Betting against Beta or Demand for Lottery *

Turan G. Bali† Stephen J. Brown‡ Scott Murray§ Yi Tang¶

This version: November 2014

Abstract

Frazzini and Pedersen (2014) document that a betting against beta strategy that takes long positions in low-beta stocks and short positions in high-beta stocks generates a large abnormal return of 6.6% per year and they attribute this phenomenon to funding liquidity risk. We find strong confirmation of their results on U.S. equity data, but provide evidence of an alternative explanation. Portfolio and regression analyses show that the betting against beta phenomenon disappears after controlling for the lottery characteristics of the stocks in our sample, while other measures of firm characteristics and risk fail to explain the effect. Furthermore, the betting against beta phenomenon only exists when the price impact of lottery demand falls disproportionately on high-beta stocks. We also find that this lottery characteristic aggregates at the portfolio level and therefore cannot be diversified away. Finally, factor models that include our lottery demand factor explain the abnormal returns of the betting against beta portfolio as well as the betting against beta factor generated by Frazzini and Pedersen.

Keywords: Beta, Betting Against Beta, Lottery Demand, Stock Returns, Funding Liquidity

*Recipient of 2014 Jack Treynor Prize sponsored by the Q-Group (The Institute for Quantitative Research in Finance). We thank Reena Aggarwal, Bill Baber, Jennie Bai, Nicholas Barberis, Preeti Choudhary, Jess Cornaggia, Richard DeFusco, Ozgur Demirtas, John Geppert, Bruce Grundy, Campbell Harvey, Allison Koester, Katie McDermott, Stanislava Nikolova, Lasse Pedersen, Manferd Peterson, Lee Pinkowitz, Rob Schoen, Wei Tang, Gary Twite, Robert Whitelaw, Rohan Williamson, Jie Yang, Kamil Yilmaz, Yichao Zhu, and seminar participants at Georgetown University, Koc University, Lancaster University, Monash University, Sabanci University, the University of Melbourne, the University of Minho, the University of Nebraska - Lincoln, and the University of South Australia for extremely helpful comments that have substantially improved the paper.

†Robert S. Parker Chair Professor of Finance, McDonough School of Business, Georgetown University, Washington, DC 20057; phone (202) 687-5388; fax (202) 687-4031; email turan.bali@georgetown.edu.

‡David S. Loeb Professor of Finance, Stern School of Business, New York University, New York, NY 10012, and Professorial Fellow, University of Melbourne; email sbrown@stern.nyu.edu.

§Assistant Professor of Finance, College of Business Administration, University of Nebraska – Lincoln, PO Box 880490, Lincoln, NE 68588-0490; phone (402) 472-2432; fax (402) 472-5140; email smurray6@unl.edu.

¶Associate Professor of Finance, Schools of Business, Fordham University, 1790 Broadway, New York, NY 10019; phone (646) 312-8292; fax (646) 312-8295; email ytang@fordham.edu.

1 Introduction

The positive (negative) abnormal returns of portfolios comprised of low-beta (high-beta) stocks, first documented by Black, Jensen, and Scholes (1972), are arguably the most persistent and widely studied anomaly in empirical research of security returns.[1] In an important recent study, Frazzini and Pedersen (2014, FP hereafter) attribute this betting against beta phenomenon to market pressures exerted by leverage-constrained investors attempting to boost expected returns by purchasing high-beta stocks. According to FP's model, investors who are constrained with respect to the amount of leverage they can employ in their portfolios (pension funds, mutual funds) chase returns by over weighting (under weighting) high-beta (low-beta) securities in their portfolios, thus pushing up (down) the prices of high-beta (low-beta) securities. As a result, the security market line has a lower (although still positive) slope and greater intercept than would be predicted by the Capital Asset Pricing Model (CAPM, Sharpe (1964), Lintner (1965), Mossin (1966)) and stocks with high (low) betas generate negative (positive) risk-adjusted returns relative to standard risk models.[2] Empirically, FP demonstrate that the predictions of their theoretical model hold across several different classes of securities in both the U.S. and international markets. While the compelling theoretical and empirical evidence presented by FP unquestionably represents a major contribution to our understanding of equilibrium in financial markets, there may be other plausible explanations for the betting against beta phenomenon. Given the prominent and important role the betting against beta phenomenon plays in financial markets, it is important to carefully examine what might be responsible for this persistent effect.

In this paper, we suggest an alternative explanation for the betting against beta phenomenon. We propose that demand for lottery-like stocks, a phenomenon documented by Kumar (2009) and Bali, Cakici, and Whitelaw (2011), produces the betting against beta effect.[3] Our mechanism is

[1] This phenomenon has also been documented by several subsequent papers, including Blume and Friend (1973), Fama and MacBeth (1973), Reinganum (1981), Lakonishok and Shapiro (1986), and Fama and French (1992, 1993).

[2] A similar explanation was initially proposed, but not empirically investigated, by Black et al. (1972), who suggest that divergent risk-free borrowing and lending rates explain the positive intercept of the line describing the relation between expected excess returns and beta. Brennan (1971) and Black (1972) formalize this notion with theoretical models. This has become the standard textbook explanation for this phenomenon (Elton, Gruber, Brown, and Goetzmann (2014, Ch. 14)).

[3] Bali et al. (2011) demonstrate that lottery demand is negatively related to future raw and risk-adjusted stock returns. This empirical finding is consistent with cumulative prospect theory (Tversky and Kahneman (1992)) as modeled by Barberis and Huang (2008), which predicts that errors in the probability weighting of investors cause them to overvalue stocks that have a small probability of a large positive return. Thaler and Ziemba (1988) demonstrate demand for lottery in the context of betting on horse races and playing the lottery.

similar to that of FP in that a disproportionately high (low) amount of upward price pressure is exerted on high-beta (low-beta) stocks. However, in the context of the U.S. equity markets, the main driver of this price pressure appears to be lottery demand.

Our rationale is as follows. As discussed by both Kumar (2009) and Bali et al. (2011), lottery investors generate demand for stocks with high probabilities of large short-term up moves in the stock price. Such up moves are partially generated by a stock's sensitivity to the overall market—market beta. A disproportionately high (low) amount of lottery demand-based price pressure is therefore exerted on high-beta (low-beta) stocks, pushing the prices of such stocks up (down) and therefore decreasing (increasing) future returns. This price pressure generates an intercept greater than the risk-free rate (positive alpha for stocks with beta of zero) and a slope less than the market risk premium (negative alpha for high-beta stocks) for the line describing the relation between beta and expected stock returns.

We test our hypothesis in several ways. First, we demonstrate that the betting against beta phenomenon is in fact explained by lottery demand. Following Bali et al. (2011), we proxy for lottery demand with MAX, defined as the average of the five highest daily returns of the given stock in a given month.[4] Bivariate portfolio analyses demonstrate that the abnormal returns of a zero-cost portfolio that is long high-beta stocks and short low-beta stocks (High−Low beta portfolio) disappear when the portfolio is constrained to be neutral to MAX. Fama and MacBeth (1973, FM hereafter) regressions indicate a significantly positive relation between beta and stock returns when MAX is included in the regression specification and the magnitudes of the coefficients on beta are highly consistent with estimates of the market risk premium. Univariate portfolio analyses fail to detect the betting against beta phenomenon when the component of beta that is orthogonal to MAX (instead of beta itself) is used as the sort variable.

We also generate a factor, FMAX, designed to capture the returns associated with lottery demand. We show that the abnormal returns of the High−Low beta portfolio relative to the commonly used Fama and French (1993) and Carhart (1997) four-factor (FFC4) model and the FFC4 model augmented with Pastor and Stambaugh's (2003) liquidity factor disappear completely when FMAX is included in the factor model. Similarly, the FMAX factor completely explains the

[4] In the online appendix, we show that our results are robust to alternative definitions of MAX. Specifically, our results persist when MAX is defined as the average of the k highest daily returns of the given stock within the given month, for $k \in \{1, 2, 3, 4, 5\}$.

abnormal returns of FP's BAB (for **b**etting **a**gainst **b**eta) factor, since the abnormal returns of the BAB factor are small and insignificant when FMAX is included in the factor model. The BAB factor, however, fails to explain the returns associated with the FMAX factor. The results indicate that the betting against beta phenomenon is a manifestation of the effect of lottery demand on stock returns. Additionally, we find that a portfolio of high-MAX (low-MAX) stocks is itself a high-MAX (low-MAX) asset. This result also holds for portfolios sorted on the portion of MAX that is orthogonal to beta. This is important because it indicates that the lottery-like features of individual stocks aggregate at the portfolio level, meaning that lottery-demand is not diversifiable.

In addition to showing that lottery demand explains the betting against beta phenomenon, we demonstrate that disproportionate lottery demand for high-beta stocks is in fact the channel that generates the betting against beta phenomenon. We accomplish this in several steps. First, we show that beta is highly cross-sectionally correlated with MAX, indicating that in the average month, lottery demand price pressure falls predominantly on high-beta stocks. We then show that in months where this correlation is low — months when lottery demand price pressure is not disproportionally exerted on high-beta stocks — the betting against beta phenomenon does not exist. When this correlation is high, indicating highly disproportionate price pressure on high-beta stocks, the betting against beta phenomenon is very strong. The results indicate that disproportional lottery demand-based price pressure on high-beta stocks is driving the betting against beta phenomenon. We also demonstrate that the months where this correlation is high are characterized by high aggregate lottery demand and poor economic conditions. Finally, as would be expected given that lottery demand is driven by individual (not institutional) investors (Kumar (2009)), we show that the betting against beta phenomenon only exists among stocks with a low proportion of institutional shareholders.

The remainder of this paper proceeds as follows. Section 2 provides data and variable definitions. Section 3 illustrates the betting against beta and lottery demand phenomena. Section 4 demonstrates that lottery demand explains the betting against beta phenomenon. Section 5 shows that lottery demand-based price pressure generates the betting against beta phenomenon. Section 6 introduces a lottery-demand factor and shows that it explains the returns of the betting against beta factor, while the betting against beta factor fails to explain the returns of the lottery-demand factor. Section 7 concludes.

2 Data and Variables

Market beta and the amount of lottery demand for a stock are the two primary variables in our analyses. We estimate a stock's market beta (β) for month t to be the slope coefficient from a regression of excess stock returns on excess market returns using daily returns from the 12-month period up to and including month t. When calculating beta, we require that a minimum of 200 valid daily returns be used in the regression.[5]

Following Bali et al. (2011), we measure a stock's lottery demand using MAX, calculated as the average of the five highest daily returns of the stock during the given month t. We require a minimum of 15 daily return observations within the given month to calculate MAX.

The main dependent variable of interest is the one-month-ahead excess stock return, which we denote R. We calculate the monthly excess return of a stock to be the return of the stock, adjusted for delistings following Shumway (1997), minus the return on the risk-free security.

We examine several other potential explanations for the betting against beta phenomenon. The possible alternative explanations are grouped into three main categories. The first category is firm characteristics, which includes market capitalization, the book-to-market ratio, momentum, stock illiquidity, and idiosyncratic volatility. The second category is comprised of measures of risk, including co-skewness, total skewness, downside beta, and tail beta. The third and final group includes measures of stock sensitivity to aggregate funding liquidity factors. The motivation for this group is FP's claim that funding constraints are the primary driver of the betting against beta phenomenon. In the ensuing sections, we briefly describe the calculation of the variables in each of these categories. More details on the calculation of all of the variables used in this study are available in Section I of the online appendix.

2.1 Firm Characteristics

To examine the possibility that the size and/or value effects of Fama and French (1992) play a role in the betting against beta phenomenon, we define $MKTCAP$ as the stock's market capitalization and BM as the log of the firm's book-to-market ratio.[6] Since the cross-sectional distribution of

[5] FP use an alternative definition of market beta. As we discuss in Section 6.3 and demonstrate in the online appendix, our results are robust when beta is measured according to FP.

[6] We calculate the book-to-market ratio following Fama and French (1992).

market capitalization is highly skewed, we use the natural log of market capitalization, denoted $SIZE$, in regression analyses. Following Jegadeesh and Titman (1993), who find a medium-term momentum effect in stock returns, we measure the momentum (MOM) of a stock in month t as the 11-month return during months $t-11$ through $t-1$, inclusive. Stock illiquidity ($ILLIQ$), shown by Amihud (2002) to be positively related to stock returns, is calculated as the absolute daily return divided by the daily dollar trading volume, averaged over one month. Ang, Hodrick, Xing, and Zhang (2006) show that idiosyncratic volatility and future stock returns have a strong negative relation. To measure idiosyncratic volatility, we define $IVOL$ as the standard deviation of the residuals from a regression of excess stock returns on the excess market return and the size (SMB) and book-to-market (HML) factor-mimicking portfolio returns of Fama and French (1993) using one month of daily return data. When calculating $ILLIQ$ and $IVOL$, we require 15 days of valid daily return observations within the given month.

2.2 Risk Measures

Our analyses examine the impact of several different measures of risk on the betting against beta phenomenon. Co-skewness ($COSKEW$), shown by Harvey and Siddique (2000) to be negatively related to stock returns, is calculated as the slope coefficient on the excess market return squared term from a regression of stock excess returns on the market excess returns and the market excess returns squared, using one year's worth of daily data. We define total skewness ($TSKEW$) as the skewness of daily stock returns over the past year. Downside beta ($DRISK$) of Ang, Chen, and Xing (2006) is measured as the slope coefficient from a regression of stock excess returns on the market excess returns, using only days for which the market return was below the average daily market return during the past year. Following Kelly and Jiang (2013) and Ruenzi and Weigert (2013), we define tail beta ($TRISK$) as the slope coefficient from a regression of stock excess returns on market excess returns using only daily observations in the bottom 10% of market excess returns over the past year. We require a minimum of 200 valid daily stock return observations to calculate each of these risk measures.

2.3 Funding Liquidity Measures

FP provide evidence that the betting against beta phenomenon is driven by funding liquidity. While funding liquidity has been shown to be closely related to market liquidity (Chen and Lu (2014)) and they have been jointly modeled (Brunnermeier and Pedersen (2009)), the two are fundamentally different concepts. Market liquidity is the ease with which a security can be traded in the secondary market. This characteristic, measured by Amihud's (2002) illiquidity measure ($ILLIQ$, discussed above), is a firm-level characteristic. Funding liquidity is a market-level characteristic that describes the general availability of financing to investors. Low funding liquidity essentially means that investors who employ leverage will be forced, by those financing their levered positions, to satisfy more restrictive margin requirements. When this happens, levered investors will be forced to liquidate positions, potentially at an undesirable time. Since different stocks have different margin requirements, in the cross-section, securities' prices—and thus returns—exhibit cross-sectional variation in their sensitivities to funding liquidity.

We measure the funding liquidity sensitivity of a stock relative to four widely accepted factors that proxy for funding liquidity (FP, Chen and Lu (2014), and the references therein). The first is the TED spread (TED), calculated as the difference between the three-month LIBOR rate and the rate on three-month U.S. Treasury bills.[7] The second is volatility of the TED spread ($VOLTED$), which is defined as the standard deviation of the daily TED spreads within the given month. FP use $VOLTED$ as a proxy for funding liquidity risk. The third is the U.S. Treasury bill rate ($TBILL$), taken to be the month-end rate on three-month U.S. Treasury bills. The fourth is financial sector leverage ($FLEV$), defined as the sum of total assets across all financial sector firms divided by the total market value of the equity of the firms in this sector. While financial sector leverage is not as widely used as TED or $TBILL$, it is perhaps the most appropriate measure of funding liquidity in this setting, since it directly measures the ability of financial institutions to provide leverage to investors.

Each of these aggregate funding liquidity proxies (TED, $VOLTED$, $TBILL$, and $FLEV$) are measured at a monthly frequency. Stock-level sensitivity to the TED spread (TED), denoted β_{TED}, is calculated as the slope coefficient from a regression of excess stock returns on TED using five

[7] As discussed in FP and Gârleanu and Pedersen (2011), the TED spread serves as a measure of funding conditions.

years worth of monthly data. Sensitivities to $VOLTED$, $TBILL$, and $FLEV$, denoted β_{VOLTED}, β_{TBILL}, and β_{FLEV}, respectively, are calculated analogously. We require a minimum of 24 valid monthly stock return observations to calculate these measures of exposure to aggregate funding liquidity.

As TED, $VOLTED$, $TBILL$, and $FLEV$ all take on low values when funding liquidity is high and vice versa, our measures may more aptly be termed sensitivities to funding *il*liquidity. Nevertheless, for simplicity and consistency with previous work, we continue to refer to β_{TED}, β_{VOLTED}, β_{TBILL}, and β_{FLEV} as measures of funding liquidity sensitivity.

2.4 Data Sources and Sample

Daily and monthly stock data were collected from the Center for Research in Security Prices (CRSP). Balance sheet data, used to calculate the book-to-market ratio and financial industry leverage ($FLEV$), come from Compustat. Daily and monthly market excess returns and risk factor returns are from Kenneth French's data library.[8] Three-month LIBOR and U.S. Treasury bill yields are downloaded from Global Insight.

The sample used throughout this paper covers the 593 months t from August 1963 through December 2012. Each month, the sample contains all U.S.-based common stocks trading on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ with a stock price at the end of month $t-1$ of \$5 or more.[9] Since month-end TED spread data are available beginning in January 1963 and a minimum of 24 months of data are required to calculate β_{TED}, analyses using β_{TED} cover the period January 1965 through December 2012. Similarly, the daily TED spread data required to calculate $VOLTED$ are available beginning in January 1977; thus analyses using β_{VOLTED} cover the period from January 1979 through December 2012.

3 Betting against Beta and Demand for Lottery

We begin by demonstrating the betting against beta and lottery demand phenomena.

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[9] U.S.-based common stocks are the CRSP securities with share code field (SHRCD) 10 or 11.

3.1 Betting Against Beta Phenomenon

The betting against beta phenomenon refers to the fact that a portfolio that is long high-beta stocks and short low-beta stocks generates a negative abnormal return. To demonstrate the betting against beta phenomenon, each month we sort all stocks in our sample into 10 decile portfolios based on an ascending sort of market beta (β), measured at the end of month $t-1$, with each portfolio having an equal number of stocks. The panel labeled β and Returns in Table 1 presents the time-series means of the individual stocks' β, the average monthly portfolio excess return (R), and the FFC4 alpha (FFC4 α) for the equal-weighted decile portfolios (columns labeled 1 through 10) and for the difference between decile 10 and decile 1 (column labeled High$-$Low).[10] The numbers in parentheses are t-statistics, adjusted following Newey and West (1987, NW hereafter) using six lags, testing the null hypothesis that the average excess return or FFC4 α is equal to zero.

The results in Table 1 show that the average market beta (β) increases monotonically (by construction) from a beta of -0.0007 for the first decile portfolio to a beta of 2.02 for the 10th decile. The average excess returns (R) of the beta-sorted decile portfolios tend to decrease, albeit not monotonically, from 0.69% per month for the low-beta decile (decile 1) to 0.35% for the high-beta decile (decile 10). The average monthly return difference between decile 10 and decile 1 (High–Low) of -0.35% per month is not statistically distinguishable from zero, indicating no difference in average returns between stocks with high market betas and stocks with low market betas. This result contrasts with the central prediction of the CAPM of a positive relation between market beta and expected return.

The abnormal returns of the decile portfolios relative to the FFC4 risk model exhibit a strong and nearly monotonically decreasing (the exception is decile 1) pattern across the deciles of market beta. The lowest beta decile portfolio's abnormal return of 0.22% per month is statistically significant, with a corresponding t-statistic of 2.22. On the other hand, the highest beta portfolio generates a significantly negative abnormal return of -0.29% per month (t-statistic = -2.22). The difference in abnormal returns between the high-beta and low-beta portfolios of -0.51% per month

[10] The FFC4 alpha is the estimated intercept coefficient from a regression of the excess portfolio return on the contemporaneous excess return of the market portfolio ($MKTRF$), the return of a zero-cost long-short size-based portfolio that is long stocks with low market capitalization and short stocks with high market capitalization (SMB), the return of a zero-cost long-short book-to-market ratio-based portfolio that is long stocks with high book-to-market ratios and short stocks with low book-to-market ratios (HML), and the return of a portfolio that is long stocks with high momentum and short stocks with low momentum (UMD).

is highly significant, with a t-statistic of -2.50.

The last result discussed in the previous paragraph, namely, the large negative FFC4 alpha of the High−Low portfolio, is the starting point for this paper. The result (FFC4 alpha) indicates that the betting against beta phenomenon documented by FP is both economically strong and statistically significant in our sample.[11]

To obtain an understanding of the composition of the beta portfolios, the remainder of Table 1 presents summary statistics for the stocks in the decile portfolios. Specifically, the table reports the average values of the firm characteristics, risk variables, and measures of funding liquidity sensitivity for the stocks in each portfolio, averaged across the months.

The results indicate that market beta (β) has a strong cross-sectional relation with each of the firm characteristic variables. β is positively related to lottery demand (MAX), market capitalization ($MKTCAP$), momentum (MOM), and idiosyncratic volatility ($IVOL$) and negatively related to the book-to-market ratio (BM) and illiquidity ($ILLIQ$). The final row in the Firm Characteristics panel of Table 1 presents the percentage of total market capitalization that is held in each beta decile. The results indicate that the low-beta portfolio holds a substantially smaller percentage of total market capitalization than the high-beta portfolio, with decile 1 comprising only 1.92% of total market capitalization and decile 10 holding 12.86%. The results in the Risk Measures panel show that co-skewness ($COSKEW$), downside beta ($DRISK$), and tail beta ($TRISK$) are all positively related to market beta (β), while total skewness ($TSKEW$) and market beta exhibit a negative relation.

Finally, Table 1 reports the cross-sectional average values of individual stocks' exposures to the funding liquidity factors. As discussed in Section 2.3, the TED spread, TED spread volatility, U.S. Treasury bill rates, and financial sector leverage all take on low values when funding liquidity is high. In other words, β_{TED}, β_{VOLTED}, β_{TBILL}, and β_{FLEV} are measures of funding illiquidity beta, indicating a theoretically negative link with future stock returns. As shown in the Funding Liquidity Measures panel of Table 1, the low-beta portfolio, which has higher alpha, contains stocks with lower levels of β_{TED} and β_{VOLTED} compared to the high-beta portfolio. Hence, the betting

[11]In Section II and Table A1 of the online appendix, we demonstrate that this result is robust to the use of alternative measures of beta developed by Scholes and Williams (1977) and Dimson (1979) designed to account for non-synchronous and infrequent trading, respectively. In Section IV and Table A3 of the online appendix, we demonstrate that the cross-sectional patterns in β decile portfolio performance are robust when using the manipulation-proof performance measure of Ingersoll, Spiegel, Goetzmann, and Welch (2007).

against beta phenomenon is potentially driven by funding liquidity risk as measured by β_{TED} or β_{VOLTED}. On the other hand, values of β_{TBILL} and β_{FLEV} are on average higher for stocks with low values of β than for stocks with high values of β. Therefore, β_{TBILL} and β_{FLEV} are unlikely to explain the betting against beta phenomenon.

3.2 Lottery Demand Phenomenon

As with the betting against beta phenomenon, we demonstrate the lottery demand phenomenon with a univariate decile portfolio analysis, this time sorting on MAX instead of β. The results are presented in Table 2. Consistent with Bali et al. (2011), we find a strong negative relation between MAX and future stock returns. The average monthly return difference between the decile 10 and decile 1 portfolios of -1.15% per month is both economically large and highly statistically significant, with a t-statistic of -4.41. Furthermore, with the exception of the first decile portfolio, the excess returns of the decile portfolios decrease monotonically across the deciles of MAX. The FFC4 alphas of the MAX decile portfolios exhibit patterns very similar to those of the excess returns. The abnormal return of the High$-$Low MAX portfolio of -1.40% per month is both large and highly significant (t-statistic = -8.95). As with the excess returns, the risk-adjusted alphas decrease monotonically from MAX decile 2 through decile 10. In Section III and Table A2 of the online appendix, we show that these results are robust when MAX is defined as the average of the k highest daily returns of the stock within the given month for $k \in \{1, 2, 3, 4, 5\}$.[12,13]

4 Lottery Demand Explains Betting against Beta

Having demonstrated that the betting against beta and lottery demand phenomena are both strong in our sample, we proceed to examine whether lottery demand, or any of the other firm characteristics, risk variables, or funding liquidity measures, can explain the betting against beta effect.

[12]In Section IV and Table A3 of the online appendix, we demonstrate that the cross-sectional patterns in MAX decile portfolio performance are robust when using the manipulation-proof performance measure of Ingersoll et al. (2007).

[13]In Section V and Table A4 of the online appendix, we demonstrate that the high (low) MAX portfolio is a high (low) MAX asset. In the spirit of Brown, Gregoriou, and Pascalau (2012), who show that tail risk (negative skewness) is not diversified away as funds of hedge funds become more diversified, we calculate the portfolio-level MAX for each of the decile portfolios sorted on MAX. We find that portfolio-level MAX increases monotonically across the MAX-sorted decile portfolios. The result indicates that MAX aggregates, in the sense that a lottery investor who invests in a large number of high MAX stocks has invested in a high-MAX portfolio.

4.1 Bivariate Portfolio Analysis

We begin by employing bivariate portfolio analyses to assess the relation between market beta and future stock returns after controlling for MAX and each of the other variables discussed in Table 1. Each month, we group all stocks in the sample into deciles based on an ascending sort of one of these variables, which we refer to as the control variable. We then sort all stocks in each of the control variable deciles into 10 decile portfolios based on an ascending ordering of β. The monthly excess return of each portfolio is calculated as the equal-weighted one-month-ahead excess return. Finally, each month, within each decile of β, we take the average portfolio return across all deciles of the control variable. Table 3 presents the time-series average excess returns of these portfolios for each decile of β, as well as for the High−Low β difference, the corresponding FFC4 alphas, and NW-adjusted t-statistics (in parentheses). The first column of the table indicates the control variable.

The results for the firm characteristic variables in Table 3 indicate that, after controlling for the effect of lottery demand by first sorting on MAX, the betting against beta phenomenon disappears, since the FFC4 alpha of the High−Low beta portfolio is only -0.14% per month, economically small, and statistically insignificant, with a t-statistic of -0.85. The magnitude of the alpha of this portfolio is slightly more than one-quarter of that generated by the unconditional portfolio analysis (Table 1) and less than half of the corresponding values for the other bivariate portfolio analyses presented in Table 3. This is our preliminary evidence that lottery demand explains the betting against beta phenomenon. In Section VI and Table A5 of the online appendix, we demonstrate that this result is robust when measuring lottery demand as the average of the k highest daily returns of the given stock within the given month, for $k \in \{1, 2, 3, 4, 5\}$. In Section VII and Table A6 of the online appendix, we demonstrate that the ability of lottery demand to explain the abnormal returns of the betting against beta phenomenon persists in periods of expansion and contraction, measured by positive and negative values, respectively, of the Chicago Fed National Activity Index (CFNAI), and that the result is not driven by the financial crisis of 2007 through 2009.

The remaining results in the Firm Characteristics portion of Table 3 indicate that the betting against beta phenomenon persists after controlling for market capitalization ($MKTCAP$), the book-to-market ratio (BM), momentum (MOM), illiquidity ($ILLIQ$), and idiosyncratic volatility

($IVOL$), since the FFC4 alpha of the High−Low market beta portfolio remains negative, economically large, and statistically significant after controlling for each of these variables. Thus, of the firm characteristics, only lottery demand explains the betting against beta phenomenon.

Moving on to the analyses that control for the risk measures and funding liquidity sensitivity measures, presented in the bottom two panels of Table 3, the results indicate that none of these variables are able to explain the betting against beta phenomenon. The FFC4 alphas of the High−Low beta portfolios in these analyses are very similar to those generated by the univariate portfolio analysis, ranging from -0.36% to -0.59% per month, with corresponding t-statistics between -2.22 and -3.02.

In summary, the results of the bivariate portfolio analyses indicate that lottery demand explains the betting against beta phenomenon, since the effect disappears when controlling for MAX. The betting against beta phenomenon persists when controlling for all other firm characteristics, risk measures, and funding liquidity sensitivities.

4.2 Regression Analysis

We continue our analysis of the betting against beta phenomenon by running FM regressions of future stock returns on market beta and combinations of the firm characteristic, risk, and funding liquidity sensitivity variables. Doing so allows us to simultaneously control for all other effects when assessing the relation between market beta and future stock returns.

Each month, we run a cross-sectional regression of one-month-ahead future stock excess returns (R) on β and combinations of the control variables. To isolate the effect of controlling for lottery demand on the relation between beta and future stock returns, we run each regression specification with and without MAX as an independent variable. The full cross-sectional regression specification is

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t-1} + \lambda_{2,t}MAX_{i,t-1} + \mathbf{\Lambda_t X_{i,t-1}} + \epsilon_{i,t} \quad (1)$$

where $X_{i,t-1}$ is a vector containing the measures of firm characteristics (excluding MAX), risk, and funding liquidity sensitivity. Table 4 presents the time-series averages of the regression coefficients, along with NW-adjusted t-statistics testing the null hypothesis that the average slope coefficient is equal to zero (in parentheses).

The left panel of Table 4 shows that when the regression specification does not include MAX (models (1) through (3)), the average coefficient on β is statistically indistinguishable from zero, with values ranging from 0.060 to 0.263 and t-statistics between 0.44 and 1.08. When MAX is added to the regression specification (models (4) through (6)), the average coefficients on β increase dramatically, becoming positive and statistically significant, with values ranging from 0.265 to 0.470 and t-statistics between 1.90 and 2.34. Compared to the corresponding regression specifications without MAX, including MAX as an independent variable increases the coefficient on β by at least 0.20. The regression analyses indicate that the inclusion of MAX as an independent variable results in the detection of a positive and statistically significant relation between β and future stock returns, consistent with theoretical predictions.

Interpreting the coefficient on β as an estimate of the market risk premium, the regression specification that includes all variables (regression model (6) in Table 4) indicates a market risk premium of 0.47% per month, or 5.64% per year. Alternatively, this coefficient suggests that, all else being equal, the difference in average monthly expected return for stocks in the highest quintile of market beta compared to stocks in the lowest quintile of market beta is 0.76% per month, or 9.12% per year.[14] Both of the numbers are quite reasonable estimates of the premium associated with taking market risk.

Consistent with the negative relation between lottery demand and future stock returns documented by Bali et al. (2011), the results in Table 4 reveal a strong negative cross-sectional relation between MAX and future stock returns after controlling for the other effects, since the average slopes on MAX range from -0.223 to -0.358, with corresponding t-statistics between -6.16 and -8.49.

The relations between firm characteristics and stock returns are also as predicted by previous research. The log of market capitalization ($SIZE$) exhibits a negative relation with future stock excess returns (R), while the analyses detect a positive relation between excess stock returns and the book-to-market ratio (BM) and momentum (MOM). The relation between illiquidity ($ILLIQ$) and excess stock returns is statistically insignificant. Consistent with the results of Ang, Hodrick,

[14] The average market beta for stocks in the first (fifth) beta quintile is 0.125 (1.740). These values are calculated by taking the average market beta from decile portfolios 1 and 2 (9 and 10) from Table 1. The difference of 1.615 (1.740−0.125) between the top- and bottom-quintile beta is then multiplied by the regression coefficient 0.47 to obtain 0.76% per month.

Xing, and Zhang (2006), when MAX is not included in the regression specification, the average coefficient on idiosyncratic volatility ($IVOL$) is negative and highly statistically significant. As demonstrated by Bali et al. (2011), when MAX is added to the specifications without the funding liquidity sensitivities, the coefficient on $IVOL$ flips signs and becomes positive. When funding liquidity sensitivities and MAX are included, the regression analysis detects no relation between idiosyncratic volatility and future stock returns.

As for the measures of risk, total skewness ($TSKEW$) exhibits a significantly negative relation with future stock returns. The results indicate no relation between stock returns and co-skewness ($COSKEW$) or tail beta ($TRISK$), since the average coefficients on these variables are small and statistically insignificant. In the specifications that include the full set of control variables, the regressions detect a negative relation between downside beta ($DRISK$) and future stock returns. The regressions fail to detect any relation between the measures of funding liquidity sensitivity (β_{TED}, β_{VOLTED}, β_{TBILL}, β_{FLEV}) and future stock returns, since the average slope on each of these variables is statistically insignificant in all specifications.

4.3 Bivariate Portfolio Analysis of β and MAX

We now present the results of a bivariate independent sort portfolio analysis of the relations between each of β and MAX and future stock returns. Each month, all stocks are grouped into deciles based on independent ascending sorts of both β and MAX. The intersections of each of the decile groups are then used to form 100 portfolios. To better understand the relation between β and MAX, Figure 1 presents a heat map of the number of stocks in each of the 100 portfolios. Light purple cells represent a high number of stocks, while light blue cells represent portfolios with a small number of stocks. The figure shows that stocks with high (low) market betas also tend to have high (low) values of MAX. The figure also indicates that across all levels of β and MAX, there appears to be a strong positive relation, since portfolios along the diagonal from the bottom left to the top right of the map tend to contain more stocks than portfolios holding high-beta and low-MAX stocks or vice versa.

Table 5 presents the time-series average monthly excess returns for each of the equal-weighted portfolios. The row (column) labeled High−Low shows the returns of the zero-cost portfolio that is long the β (MAX) decile 10 portfolio and short the β (MAX) decile 1 portfolio within the given decile of MAX (β), and the FFC4 α row (column) presents the corresponding abnormal returns relative to the FFC4 model.

The last two rows of Table 5 show that the betting against beta effect disappears after controlling for MAX in independent bivariate portfolios. Specifically, within each MAX decile, the average return and alpha differences between the high-β and low-β portfolios are economically and statistically insignificant. In unreported results, we find that the average High$-$Low β portfolio across all deciles of MAX generates an average monthly return of -0.03% (t-statistic $= -0.13$) and an FFC4 alpha of -0.15% per month (t-statistic $= -0.76$). Consistent with previous analyses, these results indicate that the negative risk-adjusted return of the High$-$Low β portfolio is driven by the relation between β and MAX, since the effect disappears when the portfolios are constructed to be neutral to MAX. The analysis demonstrates that the betting against beta phenomenon is a manifestation of lottery demand.

The last two columns of Table 5 show that the negative relation between MAX and future stock returns persists after controlling for the effect of β. Within each β decile, the High$-$Low MAX portfolio generates economically large and statistically significant average returns ranging from -0.81% to -1.94% per month. The average High$-$Low MAX portfolio (unreported) generates an average return of -1.33% per month, with a corresponding t-statistic of -6.59. Examination of the risk-adjusted returns leads to similar conclusions, since the FFC4 alphas of the High$-$Low MAX portfolios range from -1.23% to -2.20% per month, with t-statistics between -2.70 and -7.43. The FFC4 alpha of the average High$-$Low MAX portfolio (unreported) is -1.64% per month (t-statistic $= -9.99$). The results therefore demonstrate that the negative relation between MAX and future excess stock returns (R) is not driven by market beta, since the relation persists after controlling for β.

The results of the independent bivariate sort portfolio analysis indicate that the betting against beta phenomenon is driven by the relation between lottery demand and future stock returns. The negative relation between lottery demand and stock returns, however, persists after controlling for market beta. To assess the robustness of these relations to the design of the portfolio analysis, we repeat the analysis using a dependent sort procedure, sorting first on MAX and then on β and then using the alternative sort order. The results of these analyses, presented in Section VII and

Table A7 of the online appendix, are consistent with the independent sort analyses.[15]

4.4 Orthogonal Components of β and MAX

Our final examinations of the joint roles of market beta and lottery demand in predicting future stock returns are univariate portfolio analyses using the portion of β that is orthogonal to MAX ($\beta_{\perp MAX}$) and the portion of MAX that is orthogonal to β ($MAX_{\perp\beta}$) as sort variables. $\beta_{\perp MAX}$ is calculated as the intercept term plus the residual from a cross-sectional regression of β on MAX. $MAX_{\perp\beta}$ is calculated analogously by taking the intercept plus the residual from a cross-sectional regression of MAX on β.

The top of Table 6 presents the results of a univariate portfolio analysis using the portion of β that is orthogonal to MAX ($\beta_{\perp MAX}$) as the sort variable. The results show that the average values of $\beta_{\perp MAX}$ are quite similar in magnitude to the average values of β for the β decile portfolios (see Table 1), with average values ranging from -0.02 for the $\beta_{\perp MAX}$ decile 1 portfolio to 1.90 for the decile 10 portfolio. The similarities between the portfolios end here, however. Looking first at the excess returns, we find that the High$-$Low $\beta_{\perp MAX}$ portfolio generates a positive but insignificant average monthly return of 0.13%, compared to a negative and insignificant return of -0.35% for the β-sorted portfolios. More importantly, the FFC4 alpha of the High$-$Low $\beta_{\perp MAX}$ portfolio of 0.05% per month is statistically indistinguishable from zero. Furthermore, the abnormal returns of each of the $\beta_{\perp MAX}$ decile portfolios are statistically indistinguishable from zero, with decile 2 being the one exception. The results indicate that the abnormal returns of the portfolios formed by sorting on β are a manifestation of the relation between MAX and β, since the effect disappears when only the portion of β that is orthogonal to MAX is used to form the portfolios. The betting against beta phenomenon does not exist when only the portion of market beta that is orthogonal to lottery demand is used to form the portfolios.

The results of the univariate portfolio analysis of the relation between $MAX_{\perp\beta}$ and future excess stock returns (R), presented in the last panel of Table 6, indicate that $MAX_{\perp\beta}$ has a strong negative cross-sectional relation with future stock returns, since the -1.19% average monthly return difference between the decile 10 and decile 1 portfolios is highly statistically significant, with a t-

[15] A summary of the dependent sort analysis sorting on MAX and then β was previously presented in the first row of the Firm Characteristics panel in Table 3.

statistic of −6.72. Similarly, the four-factor alpha of the High−Low portfolio is −1.44% (t-statistic = −10.62). Furthermore, the abnormal returns of the portfolios decrease monotonically across deciles of $MAX_{\perp\beta}$. Consistent with previous analyses (Table 5), the results indicate that the negative relation between MAX and future stock returns is not driven by the relation between MAX and β, since the univariate portfolio analysis results generated using $MAX_{\perp\beta}$ as the sort variable are very similar to those from the analysis sorting on MAX.[16]

In this section, we have used several different implementations of portfolio and regression analysis to disentangle the joint relation between market beta, lottery demand, and future stock returns. The results lead to two conclusions. First and most importantly, the analyses demonstrate that the betting against beta phenomenon documented by FP is driven by the demand for lottery-like assets. Using several different approaches to control for the effect of lottery demand, we find that all approaches indicate that once the effect of lottery demand is accounted for, the betting against beta phenomenon ceases to exist. Second, the negative relation between lottery demand and future stock returns persists after accounting for the effect of market beta.

5 Lottery Demand Price Pressure

Having demonstrated that the betting against beta phenomenon is explained by lottery demand, we now further examine the channel via which lottery demand impacts the slope of the capital market line. Specifically, we investigate our hypothesis that high lottery demand stocks are also predominantly high beta stocks, resulting in lottery demand-based upward price pressure on high-beta stocks. The result of this price pressure is an increase in the prices of high lottery demand—and therefore high-beta—stocks, and a corresponding decrease in the future returns of such stocks. Additionally, following Kumar (2009), who demonstrates that demand for lottery-like stocks is driven by individuals and not by institutional investors, we demonstrate that the betting against beta phenomenon only exists among stocks with a low proportion of institutional owners and disappears in stocks that are largely held by institutions. We find the same effect in the lottery demand phenomenon.

[16] In Section V and Table A4 of the online appendix, we demonstrate that the high (low) $MAX_{\perp\beta}$ portfolio is in fact a high (low) MAX asset. We show that portfolio-level MAX for $MAX_{\perp\beta}$-sorted portfolios is nearly monotonically increasing across the $MAX_{\perp\beta}$ deciles, indicating that a lottery investor who invests in a large number of high $MAX_{\perp\beta}$ stocks has invested in a high-MAX portfolio.

5.1 Correlation between β and MAX

We begin by analyzing the cross-sectional relation between lottery demand and beta. If high lottery demand stocks are also predominantly high beta stocks, we expect a strong positive cross-sectional relation between β and MAX. The increasing average MAX values across deciles of β observed in Table 1 provides preliminary evidence that this is the case. Here, we examine this relation in more detail.

Each month, we calculate the cross-sectional Pearson product moment correlations between β and MAX, which we denote $\rho_{\beta,MAX}$. β and MAX are highly cross-sectionally correlated, since the average (median) value of $\rho_{\beta,MAX}$ is 0.30 (0.29). Furthermore, values of $\rho_{\beta,MAX}$ range from -0.03 to 0.84, with only four of the 593 months in the sample period generating a negative cross-sectional correlation between β and MAX. Consistent with our hypothesis, therefore, in most months, lottery stocks are predominantly high-beta stocks. Price pressure exerted by lottery demand will therefore fall disproportionately on high-beta stocks, resulting in a flattening of the security market line, which is tantamount to the betting against beta phenomenon.

5.2 Betting against Beta and $\rho_{\beta,MAX}$

The driving factor behind our explanation for why lottery demand generates the betting against beta phenomenon is that lottery demand-based price pressure falls heavily on high-beta stocks. As discussed previously, in the average month, this is the case. However, there are several months in which the cross-sectional correlation between β and MAX is not high, meaning that lottery demand-based price pressure should fall nearly equally on high- and low-beta stocks. If our hypothesis for why lottery demand produces the betting against beta effect is correct, then the betting against beta phenomenon should exist only in months in which lottery demand-based price pressure is predominantly exerted on high-beta stocks. When the price pressure exerted by lottery demand is similar for low-beta and high-beta stocks, the betting against beta phenomenon should not exist. To test whether this is the case, we divide the months in our sample into those with high and low cross-sectional correlation between β and MAX ($\rho_{\beta,MAX}$) and analyze the returns of the β-sorted decile portfolios in each of these subsets. High-$\rho_{\beta,MAX}$ (low-$\rho_{\beta,MAX}$) months are taken to be those months with values of $\rho_{\beta,MAX}$ greater than or equal to (less than) the median $\rho_{\beta,MAX}$.

Panel A of Table 7 presents the results of univariate portfolio analyses of the relation between β and future excess stock returns (R) for the high- and low-$\rho_{\beta,MAX}$ months. The results show that, in high-$\rho_{\beta,MAX}$ months, the High$-$Low β portfolio generates an economically large, albeit statistically insignificant, average monthly return of -0.68%. The FFC4 alpha of -0.72% per month is highly statistically significant, with a t-statistic of -2.86. In low-$\rho_{\beta,MAX}$ months, the average High$-$Low portfolio return is -0.01% per month and the risk-adjusted alpha is only -0.26% per month, both statistically indistinguishable from zero. Consistent with the hypothesis that the betting against beta effect is a manifestation of disproportionate lottery demand price pressure on high-beta stocks, the phenomenon only exists in months in which the cross-sectional relation between MAX and β is high. When these two variables are not strongly related, betting against beta fails to generate economically important or statistically significant abnormal returns.

To demonstrate that lottery demand-based price pressure persists in both high-$\rho_{\beta,MAX}$ and low-$\rho_{\beta,MAX}$ months, we present the results of univariate portfolio analyses of the relation between MAX and future excess stock returns (R) for each subset of months in Panel B of Table 7. In high-$\rho_{\beta,MAX}$ months, the average High$-$Low return of -1.55% per month and FFC4 alpha of -1.76% per month are economically large and highly statistically significant. In months in which $\rho_{\beta,MAX}$ is low, the relation remains strong, since the average High$-$Low return of -0.74% per month is both economically and statistically significant (t-statistic $= -2.26$). The same is true for the risk-adjusted alpha of -1.05% per month (t-statistic $= -5.77$). The results demonstrate that the effect of lottery demand on prices exists in both high-$\rho_{\beta,MAX}$ and low-$\rho_{\beta,MAX}$ months. Interestingly, this effect appears to be stronger in months in which $\rho_{\beta,MAX}$ is high. As demonstrated in the next section, high-$\rho_{\beta,MAX}$ months are characterized by high aggregate lottery demand, that is, months in which lottery demand has a stronger cross-sectional impact on prices.

5.3 Aggregate Lottery Demand and $\rho_{\beta,MAX}$

The next check of our proposed channel via which lottery demand generates the betting against beta phenomenon is to examine the economic conditions in months characterized by high and low correlation between beta and MAX ($\rho_{\beta,MAX}$). Specifically, we examine the level of aggregate lottery demand in high- and low-$\rho_{\beta,MAX}$ correlation months. Since substantial aggregate lottery demand is a necessary component of the link between lottery demand and the betting against beta effect and the betting against beta phenomenon only exists in high-$\rho_{\beta,MAX}$ months, we expect high-$\rho_{\beta,MAX}$ months to be characterized by high aggregate lottery demand.

We use five measures of aggregate lottery demand. The first three are the Aruoba-Diebold-Scotti Business Conditions Index (ADS), the Chicago Fed National Activity Index (CFNAI), and the volatility of daily market returns during the given month.[17] Our fourth measure is the value of MAX calculated for the market portfolio and our final measure is the value-weighted average value of MAX across all stocks in the sample. The results of these analyses, presented and discussed in detail in Section VIII and Table A8 of the online appendix, demonstrate that aggregate lottery is significantly higher during months with high cross-sectional correlation between β and MAX. High-$\rho_{\beta,MAX}$ months are more likely to be categorized as recessions (CFNAI and ADS) and to have high market volatility, market MAX, and average MAX than low-$\rho_{\beta,MAX}$ months.

5.4 Institutional Holdings and Betting against Beta

Our final analysis demonstrating that the abnormal returns of the betting against beta strategy are driven by lottery demand-based price pressure examines the strength of the betting against beta phenomenon among stocks with differing levels of institutional ownership. An implication of the FP story is that the betting against beta phenomenon is strongest for those stocks with the greatest degree of institutional ownership (pension funds and mutual funds), since these investors would be expected to face the most serious margin constraints. Kumar (2009) demonstrates that lottery demand is prominent among individual investors but not among institutional investors. If the betting against beta phenomenon is in fact driven by lottery demand, the alpha of the betting against beta strategy is expected to be concentrated in stocks with low institutional ownership and to not exist in stocks predominantly owned by institutions. To measure institutional holdings, we define $INST$ to be the fraction of total shares outstanding that are owned by institutional investors as of the end of the most recent fiscal quarter. Values of $INST$ are collected from the Thomson-Reuters Institutional Holdings (13F) database.

To examine the strength of the betting against beta phenomenon among stocks with differing levels of institutional ownership, we use a bivariate dependent sort portfolio analysis. Each month,

[17]Kumar (2009) demonstrates that aggregate lottery demand is highest during economic downturns. ADS and CFNAI are designed to measure overall economic conditions. High market volatility is indicative of deteriorating economic conditions.

all stocks in the sample are grouped into deciles based on an ascending sort of the percentage of shares owned by institutional investors ($INST$). Within each decile of $INST$, we form decile portfolios based on an ascending sort of β. In Panel A of Table 8, we present the time-series average of the one-month-ahead equal-weighted portfolio returns for each of the 100 resulting portfolios, as well as the average return, FFC4 alpha, and associated t-statistics, of the High–Low β portfolio within each decile of $INST$. The results demonstrate that the betting against beta phenomenon is very strong among stocks with low institutional ownership and non-existent for stocks with high institutional ownership. The magnitudes of the average returns and FFC4 alphas of the High–Low β portfolio are decreasing (nearly monotonically) across the deciles of $INST$. For decile one through decile five of $INST$, the average returns and FFC4 alphas of the High–Low β portfolios are negative, economically large, and highly statistically significant. For $INST$ decile seven through decile 10, the returns and alphas of the High–Low β portfolios are statistically insignificant. The betting against beta strategy, therefore, generates large abnormal returns when implemented on stocks with low institutional holdings but is ineffective when implemented only on stocks with high institutional holdings, consistent with our hypothesis that demand for lottery generates the betting against beta phenomenon.

To ensure that, in our sample, it is in fact individual investors that drive the lottery demand phenomenon, we repeat the bivariate dependent sort portfolio analysis, sorting on $INST$ and then MAX. As shown in Panel B of Table 8, the magnitudes of the returns and FFC4 alphas of the High–Low MAX portfolios are the largest and most statistically significant in the low deciles of $INST$, and decrease substantially across the deciles of $INST$. The results demonstrate that, among stocks with low institutional ownership, the lottery demand phenomenon is strong, but for stocks with a high degree of institutional ownership, the lottery demand phenomenon does not exist.

In summary, in this section, we provide strong evidence that a disproportionate amount of lottery demand-based price pressure on high-beta stocks generates the betting against beta phenomenon. Specifically, we show that there is high cross-sectional correlation between β and MAX, indicating that lottery demand price pressure is predominantly exerted on high-beta stocks. We then show that in months where this correlation is low (high), the betting against beta portfolio does not (does) generate significant abnormal returns, indicating that when lottery demand does not (does) place disproportionate price pressure on high-beta stocks, the betting against beta effect is non-existent (strong). In other words, without lottery demand-based priced pressure on high-beta stocks, the betting against beta phenomenon does not exist. Since substantial aggregate lottery demand is a necessary component of our proposed mechanism, we show that months with a high cross-sectional correlation between β and MAX—months when the betting against beta phenomenon exists—are characterized by high aggregate lottery demand and poor economic conditions. Finally, we show that the betting against beta phenomenon only exists in stocks that are most susceptible to lottery demand price pressure, namely, those stocks with low institutional ownership.

6 Lottery-Demand Factor

We proceed now to generate a factor capturing the returns associated with lottery demand. We then show that this lottery demand factor explains both the returns of the High−Low β portfolio as well as the returns of the BAB factor generated by FP.

We form our lottery-demand factor, denoted FMAX, using the factor-forming technique pioneered by Fama and French (1993). Each month, we sort all stocks into two groups based on market capitalization, with the breakpoint dividing the two groups based on the median market capitalization of stocks traded on the NYSE. We independently sort all stocks in our sample into three groups based on an ascending sort of MAX. The intersections of the two market capitalization-based groups and the three MAX groups generate six portfolios. The FMAX factor return is taken to be the average return of the two value-weighted high-MAX portfolios minus the average return of the two value-weighted low-MAX portfolios. As such, the FMAX factor portfolio is designed to capture returns associated with lottery demand while maintaining neutrality to market capitalization. The FMAX factor generates an average monthly return of -0.54% with an NW t-statistic of -2.55.

6.1 FMAX Factor and β-Sorted Portfolio

We now assess the abnormal returns of the β-based portfolios relative to four different factor models. The first model is the FFC4 model used throughout this paper. We then augment this model with

Pastor and Stambaugh's (2003) traded liquidity factor (PS).[18] Each of these models is then further augmented with the FMAX factor. The portfolios used in our analysis are the same univariate β-sorted decile portfolios used to generate the results in Table 1.

Panel A of Table 9 presents the risk-adjusted alphas (column labeled α) as well as factor sensitivities of the High−Low β portfolio, using each of the factor models. Using the FFC4 model, as seen previously, the High−Low β portfolio generates an economically large and statistically significant risk-adjusted return of −0.51% (t-statistic = −2.50) per month. The portfolio also has significant positive sensitivities to the market factor (MKTRF) and the size factor (SMB) and negative sensitivities to the value factor (HML) and momentum factor (UMD). Including the PS factor in the model (FFC4+PS) has very little effect on the abnormal return or the factor sensitivities. Using this model, the alpha of the High−Low portfolio is −0.49% per month, with a t-statistic of −2.26.

Inclusion of the FMAX factor in the risk model has dramatic effects on both the abnormal returns and factor sensitivities. When the FFC4 model is augmented with the FMAX factor (FFC4+FMAX), the alpha of the High−Low portfolio of 0.06% per month is both economically small and statistically indistinguishable from zero, with a t-statistic of 0.35. A similar result holds when the illiquidity factor is also included (FFC4+PS+FMAX). Using this model, the High−Low β portfolio's alpha is 0.04% per month, with a t-statistic of 0.22. The results indicate that the inclusion of the lottery demand factor (FMAX) in the factor model explains the abnormal returns of the High-Low β portfolio. Furthermore, inclusion of the FMAX factor substantially decreases the sensitivity of the High−Low β portfolio to the market (MKTRF), size (SMB), and value (HML) factors, with the size factor sensitivity being statistically indistinguishable from zero in models that include FMAX. The portfolio is highly sensitive to the FMAX factor, since the sensitivities using the FFC4+FMAX and FFC4+PS+FMAX models of 0.85 (t-statistic = 12.49) and 0.82 (t-statistic = 11.72), respectively, are highly statistically significant.

For robustness, we repeat the analysis in Panel A of Table 9 using only months with high correlation between β and MAX and then, again, using only months with low correlation. The results of these analyses, presented in Section IX and Table A9 of the online appendix, show that in

[18]The PS factor returns are only available for months beginning with January 1968. Thus, analyses that include the PS factor are restricted to this time period.

high-correlation months, augmenting the FFC4 or FFC4+PS factor models with FMAX explains the abnormal returns of the High−Low beta portfolio. For low-correlation months, the High−Low β portfolio does not generate significant risk-adjusted returns relative to the FFC4 or FFC4+PS model. When the FMAX factor is appended to the model, the estimated alpha goes from negative to positive but remains statistically insignificant. The results therefore indicate that even in states of the world in which the betting against beta phenomenon is strong, the FMAX factor explains the returns associated with the High−Low β portfolio. There are no instances in which the High−Low β portfolio generates significant returns relative to a model that includes the FMAX factor.

In Panel B of Table 9, we present the abnormal returns for the β-sorted decile portfolios using each of the factor models. The results for the FFC4 and FFC4+PS models show that the alpha of the High−Low β portfolio is generated by both the high-β and low-β portfolios, since these portfolios have abnormal returns of −0.29% (t-statistic = −2.22) and 0.22% (t-statistic = 2.22), respectively, for the FFC4 model and −0.26% (t-statistic = −1.91) and 0.23% (t-statistic = 2.12), respectively, for the FFC4+PS model. Thus, both the high-β and low-β portfolios generate economically important and statistically significant abnormal returns, with the magnitude of the abnormal returns of the high-β and low-β portfolios being approximately the same. Furthermore, the alphas of the portfolios are nearly monotonically decreasing across the deciles of β.

When the FMAX factor is added to the FFC4 factor model, neither the low-β nor high-β portfolio generates abnormal returns that are statistically distinguishable from zero, since the high-β (low-β) portfolio generates an alpha of 0.14% per month, with a t-statistic of 1.37 (0.08% per month, with a t-statistic of 0.85), using the FFC4+FMAX model. The results are similar when using the FFC4+PS+FMAX model. Furthermore, the alphas of the decile portfolios using models that include FMAX are not monotonic. The results indicate that inclusion of the FMAX factor in the factor model explains not only the alpha of the High−Low portfolio, but also the alpha of the each of the high-β and low-β portfolios, along with any patterns in the alphas across the β deciles.

6.2 BAB Factor or FMAX Factor

Having demonstrated that augmenting standard factor models with the FMAX factor explains the abnormal returns of the High−Low β portfolio, we proceed by analyzing the returns of FP's BAB factor using factor models that include our lottery demand factor, FMAX, and vice versa.

We obtained monthly U.S. equity BAB factor returns for August 1963 through March 2012 from Lasse Pedersen's website.[19] Each month, FP create the BAB factor by forming two portfolios, one holding stocks with market betas that are below the median beta and the other holding stocks with above-median betas.[20] The low-beta (high-beta) portfolio is weighted such that stocks with the lowest (highest) betas have the highest weights. Both the low-beta and high-beta portfolios are then rescaled to have a weighted average beta of one. The BAB factor return is then taken to be the excess return of the low-beta portfolio minus the excess return of the high-beta portfolio. It is worth noting that this portfolio is constructed to be neutral to market beta, not to have equal dollars invested in the long and short portfolios. The difference in market values between the long and short portfolios is accounted for by borrowing at the risk-free rate or investing in the risk-free security. As such, the BAB factor portfolio is a zero-cost, beta-neutral portfolio.[21]

We analyze the BAB factor by regressing its monthly returns against the returns of the market portfolio (MKTRF), as well as the size (SMB), value (HML), momentum (UMD), liquidity (PS), and lottery demand (FMAX) factors. The results of the analysis using different models are presented in Panel A of Table 10. Consistent with the results of FP, we find that the BAB factor generates an economically large and statistically significant alpha of 0.54% (0.57%) per month relative to the FFC4 (FFC4+PS) risk model. As expected, given the construction of the portfolio, the BAB factor returns exhibit no statistically discernable relation to the market portfolio. The returns are positively related to the value factor (HML) and momentum (UMD) factor returns.

When the FMAX factor is included in the model, the results in Panel A of Table 10 indicate that the BAB factor no longer generates statistically positive abnormal returns, since the alphas relative to the FFC4+FMAX and FFC4+PS+FMAX models are 0.17% (t-statistic = 1.23) and 0.22% (t-statistic = 1.39) per month, respectively. The results show that the premium captured by the BAB factor is completely explained by the inclusion of the FMAX factor in the model. The results also indicate substantial negative covariation in the returns of the BAB and FMAX factors, since the sensitivity of the BAB factor returns to the FMAX factor is -0.55 (t-statistic = -11.84)

[19] The data were downloaded from http://www.lhpedersen.com/data. BAB factor returns for April 2012 through December 2012 were not available.

[20] The calculation of market beta used by FP is not the same as our measure's. The details of their measure of market beta are presented in their Section 3.1 and equation (14). We address this issue in robustness checks discussed in Section 6.3.

[21] The details of generating the BAB factor are presented in FP's Section 3.2 and equations (16) and (17).

using the FFC4+FMAX model and −0.54 (t-statistic = −11.11) using the FFC4+PS+FMAX model. Furthermore, the adjusted R-squared values of the factor regressions increase dramatically from around 22% when the FMAX factor is not included in the risk model to approximately 47% when FMAX is included. Interestingly, despite the intent to design the BAB factor portfolio to have no sensitivity to the excess market portfolio returns, when the FMAX factor is included in the risk model, the regressions detect a positive and highly statistically significant sensitivity of the BAB factor returns to the market excess return. This result is consistent with our earlier findings in multivariate cross-sectional regressions. As presented in Table 4, when MAX is included as an independent variable in the FM regressions, the average slope on β becomes positive and statistically significant. In Section X and Table A10 of the online appendix, we demonstrate that when lottery demand is measured using the k highest daily returns of the given stock, $k \in \{1, 2, 3, 4, 5\}$, and the lottery demand factor is created based on these alternative lottery demand measures, the ability of the lottery demand factor to explain the returns of the BAB factor is robust.

We now repeat the factor analysis, reversing the roles of FMAX and BAB. The results are presented in Panel B of Table 10. Consistent with previous results, the FFC4 and FFC4+PS factor models both indicate that the FMAX factor generates abnormal returns, since the alphas of −0.67% and −0.65% per month, respectively, are highly statistically significant (t-statistics of −5.12 and −4.60, respectively). When the BAB factor is added to the risk models, the FMAX factor alphas of −0.35% (t-statistic = −2.88) and −0.32% (t-statistic = −2.32) per month for the FFC4+BAB and FFC4+PS+BAB models, respectively, remain economically large and highly statistically significant. Similar to Panel A, the regressions detect a statistically significant negative relation between the FMAX and BAB factor returns. Despite substantial covariation between the BAB and FMAX factors, the results show that the premium captured by the FMAX factor is not explained by the BAB factor.[22]

[22] In unreported analyses, we find that the time-series correlation between the sentiment index of Baker and Wurgler (2006) and the FMAX factor of -0.18 is highly statistically significant. The results are similar when using FMAX factors created from alternative definitions of MAX as the average of the one, two, three, four, or five highest daily returns of the stock within the given month. This indicates that when sentiment is high, FMAX is low (large negative return), indicating that investors have higher demand for lottery-like stocks when sentiment is high and hence are willing to accept lower returns on such stocks, consistent with the main finding of Stambaugh, Yu, and Yuan (2012).

6.3 Frazzini and Pedersen's Beta and Sample

The previously presented results give strong indications that the betting against beta phenomenon documented by FP is actually a manifestation of lottery demand. However, there are a few notable differences between the analyses performed by FP and those in this paper. The first is that FP use a different methodology to estimate market beta. The second is that FP use a sample that includes all stocks, while we exclude stocks with a market price of less than \$5 per share. In Section XI of the online appendix, we demonstrate that the results presented throughout this paper are robust to the use of FP's measure of beta and the different sample constructions.

In summary, in this section (Section 6) we created a lottery demand factor, FMAX, and examined its ability to explain the returns associated with the betting against beta phenomenon. We find that the alpha of the High−Low β portfolio is economically small and statistically indistinguishable from zero when FMAX is included in the factor model. We also show that the FMAX factor explains the returns of the BAB factor generated by FP, since the abnormal returns of the BAB factor are statistically insignificant relative to factor models that include FMAX. The opposite is not the case, however, since augmenting standard risk models with the BAB factor fails to explain the abnormal returns of the FMAX factor. Finally, we show that our results are not driven by sample differences or differences in the calculation of market beta between this paper and FP's. In short, we demonstrate that the FMAX factor explains the betting against beta phenomenon, but the betting against beta factor cannot explain the lottery demand phenomenon.

7 Conclusion

Frazzini and Pedersen (2014) demonstrate that an investment strategy that takes a short position in stocks with high market beta and a long position in stocks with low market beta generates economically large abnormal returns relative to standard risk models. In their highly acclaimed paper, Frazzini and Pedersen develop an equilibrium model in which leverage constraints generate this betting against beta phenomenon. Consistent with the model's predictions, they demonstrate that the phenomenon is present in the markets for several different security classes in many different nations. The prevalence and persistence of the betting against beta phenomenon in security markets makes understanding its drivers a topic of great importance for both financial market participants and researchers.

In this paper, we find strong empirical confirmation of Frazzini and Pedersen's findings using data from U.S. equity markets. Their findings are robust to the definitions of the variables used and the characteristics of their sample. We propose a behavioral phenomenon, demand for lottery-like assets (Kumar (2009), Bali et al. (2011)), as an alternative driver of the betting against beta effect. Lottery demanders exert upward price pressure on stocks with high probabilities of large up moves. Since such up moves are partially driven by sensitivity to the market portfolio, lottery demanders put disproportionate upward price pressure on high-beta stocks. This results in a flattening of the security market line and positive alpha for a portfolio that is long low-beta stocks and short high-beta stocks, consistent with the betting against beta phenomenon reported by FP.

Measuring lottery demand using MAX, defined as the average of the five highest daily returns over the past month, we find strong and robust evidence that controlling for MAX explains the betting against beta phenomenon. Bivariate portfolio analyses demonstrate that the abnormal returns of the betting against beta portfolio disappear when the portfolio is constructed to be neutral to MAX. Fama and MacBeth (1973) regressions show that market beta is positively related to future stock returns when the regression specification includes MAX. Univariate portfolio analysis that sorts on the portion of beta that is orthogonal to MAX fails to detect a pattern in returns. When our lottery demand factor, FMAX, is included in factor models, the abnormal returns of the betting against beta portfolio become economically small and statistically indistinguishable from zero. We also find that the FMAX factor explains the returns of the betting against beta factor generated by Frazzini and Pedersen (2014). In all of our analyses, the economic and statistical significance of the lottery demand phenomenon persists after controlling for the betting against beta effect. Several measures of firm characteristics, risk, and sensitivity to funding liquidity factors fail to explain the betting against beta phenomenon.

We also show that the channel by which lottery demand generates the betting against beta is disproportionate lottery demand price pressure on high-beta stocks. Our results demonstrate that, in the average month, market beta and lottery demand have a high positive cross-sectional correlation, indicating that lottery demand-based price pressure falls predominantly on high-beta stocks. We also find that when this correlation is low (high), the betting against beta phenomenon disappears (is strong), indicating that disproportionate lottery demand-based price pressure on high-beta stocks is in fact the driver of the betting against beta phenomenon. Additionally, we demonstrate that the months in which this effect is strongest are characterized by high aggregate lottery demand and poor economic conditions. Finally, consistent with previous evidence that lottery demand is attributable to individual, not institutional, investors, we show that the betting against beta phenomenon only exists in stocks that have low institutional ownership.

The results provide overwhelming support for our conclusion that, in the U.S. equity markets, the abnormal returns generated by a portfolio that has short positions in high-beta stocks and long positions in low-beta stocks are driven by demand for lottery-like stocks. This does not at all rule out the possibility that the funding liquidity explanation presented by Frazzini and Pedersen (2014) explains the betting against beta phenomenon in other markets or in other countries. Their results persist not only in 20 different international equity markets, but also in the markets for U.S. Treasury bonds, corporate bonds, and futures. Generalization of the results in our study beyond the scope of the U.S. equity markets therefore represents an important direction for future research.

References

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

Ang, A., Chen, J., and Xing, Y. 2006. Downside risk. Review of Financial Studies, 19(4), 1191–1239.

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.

Baker, M. and Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance, 61(4), 1645–1680.

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.

Barberis, N. and Huang, M. 2008. Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review, 98(5), 2066–2100.

Black, F. 1972. Capital market equilibrium with restricted borrowing. The Journal of Business, 45(3), 444–455.

Black, F., Jensen, M. C., and Scholes, M. S. *Studies in the Theory of Capital Markets*, chapter The Capital Asset Pricing Model: Some Empirical Tests. Praeger, New York, 1972.

Blume, M. E. and Friend, I. 1973. A new look at the capital asset pricing model. Journal of Finance, 28(1), 19–33.

Brennan, M. J. 1971. Capital market equilibrium with divergent borrowing and lending rates. Journal of Financial and Quantitative Analysis, 6(5), 1197–1205.

Brown, S. J., Gregoriou, G. N., and Pascalau, R. 2012. Diversification in funds of hedge funds: Is it possible to overdiversify? Review of Asset Pricing Studies, 2(1), 89–110.

Brunnermeier, M. K. and Pedersen, L. H. 2009. Market liquidity and funding liquidity. Review of Financial Studies, 22(6), 2201–2238.

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

Chen, Z. and Lu, A. 2014. A market-based funding liquidity measure. SSRN eLibrary.

Dimson, E. 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics, 7(2), 197–226.

Elton, E. J., Gruber, M. J., Brown, S. J., and Goetzmann, W. N. *Modern Portfolio Theory and Investment Analysis*. John Wiley & Sons, Hoboken, NJ, ninth edition, 2014.

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 MacBeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607.

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

Gârleanu, N. and Pedersen, L. H. 2011. Margin-based asset pricing and deviations from the law of one price. Review of Financial Studies, 24(6), 1980–2022.

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

Ingersoll, J., Spiegel, M., Goetzmann, W., and Welch, I. 2007. Portfolio performance manipulation and manipulation-proof performance measures. Review of Financial Studies, 20(5), 1503–1546.

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.

Kelly, B. T. and Jiang, H. 2013. Tail risk and asset prices. Working Paper, University of Chicago.

Kumar, A. 2009. Who gambles in the stock market? Journal of Finance, 64(4), 1889–1933.

Lakonishok, J. and Shapiro, A. 1986. Systematic risk, total risk and size as determinants of stock market returns. Journal of Banking & Finance, 10(1), 115–132.

Lintner, J. 1965. Security prices, risk, and maximal gains from diversification. Journal of Finance, 20(4), 687–615.

Mossin, J. 1966. Equilibrium in a capital asset market. Econometrica, 34(4), 768–783.

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

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

Reinganum, M. R. 1981. A new empirical perspective of the CAPM. Journal of Quantitive and Empirical Finance, 16(4), 439–462.

Ruenzi, S. and Weigert, F. 2013. Crash sensitivity and the cross-section of expected stock returns. Working Paper, University of Mannheim.

Scholes, M. and Williams, J. T. 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics, 5(3), 309–327.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19(3), 425–442.

Shumway, T. 1997. The delisting bias in CRSP data. Journal of Finance, 52(1), 327–340.

Stambaugh, R. F., Yu, J., and Yuan, Y. 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics, 104(2), 288–302.

Thaler, R. H. and Ziemba, W. T. 1988. Paramutuel betting markets: Racetracks and lotteries. Journal of Economic Perspectives, 2(2), 161–174.

Tversky, A. and Kahneman, D. 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5(4), 297–323.

Table 1: Univariate Portfolios Sorted on β

Each month, all stocks are sorted into ascending β decile portfolios. The panel labeled β and Returns presents the time-series means of the monthly equal-weighted portfolio betas (β), excess returns (R), and Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α). The column labeled High-Low presents the mean difference between decile ten and decile one. t-statistics, adjusted following Newey and West (1987), testing the null hypothesis of a zero mean or alpha, are shown in parentheses. The Firm Characteristics panel presents the average firm characteristics among firms in each of the decile portfolios. The firm characteristics are market capitalization ($MKTCAP$), log of book-to-market ratio (BM), momentum (MOM), illiquidity ($ILLIQ$), idiosyncratic volatility ($IVOL$), and lottery demand (MAX). The row labeled Mkt Shr presents the percentage of total market capitalization in each portfolio. The Risk Measures panel shows average portfolio values of co-skewness ($COSKEW$), total skewness ($TSKEW$), downside beta ($DRISK$), and tail beta ($TRISK$). The Funding Liquidity Measures panel displays average portfolio values of TED spread sensitivity (β_{TED}), TED spread volatility sensitivity (β_{VOLTED}), sensitivity to the yield on U.S. Treasury bills (β_{TBILL}), and financial sector leverage sensitivity (β_{FLEV}). The sample covers the months from August of 1963 through December of 2012 and includes all U.S. based publicly traded common stocks with share price of at least $5.

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
						β and Returns					
β	-0.00	0.25	0.42	0.56	0.70	0.84	1.00	1.19	1.46	2.02	
R	0.69	0.78	0.78	0.77	0.81	0.73	0.71	0.65	0.51	0.35	-0.35
	(3.74)	(3.90)	(3.74)	(3.54)	(3.42)	(2.90)	(2.66)	(2.26)	(1.58)	(0.89)	(-1.13)
FFC4 α	0.22	0.24	0.16	0.11	0.10	-0.02	-0.05	-0.11	-0.18	-0.29	-0.51
	(2.22)	(2.77)	(2.31)	(1.59)	(1.69)	(-0.30)	(-0.80)	(-1.83)	(-2.20)	(-2.22)	(-2.50)
						Firm Characteristics					
MAX	2.52	2.37	2.52	2.66	2.82	3.01	3.22	3.50	3.90	4.61	
$MKTCAP$	288	1,111	1,636	1,827	1,689	1,619	1,652	1,794	1,894	1,775	
BM	1.10	1.04	0.95	0.90	0.86	0.83	0.80	0.76	0.72	0.65	
MOM	17.03	16.33	17.15	17.50	17.99	18.77	20.37	22.63	25.83	35.74	
$ILLIQ$	3.75	1.92	1.30	1.07	0.94	0.79	0.69	0.59	0.48	0.35	
$IVOL$	2.01	1.80	1.83	1.88	1.95	2.03	2.13	2.27	2.47	2.79	
Mkt Shr	1.92%	4.71%	7.52%	9.14%	10.16%	11.20%	12.73%	14.59%	15.17%	12.86%	
						Risk Measures					
$COSKEW$	-4.75	-5.02	-5.34	-5.30	-5.22	-5.03	-4.89	-4.82	-4.52	-1.96	
$TSKEW$	0.86	0.67	0.57	0.51	0.47	0.45	0.44	0.44	0.44	0.47	
$DRISK$	0.09	0.35	0.52	0.67	0.81	0.95	1.11	1.31	1.58	2.10	
$TRISK$	0.13	0.41	0.60	0.74	0.87	1.02	1.18	1.38	1.65	2.15	
						Funding Liquidity Measures					
β_{TED}	-2.10	-1.88	-1.60	-1.56	-1.52	-1.54	-1.53	-1.35	-0.99	-0.10	
β_{VOLTED}	-11.41	-10.25	-7.82	-6.23	-5.32	-5.54	-4.89	-4.64	-3.77	-1.19	
β_{TBILL}	-0.51	-0.54	-0.55	-0.56	-0.58	-0.60	-0.64	-0.71	-0.79	-0.94	
β_{FLEV}	-0.54	-0.61	-0.68	-0.72	-0.76	-0.80	-0.83	-0.87	-0.88	-0.91	

Table 2: Univariate Portfolios Sorted on MAX

Each month, all stocks are sorted into ascending MAX decile portfolios. The table presents the time-series means of the monthly equal-weighted portfolio values of MAX, excess returns (R), and Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α). The column labeled High-Low presents the mean difference between decile ten and decile one. t-statistics, adjusted following Newey and West (1987), testing the null hypothesis of a zero mean or alpha, are shown in parentheses.

Value	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
MAX	0.66	1.25	1.69	2.09	2.49	2.91	3.41	4.04	4.98	7.62	
R	0.74	1.00	0.96	0.94	0.90	0.82	0.80	0.67	0.36	-0.40	-1.15
	(4.07)	(4.95)	(4.59)	(4.25)	(3.84)	(3.29)	(2.93)	(2.29)	(1.10)	(-1.11)	(-4.41)
FFC4 α	0.27	0.42	0.35	0.30	0.23	0.12	0.08	-0.07	-0.38	-1.14	-1.40
	(3.01)	(5.90)	(5.89)	(5.18)	(3.95)	(2.20)	(1.53)	(-1.50)	(-6.05)	(-10.43)	(-8.95)

Table 3: Bivariate Portfolio Analyses of Relation Between β and Returns

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between market beta (β) and future stock returns after controlling for firm characteristics (Firm Characteristics panel), measures of risk (Risk Measures panel), and measures of funding liquidity sensitivity (Funding Liquidity Measures panel). Each month, all stocks are sorted into 100 portfolios based on dependent decile sorts on the control variable and then β. The table presents the time-series means of equal-weighted excess returns (R) for the average control variable decile portfolio within each decile of β, as well as the mean return differences between the high and low beta portfolios (High-Low), and the Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α) for the High-Low portfolios. t-statistics for the High-Low returns and FFC4 alphas, adjusted following Newey and West (1987) using six lags, are in parentheses.

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	FFC4 α
Firm Characteristics												
MAX	0.70	0.69	0.67	0.68	0.67	0.70	0.66	0.65	0.70	0.68	-0.02	**-0.14**
											(-0.10)	**(-0.85)**
$MKTCAP$	0.62	0.69	0.78	0.77	0.80	0.80	0.73	0.70	0.56	0.35	-0.28	-0.45
											(-0.91)	(-2.48)
BM	0.66	0.65	0.67	0.72	0.69	0.70	0.70	0.65	0.70	0.59	-0.06	-0.33
											(-0.26)	(-1.87)
MOM	0.74	0.81	0.85	0.76	0.81	0.77	0.71	0.65	0.54	0.29	-0.45	-0.63
											(-1.83)	(-3.55)
$ILLIQ$	0.68	0.78	0.79	0.80	0.78	0.79	0.76	0.67	0.56	0.24	-0.44	-0.56
											(-1.42)	(-3.16)
$IVOL$	0.78	0.77	0.75	0.71	0.71	0.70	0.66	0.59	0.60	0.51	-0.28	-0.41
											(-1.17)	(-2.36)
Risk Measures												
$COSKEW$	0.72	0.77	0.75	0.78	0.70	0.74	0.68	0.67	0.60	0.37	-0.35	-0.50
											(-1.23)	(-2.60)
$TSKEW$	0.69	0.75	0.78	0.79	0.77	0.75	0.71	0.66	0.56	0.32	-0.37	-0.52
											(-1.24)	(-2.63)
$DRISK$	0.77	0.76	0.73	0.79	0.72	0.71	0.67	0.60	0.62	0.42	-0.35	-0.36
											(-2.36)	(-2.97)
$TRISK$	0.75	0.75	0.79	0.75	0.72	0.67	0.73	0.65	0.59	0.37	-0.38	-0.45
											(-1.46)	(-2.63)
Funding Liquidity Measures												
β_{TED}	0.70	0.79	0.74	0.78	0.70	0.72	0.64	0.57	0.50	0.31	-0.40	-0.54
											(-1.58)	(-2.88)
β_{VOLTED}	0.80	0.89	0.85	0.82	0.81	0.81	0.75	0.73	0.64	0.40	-0.40	-0.59
											(-1.18)	(-2.22)
β_{TBILL}	0.76	0.80	0.85	0.80	0.77	0.79	0.72	0.71	0.61	0.45	-0.43	-0.57
											(-1.57)	(-3.02)
β_{FLEV}	0.74	0.81	0.85	0.76	0.81	0.77	0.71	0.65	0.54	0.29	-0.34	-0.52
											(-1.32)	(-2.82)

Table 4: Fama-MacBeth Regressions

The table below presents the results of Fama and MacBeth (1973) regression analyses of the relation between market beta and future stock returns. Each month, we run a cross-sectional regression of one-month-ahead stock excess returns (R) on β and combinations of the firm characteristics, risk measures, and funding liquidity sensitivity measures. The table presents the time-series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the average coefficient is equal to zero, are shown in parentheses. The row labeled n presents the average number of observations used in the monthly cross-sectional regressions. The average adjusted r-squared of the cross-sectional regressions is presented in the row labeled Adj. R^2.

	Regressions without MAX			**Regressions with MAX**		
	(1)	(2)	(3)	(4)	(5)	(6)
β	0.060	0.174	0.263	**0.265**	**0.427**	**0.470**
	(0.44)	(0.97)	(1.08)	**(1.93)**	**(2.34)**	**(1.90)**
MAX				-0.355	-0.358	-0.223
				(-8.43)	(-8.49)	(-6.16)
$SIZE$	-0.176	-0.180	-0.101	-0.165	-0.168	-0.102
	(-4.51)	(-4.70)	(-2.57)	(-4.26)	(-4.41)	(-2.70)
BM	0.176	0.176	0.181	0.189	0.186	0.173
	(3.00)	(3.03)	(2.81)	(3.20)	(3.17)	(2.71)
MOM	0.008	0.008	0.007	0.008	0.008	0.007
	(5.89)	(6.21)	(5.87)	(5.52)	(5.80)	(5.11)
$ILLIQ$	-0.011	-0.011	-0.012	-0.010	-0.011	-0.009
	(-0.64)	(-0.64)	(-1.13)	(-0.60)	(-0.64)	(-0.79)
$IVOL$	-0.345	-0.339	-0.266	0.110	0.117	-0.023
	(-11.90)	(-11.85)	(-8.34)	(1.84)	(1.97)	(-0.55)
$COSKEW$		-0.006	-0.010		-0.008	-0.011
		(-1.01)	(-1.16)		(-1.30)	(-1.20)
$TSKEW$		-0.065	-0.045		-0.043	-0.044
		(-3.57)	(-2.42)		(-2.37)	(-2.39)
$DRISK$		-0.053	-0.240		-0.097	-0.260
		(-0.55)	(-1.78)		(-1.03)	(-1.96)
$TRISK$		-0.057	-0.036		-0.060	-0.036
		(-1.50)	(-0.69)		(-1.50)	(-0.65)
β_{TED}			-0.005			-0.005
			(-0.37)			(-0.37)
β_{VOLTED}			-0.001			-0.001
			(-0.35)			(-0.39)
β_{TBILL}			0.009			-0.009
			(0.33)			(-0.36)
β_{FLEV}			-0.024			-0.032
			(-0.80)			(-1.15)
Intercept	2.121	2.144	1.754	2.076	2.096	1.827
	(6.94)	(7.01)	(5.09)	(6.86)	(6.90)	(5.46)
n	2,450	2,450	2,931	2,450	2,450	2,931
Adj. R^2	6.56%	6.99%	6.34%	6.97%	7.37%	6.54%

Table 5: Bivariate Independent Sort Portfolio Analysis of β and MAX

The table below presents the results of an independent sort bivariate portfolio analysis of the relation between future stock returns and each of market beta (β) and MAX. The table shows the time-series means of the monthly equal-weighted excess returns for portfolios formed on intersections of β and MAX deciles. t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the mean monthly High-Low return difference or Fama and French (1993) and Carhart (1997) four-factor alpha is equal to zero, are in parentheses.

	MAX 1	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10	High - Low	FFC4 α
β 1 (Low)	0.61	0.94	0.94	1.05	0.96	0.93	0.86	0.71	0.66	-0.20	-0.81	-1.31
											(-2.75)	(-5.43)
β 2	0.71	1.00	0.95	0.92	0.77	0.97	1.00	0.68	0.47	-0.20	-0.92	-1.23
											(-3.98)	(-5.95)
β 3	0.77	0.94	1.00	0.92	0.83	0.88	0.78	0.85	0.44	-0.55	-1.32	-1.57
											(-5.41)	(-6.97)
β 4	0.92	1.03	0.92	0.88	1.00	0.75	0.65	0.75	0.24	-0.37	-1.28	-1.60
											(-5.60)	(-7.43)
β 5	1.00	0.98	1.04	1.08	0.95	0.73	0.79	0.66	0.34	-0.26	-1.26	-1.48
											(-4.68)	(-5.91)
β 6	1.10	1.04	1.00	0.93	0.96	0.78	0.70	0.59	0.24	-0.43	-1.50	-1.82
											(-5.74)	(-6.93)
β 7	0.90	1.14	0.95	0.77	0.89	0.88	0.87	0.56	0.35	-0.22	-1.19	-1.48
											(-3.82)	(-5.29)
β 8	1.38	1.10	0.94	0.82	0.85	0.81	0.85	0.72	0.41	-0.40	-1.75	-2.20
											(-5.54)	(-6.39)
β 9	1.45	0.87	0.97	0.88	0.84	0.73	0.80	0.54	0.22	-0.45	-1.94	-2.11
											(-4.36)	(-5.05)
β 10 (High)	0.33	1.36	1.32	1.25	0.93	0.78	0.66	0.79	0.28	-0.65	-1.05	-1.58
											(-1.83)	(-2.70)
High-Low	-0.19	0.40	0.36	0.16	-0.05	-0.16	-0.20	0.07	-0.38	-0.42		
	(-0.35)	(1.05)	(0.94)	(0.47)	(-0.15)	(-0.51)	(-0.60)	(0.23)	(-1.15)	(-1.09)		
FFC4 α	0.00	-0.03	0.02	0.05	-0.29	-0.30	-0.30	0.02	-0.38	-0.31		
	(0.00)	(-0.08)	(0.04)	(0.16)	(-0.96)	(-1.12)	(-1.18)	(0.06)	(-1.61)	(-1.02)		

Table 6: Univariate Portfolios Sorted on $\beta_{\perp MAX}$ and $MAX_{\perp\beta}$

The table below presents the time-series averages of monthly average sort variable values, excess returns (R), and Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α) for decile portfolios formed by sorting on each of the portion of β that is orthogonal to MAX ($\beta_{\perp MAX}$) and the portion of MAX that is orthogonal to β ($MAX_{\perp\beta}$). t-statistics testing the null hypothesis that the average excess return or alpha is equal to zero, adjusted following Newey and West (1987) using six lags, are in parentheses.

Sort Variable	**Value**	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
$\beta_{\perp Max}$	$\beta_{\perp MAX}$	-0.02	0.31	0.47	0.60	0.73	0.85	0.99	1.16	1.40	1.90	
	R	0.45	0.70	0.71	0.71	0.74	0.79	0.77	0.73	0.61	0.58	0.13
		(2.01)	(3.43)	(3.36)	(3.21)	(3.17)	(3.21)	(2.99)	(2.66)	(2.00)	(1.56)	(0.50)
	FFC4 α	-0.11	0.16	0.11	0.05	0.05	0.07	0.02	-0.03	-0.09	-0.06	0.05
		(-1.12)	(2.11)	(1.58)	(0.90)	(0.91)	(1.23)	(0.40)	(-0.56)	(-1.17)	(-0.49)	(0.25)
$MAX_{\perp\beta}$	$Max_{\perp\beta}$	-0.03	0.57	0.91	1.24	1.57	1.94	2.38	2.94	3.81	6.44	
	R	0.90	0.91	0.89	0.85	0.90	0.82	0.77	0.61	0.43	-0.29	-1.19
		(3.75)	(4.21)	(4.19)	(3.83)	(3.92)	(3.36)	(3.00)	(2.24)	(1.49)	(-0.88)	(-6.72)
	FFC4 α	0.35	0.34	0.31	0.25	0.27	0.14	0.07	-0.11	-0.33	-1.09	-1.44
		(3.85)	(5.77)	(5.68)	(4.92)	(5.19)	(2.97)	(1.41)	(-2.22)	(-6.11)	(-11.99)	(-10.62)

Table 7: Univariate Portfolios for Months with High and Low $\rho_{\beta,MAX}$

The table below presents the time-series averages of monthly average sort variable values, excess returns (R), and Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α) for decile portfolios formed by sorting on β (Panel A) and MAX (Panel B). Each panel presents results for the subset of months when the cross-sectional correlation between β and MAX ($\rho_{\beta,MAX}$) is high and low, where the cutoff between high and low $\rho_{\beta,MAX}$ is taken to be the median month's cross-sectional correlation of 0.2917. t-statistics testing the null hypothesis that the average excess return or alpha is equal to zero, adjusted following Newey and West (1987) using six lags, are in parentheses.

Panel A: Portfolios Sorted on β

$\boldsymbol{\rho_{\beta,MAX}}$	**Value**	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
High	β	0.05	0.27	0.43	0.57	0.71	0.86	1.02	1.23	1.52	2.09	
	R	0.74	0.88	0.93	0.94	1.02	0.84	0.81	0.68	0.40	0.05	-0.68
		(2.72)	(2.86)	(2.86)	(2.65)	(2.67)	(2.07)	(1.86)	(1.42)	(0.74)	(0.08)	(-1.34)
	FFC4 α	0.23	0.29	0.29	0.24	0.30	0.09	0.07	-0.05	-0.23	-0.49	-0.72
		(1.84)	(2.56)	(3.35)	(2.52)	(3.30)	(1.14)	(0.72)	(-0.56)	(-1.83)	(-2.76)	(-2.86)
Low	β	-0.06	0.23	0.41	0.55	0.69	0.83	0.98	1.16	1.41	1.94	
	R	0.65	0.69	0.62	0.61	0.60	0.61	0.61	0.62	0.62	0.64	-0.01
		(3.00)	(3.07)	(2.83)	(2.68)	(2.44)	(2.39)	(2.29)	(2.15)	(1.92)	(1.54)	(-0.02)
	FFC4 α	0.19	0.18	0.01	-0.03	-0.10	-0.12	-0.17	-0.18	-0.17	-0.08	-0.26
		(1.21)	(1.32)	(0.12)	(-0.32)	(-1.39)	(-1.54)	(-2.63)	(-2.70)	(-1.93)	(-0.40)	(-0.86)

Panel B: Portfolios Sorted on MAX

$\boldsymbol{\rho_{\beta,MAX}}$	**Value**	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
High	MAX	0.61	1.19	1.67	2.12	2.54	3.00	3.52	4.18	5.15	7.71	
	R	0.84	1.16	1.11	1.05	1.01	0.92	0.89	0.73	0.28	-0.71	-1.55
		(2.89)	(3.59)	(3.30)	(3.01)	(2.73)	(2.30)	(2.00)	(1.54)	(0.54)	(-1.22)	(-3.97)
	FFC4 α	0.31	0.56	0.50	0.45	0.37	0.25	0.18	0.00	-0.45	-1.44	-1.76
		(2.53)	(5.65)	(5.59)	(5.50)	(4.32)	(3.07)	(2.15)	(0.04)	(-4.52)	(-9.14)	(-7.63)
Low	MAX	0.71	1.32	1.71	2.07	2.43	2.83	3.30	3.90	4.81	7.53	
	R	0.65	0.84	0.82	0.83	0.78	0.72	0.71	0.60	0.43	-0.09	-0.74
		(3.43)	(3.96)	(3.72)	(3.59)	(3.14)	(2.84)	(2.58)	(2.03)	(1.27)	(-0.23)	(-2.26)
	FFC4 α	0.18	0.25	0.20	0.14	0.10	0.00	0.00	-0.15	-0.32	-0.87	-1.05
		(1.63)	(2.73)	(2.41)	(1.85)	(1.31)	(-0.03)	(-0.03)	(-2.44)	(-3.82)	(-7.03)	(-5.77)

Table 8: Institutional Holdings, Betting Against Beta, and Lottery Demand
The table below presents the results of dependent sort bivariate portfolio analyses of the relation between future stock returns and each of market beta (β, Panel A) and lottery demand (MAX, panel B) after controlling for institutional holdings ($INST$). The table shows the time-series means of the monthly equal-weighted excess returns for portfolios formed by sorting all stocks into deciles of $INST$ and then, within each decile of $INST$, into deciles of β or MAX. t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the mean monthly High-Low return difference or Fama and French (1993) and Carhart (1997) four-factor alpha is equal to zero, are in parentheses.

Panel A: Portfolios Sorted on $INST$ then β

	$INST$ 1	$INST$ 2	$INST$ 3	$INST$ 4	$INST$ 5	$INST$ 6	$INST$ 7	$INST$ 8	$INST$ 9	$INST$ 10
β 1 (Low)	0.45	0.93	0.85	0.82	0.85	0.74	0.68	0.86	0.76	0.75
β 2	0.59	1.08	0.94	0.82	0.91	0.77	0.90	0.74	0.78	0.84
β 3	0.72	0.75	0.80	0.91	0.82	0.78	0.83	0.84	0.90	0.67
β 4	0.67	0.86	0.91	0.76	0.81	0.87	0.92	0.88	0.84	0.99
β 5	0.76	0.76	0.78	0.88	0.95	0.76	0.85	0.89	0.91	0.90
β 6	0.61	0.47	0.63	0.59	0.66	0.64	0.95	0.72	0.81	0.94
β 7	0.45	0.47	0.45	0.71	0.70	0.68	0.74	0.92	0.95	1.03
β 8	0.37	0.24	0.37	0.50	0.50	0.60	1.02	0.98	0.93	1.05
β 9	-0.30	-0.27	0.17	0.20	0.24	0.58	0.65	0.77	0.92	1.21
β 10 (High)	-1.16	-0.87	-0.44	-0.31	-0.06	0.10	0.50	0.81	0.88	1.18
High-Low	-1.61	-1.80	-1.29	-1.13	-0.91	-0.64	-0.18	-0.05	0.12	0.43
	(-4.42)	(-4.10)	(-2.87)	(-2.44)	(-1.98)	(-1.43)	(-0.43)	(-0.12)	(0.29)	(1.02)
FFC4 α	-1.91	-1.91	-1.31	-1.22	-1.01	-0.75	-0.18	-0.03	0.11	0.41
	(-6.88)	(-6.00)	(-3.59)	(-3.15)	(-3.07)	(-2.77)	(-0.64)	(-0.10)	(0.31)	(1.17)

Panel B: Portfolios Sorted on $INST$ then MAX

	$INST$ 1	$INST$ 2	$INST$ 3	$INST$ 4	$INST$ 5	$INST$ 6	$INST$ 7	$INST$ 8	$INST$ 9	$INST$ 10
MAX 1 (Low)	0.53	0.83	0.57	0.86	0.69	0.84	0.86	1.00	1.17	1.06
MAX 2	0.94	0.97	1.00	1.02	0.95	0.91	1.09	1.13	1.03	1.11
MAX 3	0.99	0.96	0.93	1.05	1.01	0.96	1.07	0.89	1.04	1.01
MAX 4	0.79	0.93	0.94	1.08	0.83	0.88	0.89	1.03	0.86	0.93
MAX 5	0.88	0.85	1.02	0.91	0.82	0.86	1.02	0.87	0.86	0.91
MAX 6	0.69	0.44	0.62	0.79	0.93	0.60	0.84	0.72	0.93	0.91
MAX 7	0.43	0.55	0.60	0.63	0.72	0.67	0.94	0.75	0.81	0.87
MAX 8	0.18	0.33	0.54	0.36	0.44	0.72	0.65	0.87	0.95	0.89
MAX 9	-0.48	-0.32	0.03	-0.13	0.22	0.34	0.44	0.72	0.50	0.94
MAX 10 (High)	-1.82	-1.12	-0.80	-0.68	-0.23	-0.26	0.21	0.46	0.56	0.92
High-Low	-2.36	-1.94	-1.37	-1.53	-0.92	-1.10	-0.64	-0.54	-0.60	-0.14
	(-6.54)	(-5.32)	(-3.01)	(-3.71)	(-2.09)	(-2.71)	(-1.67)	(-1.42)	(-1.72)	(-0.41)
FFC4 α	-2.68	-2.14	-1.55	-1.73	-1.11	-1.22	-0.80	-0.65	-0.74	-0.19
	(-9.18)	(-7.58)	(-4.93)	(-6.33)	(-3.60)	(-4.35)	(-2.82)	(-2.25)	(-2.57)	(-0.73)

Table 9: Factor Sensitivities and Risk-Adjusted Alphas for β Portfolios
Panel A presents factor sensitivities of the High-Low univariate sort beta portfolio returns using several different risk models. The columns labeled β_F, $F \in \{MKTRF, SMB, HML, UMD, PS, FMAX\}$, present the factor sensitivities. N indicates the number of months for which factor returns are available. Adj. R^2 is the adjusted r-squared of the factor model regression. Panel B presents the risk-adjusted alphas for each of the decile portfolios, as well as the High-Low β portfolio, for each of the risk models. t-statistics, adjusted following Newey and West (1987) using six lags, are in parentheses.

Panel A: Factor Sensitivities

	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{FMAX}	N	Adj. R^2
FFC4	-0.51	0.98	0.58	-0.74	-0.21			593	73.43%
	(-2.50)	(13.46)	(8.26)	(-6.36)	(-2.68)				
FFC4+PS	-0.49	0.98	0.53	-0.77	-0.24	-0.09		540	74.58%
	(-2.26)	(13.17)	(7.34)	(-6.60)	(-3.05)	(-1.35)			
FFC4+FMAX	**0.06**	0.61	0.09	-0.30	-0.19		0.85	593	84.79%
	(0.35)	(10.31)	(1.12)	(-4.69)	(-4.11)		(12.49)		
FFC4+PS+FMAX	**0.04**	0.63	0.07	-0.32	-0.21	-0.03	0.82	540	85.06%
	(0.22)	(10.50)	(0.92)	(-4.79)	(-4.21)	(-0.75)	(11.72)		

Panel B: Portfolio Alphas

	(Low)	2	3	4	5	6	7	8	9	(High)	High-Low
FFC4	0.22	0.24	0.16	0.11	0.10	-0.02	-0.05	-0.11	-0.18	-0.29	-0.51
	(2.22)	(2.77)	(2.31)	(1.59)	(1.69)	(-0.30)	(-0.80)	(-1.83)	(-2.20)	(-2.22)	(-2.50)
FFC4 + PS	0.23	0.24	0.16	0.10	0.09	-0.03	-0.07	-0.10	-0.18	-0.26	-0.49
	(2.12)	(2.51)	(2.09)	(1.34)	(1.36)	(-0.48)	(-1.04)	(-1.76)	(-2.18)	(-1.91)	(-2.26)
FFC4 + FMAX	**0.08**	0.06	-0.04	-0.09	-0.05	-0.15	-0.12	-0.10	-0.01	**0.14**	**0.06**
	(0.85)	(0.83)	(-0.66)	(-1.64)	(-0.92)	(-2.56)	(-2.01)	(-1.69)	(-0.17)	**(1.37)**	**(0.35)**
FFC4 + PS + FMAX	**0.10**	0.07	-0.03	-0.09	-0.06	-0.16	-0.15	-0.11	-0.03	**0.14**	**0.04**
	(0.92)	(0.86)	(-0.55)	(-1.64)	(-1.14)	(-2.66)	(-2.26)	(-1.71)	(-0.36)	**(1.23)**	**(0.22)**

Table 10: Factor Sensitivities for BAB and FMAX Factors

The table below presents the alphas and factor sensitivities for the BAB factor (Panel A) and the FMAX factor (Panel B) using several factor models. The column labeled α presents the risk-adjusted alpha for each of the factor models. The columns labeled β_f, $f \in \{MKTRF, SMB, HML, UMD, PS, FMAX, BAB\}$ present the sensitivities of the BAB or FMAX factor returns to the given factor. The BAB factor is taken from Lasse H. Pedersen's website. The sample covers the period from August of 1963 through March of 2012. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the coefficient is equal to zero. The column labeled N indicates the number of monthly returns used to fit the factor model. The column labeled Adj. R^2 presents the adjusted r-squared of the factor model regression.

Panel A: Sensitivities of BAB Factor

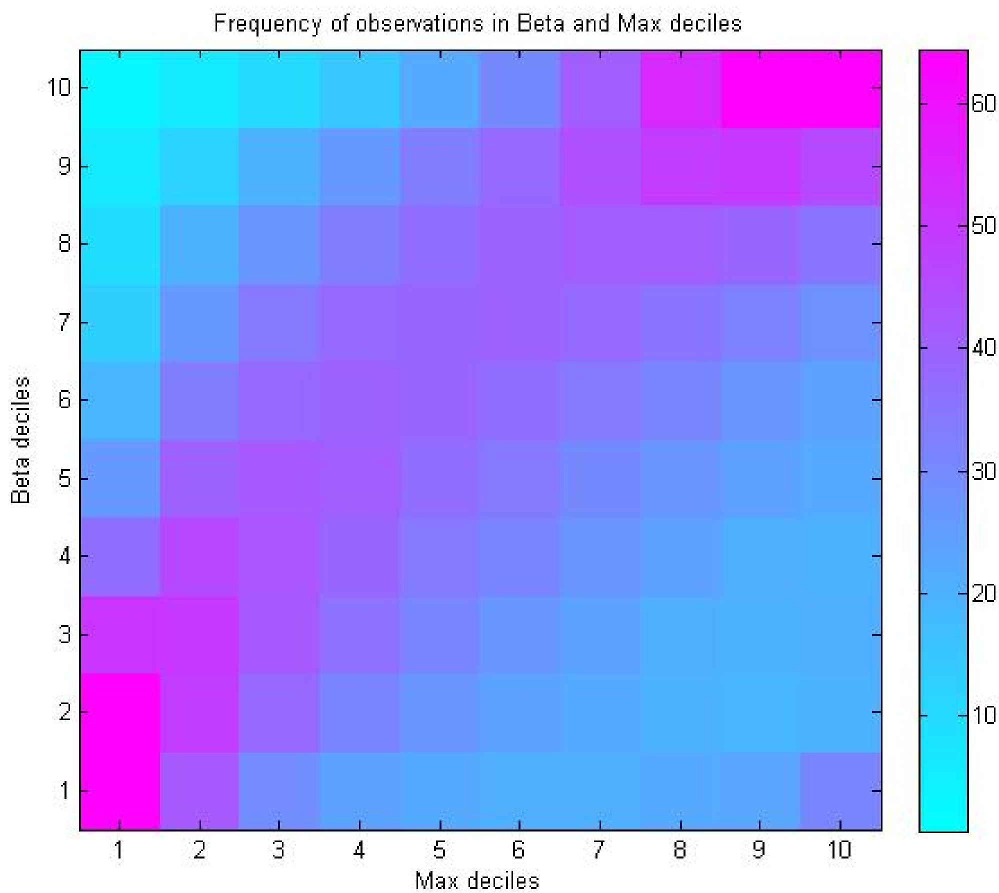
Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{FMAX}	N	Adj. R^2
FFC4	0.54	0.05	-0.01	0.51	0.18			584	21.03%
	(3.38)	(1.06)	(-0.09)	(5.01)	(2.87)				
FFC4+PS	0.57	0.06	0.02	0.53	0.20	0.06		531	23.44%
	(3.34)	(1.23)	(0.30)	(5.18)	(3.13)	(0.96)			
FFC4+FMAX	**0.17**	0.29	0.31	0.21	0.17		-0.55	584	46.95%
	(1.23)	(8.22)	(5.46)	(3.49)	(4.39)		(-11.84)		
FFC4+PS+FMAX	**0.22**	0.29	0.32	0.24	0.19	0.03	-0.54	531	47.38%
	(1.39)	(7.96)	(5.29)	(3.72)	(4.43)	(0.63)	(-11.11)		

Panel B: Sensitivities of FMAX Factor

Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{BAB}	N	Adj. R^2
FFC4	-0.67	0.43	0.58	-0.53	-0.01			584	62.24%
	(-5.12)	(8.36)	(6.39)	(-4.59)	(-0.19)				
FFC4+PS	-0.65	0.42	0.56	-0.54	-0.03	-0.06		540	62.36%
	(-4.60)	(8.17)	(5.51)	(-4.72)	(-0.41)	(-1.00)			
FFC4+BAB	-0.35	0.46	0.58	-0.23	0.09		-0.60	584	74.64%
	(-2.88)	(13.06)	(8.22)	(-3.09)	(1.67)		(-11.44)		
FFC4+PS+BAB	-0.32	0.46	0.57	-0.24	0.09	-0.02	-0.59	531	74.20%
	(-2.32)	(12.66)	(7.35)	(-3.11)	(1.46)	(-0.55)	(-10.90)		

Figure 1: Heat Map of β and MAX

The figure below is a heat map of the number of stocks in the 100 portfolios formed using an independent decile sort on β and MAX. The colors in each of the cells indicate the average number of stocks in each of the portfolios, as shown by the scale on the right side of the map.



Betting Against Beta or Demand for Lottery

Online Appendix

Section I provides details on the calculation of the variables used in the paper. In Section II we demonstrate that the insignificant relation between β and future stock returns and the negative and significant relation between β and risk-adjusted alpha (the betting against beta phenomenon) are robust when using alternative measures of market beta. In Section III we show that the negative relation between lottery demand and stock returns is robust to alternative measures of lottery demand. In Section IV we examine the betting against beta and lottery demand phenomena using the manipulation proof performance measure of Ingersoll, Spiegel, Goetzmann, and Welch (2007). In Section V we demonstrate that MAX aggregates by showing that the high (low) MAX portfolio is itself a high (low) MAX asset. Section VI presents the results of bivariate-sort analyses examining the ability of lottery demand to explain the betting against beta phenomenon using alternative definitions of lottery demand. In Section VII we show that the results of the bivariate independent sort portfolio analyses of the relation between future stock returns and each of β and MAX are robust when a dependent sort portfolio analysis is used. We also show demonstrate that the ability of lottery demand to explain the betting against beta phenomenon persists under different economic conditions. In Section VIII we demonstrate that months in which there is high cross-sectional correlation between beta and lottery demand are characterized by poor economic conditions and high aggregate lottery demand. Section IX presents evidence that in both high and low β, MAX correlation months, the alpha of the High$-$Low β portfolio is statistically insignificant when FMAX is included in the factor model. In Section X we demonstrate the the ability of the lottery demand factor to explain the returns of the BAB factor is robust to the use of alternative measures of lottery demand when creating the lottery demand factor. Section XI demonstrates that the joint relations between future stock returns, market beta, and lottery demand persist when market beta is measured according to Frazzini and Pedersen (2014) and are not sample specific.

I Variables

In this Section, we describe in detail how each of the variables used in this paper is calculated. For variables calculated using one year's worth of daily data (β, $COSKEW$, $TSKEW$, $DRISK$, $TRISK$), we require a minimum of 200 valid daily return observations during the calculation period. For variables calculated using one month's worth of daily data (MAX, $IVOL$, $ILLIQ$), we require 15 valid daily return observations during the given month. For variables calculated using five years' worth of monthly data (β_{TED}, β_{VOLTED}, β_{TBILL}, and β_{FLEV}), we require a minimum of 24 valid monthly return observations during the five-year measurement period. Observations not satisfying these requirements are discarded. Variables that are measured on a return scale (R, MAX, MOM, $IVOL$) are recorded as percentages.

Market Beta (β): We calculate β using a one factor market model regression specification applied to one year worth of daily return data. The regression specification is

$$r_{i,d} = a + b_1 MKTRF_d + e_{i,d}, \tag{A1}$$

where $r_{i,d}$ and $MKTRF_d$ are the excess returns of the stock and the market portfolio, respectively, on day d. β is taken to be the fitted value of the regression coefficient b_1. The regression is fit using daily return data covering the 12-months up to and including the month for which β is being calculated. Daily stock return data come from CRSP. Daily market excess return and risk-free security return data are taken from Kenneth French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The stock excess return is calculated as the stock return minus the return on the risk-free security.

Monthly Stock Excess Return (R): The monthly excess return of a stock (R) is calculated as the monthly return of the stock, taken from the CRSP database, minus the monthly return of the risk-free security, taken from Kenneth French's data library. We adjust the monthly returns from CRSP for delisting according to Shumway (1997). Specifically, if a delisting return is provided in the CRSP database, we take the monthly return of the stock to be the delisting return. If no delisting return is available, then we determine the stock's monthly return based on the delisting code in CRSP. If the delisting code is 500 (reason unavailable), 520 (went to OTC), 551–573 or 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines), we take the stock's return during the delisting month to be -30%. If the delisting code has a value other than the previously mentioned values and there is no delisting return, we take the stock's return during the delisting month to be -100%.

Market Capitalization and Size ($MKTCAP$ and $SIZE$): We calculate the market capitalization ($MKTCAP$) of a stock as the month-end stock price times the number of shares outstanding, taken from CRSP and measured in millions of dollars. Since the distribution of $MKTCAP$ is highly skewed, in statistical analyses that rely on the magnitude of market capitalization, we use the natural log of $MKTCAP$, which we denote $SIZE$.

Book-to-Market Ratio (BM): Following Fama and French (1992, 1993), we define the book-to-market ratio for the months from June of year y through May of year $y+1$ to be the book value of equity of the stock, calculated using balance sheet data from Compustat for the fiscal year ending in calendar year $y-1$, divided by the market capitalization of the stock at the end of calendar year $y-1$. The book value of equity is defined as stockholders' equity plus balance sheet deferred taxes plus investment tax credit minus the book value of preferred stock. The book value of preferred stock is taken to be either the redemption value, the liquidating value, or the convertible value, taken as available in that order. For observations where the book value is negative, we deem the book-to-market ratio to be missing. We define our main measure of book-to-market ratio, BM, to be the natural log of the book-to-market ratio.

Momentum (MOM): To control for the medium-term momentum effect of Jegadeesh and Titman (1993), we define the momentum variable (MOM) to be the stock return during the 11-month period up to but not including the current month. MOM is calculated using monthly return data from CRSP.

Illiquidity ($ILLIQ$): We define illiquidity ($ILLIQ$) following Amihud (2002) as the average of the absolute value of the stock's return (taken as a decimal) divided by the dollar volume traded in the stock (in millions of dollars), calculated using daily data from the month for which $ILLIQ$ is being calculated. Following Gao and Ritter (2010), we adjust for institutional features of the way that volume on the NASDAQ is reported. Specifically, we divide the volume reported in CRSP for stocks that trade on the NASDAQ by 2.0, 1.8, 1.6, and 1 for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and during or subsequent to January 2004, respectively. $ILLIQ$ is defined as

$$ILLIQ = \frac{\sum_{d=1}^{n} \frac{|r_d|}{Volume\$_d}}{n}, \tag{A2}$$

where r_d is the stock's return on day d, $Volume\$_d$ is the dollar volume traded in the stock on day d, and the summation is taken over all trading days in the given month. $Volume\$_d$ is calculated as the last trade price times the number of shares traded, both on day d.

Idiosyncratic Volatility ($IVOL$): We calculate idiosyncratic volatility ($IVOL$) following Ang, Hodrick, Xing, and Zhang (2006) as the standard deviation of the residuals from a Fama and French (1993) three-factor regression of the stock's excess return on the market excess return ($MKTRF$), size (SMB), and book-to-market ratio (HML) factors using daily return data from the month for which idiosyncratic volatility is being calculated. The regression specification is

$$r_{i,d} = a + b_1 MKTRF_d + b_2 SMB_d + b_3 HML_d + e_{i,d}, \tag{A3}$$

where SMB_d and HML_d are the returns of the size and book-to-market factors of Fama and French (1993), respectively, on day d.

Lottery Demand (MAX): Following Bali et al. (2011), we measure lottery demand using MAX. MAX is calculated as the average of the five highest daily returns of the given stock during the given month.

Co-Skewness ($COSKEW$): Following Harvey and Siddique (2000), we define the co-skewness ($COSKEW$) of a stock in any month to be the estimated slope coefficient on the squared market excess return from a regression of the stock's excess return on the market's excess return and the squared market excess return using one year of daily data up to and including the given month. Specifically, $COSKEW$ is the estimated b_2 coefficient from the regression specification

$$r_{i,d} = a + b_1 MKTRF_d + b_2 MKTRF_d^2 + e_{i,d}. \tag{A4}$$

Total Skewness ($TSKEW$): We define the total skewness ($TSKEW$) of a stock to be the skewness of the stock's daily returns calculated using one year of data up to and including the given month.

Downside Beta ($DRISK$): Following Ang, Chen, and Xing (2006), we define downside beta ($DRISK$) as the fitted slope coefficient from a one-factor market model regression using daily returns from the past year from days when the market return was below the average daily market return during that year. The regression specification is given in equation (A1). $DRISK$ is taken to be the fitted value of the coefficient b_1.

Tail Beta ($TRISK$): Tail beta ($TRISK$) is calculated as the fitted slope coefficient from a one-factor market model regression using daily returns from the past year from days when the market return was in the bottom 10% of market returns during that year. The regression specification is given in equation (A1). $TRISK$ is taken to be the fitted value of the coefficient b_1.

TED Spread Sensitivity (β_{TED}): The TED spread sensitivity (β_{TED}) of a stock is defined as the fitted slope coefficient from a regression of the stock's monthly excess returns on the TED spread using five years' worth of monthly data. The TED spread is defined as the difference between the three-month LIBOR and the yield on three-month U.S. Treasury bills. The regression specification is

$$R_{i,t} = a + b_1 TED_t + e_{i,t}, \tag{A5}$$

where $R_{i,t}$ is the excess return of stock i during month t and TED_t is the TED spread at the end of month t. Three-month LIBOR and U.S. Treasury bill yields are downloaded from Global Insight. Month-end TED spread data is available beginning in January of 1963, thus β_{TED} is only available beginning in January 1965.

TED Spread Volatility Sensitivity (β_{VOLTED}): The sensitivity to TED spread volatility (β_{VOLTED}) of a stock is defined as the fitted slope coefficient from a regression of the stock's monthly excess returns on TED spread volatility using five years worth of monthly data. The TED spread volatility for a given month is defined as the standard deviation of the daily TED spreads within the given month. The regression specification is

$$R_{i,t} = a + b_1 VOLTED_t + e_{i,t}, \tag{A6}$$

where $R_{i,t}$ is the excess return of stock i during month t and $VOLTED_t$ is the TED spread volatility during month t. Daily TED spread data is available beginning in January 1977, thus β_{VOLTED} is available beginning in January of 1979.

Treasury Bill Sensitivity (β_{TBILL}): The sensitivity to U.S. Treasury bill rates (β_{TBILL}) of a stock is defined as the fitted slope coefficient from a regression of the stock's monthly excess returns on the three-month U.S. Treasury bill rate using five years' worth of monthly data. The regression specification is

$$R_{i,t} = a + b_1 TBILL_t + e_{i,t}, \tag{A7}$$

where $R_{i,t}$ is the excess return of stock i during month t and $TBILL_t$ is the yield on the three-month U.S. Treasury bill at the end of month t. Yields on the three-month U.S. Treasury bills are taken from the FRED database.

Financial Sector Leverage Sensitivity (β_{FLEV}): The financial sector leverage sensitivity (β_{FLEV}) of a stock is defined as the fitted slope coefficient from a regression of the stock's monthly excess returns on the month-end leverage of the financial sector ($FLEV$) using five years' worth of monthly data. The regression specification is

$$R_{i,t} = a + b_1 FLEV_t + e_{i,t}, \tag{A8}$$

where $R_{i,t}$ is the excess return of stock i during month t and $FLEV_t$ is the financial sector leverage at the end of month t. Financial sector leverage is defined as the total balance sheet assets of all financial sector firms divided by the total market value of equity of all financial sector firms. Firm-level balance sheet assets are taken from Compustat's quarterly database and aggregated to calculate the total balance sheet assets of all firms in the sector. Since the firm-level assets are reported quarterly, to obtain monthly firm-level assets, we use the balance sheet assets reported for the fiscal quarter ending in month t as the assets for months $t-1$ and months $t+1$ as well. Firm level market capitalization is simply $MKTCAP$, defined above, and is aggregated in the same manner. Financial sector firms are taken to be firms with Standard Industrial Classification (SIC) codes between 6000 and 6999, inclusive.

Orthogonal Portion of β to MAX ($\beta_{\perp MAX}$): The component of β that is orthogonal to MAX is calculated as the fitted intercept coefficient plus the residual from a cross-sectional regression of

β on MAX. The regression specification is

$$\beta_i = a + b_1 MAX_i + \epsilon_i. \tag{A9}$$

$\beta_{\perp MAX}$ is then defined as

$$\beta_{\perp MAX,i} = a + \epsilon_i. \tag{A10}$$

Orthogonal Portion of MAX to β ($MAX_{\perp\beta}$): The component of MAX that is orthogonal to β is calculated as the fitted intercept coefficient plus the residual from a cross-sectional regression of MAX on β. The regression specification is

$$MAX_i = a + b_1 \beta_i + \epsilon_i. \tag{A11}$$

$MAX_{\perp\beta}$ is defined as:

$$MAX_{\perp\beta,i} = a + \epsilon_i. \tag{A12}$$

FP Beta (β_{FP}): FP calculate market beta as

$$\beta_{FP,i} = 0.6\rho_i \frac{\sigma_i}{\sigma_m} + 0.4 \tag{A13}$$

where ρ_i is the correlation between three-day log returns of the stock and three-day log returns of the market, calculated using five years' worth of daily return data. Specifically, defining the three-day log return on day d as $r^{3d}_{i,d} = \sum_{j=0}^{2} ln(1 + r_{i,d-j})$, where $r_{i,d}$ is the stock's return on day d, the correlation ρ_i is calculated as the correlation between this measure calculated for the stock and for the market portfolio (using excess returns) on each day during the past five years. The objective of FP in taking three-day returns is to control for nonsynchronous trading. Five years of data are used because correlations tend to move slowly. A total of 750 days of valid stock returns are required when calculating ρ_i. σ_i and σ_m are the standard deviations of daily log stock returns and daily log market excess returns, respectively, using one year's worth of data. At least 120 days of stock return data during the calculation period are required when calculating σ_i. The time period used for the calculation of the standard deviation is shorter because volatilities tend to change more quickly than correlations. Multiplication by 0.6 and the addition of 0.4 come from an effort to reduce outliers. More discussion of the calculation of β_{FP} can be found in Section 3.1 of FP.

II Alternative Measures of Beta and Returns

In this section we demonstrate that the results of the univariate portfolio analysis examining the relation between market beta and future stock returns are robust to the use of alternative measures of market beta. Scholes and Williams (1977) find that when trading is non-synchronous, the standard CAPM-regression method of estimating beta used in our primary calculation of market beta—β, described in the main paper—may be biased. To adjust for this bias, Scholes and Williams (1977) propose calculating beta as the sum of estimated slope coefficients from separate regressions of the stock's excess return on each of the contemporaneous, one-day lagged, and one-day ahead market excess return, divided by one plus two times the serial correlation of the market excess return, all calculated using one year's worth of daily return data up to and including month t. Thus, we define β_{SW} as

$$\beta_{SW} = \frac{\hat{b_1} + \hat{b_2} + \hat{b_3}}{1 + 2\rho_m} \tag{A14}$$

where ρ_m is the serial correlation of the market excess return, $\hat{b_1}$, $\hat{b_2}$, and $\hat{b_3}$ are the fitted slope coefficients from regression models

$$r_{i,d} = a + b_1 r_{m,d-1} + e_{i,d}, \tag{A15}$$

$$r_{i,d} = a + b_2 r_{m,d} + e_{i,d}, \tag{A16}$$

and

$$r_{i,d} = a + b_3 r_{m,d+1} + e_{i,d} \tag{A17}$$

and $r_{i,d}$ and $r_{m,d}$ are the excess returns of the stock i and the market, respectively, on day d.

Similarly, Dimson (1979) finds that for infrequently traded securities the standard estimates of beta may be biased, and shows that this bias can be addressed by estimating beta as the sum of the slope coefficients from a regression of stock excess returns on the contemporaneous market excess returns along with the market excess returns from each of the previous and next five days. Thus, following Dimson (1979), we define β_D as

$$\beta_D = \sum_{k=-5}^{k=5} \hat{b_k} \tag{A18}$$

where the $\hat{b_k}$ represent the estimated slope coefficients from regression model

$$R_{i,d} = a + \sum_{k=-5}^{k=5} b_k R_{m,d+k} + e_{i,d}. \tag{A19}$$

The results of univariate decile portfolio analyses of the relation between market beta and future stock returns using each of the alternative measures of market beta are presented in Table A1. The results are highly similar to those generated using the standard measure of market beta (β) used in the main paper (repeated in Table A1 to facilitate comparison). Regardless of the measure of beta, the average monthly return difference between the decile ten and decile one portfolios (High−Low portfolio) is negative but statistically insignificant. The risk-adjusted alpha relative to the Fama and French (1993) and Carhart (1997) four-factor (FFC4) model is negative and statistically significant. This result indicates that the betting against beta phenomenon is robust to the use of alternative measures of market beta.

III Alternative Measures of Lottery Demand and Returns

In this section we show that the negative relation between lottery demand and future stock returns is robust to alternative measures of lottery demand. Specifically, we calculate lottery demand to be $MAX(k)$, $k \in \{1, 2, 3, 4, 5\}$, where $MAX(k)$ is defined as the average of the k highest daily returns of the given stock within the given month. In Table A2 of this online appendix we present the results of univariate decile portfolio analyses of the relation between lottery demand and future stock returns using each of these measures of lottery demand as the sort variable. The table shows that the negative relation between lottery demand and future stock returns is strong regardless of which measure of lottery demand is used. The average monthly returns of the zero-cost portfolio that is long the decile 10 portfolio and short the decile 1 portfolio range from -0.95% for portfolios formed by sorting on $MAX(1)$ to -1.15% for portfolios sorted on $MAX(5)$, with Newey and West

(1987) t-statistics of -3.91 and -4.41, respectively. The Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α) for these portfolios range from -1.05% to -1.15% per month with t-statistics between -8.95 and -9.12. The results indicate that the negative relation between lottery demand and future stock returns is robust regardless of the measure of lottery demand.

IV Manipulation Proof Performance Measure

In this section, we analyze the performance of decile portfolios formed by sorting on each of β and MAX using the manipulation proof performance measure (MPPM) of Ingersoll, Spiegel, Goetzmann, and Welch (2007). The objective of this analysis is to ensure that the betting against beta and lottery demand phenomena are not driven by active portfolio management designed to generate an indication of positive abnormal returns when in fact none exist.

The MPPM of a portfolio p is calculated as:

$$\text{MPPM} = \frac{12}{1-\rho} \ln \left(\frac{1}{M} \sum_{m=1}^{M} \left[(1 + r_{p,m}) \, / \, (1 + r_{f,m}) \right]^{1-\rho} \right) \tag{A20}$$

where $r_{p,m}$ and $r_{f,m}$ are the return of the portfolio and the risk-free security, respectively, in month m, $M = 593$ is the total number of months in our sample, and $\rho = 2.2$ is found by maximizing the value of MPPM with respect to ρ when the calculation is applied to the returns of the CRSP value-weighted index. MPPM is interpreted as an annualized continuously compounded excess return certainty equivalent for the portfolio. This means that an investor is indifferent between owning the portfolio in question and a risk-free portfolio earning an annual return of $e^{\ln(1+r_f)+\text{MPPM}}$.

To assess the statistical significance of MPPM for a portfolio, standard errors are calculated using a bootstrap approach. We randomly select 593 months, with replacement, from our sample period, and calculate MPPM using the returns of the given portfolio and the risk-free security for the selected months. We repeat this process 1,000 times, and take the standard error of MPPM to be the standard deviation of the 1,000 MPPM values. t-statistics for MPPM are then calculated as the estimated MPPM using the full sample divided by the standard errors estimated from the bootstrap procedure.

The MPPM and associated t-statistics for each of the β-sorted decile portfolios, shown in the row labeled β in Table A3, indicate that the betting against beta phenomenon is not a result of performance manipulation. MPPM is nearly monotonically decreasing across the deciles of β. As with the FFC4 alpha (see Table 1 of the main paper), the exception is decile 1. The MPPM for the High-Low portfolio of -16.96 is both economically large and highly statistically significant with an associated t-statistic of -6.34. The results indicate that for the β-sorted portfolios, assessing portfolio performance using the FFC4 alpha and the MPPM lead to the same conclusion. On a risk-adjusted basis, a portfolio that is long stocks in the highest decile of beta and short stocks in the lowest decile of beta exhibits economically large and statistically significant under-performance.

The MPPM for each of the MAX-sorted decile portfolios are shown in the row labeled MAX in Table A3. Portfolio MPPM decreases from 9.46% per annum for decile 2 of MAX to -13.65% per annum for MAX decile 10. The annual MPPM of the High-Low MAX portfolio is -23.78% with a corresponding t-statistic of -9.92. The results indicate that the lottery-demand phenomenon is not a result of performance manipulation.

V Portfolio-Level MAX

In this section, we examine whether MAX aggregates by testing whether the high (low) MAX portfolio is in fact a high (low) MAX asset. Each month we sort all stocks into decile portfolios based on an ascending sort of MAX or the component of MAX that is cross-sectionally orthogonal to market beta ($MAX_{\perp\beta}$). We then calculate daily returns for each decile portfolio over all days in the month subsequent to portfolio formation. The portfolio-level MAX is taken to be the average of the five highest daily returns of the given portfolio within the given month.

Table A4 presents the time-series averages of the monthly portfolio-level values of MAX for each of the decile portfolios. The column labeled High-Low shows the average difference between the decile 10 and decile 1 portfolio-level MAX along with the Newey and West (1987) adjusted t-statistic testing the null hypothesis that the average difference in portfolio-level MAX between the decile ten and decile one portfolios is equal to zero. The results show that when the portfolios are formed by sorting on MAX, the portfolio-level values of MAX are monotonically increasing from 0.50% to 1.41% across the deciles of MAX. The average difference between decile 10 and decile 1 of 0.91% is both economically large and highly statistically significant, with a t-statistic of

13.13. This indicates that by investing in a portfolio with a large number of high-MAX stocks, a lottery investor has not diversified away the lottery-like feature of the investment, as the resulting portfolio is itself a high-MAX asset. When sorting on $MAX_{\perp\beta}$, the results are similar, but not quite as strong. The average portfolio-level value of MAX increases (nearly monotonically, the exception is decile portfolio one) from 0.91% for decile 1 to 1.16% for decile 10, giving an average High-Low difference of 0.25% with a corresponding t-statistic of 8.50. This result indicates that it is not the cross-sectional correlation between β and MAX that causes MAX to aggregate, as the high (low) $MAX_{\perp\beta}$ portfolio is, in and of itself, a high (low) MAX asset.

VI Bivariate Sort Analyses with Alternative Measures of Lottery Demand

In this section we present the results of bivariate dependent sort portfolio analyses examining the robustness of the ability of lottery demand to explain the betting against beta phenomenon. Each month, all stocks in the sample are grouped into ascending deciles of $MAX(k)$, where $MAX(k)$ is defined as the average of the k highest daily returns of the given stock within the given month. Within each decile of $MAX(k)$, we then sort all stocks into ten decile portfolios based on an ascending sort of β. The excess return of each of these 100 portfolios is then taken to be the equal-weighted average excess return of all stocks in the given portfolio. Each month, the average excess return, within each decile of β, across all deciles of the given measure of lottery demand, is calculated. Table A5 presents the average monthly return for each of these β-decile portfolios as well as the High–Low β portfolio, along with the Fama and French (1993) and Carhart (1997) four-factor alpha (FFC4 α) of the High–Low β portfolio. t-statistics, adjusted following Newey and West (1987) using six lags, are presented in parentheses. The results demonstrate that regardless of which measure of lottery demand is used, lottery demand explains the betting against beta phenomenon, as all of the High–Low β portfolios have excess and abnormal returns that are statistically indistinguishable from zero.

VII Bivariate Dependent Sort Analyses with β and MAX

We begin this section by investigating whether the ability of lottery demand to explain the betting against beta phenomenon persists across different economic conditions. To do so, we examine three subsets of the months during our sample period. The first subset of months consists of those months where the Chicago Fed National Activity Index (CFNAI) is less than or equal to zero. Such months represent months where economic conditions are at or below median levels. The second subset is comprised of months where the CFNAI is greater than zero, and therefore corresponds to months with above median economic activity. Finally, to ensure that our results are not driven by the financial crisis beginning in 2007, we examine the subset of non-crisis months. Crisis months are taken to be December 2007 through June 2009, inclusive. All remaining months during our sample period from August 1963 through December 2012 are considered non-crisis months.

In Table A6 of this online appendix we report the results of the bivariate dependent sort portfolio analysis of the relation between β and future stock returns after controlling for MAX (sort first on MAX and then on β). Each month, all stocks are grouped into ascending deciles of MAX. Within each MAX decile, all stocks are sorted into portfolios based on ascending deciles of β. The table presents the time-series average of the monthly portfolio excess returns within each decile of β. The excess return for a given β decile portfolio in a given month is taken to be the average, across all deciles of MAX and within the given decile of β, of the individual portfolios formed by sorting on MAX then β. The table shows that, after controlling for MAX, the average excess return as well as the FFC4 alpha of the High–Low β portfolio is statistically insignificant for each subset. The results indicate that the ability of lottery demand to explain the betting against beta phenomenon persists under all economic conditions.

We proceed by checking the robustness of the bivariate independent sort portfolio analysis of the relations between future stock returns and each of β and MAX, presented in Section 3 and Table 5 of the main paper, by performing dependent sort analyses of these same relations. Panel A of Table A7 presents the average excess returns of each of the 100 resulting portfolios as well as the difference in returns and FFC4 alphas of the zero-cost portfolios that are long the β decile ten portfolio and short the β decile one portfolio (High−Low portfolio) within each MAX decile. The results are consistent with the independent sort portfolio analysis presented in the main paper. The average returns and risk-adjusted alphas of the High−Low portfolios are all statistically indistinguishable from zero, with the one exception being the first decile of MAX, for which the return difference is positive and statistically significant. In unreported results, we find that the average High−Low β portfolio, across all deciles of MAX, returns -0.02% per month (t-statistic = -0.10) and generates an FFC4 alpha of -0.14% (t-statistic = -0.85) per month. The analysis indicates that after controlling for the effect of lottery demand (MAX), the abnormal return of the High−Low market beta portfolio disappears.

To assess the relation between MAX and returns after controlling for β, we repeat the bivariate dependent sort portfolio analysis, this time sorting on β then MAX. The results are shown in Panel B of Table A7. Once again consistent with the results from the independent sort analysis in the main paper, we find that the negative returns and risk-adjusted alphas of the High−Low MAX portfolios persist after controlling for β, as eight of the ten β deciles produce High−Low MAX portfolio returns that are statistically negative, and the risk-adjusted alphas of all ten of these portfolios are negative and statistically distinguishable from zero. Taking the average across all deciles of β (unreported in the table), we find that the average High−Low MAX portfolio generates a return of -1.12% per month (t-statistic = -6.62) and a monthly FFC4 alpha of -1.36% (t-statistic = -11.32). The results show that after controlling for the effect of market beta, the negative relation between lottery demand and future stock returns persists.

VIII Aggregate Lottery Demand and $\rho_{\beta,MAX}$

In this section, we examine the aggregate lottery demand in months characterized by high and low correlation between beta and MAX ($\rho_{\beta,MAX}$). We use five measures of aggregate lottery demand. Kumar (2009) demonstrates that aggregate lottery demand is highest during economic downturns. Our first two measures are therefore based on the Aruoba-Diebold-Scotti Business Conditions Index (ADS) and the Chicago Fed National Activity Index (CFNAI).[1] Both variables are dummy variables indicating recession. We define REC_{ADS} to be 1 if the ADS index has a value of less than -0.50 at the end of the given month, and 0 otherwise. Similarly, we take REC_{CFNAI} to be 1 if the CFNAI index is less than -0.70 for the given month, and 0 otherwise. Next, as high market volatility is

[1] ADS data are from the Federal Reserve Bank of Philadelphia. CFNAI data are from the Federal Reserve Bank of Chicago.

an indication of deteriorating economic conditions, our third measure of aggregate lottery demand is the annualized standard deviation of the daily returns of the CRSP value-weighted portfolio, denoted VOL_{MKTRF}. Our fourth measure, MAX_{MKTRF}, is the value of MAX for the CRSP value-weighted portfolio, and our final measure, MAX_{Agg}, is the value-weighted average value of MAX across all stocks in the sample.

Table A8 presents the average value of each measure of aggregate lottery demand during high-$\rho_{\beta,MAX}$ and low-$\rho_{\beta,MAX}$ months. The table demonstrates that, regardless of the measure used, aggregate lottery demand is substantially higher during months with high cross-sectional correlation between β and MAX. The results using ADS indicate that high-$\rho_{\beta,MAX}$ months have a 30% chance of being characterized as recessions, compared to only a 10% chance for low-$\rho_{\beta,MAX}$ months. The difference of 20% is highly significant, both economically and statistically, with a t-statistic of 3.71. The results are similar using the CFNAI. Market volatility (VOL_{MKTRF}) is also much higher during months characterized by high-$\rho_{\beta,MAX}$, with an average value of 15.56%, compared to an average of 11.18% during months with low-$\rho_{\beta,MAX}$, resulting in an economically large and statistically significant difference of 4.38% (t-statistic = 3.71). Finally, MAX_{MKTRF} and MAX_{Agg} are both higher in high-$\rho_{\beta,MAX}$ months than in low $\rho_{\beta,MAX}$ months, with differences of 0.37 (t-statistic = 4.15) and 0.43 (t-statistic = 3.62), respectively. The results provide strong evidence that months with high cross-sectional correlation between β and MAX are characterized by poor economic conditions and high aggregate lottery demand.

IX Months with High and Low β, MAX Correlation

In this section we demonstrate that the ability of factor models that include FMAX to explain the returns of the High−Low β portfolio is robust in both high and low β, MAX correlation months. We begin by dividing the sample into months for which the cross-sectional correlation between β and MAX is low and those in which the correlation is high, as described in Section 5.2 of the main paper. We then calculate the risk-adjusted alphas and factor loadings of the High−Low β portfolio relative to four different factor models. The first model is the FFC4 model. The second is the FFC4 model augmented with Pastor and Stambaugh's (2003) liquidity factor (FFC4+PS).[2]

[2]PS factor returns are only available for January 1968 and after. Thus, analyses that include the PS factor are restricted to this time period.

The third and fourth models are formed by adding the FMAX factor to each of the FFC4 and FFC4+PS models (FFC4+FMAX, FFC4+PS+FMAX). The portfolios used in our analysis are the same univariate β-sorted decile portfolios used to generate the results in Table 1 of the main paper.

The results of the factor analysis for high β, MAX correlation months, presented in Panel A of Table A9, indicate that, consistent with what is demonstrated in Section 5.2 and Table 7 of the main paper, the alpha of the High−Low β portfolio is negative and statistically significant relative to the FFC4 and FFC4+PS models. When FMAX is included in the factor model, however, even in the high β, MAX correlation months, the alpha of the High−Low β portfolio becomes positive and statistically indistinguishable from zero. Thus, the addition of FMAX to the model explains the abnormal return (relative to other models) of the High−Low β portfolio. In months where the correlation between β and MAX is low, the alpha of the High−Low β portfolio is statistically insignificant regardless of the factor model being employed.

X Alternative Lottery Demand Factors

In this section, we examine whether alternative lottery demand factors created using $MAX(k)$ as the measure of lottery demand, can explain the returns of Frazzini and Pedersen's BAB factor. $MAX(k)$ is defined as the average of the k highest daily returns of the given stock in the given month, and we examine $k \in \{1,2,3,4,5\}$. We define the $FMAX(k)$ factor as the factor created using $MAX(k)$ as the measure of lottery demand. The $FMAX(k)$ factors are created using the same procedure defined in Section 6 of the main paper. The only difference is that instead of using $MAX = MAX(5)$ as the measure of lottery demand, here we use $MAX(k)$, $k \in \{1,2,3,4,5\}$.

In Table A10 we present the alphas and factor sensitivities of the BAB factor relative to several different factor models. Specifically, we present results for the factor models that include the Fama and French (1993) and Carhart (1997) factors augmented with the FMAX(k) factor (FFC4+FMAX(k), $k \in \{1,2,3,4,5\}$) as well as for the FFC4 factors augmented with the Pastor and Stambaugh (2003) factor and the FMAX(k) factor (FFC4+PS+FMAX(k)). The results indicate that regardless of which measure of lottery demand is used to create the lottery demand factor, the lottery demand factor explains the returns of the BAB factor, as the abnormal return of the BAB factor is economically small and statistically insignificant when any version of the lottery demand factor is included in the factor model.

XI Frazzini and Pedersen (2014) Beta and Sample

In this section, we demonstrate that the main results of the paper are robust when market beta is calculated following Frazzini and Pedersen (2014, FP hereafter) and are not sample specific.

FP estimate a stock's market beta using a two-step process. First, they calculate an estimated beta to be the product of the correlation between the stock return and the excess market return, multiplied by the ratio of the standard deviation of the stock's return to that of the market. In calculating this value, they measure the correlation (ρ_i) using five years' worth of overlapping three-day log returns. The standard deviations (σ_i and σ_m) are calculated using one year of daily log return data. They take their final measure of beta, which we denote β_{FP}, to be 0.6 times the previously described value plus 0.4:

$$\beta_{FP,i} = 0.6\rho_i \frac{\sigma_i}{\sigma_m} + 0.4. \tag{A21}$$

The rationale for this measure is discussed in FP's Section 3.3. A more detailed description of the calculation and further discussion is provided in Section I of this online appendix.

We begin our analysis of the relation between β_{FP} and future stock returns with a univariate decile portfolio analysis using β_{FP} as the sort variable. The results of this analysis are presented in Table A11. Similar to the results for portfolios sorted on β (Table 1 of the main paper), the average return of the High−Low β_{FP} portfolio of −0.20% per month is negative but statistically indistinguishable from zero with a t-statistic of −1.30. Assessing the returns of this portfolio using the FFC4 and FFC4+PS risk models, we see that both models indicate that this portfolio generates economically important negative and statistically significant abnormal returns. The High−Low β_{FP} portfolio generates an alpha of −0.31% per month (t-statistic = −2.67) using the FFC4 model and −0.29% per month (t-statistic = −2.49) using the FFC4+PS model. Adding the FMAX factor to each of the risk models reduces the abnormal return to a statistically insignificant −0.07% per month for the FFC4+FMAX model and -0.08% per month for the FFC4+PS+FMAX model, indicating that the FMAX factor explains the returns of the High−Low β_{FP} portfolio. Furthermore, none of the decile portfolios generate risk-adjusted returns that are statistically different than zero when FMAX is included in the factor model. As with the results for the β-based portfolios presented in Section 6 of the main paper, inclusion of the FMAX factor in the risk model explains the abnormal returns of the High$-$Low β_{FP}-based portfolio.

We then repeat the portfolio analysis, this time sorting on the portion of β_{FP} that is orthogonal to MAX, denoted $\beta_{FP \perp MAX}$, which we calculate by running a cross-sectional regression of β_{FP} on MAX and taking a stock's $\beta_{FP \perp MAX}$ to be the estimated intercept coefficient plus the residual from the regression. The results of this portfolio analysis show that, similar to the results for $\beta_{\perp MAX}$ (Table 6 of the main paper), the High$-$Low FFC4 alpha is substantially reduced to only -0.15% per month and is no longer statistically distinguishable from zero, indicating that negative alpha of the High$-$Low β_{FP} portfolio is driven by the relation between β_{FP} and MAX. When the effect of MAX on β_{FP} is removed, the High$-$Low portfolio no longer generates negative alpha. When we sort on the portion of MAX that is orthogonal to β_{FP} ($MAX_{\perp \beta_{FP}}$), we find that both the returns and alpha of the High-Low $MAX_{\perp \beta_{FP}}$ portfolio are negative, economically large in magnitude, and highly statistically significant, demonstrating that the negative returns and alpha of the High$-$Low MAX portfolio persist when only the portion of MAX that is orthogonal to β_{FP} is used as the sort variable. This result is consistent with the results using $MAX_{\perp \beta}$ from Table 6 of the main paper.

In Table A12 we present the results of a bivariate independent sort portfolio analysis of the relation between future stock returns and each of β_{FP} and MAX. Within each MAX decile, the average return of the High$-$Low β_{FP} portfolio, as well as the abnormal return relative to the FFC4 model, is statistically indistinguishable from zero, indicating that after controlling for the effect of MAX there is no relation between β_{FP} and future stock returns. Unreported results show that the return of the average High-Low β_{FP} portfolio across all MAX deciles is -0.06% per month (t-statistic = -0.52), and the FFC4 alpha of this portfolio is -0.11% per month (t-statistic = -1.23). The results indicate that the negative abnormal return of the High$-$Low β_{FP} portfolio is explained by MAX. The relation between MAX and future stock returns, however, remains negative and highly statistically significant after controlling for β_{FP}, as the High$-$Low MAX average return and risk-adjusted alpha is negative, economically large, and statistically significant for each decile of β_{FP}. Across all β_{FP} deciles, unreported results show that average monthly return of the High$-$Low

MAX portfolio is -0.98% per month (t-statistic $= -4.47$), and the FFC4 alpha of this portfolio is -1.24% per month (t-statistc $= -9.14$). The results presented in Table A12 are very similar to those found when using the standard CAPM measure of market beta (β, Table 5 of the main paper). The abnormal return of the High$-$Low portfolio formed on market beta disappears after controlling for lottery demand, yet the returns of the High$-$Low lottery demand portfolio remain significantly negative after controlling for β.

We check the robustness of the independent sort portfolio analysis by using dependent sort analyses. The results of bivariate dependent sort portfolio analyses of the conditional relations between future stock returns and each of β_{FP} and MAX are presented in Table A13. The results in Panel A show that within each MAX decile the FFC4 alpha of the High$-$Low β_{FP} portfolio is small in magnitude and statistically indistinguishable from zero. In unreported results we find that the average abnormal return of the High$-$Low β_{FP} portfolio, across all deciles of MAX, is -0.07% per month with a corresponding t-statistic of -0.73. Panel B shows the results of the portfolio analysis that sorts first on β_{FP} and then on MAX. The results demonstrate that the average return and FFC4 alpha of the High$-$Low MAX portfolio within each decile of β_{FP} is negative and highly statistically significant. The average High$-$Low MAX portfolio across all deciles of β_{FP} generates average monthly returns of -0.99% (t-statistic $= -4.61$) and an FFC4 alpha of -1.24% per month (t-statistic $= -8.97$). The results in both Panels of Table A13 are consistent with those found when using the standard measure of market beta (β, results in Table A7 of this online appendix).

Finally, we examine whether the different beta calculation or different sample used by FP has an impact on our analyses of the BAB and FMAX factor returns. To do so, we repeat the factor analyses in Table 10 of the main paper using a betting against beta factor constructed from our sample using our standard measure of market beta (β). All other aspects of the portfolio, including the weighting scheme and zero-beta construction, are identical to those used for FP's BAB factor as described in FP's Section 3.2 and equations (16) and (17). We denote this new factor BAB_\$5. The results of the factor analyses of the BAB_\$5 and FMAX returns, presented in Table A14, are consistent with the results in Table 10 of the main paper. Using models that do not include the FMAX factor, BAB_\$5 generates a positive and statistically significant alpha. When the FMAX factor is included in the model, the alpha decreases to an economically insignificant level and is no longer statistically distinguishable from zero. In untabulated analyses, we find that this result is robust when the lottery demand factor is created using alternative measures of lottery demand defined as the average of the k highest daily returns of the given stock in the given month for $k \in \{1, 2, 3, 4, 5\}$. On the other hand, the FMAX alpha remains negative and statistically significant regardless of whether or not BAB_$5 is included in the factor model.

In summary, the results in Tables A11, A12, and A13 demonstrate that the main findings regarding the relation between market beta and future stock returns are similar regardless of whether we use the standard measure of beta (β) or the FP measure. The portfolio that is long high-beta stocks and short low-beta stocks generates negative risk-adjusted returns relative to standard risk models. When the portfolio is formed to be neutral to lottery demand (MAX), this result disappears. Using a factor model approach, adding a lottery demand factor (FMAX) to the risk models explains the alpha of the beta-based portfolio. Finally, the results in Table A14 demonstrate that the results are not driven by the difference in samples between this paper and FP, as a betting against beta factor constructed using only stocks from our sample produces results that are qualitatively the same as the results generated using FP's BAB factor.

References

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

Ang, A., Chen, J., and Xing, Y. 2006. Downside risk. Review of Financial Studies, 19(4), 1191–1239.

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.

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.

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

Dimson, E. 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics, 7(2), 197–226.

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.

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

Gao, X. and Ritter, J. R. 2010. The marketing of seasoned equity offerings. Journal of Financial Economics, 97(1), 33–52.

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

Ingersoll, J., Spiegel, M., Goetzmann, W., and Welch, I. 2007. Portfolio performance manipulation and manipulation-proof performance measures. Review of Financial Studies, 20(5), 1503–1546.

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.

Kumar, A. 2009. Who gambles in the stock market? Journal of Finance, 64(4), 1889–1933.

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

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

Scholes, M. and Williams, J. T. 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics, 5(3), 309–327.

Shumway, T. 1997. The delisting bias in CRSP data. Journal of Finance, 52(1), 327–340.

Table A1: Univariate Portfolios Sorted on Alternative Measures of Market Beta
Each month, all stocks are sorted into ascending decile portfolios based on a measure of market beta. β is the standard CAPM regression-based measure of beta. β_{SW} is calculated following Scholes and Williams (1977) and β_D is calculated following Dimson (1979). The table presents the time-series means of the monthly equal-weighted excess returns for each of the decile portfolios. The column labeled High-Low presents the mean difference between decile ten and decile one. The row labeled FFC4 α presents the alpha of the High-Low portfolio relative to the Fama and French (1993) and Carhart (1997) four-factor model. t-statistics, adjusted following Newey and West (1987), testing the null hypothesis of a zero mean return or alpha, are shown in parentheses.

Sort Variable	**Value**	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
β	β	-0.00	0.25	0.42	0.56	0.70	0.84	1.00	1.19	1.46	2.02	
	R	0.69	0.78	0.78	0.77	0.81	0.73	0.71	0.65	0.51	0.35	-0.35
		(3.74)	(3.90)	(3.74)	(3.54)	(3.42)	(2.90)	(2.66)	(2.26)	(1.58)	(0.89)	(-1.13)
	FFC4 α	0.22	0.24	0.16	0.11	0.10	-0.02	-0.05	-0.11	-0.18	-0.29	-0.51
		(2.22)	(2.77)	(2.31)	(1.59)	(1.69)	(-0.30)	(-0.80)	(-1.83)	(-2.20)	(-2.22)	(-2.50)
β_{SW}	β_{SW}	0.00	0.30	0.48	0.63	0.78	0.94	1.10	1.31	1.59	2.18	
	R	0.63	0.77	0.77	0.76	0.79	0.75	0.75	0.68	0.55	0.35	-0.28
		(3.38)	(4.05)	(3.83)	(3.41)	(3.34)	(2.98)	(2.85)	(2.33)	(1.67)	(0.87)	(-0.90)
	FFC4 α	0.14	0.23	0.16	0.08	0.08	0.02	0.00	-0.05	-0.15	-0.30	-0.44
		(1.44)	(2.82)	(2.39)	(1.22)	(1.32)	(0.25)	(-0.01)	(-0.88)	(-2.04)	(-2.45)	(-2.27)
β_D	β_D	-0.21	0.26	0.50	0.69	0.88	1.07	1.29	1.55	1.91	2.74	
	R	0.51	0.66	0.73	0.75	0.82	0.80	0.81	0.80	0.66	0.25	-0.25
		(2.53)	(3.39)	(3.59)	(3.47)	(3.51)	(3.27)	(3.14)	(2.78)	(2.02)	(0.66)	(-0.96)
	FFC4 α	-0.06	0.09	0.12	0.08	0.12	0.09	0.10	0.08	-0.03	-0.41	-0.35
		(-0.74)	(1.25)	(1.77)	(1.33)	(1.94)	(1.50)	(1.92)	(1.50)	(-0.42)	(-3.82)	(-2.12)

Table A2: Univariate Portfolios Sorted on Alternative Measures of Lottery Demand Each month, all stocks are sorted into ascending decile portfolios based on a measure of lottery demand. The measures of lottery demand are $MAX(k)$, $k \in \{1, 2, 3, 4, 5\}$, where $MAX(k)$ is defined as the average of the k highest daily returns of the given stock within the given month. The table presents the time-series means of the monthly equal-weighted excess returns for each of the decile portfolios. The column labeled High-Low presents the mean difference between decile ten and decile one. The row labeled FFC4 α presents the alpha of the High-Low portfolio relative to the Fama and French (1993) and Carhart (1997) four-factor model. t-statistics, adjusted following Newey and West (1987), testing the null hypothesis of a zero mean return or alpha, are shown in parentheses.

Sort Variable	**Value**	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
$MAX(5)$	$MAX(5)$	0.66	1.25	1.69	2.09	2.49	2.91	3.41	4.04	4.98	7.62	
	R	0.74	1.00	0.96	0.94	0.90	0.82	0.80	0.67	0.36	-0.40	-1.15
		(4.07)	(4.95)	(4.59)	(4.25)	(3.84)	(3.29)	(2.93)	(2.29)	(1.10)	(-1.11)	(-4.41)
	FFC4 α	0.27	0.42	0.35	0.30	0.23	0.12	0.08	-0.07	-0.38	-1.14	-1.40
		(3.01)	(5.90)	(5.89)	(5.18)	(3.95)	(2.20)	(1.53)	(-1.50)	(-6.05)	(-10.43)	(-8.95)
$MAX(4)$	$MAX(4)$	0.78	1.45	1.95	2.38	2.81	3.28	3.83	4.54	5.60	8.63	
	R	0.73	0.98	0.92	0.97	0.90	0.83	0.81	0.68	0.35	-0.40	-1.13
		(4.05)	(4.99)	(4.43)	(4.35)	(3.78)	(3.36)	(2.94)	(2.35)	(1.07)	(-1.10)	(-4.35)
	FFC4 α	0.26	0.40	0.33	0.33	0.22	0.13	0.08	-0.05	-0.39	-1.12	-1.38
		(2.93)	(6.18)	(5.42)	(5.45)	(3.61)	(2.34)	(1.49)	(-0.95)	(-6.35)	(-10.64)	(-8.98)
$MAX(3)$	$MAX(3)$	0.91	1.70	2.24	2.70	3.18	3.71	4.34	5.15	6.37	9.98	
	R	0.73	0.94	0.95	0.96	0.89	0.87	0.81	0.65	0.36	-0.38	-1.11
		(4.14)	(4.76)	(4.54)	(4.28)	(3.76)	(3.46)	(2.97)	(2.21)	(1.12)	(-1.07)	(-4.30)
	FFC4 α	0.26	0.36	0.33	0.32	0.21	0.17	0.08	-0.08	-0.37	-1.10	-1.36
		(3.01)	(5.74)	(5.52)	(5.33)	(3.58)	(3.02)	(1.55)	(-1.66)	(-6.03)	(-10.74)	(-9.12)
$MAX(2)$	$MAX(2)$	1.09	2.00	2.57	3.09	3.64	4.26	4.99	5.96	7.43	11.99	
	R	0.71	0.92	0.93	0.99	0.90	0.90	0.79	0.65	0.35	-0.34	-1.05
		(4.06)	(4.68)	(4.40)	(4.43)	(3.76)	(3.50)	(2.89)	(2.22)	(1.09)	(-0.97)	(-4.14)
	FFC4 α	0.23	0.34	0.31	0.34	0.23	0.18	0.06	-0.08	-0.37	-1.05	-1.28
		(2.74)	(5.54)	(5.37)	(5.72)	(3.95)	(3.26)	(1.09)	(-1.54)	(-6.18)	(-10.57)	(-8.91)
$MAX(1)$	$MAX(1)$	1.35	2.33	2.98	3.61	4.27	5.03	5.95	7.17	9.11	15.77	
	R	0.72	0.89	0.94	0.93	0.94	0.87	0.76	0.61	0.36	-0.23	-0.95
		(4.14)	(4.54)	(4.44)	(4.12)	(3.86)	(3.42)	(2.70)	(2.10)	(1.13)	(-0.67)	(-3.91)
	FFC4 α	0.23	0.31	0.32	0.28	0.26	0.16	0.02	-0.11	-0.36	-0.93	-1.15
		(2.89)	(5.10)	(5.59)	(4.87)	(4.36)	(3.28)	(0.44)	(-2.25)	(-5.97)	(-10.40)	(-8.95)

Table A3: Univariate Portfolio MPPM
Each month, all stocks are sorted into decile portfolios based on ascending sorts of either β or MAX. The table presents the manipulation proof performance measure (MPPM) of Ingersoll, Spiegel, Goetzmann, and Welch (2007) for each of the decile portfolios. t-statistics, calculated using standard errors generated using a bootstrap approach, testing the null hypothesis of a zero MPPM, are shown in parentheses.

Sort Variable	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
β	6.81	7.42	6.83	6.28	6.12	4.58	3.65	1.98	-1.56	-7.82	-16.96
	(5.26)	(5.74)	(4.95)	(4.57)	(4.20)	(3.28)	(2.63)	(1.42)	(-0.97)	(-2.80)	(-6.34)
MAX	7.23	9.46	8.67	8.01	7.14	5.64	4.66	2.23	-2.91	-13.65	-23.78
	(5.79)	(7.06)	(6.67)	(6.13)	(5.40)	(4.12)	(3.28)	(1.53)	(-1.64)	(-5.78)	(-9.92)

Table A4: Portfolio-Level MAX
Each month, all stocks are sorted into ascending decile portfolios based on either MAX or the portion of MAX that is orthogonal to beta ($MAX_{\perp\beta}$). The portfolio-level MAX for each decile portfolio is calculated as the average of the five highest daily portfolio-level returns in the month subsequent to portfolio formation. The table presents the time-series averages of the portfolio-level values of MAX for each of the decile portfolios. The column labeled High-Low presents the mean difference between decile ten and decile one. t-statistics, adjusted following Newey and West (1987), testing the null hypothesis that average difference in portfolio-level MAX between the decile ten and decile one portfolios is zero, are shown in parentheses.

Sort Variable	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
MAX	0.50	0.70	0.81	0.89	0.97	1.04	1.13	1.23	1.33	1.41	0.91
											(13.13)
$MAX_{\perp\beta}$	0.91	0.86	0.88	0.92	0.97	1.00	1.04	1.08	1.13	1.16	0.25
											(8.50)

Table A5: Bivariate Dependent Sort Portfolio Analyses - Alternative Measures of Lottery Demand

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and β after controlling for lottery demand. The measures of lottery demand are $MAX\,(k)$, $k \in \{1, 2, 3, 4, 5\}$, where $MAX\,(k)$ is defined as the average of the k highest daily returns of the given stock within the given month. Each month, all stocks in the sample are sorted into ten groups, each having an equal number of stocks, based on an ascending sort of the given measure of lottery demand. Within each group, decile portfolios based on an ascending sort of β are created. The table presents the time-series means of equal-weighted excess returns (R) for the average lottery demand decile portfolio within each decile of β, as well as the mean return differences between the high and low beta portfolios (High-Low), and the Fama and French (1993) and Carhart (1997) four-factor alphas (FFC4 α) for the High-Low portfolios. t-statistics for the High-Low returns and FFC4 alphas, adjusted following Newey and West (1987) using six lags, are in parentheses.

Lottery Demand Measure	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	FFC4 α
$MAX(5)$	0.70	0.69	0.67	0.68	0.67	0.70	0.66	0.65	0.70	0.68	-0.02	-0.14
											(-0.10)	(-0.85)
$MAX(4)$	0.73	0.68	0.67	0.66	0.67	0.72	0.66	0.63	0.70	0.66	-0.07	-0.18
											(-0.29)	(-1.07)
$MAX(3)$	0.74	0.68	0.70	0.65	0.69	0.70	0.66	0.61	0.69	0.67	-0.07	-0.21
											(-0.33)	(-1.20)
$MAX(2)$	0.73	0.72	0.71	0.64	0.69	0.70	0.65	0.66	0.66	0.63	-0.10	-0.24
											(-0.45)	(-1.37)
$MAX(1)$	0.75	0.71	0.73	0.66	0.68	0.72	0.67	0.64	0.65	0.58	-0.17	-0.31
											(-0.70)	(-1.77)

Table A6: Sub-Period Bivariate Dependent Sort Portfolio Analyses

The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and β after controlling for MAX for different subsets of months covered by our sample. The table presents results for the subset of months for which the Chicago Fed National Activity Index (CFNAI) is less than or equal to zero (CFNAI ≤ 0), months for which the CFNAI is greater than zero (CFNAI > 0), and months that are not part of the financial crisis of 2007 through 2009 (Non-Crisis). Non-crisis months are taken to be all months except for those from December 2007 through June 2009, inclusive. Each month, all stocks in the sample are sorted into 10 groups, each having an equal number of stocks, based on an ascending sort of MAX. Within each control variable group, decile portfolios based on an ascending sort of β are created. Each month, the equal-weighted one-month-ahead excess returns for each of the resulting portfolios is calculated. The excess return in each month for each β decile is then taken to be the average excess return, across all deciles of MAX, of the portfolios in the given decile of β. The table presents the time-series average excess return for each of these β decile portfolios. The row labeled High-Low presents the mean monthly return difference between the β decile 10 and decile 1 portfolio. The row labeled FFC4 α presents the risk-adjusted alpha of the High–Low portfolio relative to the Fama and French (1993) and Carhart (1997) four-factor risk model. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the mean monthly return or risk-adjusted alpha is equal to zero.

Market Conditions	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low	FFC4 α
CFNAI ≤ 0	0.49	0.55	0.60	0.61	0.73	0.75	0.66	0.70	0.75	0.70	0.21	0.07
											(0.58)	(0.30)
CFNAI > 0	0.90	0.82	0.72	0.75	0.61	0.64	0.67	0.61	0.64	0.66	-0.24	-0.35
											(-0.92)	(-1.50)
Non-Crisis	0.80	0.77	0.75	0.78	0.75	0.77	0.75	0.73	0.78	0.76	-0.04	-0.19
											(-0.18)	(-1.10)

Table A7: Bivariate Dependent Sort Portfolio Analyses - β and MAX
The table below presents the results of bivariate dependent sort portfolio analyses of the relation between future stock returns and each of β (Panel A) and MAX (Panel B) after controlling for the other. Each month, all stocks in the sample are sorted into ten groups, each having an equal number of stocks, based on an ascending sort of the control variable (MAX in Panel A, β in Panel B). Within each control variable group, decile portfolios based on an ascending sort of the predictive variable (β in Panel A, MAX in Panel B) are created. The table presents the time-series means of the equal-weighted one-month-ahead excess returns for each of the portfolios. The row labeled High-Low presents the mean monthly return difference between the β (MAX) decile ten and decile one portfolio for the given MAX (β) decile. The row labeled FFC4 α presents the risk-adjusted alpha of the difference portfolio relative to the Fama and French (1993) and Carhart (1997) four-factor risk model. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the mean monthly return difference or risk-adjusted alpha is equal to zero.

Panel A: Sort By MAX then β

	$MAX1$	$MAX2$	$MAX3$	$MAX4$	$MAX5$	$MAX6$	$MAX7$	$MAX8$	$MAX9$	$MAX10$
β 1 (Low)	0.52	0.95	0.91	0.99	0.91	0.86	0.94	0.73	0.51	-0.30
β 2	0.62	1.02	0.92	0.93	0.83	1.02	0.84	0.76	0.37	-0.42
β 3	0.60	0.84	1.00	0.92	0.84	0.79	0.68	0.75	0.46	-0.19
β 4	0.60	0.99	0.96	0.87	1.07	0.74	0.78	0.55	0.48	-0.23
β 5	0.65	0.92	0.95	1.07	0.87	0.73	0.80	0.63	0.25	-0.18
β 6	0.71	0.94	0.93	1.00	0.98	0.86	0.82	0.61	0.48	-0.37
β 7	0.84	0.97	0.96	0.94	0.84	0.90	0.88	0.58	0.25	-0.55
β 8	0.80	1.16	0.97	0.82	0.87	0.76	0.81	0.59	0.22	-0.50
β 9	1.02	1.13	1.01	0.83	0.91	0.75	0.78	0.72	0.39	-0.56
β 10 (High)	1.11	1.10	1.05	1.02	0.83	0.79	0.68	0.75	0.16	-0.72
High-Low	0.59	0.16	0.14	0.04	-0.08	-0.06	-0.25	0.02	-0.35	-0.42
	(3.03)	(0.87)	(0.71)	(0.16)	(-0.34)	(-0.23)	(-0.82)	0.06	(-1.04)	(-1.01)
FFC4 α	0.27	-0.09	-0.10	-0.17	-0.27	-0.16	-0.33	-0.06	-0.28	-0.24
	(1.78)	(-0.56)	(-0.54)	(-0.89)	(-1.30)	(-0.69)	(-1.36)	(-0.22)	(-1.00)	(-0.74)

Table A7: Bivariate Dependent Sort Portfolio Analyses - β and MAX - continued

Panel B: Sort By β then MAX

	β 1	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	β 10
MAX 1 (Low)	0.35	0.47	0.71	0.90	0.98	1.06	1.08	1.04	0.98	1.04
MAX 2	0.75	0.85	0.93	1.07	1.02	0.95	0.90	0.93	0.99	0.86
MAX 3	0.73	0.95	0.93	0.92	0.93	0.95	0.83	0.86	0.77	0.82
MAX 4	0.85	1.03	0.91	0.89	1.11	0.93	0.97	0.79	0.73	0.77
MAX 5	0.95	1.03	0.95	0.91	1.02	0.99	0.86	0.87	0.76	0.69
MAX 6	0.97	0.83	0.93	1.02	0.89	0.87	0.91	0.87	0.59	0.46
MAX 7	1.03	0.89	0.93	0.86	0.79	0.75	0.79	0.64	0.44	0.15
MAX 8	0.91	0.80	0.77	0.59	0.72	0.59	0.63	0.58	0.42	0.06
MAX 9	0.46	0.80	0.69	0.59	0.61	0.48	0.38	0.36	0.13	-0.31
MAX 10 (High)	-0.01	0.19	0.03	-0.03	0.01	-0.33	-0.23	-0.46	-0.71	-1.07
High-Low	-0.36	-0.28	-0.68	-0.93	-0.97	-1.39	-1.31	-1.50	-1.69	-2.11
	(-1.45)	(-1.66)	(-3.50)	(-5.21)	(-4.56)	(-6.75)	(-4.82)	(-6.87)	(-5.86)	(-7.48)
FFC4 α	-0.83	-0.59	-0.88	-1.21	-1.18	-1.64	-1.54	-1.66	-1.97	-2.14
	(-4.14)	(-3.88)	(-5.23)	(-7.76)	(-6.49)	(-8.69)	(-7.81)	(-7.77)	(-8.37)	(-8.59)

Table A8: Aggregate Lottery Demand and $\rho_{\beta,MAX}$

The table below presents the average values of measures characterizing market conditions in months with high and low $\rho_{\beta,MAX}$. REC_{ADS} and REC_{CFNAI} are dummies indicating a recession period according to the Aruoba-Diebold-Scotti Business Conditions Index (ADS) and the Chicago Fed National Activity Index (CFNAI), respectively. Values of ADS less than -0.5 and values of CFNAI less than -0.7 are taken to indicate recession. MAX_{MKTRF} and MAX_{Agg} are measures of aggregate lottery demand. VOL_{MKTRF} is the realized annualized volatility of the MKTRF factor during the month. MAX_{MKTRF} is the average of the five highest daily returns of the MKTRF factor during the given month. MAX_{Agg} is the value-weighted average MAX across all stocks in the sample during the given month. The row labeled high (low) presents the average value for the given variable during months with above (below) median $\rho_{\beta,MAX}$, and the row labeled High-Low presents the difference. The t-statistic testing the null hypothesis that the difference is equal to zero, adjusted following Newey and West (1987) using six lags, is presented in parentheses.

$\boldsymbol{\rho_{\beta,MAX}}$	REC_{ADS}	REC_{CFNAI}	VOL_{MKTRF}	MAX_{MKTRF}	MAX_{Agg}
High	0.30	0.24	15.56	1.28	2.53
Low	0.10	0.11	11.18	0.91	2.10
High-Low	0.20	0.13	4.38	0.37	0.43
	(3.71)	(2.37)	(3.71)	(4.15)	(3.62)

Table A9: High and Low β, MAX Correlation Factor Sensitivities
Panel A presents factor sensitivities of the High-Low univariate sort beta portfolio returns using several different risk models for months where the cross-sectional correlation between β and MAX is high. Panel B presents the results for months when the correlation is low. The columns labeled β_F, $F \in \{MKTRF, SMB, HML, UMD, PS, FMAX\}$, present the factor sensitivities. N indicates the number of months for which factor returns are available. Adj. R^2 is the adjusted r-squared of the factor model regression. t-statistics, adjusted following Newey and West (1987) using six lags, are in parentheses.

Panel A: High β, MAX Correlation

	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{FMAX}	N	Adj. R^2
FFC4	-0.72	1.08	0.60	-0.79	-0.15			296	77.34%
	(-2.86)	(11.17)	(5.21)	(-5.34)	(-1.73)				
FFC4+PS	-0.72	1.10	0.52	-0.78	-0.19	-0.15		269	78.66%
	(-2.63)	(11.63)	(4.28)	(-5.82)	(-2.15)	(-1.70)			
FFC4+FMAX	**0.09**	0.53	0.13	-0.18	-0.09		1.07	296	91.67%
	(0.53)	(9.22)	(2.16)	(-3.53)	(-2.26)		(18.82)		
FFC4+PS+FMAX	**0.03**	0.56	0.11	-0.18	-0.10	-0.01	1.04	269	91.89%
	(0.19)	(9.49)	(1.83)	(-3.21)	(-2.28)	(-0.30)	(17.54)		

Panel B: Low β, MAX Correlation

	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{FMAX}	N	Adj. R^2
FFC4	**-0.26**	0.83	0.57	-0.63	-0.21			297	66.11%
	(-0.86)	(8.96)	(6.13)	(-4.08)	(-2.27)				
FFC4+PS	**-0.19**	0.82	0.56	-0.68	-0.24	-0.01		271	67.10%
	(-0.62)	(8.57)	(6.09)	(-4.47)	(-2.54)	(-0.09)			
FFC4+FMAX	**0.08**	0.65	0.15	-0.44	-0.30		0.59	297	73.04%
	(0.30)	(7.72)	(0.94)	(-3.68)	(-3.41)		(4.65)		
FFC4+PS+FMAX	**0.11**	0.66	0.15	-0.49	-0.32	-0.01	0.56	271	73.25%
	(0.41)	(7.50)	(0.98)	(-3.96)	(-3.37)	(-0.12)	(4.38)		

Table A10: Factor Sensitivities of BAB to Alternative FMAX Factors

The table below presents the alphas and factor sensitivities for the BAB factor using several factor models. The column labeled α presents the risk-adjusted alpha for each of the factor models. The columns labeled β_f, $f \in \{MKTRF, SMB, HML, UMD, PS, FMAX\}$ present the sensitivities of the BAB factor returns to the given factor. The BAB factor is taken from Lasse H. Pedersen's website. The difference versions of the FMAX factor are created using the factor creation procedure of Fama and French (1993), taking $MAX(k)$, defined as the average of the k highest daily returns of the given stock in the given month, as the measure of lottery demand. The factor created using $MAX(k)$ as the measure of lottery demand is denoted FMAX(k). The sample covers the period from August of 1963 through March of 2012. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the coefficient is equal to zero. The column labeled N indicates the number of monthly returns used to fit the factor model. The column labeled Adj. R^2 presents the adjusted r-squared of the factor model regression.

Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	$\beta_{FMAX(5)}$	$\beta_{FMAX(4)}$	$\beta_{FMAX(3)}$	$\beta_{FMAX(2)}$	$\beta_{FMAX(1)}$	N	Adj. R^2
FFC4+FMAX(5)	0.17	0.29	0.31	0.21	0.17		-0.55					584	46.95%
	(1.23)	(8.22)	(5.46)	(3.49)	(4.39)		(-11.84)						
FFC4+PS+FMAX(5)	0.22	0.29	0.32	0.24	0.19	0.03	-0.55					531	47.38%
	(1.59)	(8.20)	(5.50)	(3.58)	(4.39)	(2.56)	(-11.11)						
FFC4+FMAX(4)	0.17	0.29	0.35	0.22	0.17			-0.57				584	47.20%
	(1.27)	(8.29)	(6.19)	(3.50)	(4.15)			(-11.82)					
FFC4+PS+FMAX(4)	0.22	0.30	0.35	0.24	0.18	0.04		-0.55				531	47.74%
	(1.48)	(8.04)	(6.00)	(3.73)	(4.23)	(0.73)		(-11.11)					
FFC4+FMAX(3)	0.18	0.29	0.36	0.22	0.16				-0.58			584	47.35%
	(1.37)	(8.34)	(6.25)	(3.48)	(4.04)				(-11.66)				
FFC4+PS+FMAX(3)	0.24	0.30	0.36	0.24	0.17	0.03			-0.57			531	47.87%
	(1.61)	(8.06)	(6.08)	(3.70)	(4.13)	(0.66)			(-10.86)				
FFC4+FMAX(2)	0.20	0.29	0.38	0.21	0.15					-0.60		584	47.37%
	(1.45)	(8.35)	(6.48)	(3.39)	(3.94)					(-11.57)			
FFC4+PS+FMAX(2)	0.25	0.30	0.38	0.23	0.16	0.03				-0.59		531	47.90%
	(1.73)	(8.08)	(6.30)	(3.60)	(4.03)	(0.62)				(-10.72)			
FFC4+FMAX(1)	0.21	0.29	0.38	0.20	0.14						-0.64	584	47.51%
	(1.58)	(8.41)	(6.33)	(3.32)	(3.62)						(-11.41)		
FFC4+PS+FMAX(1)	0.27	0.29	0.38	0.23	0.15	0.03					-0.62	531	48.28%
	(1.82)	(8.13)	(6.22)	(3.54)	(3.78)	(0.68)					(-10.75)		

Table A11: Univariate Portfolio Results Sorting on β_{FP}, $\beta_{FP\perp MAX}$, and $MAX_{\perp\beta_{FP}}$
The table below presents the results of univariate portfolio analyses of the relation between future stock returns and each of FP's market beta (β_{FP}), the portion of β_{FP} that is orthogonal to MAX ($\beta_{FP\perp MAX}$), and the portion of MAX that is orthogonal to β_{FP} ($MAX_{\perp\beta_{FP}}$). t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the average monthly excess return, alpha, or sensitivity, is equal to zero, are presented in parentheses.

Sort Variable	**Value**	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
β_{FP}	β_{FP}	0.64	0.76	0.83	0.88	0.93	0.99	1.04	1.11	1.20	1.41	
	R	0.83	0.81	0.80	0.79	0.80	0.75	0.73	0.70	0.64	0.63	-0.20
		(4.19)	(3.90)	(3.62)	(3.50)	(3.40)	(3.12)	(2.82)	(2.63)	(2.35)	(2.12)	(-1.30)
	FFC4 α	0.22	0.18	0.13	0.13	0.12	0.06	0.02	-0.02	-0.06	-0.08	-0.31
		(3.44)	(3.24)	(2.33)	(2.70)	(2.41)	(1.30)	(0.36)	(-0.33)	(-1.13)	(-1.09)	(-2.67)
	FFC4 + PS α	0.23	0.19	0.14	0.15	0.11	0.05	0.01	-0.05	-0.08	-0.07	-0.29
		(3.31)	(3.26)	(2.28)	(2.97)	(1.94)	(0.97)	(0.19)	(-1.01)	(-1.41)	(-0.88)	(-2.49)
	FFC4 + FMAX α	0.09	0.05	0.02	0.03	0.03	0.00	-0.02	-0.03	-0.05	0.02	-0.07
		(1.46)	(0.99)	(0.46)	(0.66)	(0.56)	(-0.08)	(-0.45)	(-0.70)	(-0.76)	(0.21)	(-0.68)
	FFC4 + PS + FMAX α	0.09	0.06	0.04	0.05	0.01	-0.02	-0.04	-0.07	-0.08	0.01	-0.08
		(1.43)	(1.18)	(0.63)	(1.05)	(0.21)	(-0.38)	(-0.67)	(-1.41)	(-1.23)	(0.11)	(-0.74)
$\beta_{FP\perp MAX}$	$\beta_{FP\perp MAX}$	0.60	0.72	0.79	0.84	0.89	0.95	1.00	1.07	1.16	1.36	
	R	0.76	0.77	0.80	0.74	0.80	0.77	0.69	0.76	0.69	0.71	-0.05
		(3.66)	(3.59)	(3.56)	(3.24)	(3.38)	(3.23)	(2.69)	(2.94)	(2.56)	(2.49)	(-0.39)
	FFC4 α	0.15	0.13	0.14	0.07	0.11	0.09	-0.01	0.05	-0.03	0.00	-0.15
		(2.38)	(2.46)	(2.40)	(1.52)	(2.12)	(1.97)	(-0.25)	(1.06)	(-0.51)	(0.04)	(-1.48)
$MAX_{\perp\beta_{FP}}$	$MAX_{\perp\beta_{FP}}$	-1.19	-0.19	0.42	1.00	1.60	2.28	3.11	4.24	6.04	12.39	
	R	0.80	0.89	0.94	0.88	0.95	0.94	0.87	0.68	0.53	0.01	-0.79
		(4.13)	(4.35)	(4.47)	(4.01)	(4.10)	(3.82)	(3.30)	(2.49)	(1.79)	(0.02)	(-4.04)
	FFC4 α	0.27	0.29	0.32	0.24	0.26	0.24	0.10	-0.07	-0.22	-0.74	-1.01
		(3.48)	(4.46)	(5.78)	(4.71)	(4.78)	(4.59)	(1.99)	(-1.39)	(-3.76)	(-8.66)	(-8.57)

Table A12: Bivariate Independent Sort Portfolio Analysis for β_{FP} and MAX
The table below presents the results of an independent sort bivariate portfolio analysis of the relation between future stock returns and each of FP's market beta (β_{FP}) and MAX. The table shows the time-series means of the monthly equal-weighted excess returns based for portfolios formed on intersections of β and MAX deciles. t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the mean monthly High-Low return difference or Fama and French (1993) and Carhart (1997) four-factor alpha is equal to zero, are in parentheses.

	MAX 1	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10	MAX Avg.	High - Low	FFC4 α
β_{FP} 1 (Low)	0.81	0.89	0.97	1.02	0.99	0.87	0.98	0.99	0.73	0.00	0.83	-0.80	-1.17
												(-2.89)	(-4.96)
β_{FP} 2	0.74	1.03	1.08	0.89	1.01	0.98	0.86	0.91	0.45	-0.07	0.79	-0.82	-1.09
												(-3.40)	(-5.51)
β_{FP} 3	0.80	0.99	0.87	0.98	0.93	0.89	0.95	0.73	0.60	-0.12	0.76	-0.92	-1.14
												(-3.62)	(-5.78)
β_{FP} 4	0.92	1.00	0.94	0.95	0.93	0.80	0.76	0.83	0.37	0.06	0.76	-0.86	-1.05
												(-2.80)	(-4.07)
β_{FP} 5	0.98	0.96	1.05	0.98	0.81	0.91	0.85	0.84	0.55	0.11	0.80	-0.87	-1.07
												(-3.32)	(-5.71)
β_{FP} 6	0.92	1.12	1.07	0.78	0.91	0.84	0.71	0.83	0.47	-0.24	0.74	-1.16	-1.50
												(-4.60)	(-7.82)
β_{FP} 7	0.88	1.10	1.06	0.93	0.95	0.76	0.79	0.64	0.55	-0.05	0.76	-0.93	-1.26
												(-3.21)	(-5.93)
β_{FP} 8	1.00	1.04	1.03	0.91	0.93	0.83	0.76	0.73	0.50	-0.24	0.75	-1.23	-1.42
												(-4.52)	(-6.26)
β_{FP} 9	0.85	1.19	0.81	0.93	0.99	0.79	0.93	0.67	0.32	-0.22	0.72	-1.07	-1.31
												(-3.87)	(-5.63)
β_{FP} 10 (High)	0.78	1.00	1.23	0.95	1.01	0.89	0.86	0.75	0.47	-0.32	0.76	-1.10	-1.38
												(-3.60)	(-5.87)
β Avg.	0.87	1.03	1.01	0.93	0.95	0.86	0.84	0.79	0.50	-0.11			
High-Low	-0.03	0.11	0.27	-0.08	0.02	0.02	-0.12	-0.24	-0.25	-0.32			
	(-0.13)	(0.85)	(1.39)	(-0.49)	(0.10)	(0.12)	(-0.62)	(-1.33)	(-1.06)	(-0.78)			
FFC4 α	-0.05	0.01	0.15	-0.16	-0.08	-0.03	-0.11	-0.29	-0.30	-0.20			
	(-0.30)	(0.06)	(0.87)	(-1.04)	(-0.55)	(-0.23)	(-0.60)	(-1.77)	(-1.36)	(-0.80)			

Table A13: Bivariate Dependent Sort Portfolio Analyses - β_{FP} and MAX

The table below presents the results of dependent sort bivariate portfolio analyses of the relation between future stock returns and each of β_{FP} (Panel A) and MAX (Panel B) after controlling for the other. Each month, all stocks in the sample are sorted into ten groups, each having an equal number of stocks, based on an ascending sort of the control variable (MAX in Panel A, β_{FP} in Panel B). Within each control variable group, decile portfolios based on an ascending sort of the predictive variable (β_{FP} in Panel A, MAX in Panel B) are created. The table presents the time-series means of the equal-weighted one-month-ahead excess returns for each of the portfolios. The row labeled High-Low presents the mean monthly return difference between the β_{FP} (MAX) decile ten and decile one portfolio for the given MAX (β_{FP}) decile. The row labeled FFC4 α presents the risk-adjusted alpha of the difference portfolio relative to the Fama and French (1993) and Carhart (1997) four-factor risk model. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the mean monthly return difference or risk-adjusted alpha is equal to zero.

Panel A: Sort By MAX then β_{FP}

	MAX 1	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10	MAX Avg.
β_{FP} 1 (Low)	0.74	0.86	0.93	1.00	0.95	0.93	0.95	0.89	0.52	-0.01	0.78
β_{FP} 2	0.82	0.97	1.04	0.96	1.02	0.88	0.90	0.81	0.49	-0.25	0.76
β_{FP} 3	0.78	1.01	0.98	0.90	0.84	0.85	0.90	0.83	0.57	0.18	0.79
β_{FP} 4	0.75	1.05	0.82	0.97	1.03	0.83	0.77	0.85	0.50	-0.12	0.75
β_{FP} 5	0.81	0.97	1.03	0.91	0.75	0.93	0.87	0.81	0.59	-0.24	0.74
β_{FP} 6	0.91	0.95	1.04	0.89	1.02	0.82	0.70	0.63	0.43	-0.17	0.72
β_{FP} 7	1.03	1.06	0.97	0.80	0.92	0.84	0.73	0.72	0.49	-0.07	0.75
β_{FP} 8	0.77	1.09	1.05	1.02	0.85	0.87	0.85	0.80	0.41	-0.23	0.75
β_{FP} 9	0.92	1.04	0.91	0.89	0.96	0.76	0.87	0.64	0.32	-0.44	0.69
β_{FP} 10 (High)	0.89	1.03	1.02	0.94	1.00	0.82	0.86	0.74	0.54	-0.25	0.76
High-Low	0.15	0.17	0.09	-0.06	0.05	-0.11	-0.09	-0.15	0.02	-0.23	-0.02
	(1.16)	(1.49)	(0.66)	(-0.42)	(0.34)	(-0.72)	(-0.49)	(-0.88)	(0.11)	(-0.96)	(-0.14)
FFC4 α	0.09	0.05	0.00	-0.12	-0.05	-0.15	-0.08	-0.19	0.00	-0.22	-0.07
	(0.66)	(0.39)	(0.03)	(-0.85)	(-0.35)	(-1.02)	(-0.52)	(-1.21)	(-0.01)	(-0.97)	(-0.73)

Table A13: Bivariate Dependent Sort Portfolio Analyses - β_{FP} and MAX - continued

Panel B: Sort By β_{FP} then MAX

	β_{FP} 1	β_{FP} 2	β_{FP} 3	β_{FP} 4	β_{FP} 5	β_{FP} 6	β_{FP} 7	β_{FP} 8	β_{FP} 9	β_{FP} 10	β_{FP} Avg.
MAX 1 (Low)	0.73	0.72	0.74	0.91	0.93	0.94	0.90	0.95	0.93	1.01	0.88
MAX 2	0.87	0.94	1.02	1.00	0.97	1.10	1.04	0.99	0.96	0.93	0.98
MAX 3	0.97	1.02	0.97	0.99	1.07	1.04	1.02	0.99	0.83	0.96	0.99
MAX 4	0.96	1.04	0.86	0.92	0.88	0.82	0.89	0.90	0.88	0.76	0.89
MAX 5	0.97	0.98	1.02	0.91	0.83	0.96	0.84	0.89	0.99	0.95	0.93
MAX 6	0.85	0.92	0.90	0.81	0.96	0.74	0.70	0.83	0.84	0.71	0.83
MAX 7	0.99	0.83	0.89	0.77	0.83	0.79	0.78	0.74	0.65	0.84	0.81
MAX 8	0.89	0.93	0.81	0.85	0.90	0.85	0.55	0.59	0.53	0.46	0.74
MAX 9	0.87	0.64	0.78	0.65	0.53	0.49	0.59	0.47	0.10	0.20	0.53
MAX 10 (High)	0.17	0.05	-0.03	0.12	0.13	-0.25	-0.10	-0.36	-0.30	-0.53	-0.11
High-Low	-0.55	-0.67	-0.78	-0.79	-0.80	-1.19	-1.01	-1.32	-1.23	-1.55	-0.99
	(-2.42)	(-3.23)	(-3.37)	(-2.93)	(-3.35)	(-4.84)	(-3.49)	(-4.95)	(-4.37)	(-5.03)	(-4.61)
FFC4 α	-0.91	-0.96	-1.00	-1.00	-0.99	-1.53	-1.33	-1.52	-1.44	-1.71	-1.24
	(-5.04)	(-5.98)	(-5.46)	(-4.50)	(-6.06)	(-8.06)	(-6.11)	(-7.29)	(-6.24)	(-6.53)	(-8.97)

Table A14: Factor Sensitivities for BAB_\$5 and FMAX Factors
The table below presents the alphas and factor sensitivities for the \$5 stock BAB_\$5 factor (Panel A) and FMAX factor (Panel B) using several factor models. The column labeled α presents the risk-adjusted alpha for each of the factor models. The columns labeled β_f, $f \in \{MKTRF, SMB, HML, UMD, PS, FMAX, BAB\_\$5\}$ present the sensitivities of the BAB_\$5 or FMAX factor returns to the given factor. The BAB_\$5 factor is constructed following equations (16) and (17) in Frazzini and Pedersen (2014) using only stocks with share price greater than \$5.00. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the coefficient is equal to zero. The column labeled N indicates the number of monthly returns used to fit the factor model. The column labeled Adj. R^2 presents the adjusted r-squared of the factor model regression.

Panel A: Sensitivities of BAB_\$5 Factor

Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{FMAX}	N	Adj. R^2
FFC4	0.30	0.21	0.07	0.29	0.07			593	29.60%
	(3.38)	(6.75)	(1.56)	(5.68)	(2.22)				
FFC4+PS	0.32	0.22	0.09	0.30	0.09	0.03		540	33.08%
	(3.44)	(6.99)	(1.85)	(5.90)	(2.57)	(1.03)			
FFC4+FMAX	**0.10**	0.33	0.24	0.13	0.07		-0.29	593	49.67%
	(1.30)	(12.62)	(7.25)	(3.77)	(3.31)		(-10.66)		
FFC4+PS+FMAX	**0.14**	0.33	0.24	0.15	0.08	0.01	-0.28	540	51.27%
	(1.60)	(12.31)	(7.01)	(4.15)	(3.59)	(0.69)	(-9.77)		

Panel B: Sensitivities of FMAX Factor

Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	$\beta_{BAB\_\$5}$	N	Adj. R^2
FFC4	-0.67	0.43	0.58	-0.53	-0.02			593	62.14%
	(-5.12)	(8.36)	(6.39)	(-4.59)	(-0.19)				
FFC4+PS	-0.65	0.42	0.56	-0.54	-0.03	-0.06		540	62.36%
	(-4.60)	(8.17)	(5.51)	(-4.72)	(-0.41)	(-1.00)			
FFC4+BAB_\$5	-0.37	0.63	0.65	-0.24	0.06		-0.99	593	72.93%
	(-3.15)	(13.95)	(9.78)	(-3.03)	(0.99)		(-10.02)		
FFC4+PS+BAB_\$5	-0.34	0.64	0.64	-0.25	0.05	-0.03	-0.98	540	72.59%
	(-2.54)	(13.68)	(8.74)	(-2.98)	(0.87)	(-0.71)	(-9.59)		