	**(4.14)**	0.17	(1.28)	0.14	(1.59)	0.03	(0.67)
Profitability	0.28	(2.05)	0.09	(0.80)	0.05	(0.57)	0.03	(0.57)
External Fin.	−0.23	(−1.50)	−0.00	(−0.02)	−0.07	(−0.80)	0.03	(0.72)
Z score	0.03	(0.18)	0.02	(0.17)	−0.11	(−1.11)	−0.01	(−0.25)

graphical representation of the reduction in alphas. The IPCA model manages to eliminate most of the alphas, with most of the portfolios located on the horizontal line corresponding to zero alphas. On the other hand, in the case of the other models, most of the portfolios lie on the diagonal line which we designate as no risk-adjustment.

Figure 3: IPCA alphas

The figure plots portfolio alphas against portfolio returns for 10−1 portfolios of delta-hedged call returns. We consider the same three factor models (FF+, BCSZ, and HVX) from Table 1 and the IPCA factor model from Table 9. Data spans the period between January 1996 and November 2020.



To shed some light on how the risk adjustment works, we focus on one strategy, RV−IV. We choose this strategy as an example for a few reasons. First, RV−IV is the strongest predictor of option returns in the cross-section. Second, at least for 10−1 portfolios, this strategy still presents an alpha even if the IPCA factors are strongly related to the strategy portfolio (see Table 6). Third, RV−IV is the most important characteristics for conditional betas (see Table 8).

We show several quantities of interest for all the RV−IV decile portfolios in Table 10.

Table 10: RV−IV expected IPCA returns decomposition

The table presents a decomposition of the returns of decile portfolios constructed by sorting stocks based on the difference between realized and implied volatility (RV−IV). Expected return and IPCA alpha are derived from the IPCA model estimated with four factors, discussed in previous tables. Data spans the period between January 1996 and November 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret	−2.65	−0.73	−0.36	−0.29	−0.20	−0.03	0.02	0.16	0.49	0.92
E[Ret]	−1.89	−1.19	−0.85	−0.54	−0.25	0.00	0.26	0.48	0.64	0.64
α_{IPCA}	−0.76	0.46	0.49	0.25	0.05	−0.03	−0.24	−0.33	−0.15	0.27
β_{F1} E[F1]	−1.85	−1.15	−0.79	−0.48	−0.21	−0.02	0.22	0.37	0.43	0.31
β_{F2} E[F2]	0.13	0.11	0.10	0.10	0.10	0.10	0.11	0.12	0.13	0.14
β_{F3} E[F3]	0.17	0.14	0.13	0.14	0.15	0.18	0.19	0.22	0.25	0.30
β_{F4} E[F4]	−0.37	−0.35	−0.32	−0.30	−0.27	−0.24	−0.22	−0.19	−0.17	−0.14
RV–IV	−0.45	−0.35	−0.25	−0.15	−0.05	0.04	0.15	0.25	0.35	0.45
Asset	−0.16	−0.04	0.03	0.07	0.09	0.06	0.07	0.03	−0.04	−0.15
Mrkt Cap	−0.20	−0.04	0.03	0.07	0.09	0.08	0.08	0.03	−0.03	−0.15
SReturn -11	−0.08	−0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	−0.03
IV	0.29	0.08	−0.03	−0.09	−0.12	−0.10	−0.11	−0.07	0.01	0.14

Both realized and IPCA expected returns monotonically increase across the ten decile portfolios. The IPCA model does a very good job at pricing 9 of the 10 portfolios; only decile one has a significant alpha that lines up with the average return. We decompose the expected return into the contribution of each factor and its relative conditional beta. Most of the variation in realized return across the ten portfolios is addressed by the first factor, which contributes most of the the risk adjustment to decile one (i.e., 1.85% of the total 1.92%), but only half of the expected return of portfolio 10 (i.e., 0.31% versus 0.64%). As we show in Table 6, the first factor is mostly related to RV−IV portfolio, and its beta is mostly driven by the spread in RV and IV at the option position level. It is, therefore, comforting that the contribution of F1 lines up so well with the average returns.

The other three factors have lower contributions and tend to cancel each other out for the first six portfolios, while they substantially increase the expected return for the last three portfolios. We investigate next how that happens. We observe that the contribution of F3 is U-shaped, and it is mostly responsible for pushing the expected returns of the last three deciles. Examining the portfolio averages of the five most important (ranked scaled) characteristics, we find similar U-shaped patterns for Asset, Market cap, and IV ATM. Figure 2 shows that Asset has the largest gamma for F3, and thus helps explain the patterns in the risk-adjustment induced by the factor. Notably, even if betas are linear functions of individual characteristics, the model can still generate non-linear factor betas, once all characteristics contribution is considered.

4.6 Robustness checks

We conduct several robustness checks, by selecting a subset of the characteristics used to inform the IPCA procedure and by considering particular cross-sections based on properties of the data. We urge a note of caution in interpreting the results in this subsection. The IPCA procedure is a data driven procedure: both the identification of the factors and the importance of the characteristics used to determine the structure of conditional betas depends on the input fed into the procedure. When comparing the results from different cross-sections of the data, it is important to remember that both the data that are to be explained (i.e., the left hand side) and the factors/betas (i.e., the right hand side) are different. Therefore, rather than comparing results from different sub-samples, it is more instructive to compare results from different models for the same sub-sample.

4.6.1 Removing insignificant characteristics

While motivated by existing literature, our choice of conditioning characteristic is still arbitrary. On the one hand, more information could be used, but, on the other, some of the information that we use appears to be redundant according to Table 8. Accordingly, we remove characteristics that are insignificant in Table 8 and rerun the IPCA procedure. We obtain a very similar fit in the IPCA model with fewer characteristics. For example, the relative pricing error increase from 96.8% to 97.2% for stocks, and from 0.2% to 0.3% for managed portfolios, for restricted versus full IPCA, respectively.

4.6.2 Impact of liquidity

Christoffersen, Goyenko, Jacobs, and Karoui (2018), Muravyev (2016), and Muravyev and Pearson (2020) show that liquidity plays an important role in determining option prices and effective realized returns. Therefore, We perform sensitivity analysis of the base case results in three different ways. First, we consider only options which have a positive trading volume on the position initiation day (recall that the base case considers options where either the volume or the open interest is positive), Second, we split the sample by the option dollar open interest. Third, we split the sample by the size of the option bid-ask spread.

We perform IPCA with four latent factors for each of the sub-sample and report the results of the analysis in Table 11. We report the performance measures of Section 3.3 for stock level option positions and for managed portfolios as in Table 3. In addition, we redo

Table 11: Liquidity stratification

The table presents results from IPCA estimation of subsamples of the data constructed by imposing filtering constraints related to liquidity of the option contracts. The first column contains only the delta-hedged call returns for which the contract volume on the return origination date is greater than zero. The columns after this separate observations for which dollar open interest and bid-ask spread are above or below their respective cross-sectional medians, also at the trade origination date. Each estimation extracts four IPCA factors. We report IPCA fit performance measures as in Table 3 and alphas of 10−1 portfolios and signal-weighted portfolios as in Table 9. Data spans the period between January 1996 and November 2020.

	Volume>0	Open Interest		Bid-Ask	
		Low	High	Low	High
	Stock Level Option Positions				
Total R^2	10.66	8.81	11.66	12.92	8.75
Time Series R^2	11.28	9.21	11.47	12.89	9.18
Cross Section R^2	8.60	7.43	9.19	9.47	7.66
Relative Pricing Error	86.67	94.20	85.84	87.16	93.85
	Managed Portfolios				
Total R^2	94.11	93.41	93.71	94.61	92.95
Time Series R^2	71.73	68.54	70.97	71.98	69.37
Cross Section R^2	77.40	76.12	78.90	78.37	77.09
Relative Pricing Error	0.50	1.19	0.24	0.87	0.44
	10−1 Portfolios				
Average alpha:					
IPCA	0.21	0.21	0.19	0.16	0.25
FF+	0.63	0.64	0.73	0.38	0.98
BCSZ	0.59	0.64	0.61	0.37	0.91
HVX	0.33	0.45	0.35	0.26	0.66
# significant alpha:					
IPCA	8	5	8	6	7
FF+	30	19	31	18	34
BCSZ	32	27	30	20	34
HVX	15	17	17	8	25
	Signal Weighted Portfolios				
Average alpha:					
IPCA	0.04	0.05	0.04	0.04	0.05
FF+	0.31	0.37	0.36	0.18	0.59
BCSZ	0.32	0.38	0.32	0.21	0.54
HVX	0.18	0.27	0.18	0.15	0.39
# significant alpha:					
IPCA	0	0	1	2	1
FF+	28	26	33	15	37
BCSZ	30	28	30	21	36
HVX	15	23	13	7	29

the analysis of Section 4.5 and report average absolute alphas and number of significant (at conventional 95% level) alphas of 10−1 portfolios and signal-weighted portfolios. These alphas are computed for the FF+, BCSZ, and HVX models.

Regarding IPCA fit, Table 11 shows that fit (measured by R^2 or the relative pricing error) improves with liquidity. This is to be expected given the prior literature's findings of more variation in option returns for less liquid options. The lone exception is the relative pricing error for managed portfolios which is higher for low bid-ask spread (more liquid) positions.

The main objective of our paper, however, is to show that the IPCA model leaves a lot less alpha on the table. We find that the average alpha of 10−1 and managed portfolios produced by risk-adjustment through IPCA is relatively stable across open interest positions and volume restrictions, and varies a little across different bid-ask spread groups. For example, we obtain average absolute alphas of 13bps versus 25bps per month for low and high bid-ask spread in the case of 10−1 portfolios, and 8bps and 6bps, respectively, for managed portfolios. Other factor models produce higher absolute alphas and exhibit more variation in their ability to price different sets of stock option positions. For example, the most successful competing model, HVX, produces average absolute alphas of 15bps and 39bps per month for managed portfolios across different bid-ask sub-samples.

Equally noteworthy is the number of statistically significant alphas produced by different factor models. The IPCA model leaves only one significant alpha for high open interest sub-sample and no significant alpha for low open interest sub-sample. In contrast, the HVX model produces 23 and 13 significant alphas for the two subgroups. We find similar results for samples stratified by option bid-ask spread.

Overall, we conclude that partitioning the data along measures that proxy for liquidity does not impact the ability of IPCA to control for risk, and leaves very few trading strategies with significant alphas, in contrast to other factor models which produce more significant alphas even for more liquid options.

4.6.3 Moneyness intervals

Our baseline analysis uses the options that are closest to ATM. Although the average moneyness (i.e., ratio of option strike to stock price) is in fact close to 1.0, the sample contains options which moneyness varies between 0.8 and 1.2. While our choice of this relatively large moneyness interval is in line with Zhan, Han, Cao, and Tong (2022), it is not the only approach in the literature. For example, Goyal and Saretto (2009) use a much tighter interval of between 0.975 and 1.025. Moreover, equity and index option returns show systematic variation along the moneyness dimension (Karakaya, 2013 and Büchner and Kelly, 2022), so it is worth investigating whether IPCA can account for such differences.

Table 12: Moneyness stratification

The table presents results from IPCA estimation of alternative data samples created by restricting the moneyness of option contracts to narrower bands, than those used for the main analysis (i.e., closest moneyness to ATM in the 0.8 and 1.2 interval). We consider subgroups where we select the option contract that is closest to the middle of five intervals: between 0.8 and 0.9, between 0.9 and 0.975, between 0.975 and 1.025, between 1.025 and 1.1, and between 1.1 and 1.2. Each estimation extracts four IPCA factors. We report IPCA fit performance measures as in Table 3 and alphas of 10−1 portfolios and signal-weighted portfolios as in Table 9. Data spans the period between January 1996 and November 2020.

	0.8–0.9	0.9–0.975	0.975–1.025	1.025–1.1	1.1–1.2
	Stock Level Option Positions				
Total R^2	11.85	12.07	11.56	10.68	9.58
Time Series R^2	9.58	12.09	11.98	11.58	10.99
Cross Section R^2	10.00	9.58	8.89	8.54	8.32
Relative Pricing Error	88.95	91.44	92.73	90.04	94.57
	Managed Portfolios				
Total R^2	93.80	94.39	93.93	94.15	92.49
Time Series R^2	74.93	73.42	71.00	69.37	63.56
Cross Section R^2	78.38	79.70	76.24	77.53	75.07
Relative Pricing Error	0.49	0.38	0.98	2.38	4.44
	10−1 Portfolios				
Average alpha:					
IPCA	0.13	0.15	0.13	0.16	0.20
FF+	0.37	0.40	0.36	0.54	0.71
BCSZ	0.34	0.40	0.41	0.54	0.64
HVX	0.20	0.26	0.29	0.32	0.40
# significant alpha:					
IPCA	7	9	5	5	3
FF+	20	21	16	23	20
BCSZ	21	27	19	23	19
HVX	9	16	10	10	9
	Signal Weighted Portfolios				
Average alpha:					
IPCA	0.03	0.03	0.04	0.06	0.09
FF+	0.18	0.19	0.20	0.30	0.40
BCSZ	0.17	0.21	0.24	0.32	0.39
HVX	0.12	0.14	0.15	0.19	0.25
# significant alpha:					
IPCA	1	0	0	1	1
FF+	16	19	16	22	22
BCSZ	19	26	21	27	22
HVX	13	12	9	13	12

We check the robustness of our baseline choice by splitting the sample in different moneyness categories: between 0.8 and 0.9, between 0.9 and 0.975, between 0.975 and 1.025, between 1.025 and 1.1, and between 1.1 and 1.2. Due to the fact that strike prices are rather coarse, especially for stocks with low price, some stocks have only one contract in the entire interval of 0.8 and 1.2. Other stocks have multiple positions, and thus potentially contribute one option position to each of the five sub-sample splits. Table 12 presents the results in the same format as Table 11 for four-factor IPCA model.

As Table 9 suggests, delta-hedged option returns are increasing with moneyness in our baseline sample. This is also true across the five moneyness groups: the average return (not reported in the table) in the first group (i.e., moneyness between 0.8 and 0.9) is -0.4% while the average return in the last group (i.e., moneyness between 1.1 and 1.2) is close to zero. While the average return increases monotonically across moneyness groups, the standard deviation of option returns moves in the opposite direction (from 6% to 15% per month). The increase in volatility of option returns explains why the IPCA fit declines in general as we move from left to right columns (from ITM to OTM). For instance, the relative pricing error for managed portfolios is 0.5% and 4.4% for ITM and OTM options.

Turning to the analysis of alphas, we find that, as with average returns, the average absolute alpha increases from ITM to OTM options. For instance, for signal-weighted portfolios, the average absolute IPCA alpha is 5bps and 21bps per month for ITM and OTM options, respectively. At the same time, the number of strategies that remain statistically significant increases only moderately as we increase the moneyness. Other factor models have similar difficulties in pricing OTM options. More important for us, as before, we find that other factor models leave higher average absolute alphas and more statistically significant alphas across each moneyness group than does IPCA.

4.6.4 Alternative option positions

In the main analysis we consider delta-hedged call option (DH Call) returns as a way for investor to profit from volatility exposure of options. Delta-hedged put returns (DH Put) theoretically speaking should give the same return as DH Call, but in practice can differ because of demand induced price pressure (Ramachandran and Tayal, 2021). While delta-hedged positions are neutral to movements in the underlying, they are not the only way to obtain volatility exposure: ATM straddles are also commonly considered as, for example, in Vasquez (2017).

We repeat the IPCA analysis by considering DH Put and Straddles as alternative to DH Calls, and we tabulate results in Table 13. We also consider a joint estimation model where

Table 13: Alternative option positions

The table presents results from IPCA estimation that are fit to explain different ways for investors to profit from volatility exposure of options which at the onset of the position is neutral to movements in the underlying. In addition to ATM delta-hedged calls (DH Call), we consider ATM delta-hedged puts (DH Put) and ATM straddles (Straddle). We also provide the output from a joint estimation where we pool alternative positions. In this case, for each stock/month there will be returns from three different option positions (DH Call, DH put, and ATM straddle). Each estimation extracts five IPCA factors. In the joint estimation, there is a unique set of five factors, but conditional betas are position specific (i.e., there are three sets of Γ_βs, each associated with one of the possible option position). We report IPCA fit performance measures as in Table 3 and alphas of 10−1 portfolios and signal-weighted portfolios as in Table 9. Data spans the period between January 1996 and November 2020.

	DH-Call	DH-Put	Straddle	Joint
	Stock Level Option Positions			
Total R^2	9.61	9.82	11.10	10.93
Time Series R^2	11.14	11.21	11.32	10.72
Cross Section R^2	7.76	7.21	9.41	9.21
Relative Pricing Error	96.01	93.49	94.06	94.32
	Managed Portfolios			
Total R^2	96.24	96.22	94.96	94.20
Time Series R^2	77.08	75.65	69.13	64.37
Cross Section R^2	84.44	83.26	84.93	83.68
Relative Pricing Error	0.29	0.60	3.25	2.36
	10−1 Portfolios			
Average absolute alpha:				
IPCA	0.18	0.15	0.80	0.37
FF+	0.67	0.45	2.89	1.34
BCSZ	0.63	0.48	3.09	1.39
HVX	0.37	0.34	2.36	1.02
# significant alphas:				
IPCA	8	10	6	24
FF+	35	29	33	99
BCSZ	33	29	31	95
HVX	24	19	24	67
	Signal Weighted Portfolios			
Average absolute alpha:				
IPCA	0.08	0.08	0.46	0.20
FF+	0.35	0.22	1.72	0.77
BCSZ	0.35	0.24	1.91	0.83
HVX	0.20	0.16	1.38	0.58
# significant alphas:				
IPCA	2	3	6	12
FF+	31	25	27	85
BCSZ	34	28	29	93
HVX	20	18	18	57

we pool alternative positions. In this joint case, for each stock/month there are returns from three different option positions (DH Call, DH put, and ATM straddle). The IPCA model for the joint case has a unique set of factors, but the conditional betas are position specific (i.e., there will be three sets of Γ_βs, each associated with one of the possible option position). However, when constructing 10−1 portfolios and signal-weighted portfolios for the joint sample, we do not pool the DH call, DH put, and straddle returns. Therefore, the number of strategies in the last column is the sum of strategies in the columns of DH Call, DH Put, and Straddles.

Since straddle returns are much more volatile than DH Call returns, our preliminary checks show that straddles require five IPCA factors (in contrast to four factors as in the rest of the paper). In order to standardize the columns across Table 13, we consider five factors in each estimation. Thus, in the first column, we report results for DH Call which are slightly different than those reported in the previous tables.

Table 13 shows that IPCA explains DH Put returns equally as well as DH Call returns. The average absolute alpha as well as number of statistically significant alphas is also similar for DH calls and DH puts. Competing factor models have as hard a time explaining DH Puts as that for DH Calls, although all models produce smaller alphas for DH Puts than they do for DH Calls.

Straddle returns are harder to explain for IPCA as well as for competing factor models; they have lower R^2, larger pricing errors, higher average absolute alphas, and larger numbers of strategies with statistically significant alphas. For instance, the IPCA model produces 6 statistically significant alphas for signal-weighted portfolios of Straddle returns (versus 2 and 3 for DH Call and DH Put returns, respectively). The average absolute alpha is also 46bps per month for Straddle returns while it is only 8bps for both DH Call and DH Put returns.

Interestingly, the joint estimation does not compound the problems generated by the much more volatile straddle returns, but delivers intermediate results. For example the number of strategies that have significant alphas is about the same as the sum of the unexplained strategies in the stand alone estimation of the three individual components of DH Call, DH Put, and Straddles.[2] The contrast with the number of statistically significant alphas from different factor models is striking. For the joint estimation, signal-weighted portfolios have 12, 85, 93, and 57 statistically significant alphas from the IPCA, FF+, BCSZ, and the HVX models.

[2]Since the IPCA factors in the joint estimation are different from those in individual estimation, there is no mechanical reason to expect that the number of statistically significant alphas for the joint estimation will be the same as the sum of statistically significant alphas in the individual estimations. The fact that the difference in these two numbers is small indicates that the IPCA factors across different estimations are capturing similar common elements but the dynamic betas vary across estimations.

We conclude that IPCA is a relatively flexible instrument, and can account for substantial differences in the data being explained.

5 Conclusion

Explaining the returns from option position is a daunting task. Option returns are extremely volatile and carry sizable liquidity premia. We unify the knowledge accumulated in the extant literature about cross-sectional characteristics that predicts option returns and recent advances in asset pricing methods, and show how much of the profitability of option returns can be explained away by an IPCA factor model with conditional betas. Our results are important because they reaffirm the idea that market efficiency is still a valid framework to think about how prices form in markets. The fact that this is true even in a market that is highly segmented and riddled with informational advantages, as the stock option market is, is quite remarkable.

Appendices

A Variable construction

1. We construct measures related to risk neutral distribution of returns as follows:

   1.1. IV ATM: The ATM implied volatility extracted from the 30 days volatility surface.

   1.2. IV slope: The difference between the OTM implied volatility (i.e., ratio of strike to underlying equal to 0.8) extracted from the 30 days volatility surface and the corresponding ATM implied volatility.

   1.3. IV term: The difference between the ATM implied volatility extracted from the 360 days volatility surface and the corresponding implied volatility extracted from the 30 days surface as in Vasquez (2017).

   1.4. IV vol: Volatility of implied volatility from the volatility surface of OptionMetrics. We use implied volatility of calls with 30 days to maturity with a delta of 0.5 and calculate the standard deviation using daily data over the last month with a minimum of 15 days.

   1.5. MF vol: model-free implied volatility is constructed from 30 days OTM call and OTM put option prices as in Bakshi, Kapadia, and Madan (2003). In particular we follow the procedure described in Hansis, Schlag, and Vilkov (2010), whose code is available on Grigory Vilkov's page.

   1.6. MF skew: model-free implied skewness is constructed from 30 days OTM call and OTM put option prices as in Bakshi, Kapadia, and Madan (2003). In particular we follow the procedure described in Hansis, Schlag, and Vilkov (2010), whose code is available on Grigory Vilkov's page.

   1.7. MF kurt: model-free implied kurtosis is constructed from 30 days OTM call and OTM put option prices as in Bakshi, Kapadia, and Madan (2003). In particular we follow the procedure described in Hansis, Schlag, and Vilkov (2010), whose code is available on Grigory Vilkov's page.

2. We construct measures related to contract characteristics as follows:

   2.1. IV: the implied volatility of the contracts involved in the construction of the return. In the case of the straddle we average the IV of the call and the IV of the put.

   2.2. Moneyness: Moneyness defined as the ratio of strike to underlying price.

   2.3. Bid-ask spread: Bid-ask spread of the contract on the initiation day of the strategy.

   2.4. Open interest: Dollar open interest of the contract (i.e., open interest defined as number of contracts times the most recent option price).

   2.5. Option price: Option price calculated as the midpoint of the bid and ask quotes.

2.6. Delta: Option delta.

2.7. Volume: Dollar option volume on the initiation day of the strategy (i.e., volume defined as number of contracts times the most recent option price).

3. We construct measures related to physical distribution of returns as follows:

3.1. Stock return: Monthly stock return.

3.2. Realized vol: Volatility of log returns calculated using daily data over the last 12 months with a minimum of 150 observations.

3.3. Realized skew: Skewness of log returns calculated using daily data over the last 12 months with a minimum of 150 observations.

3.4. Realized kurt: Kurtosis of log returns calculated using daily data over the last 12 months with a minimum of 150 observations.

3.5. Autocorrelation: Autocorrelation of returns calculated using daily data over the last 6 months with a minimum of 100 observations, following Jeon, Kan, and Li (2021).

3.6. Stock return11: Stock return over the last 11 months skipping the most recent month.

3.7. Max10: Average of the 10 highest daily returns over the last 3 months, following Bali, Cakici, and Whitelaw (2011).

3.8. Turnover: Ratio of number of shares traded over the last month to total shares outstanding.

3.9. Idiosyncratic vol: Standard deviation of residuals from Fama and French (1993) three-factor model. We use daily data over the last month with a minimum of 10 days.

4. We construct measures related to differences between physical and risk-neutral distribution of returns as follows:

4.1. RV−IV: difference between realized and option implied volatility.

4.2. Rskew−MFskew: difference between realized and model free skewness.

4.3. Rkurt−MFkurt: difference between realized and model free kurtosis.

5. We construct stock level variables as follows:

5.1. BM: Book-to-market ratio is calculated as the ratio of book value of equity, calculated as in Fama and French (1992) to the current market value of equity.

5.2. Profits: Profitability, as in Novy-Marx (2013), is calculated as the ratio of gross profits (`GP`) to total assets (`AT`).

5.3. Inst own: Institutional ownership percentage (`instown_perc`) from Thomson Reuters 13f holdings.

5.4. Market cap: Market capitalization.

5.5. RSI: The ratio of shares that are sold short (`shortintadj` in Compustat short interest file) to the total shares outstanding, as in Ramachandran and Tayal (2021).

5.6. Assets: Total assets (`AT`).

5.7. Financial Debt: Total debt defined as the sum of long-term debt (`DLTT`) and debt in current liabilities (`DLC`).

5.8. Leverage: Ratio of financial debt to assets.

5.9. Cash flow var: Cash flow variance, as in Haugen and Baker (1996), is computed as the variance of the monthly ratio of cash flow to market value of equity over the last 60 months. Cash flow is net income (`IB`) plus depreciation and amortization (`DP`).

5.10. Cash to asset: The cash-to-assets ratio, as in Palazzo (2012), is the value of corporate cash holdings (`CHE`) over the value of the firm's total assets (`AT`).

5.11. Analyst disp: Analyst earnings forecast dispersion, as in Diether, Malloy, and Scherbina (2002), computed as the standard deviation (`stdev`) of annual earnings-per-share forecasts (`EPS1`) scaled by the absolute value of the average outstanding forecasts (`meanest`).

5.12. 1 yr new iss: 1-year new issues, as in Pontiff and Woodgate (2008), measured as the change in log of shares outstanding (`shrout`) from 11 months ago. Shares outsanding are adjusted for splits using the cumulative adjustment factor to adjust shares (`cfacshr`).

5.13. 5 yr new iss: 5-year new issues, as in Daniel and Titman (2006), measured as five-year real change in log of number of shares outstanding.

5.14. Profit margin: Profit margin, as in Soliman (2008), calculated as earnings before interest and tax (`OIADP`) scaled by revenues (`SALE`).

5.15. Stock price: The log of stock price at the end of last month, as in Blume and Husic (1972).

5.16. Profitability: Profitability, as in Fama and French (2006), calculated as earnings divided by book equity, in which earnings is defined as income before extraordinary items (`IB`), and book equity is calculated as in Fama and French (1992).

5.17. External fin: Total external financing, as in Bradshaw, Richardson, and Sloan (2006), calculated as net share issuance plus net debt issuance minus cash dividends, scaled by total assets (`AT`). Net share issuance is computed as net cash received from the sale (and/or purchase) of common and preferred stock (`SSTK` less `PRSTKC`) less cash dividends paid (`DV`). Net debt issuance represents net cash received from the issuance (and/or reduction) of debt (`DLTIS` less `DLTR` plus `DLCCH`). `DLCCH` is set to zero if missing.

5.18. Z score: Z-Score, as in Dichev (1998) constructed as [1.2×(Working Capital/Assets) + 1.4×(Retained Earnings/Assets) + 3.3×(EBIT/Assets) + 0.6×(Market Value of Equity/Book Value of Total Liabilities) + (Revenues/Assets)]. Working capital is the difference between `ACT` and `LCT`, Retained earnings are `RE`, EBIT is `OIADP`, Revenues are `SALE`, Total Liabilities are `LT`, Assets are `AT`, and the market value of equity is the market capitalization at fiscal year-end.

B IPCA Alpha Standard Error Calculation

Consider a portfolio with returns R_{t+1} and characteristics Z_t. The alpha of this portfolio is defined in equation (11) as $\hat{\alpha} = \sum_t \left(R_{t+1} - Z_t' \hat{\Gamma}_\beta \hat{F}_{t+1} \right) / T$. Define $\hat{\alpha}_{t+1} = R_{t+1} - Z_t' \hat{\Gamma}_\beta \hat{F}_{t+1}$. Then we have:

$$\begin{aligned} \hat{\alpha}_{t+1} &= R_{t+1} - Z_t' \hat{\Gamma}_\beta \hat{F}_{t+1} \\ &= \left(R_{t+1} - Z_t' \overline{\Gamma}_\beta \hat{F}_{t+1} \right) - Z_t' E_\beta \hat{F}_{t+1}, \end{aligned} \tag{B1}$$

where we have accounted for the fact that the $L \times K$ matrix $\hat{\Gamma}_\beta$ has estimation error specified by E_β. The standard error of $\hat{\alpha}$ needs to correct for the estimation error in $\hat{\Gamma}_\beta$ and $\hat{F}$. Obtaining an analytical expression for the the variance of $\hat{\alpha}$ is a difficult, if not impossible, task. We make some simplifying conservative assumptions below to make some headway in this issue.

First, ignoring the estimation error in the latent factor estimates, we have:

$$\begin{aligned} \text{var}(\hat{\alpha}_{t+1}) &= \text{var}\left(R_{t+1} - Z_t' \overline{\Gamma}_\beta F_{t+1} \right) + \text{var}\left(Z_t' E_\beta F_{t+1} \right) \\ &\quad -2\text{cov}\left(R_{t+1} - Z_t' \overline{\Gamma}_\beta F_{t+1}, Z_t' E_\beta F_{t+1} \right) \\ &= \text{var}\left(R_{t+1} - Z_t' \overline{\Gamma}_\beta F_{t+1} \right) + \text{var}\left(Z_t' E_\beta F_{t+1} \right). \end{aligned} \tag{B2}$$

where, in the second line, we have made use of the second simplifying assumption that E_β is uncorrelated with R, Z, and F.

Note that $Z_t' E_\beta F_{t+1} = \sum_{l=1}^{L} Z_{t,l} E_{\beta,l}' F_{t+1}$, where $Z_{t,l}$ is the lth characteristic at time t and $E_{\beta,l}$ is $K \times 1$ vector of estimation errors in Γ_β estimates for the lth characteristics. We now make the third simplifying assumption that the estimation error in betas across different characteristics are uncorrelated. We then have:

$$\text{var}\left(Z_t' E_\beta F_{t+1} \right) = \sum_{l=1}^{L} \text{var}\left(Z_{t,l} E_{\beta,l}' F_{t+1} \right). \tag{B3}$$

Since $Z_{t,l} E_{\beta,l}' F_{t+1} = \sum_{k=1}^{K} Z_{t,l} E_{\beta,l,k} F_{t+1,k}$, we have:

$$\begin{aligned} \text{var}\left(Z_{t,l} E_{\beta,l,k} F_{t+1,k} \right) &= \text{var}(Z_{t,l} F_{t+1,k}) \times \left[\text{var}(E_{\beta,l,k}) + \overline{Z_{t,l} F_{t+1,k}}^2 \right] \\ \text{cov}\left(Z_{t,l} E_{\beta,l,k_1} F_{t+1,k_1}, Z_{t,l} E_{\beta,l,k_2} F_{t+1,k_2} \right) &= \text{cov}(E_{\beta,l,k_1}, E_{\beta,l,k_2}) \times \overline{Z_{t,l}^2 F_{t+1,k_1} F_{t+1,k_2}}. \end{aligned} \tag{B4}$$

Combining equations (B2) to (B4), we get:

$$
\begin{aligned}
\text{var}(\hat{\alpha}_{t+1}) \quad = \quad & \text{var}\left(R_{t+1} - Z_t'\overline{\Gamma}_\beta F_{t+1}\right) \\
& + \sum_{l=1}^{L} \left\{ \sum_{k=1}^{K} \text{var}(Z_{t,l}F_{t+1,k}) \times \left[\text{var}(E_{\beta,l,k}) + \overline{Z_{t,l}F_{t+1,k}}^2 \right] \right. \\
& \left. + \sum_{k_1=1}^{K} \sum_{k_2=1,k_2\neq k_1}^{K} \text{cov}(E_{\beta,l,k_1}, E_{\beta,l,k_2}) \times \overline{Z_{t,l}^2 F_{t+1,k_1} F_{t+1,k_2}} \right\}. \qquad \text{(B5)}
\end{aligned}
$$

Finally, the standard error of $\hat{\alpha}$ is given as usual by $\sqrt{\text{var}(\hat{\alpha}_{t+1})/T}$. Equation (B5) requires variances of covariances of E_β. Fortunately, these are already available via our bootstrap procedure from Section 3.2 and used in Section 4.4 on characteristic importance. The other quantities in equation (B5) are replaced by their sample counterparts.

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