In Search of a Factor Model for Optionable Stocks*

Turan G. Bali† Scott Murray‡

April 2020

Abstract

We propose the first factor model that explains cross-sectional variation in optionable stock returns. Our model includes new factors based on option-implied volatility minus realized volatility, the call minus put implied volatility spread, and the difference between changes in call and put implied volatilities, along with the market factor. The model outperforms previously-proposed factor models at explaining the performance of portfolios of optionable stocks formed by sorting on other option-based predictors, as well as other well-known stock return predictors. Our model provides a benchmark for assessing whether portfolios of optionable stocks generate returns that are not explained by previously-documented phenomena.

Keywords: Optionable stocks, factor model, cross section of stock returns.
JEL Classifications: G11, G12, G13.

---

*We thank Adrian Buss, Tarun Chordia, Zhi Da, Ozgur Demirtas, Cam Harvey, and Quan Wen for insightful comments that have substantially improved the paper. We also benefited from discussions with seminar participants at Georgetown University and Sabanci University. This work used the Extreme Science and Engineering Discovery Environment (XSEDE), which is supported by National Science Foundation grant number ACI-1548562 (Towns et al. (2014)).

†Robert S. Parker Chair Professor of Finance, McDonough School of Business, Georgetown University, turan.bali@georgetown.edu.

‡Assistant Professor of Finance, J. Mack Robinson College of Business, Georgia State University, smurray19@gsu.edu.

1 Introduction

Research investigating the drivers of expected stock returns has documented a large number of variables that have the ability to predict the cross section of future stock returns.[1] Several recent papers (Fama and French (2015), Hou, Xue, and Zhang (2015), Stambaugh and Yuan (2017), and Daniel, Hirshleifer, and Sun (2020)) put forth empirical factor models that are successful at explaining the average returns of most portfolios formed by sorting on these return predictors. While these papers examine the ability of their models to capture patterns in average returns associated with a large number of variables calculated from historical stock market and accounting data, they do not examine the ability of their models to explain anomalies related to variables calculated from stock option prices (option-based variables hereafter). One potential reason for the omission of option-based variables from previous studies is that these variables are only available for optionable stocks, whereas most studies testing the efficacy of a factor model examine the entire cross section of US common stocks. While historically only 25% to 75% of all stocks are optionable, these stocks account for between 85% and 98% of total stock market capitalization, and tend to be more liquid than non-optionable stocks. These facts suggest that it is important for a factor model to explain predictable patterns in average excess returns among optionable stocks.

The objective of this paper is to put forth a factor model capable of explaining cross-sectional variation in average returns of portfolios of optionable stocks. Specifically, we aim to produce the simplest factor model that explains the returns of portfolios of optionable stocks formed by sorting on option-based variables and other known predictors of cross-sectional variation in future stock returns (traditional asset pricing variables hereafter).

The theoretical prediction that a single factor model should price all securities may seem contradictory to our objective of creating a factor model for optionable stocks. However, ever since Fama and French (1993), who find significant covariation between bond and stock returns but nonetheless propose different factor models for each market, the literature has embraced the practice of using different empirical factor models for different types of securities.[2] Nonetheless, for the reader who is uncomfortable with the idea of using different

[1]Hou, Xue, and Zhang (2015), Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), and Linnainmaa and Roberts (2018) list and categorize many of these predictors.

[2]Fama and French (1993) propose using a two-factor model with term and default factors for empirical analyses of bond returns, and a three-factor model with the stock market factor, a size factor, and a value

factor models for different subsets of stocks, an alternative interpretation of our objective is that we aim to create a factor model that spans the dimensions of stock return predictability arising from known option-based stock return predictors. This model can serve both as a benchmark for evaluating whether the predictive power of option-based variables proposed by future research is spanned by previously-known predictors, and also as a benchmark for assessing whether the predictive power of variables applicable to the broader set of all stocks is spanned by option-based predictors.

There are at least three reasons that a factor model for optionable stocks is needed. First, as we will show, previously-proposed factor models, including those that can explain the returns associated with a large number of anomaly variables, do not explain the returns of portfolios formed by sorting on option-based variables. While option-based variables are only available for optionable stocks, this set of predictors is important because the options market is the main venue, other than the stock market, in which investors can trade based on information or beliefs related to individual stocks. It is for this reason that the predictive power of option-based variables is most commonly attributed to informed trading. Second, because the OptionMetrics data used by most studies examining the ability of option-based variables to predict the cross section of future stock returns begin in 1996, the length of the period for which these data are available is becoming more conducive for this type of research. A factor model that captures the previously-established predictive power of option-based variables serves as a baseline for ensuring that return predictability documented by subsequent studies is distinct from these previously-known effects. Third, the universe of optionable stocks differs substantially from the universe of all stocks in that optionable stocks tend to be larger and more liquid than other stocks. As a result of this decreased heterogeneity, the predictive power of most traditional asset pricing variables is weak or non-existent among optionable stocks. This makes factor models aimed at explaining the predictive power of these traditional variables less useful for these stocks.

Our study focuses on seven previously-established option-based stock return predictors. Bali and Hovakimian (2009) show that the cross section of future stock returns is positively related to the difference between option-implied volatility and historical realized volatility

factor for empirical analyses of stock returns. Lustig, Roussanov, and Verdelhan (2011), Szymanowska, De Roon, Nijman, and Van Den Goorbergh (2014), Bai, Bali, and Wen (2019), and Liu, Tsyvinski, and Wu (2019) develop factor models for the currency, commodity, corporate bond, and cryptocurrency markets, respectively.

($IV - RV$) and to the difference between the implied volatilities of near-the-money call and put options ($CIV - PIV$). Cremers and Weinbaum (2010) find that stocks with higher volatility spreads, measured as the difference between call-implied volatilities and expiration- and strike-matched put-implied volatilities (VS) have relatively higher future returns. Xing, Zhang, and Zhao (2010) demonstrate that the difference between the implied volatility of an at-the-money (ATM hereafter) call option and an out-of-the-money (OTM hereafter) put option ($Skew$), a measure of skewness, is positively related to the cross section of future stock returns. Johnson and So (2012) find a positive relation between the ratio of trading volume in the stock to option trading volume (S/O) and future stock returns. An, Ang, Bali, and Cakici (2014) show that the difference between changes in ATM call-implied volatility and changes in ATM put-implied volatility ($\Delta CIV - \Delta PIV$) is positively related to future stock returns. Finally, Baltussen, Van Bekkum, and Van Der Grient (2018) find that the volatility of implied volatility has a negative cross-sectional relation with future stock returns.[3]

We begin by examining the ability of our focal variables to predict the cross section of future stock returns. Our analyses demonstrate that for five of the seven option-based variables, $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$, a value-weighted portfolio that is long stocks with high values of the variable and short stocks with low values of the variable generates an economically large and highly statistically significant average excess return. This holds not only during the full 1996-2017 sample period covered by our study, but also in the portion of this period subsequent to the sample period used in the original study. The persistence of the predictive power of these variables after the original studies' sample periods indicates that these effects are not a result of data-snooping or publication bias (Harvey, Liu, and Zhu (2016)) and do not represent short-lived mispricing that is eas-

[3]In their expositions, many of the papers find a negative relation between their variables and future stock returns. So that all of our focal variables have a positive cross-sectional relation with future stock returns, for variables documented to have a negative relation with future returns, we define our versions of these variables as the negative or inverse of the versions used in the original papers. Specifically, Bali and Hovakimian (2009) find a negative cross-sectional relation between future stock returns and the difference between realized and implied volatility. Xing et al. (2010) find a negative relation between future returns and the difference between OTM put-implied volatility and ATM call-implied volatility. Johnson and So (2012) find a negative relation between the ratio of option volume to stock volume. An et al. (2014) find a negative relation between the changes in put-implied volatility and changes in call-implied volatility. Similarly, since Baltussen et al. (2018) find a negative relation between the volatility of implied volatility and future stock returns, we will define our volatility of implied volatility variable, VoV, as the negative of the variable used in Baltussen et al. (2018).

ily corrected once publicized (McLean and Pontiff (2016)). As such, any factor model for optionable stocks must be able to account for these pricing effects.

Next, we use the Fama and French (1993) methodology to generate factor portfolios associated with each of $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ (option-based factors hereafter). We then search for the smallest subset of option-based factors that, when combined with the market factor (MKT), produces a factor model that explains the average returns of all of the option-based factors. We find that a factor model that includes MKT and factors based on $IV - RV$ (F_{IV-RV}), VS (F_{VS}), and $\Delta CIV - \Delta PIV$ ($F_{\Delta CIV - \Delta PIV}$) explains the average returns of all of the option-based factors. No other model that combines MKT with three or fewer option-based factors satisfies this criterion. We therefore settle on a model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ as our benchmark model.

The fact that fewer than five option-based factors are needed to explain the average returns of all five factors is not unexpected. As discussed in the original papers examining these variables, the evidence suggests that each of the option-based variables captures trading of informed investors. As described in Easley, O'Hara, and Srinivas (1998), informed investors may chose to trade in the options market. Insofar as informed investors have positive (negative) information about a stock, they will buy (sell) calls and sell (buy) puts, and this demand will have an impact on option prices (Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009)), causing the implied volatility of calls (puts) to be higher than that of puts (calls). Furthermore, $CIV - PIV$, $Skew$, VS, and $\Delta CIV - \Delta PIV$ all capture differences between the implied volatility of calls and that of puts. Given the similarities between the option-based measures, it is not surprising that a model that includes only three option-based factors explains the average returns of all five factors. The fact that we cannot explain the average excess returns of all five factors with fewer than three non-market factors indicates that the measures underlying each of these factors captures a distinct dimension of stock return predictability.

To test our model, we investigate its ability to explain the average returns generated by portfolios of optionable stocks formed by sorting on option-based variables and traditional asset pricing variables. Not surprisingly given the methodology we use to select the factors included in our model, we find that our four-factor model explains the average returns of portfolios sorted on all of the option-based variables. More importantly, we find that portfolios of optionable stocks formed by sorting on traditional asset pricing variables generate insignificant alphas relative to our four-factor model. Our results hold not only for long-short portfolios that are long (short) stocks with high (low) values of the given variable, but also for long-only portfolios of optionable stocks with different values of these variables. Finally, we find that the Sharpe ratio of the tangency portfolio constructed from the factors in our model is significantly higher than that of previously-established factor models.

Interestingly, we find that our model is particularly relevant for explaining the betting against beta anomaly of Frazzini and Pedersen (2014) and the idiosyncratic volatility puzzle of Ang, Hodrick, Xing, and Zhang (2006), both of which are commonly referred to as "low-risk anomalies". Our model is also important for explaining the lottery demand effect of Bali, Cakici, and Whitelaw (2011), which has been shown by Bali, Brown, Murray, and Tang (2017) to drive the betting against beta effect and by Bali et al. (2011) to drive the idiosyncratic volatility puzzle. These findings suggest a link between the option-based variables and low-risk anomalies in the sample of optionable stocks. Our model is also particularly important for explaining variation in average returns of optionable stock portfolios formed by sorting on measures of profitability proposed by Fama and French (2015) and Hou et al. (2015).

The remainder of this paper proceeds as follows. In Section 2 we contextualize our contributions in the extant literature. Section 3 describes our sample and demonstrates the predictive power of previously-studied option-based variables. In Section 4 we construct our option-based factors and select the factors to be included in our model. Section 5 demonstrates that our four-factor model does a better job than previously-proposed factor models at explaining the average returns of portfolios of optionable stocks. Section 6 concludes.

2 Literature Review

Our work contributes directly to two main lines of research. First, we add to the work that aims to produce empirically-motivated factor models that explain cross-sectional variation in average stock returns. The seminal paper in this area is Fama and French (1993), who pioneered the methodology most commonly used for generating factor portfolios and whose three-factor model (FF model hereafter) that includes a market factor, a size factor, and a value factor, was the standard for many years. Carhart (1997) proposed a four-factor model

(FFC model hereafter) that augments the FF model with a momentum factor designed to capture variation in average returns associated with the momentum effect of Jegadeesh and Titman (1993). Pastor and Stambaugh (2003) developed an aggregate liquidity factor that led many researchers to adopt a five-factor model (FFCPS model hereafter) that included the four factors in the FFC model and the aggregate liquidity factor. Subsequent to this, the large proliferation in documented anomalies led to the proposal of several alternative factor models designed to capture return variation common to several pricing effects. Fama and French (2015) propose a five-factor model (FF5 model hereafter) that includes a market factor, a size factor, a value factor, an investment factor, and a profitability factor. Hou et al. (2015) propose a four-factor model (Q model hereafter) that includes the market factor, a size factor, an investment factor, and a profitability factor. Stambaugh and Yuan (2017) put forth a three factor model (SY model hereafter) that includes the market factor and two "mispricing" factors based on combinations of previously documented anomalies. Finally, Daniel, Hirshleifer, and Sun (2020) argue for a three-factor model (DHS model hereafter) based on investor psychology that augments the market factor with short-horizon and long-horizon mispricing factors. The objective of all of these previous papers is to explain anomalies based on variables constructed from accounting and historical stock market data that are present in the entire cross section of US common stocks. Our objective differs from that of previous work in that we focus only on optionable stocks. The anomalies explained by previous work tend to be weak among optionable stocks, whereas the anomalies related to option-based variables are strong among this set of stocks, even after accounting for variation in returns captured by each of the previously-proposed factor models. To our knowledge, our factor model is the first to be able to explain cross-sectional variation in returns associated with option-based variables.

Second, we contribute to the line of research that examines the ability of option-based variables to predict the cross section of future stock returns. In addition to the papers, discussed above, that originally document the effects that we focus on, Pan and Poteshman (2006) find that, when looking only at volume initiated by buyers to open new positions, the ratio of put to call option volume is negatively related to the cross section of future stock returns. We do not investigate this effect because it requires proprietary data that are not available publicly. As discussed by Pan and Poteshman (2006), the ratio of put to call option volume for all trades, which is publicly available, has no ability to predict the cross section of future stock returns. Conrad, Dittmar, and Ghysels (2013) demonstrate that average historical option-implied skewness is negatively related to the cross section of future stock returns.[4] We do not investigate their measure because the data requirements for calculating this measure are only satisfied by a small proportion of optionable stocks. Consistent with Xing et al. (2010), Rehman and Vilkov (2012) and Chordia, Lin, and Xiang (2020) find that risk-neutral skewness positively predicts the cross-section of stock returns, a result that Chordia et al. (2020) attribute to informed trading. Finally, Clements, Kalesnik, and Linnainmaa (2019) find that the predictive power of several option-based variables is stronger when the predictive measures are constructed from long-dated options instead of short-dated options. We contribute to this line of work by showing that the predictive power of a large number of these option-based predictors is captured by a factor model that includes only four factors, one of which is the market factor. Our results indicate that while most of these measures robustly predict the cross section of future stock returns, the predictive power of some measures is redundant. We are also the first paper to simultaneously examine the predictive power of option-based and traditional asset pricing variables. Most importantly, we provide a factor model to be used as a benchmark by future research examining relations between option-based variables and the cross section of average stock returns.

More broadly, our work is related to several other lines of work. Many papers have used option-based measures to predict the returns of securities other than stocks. Among these are Cao, Goyal, Xiao, and Zhan (2020b), who find that changes in option-implied volatility predict the cross section of future corporate bond returns, and Driessen, Maenhout, and Vilkov (2009), Goyal and Saretto (2009), and Hu and Jacobs (2020), who detect relations between predictors generated from option prices and the cross section of future option returns.[5] Other papers, such as Ang, Hodrick, Xing, and Zhang (2006), Chang, Christoffersen, and Jacobs (2013), Cremers, Halling, and Weinbaum (2015), and Lu and Murray (2019), detect relations between expected stock returns and exposure to factors from S&P 500 index options prices. Exposure to index option return-based factors has also been shown by Fung and Hsieh (2001), Agarwal and Naik (2004), and Jurek and Stafford (2015) to explain variation in hedge fund returns.

[4]Amaya, Christoffersen, Jacobs, and Vasquez (2015) find similar results using a measure of skewness generated from high-frequency stock return data.

[5]Cao and Han (2013) find that idiosyncratic volatility measured from stock returns predicts the cross-section of future option returns.

Finally, a large number of papers have used option-based variables in other asset pricing contexts. An incomplete list of such papers is as follows. Roll, Schwartz, and Subrahmanyam (2010) find a contemporaneous (but not predictive) relation between option trading volume and stock returns. DeMiguel, Plyakha, Uppal, and Vilkov (2013) show that incorporating information from option prices when constructing portfolios can help decrease portfolio volatility and increase the portfolio's Sharpe ratio. Buss and Vilkov (2012) and Chang, Christoffersen, Jacobs, and Vainberg (2012) generate forward-looking measures of risk from option data. Cao, Goyal, Ke, and Zhan (2020a) find that the price informativeness of a stock increases when options on the stock are first listed.

3 Data, Variables, and Sample

Option data are from OptionMetrics (OM hereafter). We use OM's traded options data and OM's implied volatility surface. The traded options data include daily end-of-day best bid, best ask, implied volatility, and Greeks for options traded on the Chicago Board Options Exchange. To ensure data quality, we keep only observations with a positive best bid price, a best offer price that is greater than the best bid price, a positive implied volatility, which indicates that the option price does not violate simple no-arbitrage conditions, positive open interest, and whose bid-ask spread scaled by the mid price is less than 0.5. The volatility surface data contain implied volatilities for options with fixed times to expiration and deltas constructed using interpolation. Stock price, return, volume, and shares outstanding data are from CRSP. Accounting data are from COMPUSTAT. We gather daily and monthly returns for the market, size, and value factors of Fama and French (1993), a momentum factor, the size, value, investment, and profitability factors of Fama and French (2015), and the risk-free asset from Ken French's data library.[6] We collect the returns of the Pastor and Stambaugh (2003) traded liquidity factor from Lubos Pastor's website.[7] We thank Chen Xue for providing the data for the market, size, investment, and profitability factors of Hou et al. (2015). We gather returns of the size, management, and performance factors of Stambaugh and Yuan (2017) from Robert Stambaugh's website.[8] Finally, we thank David Hirshleifer for

[6]Ken French's data library is at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7]Lubos Pastor's website is http://faculty.chicagobooth.edu/lubos.pastor/research/.

[8]Robert Stambaugh's website is http://finance.wharton.upenn.edu/ stambaug/. Data for the Stambaugh and Yuan (2017) factors end in December 2016, thus analyses using these data also end in December 2016.

providing the data for the financing and post-earnings announcement drift factors of Daniel et al. (2020).

3.1 Variables

To the extent possible, we calculate the option-based variables in the same manner as in the original studies of these variables. Since these variables are well-established in the literature, we provide a brief description of their calculation here, and relegate detailed descriptions to Appendix A. All variables are calculated at the end of each month for all stocks for which the data requisite for the calculation of the given variable are available.

$IV - RV$ and $CIV - PIV$ are calculated following Bali and Hovakimian (2009) as the difference between ATM option-implied and historical realized volatility, and the difference between ATM call-implied volatility and ATM put-implied volatility, respectively. VS is calculated following Cremers and Weinbaum (2010) as the weighted-average difference between strike- and maturity-matched call-implied and put-implied volatilities, with weights determined by open interest. $Skew$ is calculated following Xing et al. (2010) as the implied volatility of an ATM call minus the implied volatility of an OTM put. S/O is calculated following Johnson and So (2012) as trading volume in stocks divided by the trading volume in options. Since Johnson and So (2012) focus on weekly returns and our study focuses on monthly returns, we make reasonable modifications of their variable to accommodate our monthly frequency. $\Delta CIV - \Delta PIV$ is calculated following An et al. (2014) as the one-month change in ATM call-implied volatility minus the one-month change in put-implied volatility. Finally, volatility of implied volatility (VoV) is calculated following Baltussen et al. (2018) as the negative of the standard deviation of the daily implied volatility of the stock's ATM options over the past month, scaled by the mean of the implied volatilities. Following the original papers, the calculation of $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, and VoV uses OM's traded option data, and the calculation of $\Delta CIV - \Delta PIV$ uses data from OM's implied volatility surface.

The original studies of $IV - RV$, $Skew$, $\Delta CIV - \Delta PIV$, and VoV actually use $RV - IV$, $-Skew$, $\Delta PIV - \Delta CIV$, and $-VoV$, the negative of our variables, and find negative cross-sectional relations between their variables and future stock returns. Similarly, Johnson and So (2012) use the ratio of option to stock volume (O/S) and find a negative relation between that and future stock returns. We use the negative or inverse of these variables so that all of our variables have a positive relation with future stock returns. Throughout this paper, all volatilities used to calculate $IV - RV$, $CIV - PIV$, VS, $Skew$, $\Delta CIV - \Delta PIV$, and VoV are recorded in percent. Thus, for example, if $IV - RV$ has a value of 1.00, this indicates that the implied volatility of the stock is one percentage point higher than the stock's realized volatility.

3.2 Sample

Our sample consists of all optionable US-based common stocks that trade on the NYSE, AMEX, or NASDAQ (optionable stocks hereafter) and covers the 1996-2017 period for which OM data are available. Specifically, the sample created at the end of each month t, which will be used to examine the cross-sectional relation between variables calculated at the end of month t and stock returns in month $t+1$, includes each optionable stock that, as of the end of month t, is both a US-based common stock and trades on either the NYSE, AMEX, or NASDAQ.[9] A stock is considered optionable if, on the last trading day of month t, it appears in OM's traded options data. We also require that each stock in the month t sample has a non-missing price and positive number of shares outstanding at the end of month t. Our sample includes the 263 sample formation months t (future return months $t+1$) from February (March) 1996 through December 2017 (January 2018). Our first sample formation month t is February 1996, instead of January 1996, because $\Delta CIV - \Delta PIV$, one of our focal variables, requires data from both months t and $t-1$, making February 1996 the first month for which this measure is available.

Table 1, Panel A presents summary statistics for the focal variables used in our study. Each month t, we calculate the cross-sectional mean, standard deviation, and median value of each variable, as well as the number of stocks for which the variable can be calculated. The table presents the time-series means of the monthly cross-sectional summary statistics. $IV - RV$ is positive in both mean and median, indicating that implied volatilities tend to be higher than realized volatilities. Both $CIV - PIV$ and VS have a negative mean and median, indicating that both the average and majority of stocks have higher put implied volatilities

[9]US-based common stocks are taken to be stocks with CRSP share code (shrcd field) value of 10 or 11. Stocks with CRSP exchange code (exchcd field) value of 1, 2, or 3 are taken to trade on the NYSE, AMEX, and NASDAQ, respectively.

than call implied volatilities. $Skew$ is, on average and in median, negative, indicating that ATM call implied volatilities tend to be lower than OTM put implied volatilities. S/O is 96.58 (46.93) on average (in median), indicating that stock trading volume is much higher than option trading volume. $\Delta CIV - \Delta PIV$ is close to zero in both mean and median, indicating that neither call implied volatilities nor put implied volatilities have a tendency to increase more than the other. Finally, VoV has a mean (median) of -7.84 (-6.86), indicating that for the mean (median) stock, the daily variation in implied volatility is approximately 8% (7%) of the level of implied volatility.

The time-series averages of monthly cross-sectional correlations between the variables are shown in Panel B of Table 1. The results indicate that pairwise correlations between $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ are all strongly positive. This is not surprising because each of these variables, in some way, captures the difference between the implied volatility of calls and the implied volatility of puts. VoV has a modest positive correlation with each of $IV - RV$ and S/O. Aside from this, $IV - RV$, VoV, and S/O each have near-zero correlations with all of the other variables.

To compare the sample of optionable stocks to that of all US-based common stocks listed on the NYSE, AMEX, and NASDAQ (all stocks hereafter), in Table 2 we present summary statistics for market capitalization ($MktCap_{ShareClass}$), illiquidity ($Illiq$), Price ($Price$), share volume ($Volume$), and dollar trading volume ($Volume\$$) for both optionable stocks and the sample of all stocks. $MktCap_{ShareClass}$ for stock i in month t is measured as the share price times the number of shares outstanding of the stock, as of the end of month t, recorded in millions of US dollars. We include the subscript $ShareClass$ on $MktCap_{ShareClass}$ to stress that this variable is measured at the share class level, and not aggregated across share classes to the firm level. This distinction is notable here because for firms with multiple share classes, some share classes may be optionable and others may not be. $Illiq$ for stock i in month t is calculated following Amihud (2002) as the average, over all days in months $t - 11$ through t, inclusive, of the absolute daily return (mesaured in percent) divided by dollar trading volume (measured in millions of US dollars). $Price$ is the price of the stock at the end of the month. $Volume$ is the number of shares of the stock traded in the given month, recorded in thousands of shares. $Volume\$$ is the dollar trading volume of the stock, calculated as $Volume \times Price/1000$, and thus is recorded in millions of dollars. The month t sample of all stocks is constructed in exactly the same way as our focal sample, except we do not require a stock to be optionable for it to enter the sample of all stocks.

Table 2 demonstrates that there are substantial differences between the sample of optionable stocks that we focus on in this paper and the broader sample of all US-based common stocks. In the average month, a little less than half of all stocks are optionable, the median market capitalization of optionable stocks is more than 3.5 times that of all stocks, and the median value of *Illiq* for optionable stocks of 0.31 is less than one 20th that of all stocks. The price of the median optionable stock is \$23.04 and that of all stocks is \$14.52. Share volume (dollar trading volume) of optionable stocks is, in median, a little more than three (five) times that of all stocks. The results clearly demonstrate that optionable stocks tend to be larger and more liquid than stocks in the broader sample of US-based common stocks. Interestingly, due to a small number of stocks that are not optionable but have very high prices, the mean price of optionable stocks is substantially lower than the mean price of all stocks.

We continue our comparison of the optionable stock sample and all stocks sample by constructing time-series plots of the number of stocks, the total market capitalization of the stocks, and the total dollar trading volume of the stocks in each sample. Figure 1 plots the number of all stocks as well as the number of stocks that are optionable, through time. The figure shows that at the end of February 1996 (the beginning of our sample period), only 1,574 of the 6,982, or about 22.5% of all stocks were optionable. However, by the end of our sample period in December 2017, 2,650 out of 3,605 such stocks (73.5%) were optionable. Interestingly, the increase in the percentage of all stocks that are optionable is as much a manifestation of a decrease in the total number of all stocks as it is of an increase in the number of optionable stocks.

Figures 2 and 3 show the total market capitalization and total monthly dollar trading volume for both all stocks and optionable stocks. Despite the fact that the maximum percentage of stocks that are optionable is 75.9% (in August 2016), the percentage of total market capitalization (dollar trading volume) for all stocks that comes from optionable stocks ranges from a minimum of 85.5% in September 1996 (85.0% in June 1996) to 98.5% in August 2016 (99.7% in March 2016). Thus, even during the early part of our sample period when most stocks were not optionable, the sample of optionable stocks accounted for the vast majority of total market capitalization and total dollar trading volume of all stocks. These results demonstrate the importance of understanding patterns in the returns of optionable stocks.

3.3 Ability of Option-Based Variables to Predict Future Returns

Our first asset pricing tests are portfolio analyses examining the ability of our focal option-based variables to predict the cross section of future stock returns. At the end of each month t, we group all optionable stocks into five portfolios based on ascending values of the given variable. The breakpoints used to group the stocks are the 20th, 40th, 60th, and 80th percentile values of the variable among NYSE-listed optionable stocks. We then calculate the month $t+1$ $MktCap_{ShareClass}$-weighted (value-weighted hereafter) average excess return for stocks in each portfolio, as well as that of a portfolio that is long the fifth quintile portfolio and short the first quintile portfolio in equal dollar amounts (long-short portfolios hereafter). Our decision to use NYSE breakpoints and value-weighted portfolios follows Hou et al. (2015), who find that this methodology provides a more stringent test than using breakpoints based on all stocks or equal-weighted portfolios. This portfolio construction methodology is also consistent with well-established research practice (Fama and French (1993, 2015), Hou et al. (2015), Stambaugh and Yuan (2017), and Daniel et al. (2020)). In Section I and Tables IA1-IA7 of the Internet Appendix, we show that our conclusions are unchanged when we examine portfolios constructed using breakpoints calculated from all optionable stocks.

Table 3 presents the time-series averages of the monthly excess returns for each value-weighted long-short portfolio, along with a Newey and West (1987)-adjusted t-statistic testing the null hypothesis that the portfolio's average excess return is zero. The table also presents alphas relative to a one-factor market model (CAPM model) that includes only the market factor, and the FF, FFC, FFCPS, FF5, Q, SY, and DHS factor models. The factors in other models are described in Section 2. The alphas are the intercept terms from a time-series regression of long-short portfolio excess returns on the factors included in the model. All excess and risk-adjusted returns presented in Table 3 and the remainder of this paper are in percent per month. For example, a value of 1.00 indicates an excess return or alpha of 1.00% per month.

The results of the portfolio analyses for the full March 1996 through January 2018 period are presented in Panel A of Table 3. The results show that the value-weighted long-short portfolios formed by sorting on $IV-RV$, $CIV-PIV$, VS, $Skew$, and $\Delta CIV-\Delta PIV$ generate economically large and highly statistically significant average excess returns during this period, ranging from 0.49% per month (t-statistic = 2.86) for the $Skew$ portfolio to

0.85% per month (t-statistic = 4.25) for the VS portfolio. For each of these portfolios, the alpha relative to all factor models is positive, economically large, and highly statistically significant, with the only exception being the alpha of the $IV - RV$ portfolio relative to the SY model. The results indicate that previously proposed factor models that have been shown to explain cross-sectional variation in future returns associated with a large number of predictive variables do not explain the average returns of portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$.

The long-short portfolio formed by sorting on S/O generates an insignificant average excess return 0.29% per month (t-statistic=1.22), significant positive alphas relative to the FFC and FFCPS models, but insignificant alphas with respect to other models. There are several potential reasons for the relatively weak predictive power of S/O in our sample. First, since our sample includes seven years of data (2011-2017) not included in Johnson and So (2012)'s sample, it is possible that the predictive power of S/O is weak during these years. We examine this possibility shortly. Second, Johnson and So (2012) use weekly returns and equal-weighted decile portfolios, whereas we use monthly returns and value-weighted quintile portfolios. It is possible that these methodological differences account for the weak predictive power of S/O.[10]

Finally, the VoV long-short portfolio produces an average excess return of 0.26% per month (t-statistic = 1.14). The weak results for this portfolio are a bit more surprising than those for the S/O portfolio given that the main empirical difference between our analysis and that in Baltussen et al. (2018) is that our sample period includes the November 2014 through January 2018 period coming after the sample period in the original study. Our analysis suggests that the VoV effect may be weak during the November 2014 through January 2018 period, a result we verify shortly.[11]

Two potential concerns with the results in Panel A of Table 3 for the portfolios formed

[10] In unreported results, we find that a monthly long-short portfolio constructed from equal-weighted decile portfolios generates a significantly positive average excess return and alphas with respect to most models during the February 1996-December 2010 period. This suggests that our use of monthly data does not cause our results do diverge from those in Johnson and So (2012). Results in Table 2 of Johnson and So (2012) suggest that a large component of the S/O effect is driven by the extreme deciles. While Johnson and So (2012) find that their results hold when comparing deciles one and two of S/O to deciles nine and ten of S/O, their analysis takes the equal-weighted average of deciles one and two, and the same for deciles nine and ten. Our quintile portfolios weight the deciles according to the aggregate market cap in each decile.

[11] In unreported results, we verify that the VoV long-short portfolio generates a positive and statistically significant FF alpha during the February 1996 through October 2014 period.

by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ are that, because the March 1996 through January 2018 sample period examined in these tests includes the sample period used in the original studies, the results in Panel A may be simply a manifestation of publication bias (Harvey et al. (2016)) or are potentially no longer relevant because mispricing was corrected after the original paper was made public (McLean and Pontiff (2016)).

To address these concerns, in Panel B of Table 3, we present the results of analyses of the performance of the long-short portfolios during the period subsequent to the sample period used in the original study.[12] The results indicate that the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ all continue to generate positive average excess and risk-adjusted returns in the period subsequent to that used by the original studies of these variables. For $IV - RV$, $CIV - PIV$, VS, and $Skew$, the average returns and alphas of the long-short portfolios are all economically large and, with a few minor exceptions, highly statistically significant. The only notable exception is the 0.36% per month SY model alpha of the $IV - RV$ portfolio, which is positive but statistically insignificant (t-statistic = 1.35). The long-short portfolio formed by sorting on $\Delta CIV - \Delta PIV$ generates a statistically insignificant average monthly excess return of 0.28% (t-statistic = 1.57). However, the short post-original study period examined by this test, February 2012 through January 2018, causes this test to have low power. We therefore interpret this result as suggesting that the positive relation between $\Delta CIV - \Delta PIV$ and future stock returns persists beyond the period examined in the original study. The S/O long-short portfolio generates an average excess return of 0.01% per month (t-statistic = 0.08) during the January 2011 through January 2018 period subsequent to that used by Johnson and So (2012), suggesting that S/O does not have strong out-of-sample predictive power. The results for the long-short portfolios formed by sorting on VoV show that this portfolio generates economically large and (with the exception of the alpha with respect to the SY model) statistically significant *negative* average excess returns and alphas. Thus, while VoV is positively related to future stock returns during the March 1996 through October 2014 sample period studied by Baltussen et al. (2018), our results indicate a strong

[12]The original studies using $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, $\Delta CIV - \Delta PIV$, and VoV use sample periods ending in portfolio formation (return) months December 2004 (January 2005), December 2004 (January 2005), December 2005 (January 2006), December 2005 (January 2006), November 2010 (December 2010), December 2011 (January 2012), and September 2014 (October 2014), respectively.

negative relation between VoV and future stock returns during the November 2014 through January 2018 period.[13]

From the results in Table 3, we conclude that $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ are all positively related to future stock returns in the cross section. There does not appear to be a robust relation between expected stock returns and S/O or VoV. The analyses in the remainder of the paper, therefore, use only $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ as option-based variables.

4 Option-Based Factors

We proceed now to the main objective of the paper, which is to generate a factor model that explains the average returns of portfolios of optionable stocks.

4.1 Factor Construction

We begin by creating a factor based on each of $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The factors are constructed using a methodology similar to that of Fama and French (1993). At the end of each month t, all optionable stocks are divided into two groups based on firm-level market capitalization ($MktCap_{Firm}$) and three groups based on the given option-based variable. $MktCap_{Firm}$ for stock i is defined as the sum of $MktCap_{ShareClass}$ across all share classes for the firm issuing stock i. The reason for sorting on market capitalization is to make the portfolio largely neutral to the size effect documented by Fama and French (1992), who show that stocks of firms with low market equity tend to generate higher returns than stocks of firms with high market equity. We use $MktCap_{Firm}$ instead of $MktCap_{ShareClass}$ when sorting stocks into market capitalization groups to align our portfolio construction methodology with Fama and French (1993)'s view that the size effect exists because the stocks of small firms are exposed to priced risks that stocks of large firms are not

[13] As a robustness check, in Section II and Table IA8 of the Internet Appendix, we demonstrate that our results are qualitatively similar when using only the subset of stocks for which all seven option-based predictors can be calculated. In Section III and Table IA9 of the Internet Appendix we show that the long leg of the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ generate positive and statistically significant (with a few minor exceptions) alphas, indicating that our results are not driven by mispricing due to short-sale constraints (Miller (1977)) or other limits to arbitrage (Shleifer and Vishny (1997)).

exposed to. The $MktCap_{Firm}$ breakpoint is the median $MktCap_{Firm}$ among all optionable stocks listed on the NYSE. The breakpoints for the option-based variable are the 30th and 70th percentile values of the given variable among optionable NYSE-listed stocks.

We then sort all optionable stocks into six portfolios using the breakpoints calculated from only NYSE-listed optionable stocks, and take the month $t+1$ excess return of each portfolio to be the $MktCap_{ShareClass}$-weighted average excess return of the stocks in the portfolio. Finally, the month $t+1$ factor return is defined as the average excess return of the above-median and below-median $MktCap_{Firm}$ portfolios for the stocks with high values of the given option-based variable minus that of the above-median and below-median $MktCap_{Firm}$ portfolios for the stocks with low values of the given option-based variable. We use F_X to denote the returns of the factor constructed from the variable X.

Table 4 presents summary statistics for the full March 1996 through January 2018 period (Panel A), summary statistics for the period subsequent to the sample period used in the original study of the given option-based variable (Panel B), and correlations for the full sample period (Panel C) for the excess returns of the option-based factors and the market factor (MKT). The summary statistics demonstrate that each factor generates a positive, economically large, and highly statistically significant average excess return both during the full sample period, and during the period subsequent to the original study of the option-based variable used to construct the factor. The correlations show that, as expected based on the correlations between the stock-level variables (see Table 1, Panel B), $F_{CIV-PIV}$, F_{VS}, F_{Skew}, and $F_{\Delta CIV-\Delta PIV}$ are all strongly positively correlated. The correlation between each of these factors and MKT is small. F_{IV-RV} has a moderate positive correlation with F_{Skew}, a negative correlation with the MKT, and close to zero correlation with the other factors.

We next examine whether the option-based factors' average excess returns can be explained by previously proposed factor models by examining the alpha of each option-based factor relative to each of the previously-proposed factor models. The results of these analyses, shown in Table 5, indicate that the CAPM, FF, FFC, FFCPS, FF5, Q, SY, and DHS factor models all fail to explain the positive average excess returns generated by each of the option-based factors. With one exception, the alpha of each of the option-based factors with respect to each factor model is positive and highly statistically significant. The one exception is the 0.26% per month alpha of F_{IV-RV} relative to the SY model, which is statistically weak at conventional levels with a t-statistic of 1.73.

4.2 Option-Based Factor Model

Having demonstrated that previously-established factor models do not explain the average returns of the option-based factors, We proceed to determining which factors should be included in our optionable stock factor model. While previously-proposed factor models do not explain the average returns of the option-based factors, the high correlations between many of the option-based factors suggest that the returns generated by one or more of these factors may be explained by some combination of other option-based factors. If this is the case, a factor model that includes only a subset of the option-based factors may suffice for explaining the cross section of optionable stock returns. The objective of our factor selection methodology is to find the smallest subset of option-based factors that spans all dimensions of return predictability captured by the full set of factors.

To determine which option-based factors should be included in our model, we begin by examining whether the average return generated by each option-based factor can be explained by a five-factor model that includes MKT and the other four option-based factors. We include MKT in the factor models because, as discussed in Fama and French (1993), "the market factor is needed to explain why stock returns are on average above the one-month bill rate." Thus, while the MKT factor may not be important for explaining the average returns of long-short portfolios such as the option-based factors, it is likely to be important for explaining the average returns generated by long-only stock portfolios.

The results of these analyses, presented in Table 6 Panel A, show that the alpha of each of F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ relative to a factor model that includes MKT and the other option-based factors is positive and highly statistically significant. This indicates that the average return generated by each of these factors is not explained by a linear combination of the other option-based factors. The alphas generated by $F_{CIV-PIV}$ and F_{Skew}, on the other hand, are small and statistically insignificant, indicating that the average return generated by each of these factors is captured by a linear combination of other option-based factors and MKT. The slope coefficients from these regressions indicates that $F_{CIV-PIV}$ loads heavily on F_{VS} and has relatively small but statistically significant loadings on F_{Skew} and $F_{\Delta CIV-\Delta PIV}$. F_{Skew} loads heavily on $F_{CIV-PIV}$ and has a small but significant loading on F_{IV-RV}.

Since the average returns generated by $F_{CIV-PIV}$ and F_{Skew} are explained by combinations of the other option-based factors, we proceed to examine whether a model with only MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ can explain the average returns generated by

$F_{CIV-PIV}$ and F_{Skew}. Panel B of Table 6 shows the results of regressions of each of $F_{CIV-PIV}$ and F_{Skew} on MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$. The results indicate that the four-factor model with MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ explains the average returns generated by $F_{CIV-PIV}$ and F_{Skew}. For both $F_{CIV-PIV}$ and F_{Skew}, the alpha relative to the four-factor model is small and statistically indistinguishable from zero. In Section IV and Table IA10 of the Internet Appendix, we show that the factor model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ is the only model that includes MKT and three or fewer of the option-based factors that explains the average returns of all of the option-based factors.

The results in this section suggest that a four-factor model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ explains the average returns of all of the option-based factors, and that $F_{CIV-PIV}$ and F_{Skew} are redundant. We therefore propose this four-factor model, which we refer to as the OPT model, as a benchmark for measuring the abnormal returns generated by portfolios of optionable stocks.

5 Pricing Tests

The remainder of this paper tests the effectiveness of the OPT model on a broad set of optionable stock portfolios and compares the performance of the OPT model to that of previously-proposed factor models.

5.1 Portfolios Formed by Sorting on Option-Based Variables

The first tests of our OPT model examine whether the model can explain the average returns of long-short portfolios formed by sorting stocks based on $IV-RV$, $CIV-PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The long-short portfolios we examine here are the exact same long-short portfolios examined in Section 3.3 and Table 3. Table 7 presents the results of factor regressions of long-short portfolio excess returns on the four factors in the OPT model. The alpha of each of the long-short portfolios relative to the OPT model is economically small and statistically insignificant, indicating that our model does a good job at explaining the average returns of these long-short portfolios.

The estimated factor exposures provide some insight into which factors are important for explaining the average returns generated by the long-short portfolios. We focus our discussion here on the $CIV - PIV$ and $Skew$ long-short portfolios because these portfolios are constructed from variables other than those upon which the factors in our model are formed. The $CIV - PIV$ portfolio has a large and highly significant positive loading on F_{VS}, indicating that this factor is important for explaining the average return generated by the $CIV - PIV$ portfolios. The $CIV - PIV$ portfolio also has a significant but economically smaller negative loading of -0.17 on F_{IV-RV}. The $Skew$ long-short portfolio has a large and highly significant positive loading of 0.60 (t-statistic = 4.56) on $F_{\Delta CIV-\Delta PIV}$ and small and insignificant loadings on all other factors, suggesting that the average return earned by the $Skew$ long-short portfolio is explained by its exposure to $F_{\Delta CIV-\Delta PIV}$.

To further test whether our factor model captures all dimensions of stock return predictability arising from the option-based variables, we construct portfolios based on a principal component (PC hereafter) analysis of the excess returns of the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The return of the kth PC portfolio in any month t is calculated by summing, across all five long-short portfolios, the weight of the given long-short portfolio in the kth PC times the month-t excess return of the long-short portfolio.[14] Panel A of Table 8 shows that the average excess returns of the first three PC portfolios are large and significant (only marginally so for the third PC), whereas the average excess return of the fourth and fifth PC portfolios are small and insignificant. The alphas of all five PC portfolios with respect to our four-factor OPT model are small and insignificant. Panel B shows that, when subjected to established factor models, the first three PC portfolios all generate economically substantial and, with the exception of the third PC portfolio for some models, highly significant alphas, whereas the alphas of the fourth and fifth PC portfolios are all small and insignificant. Taken together, the results confirm our finding that only three factors are needed to span the return predictability of all of the option-based variables, and that these dimensions of return predictability are not captured by established factor models.

Our next tests examine the ability of our four-factor OPT model to explain the average returns generated by each of the individual quintile portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The rows labeled "Excess Return" in Table

[14]Section V and Tables IA11-IA12 of the Internet Appendix present the weights of each long-short portfolio in each principal component portfolio, the amount of the total variance of the principal components that is captured by each component, and correlations between the excess returns of the long-short portfolios and the principal component portfolios.

9 present the average excess return for each of these quintile portfolios, as well as for the long-short portfolios examined in Table 7. The results show that all five portfolios formed by sorting on each variable generate a positive average excess return, and for quintile portfolios 3, 4, and 5, this average excess return is statistically significant. The rows labeled "α^{OPT}" present the alphas of these portfolios relative to the OPT model. For each sort variable, the alphas of all five quintile portfolios are small and statistically insignificant. Thus, the OPT model explains not only the average returns of the long-short portfolios, but also the average returns of each of the individual quintile portfolios.

To rigorously compare the ability of the OPT model to explain the average returns of the portfolios formed by sorting on the option-based variables to that of other factor models, we calculate the average absolute alphas and perform Gibbons, Ross, and Shanken (1989, GRS hereafter) tests using the quintile portfolios formed by sorting on the option-based variables using each factor model. In addition to examining portfolios formed by sorting on each option-based variable individually, we repeat the tests using all of the portfolios formed by sorting on the variables used to construct the factors in the OPT model ($IV - RV$, VS, and $\Delta CIV - \Delta PIV$), the option-based variables not used to construct factors in the OPT model ($CIV - PIV$ and $Skew$), and all five of the option-based variables. The results of these tests are shown in Table 10. For each combination of sort variables, the results strongly suggest that the OPT model performs better than other factor models. Focusing on the tests that jointly examine the portfolios formed by sorting on all of the option-based variables (the last three rows in Table 10), the OPT model produces an average absolute alpha of 0.06% per month and a GRS test statistic of 0.54 (p-value = 0.97). The smallest average absolute alpha produced by any other model is 0.20% per month by the SY model. Furthermore, the null hypothesis of the GRS test, that the factor model explains the returns of all portfolios examined, is strongly rejected for all other models, with p-values of less than 0.005 in all cases.

5.2 Traditional Asset Pricing Variable Portfolios

As alluded to in Lewellen, Nagel, and Shanken (2010), the tests in Tables 7-10 using the portfolios formed by sorting on $IV - RV$, VS, and $\Delta CIV - \Delta PIV$ are a low bar for demonstrating the effectiveness of the OPT factor model because both the factors and the portfolios whose returns are to be explained are constructed by sorting on the same variables. Furthermore, the reason that factors based on $CIV - PIV$ and $Skew$ are not included in our factor model is that the average returns generated by these factors are explained by factors based on $IV - RV$, VS, and $\Delta CIV - \Delta PIV$. Thus, an extension of the Lewellen et al. (2010) argument holds for the portfolios formed by sorting on $CIV - PIV$ and $Skew$ as well. We therefore view the ability of the OPT factor model to explain the average returns of these portfolios as a necessary but insufficient condition for demonstrating that our model achieves its objective of explaining the average returns of portfolios of optionable stocks.

To address these concerns, we investigate the ability of the OPT model to explain the returns of portfolios of optionable stocks formed by sorting on variables whose relation to the cross section of future stock returns in the universe of all stocks is well-established by previous empirical and theoretical research. Specifically, we examine the ability of the OPT model to explain the average returns of portfolios formed by sorting on market beta (β), market capitalization ($MktCap_{Firm}$), book-to-market ratio (BM), operating profitability (OP), investment (Inv), return on equity (ROE), momentum (Mom), reversal (Rev), illiquidity ($Illiq$), idiosyncratic volatility ($IdioVol$), and maximum daily return (Max). We refer to these variables as traditional asset pricing variables.

The month t values of the traditional asset pricing variables for each stock are calculated as follows. β is the slope coefficient from a regression of excess stock returns on MKT using daily data from months $t-11$ through t, inclusive. We require a minimum of 200 daily return observations to calculate β. $MktCap_{Firm}$ is defined in Section 4.1. BM for months t from June of year y through May of year $y+1$ is calculated following Fama and French (1993) as the firm's book value of equity as of the end of the fiscal year ending in calendar year $y-1$ divided by the market value of the firm's equity as of the end of calendar year $y-1$. Values of OP and Inv for months t from June of year y through May of year $y+1$ are calculated following Fama and French (2015). OP is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, all divided by book equity, with all values taken as of the end of the fiscal year ending in calendar year $y-1$. Inv is the firm's total assets as of the end of the fiscal year ending in calendar year $y-1$, divided by the same from the fiscal year ending in calendar year $y-2$, minus one. ROE is calculated following Hou et al. (2015) as income before extraordinary items for the fiscal quarter whose earnings were most recently announced prior to the end of month t, divided by one-quarter-lagged book equity, where book equity is taken to be shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stocks. Mom is calculated as the 11-month stock return during months $t-11$ through $t-1$ inclusive (skipping month t). Rev is the stock return in month t. The calculation of $Illiq$ is described in Section 3.2. $CoSkew$ is calculated following Harvey and Siddique (2000) as the slope coefficient on MKT^2 from a regression of excess stock returns on MKT and MKT^2 using five years of monthly return data covering months $t-59$ through t, inclusive. We require a minimum of 24 monthly return observations to calculate $CoSkew$. $IdioVol$ is calculated following Ang et al. (2006) as the square root of 252 times the standard deviation of the residuals from a regression of excess stock returns on MKT, SMB, and HML using daily return data from days in month t. Finally, Max is calculated following Bali et al. (2011) as the maximum daily return of the stock during month t. We require a minimum of 15 daily returns to calculate $IdioVol$ and Max.

For each of the traditional asset pricing variables, we form value-weighted quintile and long-short portfolios using the same procedure as was used to form the portfolios constructed using the option-based variables, described in Section 3.3. Table 11 presents the average monthly excess return, alpha relative to the CAPM factor model, and alpha relative to our OPT model, for each of these portfolios. We examine the CAPM alphas but not FF, FFC, FFCPS, FF5, Q, SY, or DHS alphas here because the CAPM model has a strong theoretical foundation and it is the only factor model that was not explicitly designed with the intent of explaining variation in average returns associated with one or more of the sort variables.

The results in Table 11 demonstrate that none of the long-short portfolios generates a statistically significant average excess return. The CAPM alphas of the long-short portfolios formed by sorting on β, OP, ROE, $IdioVol$, and Max, however, are all highly statistically significant, indicating that after adjusting for exposure to the market factor, there is strong cross-sectional variation in the performance of optionable stocks associated with each of these variables. The alpha of each of these long-short portfolios relative to our OPT model is much smaller in magnitude than the corresponding CAPM alpha and statistically insignificant, indicating that our four-factor model explains the cross-sectional variation in risk-adjusted returns associated with β, OP, ROE, $IdioVol$, and Max. Furthermore, the alphas relative to the OPT model for the long-short portfolios formed by sorting on each of the other traditional asset pricing variables are all statistically insignificant.

Examining the individual quintile portfolios formed by sorting on all of the traditional asset pricing variables, only three out of a total of 60 portfolios, or 5% of the portfolios, generate OPT model alphas that are statistically significant at the 5% level, as indicated by a t-statistic of 1.96 or greater in magnitude. This is exactly what would be expected under the null hypothesis that none of these portfolios generates a non-zero alpha relative to the OPT model. For nine out of the 12 traditional asset pricing variables, the average absolute alpha of the quintile portfolios is smaller under the OPT model than under the CAPM model. For these same nine variables, the GRS test statistic is lower and less statistically significant using the OPT model than the CAPM model. For all 12 variables, the p-value associated with the GRS test statistic using the OPT model is 0.14 or higher, indicating that the GRS test fails to reject the OPT model for any of the traditional asset pricing variables. The GRS test statistic for the OPT model calculated using all 60 quintile portfolios formed by sorting on all of the variables (untabulated) is 1.05 with a p-value of 0.38, indicating that the test fails to reject the null hypothesis that the OPT model explains the average returns of all 60 portfolios. The corresponding statistic using the CAPM model is 1.14 (p-value = 0.25), suggesting that the performance of the OPT model is superior to that of the CAPM across all of the test assets. The results strongly suggest that our OPT model does a good job at capturing cross-sectional variation in average returns of portfolios of optionable stocks.

Because our objective is to generate a factor model that explains the average returns of optionable stocks, only optionable stocks are included in the portfolios constructed by sorting on traditional asset pricing variables. In Section VI and Table IA13 of the Internet Appendix, we repeat the portfolio analyses whose results are shown in Table 11 using portfolios constructed from the sample of all stocks, and find similar results. In unreported results, we find that a GRS test performed using all such portfolios generates a p-value of 0.06 for the CAPM and 0.32 for the OPT model. The results suggest that our model may be useful not only for optionable stocks, but also for analyses of the universe of all stocks.

The five variables whose long-short portfolios generate significant CAPM alphas are easily categorized into two groups. First, β, $IdioVol$, and Max are all related to anomalies commonly referred to as "low-risk" anomalies. β measures a stock's exposure to the market risk factor. As shown by Black et al. (1972) and Frazzini and Pedersen (2014) and reflected in our β portfolio results, stocks with low (high) market risk exposure tend to generate positive (negative) CAPM alphas. Similarly, as shown by Ang et al. (2006) and reflected in our

$IdioVol$ portfolio results, stocks with low (high) idiosyncratic volatility tend to generate high (low) CAPM alphas. We consider Max, which measures lottery demand, to be related to low-risk anomalies because lottery demand has been shown to explain the abnormal returns associated with both market risk exposure (Bali et al. (2017)) and idiosyncratic volatility (Bali et al. (2011)). OP and ROE are both measures of profitability, which previous research (Fama and French (2015), Hou et al. (2015)) finds is positively related to the cross section of expected stock returns. The ability of our OPT model to explain these effects suggests a link between the drivers of the option-based variables' predictive power and the low-risk and profitability effects in the sample of optionable stocks.

While a full investigation of the economic drivers of the low-risk anomalies and profitability effects is beyond the scope of this paper, we provide some preliminary results that may guide future research on this topic. Specifically, we investigate which option-based factor(s) are important for explaining the CAPM alphas of the β, $IdioVol$, Max, OP, and ROE long-short portfolios. Table 12 presents the factor sensitivities of each of these portfolios to the factors in the OPT model. The long-short portfolios for β, $IdioVol$, and Max all have large positive loadings on MKT. This could have been inferred from the fact that the CAPM alphas of these portfolios are substantially lower than their average excess returns. Each of these portfolios also has a large, negative, and highly statistically significant loading on F_{IV-RV}. Since the difference between implied and realized volatility, captured by $IV - RV$, is commonly viewed as a measure of volatility risk, the significant loadings of the β, $IdioVol$, and Max long-short portfolios on F_{IV-RV} suggest a potential relation between volatility risk and low-risk anomalies. The $IdioVol$ and Max long-short portfolios also have large, negative, and highly significant loadings on F_{VS}, while the coefficient of the β long-short portfolio on F_{VS} is substantially smaller and statistically insignificant. Cremers and Weinbaum (2010) attribute the ability of VS to predict the cross section of future stock returns to informed trading. The large negative loadings of the $IdioVol$ and Max long-short portfolios on F_{VS} therefore indicate a relation between informed trading and the idiosyncratic volatility and lottery demand effects in optionable stocks. Finally, while the β, $IdioVol$, and Max long-short portfolios all have economically large positive loadings on $F_{\Delta CIV-\Delta PIV}$, only that of the Max long-short portfolio is significant. An et al. (2014) conclude that the cross-sectional relation between $\Delta CIV - \Delta PIV$ and future stock returns is also a manifestation of informed trading. The large coefficients on $F_{\Delta CIV-\Delta PIV}$ are therefore further evidence of a relation between informed trading and the low-risk anomalies for optionable stocks.

The long-short portfolios formed by sorting on the profitability measures, OP and ROE, have significantly negative loadings on MKT and $F_{\Delta CIV-\Delta PIV}$ and significantly positive loadings on F_{IV-RV} and F_{VS}. These loadings all have the opposite sign of the corresponding loadings on the β, $IdioVol$, and Max portfolios. This is not surprising given that the CAPM alphas of the OP and ROE long-short portfolios are positive, while those of the β, $IdioVol$, and Max long-short portfolios are negative. These results suggest that, as with the low-risk anomalies, the cross-sectional relation between profitability and future optionable stock returns is related to volatility risk and informed trading.

A potential concern with our results showing that our OPT-model captures variation in average returns associated with traditional asset pricing variables is that, because options data are only available beginning in 1996, it is not possible to perfectly assess how our model may have performed during the pre-1996 period. It is possible, however, to examine whether the performance of the portfolios formed by sorting on traditional asset pricing variables differs during our sample period, compared to during the period prior to our sample period. If the performance of these portfolios is similar during both periods, then, assuming that the performance of our factors is similar during both periods, it would suggest that our model would perform similarly during the pre-1996 period.

We compare the performance of the long-short portfolios formed by sorting on traditional asset pricing variables during the March 1996 through January 2018 period covered by our analyses, and the July 1963 through February 1996 period prior to our sample period, by running regressions of the excess returns of these portfolios on an indicator variable, I_{199603}, set to 1 for return months $t+1$ during or after March 1996 and zero otherwise. Specifically, we run two regression specifications. The first includes only I_{199603} as an independent variable. The second includes I_{199603} and MKT. A significant coefficient on I_{199603} in these regressions indicates a difference in average excess returns or CAPM alpha, respectively, during the period we examine compared to the period prior to our sample period. We run these tests on two subsets of stocks. The first set of stocks, which we refer to as the extended optionable stock sample, is designed to approximate the set of stocks that would have been optionable prior to March 1996. Specifically, for return months $t+1$ during or after March 1996, the extended optionable stock sample contains exactly the same set of stocks included in our focal tests. For return months $t+1$ prior to March 1996, we approximate the set of stocks that would have been optionable during any given month by taking stocks, in order from largest to smallest value of $MktCap_{ShareClass}$, until 85% of the total market capitalization of all stocks in the given month has been included. We choose 85% as the cutoff because, as of the end of February 1996, optionable stocks comprised approximately 85% of the total market value of all stocks (see Figure 2). The second set of stocks is simply the set of all stocks. The results of these tests, described in Section VII and Table IA14 of the Internet Appendix, find no evidence of differences in the performance of the long-short portfolios formed by sorting on traditional asset pricing variables during the two sub-periods. For all portfolios, the coefficient on I_{199603} in each of the regression specifications is statistically insignificant. The results suggest that, were we able to construct our factors for the period prior to March 1996, the performance of our OPT model during this period would likely have been similar to that of the period we examine.

5.3 Comparison of Factor Models Using All Portfolios

Our next analyses compare the effectiveness of all of the factor models at explaining the average returns of portfolios formed by sorting on the traditional asset pricing variables and option-based variables. Specifically, for each factor model, we calculate the average absolute alpha and perform a GRS test using the quintile portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, Max, $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. Since there are 17 sort variables and five portfolios per variable, these tests are conducted using 85 test portfolios. We also count, for each factor model, the number of variables whose long-short portfolios produce alpha that is statistically significant at the 5% level.

The results of these analyses, reported in Table 13, show that the OPT model's average absolute alpha of 0.10% per month is lower than that of all other factor models. The OPT model's GRS test statistic of 1.02 is also the lowest of any of the factor models, and the GRS test p-value of 0.45 is substantially higher than that of all other models, all but one of which have GRS test p-values of 0.01 or lower, with the only exception being the SY model which has a GRS test p-value of 0.08. None of the long-short portfolios generate significant alpha relative to the OPT model, whereas between four and 13 long-short portfolios generate significant alpha relative to the other factor models. Table 13 summarizes the key findings of this paper, that for portfolios of optionable stocks, the OPT model outperforms other models at explaining variation in average returns of portfolios formed by sorting on variables known to predict the cross section of future stock returns.

5.4 Sharpe Ratios

Barillas and Shanken (2017, 2018) show that the most relevant statistic for comparing factor models is the Sharpe ratio of the tangency portfolios constructed from the models' factors.[15] Our final analyses, therefore, are comparisons of the different factor models using the Sharpe ratio.

Panel A of Table 14 presents the Sharpe ratio for each individual factor, along with a 95% confidence interval for each factor's Sharpe ratio calculated following Lo (2002). The Sharpe ratios for F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ of 0.81, 1.55, and 1.29, respectively, are the three highest Sharpe ratios for any individual factors. Furthermore, the low end of the 95% confidence intervals for F_{VS} and $F_{\Delta CIV-\Delta PIV}$ of 1.32 and 1.05, respectively, are greater than the high end of the 95% confidence interval for any other factors. The results indicate that the individual non-market factors in the OPT model generate substantially higher Sharpe ratios than factors is other models.

We construct the returns of the tangency portfolio for each factor model in two ways. First, we generate tangency portfolio weights by taking the expected excess returns of the factors and the covariance matrix of the factor excess returns to be the corresponding sample values estimated from the full March 1996 through January 2018 sample period. Because these weights are calculated from the full sample period, the results of this analysis do not reflect attainable investment outcomes. We therefore also calculate weights using an expanding window methodology. Specifically, at the end of each month t beginning in February 2001, we calculate tangency portfolio weights from expected excess factor returns and factor excess returns covariances estimated using data from March 1996 through t. We then calculate the month $t+1$ excess return of the tangency portfolio using these weights. The tests using the expanding window therefore cover return months $t+1$ from March 2001 through

[15]Barillas and Shanken (2017, 2018) focus on the squared Sharpe ratio, which accounts for the possibility that a Sharpe ratio may be negative while maintaining the ordering of the magnitude of the Sharpe ratios when comparing models. Since all of the Sharpe ratios we examine are positive, we focus on the Sharpe ratio itself instead of the squared Sharpe ratio.

January 2018.

The Sharpe ratios for the tangency portfolios constructed from the factors in the OPT model, shown in Panel B of Table 14, are 2.00 using the full sample methodology and 1.73 using the rolling window methodology. The corresponding 95% confidence intervals are (1.75, 2.24) and (1.46, 2.00), respectively. For both methodologies, the low end of the 95% confidence interval for the OPT-model Sharpe ratio is greater than the high end of 95% confidence interval for any other factor model. The results clearly demonstrate that the Sharpe ratio of the tangency portfolio constructed from the factors in the OPT model is higher than that of any other model.

6 Conclusion

In this paper we develop a factor model that explains cross-sectional variation in average returns of optionable stocks. We show that the universe of optionable stocks differs from the universe of all stocks in that optionable stocks tend to be larger and more liquid than other stocks. Not surprisingly, therefore, we find that the predictive power of many traditional asset pricing variables is weak or non-existent among optionable stocks. This makes factor models aimed at explaining the predictive power of these traditional variables less useful for studies of optionable stocks.

While the predictive power of traditional asset pricing variables is weak among optionable stocks, we certify previous work showing that several option-based variables have strong ability to predict the cross section of future optionable stock returns. Specifically, the difference between option-implied and historical realized volatility ($IV - RV$, Bali and Hovakimian (2009)), the difference between ATM call and put implied volatilities ($CIV - PIV$, Bali and Hovakimian (2009)), the call minus put volatility spread for expiration- and strike-matched calls and puts (VS, Cremers and Weinbaum (2010)), the difference between ATM call implied volatility and OTM put implied volatility ($Skew$, Xing et al. (2010)), and the change in call-implied volatility minus the change in put implied volatility ($\Delta CIV - \Delta PIV$, An et al. (2014)) are all strongly related to the cross section of future stock returns. We show that this predictive power persists in the period subsequent to that examined in the original studies examining these predictors, indicating that the phenomena are not a manifestation of publication bias and that any mispricing associated with these variables is not easily corrected once the predictive power becomes widely known.

To construct our factor model, we form factors based on each of the option-based variables. We then search for the smallest subset of these option-based factors that, when combined with the market factor, explains the average returns of all of the factors. Our results demonstrate that a four-factor model that includes a factor based on each of $IV - RV$, VS, and $\Delta CIV - \Delta PIV$, along with the market factor, explains the average returns of all of the option-based factors. We refer to this model as the OPT model.

We then test the ability of the OPT model to explain the average returns of a large number of portfolios formed by sorting optionable stocks on both option-based variables and traditional asset pricing variables. The OPT model outperforms other factor models when explaining the returns of portfolios formed by sorting on option-based variables. The model also performs well at explaining the performance of portfolios formed by sorting on beta, market capitalization, book-to-market ratio, operating profitability, investment, return on equity, momentum, reversal, illiquidity, coskewness, idiosyncratic volatility, and the maximum daily return. The OPT model alphas of long-short portfolios formed by sorting on each of these variables are small and insignificant. Notably, while long-short portfolios of optionable stocks formed by sorting on beta, operating profitability, return on equity, idiosyncratic volatility, and the maximum daily return all generate large and significant alphas with respect to the CAPM model, these alphas are explained by the OPT model. Finally, we construct test portfolios based on the entire set of traditional and option-based variables and investigate the relative performance of all of the factor models at explaining the average returns of these test portfolios. The economic magnitude of the alphas and the corresponding GRS statistics, along with the Sharpe ratios of the tangency portfolios constructed using the factors in each model, indicate superior performance of the OPT model compared to the previously-proposed factor models.

We conclude that the OPT model does a good job at capturing cross-sectional variation in average returns among optionable stocks. We therefore propose the OPT model as a benchmark for future research examining the cross section of average returns among optionable stocks.

Appendix A Calculation of Option-Based Variables

In this appendix we describe how each of the option-based variables is calculated.

A.1 $IV - RV$ and $CIV - PIV$

$IV - RV$ and $CIV - PIV$ are calculated following Bali and Hovakimian (2009) using traded options data. For each stock i and each month t, we define IV, CIV, and PIV to be the average implied volatility of calls and puts, calls, and puts, respectively, on the last trading day of month t. IV, CIV, and PIV are calculated using options on stock i with between 30 and 91 days to expiration (inclusive) and with absolute log moneyness, defined as the absolute value of the natural log of the ratio of the strike price of the option to the spot price of the stock, less than or equal to 0.1. RV is defined as the the square root of 252 times the standard deviation of the daily returns of the given stock during month t. We require a minimum of 15 daily returns to calculate RV. For stock, month observations not satisfying this criterion, $IV - RV$ is considered missing. Bali and Hovakimian (2009) find a negative cross-sectional relation between $RV - IV$ and future stock returns and a positive cross-sectional relation between $CIV - PIV$ and future stock returns. To simplify our analyses, we use $IV - RV$, instead of $RV - IV$ as in Bali and Hovakimian (2009), so that our measure has a positive relation with future stock returns.

A.2 VS

VS is calculated following Cremers and Weinbaum (2010) using traded options data from the last trading day of each month. For each stock i and each month t, we take all combinations of expiration date and strike price for which data for both a call and a put are available. For each such combination, we calculate the difference between the implied volatility of the call and the implied volatility of the put. VS is defined as the weighted average of these differences, with the weight for each expiration date and strike price combination being proportional to the average of the call open interest and the put open interest for the given combination. For stock, month observations having no expiration date and strike price combinations with data for both a call and a put option, VS is taken to be missing.

A.3 *Skew*

Skew is calculated following Xing, Zhang, and Zhao (2010) using traded options data from the last trading day of each month for options with between 10 and 60 days to expiration (inclusive). For each stock i and month t, *Skew* is defined as the implied volatility of an ATM call option minus the implied volatility of an OTM put option. The ATM call implied volatility is that of the call option with moneyness closest to 1.0, requiring that the option's moneyness be between 0.95 and 1.05. The OTM put implied volatility is taken from the put option with moneyness closest to but less than 0.95, requiring that the moneyness be at least 0.8. Moneyness is defined as the ratio of the strike price of the option to the spot price of the stock. For stock, month observations where either the ATM call implied volatility or the OTM put implied volatility cannot be calculated, *Skew* is taken to be missing. Xing et al. (2010) define their skewness variable as the OTM put implied volatility minus the ATM call implied volatility, and find a negative cross-sectional relation between this measure and future stock returns. We define *Skew* as the ATM call implied volatility minus the OTM put implied volatility so that our variable has a positive relation with future stock returns. Furthermore, our definition of *Skew* is more consistent with the notion that a distribution with a relatively long left tail, as captured by a relatively high OTM put implied volatility compared to ATM call implied volatility, has more negative skewness.

A.4 S/O

S/O is calculated using a methodology similar to that used by Johnson and So (2012). We do not use their exact methodology because their study focuses on weekly returns whereas ours focuses on monthly returns. For each stock i and each month t, S/O is taken to be the total number of shares of the stock traded in month t divided by 100 times the total number of option contracts on the stock traded in month t. The total number of option contracts traded on the stock is calculated using only options with between five and 34 days to expiration, inclusive, on the day of trading. We multiply the number of contracts by 100 because each contract has 100 underlying shares. Monthly trading volumes for both stocks and options are calculated by summing daily volumes across all days in the month, where the daily values have been adjusted for splits and stock dividends with ex dates between the given date and the last day of the month. Finally, to calculate S/O, we require that there be positive stock volume, and at least 100 call option contracts and 100 put option contracts traded in the given month.

A.5 $\Delta CIV - \Delta PIV$

$\Delta CIV - \Delta PIV$ is calculated following An, Ang, Bali, and Cakici (2014) using volatility surface data from the last trading day of the given month and the last trading day of the prior month. For each stock i and month t, ΔCIV (ΔPIV) is defined as the implied volatility of the call (put) option with delta of 0.5 (-0.5) and 30 days to expiration on the last trading day of month t minus the same from the last trading day of month $t-1$. For observations where any of the four required implied volatilities is unavailable, we take $\Delta CIV - \Delta PIV$ to be missing. An et al. (2014) find a negative cross-sectional relation between $\Delta PIV - \Delta CIV$ and future stock returns. We use $\Delta CIV - \Delta PIV$ instead of $\Delta PIV - \Delta CIV$ so that our measure has a positive relation with future stock returns.

A.6 VoV

Volatility of implied volatility, VoV, is calculated following Baltussen et al. (2018) using traded options data for options with between 10 and 52 days to expiration (inclusive). For each stock i and month t, VoV is defined as the negative of the standard deviation of the stock's ATM implied volatilities over all days in the given month divided by the mean of these same implied volatilities. The ATM implied volatility for a stock on any given day is the average of the ATM call and ATM put implied volatilities. The ATM call (put) implied volatility is the implied volatility of the call (put) with moneyness, defined as the ratio of the option's strike price to the stock's spot price, closest to 1.0, with the requirement that it be at least 0.95 and at most 1.05. If either a call or put implied volatility is missing, the ATM implied volatility for that day is considered missing. We require at least 12 daily ATM implied volatilities for the given stock in the given month to calculate VoV.[16] Baltussen et al. (2018) find a negative relation between the standard deviation of the stock's ATM implied volatilities scaled by their mean. We take VoV to be the negative of this measure so that our measure has a positive relation with future stock returns.

[16] Due to data issues, there are no stocks with 12 daily ATM implied volatilities in November 2015. Thus, when calculating VoV for November 2015, we require only 11 daily implied volatilities.

References

Agarwal, V. and Naik, N. Y. 2004. Risks and portfolio decisions involving hedge funds. Review of Financial Studies, 17(1), 63–98.

Amaya, D., Christoffersen, P., Jacobs, K., and Vasquez, A. 2015. Does realized skewness predict the cross-section of equity returns? Journal of Financial Economics, 118(1), 135–167.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 5(1), 31–56.

An, B.-J., Ang, A., Bali, T. G., and Cakici, N. 2014. The joint cross section of stocks and options. Journal of Finance, 69(5), 2279–2337.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. 2006. The cross-section of volatility and expected returns. Journal of Finance, 61(1), 259–299.

Bai, J., Bali, T. G., and Wen, Q. 2019. Common risk factors in the cross-section of corporate bond returns. Journal of Financial Economics, 131(3), 619–642.

Bali, T. G., Brown, S. J., Murray, S., and Tang, Y. 2017. A lottery demand-based explanation of the beta anomaly. Journal of Financial and Quantitative Analysis, 52(6), 2369–2397.

Bali, T. G., Cakici, N., and Whitelaw, R. F. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics, 99(2), 427–446.

Bali, T. G. and Hovakimian, A. 2009. Volatility spreads and expected stock returns. Management Science, 55(11), 1797–1812.

Baltussen, G., Van Bekkum, S., and Van Der Grient, B. 2018. Unknown unknowns: Uncertainty about risk and stock returns. Journal of Financial and Quantitative Analysis, 53(4), 1615–1651.

Barillas, F. and Shanken, J. 2017. Which alpha? Review of Financial Studies, 30(4), 1316–1338.

Barillas, F. and Shanken, J. 2018. Comparing asset pricing models. The Journal of Finance, 73(2), 715–754.

Black, F., Jensen, M. C., and Scholes, M. S. The capital asset pricing model: Some empirical tests. In M. C. Jensen, editor, *Studies in the Theory of Capital Markets*. Praeger, New York, 1972.

Bollen, N. P. B. and Whaley, R. E. 2004. Does net buying pressure affect the shape of implied volatility functions. Journal of Finance, 59(2), 711–753.

Buss, A. and Vilkov, G. 2012. Measuring equity risk with option-implied correlations. Review of Financial Studies, 25(10), 3113–3140.

Cao, J., Goyal, A., Ke, S., and Zhan, X. 2020a. Options trading and stock price informativeness. Available at SSRN: https://ssrn.com/abstract=3401806.

Cao, J., Goyal, A., Xiao, X., and Zhan, X. 2020b. Implied volatility changes and corporate bond returns. Available at SSRN: https://ssrn.com/abstract=3400694.

Cao, J. and Han, B. 2013. Cross-section of option returns and idiosyncratic stock volatility. Journal of Financial Economics, 108(1), 231–249.

Carhart, M. M. 1997. On persistence in mutual fund performance. Journal of Finance, 52(1), 57–82.

Chang, B. Y., Christoffersen, P., and Jacobs, K. 2013. Market skewness risk and the cross section of stock returns. Journal of Financial Economics, 107(1), 46–68.

Chang, B.-Y., Christoffersen, P., Jacobs, K., and Vainberg, G. 2012. Option-implied measures of equity risk. Review of Finance, 16(2), 385–428.

Chordia, T., Lin, T.-C., and Xiang, V. 2020. Risk-neutral skewness, informed trading, and the cross-section of stock returns. forthcoming, Journal of Financial and Quantitative Analysis.

Clements, M., Kalesnik, V., and Linnainmaa, J. 2019. Older and wiser: Informed traders and the choice of option maturity. 2020 American Finance Association Annual Meeting.

Conrad, J. S., Dittmar, R. F., and Ghysels, E. 2013. Ex ante skewness and expected stock returns. Journal of Finance, 68(1), 85–124.

Cremers, M., Halling, M., and Weinbaum, D. 2015. Aggregate jump and volatility risk in the cross-section of stock returns. Journal of Finance, 70(2), 577–614.

Cremers, M. and Weinbaum, D. 2010. Deviations from put-call parity and stock return predictability. Journal of Financial Quantitative Analysis, 45(2), 335–367.

Daniel, K., Hirshleifer, D., and Sun, L. 2020. Short-and long-horizon behavioral factors. Review of Financial Studies, 33(4), 1673–1736.

DeMiguel, V., Plyakha, Y., Uppal, R., and Vilkov, G. 2013. Improving portfolio selection using option-implied volatility and skewness. Journal of Financial and Quantitative Analysis, 48(6), 1813–1845.

Driessen, J., Maenhout, P. J., and Vilkov, G. 2009. The price of correlation risk: Evidence from equity options. Journal of Finance, 64(3), 1377–1406.

Easley, D., O'Hara, M., and Srinivas, P. 1998. Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance, 53(2), 431–465.

Fama, E. F. and French, K. R. 1992. The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465.

Fama, E. F. and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

Fama, E. F. and French, K. R. 2015. A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22.

Frazzini, A. and Pedersen, L. H. 2014. Betting against beta. Journal of Financial Economics, 111(1), 1–25.

Fung, W. and Hsieh, D. A. 2001. The risk in hedge fund strategies: Theory and evidence from trend followers. Review of Financial Studies, 14(2), 313–341.

Garleanu, N., Pedersen, L. H., and Poteshman, A. M. 2009. Demand-based option pricing. Review of Financial Studies, 22(10), 4259–4299.

Gibbons, M. R., Ross, S. A., and Shanken, J. 1989. A test of the efficiency of a given portfolio. Econometrica, 57(5), 1121–1152.

Goyal, A. and Saretto, A. 2009. Cross-section of option returns and volatility. Journal of Financial Economics, 94(2), 310 – 326.

Harvey, C. R., Liu, Y., and Zhu, H. 2016. ... and the cross-section of expected returns. Review of Financial Studies, 29(1), 5–68.

Harvey, C. R. and Siddique, A. 2000. Conditional skewness in asset pricing tests. Journal of Finance, 55(3), 1263–1295.

Hou, K., Xue, C., and Zhang, L. 2015. Digesting anomalies: An investment approach. Review of Financial Studies, 28(3), 650–705.

Hu, G. and Jacobs, K. 2020. Volatility and expected option returns. Journal of Financial and Quantitative Analysis, 55(3), 1025–1060.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65–91.

Johnson, T. L. and So, E. C. 2012. The option to stock volume ratio and future returns. Journal of Financial Economics, 106(2), 262–286.

Jurek, J. W. and Stafford, E. 2015. The cost of capital for alternative investments. The Journal of Finance, 70(5), 2185–2226.

Lewellen, J., Nagel, S., and Shanken, J. 2010. A skeptical appraisal of asset pricing tests. Journal of Financial Economics, 96(2), 175–194.

Linnainmaa, J. T. and Roberts, M. R. 2018. The history of the cross-section of stock returns. The Review of Financial Studies, 31(7), 2606–2649.

Liu, Y., Tsyvinski, A., and Wu, X. 2019. Common risk factors in cryptocurrency. Available at SSRN: https://ssrn.com/abstract=3379131.

Lo, A. W. 2002. The statistics of sharpe ratios. Financial analysts journal, 58(4), 36–52.

Lu, Z. and Murray, S. 2019. Bear beta. Journal of Financial Economics, 131(3), 736–760.

Lustig, H., Roussanov, N., and Verdelhan, A. 2011. Common risk factors in currency markets. Review of Financial Studies, 24(11), 3731–3777.

McLean, R. D. and Pontiff, J. 2016. Does academic research destroy stock return predictability? Journal of Finance, 71(1), 5–32.

Miller, E. M. 1977. Risk, uncertainty, and divergence of opinion. Journal of Finance, 32(4), 1151–1168.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Pan, J. and Poteshman, A. M. 2006. The information in option volume for future stock prices. Review of Financial Studies, 19(3), 871–908.

Pastor, L. and Stambaugh, R. F. 2003. Liquidity risk and expected stock returns. Journal of Political Economy, 111(3), 642–685.

Rehman, Z. and Vilkov, G. 2012. Risk-neutral skewness: Return predictability and its sources. Available at SSRN: https://ssrn.com/abstract=1301648.

Roll, R., Schwartz, E., and Subrahmanyam, A. 2010. O/s: The relative trading activity in options and stock. Journal of Financial Economics, 96(1), 1–17.

Shleifer, A. and Vishny, R. W. 1997. The limits of arbitrage. Journal of finance, 52(1), 35–55.

Stambaugh, R. F. and Yuan, Y. 2017. Mispricing factors. Review of Financial Studies, 30(4), 1270–1315.

Szymanowska, M., De Roon, F., Nijman, T., and Van Den Goorbergh, R. 2014. An anatomy of commodity futures risk premia. Journal of Finance, 69(1), 453–482.

Towns, J., Cockerill, T., Dahan, M., Foster, I., Gaither, K., Grimshaw, A., Hazlewood, V., Lathrop, S., Lifka, D., Peterson, G. D., et al. 2014. XSEDE: accelerating scientific discovery. Computing in Science & Engineering, 16(5), 62–74.

Xing, Y., Zhang, X., and Zhao, R. 2010. What does the individual option volatility smirk tell us about future equity returns? Journal of Financial and Quantitative Analysis, 45(3), 641–662.

Figure 1: Number of Optionable Stocks

This figure shows the total number of US-based common stocks listed on the NYSE, AMEX, and NASDAQ (dashed red line, left axis), the total number of such stocks that are optionable (dotted green line, left axis), and the percent of such stocks that are optionable (solid black line, right axis) as of the end of each month from February 1996 through December 2017.

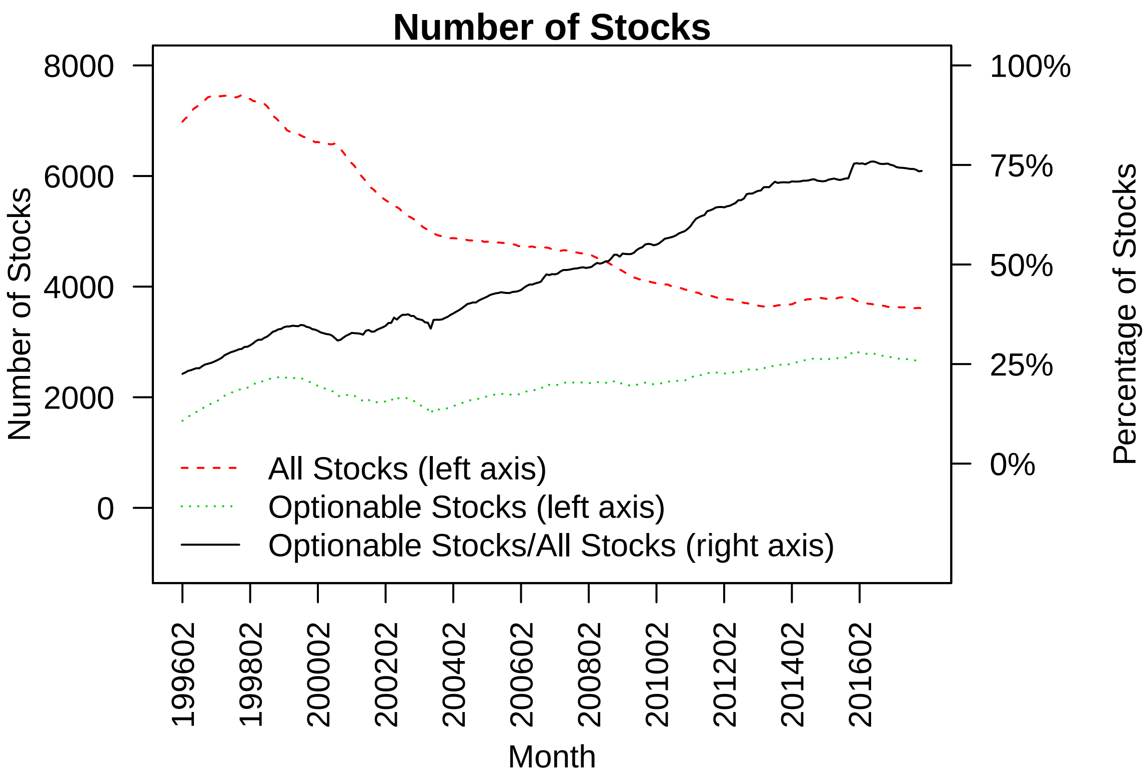

Figure 2: Market Capitalization of Optionable Stocks
This figure shows the total market capitalization (in $trillions) of US-based common stocks listed on the NYSE, AMEX, and NASDAQ (dashed red line, left axis), the total market capitalization of such stocks that are optionable (dotted green line, left axis), and the percent of the total market capitalization of all such stocks that comes from optionable stocks (solid black line, right axis) as of the end of each month from February 1996 through December 2017.

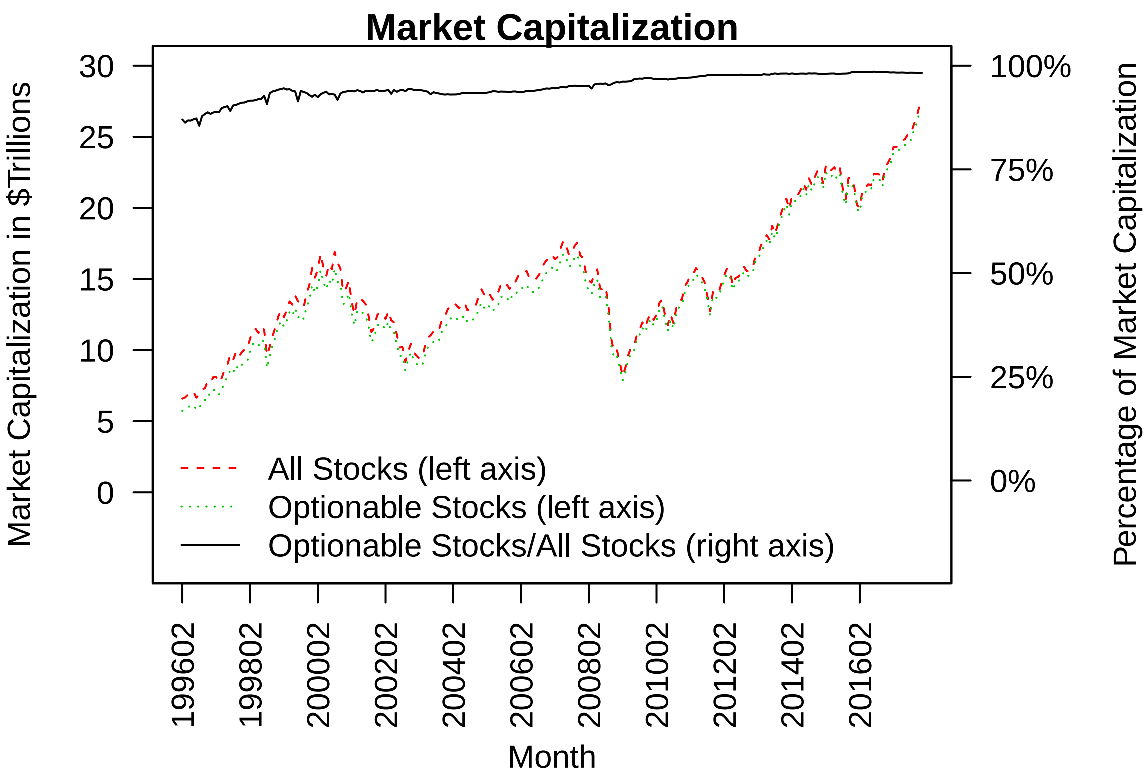

Figure 3: Dollar Trading Volume of Optionable Stocks
This chart shows the total monthly dollar trading volume (in $trillions) of US-based common stocks listed on the NYSE, AMEX, and NASDAQ (dashed red line, left axis), the total monthly dollar trading volume of such stocks that are optionable (dotted green line, left axis), and the percent of the total monthly dollar trading volume of all such stocks that comes from optionable stocks (solid black line, right axis) for each month from February 1996 through December 2017.

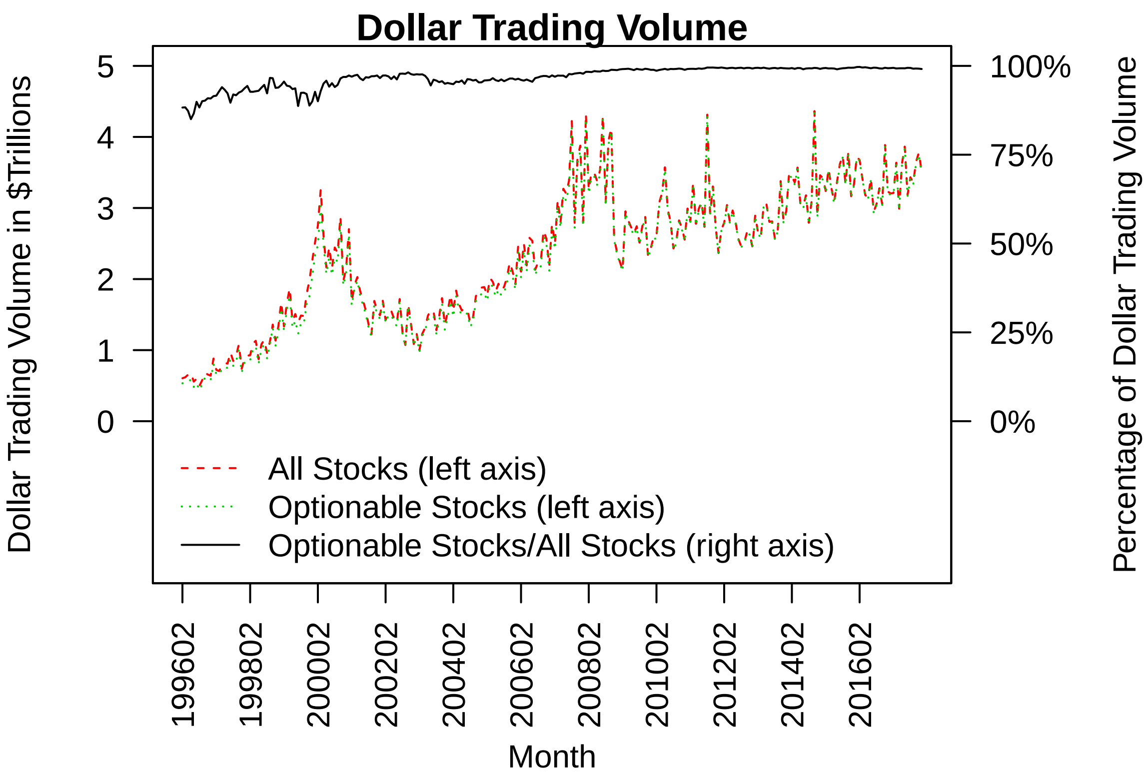

Table 1: Summary Statistics for Option-Based Variables

This table presents summary statistics and correlations for the option-based variables. $IV-RV$ is the difference between option-implied volatility and realized volatility calculated following Bali and Hovakimian (2009). $CIV-PIV$ is the difference between average call implied volatility and average put implied volatility calculated following Bali and Hovakimian (2009). VS is the average difference between the implied volatility of calls and maturity- and strike-matched puts calculated following Cremers and Weinbaum (2010). $Skew$ is the difference between the at-the-money call implied volatility and the out-of-the-money put implied volatility calculated following Xing et al. (2010). S/O is the ratio of stock trading volume to option trading volume, calculated in a manner similar to Johnson and So (2012). $\Delta CIV-\Delta PIV$ is the difference between the change in at-the-money call implied volatility and the change in at-the-money put implied volatility calculated following An et al. (2014). VoV is the negative of the standard deviation of ATM implied volatilities scaled by the mean ATM implied volatility calculated following Baltussen et al. (2018). Panel A shows the time-series averages of the monthly cross-sectional mean (Mean), standard deviation (S.D.), median (Median), and number of observations (n) for each variable. Panel B shows the time-series averages of the monthly cross-sectional Pearson product-moment correlations (above-diagonal entries) and Spearman rank correlations (below-diagonal entries) between the variables. Each variable is winsorized at the 0.5% and 99.5% levels on a monthly basis prior to calculating the cross-sectional Pearson product-moment correlations. The sample covers months t from February 1996 through December 2017 and includes all optionable US-based common stocks listed on the NYSE, AMEX, or NASDAQ.

Panel A: Summary Statistics

Variable	Mean	S.D.	Median	n
$IV-RV$	2.06	17.94	3.20	1631
$CIV-PIV$	−0.76	4.84	−0.47	1308
VS	−0.80	6.30	−0.38	1786
$Skew$	−4.91	5.71	−4.25	662
S/O	96.58	178.74	46.93	998
$\Delta CIV-\Delta PIV$	0.02	14.37	0.02	2156
VoV	−7.84	4.49	−6.86	961

Panel B: Correlations

	$IV-RV$	$CIV-PIV$	VS	$Skew$	S/O	$\Delta CIV-\Delta PIV$	VoV
$IV-RV$		−0.02	−0.01	−0.05	−0.03	0.03	0.20
$CIV-PIV$	−0.01		0.83	0.48	0.05	0.40	0.02
VS	0.01	0.75		0.51	0.05	0.34	0.03
$Skew$	−0.04	0.39	0.42		−0.00	0.25	0.08
S/O	−0.03	0.04	0.06	−0.03		−0.00	0.13
$\Delta CIV-\Delta PIV$	0.03	0.45	0.41	0.25	0.00		0.01
VoV	0.17	0.01	0.01	0.06	0.20	0.01	

Table 2: Summary Statistics for Optionable Stocks and All Stocks
This table presents summary statistics for market capitalization ($MktCap_{Shareclass}$), illiquidity ($Illiq$), price ($Price$), share trading volume ($Volume$), and dollar trading volume ($Volume\$$) for both the sample of optionable stocks and the sample of all stocks. $MktCap_{ShareClass}$ is the number of shares outstanding times the value of a share, recorded in millions of US dollars. $Illiq$ is calculated following Amihud (2002) as the average, over all days in the past year, of the absolute daily return (measured in percent) divided by the dollar trading volume (measured in millions of US dollars). $Price$ is the price of the stock. $Volume$ is the number of shares of the stock that traded in the past month, in thousands of shares. $Volume\$$ is $Volume \times Price/1000$, and represents the dollar volume traded in the past month, recorded in millions of US dollars. The table shows the time-series averages of the monthly cross-sectional mean (Mean), standard deviation (S.D.), median (Median), and number of observations (n) for each variable for the sample of optionable stocks and for all US-based common stocks.

Variable	Sample	Mean	S.D.	Median	n
$MktCap_{ShareClass}$	Optionable	6201	21632	1168	2257
	All	3341	15776	329	4963
$Illiq$	Optionable	2.70	18.52	0.31	2210
	All	298.52	1577.02	7.08	4714
$Price$	Optionable	30.35	33.17	23.04	2257
	All	50.08	1740.70	14.52	4963
$Volume$	Optionable	31356	102630	9678	2257
	All	17399	76285	3037	4963
$Volume\$$	Optionable	990	3250	211	2257
	All	537	2408	40	4963

Table 3: Performance of Long-Short Portfolios

This table presents the results of analyses examining the performance of portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, $\Delta CIV - \Delta PIV$, and VoV. At the end of each month t, all optionable stocks are sorted into five portfolios based on the given sort variable using quintile breakpoints calculated from NYSE-listed optionable stocks. We then calculate the $MktCap_{ShareClass}$-weighted month $t+1$ excess return for each portfolio, as well as for a portfolio that is long the quintile five portfolio and short the quintile one portfolio. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled "Start Month-End Month" shows the return months $t+1$ used for each analysis. The column labeled "Excess Return" presents the time-series average of the monthly excess returns of the long-short portfolio. The remaining columns present the long-short portfolio's alphas with respect to the CAPM (α^{CAPM}), FF (α^{FF}), FFC (α^{FFC}), FFCPS (α^{FFCPS}), FF5 (α^{FF5}), Q (α^{Q}), SY (α^{SY}), and DHS (α^{DHS}) factor models. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return or alpha are shown in parentheses. Excess returns and alphas are in percent per month. The analyses in Panel A cover the entire March 1996 through January 2018 sample period. The analyses in Panel B cover the sample period subsequent to that used by the original study examining the predictive power of the given variable.

Panel A: Full Sample Period

Sort Variable	Start Month -End Month	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV - RV$	199603	0.69	0.78	0.78	0.66	0.65	0.64	0.69	0.23	0.62
	-201801	(3.41)	(3.79)	(4.18)	(3.31)	(3.40)	(3.25)	(3.02)	(1.18)	(2.90)
$CIV - PIV$	199603	0.67	0.69	0.74	0.87	0.90	0.69	0.82	1.02	0.84
	-201801	(3.44)	(3.08)	(3.43)	(4.24)	(4.26)	(3.33)	(3.50)	(4.33)	(3.71)
VS	199603	0.85	0.86	0.86	0.97	0.99	0.77	0.87	0.96	0.92
	-201801	(4.25)	(3.88)	(3.84)	(4.42)	(4.60)	(3.75)	(3.88)	(4.00)	(4.09)
$Skew$	199603	0.49	0.48	0.59	0.50	0.45	0.54	0.58	0.54	0.57
	-201801	(2.86)	(2.53)	(3.63)	(3.09)	(2.77)	(3.23)	(2.98)	(2.78)	(3.07)
S/O	199603	0.29	0.45	0.27	0.35	0.33	−0.03	0.11	0.23	0.28
	-201801	(1.22)	(1.82)	(1.51)	(2.13)	(2.02)	(−0.20)	(0.54)	(1.13)	(1.68)
$\Delta CIV - \Delta PIV$	199603	0.71	0.69	0.72	0.71	0.73	0.74	0.76	0.72	0.71
	-201801	(4.36)	(3.78)	(3.77)	(3.71)	(3.76)	(4.08)	(3.77)	(3.43)	(3.47)
VoV	199603	0.26	0.42	0.29	0.24	0.18	0.02	0.06	0.14	0.18
	-201801	(1.14)	(1.75)	(1.59)	(1.26)	(0.98)	(0.09)	(0.34)	(0.65)	(0.89)

Panel B: Post-Original Study Sample Period

Sort Variable	Start Month -End Month	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV - RV$	200502	0.57	0.65	0.63	0.58	0.58	0.76	0.62	0.36	0.61
	-201801	(2.56)	(2.96)	(2.93)	(2.56)	(2.58)	(3.25)	(2.20)	(1.35)	(2.55)
$CIV - PIV$	200502	0.63	0.70	0.68	0.71	0.71	0.62	0.75	0.75	0.74
	-201801	(2.72)	(2.50)	(2.44)	(2.63)	(2.74)	(2.67)	(2.54)	(2.73)	(2.77)
VS	200602	0.61	0.62	0.61	0.63	0.61	0.51	0.59	0.60	0.52
	-201801	(2.58)	(2.11)	(2.12)	(2.18)	(2.28)	(1.96)	(2.08)	(2.17)	(1.95)
$Skew$	200602	0.46	0.49	0.39	0.37	0.40	0.37	0.41	0.43	0.65
	-201801	(2.40)	(2.23)	(1.96)	(1.88)	(2.07)	(1.94)	(1.83)	(2.44)	(3.14)
S/O	201101	0.01	−0.02	0.14	0.16	0.15	0.16	0.18	0.16	0.07
	-201801	(0.08)	(−0.15)	(0.97)	(1.09)	(1.14)	(1.30)	(1.42)	(1.07)	(0.47)
$\Delta CIV - \Delta PIV$	201202	0.28	0.17	0.18	0.17	0.21	0.18	0.25	0.18	0.16
	-201801	(1.57)	(0.65)	(0.77)	(0.75)	(1.08)	(0.77)	(1.27)	(0.92)	(0.79)
VoV	201411	−0.82	−0.92	−0.82	−0.73	−0.68	−0.76	−0.69	−0.24	−0.79
	-201801	(−2.54)	(−2.90)	(−3.02)	(−2.45)	(−2.51)	(−3.38)	(−2.71)	(−0.90)	(−2.61)

Table 4: Summary Statistics for Option-Based Factors

This table presents summary statistics and correlations for factors formed from each of the option-based variables. At the end of each month t we sort stocks into two groups based on market capitalization and three groups based on the given option-based variable. The market capitalization breakpoint is taken to be the median market capitalization among NYSE-listed optionable stocks in our sample. The breakpoints for the option-based variable in question are the 30th and 70th percentile values of the given variable among NYSE-listed optionable stocks in our sample. Portfolios are formed by assigning all stocks in the sample to one of the six groups based on these breakpoints. The value-weighted month $t+1$ excess return for each portfolio is then calculated. The month $t+1$ excess return for the factor associated with the given variable is taken to be the average excess return of the two portfolios with high values of the given option-based variable minus the average excess return of the two portfolios with low values of the given variable. Panel A presents summary statistics for the excess returns of each factor using the entire March 1996 through January 2018 sample period. In The column labeled "Factor" indicates the factor, where F_X is the factor formed using portfolios sorted on market capitalization and the option-based variable X. The columns labeled "Mean", "S.D", and "t-statistic" present the mean and standard deviation of the time-series of monthly factor excess returns. The column labeled "t-stat" presents the t statistic, adjusted following Newey and West (1987) using 3 lags, testing the null hypothesis that the mean excess return of the factor is zero. Panel B presents summary statistics for the excess returns of each factor using the sample period subsequent to that used by the original study examining the predictive power of the option-based variable used to construct the factor portfolio. The column labeled "Start Month-End Month" shows the return months $t+1$ used for each analysis. Panel C shows the Pearson product-moment correlations between the factor excess returns.

Panel A: Summary Statistics Full Sample Period

Factor	Mean	S.D.	t-stat
F_{IV-RV}	0.58	2.50	(4.25)
$F_{CIV-PIV}$	0.61	1.58	(5.95)
F_{VS}	0.72	1.60	(6.52)
F_{Skew}	0.31	2.13	(2.52)
$F_{\Delta CIV-\Delta PIV}$	0.56	1.50	(5.81)

Panel B: Summary Statistics Post-Original Sample Period

Factor	Start Month -End Month	Mean	S.D.	t-stat
F_{IV-RV}	200502-201801	0.41	1.99	(2.59)
$F_{CIV-PIV}$	200502-201801	0.52	1.33	(4.11)
F_{VS}	200602-201801	0.58	1.42	(4.09)
F_{Skew}	200602-201801	0.35	1.86	(2.41)
$F_{\Delta CIV-\Delta PIV}$	201202-201801	0.31	1.03	(2.73)

Panel C: Correlations

	MKT	F_{IV-RV}	$F_{CIV-PIV}$	F_{VS}	F_{Skew}	$F_{\Delta CIV-\Delta PIV}$
MKT		−0.24	−0.03	−0.05	−0.12	0.00
F_{IV-RV}	−0.24		0.06	0.03	0.20	0.01
$F_{CIV-PIV}$	−0.03	0.06		0.72	0.36	0.53
F_{VS}	−0.05	0.03	0.72		0.24	0.47
F_{Skew}	−0.12	0.20	0.36	0.24		0.25
$F_{\Delta CIV-\Delta PIV}$	0.00	0.01	0.53	0.47	0.25	

Table 5: Performance of Option-Based Factors

This table presents the results of analyses examining the performance of the option-based factors. The column labeled "Factor" indicates the factor being examined. The column labeled "Excess Return" presents the time-series average of the monthly excess returns of the factor. The columns labeled α^M present the factor's alphas with respect to different factor models, indicated by M. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return or alpha are shown in parentheses. Excess returns and alphas are in percent per month. The analysis covers return months from March 1996 through January 2018, inclusive.

Factor	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
F_{IV-RV}	0.58	0.67	0.67	0.58	0.58	0.48	0.52	0.26	0.49
	(4.25)	(4.61)	(4.80)	(3.92)	(4.00)	(3.68)	(3.44)	(1.73)	(3.33)
$F_{CIV-PIV}$	0.61	0.62	0.65	0.69	0.69	0.62	0.68	0.72	0.65
	(5.95)	(5.58)	(6.04)	(6.53)	(6.27)	(5.85)	(5.80)	(5.74)	(5.72)
F_{VS}	0.72	0.73	0.73	0.76	0.76	0.63	0.68	0.69	0.69
	(6.52)	(6.22)	(6.02)	(6.34)	(6.17)	(5.77)	(5.45)	(5.30)	(5.80)
F_{Skew}	0.31	0.35	0.41	0.33	0.30	0.30	0.33	0.29	0.34
	(2.52)	(2.72)	(3.36)	(2.81)	(2.53)	(2.43)	(2.77)	(2.21)	(2.47)
$F_{\Delta CIV-\Delta PIV}$	0.56	0.56	0.58	0.58	0.57	0.60	0.63	0.58	0.57
	(5.81)	(5.22)	(5.23)	(5.10)	(4.97)	(5.29)	(5.07)	(4.26)	(4.82)

Table 6: Factor Analysis of Option-Based Factors

This table presents the results of factor analyses of the option-based factors. Panel A presents the results of a time-series regression of a given option-based factor on MKT and the other option-based factors. Panel B presents the results of similar regressions using either $F_{CIV-PIV}$ or F_{Skew} as the dependent variable and MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ as independent variables. The column labeled "Factor" indicates the factor whose excess returns are the dependent variable in the regression. The column labeled α indicates the intercept coefficient from the regression. The columns labeled "β_f", for $f \in \{MKT, F_{CIV-PIV}, F_{IV-RV}, F_{VS}, F_{Skew}, F_{\Delta CIV-\Delta PIV}\}$, show the slope coefficients from the regression. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return, alpha, or slope, are shown in parentheses. Excess returns and alphas are in percent per month. The analysis covers return months from March 1996 through January 2018, inclusive.

Panel A: 5-Factor Models

Factor	α	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{CIV-PIV}}$	$\beta_{F_{VS}}$	$\beta_{F_{Skew}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
F_{IV-RV}	0.63	−0.12		0.02	−0.02	0.21	−0.07
	(2.95)	(−2.18)		(0.12)	(−0.10)	(3.08)	(−0.42)
$F_{CIV-PIV}$	0.03	0.01	0.00		0.57	0.13	0.23
	(0.33)	(0.39)	(0.12)		(6.89)	(3.61)	(2.59)
F_{VS}	0.25	−0.01	−0.00	0.67		−0.03	0.13
	(2.92)	(−0.58)	(−0.10)	(9.63)		(−0.66)	(1.71)
F_{Skew}	−0.04	−0.03	0.14	0.47	−0.09		0.13
	(−0.32)	(−0.92)	(3.04)	(3.27)	(−0.65)		(1.14)
$F_{\Delta CIV-\Delta PIV}$	0.20	0.01	−0.02	0.36	0.17	0.05	
	(2.21)	(0.31)	(−0.43)	(2.71)	(1.61)	(1.13)	

Panel B: 4-Factor Model with MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$

Factor	α	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{VS}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
$F_{CIV-PIV}$	0.03	0.00	0.02	0.59	0.26
	(0.28)	(0.13)	(0.63)	(6.94)	(3.08)
F_{Skew}	−0.03	−0.03	0.15	0.19	0.25
	(−0.22)	(−0.86)	(3.08)	(1.92)	(2.83)

Table 7: OPT Model Factor Analysis of Long-Short Portfolios

This table presents the results of factor analyses examining the performance of long-short portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ using our four-factor OPT model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ as factors. The portfolios whose performance is examined are the long-short portfolios whose performance is examined using other factor models in Table 3. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled α indicates the intercept coefficient from the factor model regression. The columns labeled "β_f", for $f \in \{MKT, F_{IV-RV}, F_{VS}, F_{\Delta CIV-\Delta PIV}\}$ show the slope coefficients from the factor model regression. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero alpha or slope coefficient are shown in parentheses. Alphas are in percent per month. The analysis covers return months from March 1996 through January 2018, inclusive.

Sort Variable	α^{OPT}	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{VS}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
$IV - RV$	0.03	0.04	1.28	−0.40	0.33
	(0.23)	(1.87)	(25.57)	(−2.73)	(2.57)
$CIV - PIV$	−0.07	−0.02	−0.17	0.98	0.28
	(−0.46)	(−0.49)	(−2.23)	(5.77)	(1.61)
VS	−0.08	−0.02	−0.18	1.24	0.29
	(−0.54)	(−0.40)	(−2.88)	(13.08)	(2.61)
$Skew$	0.09	0.02	0.05	0.04	0.60
	(0.44)	(0.32)	(0.59)	(0.20)	(4.56)
$\Delta CIV - \Delta PIV$	0.00	0.03	−0.04	0.05	1.22
	(0.02)	(1.25)	(−0.63)	(0.48)	(10.83)

Table 8: Principal Components of Long-Short Portfolios

This table presents the results of analyses of principal component portfolios constructed from the long-short portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The excess return of the kth principal component portfolio in month t is calculated by summing, across all five long-short portfolios, the product of the weight of the kth principal component on the given long-short portfolio times the month t long-short portfolio excess return. Panel A present the excess returns of each of the principal component portfolios in the column labeled "Excess Returns". The remaining columns present the results of factor analyses examining the performance of the principal component portfolios using our four-factor OPT model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV - \Delta PIV}$ as factors. The column labeled α^{OPT} indicates the intercept coefficient from the factor model regression. The columns labeled "β_f", for $f \in \{MKT, F_{IV-RV}, F_{VS}, F_{\Delta CIV - \Delta PIV}\}$ show the slope coefficients from the factor model regression. Panel B present the alphas of the principal component portfolios with respect established factor models. The remaining columns present the long-short portfolio's alphas with respect to the CAPM (α^{CAPM}), FF (α^{FF}), FFC (α^{FFC}), FFCPS (α^{FFCPS}), FF5 (α^{FF5}), Q (α^{Q}), SY (α^{SY}), and DHS (α^{DHS}) factor models. In both Panels A and B, the column labeled "PC" indicates the principal component portfolio whose results are shown in the given rows, and t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return, alpha, or slope coefficient are shown in parentheses. The analysis covers return months from March 1996 through January 2018, inclusive.

Panel A: 4-Factor Model Regressions

PC	Excess Return	α^{OPT}	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{VS}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
PC1	0.91	−0.07	−0.02	−0.76	1.44	0.75
	(3.33)	(−0.43)	(−0.49)	(−8.81)	(7.74)	(4.45)
PC2	1.20	0.04	0.04	1.02	−0.01	0.98
	(5.26)	(0.29)	(1.24)	(16.02)	(−0.07)	(8.63)
PC3	0.32	−0.11	−0.01	0.27	0.56	−0.21
	(1.95)	(−0.53)	(−0.25)	(3.99)	(3.97)	(−1.73)
PC4	0.05	0.02	0.03	−0.10	−0.46	0.73
	(0.50)	(0.16)	(1.22)	(−1.32)	(−5.21)	(5.54)
PC5	0.11	0.00	0.00	0.01	0.23	−0.12
	(1.20)	(0.03)	(0.08)	(0.22)	(1.93)	(−0.96)

Panel B: Alphas from All Factor Models

PC	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
PC1	0.88	0.95	1.11	1.13	0.92	1.05	1.38	1.10
	(2.80)	(3.09)	(3.75)	(3.74)	(3.26)	(3.26)	(4.21)	(3.64)
PC2	1.27	1.34	1.22	1.21	1.18	1.28	0.91	1.21
	(5.28)	(5.84)	(5.18)	(5.13)	(5.44)	(4.68)	(3.79)	(4.62)
PC3	0.36	0.29	0.40	0.45	0.23	0.28	0.25	0.30
	(2.02)	(1.71)	(2.34)	(2.83)	(1.26)	(1.61)	(1.27)	(1.63)
PC4	0.02	−0.00	−0.04	−0.03	0.07	0.01	−0.06	−0.03
	(0.20)	(−0.04)	(−0.36)	(−0.25)	(0.62)	(0.08)	(−0.49)	(−0.24)
PC5	0.11	0.08	0.06	0.05	0.05	0.04	−0.04	0.07
	(1.17)	(0.91)	(0.67)	(0.55)	(0.46)	(0.36)	(−0.41)	(0.61)

Table 9: OPT Model Factor Analysis of Quintile Portfolios

This table presents the results of factor analyses examining the performance of quintile portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ using our OPT model. The portfolios examined are the quintile portfolios whose construction is described in Table 3. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled "Value" indicates the value presented in the given row. Rows with "Excess Return" in the "Value" column present the time-series average excess return of the given portfolio. Rows with "α^{OPT}" in the "Value" column present the intercept coefficient from the OPT factor model regression. The columns labeled "1", "2", "3", "4", and "5" present results for the first, second, third, fourth, and fifth quintile portfolios, respectfully. The column labeled "5 − 1" presents results for the long-short portfolio that is long the quintile five portfolio and short the quintile one portfolio. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return or alpha, are shown in parentheses. Excess returns and alphas are in percent per month. The analysis covers return months from March 1996 through January 2018, inclusive.

Sort Variable	Value	1	2	3	4	5	5 − 1
$IV - RV$	Excess Return	0.37	0.56	0.72	0.94	1.07	0.69
		(0.95)	(1.99)	(2.70)	(3.40)	(3.03)	(3.41)
	α^{OPT}	−0.01	−0.05	−0.03	0.09	0.02	0.03
		(−0.16)	(−0.60)	(−0.37)	(1.03)	(0.15)	(0.23)
$CIV - PIV$	Excess Return	0.26	0.46	0.74	0.78	0.93	0.67
		(0.71)	(1.62)	(2.52)	(2.54)	(3.01)	(3.44)
	α^{OPT}	−0.00	−0.02	0.08	−0.07	−0.07	−0.07
		(−0.03)	(−0.22)	(1.12)	(−1.06)	(−0.69)	(−0.46)
VS	Excess Return	0.23	0.47	0.65	0.90	1.08	0.85
		(0.61)	(1.63)	(2.28)	(3.05)	(3.30)	(4.25)
	α^{OPT}	0.05	−0.04	−0.09	0.09	−0.02	−0.08
		(0.59)	(−0.54)	(−1.02)	(1.26)	(−0.20)	(−0.54)
$Skew$	Excess Return	0.43	0.43	0.58	0.74	0.91	0.49
		(1.31)	(1.43)	(1.91)	(2.41)	(2.76)	(2.86)
	α^{OPT}	0.03	−0.18	−0.14	0.06	0.11	0.09
		(0.19)	(−1.62)	(−1.40)	(0.59)	(0.82)	(0.44)
$\Delta CIV - \Delta PIV$	Excess Return	0.20	0.50	0.69	0.84	0.92	0.71
		(0.57)	(1.64)	(2.42)	(2.82)	(2.90)	(4.36)
	α^{OPT}	−0.06	−0.01	0.03	−0.03	−0.06	0.00
		(−0.52)	(−0.14)	(0.40)	(−0.50)	(−0.60)	(0.02)

Table 10: Comparison of OPT Model to Other Factor Models

This table presents the results of tests examining the ability of different factor models to explain the performance of quintile portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The portfolios examined are the quintile portfolios whose construction is described in Table 3. The analyses use the five quintile portfolios and not the long-short portfolios. The column labeled "Sort Variable(s)" indicates the variable(s) used to form the portfolios, where "All" refers to $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. When more than one sort variable is indicated, the portfolios examined are the quintile portfolios formed by sorting separately on each of the indicated variables. The column labeled "Value" indicates the value presented in the given row. The headers in the remaining columns indicate the factor model to which the results in the column pertain. Rows with "$\overline{|\alpha|}$" in the "Value" column present the average of the absolute value of the alpha for the portfolios being examined. Rows with "GRS" in the "Value" column present the Gibbons et al. (1989) test statistic for the test of the null hypothesis that the factor model explains the performance of all portfolios being examined. p-values associated with the Gibbons et al. (1989) test statistic are in square brackets. Average absolute alphas are in percent per month. The analysis covers return months from March 1996 through January 2018, inclusive.

Sort Variable(s)	Value	CAPM	FF	FFC	FFCPS	FF5	Q	SY	DHS	OPT
$IV - RV$	$\overline{\|\alpha\|}$	0.26	0.27	0.21	0.21	0.19	0.20	0.06	0.17	0.04
	GRS	3.24	3.11	2.20	2.13	1.59	1.94	0.28	1.74	0.42
		[0.01]	[0.01]	[0.05]	[0.06]	[0.16]	[0.09]	[0.92]	[0.13]	[0.83]
$CIV - PIV$	$\overline{\|\alpha\|}$	0.21	0.23	0.25	0.25	0.22	0.23	0.28	0.23	0.05
	GRS	4.39	6.22	6.78	7.10	5.01	5.52	6.48	5.19	0.45
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.81]
VS	$\overline{\|\alpha\|}$	0.26	0.27	0.29	0.30	0.24	0.26	0.30	0.29	0.06
	GRS	6.94	7.73	8.70	8.84	5.43	6.36	7.04	7.18	0.56
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.73]
$Skew$	$\overline{\|\alpha\|}$	0.17	0.19	0.17	0.16	0.18	0.20	0.17	0.20	0.10
	GRS	2.78	3.10	2.97	2.62	2.18	2.44	2.48	3.34	0.93
		[0.02]	[0.01]	[0.01]	[0.02]	[0.06]	[0.04]	[0.03]	[0.01]	[0.46]
$\Delta CIV - \Delta PIV$	$\overline{\|\alpha\|}$	0.21	0.23	0.21	0.21	0.24	0.23	0.22	0.20	0.04
	GRS	4.92	5.92	4.89	5.23	5.22	4.95	3.86	3.98	0.17
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.97]
$IV - RV$, VS,	$\overline{\|\alpha\|}$	0.25	0.25	0.24	0.24	0.22	0.23	0.19	0.22	0.04
and $\Delta CIV - \Delta PIV$	GRS	4.12	4.40	4.26	4.33	3.28	3.61	2.88	3.67	0.36
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.99]
$CIV - PIV$	$\overline{\|\alpha\|}$	0.19	0.21	0.21	0.20	0.20	0.22	0.22	0.22	0.08
and $Skew$	GRS	3.10	3.73	4.15	4.11	3.00	3.33	3.82	3.69	0.82
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.61]
All	$\overline{\|\alpha\|}$	0.22	0.24	0.23	0.23	0.21	0.23	0.20	0.22	0.06
	GRS	2.82	2.92	2.85	2.85	2.21	2.38	2.02	2.59	0.54
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.97]

Table 11: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables

This table presents the results of factor analyses examining the performance of quintile portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, and Max. β is the slope coefficient from a regression of excess stock returns on MKT using one year of daily data. $MktCap_{Firm}$ is the firm's market capitalization. BM is the firm's book-to-market ratio calculated following Fama and French (1993). OP is the firm's operating profibility calculated following Fama and French (2015). Inv is the firm's investment calculated following Fama and French (2015). Mom is the stock's momentum, calculated as the 11-month return during months $t-11$ through $t-1$, inclusive. Rev is the stock return during month t. $Illiq$ is the stock's illiquidity, calculated following Amihud (2002) using one year of daily data. $CoSkew$ is the stock's coskewness, calculated as the slope coefficient on MKT^2 from a regression of excess stock returns on MKT and MKT^2 using five years of monthly data. $IdioVol$ is the annualized standard deviation of the residuals of a regression of excess stock returns on MKT and the size and value factors of Fama and French (1993) calculated using one month of daily data. Max is the maximum daily return in month t. At the end of each month t, all optionable stocks in the sample are sorted into five portfolios based on the sort variable using quintile breakpoints calculated from NYSE-listed optionable stocks. We then calculate the $MktCap_{ShareClass}$-weighted month $t+1$ average excess return for stocks in each portfolio, as well as the difference between that of the quintile five portfolio and the quintile one portfolio. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled "Value" indicates the value presented in the given row. Rows with "Excess Return" in the "Value" column present the time-series average excess return of the given portfolio. Rows with "α^{CAPM}" in the "Value" column present CAPM alphas. Rows with "α^{OPT}" in the "Value" column present OPT model alphas. The columns labeled "1", "2", "3", "4", and "5" present results for the first, second, third, fourth, and fifth quintile portfolios, respectfully. The column labeled $5-1$ presents results for the long-short portfolio that is long the quintile five portfolio and short the quintile one portfolio. The column labeled "$\overline{|\alpha|}$" presents the average absolute alpha for quintile portfolios one through five. The column labeled "GRS" prsents the Gibbons et al. (1989) test statistic for the test of the null hypothesis that the factor model explains the returns of all of the quintile portfolios. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return or alpha are shown in parentheses. p-values for the GRS tests are in square brackets. Excess returns and alphas are in percent per month. The analysis return months from March 1996 through January 2018, inclusive.

Table 11: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables - continued

Sort Variable	Value	1	2	3	4	5	$5-1$	$\overline{\lvert\alpha\rvert}$	GRS
β	Excess Return	0.61	0.68	0.69	0.77	0.66	0.04		
		(3.01)	(2.76)	(2.26)	(2.22)	(1.31)	(0.11)		
	α^{CAPM}	0.29	0.20	0.08	0.04	-0.40	-0.69	0.20	1.25
		(2.04)	(1.49)	(0.51)	(0.25)	(-2.21)	(-2.42)		[0.29]
	α^{OPT}	0.13	0.01	-0.04	-0.09	-0.23	-0.36	0.10	0.37
		(0.83)	(0.05)	(-0.26)	(-0.55)	(-1.01)	(-1.07)		[0.87]
$MktCap_{Firm}$	Excess Return	0.75	0.74	0.81	0.79	0.63	-0.12		
		(1.55)	(1.90)	(2.32)	(2.45)	(2.25)	(-0.40)		
	α^{CAPM}	-0.24	-0.11	0.04	0.08	0.00	0.24	0.10	0.89
		(-1.06)	(-0.74)	(0.36)	(0.92)	(0.02)	(0.92)		[0.49]
	α^{OPT}	0.03	0.08	0.21	0.20	-0.06	-0.09	0.12	1.58
		(0.10)	(0.41)	(1.44)	(2.16)	(-1.28)	(-0.30)		[0.17]
BM	Excess Return	0.67	0.65	0.71	0.65	0.76	0.09		
		(2.23)	(2.29)	(2.47)	(1.95)	(2.41)	(0.39)		
	α^{CAPM}	0.01	0.02	0.10	0.04	0.16	0.15	0.07	0.50
		(0.15)	(0.26)	(0.80)	(0.19)	(0.80)	(0.55)		[0.77]
	α^{OPT}	-0.02	-0.11	0.03	0.15	0.20	0.22	0.10	0.79
		(-0.16)	(-1.21)	(0.28)	(0.86)	(0.96)	(0.76)		[0.56]
OP	Excess Return	0.37	0.58	0.68	0.70	0.73	0.36		
		(0.89)	(1.95)	(2.28)	(2.48)	(2.87)	(1.41)		
	α^{CAPM}	-0.50	-0.05	0.01	0.07	0.18	0.68	0.16	3.20
		(-3.51)	(-0.56)	(0.12)	(1.08)	(1.93)	(3.23)		[0.01]
	α^{OPT}	-0.21	0.02	0.03	0.03	-0.00	0.20	0.06	0.74
		(-1.66)	(0.19)	(0.34)	(0.37)	(-0.04)	(1.09)		[0.60]
Inv	Excess Return	0.80	0.66	0.76	0.76	0.57	-0.24		
		(2.65)	(2.62)	(2.86)	(2.62)	(1.48)	(-1.04)		
	α^{CAPM}	0.17	0.09	0.19	0.10	-0.25	-0.42	0.16	1.67
		(1.47)	(1.06)	(1.96)	(1.42)	(-1.80)	(-1.80)		[0.14]
	α^{OPT}	0.17	-0.03	0.06	0.08	-0.19	-0.36	0.11	1.14
		(1.36)	(-0.32)	(0.79)	(1.02)	(-1.31)	(-1.48)		[0.34]
ROE	Excess Return	0.31	0.48	0.80	0.64	0.81	0.50		
		(0.68)	(1.33)	(2.68)	(2.31)	(3.24)	(1.77)		
	α^{CAPM}	-0.61	-0.30	0.14	0.04	0.26	0.87	0.27	4.07
		(-3.67)	(-2.78)	(1.57)	(0.62)	(3.22)	(4.02)		[0.00]
	α^{OPT}	-0.22	-0.14	0.11	0.05	0.11	0.34	0.13	0.94
		(-1.52)	(-1.10)	(1.01)	(0.64)	(1.20)	(1.64)		[0.45]

Table 11: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables - continued

Sort Variable	Value	1	2	3	4	5	5 − 1	$\overline{\lvert\alpha\rvert}$	GRS
Mom	Excess Return	0.40	0.71	0.65	0.76	0.78	0.38		
		(0.79)	(2.13)	(2.31)	(3.15)	(2.29)	(0.91)		
	α^{CAPM}	−0.55	0.05	0.08	0.22	0.11	0.67	0.20	2.08
		(−2.25)	(0.28)	(0.75)	(2.56)	(0.72)	(1.84)		[0.07]
	α^{OPT}	−0.48	−0.00	−0.06	−0.00	0.25	0.72	0.16	1.68
		(−1.73)	(−0.02)	(−0.49)	(−0.02)	(1.37)	(1.73)		[0.14]
Rev	Excess Return	0.74	0.86	0.69	0.62	0.40	−0.34		
		(1.71)	(2.75)	(2.60)	(2.19)	(1.21)	(−1.25)		
	α^{CAPM}	−0.16	0.18	0.10	0.02	−0.27	−0.12	0.15	1.93
		(−0.90)	(1.88)	(1.38)	(0.20)	(−2.09)	(−0.42)		[0.09]
	α^{OPT}	−0.25	0.09	−0.05	−0.05	0.02	0.27	0.09	1.17
		(−1.48)	(0.79)	(−0.59)	(−0.54)	(0.13)	(0.96)		[0.32]
$Illiq$	Excess Return	0.63	0.83	0.76	0.78	0.80	0.17		
		(2.22)	(2.60)	(2.30)	(2.13)	(1.81)	(0.65)		
	α^{CAPM}	−0.01	0.14	0.04	−0.01	−0.10	−0.09	0.06	0.80
		(−0.19)	(1.26)	(0.32)	(−0.09)	(−0.51)	(−0.39)		[0.55]
	α^{OPT}	−0.10	0.25	0.26	0.21	0.24	0.34	0.21	1.65
		(−1.81)	(2.26)	(1.90)	(1.13)	(0.95)	(1.13)		[0.15]
$CoSkew$	Excess Return	0.77	0.71	0.71	0.65	0.54	−0.23		
		(2.10)	(2.61)	(2.73)	(2.21)	(1.46)	(−1.26)		
	α^{CAPM}	−0.03	0.11	0.14	0.02	−0.26	−0.23	0.11	1.04
		(−0.24)	(1.43)	(1.66)	(0.29)	(−2.07)	(−1.17)		[0.40]
	α^{OPT}	0.18	0.05	0.00	−0.17	−0.11	−0.29	0.10	0.98
		(1.40)	(0.51)	(0.04)	(−2.09)	(−0.66)	(−1.33)		[0.43]
$IdioVol$	Excess Return	0.81	0.71	0.57	0.76	0.52	−0.29		
		(3.61)	(2.62)	(1.82)	(1.96)	(0.92)	(−0.67)		
	α^{CAPM}	0.34	0.12	−0.12	−0.06	−0.58	−0.91	0.24	2.74
		(3.13)	(1.28)	(−1.18)	(−0.51)	(−2.50)	(−2.95)		[0.02]
	α^{OPT}	0.09	−0.04	−0.18	0.03	−0.02	−0.12	0.07	0.77
		(0.99)	(−0.36)	(−1.42)	(0.25)	(−0.10)	(−0.36)		[0.57]
Max	Excess Return	0.81	0.78	0.72	0.56	0.52	−0.29		
		(3.74)	(3.20)	(2.30)	(1.47)	(1.00)	(−0.74)		
	α^{CAPM}	0.39	0.23	0.02	−0.26	−0.53	−0.92	0.29	2.67
		(3.50)	(2.24)	(0.19)	(−2.40)	(−3.00)	(−3.43)		[0.02]
	α^{OPT}	0.19	−0.08	−0.13	−0.21	0.01	−0.18	0.12	1.32
		(1.68)	(−0.68)	(−1.18)	(−1.57)	(0.06)	(−0.60)		[0.25]

Table 12: OPT Model Factor Analysis of β, $IdioVol$, Max, OP, and ROE Long-Short Portfolios

This table presents the results of factor analyses examining the performance of long-short portfolios formed by sorting on β, $IdioVol$, Max, OP, and ROE using our OPT model. The construction of the long-short portfolios is described in Table 11. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled "α^{OPT}" indicates the alpha relative to the OPT factor model. The columns labeled "β_f", for $f \in \{MKTRF, F_{IV-RV}, F_{VS}, F_{\Delta CIV-\Delta PIV}\}$, show the slope coefficients from the factor regression. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero alpha or slope coefficient are shown in parentheses. Alphas are in percent per month. The analysis covers return months from March 1996 through January 2018, inclusive.

Sort Variable	α^{OPT}	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{VS}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
β	−0.36	1.03	−0.60	−0.34	0.57
	(−1.07)	(13.46)	(−4.87)	(−1.60)	(1.90)
$IdioVol$	−0.12	0.83	−0.69	−0.89	0.56
	(−0.36)	(11.69)	(−4.06)	(−2.33)	(1.61)
Max	−0.18	0.83	−0.87	−0.74	0.67
	(−0.60)	(12.69)	(−6.33)	(−2.24)	(2.49)
OP	0.20	−0.44	0.25	0.73	−0.41
	(1.09)	(−8.50)	(2.14)	(4.23)	(−2.15)
ROE	0.34	−0.49	0.39	0.80	−0.54
	(1.64)	(−10.23)	(3.14)	(3.56)	(−2.10)

Table 13: Comparison of Factor Models

This table presents several metrics examining the ability of different factor models to explain the average returns of portfolios formed by sorting long-short portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, Max, $IV-RV$, $CIV-PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The construction of the portfolios is described in Tables 3 and 11. The column labeled "Value" indicates the metric reported in the given row. The row with "$\overline{|\alpha|}$" in the "Value" column shows the average absolute value of alpha taken over all of quintile portfolios. The row with "GRS" in the "Value" column shows the Gibbons et al. (1989) test statistic for the test of the null hypothesis that the factor model explains the returns of all of the quintile portfolios. The values in square brackets below the GRS test statistics are p-values for the test. The results in the rows labeled "$\overline{|\alpha|}$" and "GRS" are calculated from the 85 (17 variables times 5 portfolios per variable) quintile portfolios formed by sorting on the sort variables. The row with "# Long-Short Significant" in the "Value" column shows the number of variables for which the long-short portfolio that is long the quintile 5 portfolio and short the quintile 1 portfolio generates an alpha that is statistically different from zero at the 5% level. The remaining columns present results for different factor models, indicated in the first row of each column. The analysis covers return months from March 1996 through January 2018, inclusive.

Value	CAPM	FF	FFC	FFCPS	FF5	Q	SY	DHS	OPT
$\overline{\lvert\alpha\rvert}$	0.18	0.18	0.15	0.15	0.13	0.12	0.12	0.13	0.10
GRS	1.77	1.79	1.72	1.70	1.57	1.60	1.29	1.57	1.02
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.08]	[0.01]	[0.45]
# Long-Short Significant	10	13	9	9	5	5	4	5	0

Table 14: Sharpe Ratios

This table presents Sharpe ratios for individual factors (Panel A) and for the tangency portfolio (Panel B) constructed from the factors in each factor models. The rows labeled "Mean", "S.D", "Sharpe", "95% C.I. Low", and "95% C.I. High" present the annualized mean excess return, annualized volatility, Sharpe ratio, and the low and high ends of the 95% confidence interval for the Sharpe ratio, calculated following Lo (2002, equation (10)), respectively. The analyses in Panel A covers return months from March 1996 through January 2018, inclusive. MKT is the market factor in the CAPM, FF, FFC, FFCPS, FF5, SY, DHS, and OPT models. SMB is the size factor in the FF, FFC, and FFCPS models. HML is the value factor in the FF, FFC, FFCPS, and FF5 model. MOM is the momentum factor in the FFC and FFCPS models. LIQ is the liquidity factor in the FFCPS model. $SMB5$ is the size factor in the FF5 model. RMW and CMA are the profitability and investment, respectively, factors in the FF5 model. $MKTQ$, ME, IA, and ROE are the market, size, investment, and profitability, respectively, factors in the Q model. $SMBSY$, $MGMT$, and $PERF$ are the size, management, and performance, respectively, factors in the SY model. FIN and $PEAD$ are the short-horizon and long-horizon, respectively, mispricing factors in the DHS model. In Panel B, the section with "Full Sample Period" in the "Method" column presents results using the full March 1996 through 2018 sample period, and the section with "Expanding Window" in the "Method" column presents results using an expanding window methodology. The expanding window methodology results use returns from the March 2001 through January 2018 period.

Panel A: Individual Factors

	MKT	SMB	HML	MOM	LIQ	$SMB5$	RMW	CMA	$MKTQ$	ME
Mean	7.87	1.91	2.38	4.76	5.52	2.38	4.44	2.73	7.60	3.43
S.D.	15.33	11.79	10.97	18.05	12.64	11.17	10.05	7.55	15.42	11.53
Sharpe	0.51	0.16	0.22	0.26	0.44	0.21	0.44	0.36	0.49	0.30
95% C.I. Low	0.29	−0.06	−0.01	0.04	0.21	−0.01	0.22	0.14	0.27	0.07
95% C.I. High	0.74	0.39	0.44	0.49	0.66	0.44	0.67	0.59	0.72	0.52

	IA	ROE	$SMBSY$	$MGMT$	$PERF$	FIN	$PEAD$	F_{IV-RV}	F_{VS}	$F_{\Delta CIV-\Delta PIV}$
Mean	2.47	4.48	4.47	6.30	9.07	6.82	5.13	6.96	8.58	6.71
S.D.	7.30	10.20	10.08	10.76	16.67	16.14	7.55	8.64	5.53	5.21
Sharpe	0.34	0.44	0.44	0.59	0.54	0.42	0.68	0.81	1.55	1.29
95% C.I. Low	0.11	0.21	0.21	0.35	0.31	0.20	0.45	0.58	1.32	1.05
95% C.I. High	0.56	0.67	0.67	0.82	0.78	0.65	0.91	1.03	1.79	1.52

Panel B: Tangency Portfolios

Method	Value	CAPM	FF	FFC	FFCPS	FF5	Q	SY	DHS	OPT
Full Sample Period	Mean	7.87	4.81	4.96	5.00	4.80	4.64	6.79	6.37	7.68
	S.D.	15.33	7.92	6.25	5.87	3.88	4.04	4.68	4.66	3.85
	Sharpe	0.51	0.61	0.79	0.85	1.24	1.15	1.45	1.37	2.00
	95% C.I. Low	0.29	0.38	0.57	0.62	1.00	0.92	1.21	1.13	1.75
	95% C.I. High	0.74	0.83	1.02	1.08	1.47	1.38	1.69	1.60	2.24
Expanding Window	Mean	7.24	3.11	2.66	2.57	3.72	3.30	4.57	4.66	6.32
	S.D.	14.62	6.83	5.57	5.42	3.74	3.65	4.33	4.30	3.66
	Sharpe	0.50	0.46	0.48	0.47	1.00	0.90	1.06	1.08	1.73
	95% C.I. Low	0.24	0.20	0.22	0.22	0.73	0.64	0.79	0.82	1.46
	95% C.I. High	0.75	0.71	0.73	0.73	1.26	1.16	1.33	1.35	2.00

In Search of a Factor Model for Optionable Stocks

Internet Appendix

April 2020

Abstract

Section I shows that our results hold when our test portfolios are constructed using breakpoints calculated from all optionable stocks, instead of NYSE-listed optionable stocks. Section II demonstrates that the ability of option-based variables to predict the cross-section of future stock returns persists when the sample is limited to stocks for which all seven option-based variables can be calculated. Section III shows that a significant portion of the alpha of the long-short portfolios formed by sorting on option-based variables comes from the long portion of the portfolio. Section IV demonstrates that our OPT factor model is the only model that includes the MKT factor and three or fewer option-based factors that explains the average returns of all of the option-based factors. Section V presents the details of the principal components analysis of the excess returns of the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. Section VI examines the ability of the OPT model to explain the average returns of portfolios formed by sorting all stocks, not just optionable stocks, on traditional asset pricing variables. Section VII examines whether the predictive power of traditional asset pricing variables is different during our sample period compared to the period prior to our sample period.

I Results using Optionable Stock Breakpoints

In this section, we repeat the tests whose results are reported in Tables 3, 7 and 9-13 of the main paper on test portfolios constructed using breakpoints calculated from all optionable stocks, instead of NYSE-listed optionable stocks. All other aspects of the tests remain unchanged from those described in the main paper. Importantly, the option-based factors are still constructed using breakpoints calculated from NYSE-listed optionable stocks, as in the main paper. The results of these tests, shown in Tables IA1-IA7 of this Internet Appendix, are qualitatively the same as those in the corresponding tables in the main paper. These analyses demonstrate that our main results are not a manifestation of using breakpoints constructed from optionable NYSE-listed stocks to construct our test portfolios.

II Results using Stocks for which All Option-Based Variables Can Be Calculated

In this section, we repeat the tests whose results are reported in Table 3 of the main paper using portfolios constructed from only the subset of optionable stocks for which all seven option-based variables can be calculated. Specifically, the sample used in this analysis is constructed in the same manner as the sample of optionable stocks used throughout the main paper, except we impose the additional condition that for a stock to be included in the month t sample, month t values for each of $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, $\Delta CIV - \Delta PIV$, and VoV must be available. All other aspects of the tests remain unchanged from those described in the main paper. The results of these tests, shown in Table IA8 of this Internet Appendix, show that, consistent with the results presented in the main paper, the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ generate positive and significant average excess returns, and positive and in most cases significant alphas with respect to the CAPM, FF, FFC, FFCPS, Q, FF5, SY, and DHS factor models. These analyses demonstrate that the ability of $IV - RV$, $CIV - PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ to predict the cross section of future stock returns is robust to changes in the sample of stocks included in the analysis.

III Long and Short Components of Long-Short Portfolios

In this section, we examine whether the average excess returns and alphas of the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, $\Delta CIV - \Delta PIV$, and VoV come from the long side of the portfolio or the short side of the portfolio. Table IA9 of this Internet Appendix reports the average excess return and alphas for the long component (the quintile five portfolio) and the short component (the quintile one portfolio) of the long-short portfolios examined in the main paper. The portfolios whose returns are examined in this analysis are identical to those examined in Table 3 of the main paper. The results shown for the short component of the long-short portfolio are results for a portfolio that is long the quintile one portfolio. Thus, the average excess returns and alphas of the long-short portfolios are found by subtracting the value for the short portfolio from that of the long portfolio. The results show that for portfolios formed by sorting on $IV-RV$, $CIV-PIV$, VS, $Skew$, and $\Delta CIV-\Delta PIV$, the long (short) side of the portfolio generates a positive (negative) and, in most cases, statistically significant alpha with respect to all models. The results indicate that the performance of the long-short portfolios is driven by both the long side and the short side of the portfolio.

IV Analysis of All Possible Option-Based Factor Models

In this section, we examine the ability of all possible factor models that include the market factor and one, two, or three of the option-based factors to explain the average returns of the option-based factors. The tests we run are identical to those whose results are presented in Table 6 of the main paper, except that here we run the tests using all possible factor models. Panels A, B, and C of Table IA10 of this Internet Appendix present results for all possible four-factor models, three-factor models, and two-factor models, respectively. The results show that the only factor model that explains the average excess returns of all factors not included in the model is the model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV-\Delta PIV}$ as factors.

V Principal Components Analysis

In this section, we present detailed results of the principal components analysis of the excess returns of the long-short portfolios formed by sorting on $IV-RV$, $CIV-PIV$, VS, $Skew$, and $\Delta CIV-\Delta PIV$. Panel A of Table 8 presents the weights of each of the long-short portfolio excess returns in each of the principal components. Table 8 Panel B shows the cumulative percentage of the total variance of all principal components that is captured by the first k principal components. Table IA12 presents the correlations between the principal component portfolios and the long-short portfolios.

VI Portfolios Formed by Sorting on Traditional Asset Pricing Variables Using the Sample of All Stocks

In this section, we examine the ability of the OPT model to explain the average returns of portfolios constructed using all stocks, not just optionable stocks. Except for the stocks used to form the portfolios, the analyses are identical to those whose results are presented in Table 11 of the main paper. The results of these analyses, presented in Table IA13 of this Internet Appendix, are similar to those reported in the main paper. For all variables, the alpha of the long-short portfolio with respect to the OPT model is insignificant at the 5% level. For nine of the 12 sort variables, the p-value of the GRS test using the OPT model is higher than that using the CAPM model. The results indicate that, even when examining the sample of all stocks, the OPT model outperforms the CAPM model.

VII Portfolios Formed by Sorting on Traditional Asset Pricing Variables - Pre- and Post-March 1996

In this section, we compare the ability of the traditional asset pricing variables to predict the cross section of future stock returns during the March 1996 through January 2018 period examined in our focal tests to that during the period from July 1963 through February 1996.[1] We do so using two regression specifications, both of which use the long-short portfolio excess returns as the dependent variable. The first specification includes only an indicator, I_{199603}, set to 1 for return months $t+1$ on or after March 1996, and 0 otherwise. If the coefficient on I_{199603} is significant, it indicates that the average excess return of the given long-short portfolio is different during the March 1996 through January 2018 period than during the July 1963 through February 1996 period. The second specification includes I_{199603} and MKT as independent variables. In this specification, a significant coefficient on I_{199603} indicates that the CAPM alpha of the portfolio is different during the two periods.

We run the regressions using two different samples of stocks. The first, which we refer to as the extended optionable sample, is designed to include stocks that likely would have been optionable during the month in question. For return months $t+1$ from March 1996 through January 2018, this sample is identical to the optionable stock sample used throughout the main paper. For return months $t+1$ from July 1963 through February 1996, the sample is constructed by taking stocks ordered from largest to smallest value of $MktCap_{ShareClass}$ until 85% of the total market capitalization of all stocks has been included in the sample.

[1] Due to data limitations, the analyses of portfolios formed by sorting on ROE begin in September 1974.

The second sample is simply the sample of all stocks.

The results of these tests, shown in Table IA14, provide no evidence of differential performance of the long-short portfolio formed by sorting on any of the traditional asset pricing variables during our focal sample period compared to the period from July 1963 through February 1996. Specifically, the coefficient on I_{199603} in both specifications for the long-short portfolio formed by sorting on each of the traditional asset pricing variables is statistically insignificant.

Table IA1: Performance of Long-Short Portfolios - Optionable Stock Breakpoints
This table presents the results of analyses examining the performance of portfolios formed by sorting on $IV-RV$, $CIV-PIV$, VS, $Skew$, S/O, $\Delta CIV-\Delta PIV$, and VoV. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 3 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Panel A: Full Sample Period

Sort Variable	Start Month -End Month	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV-RV$	199603	0.62	0.70	0.69	0.57	0.57	0.53	0.60	0.18	0.62
	-201801	(2.74)	(2.86)	(3.23)	(2.51)	(2.55)	(2.71)	(2.53)	(0.77)	(2.62)
$CIV-PIV$	199603	0.89	0.91	0.95	1.10	1.10	0.88	1.10	1.20	1.07
	-201801	(4.29)	(3.90)	(3.97)	(4.69)	(4.54)	(3.63)	(3.92)	(3.99)	(3.95)
VS	199603	1.03	1.04	1.05	1.19	1.22	0.97	1.14	1.21	1.20
	-201801	(4.22)	(4.01)	(4.03)	(4.68)	(4.86)	(3.99)	(4.23)	(4.37)	(4.44)
$Skew$	199603	0.48	0.46	0.58	0.49	0.45	0.58	0.62	0.54	0.61
	-201801	(2.50)	(2.11)	(3.15)	(2.71)	(2.49)	(3.08)	(2.88)	(2.42)	(2.89)
S/O	199603	0.28	0.44	0.26	0.35	0.33	−0.02	0.11	0.23	0.29
	-201801	(1.22)	(1.86)	(1.52)	(2.16)	(2.04)	(−0.15)	(0.59)	(1.18)	(1.75)
$\Delta CIV-\Delta PIV$	199603	0.78	0.79	0.79	0.80	0.83	0.76	0.80	0.76	0.87
	-201801	(4.49)	(4.14)	(3.97)	(3.99)	(4.11)	(4.10)	(3.82)	(3.35)	(3.71)
VoV	199603	0.35	0.50	0.35	0.30	0.23	0.05	0.12	0.20	0.24
	-201801	(1.38)	(1.86)	(1.69)	(1.42)	(1.12)	(0.26)	(0.58)	(0.88)	(1.05)

Panel B: Post-Original Study Sample Period

Sort Variable	Start Month -End Month	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV-RV$	200502	0.49	0.55	0.52	0.47	0.47	0.71	0.52	0.32	0.53
	-201801	(2.01)	(2.23)	(2.20)	(1.89)	(1.88)	(2.89)	(1.64)	(1.00)	(2.05)
$CIV-PIV$	200502	0.69	0.77	0.74	0.77	0.77	0.65	0.80	0.79	0.77
	-201801	(2.87)	(2.57)	(2.49)	(2.64)	(2.75)	(2.65)	(2.49)	(2.71)	(2.72)
VS	200602	0.64	0.67	0.66	0.67	0.66	0.53	0.64	0.66	0.58
	-201801	(2.41)	(2.17)	(2.18)	(2.25)	(2.33)	(1.84)	(2.17)	(2.20)	(1.99)
$Skew$	200602	0.39	0.41	0.31	0.29	0.32	0.31	0.34	0.34	0.55
	-201801	(1.96)	(1.78)	(1.51)	(1.43)	(1.57)	(1.62)	(1.53)	(1.88)	(2.50)
S/O	201101	−0.02	−0.07	0.10	0.12	0.12	0.11	0.14	0.13	0.03
	-201801	(−0.11)	(−0.38)	(0.70)	(0.83)	(0.89)	(0.88)	(1.06)	(0.81)	(0.21)
$\Delta CIV-\Delta PIV$	201202	0.40	0.33	0.34	0.35	0.36	0.32	0.38	0.23	0.28
	-201801	(1.89)	(1.57)	(1.68)	(1.86)	(1.91)	(1.60)	(1.91)	(0.99)	(1.50)
VoV	201411	−0.91	−1.05	−0.99	−0.91	−0.86	−0.95	−0.85	−0.32	−0.93
	-201801	(−2.53)	(−2.70)	(−2.99)	(−2.57)	(−2.70)	(−3.02)	(−2.65)	(−1.02)	(−2.58)

Table IA2: OPT Model Factor Analysis of Long-Short Portfolios - Optionable Stock Breakpoints

This table presents the results of factor analyses examining the performance of long-short portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ using our four-factor OPT model that includes MKT, F_{IV-RV}, F_{VS}, and $F_{\Delta CIV - \Delta PIV}$ as factors. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 7 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Sort Variable	α^{OPT}	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{VS}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
$IV - RV$	−0.05	0.06	1.46	−0.51	0.27
	(−0.40)	(2.04)	(19.93)	(−3.93)	(2.25)
$CIV - PIV$	−0.03	−0.02	−0.13	0.97	0.56
	(−0.17)	(−0.45)	(−1.55)	(5.95)	(2.79)
VS	−0.04	−0.01	−0.16	1.27	0.47
	(−0.21)	(−0.32)	(−2.15)	(9.10)	(2.95)
$Skew$	0.13	0.03	−0.03	−0.09	0.74
	(0.59)	(0.48)	(−0.25)	(−0.40)	(4.29)
$\Delta CIV - \Delta PIV$	0.08	−0.02	−0.06	0.16	1.14
	(0.55)	(−0.61)	(−0.73)	(1.42)	(8.06)

Table IA3: OPT Model Factor Analysis of Quintile Portfolios - Optionable Stock Breakpoints This table presents the results of factor analyses examining the performance of quintile portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ using our OPT model. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 9 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Sort Variable	Value	1	2	3	4	5	$5-1$
$IV - RV$	Excess Return	0.32	0.50	0.73	0.99	0.94	0.62
		(0.79)	(1.76)	(2.71)	(3.39)	(2.56)	(2.74)
	α^{OPT}	0.02	−0.07	−0.07	0.07	−0.03	−0.05
		(0.26)	(−0.81)	(−0.98)	(0.85)	(−0.20)	(−0.40)
$CIV - PIV$	Excess Return	0.14	0.47	0.76	0.76	1.03	0.89
		(0.38)	(1.63)	(2.61)	(2.40)	(3.32)	(4.29)
	α^{OPT}	0.00	−0.03	0.09	−0.10	−0.02	−0.03
		(0.04)	(−0.38)	(1.30)	(−1.20)	(−0.20)	(−0.17)
VS	Excess Return	0.14	0.44	0.62	0.95	1.17	1.03
		(0.35)	(1.45)	(2.15)	(3.20)	(3.38)	(4.22)
	α^{OPT}	0.00	0.02	−0.13	0.13	−0.03	−0.04
		(0.03)	(0.31)	(−1.55)	(1.76)	(−0.23)	(−0.21)
$Skew$	Excess Return	0.38	0.37	0.60	0.79	0.86	0.48
		(1.13)	(1.20)	(2.00)	(2.54)	(2.59)	(2.50)
	α^{OPT}	0.02	−0.22	−0.09	0.02	0.15	0.13
		(0.14)	(−1.91)	(−1.04)	(0.23)	(0.81)	(0.59)
$\Delta CIV - \Delta PIV$	Excess Return	0.16	0.40	0.69	0.88	0.94	0.78
		(0.42)	(1.29)	(2.37)	(2.99)	(2.84)	(4.49)
	α^{OPT}	−0.12	−0.01	0.00	−0.01	−0.04	0.08
		(−0.91)	(−0.17)	(0.02)	(−0.24)	(−0.34)	(0.55)

Table IA4: Comparison of OPT Model to Other Factor Models - Optionable Stock Breakpoints
This table presents the results of tests examining the ability of different factor models to explain the performance of quintile portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 10 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Sort Variable(s)	Value	CAPM	FF	FFC	FFCPS	FF5	Q	SY	DHS	OPT
$IV - RV$	$\overline{\lvert\alpha\rvert}$	0.27	0.26	0.22	0.22	0.19	0.22	0.06	0.19	0.05
	GRS	3.05	3.07	2.18	2.04	1.18	1.65	0.42	1.50	0.66
		[0.01]	[0.01]	[0.06]	[0.07]	[0.32]	[0.15]	[0.83]	[0.19]	[0.66]
$CIV - PIV$	$\overline{\lvert\alpha\rvert}$	0.25	0.27	0.30	0.30	0.27	0.30	0.33	0.29	0.05
	GRS	5.85	7.71	8.63	8.55	6.18	7.73	7.51	6.46	0.63
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.68]
VS	$\overline{\lvert\alpha\rvert}$	0.32	0.32	0.36	0.37	0.29	0.34	0.37	0.36	0.06
	GRS	8.32	8.86	10.54	10.64	6.13	7.84	8.27	8.33	1.28
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.27]
$Skew$	$\overline{\lvert\alpha\rvert}$	0.19	0.21	0.19	0.17	0.21	0.22	0.19	0.23	0.10
	GRS	3.57	3.67	3.57	3.21	2.74	2.96	2.60	3.87	1.07
		[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.01]	[0.03]	[0.00]	[0.38]
$\Delta CIV - \Delta PIV$	$\overline{\lvert\alpha\rvert}$	0.26	0.26	0.25	0.26	0.27	0.27	0.27	0.27	0.04
	GRS	6.58	7.15	6.14	6.36	6.20	6.06	4.76	5.56	0.28
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.92]
$IV - RV$, VS,	$\overline{\lvert\alpha\rvert}$	0.28	0.28	0.28	0.28	0.25	0.28	0.23	0.27	0.05
and $\Delta CIV - \Delta PIV$	GRS	4.58	4.64	4.65	4.66	3.41	4.01	3.18	4.03	0.65
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.83]
$CIV - PIV$	$\overline{\lvert\alpha\rvert}$	0.22	0.24	0.24	0.24	0.24	0.26	0.26	0.26	0.08
and $Skew$	GRS	3.98	4.43	5.24	5.06	3.47	4.43	4.30	4.32	0.91
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.52]
All	$\overline{\lvert\alpha\rvert}$	0.25	0.27	0.26	0.26	0.25	0.27	0.24	0.27	0.06
	GRS	3.17	3.15	3.18	3.13	2.35	2.66	2.23	2.74	0.75
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.80]

Table IA5: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables - Optionable Stock Breakpoints

This table presents the results of factor analyses examining the performance of quintile portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, and Max. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 11 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Sort Variable	Value	1	2	3	4	5	5 − 1	$\overline{\lvert\alpha\rvert}$	GRS
β	Excess Return	0.63	0.67	0.71	0.63	0.48	−0.15		
		(3.11)	(2.60)	(2.26)	(1.65)	(0.82)	(−0.29)		
	α^{CAPM}	0.30	0.16	0.04	−0.22	−0.73	−1.03	0.29	1.80
		(2.12)	(1.19)	(0.28)	(−1.67)	(−2.61)	(−2.69)		[0.11]
	α^{OPT}	0.12	−0.04	0.01	−0.26	−0.50	−0.62	0.19	1.38
		(0.80)	(−0.26)	(0.09)	(−1.60)	(−1.79)	(−1.60)		[0.23]
$MktCap_{Firm}$	Excess Return	0.60	0.80	0.74	0.76	0.64	0.04		
		(1.04)	(1.75)	(1.93)	(2.23)	(2.29)	(0.11)		
	α^{CAPM}	−0.50	−0.16	−0.11	0.01	0.01	0.51	0.16	0.92
		(−1.67)	(−0.75)	(−0.74)	(0.09)	(0.34)	(1.57)		[0.47]
	α^{OPT}	−0.33	0.12	0.04	0.17	−0.04	0.30	0.14	2.44
		(−1.00)	(0.49)	(0.26)	(1.32)	(−0.96)	(0.82)		[0.03]
BM	Excess Return	0.62	0.63	0.62	0.64	0.75	0.13		
		(1.89)	(2.20)	(2.10)	(2.05)	(2.30)	(0.47)		
	α^{CAPM}	−0.06	−0.02	−0.01	0.02	0.14	0.20	0.05	0.27
		(−0.40)	(−0.24)	(−0.17)	(0.16)	(0.68)	(0.62)		[0.93]
	α^{OPT}	−0.07	−0.12	−0.05	0.03	0.21	0.28	0.10	0.87
		(−0.43)	(−1.48)	(−0.53)	(0.24)	(1.09)	(0.87)		[0.50]
OP	Excess Return	0.19	0.30	0.68	0.68	0.72	0.53		
		(0.32)	(0.86)	(2.24)	(2.30)	(2.89)	(1.27)		
	α^{CAPM}	−0.92	−0.44	0.03	0.01	0.16	1.08	0.31	4.33
		(−3.00)	(−3.92)	(0.37)	(0.22)	(2.28)	(3.16)		[0.00]
	α^{OPT}	−0.48	−0.24	0.07	−0.00	0.02	0.50	0.16	1.41
		(−1.66)	(−2.50)	(0.68)	(−0.02)	(0.20)	(1.55)		[0.22]
Inv	Excess Return	0.80	0.72	0.71	0.73	0.31	−0.49		
		(2.60)	(2.81)	(2.55)	(2.12)	(0.72)	(−1.78)		
	α^{CAPM}	0.16	0.15	0.09	−0.02	−0.57	−0.73	0.20	2.50
		(1.27)	(1.66)	(1.31)	(−0.16)	(−2.75)	(−2.42)		[0.03]
	α^{OPT}	0.14	0.01	0.03	−0.05	−0.30	−0.44	0.11	0.97
		(1.08)	(0.16)	(0.35)	(−0.32)	(−1.54)	(−1.57)		[0.44]
ROE	Excess Return	0.27	0.40	0.55	0.70	0.78	0.50		
		(0.54)	(0.97)	(1.65)	(2.54)	(2.98)	(1.58)		
	α^{CAPM}	−0.69	−0.47	−0.17	0.09	0.20	0.89	0.32	3.26
		(−3.10)	(−3.07)	(−1.73)	(1.29)	(2.71)	(3.54)		[0.01]
	α^{OPT}	−0.10	−0.35	−0.02	0.06	0.10	0.19	0.12	1.19
		(−0.52)	(−2.19)	(−0.18)	(0.78)	(1.07)	(0.85)		[0.32]

Table IA5: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables - Optionable Stock Breakpoints - continued

Sort Variable	Value	1	2	3	4	5	$5-1$	$\overline{\lvert\alpha\rvert}$	GRS
Mom	Excess Return	0.20	0.65	0.63	0.71	0.81	0.61		
		(0.34)	(1.75)	(2.24)	(2.81)	(2.10)	(1.22)		
	α^{CAPM}	−0.90	−0.12	0.02	0.14	0.10	1.00	0.25	2.28
		(−3.04)	(−0.64)	(0.25)	(1.62)	(0.47)	(2.29)		[0.05]
	α^{OPT}	−0.85	−0.07	−0.13	−0.04	0.36	1.22	0.29	3.03
		(−2.64)	(−0.39)	(−1.17)	(−0.41)	(1.33)	(2.31)		[0.01]
Rev	Excess Return	0.56	0.83	0.68	0.60	0.41	−0.15		
		(1.20)	(2.49)	(2.42)	(2.02)	(1.17)	(−0.47)		
	α^{CAPM}	−0.42	0.10	0.06	−0.03	−0.27	0.15	0.17	2.73
		(−2.10)	(0.92)	(0.66)	(−0.29)	(−1.73)	(0.48)		[0.02]
	α^{OPT}	−0.49	0.00	−0.02	−0.05	0.10	0.59	0.13	1.70
		(−2.41)	(0.01)	(−0.15)	(−0.55)	(0.56)	(1.77)		[0.14]
$Illiq$	Excess Return	0.63	0.83	0.76	0.75	0.76	0.12		
		(2.25)	(2.52)	(2.14)	(1.82)	(1.54)	(0.39)		
	α^{CAPM}	−0.00	0.11	−0.02	−0.11	−0.18	−0.18	0.09	0.96
		(−0.10)	(1.02)	(−0.14)	(−0.64)	(−0.71)	(−0.63)		[0.44]
	α^{OPT}	−0.08	0.25	0.21	0.17	0.23	0.30	0.19	1.63
		(−1.64)	(1.95)	(1.28)	(0.75)	(0.71)	(0.84)		[0.15]
$CoSkew$	Excess Return	0.52	0.76	0.70	0.62	0.61	0.09		
		(1.18)	(2.78)	(2.64)	(2.15)	(1.52)	(0.44)		
	α^{CAPM}	−0.38	0.14	0.12	−0.03	−0.22	0.16	0.18	1.68
		(−1.88)	(1.82)	(1.62)	(−0.45)	(−1.55)	(0.69)		[0.14]
	α^{OPT}	0.06	0.11	−0.01	−0.22	0.05	−0.01	0.09	2.41
		(0.29)	(0.99)	(−0.12)	(−3.13)	(0.27)	(−0.04)		[0.04]
$IdioVol$	Excess Return	0.75	0.63	0.63	0.51	0.34	−0.42		
		(3.30)	(2.16)	(1.67)	(1.03)	(0.54)	(−0.85)		
	α^{CAPM}	0.25	−0.03	−0.19	−0.48	−0.91	−1.15	0.37	2.01
		(2.86)	(−0.46)	(−1.76)	(−2.33)	(−3.01)	(−3.13)		[0.08]
	α^{OPT}	0.03	−0.19	−0.08	−0.04	−0.08	−0.11	0.08	1.25
		(0.37)	(−1.84)	(−0.72)	(−0.19)	(−0.22)	(−0.26)		[0.29]
Max	Excess Return	0.81	0.68	0.65	0.40	0.31	−0.50		
		(3.85)	(2.39)	(1.82)	(0.87)	(0.53)	(−1.13)		
	α^{CAPM}	0.37	0.03	−0.16	−0.56	−0.83	−1.20	0.39	3.17
		(4.10)	(0.27)	(−1.84)	(−3.26)	(−3.55)	(−3.93)		[0.01]
	α^{OPT}	0.11	−0.17	−0.11	−0.20	−0.09	−0.21	0.14	1.30
		(1.09)	(−1.74)	(−1.12)	(−1.08)	(−0.38)	(−0.63)		[0.27]

Table IA6: OPT Model Factor Analysis of β, $IdioVol$, Max, OP, and ROE Long-Short Portfolios - Optionable Stock Breakpoints

This table presents the results of factor analyses examining the performance of long-short portfolios formed by sorting on β, $IdioVol$, Max, OP, and ROE using our OPT model. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 12 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Sort Variable	α^{OPT}	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{VS}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
β	−0.62	1.24	−0.71	−0.51	0.80
	(−1.60)	(10.91)	(−3.66)	(−1.81)	(2.57)
$IdioVol$	−0.11	0.97	−0.93	−1.38	1.05
	(−0.26)	(10.10)	(−4.31)	(−2.45)	(2.14)
Max	−0.21	0.91	−1.00	−1.07	0.81
	(−0.63)	(10.82)	(−5.87)	(−2.28)	(2.24)
OP	0.50	−0.75	0.39	1.32	−1.14
	(1.55)	(−9.91)	(1.88)	(5.03)	(−3.44)
ROE	0.19	−0.52	0.43	1.00	−0.57
	(0.85)	(−9.58)	(3.40)	(3.11)	(−1.83)

Table IA7: Comparison of Factor Models - Optionable Stock Breakpoints

This table presents several metrics examining the ability of different factor models to explain the average returns of portfolios formed by sorting long-short portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, Max, $IV-RV$, $CIV-PIV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 13 of the main paper, except that the quintile portfolios examined here are constructed using breakpoints calculated from all optionable stocks instead of NYSE-listed optionable stocks.

Value	CAPM	FF	FFC	FFCPS	FF5	Q	SY	DHS	OPT
$\overline{\lvert\alpha\rvert}$	0.24	0.24	0.19	0.19	0.15	0.13	0.14	0.16	0.12
GRS	1.60	1.59	1.50	1.47	1.32	1.43	1.22	1.44	0.92
	[0.00]	[0.01]	[0.01]	[0.02]	[0.06]	[0.02]	[0.14]	[0.02]	[0.67]
# Long-Short Significant	12	13	11	11	6	5	4	5	1

Table IA8: Performance of Long-Short Portfolios - All Option-Based Variables Available
This table presents the results of analyses examining the performance of portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, $\Delta CIV - \Delta PIV$, and VoV. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 3 of the main paper, except that only stocks for which all seven option-based variables are available are included in the portfolios.

Panel A: Full Sample Period

Sort Variable	Start Month -End Month	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV - RV$	199603	0.76	0.86	0.87	0.72	0.72	0.78	0.75	0.28	0.63
	-201801	(3.35)	(3.86)	(4.06)	(3.32)	(3.33)	(3.06)	(2.98)	(1.23)	(2.60)
$CIV - PIV$	199603	0.46	0.46	0.53	0.59	0.62	0.52	0.63	0.65	0.60
	-201801	(2.44)	(2.19)	(2.54)	(2.97)	(3.04)	(2.50)	(2.88)	(2.82)	(2.80)
VS	199603	0.58	0.62	0.62	0.67	0.72	0.47	0.54	0.51	0.57
	-201801	(2.98)	(2.95)	(2.93)	(3.07)	(3.41)	(2.22)	(2.37)	(2.15)	(2.52)
$Skew$	199603	0.42	0.37	0.49	0.41	0.37	0.48	0.52	0.49	0.49
	-201801	(2.57)	(2.05)	(3.08)	(2.50)	(2.27)	(2.80)	(2.76)	(2.39)	(2.49)
S/O	199603	0.12	0.32	0.15	0.19	0.18	-0.14	-0.03	0.03	0.17
	-201801	(0.51)	(1.33)	(0.78)	(1.08)	(1.02)	(-0.80)	(-0.15)	(0.15)	(0.93)
$\Delta CIV - \Delta PIV$	199603	0.36	0.35	0.39	0.40	0.42	0.44	0.49	0.44	0.37
	-201801	(2.07)	(1.82)	(2.06)	(2.12)	(2.15)	(2.27)	(2.36)	(1.92)	(1.80)
VoV	199603	0.15	0.29	0.18	0.13	0.06	-0.08	0.03	0.08	0.06
	-201801	(0.64)	(1.23)	(0.88)	(0.63)	(0.30)	(-0.38)	(0.13)	(0.32)	(0.26)

Panel B: Post-Original Study Sample Period

Sort Variable	Start Month -End Month	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV - RV$	200502	0.60	0.70	0.67	0.63	0.63	0.76	0.64	0.35	0.65
	-201801	(2.47)	(2.92)	(2.70)	(2.45)	(2.49)	(2.90)	(2.21)	(1.27)	(2.50)
$CIV - PIV$	200502	0.53	0.60	0.58	0.60	0.60	0.49	0.63	0.60	0.62
	-201801	(2.40)	(2.28)	(2.20)	(2.32)	(2.42)	(2.30)	(2.32)	(2.43)	(2.57)
VS	200602	0.64	0.65	0.64	0.66	0.65	0.53	0.67	0.65	0.57
	-201801	(2.66)	(2.25)	(2.17)	(2.33)	(2.45)	(2.15)	(2.24)	(2.11)	(2.19)
$Skew$	200602	0.44	0.46	0.36	0.35	0.37	0.35	0.41	0.41	0.60
	-201801	(2.35)	(2.10)	(1.92)	(1.84)	(1.99)	(2.02)	(1.94)	(2.43)	(2.87)
S/O	201101	0.16	0.14	0.28	0.30	0.30	0.31	0.32	0.28	0.23
	-201801	(0.88)	(0.79)	(1.80)	(1.81)	(1.80)	(2.41)	(2.31)	(1.41)	(1.28)
$\Delta CIV - \Delta PIV$	201202	0.12	0.07	0.07	0.02	0.06	0.07	0.10	0.12	0.07
	-201801	(0.72)	(0.31)	(0.34)	(0.09)	(0.36)	(0.34)	(0.53)	(0.66)	(0.38)
VoV	201411	-0.91	-0.92	-0.82	-0.77	-0.73	-0.78	-0.70	-0.29	-0.85
	-201801	(-3.02)	(-2.97)	(-2.93)	(-2.44)	(-2.47)	(-3.58)	(-2.77)	(-0.95)	(-2.59)

Table IA9: Performance of Long and Short Legs of Long-Short Portfolios
This table presents the results of analyses examining the performance of the long and short components of the long-short portfolios formed by sorting on $IV - RV$, $CIV - PIV$, VS, $Skew$, S/O, $\Delta CIV - \Delta PIV$, and VoV. The portfolios used to generate the results in the table are identical to the portfolios used to generate the results in Table 3 of the main paper. This table reports results for the long (quintile 5) and short (quintile 1) positions in the long-short portfolios. The results for the short portfolio are results for a portfolio that is long the quintile 1 portfolio.

Sort Variable	Position	Excess Return	α^{CAPM}	α^{FF}	α^{FFC}	α^{FFCPS}	α^{FF5}	α^{Q}	α^{SY}	α^{DHS}
$IV - RV$	Long	1.07	0.33	0.34	0.31	0.32	0.33	0.40	0.17	0.41
		(3.03)	(2.60)	(3.23)	(2.90)	(2.97)	(2.96)	(3.15)	(1.44)	(3.35)
	Short	0.37	−0.45	−0.44	−0.35	−0.34	−0.31	−0.28	−0.07	−0.20
		(0.95)	(−3.73)	(−3.71)	(−2.71)	(−2.77)	(−2.46)	(−2.09)	(−0.52)	(−1.57)
$CIV - PIV$	Long	0.93	0.22	0.23	0.36	0.38	0.23	0.34	0.54	0.38
		(3.01)	(1.89)	(2.03)	(3.15)	(3.33)	(1.83)	(2.67)	(3.90)	(3.51)
	Short	0.26	−0.46	−0.51	−0.51	−0.52	−0.45	−0.48	−0.48	−0.46
		(0.71)	(−3.05)	(−3.45)	(−3.44)	(−3.46)	(−3.51)	(−2.99)	(−3.01)	(−2.72)
VS	Long	1.08	0.33	0.31	0.46	0.45	0.32	0.46	0.57	0.53
		(3.30)	(2.51)	(2.41)	(3.62)	(3.67)	(2.40)	(3.24)	(3.60)	(3.87)
	Short	0.23	−0.53	−0.55	−0.51	−0.54	−0.45	−0.41	−0.39	−0.39
		(0.61)	(−4.03)	(−4.16)	(−3.88)	(−4.20)	(−3.66)	(−3.16)	(−2.87)	(−2.64)
$Skew$	Long	0.91	0.20	0.29	0.23	0.20	0.32	0.33	0.30	0.31
		(2.76)	(1.43)	(2.52)	(1.97)	(1.77)	(2.53)	(2.30)	(2.10)	(2.31)
	Short	0.43	−0.28	−0.31	−0.27	−0.25	−0.22	−0.26	−0.23	−0.26
		(1.31)	(−2.79)	(−3.02)	(−2.69)	(−2.45)	(−2.29)	(−2.35)	(−2.23)	(−2.34)
S/O	Long	0.83	0.23	0.14	0.19	0.18	−0.03	0.07	0.13	0.11
		(2.85)	(1.61)	(1.34)	(1.98)	(1.85)	(−0.31)	(0.60)	(1.07)	(1.09)
	Short	0.53	−0.22	−0.13	−0.16	−0.16	0.00	−0.04	−0.10	−0.17
		(1.52)	(−1.86)	(−1.41)	(−1.86)	(−1.81)	(0.05)	(−0.39)	(−1.01)	(−2.02)
$\Delta CIV - \Delta PIV$	Long	0.92	0.17	0.15	0.26	0.26	0.25	0.32	0.41	0.33
		(2.90)	(1.64)	(1.39)	(1.95)	(2.07)	(2.02)	(2.15)	(2.57)	(2.28)
	Short	0.20	−0.52	−0.57	−0.46	−0.47	−0.49	−0.44	−0.31	−0.38
		(0.57)	(−3.74)	(−4.14)	(−3.51)	(−3.55)	(−3.28)	(−2.80)	(−2.35)	(−2.49)
VoV	Long	0.72	0.14	0.10	0.05	0.02	−0.08	−0.04	−0.02	0.01
		(2.64)	(1.06)	(0.80)	(0.44)	(0.19)	(−0.62)	(−0.40)	(−0.12)	(0.07)
	Short	0.47	−0.28	−0.20	−0.19	−0.16	−0.09	−0.11	−0.16	−0.17
		(1.30)	(−2.07)	(−1.93)	(−1.89)	(−1.60)	(−0.88)	(−0.96)	(−1.32)	(−1.53)

Table IA10: Factor Analysis of Option-Based Factors - All Possible Factor Models
This table presents the results of factor analyses of the option-based factors. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 6 of the main paper. Here, we present results for factor models that include the MKT and all possible combinations of 3 (Panel A), 2 (Panel B), or 1 (Panel C) option-based factors.

Panel A: 4-Factor Models

Factor	α	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{CIV-PIV}}$	$\beta_{F_{VS}}$	$\beta_{F_{Skew}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
F_{Skew}	-0.02	-0.03	0.14	0.52	-0.07		
	(-0.12)	(-0.90)	(2.87)	(4.10)	(-0.50)		
$F_{\Delta CIV-\Delta PIV}$	0.20	0.01	-0.01	0.39	0.17		
	(2.18)	(0.24)	(-0.25)	(3.19)	(1.59)		
F_{VS}	0.28	-0.01	-0.01	0.74		-0.02	
	(3.43)	(-0.50)	(-0.18)	(10.32)		(-0.50)	
$F_{\Delta CIV-\Delta PIV}$	0.25	0.01	-0.02	0.49		0.05	
	(2.71)	(0.22)	(-0.46)	(4.87)		(1.01)	
F_{VS}	0.25	-0.01	-0.01	0.66			0.13
	(2.97)	(-0.54)	(-0.22)	(10.23)			(1.67)
F_{Skew}	-0.06	-0.03	0.14	0.41			0.12
	(-0.50)	(-0.89)	(3.07)	(4.15)			(1.02)
$F_{CIV-PIV}$	0.08	0.01	-0.00		0.66	0.15	
	(0.99)	(0.55)	(-0.01)		(10.26)	(4.61)	
$F_{\Delta CIV-\Delta PIV}$	0.23	0.01	-0.02		0.41	0.11	
	(2.86)	(0.41)	(-0.39)		(5.14)	(2.66)	
$F_{CIV-PIV}$	0.03	0.00	0.02		0.59		0.26
	(0.28)	(0.13)	(0.63)		(6.94)		(3.08)
F_{Skew}	-0.03	-0.03	0.15		0.19		0.25
	(-0.22)	(-0.86)	(3.08)		(1.92)		(2.83)
$F_{CIV-PIV}$	0.28	-0.00	0.00			0.18	0.50
	(3.03)	(-0.06)	(0.08)			(3.99)	(7.56)
F_{VS}	0.44	-0.01	-0.00			0.09	0.47
	(4.76)	(-0.50)	(-0.02)			(1.84)	(6.80)
F_{IV-RV}	0.62	-0.12		-0.00	-0.03	0.21	
	(3.05)	(-2.16)		(-0.01)	(-0.18)	(3.01)	
$F_{\Delta CIV-\Delta PIV}$	0.19	0.01		0.36	0.17	0.05	
	(2.11)	(0.40)		(2.68)	(1.63)	(1.07)	
F_{IV-RV}	0.64	-0.13		0.13	-0.04		-0.04
	(2.93)	(-2.33)		(0.65)	(-0.22)		(-0.25)
F_{Skew}	0.05	-0.05		0.49	-0.10		0.12
	(0.37)	(-1.43)		(3.23)	(-0.67)		(1.06)
F_{IV-RV}	0.63	-0.12		0.01		0.21	-0.07
	(2.94)	(-2.17)		(0.08)		(3.10)	(-0.45)
F_{VS}	0.25	-0.01		0.67		-0.03	0.13
	(3.10)	(-0.57)		(9.68)		(-0.67)	(1.72)
F_{IV-RV}	0.63	-0.12			-0.00	0.21	-0.06
	(2.99)	(-2.17)			(-0.02)	(3.27)	(-0.38)
$F_{CIV-PIV}$	0.03	0.01			0.57	0.13	0.23
	(0.36)	(0.34)			(6.87)	(3.52)	(2.57)

Table IA10: Factor Analysis of Option-Based Factors - All Possible Factor Models - continued

Panel B: 3-Factor Models

Factor	α	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{CIV-PIV}}$	$\beta_{F_{VS}}$	$\beta_{F_{Skew}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
F_{VS}	0.28	−0.01	−0.01	0.73			
	(3.45)	(−0.48)	(−0.27)	(11.34)			
F_{Skew}	−0.04	−0.03	0.14	0.47			
	(−0.28)	(−0.88)	(2.90)	(6.45)			
$F_{\Delta CIV-\Delta PIV}$	0.25	0.00	−0.01	0.51			
	(2.70)	(0.17)	(−0.29)	(5.71)			
$F_{CIV-PIV}$	0.09	0.00	0.02		0.71		
	(1.00)	(0.25)	(0.53)		(9.97)		
F_{Skew}	0.03	−0.03	0.15		0.30		
	(0.23)	(−0.81)	(2.69)		(3.17)		
$F_{\Delta CIV-\Delta PIV}$	0.24	0.01	−0.00		0.44		
	(2.88)	(0.30)	(−0.04)		(5.60)		
$F_{CIV-PIV}$	0.53	0.00	−0.01			0.27	
	(5.38)	(0.09)	(−0.14)			(4.90)	
F_{VS}	0.67	−0.01	−0.01			0.18	
	(5.81)	(−0.27)	(−0.23)			(2.86)	
$F_{\Delta CIV-\Delta PIV}$	0.51	0.01	−0.02			0.18	
	(4.93)	(0.21)	(−0.43)			(3.73)	
$F_{CIV-PIV}$	0.29	−0.01	0.03				0.56
	(3.01)	(−0.35)	(0.61)				(8.48)
F_{VS}	0.44	−0.02	0.01				0.50
	(4.75)	(−0.61)	(0.27)				(7.21)
F_{Skew}	0.05	−0.04	0.15				0.35
	(0.41)	(−0.91)	(2.97)				(4.22)
F_{IV-RV}	0.63	−0.13		0.11	−0.04		
	(3.08)	(−2.31)		(0.54)	(−0.27)		
F_{Skew}	0.07	−0.05		0.54	−0.08		
	(0.57)	(−1.40)		(3.89)	(−0.53)		
$F_{\Delta CIV-\Delta PIV}$	0.20	0.01		0.39	0.17		
	(2.12)	(0.31)		(3.20)	(1.61)		
F_{IV-RV}	0.61	−0.12		−0.02		0.21	
	(3.07)	(−2.15)		(−0.14)		(3.04)	
F_{VS}	0.28	−0.01		0.74		−0.02	
	(3.66)	(−0.48)		(10.38)		(−0.53)	
$F_{\Delta CIV-\Delta PIV}$	0.24	0.01		0.49		0.05	
	(2.55)	(0.30)		(4.78)		(0.95)	
F_{IV-RV}	0.63	−0.13		0.10			−0.05
	(2.88)	(−2.33)		(0.68)			(−0.28)
F_{VS}	0.25	−0.01		0.66			0.13
	(3.11)	(−0.51)		(10.40)			(1.69)
F_{Skew}	0.02	−0.05		0.43			0.11
	(0.19)	(−1.40)		(4.36)			(0.94)
F_{IV-RV}	0.62	−0.12			−0.03	0.21	
	(3.15)	(−2.13)			(−0.22)	(3.04)	
$F_{CIV-PIV}$	0.08	0.01			0.66	0.15	
	(1.00)	(0.52)			(10.24)	(4.54)	
$F_{\Delta CIV-\Delta PIV}$	0.22	0.01			0.41	0.11	
	(2.67)	(0.50)			(5.10)	(2.71)	
F_{IV-RV}	0.64	−0.13			0.04		−0.01
	(3.02)	(−2.34)			(0.28)		(−0.04)
$F_{CIV-PIV}$	0.04	−0.00			0.59		0.26
	(0.45)	(−0.06)			(6.79)		(3.13)
F_{Skew}	0.07	−0.05			0.20		0.25
	(0.51)	(−1.41)			(1.97)		(2.70)
F_{IV-RV}	0.63	−0.12				0.21	−0.06
	(3.17)	(−2.18)				(3.25)	(−0.42)
$F_{CIV-PIV}$	0.28	−0.00				0.18	0.50
	(2.94)	(−0.08)				(3.88)	(7.45)
F_{VS}	0.43	−0.01				0.09	0.47
	(5.04)	(−0.50)				(1.86)	(6.81)

Table IA10: Factor Analysis of Option-Based Factors - All Possible Factor Models - continued

Panel C: 2-Factor Models

Factor	α	β_{MKT}	$\beta_{F_{IV-RV}}$	$\beta_{F_{CIV-PIV}}$	$\beta_{F_{VS}}$	$\beta_{F_{Skew}}$	$\beta_{F_{\Delta CIV-\Delta PIV}}$
$F_{CIV-PIV}$	0.60	−0.01	0.03				
	(5.33)	(−0.22)	(0.48)				
F_{VS}	0.72	−0.02	0.02				
	(5.84)	(−0.41)	(0.26)				
F_{Skew}	0.25	−0.04	0.16				
	(1.86)	(−0.86)	(2.34)				
$F_{\Delta CIV-\Delta PIV}$	0.56	0.00	0.00				
	(5.10)	(0.03)	(0.08)				
F_{IV-RV}	0.62	−0.13		0.08			
	(3.07)	(−2.31)		(0.51)			
F_{VS}	0.28	−0.01		0.73			
	(3.66)	(−0.44)		(11.52)			
F_{Skew}	0.05	−0.05		0.48			
	(0.40)	(−1.38)		(6.22)			
$F_{\Delta CIV-\Delta PIV}$	0.24	0.01		0.51			
	(2.58)	(0.23)		(5.65)			
F_{IV-RV}	0.64	−0.13			0.04		
	(3.30)	(−2.31)			(0.27)		
$F_{CIV-PIV}$	0.10	0.00			0.71		
	(1.18)	(0.07)			(9.90)		
F_{Skew}	0.13	−0.05			0.31		
	(0.97)	(−1.35)			(3.14)		
$F_{\Delta CIV-\Delta PIV}$	0.24	0.01			0.44		
	(2.80)	(0.31)			(5.60)		
F_{IV-RV}	0.60	−0.12				0.20	
	(3.92)	(−2.14)				(2.84)	
$F_{CIV-PIV}$	0.53	0.00				0.27	
	(5.39)	(0.12)				(4.91)	
F_{VS}	0.67	−0.01				0.17	
	(6.08)	(−0.23)				(2.84)	
$F_{\Delta CIV-\Delta PIV}$	0.50	0.01				0.18	
	(4.87)	(0.28)				(3.80)	
F_{IV-RV}	0.66	−0.13					0.01
	(3.31)	(−2.38)					(0.08)
$F_{CIV-PIV}$	0.31	−0.01					0.56
	(3.13)	(−0.51)					(8.81)
F_{VS}	0.45	−0.02					0.50
	(5.13)	(−0.69)					(7.15)
F_{Skew}	0.16	−0.06					0.35
	(1.22)	(−1.47)					(3.88)

Table IA11: Principal Components Analysis of Long-Short Portfolios
This table presents the results of a principal components analysis of the excess returns of long-short portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$. The principal components analysis whose results are presented in this table is the same principal components analysis underlying the analysis whose results are shown in Table 7 of the main paper. The principal components analysis is conducted on the monthly excess returns of the long-short portfolios for the period from March 1996 through January 2018. Panel A presents the weights on each of the long-short portfolios for each principal component. The column labeled "Variable" indicates the sort variable used to construct the long-short portfolio. The columns labeled "PCk" for $k \in 1, \ldots, 5$ show the weights of the given long-short portfolio in the kth principal component. In Panel B, the column labeled "PCk" presents the cumulative percentage of the total variance of all principal components that is captured by principal components 1 through k.

Panel A: 4-Factor Models

Variable	PC1	PC2	PC3	PC4	PC5
$IV - RV$	−0.44	0.83	0.33	−0.11	0.01
$CIV - PIV$	0.56	0.15	0.24	−0.42	−0.66
VS	0.56	0.11	0.40	−0.10	0.71
$Skew$	0.25	0.43	−0.82	−0.23	0.16
$\Delta CIV - \Delta PIV$	0.35	0.31	−0.01	0.86	−0.19

Panel B: Cumulative Percentage of Total Variance

PC1	PC2	PC3	PC4	PC5
40.49%	68.96%	87.45%	95.38%	100.00%

Table IA12: Principal Component and Long-Short Portfolios Excess Return Correlations
This table presents the correlations between the excess returns of long-short portfolios formed by sorting on $CIV - PIV$, $IV - RV$, VS, $Skew$, and $\Delta CIV - \Delta PIV$ and the the excess returns of the associated principal component portfolios. The principal component portfolios are whose excess returns are examined in this table are the same principal component portfolios whose excess returns are examined in Table 7 of the main paper. The column labeled "Variable" indicates the sort variable used to construct the long-short portfolio. The columns labeled "PCk" for $k \in 1, \ldots, 5$ show the correlations between the excess returns of the long-short portfolio formed by sorting on the given variable and the excess returns of the kth principal component portfolio. The analysis covers excess returns from March 1996 through January 2018.

Variable	PC1	PC2	PC3	PC4	PC5
$IV - RV$	−0.52	0.81	0.26	−0.06	0.00
$CIV - PIV$	0.84	0.19	0.25	−0.28	−0.34
VS	0.83	0.14	0.40	−0.07	0.36
$Skew$	0.35	0.50	−0.77	−0.14	0.07
$\Delta CIV - \Delta PIV$	0.60	0.45	−0.01	0.66	−0.11

Table IA13: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables - All Stocks

This table presents the results of factor analyses examining the performance of quintile portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, and Max. The tests whose results are presented in the table are identical to the tests whose results are presented in Table 11 of the main paper, except that these tests use the sample of all stocks, not the sample of optionable stocks, to form the portfolios.

Sort Variable	Value	1	2	3	4	5	5 − 1	$\overline{\|\alpha\|}$	GRS
β	Excess Return	0.67	0.72	0.68	0.80	0.61	−0.05		
		(3.26)	(2.98)	(2.30)	(2.36)	(1.26)	(−0.14)		
	α^{CAPM}	0.35	0.28	0.10	0.11	−0.41	−0.76	0.25	2.07
		(2.53)	(1.78)	(0.64)	(0.59)	(−2.45)	(−2.84)		[0.07]
	α^{OPT}	0.26	0.08	−0.01	−0.01	−0.24	−0.50	0.12	0.81
		(1.78)	(0.63)	(−0.07)	(−0.07)	(−1.12)	(−1.59)		[0.55]
$MktCap_{Firm}$	Excess Return	0.78	0.91	0.79	0.77	0.63	−0.14		
		(1.80)	(2.35)	(2.20)	(2.31)	(2.29)	(−0.51)		
	α^{CAPM}	−0.01	0.08	0.01	0.04	0.01	0.02	0.03	1.52
		(−0.04)	(0.50)	(0.05)	(0.44)	(0.26)	(0.07)		[0.19]
	α^{OPT}	0.14	0.31	0.20	0.24	−0.04	−0.18	0.18	2.59
		(0.56)	(1.44)	(1.20)	(1.95)	(−1.03)	(−0.64)		[0.03]
BM	Excess Return	0.68	0.67	0.73	0.74	0.74	0.06		
		(2.28)	(2.41)	(2.56)	(2.36)	(2.32)	(0.26)		
	α^{CAPM}	0.02	0.06	0.15	0.17	0.14	0.12	0.11	0.80
		(0.24)	(0.66)	(1.11)	(0.85)	(0.70)	(0.47)		[0.55]
	α^{OPT}	−0.02	0.02	0.05	0.24	0.20	0.22	0.11	0.63
		(−0.24)	(0.18)	(0.32)	(1.39)	(0.97)	(0.81)		[0.68]
OP	Excess Return	0.37	0.60	0.66	0.69	0.77	0.40		
		(0.86)	(2.12)	(2.23)	(2.35)	(3.07)	(1.57)		
	α^{CAPM}	−0.49	0.00	0.01	0.03	0.22	0.71	0.15	3.20
		(−3.53)	(0.01)	(0.08)	(0.58)	(2.50)	(3.44)		[0.01]
	α^{OPT}	−0.18	0.08	0.02	−0.01	0.06	0.23	0.07	0.63
		(−1.32)	(0.86)	(0.18)	(−0.08)	(0.64)	(1.20)		[0.68]
Inv	Excess Return	0.82	0.69	0.75	0.76	0.57	−0.25		
		(2.59)	(2.81)	(2.79)	(2.75)	(1.54)	(−1.15)		
	α^{CAPM}	0.17	0.14	0.17	0.13	−0.22	−0.39	0.17	2.11
		(1.41)	(1.50)	(1.80)	(1.84)	(−1.70)	(−1.70)		[0.06]
	α^{OPT}	0.20	0.01	0.10	0.07	−0.16	−0.36	0.11	0.93
		(1.58)	(0.10)	(1.17)	(0.79)	(−1.17)	(−1.52)		[0.46]
ROE	Excess Return	0.28	0.52	0.77	0.68	0.79	0.51		
		(0.60)	(1.45)	(2.59)	(2.46)	(3.09)	(1.81)		
	α^{CAPM}	−0.64	−0.26	0.12	0.08	0.23	0.87	0.26	4.63
		(−3.53)	(−2.26)	(1.44)	(1.11)	(3.06)	(3.99)		[0.00]
	α^{OPT}	−0.23	−0.08	0.09	0.08	0.12	0.35	0.12	1.10
		(−1.50)	(−0.60)	(0.81)	(1.12)	(1.36)	(1.71)		[0.36]

Table IA13: OPT Model Factor Analysis of Portfolios Based on Traditional Asset Pricing Variables - All Stocks - continued

Sort Variable	Value	1	2	3	4	5	5 − 1	$\overline{\lvert\alpha\rvert}$	GRS
Mom	Excess Return	0.37	0.72	0.68	0.78	0.78	0.41		
		(0.73)	(2.16)	(2.46)	(3.24)	(2.37)	(1.02)		
	α^{CAPM}	−0.58	0.06	0.12	0.24	0.13	0.71	0.22	2.71
		(−2.40)	(0.36)	(1.07)	(2.77)	(0.86)	(2.04)		[0.02]
	α^{OPT}	−0.47	0.01	0.01	0.00	0.23	0.70	0.15	1.96
		(−1.76)	(0.09)	(0.07)	(0.04)	(1.42)	(1.79)		[0.09]
Rev	Excess Return	0.72	0.89	0.71	0.64	0.36	−0.35		
		(1.65)	(2.88)	(2.67)	(2.31)	(1.09)	(−1.26)		
	α^{CAPM}	−0.18	0.22	0.12	0.04	−0.30	−0.12	0.17	2.33
		(−1.01)	(2.30)	(1.57)	(0.51)	(−2.22)	(−0.42)		[0.04]
	α^{OPT}	−0.30	0.11	0.00	−0.02	0.05	0.35	0.10	1.09
		(−1.63)	(1.02)	(0.05)	(−0.24)	(0.28)	(1.15)		[0.36]
$Illiq$	Excess Return	0.64	0.80	0.77	0.86	0.88	0.25		
		(2.29)	(2.44)	(2.26)	(2.42)	(2.33)	(1.03)		
	α^{CAPM}	0.01	0.09	0.04	0.11	0.20	0.19	0.09	1.97
		(0.18)	(0.85)	(0.28)	(0.69)	(0.92)	(0.77)		[0.08]
	α^{OPT}	−0.07	0.28	0.22	0.33	0.44	0.51	0.27	2.32
		(−1.60)	(2.41)	(1.38)	(1.57)	(1.66)	(1.67)		[0.04]
$CoSkew$	Excess Return	0.73	0.72	0.69	0.67	0.56	−0.17		
		(1.97)	(2.58)	(2.70)	(2.33)	(1.53)	(−0.93)		
	α^{CAPM}	−0.07	0.11	0.13	0.05	−0.23	−0.15	0.12	0.97
		(−0.55)	(1.28)	(1.75)	(0.72)	(−1.93)	(−0.84)		[0.44]
	α^{OPT}	0.20	0.09	0.04	−0.17	−0.08	−0.29	0.12	0.98
		(1.39)	(0.81)	(0.52)	(−2.05)	(−0.51)	(−1.31)		[0.43]
$IdioVol$	Excess Return	0.82	0.68	0.67	0.74	0.49	−0.32		
		(3.66)	(2.56)	(2.08)	(1.90)	(0.87)	(−0.74)		
	α^{CAPM}	0.35	0.10	−0.03	−0.08	−0.59	−0.94	0.23	2.69
		(3.35)	(0.98)	(−0.33)	(−0.74)	(−2.52)	(−2.98)		[0.02]
	α^{OPT}	0.15	−0.11	−0.10	0.02	0.02	−0.13	0.08	1.26
		(1.68)	(−0.95)	(−0.76)	(0.20)	(0.08)	(−0.39)		[0.28]
Max	Excess Return	0.80	0.77	0.70	0.59	0.48	−0.33		
		(3.69)	(3.13)	(2.26)	(1.56)	(0.92)	(−0.80)		
	α^{CAPM}	0.40	0.22	0.01	−0.22	−0.56	−0.96	0.28	2.49
		(3.28)	(2.09)	(0.06)	(−2.04)	(−3.03)	(−3.37)		[0.03]
	α^{OPT}	0.14	0.01	−0.16	−0.11	−0.01	−0.15	0.09	0.77
		(1.05)	(0.05)	(−1.46)	(−0.89)	(−0.06)	(−0.47)		[0.57]

Table IA14: Predictive Power of Traditional Asset Pricing Variables - Pre- and Post-199603
This table presents the results of factor analyses examining the performance of long-short portfolios formed by sorting on β, $MktCap_{Firm}$, BM, OP, Inv, ROE, Mom, Rev, $Illiq$, $CoSkew$, $IdioVol$, and Max for stocks in the extended optionable stock sample (Panel A) and the sample of all stocks (Panel B). The procedure for constructing the portfolios is exactly the same as that used to construct the portfolios whose returns are examined in Table 11 of the main paper. For portfolio formation months t (return months $t+1$) on or after February 1996 (March 1996), the set of stocks included in the extended optionable stock sample is the same as the set of stocks used in the optionable stock sample examined throughout the main paper. For each month t prior to February 1996, the set of stocks included in the extended optionable stock sample is found by sorting stocks in descending order based on $MktCap_{ShareClass}$ and then including stocks, from largest to smallest, until 85% of the total market capitalization of all stocks in the given month has been included. The columns labeled "Model" indicates the model used to analyze the returns of the portfolios. The "Excess Return" model includes only an indicator set to 1 for return months $t+1$ on or after March 1996, and zero otherwise (I_{199603}), as an independent variable. The "CAPM" model includes I_{199603} and MKT as independent variables. The column labeled "Value" indicates the coefficient whose estimates are reported in the given row. The remaining columns present results for the long-short portfolio formed by sorting on the variable indicated in the column header. t-statistics, adjusted following Newey and West (1987) using three lags and testing the null hypothesis of a zero average excess return or alpha, are shown in parentheses. The analyses for all variables except for ROE cover excess return months from July 1963 through January 2018. Due to data limitations, the results for ROE cover excess return months from September 1974 through January 2018.

Panel A: Estimated Optionable Stock Sample

Model	Value	β	$MktCap_{Firm}$	BM	OP	Inv	ROE	Mom	Rev	$Illiq$	$CoSkew$	$IdioVol$	Max
Excess	I_{199306}	0.03	0.09	−0.13	0.09	0.01	0.23	−0.19	−0.03	0.08	−0.04	−0.29	−0.42
Return		(0.05)	(0.26)	(−0.41)	(0.30)	(0.05)	(0.67)	(−0.39)	(−0.09)	(0.28)	(−0.17)	(−0.61)	(−0.97)
	Intercept	0.02	−0.21	0.22	0.27	−0.25	0.27	0.57	−0.31	0.09	−0.19	−0.00	0.12
		(0.08)	(−1.49)	(1.19)	(1.76)	(−1.69)	(1.30)	(2.58)	(−2.09)	(0.88)	(−1.27)	(−0.03)	(0.70)
CAPM	I_{199306}	−0.13	0.16	−0.10	0.12	−0.03	0.21	−0.15	0.02	0.04	−0.03	−0.42	−0.54
		(−0.39)	(0.53)	(−0.33)	(0.45)	(−0.13)	(0.66)	(−0.34)	(0.06)	(0.17)	(−0.14)	(−1.16)	(−1.67)
	Intercept	−0.36	−0.05	0.28	0.35	−0.36	0.45	0.64	−0.20	0.01	−0.17	−0.31	−0.17
		(−1.81)	(−0.40)	(1.58)	(2.13)	(−2.74)	(2.01)	(2.77)	(−1.36)	(0.08)	(−1.17)	(−1.97)	(−1.04)
	β_{MKT}	0.82	−0.35	−0.14	−0.18	0.24	−0.24	−0.16	−0.24	0.18	−0.04	0.67	0.63
		(13.25)	(−8.00)	(−2.68)	(−3.92)	(6.06)	(−3.76)	(−1.73)	(−4.47)	(4.50)	(−0.87)	(11.67)	(10.48)

Panel B: All Stocks

Model	Value	β	$MktCap_{Firm}$	BM	OP	Inv	ROE	Mom	Rev	$Illiq$	$CoSkew$	$IdioVol$	Max
Excess	I_{199306}	−0.07	0.08	−0.33	0.19	0.05	0.22	−0.60	0.03	−0.12	0.03	−0.09	−0.24
Return		(−0.16)	(0.22)	(−1.11)	(0.67)	(0.21)	(0.62)	(−1.29)	(0.11)	(−0.39)	(0.14)	(−0.17)	(−0.51)
	Intercept	0.02	−0.22	0.39	0.21	−0.30	0.29	1.02	−0.39	0.37	−0.20	−0.24	−0.09
		(0.09)	(−0.92)	(2.10)	(1.43)	(−2.01)	(1.26)	(4.38)	(−2.34)	(1.85)	(−1.36)	(−0.95)	(−0.38)
CAPM	I_{199306}	−0.24	0.13	−0.31	0.24	0.01	0.20	−0.56	0.09	−0.15	0.04	−0.23	−0.38
		(−0.72)	(0.38)	(−1.04)	(0.90)	(0.06)	(0.62)	(−1.26)	(0.28)	(−0.48)	(0.18)	(−0.59)	(−1.09)
	Intercept	−0.36	−0.11	0.44	0.31	−0.39	0.49	1.11	−0.26	0.31	−0.18	−0.57	−0.41
		(−1.77)	(−0.51)	(2.38)	(1.99)	(−2.81)	(2.14)	(4.69)	(−1.61)	(1.66)	(−1.26)	(−2.80)	(−2.18)
	β_{MKT}	0.83	−0.24	−0.10	−0.22	0.20	−0.27	−0.20	−0.27	0.13	−0.04	0.71	0.71
		(13.44)	(−5.01)	(−1.98)	(−4.98)	(5.10)	(−4.56)	(−2.25)	(−4.81)	(2.66)	(−1.00)	(11.78)	(12.04)