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A Lottery-Demand-Based Explanation of the Beta Anomaly

Turan G. Bali, Stephen J. Brown, Scott Murray, and Yi Tang*

Abstract

The low (high) abnormal returns of stocks with high (low) beta, which we refer to as the beta anomaly, is one of the most persistent anomalies in empirical asset pricing research. This article demonstrates that investors' demand for lottery-like stocks is an important driver of the beta anomaly. The beta anomaly is no longer detected when beta-sorted portfolios are neutralized to lottery demand, regression specifications control for lottery demand, or factor models include a lottery demand factor. The beta anomaly is concentrated in stocks with low levels of institutional ownership and it exists only when the price impact of lottery demand is concentrated in high-beta stocks.

I. Introduction

The positive (negative) abnormal returns of portfolios composed of low-beta (high-beta) stocks, which we refer to as the beta anomaly, is one of the most

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persistent and widely studied anomalies in empirical research of security returns. In this article, we propose that demand for lottery-like stocks (Kumar (2009), Bali, Cakici, and Whitelaw (2011), Kumar, Page, and Spalt (2011), Doran, Jiang, and Peterson (2011), and Han and Kumar (2013)) plays an important role in explaining the beta anomaly.[1] Our hypothesis is similar to that put forth by recent papers (Shen, Yu, and Zhao (2017), An, Wang, Wang, and Yu (2015), and Wang, Yan, and Yu (2017)) investigating the relation between risk anomalies and behavioral phenomena such as lottery demand, sentiment, and overconfidence.

Our rationale is as follows. As discussed by Kumar (2009), Bali et al. (2011), and Han and Kumar (2013), 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 0) 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.[2]

We test our hypothesis in several ways. First, we demonstrate that the returns associated with the beta anomaly are no longer apparent after controlling for lottery demand. Following Bali et al. (2011), we proxy for lottery demand with MAX, defined as the average of the 5 highest daily returns of the given stock in a given month.[3] Bivariate portfolio analyses demonstrate that the abnormal returns of a 0-cost portfolio that is long high-beta stocks and short low-beta stocks (high–low beta portfolio) are no longer significant when the portfolio is constrained to be neutral to MAX. Univariate portfolio analyses fail to detect the beta anomaly when the component of beta that is orthogonal to MAX (instead of beta itself) is used as the sort variable. FM (1973) regressions indicate a positive and significant relation between beta and stock returns when MAX is included in the regression specification.

[1]The beta anomaly was first documented by Black, Jensen, and Scholes (1972). Subsequent studies detect this result in the U.S. (Black (1972), Fama and MacBeth (FM) (1973), Fama and French (1992), and Baker and Wurgler (2014)) and international (Frazzini and Pedersen (2014)) equity markets. Similarly, the lottery effect exists in U.S. (Kumar (2009), Bali et al. (2011), Kumar et al. (2011), Doran et al. (2011), Han and Kumar (2013), and An et al. (2015)) and international (Doran et al. (2011), Carpenter, Lu, and Whitelaw (2014), Annaert, De Ceuster, and Verstegen (2013), Walkshäusl (2014), and Zhong and Gray (2016)) equities. Demand for lottery-like stocks is consistent with cumulative prospect theory (Tversky and Kahneman (1992), Barberis and Huang (2008)).

[2]Black et al. (1972) and Black (1993) suggest that divergent risk-free borrowing and lending rates drive the beta anomaly. This has become the standard textbook explanation (Elton, Gruber, Brown, and Goetzmann (2014), chap. 14). Frazzini and Pedersen (2014) attribute this phenomenon to market pressures exerted by leverage-constrained investors attempting to boost expected returns by purchasing high-beta stocks.

[3]In Section VII, we show that lottery stocks identified by MAX are very similar to those identified using other measures such as stock price, idiosyncratic volatility, and idiosyncratic skewness (Kumar (2009), Han and Kumar (2013)).

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We then generate a factor, FMAX, designed to capture the returns associated with lottery demand.[4] We show that the abnormal returns of the high–low beta portfolio relative to the commonly used Fama and French (1993) and Carhart (1997) 4-factor (FFC4) model and the FFC4 model augmented with the Pastor and Stambaugh (PS) (2003) liquidity factor are insignificant when FMAX is included in the factor model.

The results of our cross-sectional analyses suggest that the beta anomaly is a manifestation of the effect of lottery demand on stock returns. We validate this conjecture in two ways. First, we show that on average, lottery demand price pressure falls predominantly on high-beta stocks, as lottery demand and beta are positively correlated in the cross section. However, there is important time variation in this relation. In months when lottery demand price pressure is not disproportionately exerted on high-beta stocks, the returns associated with the beta anomaly are very low or nonexistent. When lottery demand price pressure falls largely on high-beta stocks, the beta anomaly is very strong. Even in these months when the beta anomaly generates large returns, however, the returns are explained by the lottery demand factor. Second, as discussed in Kumar and Lee (2006), Kumar (2009), and Han and Kumar (2013) and supported by our results, the lottery demand phenomenon is attributable to individual, not institutional, investors. If lottery demand drives the beta anomaly, the beta anomaly should also be concentrated in stocks largely held by individual investors. Our analyses demonstrate that the beta anomaly is very strong among stocks with low institutional ownership and nonexistent among stocks with high institutional ownership.

The remainder of this article proceeds as follows: Section II provides data and variable definitions. Section III illustrates the beta anomaly and lottery demand phenomenon. Section IV demonstrates the role of lottery demand in generating the beta anomaly. Section V introduces a lottery demand factor and shows that it captures the returns associated with the beta anomaly. Section VI illustrates the channels by which lottery demand is responsible for the beta anomaly. Section VII shows that MAX is an effective measure of lottery demand. Section VIII concludes.

II. 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) at the end of 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.

Following Bali et al. (2011), we measure a stock's lottery demand using MAX, calculated as the average of the 5 highest daily returns of the stock during

[4]Kumar and Lee (2006) and Kumar, Page, and Spalt (2016) demonstrate that correlated trading among retail investors generates comovement among stock returns.

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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 1-month-ahead (month $t+1$) 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. The focal analyses throughout this article use β and MAX, as well as other control variables (discussed below), calculated as of the end of month t, to forecast the cross section of month $t+1$ excess stock returns.

We control for several other variables known to predict the cross section of future stock returns. These variables are grouped into 3 main categories. The first category is firm characteristics, which includes market capitalization, book-to-market ratio, momentum, stock illiquidity, and idiosyncratic volatility. The second category is composed of measures of risk, including coskewness, 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 the hypothesis, put forth by Frazzini and Pedersen (2014), that funding constraints are the primary driver of the beta anomaly. In the ensuing sections, we briefly describe the calculation of the control variables. More details on the calculation of all variables used in this study are available in Section IA-I of the Internet Appendix (available at www.jfqa.org).

A. Firm Characteristics

To examine the possibility that the size and/or value effects of Fama and French (1992) play a role in the beta anomaly, we define MKTCAP as the stock's market capitalization at the end of month t and BM as the log of the firm's book-to-market ratio, calculated following Fama and French (1992). Because the cross-sectional distribution of market capitalization is highly skewed, we use the natural log of market capitalization, denoted SIZE, in regression analyses. To control for the medium-term momentum effect originally documented by Jegadeesh and Titman (1993), we measure the momentum (MOM) of a stock at the end of month t as the stock's 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 all trading days in month t. 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 (MKTRF) and the size (SMB) and book-to-market (HML) factor-mimicking portfolio returns of Fama and French (1993) using daily return data from all trading days in month t. When calculating ILLIQ and IVOL, we require 15 days of valid daily return observations within the given month.

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B. Risk Measures

We control for several measures of risk. Each of these measures is calculated at the end of month t using daily return data from the 1-year period covering months $t-11$ through t, inclusive. Coskewness (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 excess stock returns on the excess market returns and the excess market returns squared. We define total skewness (TSKEW) as the skewness of the daily stock returns. Downside beta (DRISK) of Bawa and Lindenberg (1977) is measured as the slope coefficient from a regression of excess stock returns on the excess market returns, using only days for which the market return was below the average daily market return during the past year. Following Ruenzi and Weigert (2013), we define tail beta (TRISK) as the slope coefficient from a regression of excess stock returns on excess market returns using only daily observations in the bottom 10% of market excess returns over the past year. In calculating each of COSKEW, TSKEW, DRISK, and TRISK, we require a minimum of 200 valid daily stock return observations.

C. Funding Liquidity Measures

Frazzini and Pedersen (2014) provide evidence that the beta anomaly is driven by funding liquidity. We measure the funding liquidity sensitivity of a stock relative to 4 widely accepted factors that proxy for funding liquidity (see Gârleanu and Pedersen (2011), Frazzini and Pedersen (2014), and Chen and Lu (2014)). The first is the TED spread (TED), calculated for month t as the difference between the 3-month London Interbank Offered Rate (LIBOR) and the rate on 3-month U.S. Treasury bills on the last trading day of month t. The second is volatility of the TED spread (VOLTED). The month t-value of VOLTED is defined as the standard deviation of the daily TED spread values over all trading days in month t. The third is the U.S. Treasury bill rate (TBILL), taken to be the rate on 3-month U.S. Treasury bills as of the end of the given month t. The fourth is financial sector leverage (FLEV), defined following Chen and Lu (2014) 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. Although 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, as 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, denoted β_{TED}, is calculated at the end of month t as the slope coefficient from a regression of excess stock returns on TED using 5 years worth of monthly data covering months $t-59$ through t. Sensitivities to VOLTED, TBILL, and FLEV, denoted β_{VOLTED}, β_{TBILL}, and β_{FLEV}, respectively, are calculated

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analogously. We require a minimum of 24 valid monthly stock return observations to calculate these measures of exposure to aggregate funding liquidity.[5]

D. Data Sources and Sample

Daily and monthly stock data are from the Center for Research in Security Prices (CRSP). Balance sheet data used to calculate the book-to-market ratio and financial industry leverage come from Compustat. Daily and monthly market excess returns and factor returns are from Kenneth French's data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Monthly PS (2003) liquidity factor returns are from Lubos Pastor's Web site (http://faculty.chicagobooth.edu/lubos.pastor/research). The 3-month LIBOR and U.S. Treasury bill yields are from Global Insight. Institutional holdings data come from Thomson Reuters Institutional Holdings (13F) database.

The primary sample used throughout this article covers the 593 months t from July 1963 through Nov. 2012. The empirical analyses therefore focus on month $t+1$ returns from Aug. 1963 through Dec. 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 National Association of Securities Dealers Automated Quotation (NASDAQ) with a stock price at the end of month t of $5 or more. Because month-end TED spread data are available beginning in Jan. 1963 and 60 months of data are required to calculate β_{TED}, analyses using β_{TED} cover the months t (return months $t+1$) from Dec. 1967 (Jan. 1968) through Nov. 2012 (Dec. 2012). Similarly, the daily TED spread data required to calculate VOLTED are available beginning in Jan. 1977; thus, analyses using β_{VOLTED} cover the months t (return months $t+1$) from Dec. 1981 (Jan. 1982) through Nov. 2012 (Dec. 2012). Analyses using the PS (2003) liquidity factor (PS) cover Jan. 1968 through Dec. 2012, the period for which PS factor returns are available. Institutional holdings data are available beginning in Jan. 1980. Analyses that use institutional holdings data therefore cover the months t (return months $t+1$) from Jan. 1980 (Feb. 1980) through Nov. 2012 (Dec. 2012).

III. The Beta Anomaly and Demand for Lottery

We begin our analysis by demonstrating the beta anomaly and lottery demand phenomenon.

A. The Beta Anomaly

To demonstrate the beta anomaly, at the end of each month t we sort all stocks in our sample into 10 decile portfolios based on an ascending ordering of market beta (β), with each portfolio having an equal number of stocks. Panel A

[5]Because TED, VOLTED, TBILL, and FLEV take low (high) values when funding liquidity is high (low), our measures may more aptly be termed sensitivities to funding *il*liquidity. 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.

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in Table 1 presents the time-series means of the individual stocks' β, the average month $t+1$ (1-month-ahead) portfolio excess return (R), and alphas relative to the Fama–French (1993) and Carhart (1997) 4-factor model (FFC4 α) as well as the FFC4 model augmented with the PS factor (FFC4+PS α) for each of the decile portfolios (columns labeled β 1 through β 10) and for the 0-cost portfolio that is long the decile 10 portfolio and short the decile 1 portfolio (column labeled High–Low β). The numbers in parentheses are t-statistics, adjusted following Newey and West (NW) (1987) using 6 lags, testing the null hypothesis that the average excess return or alpha is equal to 0.

TABLE 1
Univariate Portfolios Sorted on β

Table 1 presents the results of analyses of portfolios formed by sorting on β. At the end of each month t, all stocks are sorted into ascending β decile portfolios. Panel A presents the time-series means of the monthly equal-weighted portfolio betas (β), 1-month-ahead excess returns (R), alphas relative to the Fama–French (1993) and Carhart (1997) 4-factor model (FFC4 α), and alphas relative to the Fama–French (1993), Carhart (1997), and Pastor–Stambaugh (2003) 5-factor model (FFC4+PS α) for each of the decile portfolios. Excess returns and alphas are reported in percentages per month. The column labeled High–Low β presents results for a 0-cost portfolio that is long the decile 10 portfolio and short the decile 1 portfolio. t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis of a 0 mean excess return or alpha are shown in parentheses. Panel B 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). Panel C shows average portfolio values of coskewness (COSKEW), total skewness (TSKEW), downside beta (DRISK), and tail beta (TRISK). Panel D 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 months t (return months $t+1$) from July (Aug.) 1963 through Nov. (Dec.) 2012 and includes all U.S.-based publicly traded common stocks with share price of at least \$5 at the end of month t.

Value	Low β 1	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	High β 10	High–Low β
Panel A. 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)
FFC4+PS α	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)
Panel B. 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	
Panel C. 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	
Panel D. 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	

The results in Table 1 show that the average value of β increases monotonically (by construction) from −0.0007 for the first decile portfolio to 2.02 for

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the 10th decile. The average 1-month-ahead excess returns of the β-sorted decile portfolios tend to decrease, albeit not monotonically, from 0.69% per month for the low-β decile (decile 1) to 0.35% for the high-β decile (decile 10). The average monthly return of the high–low β portfolio of −0.35% per month is not statistically distinguishable from 0, indicating no difference in average returns between stocks with high market betas and stocks with low market betas.

The abnormal returns of the decile portfolios relative to the FFC4 factor model exhibit a strong and nearly monotonically decreasing pattern (the exception is decile 1) across the β deciles. The lowest β decile portfolio's abnormal return of 0.22% per month is statistically significant, with a corresponding t-statistic of 2.22. Conversely, the high-β portfolio generates a negative and significant abnormal return of −0.29% per month (t-statistic = −2.22). The abnormal return of the high–low β portfolio of −0.51% per month is highly significant, with a t-statistic of −2.50. This result is extremely similar to the corresponding result in Frazzini and Pedersen (2014), who find a −0.55% per month difference in FFC4 alpha between the high-β and low-β decile portfolios. The results using the FFC4+PS factor model are very similar to those generated by the FFC4 model.

The main result discussed in the previous paragraph, namely, the large negative alpha of the high–low β portfolio, is the starting point for this article. This result indicates that the beta anomaly is both economically strong and statistically significant in our sample.[6]

To gain a better understanding of the composition of the β decile portfolios, the remainder of Table 1 presents 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.

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 book-to-market ratio (BM) and illiquidity (ILLIQ). The results in Panel C show that coskewness (COSKEW), downside beta (DRISK), and tail beta (TRISK) are all positively related to β, whereas total skewness (TSKEW) and β exhibit a negative relation. Finally, the table shows that β is positively related to β_{TED} and β_{VOLTED} and negatively related to β_{TBILL} and β_{FLEV}.

B. Lottery Demand Phenomenon

As with the beta anomaly, 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 of the high–low MAX portfolio of −1.15% per month is both

[6] In Section IA-II and Table IA1 of the Internet Appendix, we demonstrate that the beta anomaly is robust to the use of alternative measures of beta developed by Scholes and Williams (1977) and Dimson (1979) designed to account for nonsynchronous and infrequent trading, respectively, as well as to the use of the beta measure constructed by Frazzini and Pedersen (2014).

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TABLE 2
Univariate Portfolios Sorted on MAX

Table 2 presents the results of analyses of portfolios formed by sorting on β. At the end of each month t, all stocks are sorted into ascending MAX decile portfolios, where MAX is defined as the average of the 5 highest daily returns of the given stock in a given month. The table presents the time-series means of the monthly equal-weighted portfolio average MAX values, 1-month-ahead excess returns (R), FFC4 alphas (FFC4 α), and FFC4+PS alphas (FFC4+PS α) for each of the decile portfolios. Excess returns and alphas are reported in percentages per month. The column labeled High–Low MAX presents results for a 0-cost portfolio that is long the decile 10 portfolio and short the decile 1 portfolio. t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis of a 0 mean excess return or alpha are shown in parentheses.

Value	MAX 1 (Low)	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10 (High)	High–Low MAX
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)
FFC4+PS α	0.24	0.43	0.35	0.29	0.23	0.13	0.08	−0.07	−0.37	−1.15	−1.38
	(2.37)	(5.36)	(5.29)	(4.60)	(3.56)	(2.06)	(1.42)	(−1.41)	(−5.48)	(−9.65)	(−8.09)

economically large and highly statistically significant, with a t-statistic of −4.41. Furthermore, except for the first decile portfolio, the excess returns of the decile portfolios decrease monotonically across the MAX deciles. The FFC4 and FFC4+PS 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 relative to the FFC4 (FFC4+PS) model of −1.40% (−1.38%) per month is both large and highly significant with a t-statistic of −8.95 (−8.09). As with the excess returns, the alphas decrease monotonically from MAX decile 2 through decile 10.[7]

IV. Relation between the Beta Anomaly and Lottery Demand

Having demonstrated that the beta anomaly and lottery demand phenomenon are strong in our sample, we examine whether lottery demand, or any of the other firm characteristics, risk variables, or funding liquidity measures, plays an important role in generating the beta anomaly.

A. Bivariate Portfolio Analysis

We begin by employing bivariate portfolio analysis to assess the relation between market beta and future stock returns after controlling for MAX and each

[7]In Section IA-III.A and Table IA2 of the Internet Appendix, we show that the lottery demand phenomenon is robust when MAX is defined as the average of the k highest daily returns of the stock within the given month for $k \in \{1,2,3,4,5\}$. In Section IA-III.B and Table IA3 of the Internet Appendix, we show that this result is strong when the last trading day of month t is not used in the calculation of MAX, thus alleviating the possibility that a microstructure issue is driving this result. In Section IA-III.C and Table IA4 of the Internet Appendix, we demonstrate that the lottery demand phenomenon is robust when portfolios are formed by sorting on MAX measured in month $t-1$ as well as the average value of MAX in months $t-1$ and t.

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of the other variables discussed in Table 1. At the end of each month t, we group all stocks in the sample into deciles based on an ascending sort of one of the control variables. We then sort all stocks in each control variable decile into 10 decile portfolios based on an ascending ordering of β. Panel A of Table 3 presents the average monthly excess returns for each of the resulting portfolios when MAX is used as the first sort variable. The column labeled MAX Avg. presents results for the average MAX decile portfolio within each decile of β.

The results in Panel A of Table 3 indicate that after controlling for the effect of lottery demand by first sorting on MAX, the beta anomaly is no longer detected. Focusing first on the results for the average MAX decile, the table shows that the FFC4 (FFC4+PS) alpha of the high–low β portfolio is only -0.14% (-0.13%) per month, economically small and statistically insignificant with a t-statistic of -0.85 (-0.72). The magnitudes of the alphas of this portfolio are slightly more than one-fourth of those generated by the unconditional portfolio analysis (see Table 1). Not only is the beta anomaly not apparent in the average MAX decile, but it also is not apparent in any single MAX decile. As shown in the table, the FFC4 and FFC4+PS alphas of the high–low β portfolio within each decile of MAX are statistically indistinguishable from 0. This is our preliminary evidence of the important role that lottery demand plays in generating the beta anomaly, the main result of this article.

Panel B of Table 3 presents results of the bivariate analyses using other control variables as the first sort variable. The table shows the average monthly excess returns for the average control variable decile within each decile of β. For clarity and comparison, results from the column labeled MAX Avg. in Panel A are repeated. The results demonstrate that the beta anomaly persists when using each of the control variables (except for MAX) as the first sort variable. In each of these analyses, the FFC4 and FFC4+PS alphas of the high–low β portfolio in the average control variable decile remain negative, economically large, and statistically significant. The alphas of the high–low β portfolio after controlling for MAX are less than half of the corresponding values for each of the other bivariate portfolio analyses whose results are shown in Panel B.

Having demonstrated that lottery demand plays an important role in generating the beta anomaly, we briefly investigate whether controlling for beta can explain the lottery demand effect. To do so, we perform a bivariate portfolio analysis, this time sorting first on β and then on MAX. The results of this analysis, presented in Panel C of Table 3, show that in each β decile, the alphas of the high–low MAX portfolio are negative, economically large, and highly statistically significant. For the average β decile, the FFC4 (FFC4+PS) alpha of the high–low MAX portfolio is -1.36% (-1.34%) per month with a corresponding t-statistic of -11.28 (-9.94), indicating that the lottery demand phenomenon remains strong after controlling for market beta.

The results of the bivariate portfolio analyses indicate that lottery demand is a strong driver of the beta anomaly, as the effect is no longer detected when controlling for MAX. The anomaly persists when controlling for all other firm characteristics, risk measures, and funding liquidity sensitivities.

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TABLE 3
Bivariate Portfolio Analyses

Table 3 presents the results of bivariate dependent-sort portfolio analyses of the relation between future stock returns and β after controlling for MAX (Panel A) and other firm characteristics (Firm Characteristics portion of Panel B), measures of risk (Risk Measures portion of Panel B), and measures of funding liquidity sensitivity (Funding Liquidity Measures portion of Panel B). Panel C presents the results of a bivariate portfolio analysis of the relation between future stock returns and MAX after controlling for β. At the end of each month t, all stocks in the sample are sorted into decile groups based on an ascending sort of the control variable (MAX in Panel A, the indicated control variable in Panel B, β in Panel C). Within each control variable group, decile portfolios based on an ascending sort of the β (in Panels A and B) or MAX (in Panel C) are created. Panel A presents the time-series averages of the equal-weighted 1-month-ahead excess returns for each of the portfolios formed by sorting on MAX and then on β. The column labeled MAX Avg. presents results for the average MAX decile within the given β decile. The section labeled High–Low β Portfolios shows average returns (R), FFC4 alphas (FFC4 α), and FFC4+PS alphas (FFC4+PS α) for the 0-cost portfolio that is long the β decile 10 portfolio and short the β decile 1 portfolio within each decile of MAX. Panel B presents the average 1-month-ahead excess returns of the average control variable portfolio within each β decile for portfolios using each control variable as the sort variable. The results in Panel B are analogous to the results in the MAX Avg. column of Panel A. The columns labeled R, FFC4 α, and FFC4+PS α present the average returns, FFC4 alphas, and FFC4+PS alphas, respectively, for portfolios that are long the 10th β decile 10 portfolio and short the β decile 1 portfolio in the average control variable decile. Panel C presents similar results to Panel A using β as the first sort variable and MAX as the second sort variable. Excess returns and alphas are reported in percentages per month. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis that the mean monthly return or alpha is equal to 0. The bolded results highlight the finding that controlling for MAX explains the betting against beta phenomenon.

Panel A. Control for MAX

	MAX 1	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10	MAX Avg.
β 1 (Low)	0.52	0.95	0.91	0.99	0.91	0.86	0.94	0.73	0.51	−0.30	0.70
β 2	0.62	1.02	0.92	0.93	0.83	1.02	0.84	0.76	0.37	−0.42	0.69
β 3	0.60	0.84	1.00	0.92	0.84	0.79	0.68	0.75	0.46	−0.19	0.67
β 4	0.60	0.99	0.96	0.87	1.07	0.74	0.78	0.55	0.48	−0.23	0.68
β 5	0.65	0.92	0.95	1.07	0.87	0.73	0.80	0.63	0.25	−0.18	0.67
β 6	0.71	0.94	0.93	1.00	0.98	0.86	0.82	0.61	0.48	−0.37	0.70
β 7	0.84	0.97	0.96	0.94	0.84	0.90	0.88	0.58	0.25	−0.55	0.66
β 8	0.80	1.16	0.97	0.82	0.87	0.76	0.81	0.59	0.22	−0.50	0.65
β 9	1.02	1.13	1.01	0.83	0.91	0.75	0.78	0.72	0.39	−0.56	0.70
β 10 (High)	1.11	1.10	1.05	1.02	0.83	0.79	0.68	0.75	0.16	−0.72	0.68
High–Low β Portfolios											
R	0.59	0.16	0.14	0.04	−0.08	−0.06	−0.25	0.02	−0.35	−0.42	−0.02
	(3.03)	(0.87)	(0.71)	(0.16)	(−0.34)	(−0.23)	(−0.82)	0.06	(−1.04)	(−1.01)	(−0.10)
FFC4 α	0.27	−0.09	−0.10	−0.17	−0.27	−0.16	−0.33	−0.06	−0.28	−0.24	**(−0.14)**
	(1.78)	(−0.56)	(−0.54)	(−0.89)	(−1.30)	(−0.69)	(−1.36)	(−0.22)	(−1.00)	(−0.74)	**(−0.85)**
FFC4+PS α	0.22	−0.11	−0.08	−0.11	−0.26	−0.15	−0.31	0.02	−0.25	−0.27	**−0.13**
	(1.32)	(−0.60)	(−0.41)	(−0.54)	(−1.18)	(−0.63)	(−1.19)	(0.06)	(−0.81)	(−0.72)	**(−0.72)**

Panel B. Other Control Variables

										High–Low β Portfolios		
Control Variable	Low β 1	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	High β 10	R	FFC4 α	FFC4+PS 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**	**−0.13**
											(−0.10)	**(−0.85)**	**(−0.72)**
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	−0.43
											(−0.91)	(−2.48)	(−2.23)
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	−0.33
											(−0.26)	(−1.87)	(−1.76)
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	−0.60
											(−1.83)	(−3.55)	(−3.18)
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	−0.56
											(−1.42)	(−3.16)	(−3.02)
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	−0.41
											(−1.17)	(−2.36)	(−2.15)

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TABLE 3 (continued)
Bivariate Portfolio Analyses

Panel B. Other Control Variables (continued)

Control Variable	Low β 1	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	High β 10	High–Low β Portfolios: R	FFC4 α	FFC4+PS α
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	−0.48
											(−1.23)	(−2.60)	(−2.33)
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	−0.49
											(−1.24)	(−2.63)	(−2.35)
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	−0.32
											(−2.36)	(−2.97)	(−2.44)
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	−0.42
											(−1.46)	(−2.63)	(−2.26)
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	−0.49
											(−1.58)	(−2.88)	(−2.57)
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	−0.54
											(−1.18)	(−2.22)	(−2.04)
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	−0.54
											(−1.57)	(−3.02)	(−2.71)
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	−0.52
											(−1.32)	(−2.82)	(−2.60)

Panel C. MAX Controlling for β

	β 1	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	β 10	β Avg.
MAX 1 (Low)	0.35	0.47	0.71	0.90	0.98	1.06	1.08	1.04	0.98	1.04	0.86
MAX 2	0.75	0.85	0.93	1.07	1.02	0.95	0.90	0.93	0.99	0.86	0.93
MAX 3	0.73	0.95	0.93	0.92	0.93	0.95	0.83	0.86	0.77	0.82	0.87
MAX 4	0.85	1.03	0.91	0.89	1.11	0.93	0.97	0.79	0.73	0.77	0.90
MAX 5	0.95	1.03	0.95	0.91	1.02	0.99	0.86	0.87	0.76	0.69	0.90
MAX 6	0.97	0.83	0.93	1.02	0.89	0.87	0.91	0.87	0.59	0.46	0.83
MAX 7	1.03	0.89	0.93	0.86	0.79	0.75	0.79	0.64	0.44	0.15	0.73
MAX 8	0.91	0.80	0.77	0.59	0.72	0.59	0.63	0.58	0.42	0.06	0.61
MAX 9	0.46	0.80	0.69	0.59	0.61	0.48	0.38	0.36	0.13	−0.31	0.42
MAX 10 (High)	−0.01	0.19	0.03	−0.03	0.01	−0.33	−0.23	−0.46	−0.71	−1.07	−0.26
High–Low MAX Portfolios											
R	−0.36	−0.28	−0.68	−0.93	−0.97	−1.39	−1.31	−1.50	−1.69	−2.11	−1.12
	(−1.45)	(−1.66)	(−3.50)	(−5.21)	(−4.56)	(−6.75)	(−4.82)	(−6.87)	(−5.86)	(−7.48)	(−6.61)
FFC4 α	−0.83	−0.59	−0.88	−1.21	−1.18	−1.64	−1.54	−1.66	−1.97	−2.14	−1.36
	(−4.14)	(−3.88)	(−5.23)	(−7.76)	(−6.49)	(−8.69)	(−7.81)	(−7.77)	(−8.37)	(−8.59)	(−11.28)
FFC4+PS α	−0.81	−0.59	−0.92	−1.18	−1.12	−1.62	−1.52	−1.60	−1.91	−2.15	−1.34
	(−3.61)	(−3.80)	(−4.92)	(−6.86)	(−5.60)	(−7.80)	(−7.27)	(−6.62)	(−7.38)	(−7.77)	(−9.94)

B. Alternative Portfolio Methodologies

We perform several additional analyses to test the robustness of our results. These tests are discussed in detail in Section IA–IV of the Internet Appendix. Here, we summarize. The relevant sections and tables of the Internet Appendix are in parentheses.

First, we show that a univariate portfolio analysis using the component of β that is orthogonal to MAX as the sort variable fails to detect the beta anomaly, but the portion of MAX that is orthogonal to β reliably produces the lottery demand effect (Table IA5 of Section IA-IV.A). Next, we demonstrate that the ability of lottery demand to explain the beta anomaly persists when using bivariate independently sorted portfolios as well as value-weighted portfolios (Tables IA6, IA7,

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and IA8 of Section IA-IV.B).[8] We then show that this result holds when MAX is calculated as the average of the k highest returns in month t for $k \in \{1,2,3,4,5\}$ (Table IA9 of Section IA-IV.C) and when using the Frazzini and Pedersen (2014) measure of beta (Tables IA10, IA11, and IA12 of Section IA-IV.D). Next, we ensure that our results are not driven by a microstructure issue by repeating our analyses using beta calculated at the end of month $t-1$ and MAX calculated excluding the last trading day of month t, and find similar results (Tables IA13 and IA14 of Section IA-IV.E). Finally, we examine whether our results persist when using the sample period (1931–2012) and measure of beta (β_{5Y}, calculated from 5 years of monthly return data) of Baker and Wurgler (2014). The tests confirm that our results are robust (Tables IA15, IA16, IA17, and IA18 of Section IA-V).

C. Regression Analysis

To examine the impact of lottery demand on the beta anomaly while controlling for other effects, we continue our analysis by running FM (1973) regressions of future excess stock returns on β and combinations of the firm characteristic, risk, and funding liquidity variables. Each month t, we run a cross-sectional regression of 1-month-ahead (month $t+1$) excess stock returns on β and combinations of the control variables calculated as of the end of month t. 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

$$\text{(1)} \qquad \mathrm{R}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t} + \lambda_{2,t}\mathrm{MAX}_{i,t} + \Lambda_t \mathbf{X}_{i,t} + \epsilon_{i,t},$$

where $\mathbf{X}_{i,t}$ is a vector containing the measures of firm characteristics, risk, and funding liquidity sensitivity. Table 4 presents the time-series averages of the regression coefficients, along with NW (1987)–adjusted t-statistics testing the null hypothesis that the average slope coefficient is equal to 0 (in parentheses).

Panel A of Table 4 shows that when the regression specification does not include MAX (models 1–3), the average coefficient on β is statistically indistinguishable from 0, 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 4–6), the average coefficients on β increase substantially with values ranging from 0.265 to 0.470 and t-statistics between 1.90 and 2.34. After controlling for MAX, there is a positive and statistically significant relation between beta and expected stock returns. In other words, when the effect of lottery demand on future stock returns is accounted for, we detect a positive price of market risk.

In all specifications that include MAX, the average coefficient on MAX is negative and statistically significant. The relations between the measures of firm characteristics, risk, and funding liquidity sensitivity are consistent with previous research.

[8]We also show that the lottery demand phenomenon persists after controlling for beta using these alternative portfolio formation methodologies.

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TABLE 4
Fama–MacBeth Regressions

Table 4 presents the results of Fama–MacBeth (1973) regression analyses of the relation between market beta and future stock returns. Each month, we run a cross-sectional regression of 1-month-ahead stock excess returns (R, measured in percentages per month) 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 6 lags, testing the null hypothesis that the average coefficient is equal to 0, 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^2 of the cross-sectional regressions is presented in the row labeled Adj. R^2. The bolded results highlight the finding that after controlling for MAX, the coefficient on β becomes positive and significant.

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

V. Lottery Demand Factor

Having demonstrated the important role that lottery demand plays in generating the beta anomaly, we proceed by generating a factor capturing the returns associated with lottery demand and examining the ability of this factor to explain the returns associated with the beta anomaly. We form our lottery-demand factor, denoted FMAX, using the factor-forming technique pioneered by Fama and French (1993). At the end of each month t, we sort all stocks into 2 groups based on market capitalization (MKTCAP), with the breakpoint dividing the 2 groups being the median market capitalization of stocks traded on the NYSE. We independently sort all stocks in our sample into 3 groups based on an ascending

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sort of MAX. The intersections of the 2 market capitalization-based groups and the 3 MAX groups generate 6 portfolios. The FMAX factor return in month $t+1$ is taken to be the average return of the 2 value-weighted high-MAX portfolios minus the average return of the 2 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 a t-statistic of −2.55.

A. FMAX and β-Sorted Portfolios

To examine the ability of FMAX to explain the returns associated with beta anomaly, we calculate the abnormal returns of the univariate β-sorted portfolios whose returns are examined in Table 1 relative to the FFC4 and FFC4+PS factor models augmented with the FMAX factor. We denote the augmented models FFC4+FMAX and FFC4+PS+FMAX, respectively.

In Table 5 we present the abnormal returns for the β-sorted decile portfolios using the FFC4+FMAX and FFC4+PS+FMAX factor models. To facilitate comparison, we also include alphas relative to the FFC4 and FFC4+PS models, previously shown in Table 1. Inclusion of FMAX in the factor models has dramatic effects on the abnormal returns. When the FFC4 model is augmented with the FMAX factor (FFC4+FMAX), the alpha of the high–low β portfolio of 0.06% per month is both economically small and statistically indistinguishable from 0, with a t-statistic of 0.35. This compares to an alpha of −0.35% per month (t-statistic = −2.50) relative to the FFC4 model. A similar result holds when the PS factor is also included. Using the FFC4+PS+FMAX model, the high–low β portfolio's alpha is 0.04% per month with a t-statistic of 0.22, compared to −0.49% per month with a t-statistic of −2.26 using the FFC4+PS model.

TABLE 5

Alphas for β-Sorted Portfolios Using Models with FMAX

Table 5 presents the alphas for each of the β-sorted decile portfolios, as well as the high–low β portfolio, calculated using the FFC4 model (FFC4 α), the FFC4+PS model (FFC4+PS α), the FFC4+FMAX model (FFC4+FMAX α), and the FFC4+PS+FMAX model (FFC4+PS+FMAX α), where FMAX is the factor designed to capture returns associated with lottery demand while maintaining neutrality to market capitalization. Alphas are reported in percentages per month. t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis that the alpha is equal to 0, are in parentheses. The bolded results highlight the finding that including the FMAX factor explains the betting against beta phenomenon.

Value	β 1 (Low)	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	β 10 (High)	High–Low β
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)
FFC4+PS α	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 α	**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 α	**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)**

Additionally, Table 5 shows that when the FMAX factor is added to the FFC4 and FFC4+PS factor models, neither the low-β nor high-β portfolio generates abnormal returns that are statistically distinguishable from 0. The high-β portfolio

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generates an FFC4+FMAX alpha of 0.14% per month (t-statistic = 1.37) and FFC4+PS+FMAX alpha of 0.14% per month (t-statistic = 1.23). Similarly, the low-β portfolio produces an FFC4+FMAX alpha 0.08% per month (t-statistic = 0.85) and FFC4+PS+FMAX alpha of 0.10% per month (t-statistic = 0.92). This is in stark contrast to the corresponding alphas relative to the FFC4 and FFC4+PS models. When using the models that exclude FMAX, the alphas of the low-β portfolio are positive and significant and the alphas of the high-β portfolio are negative and significant. Furthermore, the alphas of the decile portfolios using models that include FMAX are not monotonic. The results indicate that when FMAX is included in the factor model, the alpha of the high–low β portfolio as well as the alphas of the high-β and low-β portfolios are no longer detected.[9]

B. BAB and FMAX Factors

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 Frazzini and Pedersen's (2014) BAB (for **b**etting **a**gainst **b**eta) factor using factor models that include our lottery demand factor, FMAX, and vice versa. We obtain monthly U.S. equity BAB factor returns for Aug. 1963 through Mar. 2012 from Lasse Pedersen's Web site (http://www.lhpedersen.com/data). Each month, Frazzini and Pedersen (2014) create the BAB factor by forming 2 portfolios, one holding stocks with below-median market betas and the other holding stocks with above-median betas. 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.

We analyze the BAB factor by regressing its monthly returns on the excess 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 analyses using different models are presented in Panel A of Table 6. Consistent with the results of Frazzini and Pedersen (2014), 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) model. Because the BAB factor returns are constructed by Frazzini and Pedersen to have no market factor exposure, the BAB factor returns exhibit no statistically discernible relation to the excess returns of the market portfolio. BAB factor returns are positively related to the value factor (HML) and momentum factor (UMD) returns.

When the FMAX factor is included in the model, the results in Panel A of Table 6 indicate that the BAB factor no longer generates statistically positive abnormal returns, with alphas relative to the FFC4+FMAX and FFC4+PS+FMAX models of 0.17% (t-statistic = 1.23) and 0.22% (t-statistic = 1.39) per month, respectively. The results show that the returns generated by the BAB factor are captured by the inclusion of FMAX in the factor model. There is substantial negative covariation in the returns of the BAB and FMAX factors, as the

[9]In Section IA-VI.A and Table IA19 of the Internet Appendix, we show that the ability of the FMAX factor to explain the returns of the beta-sorted portfolios is robust when using the Frazzini and Pedersen (2014) measure of beta. In Section IA-V.A and Tables IA15 and IA16 of the Internet Appendix, we show that this result is robust when using the sample period (1931–2012) and measure of beta (β_{5Y}) used by Baker and Wurgler (2014).

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TABLE 6
Alphas and Factor Sensitivities for BAB and FMAX Factors

Table 6 presents the alphas and factor sensitivities for the Betting-against-Beta (BAB) factor (Panel A) and the FMAX factor (Panel B) using several factor models. The column labeled α presents the alpha (in percentages per month) relative to each of the factor models. The columns labeled β_f, $f \in \{\text{MKTRF, SMB, HML, UMD, PS, FMAX, BAB}\}$ present the sensitivities of the BAB (Panel A) or FMAX (Panel B) factor returns to the given factor. The column labeled Specification indicates the factor model. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis that the coefficient is equal to 0. The column labeled M indicates the number of monthly returns used to fit the factor model. The column labeled Adj. R^2 presents the adjusted R^2 of the factor model regression. The bolded results highlight the finding that including the FMAX factor explains the betting against beta phenomenon.

Panel A. Factor Sensitivities of the BAB Factor

Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{FMAX}	M	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. Factor Sensitivities of the FMAX Factor

Specification	α	β_{MKTRF}	β_{SMB}	β_{HML}	β_{UMD}	β_{PS}	β_{BAB}	M	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)		

sensitivity of the BAB factor returns to the FMAX factor is −0.55 (t-statistic = −11.84) using the FFC4+FMAX model and −0.54 (t-statistic = −11.11) using the FFC4+PS+FMAX model. Furthermore, the adjusted R^2 values of the factor regressions increase dramatically from around 22% when the FMAX factor is not included in the 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.[10] 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 (1973) regressions, the average slope on β becomes positive and statistically significant.

We now repeat the factor analyses, reversing the roles of FMAX and BAB. The results are presented in Panel B of Table 6. Consistent with previous results, the FFC4 and FFC4+PS factor models both indicate that the FMAX factor generates abnormal returns, as the alphas of −0.67% and −0.65% per month, respectively, are highly statistically significant (t-statistics = −5.12 and −4.60,

[10]In Section IA-VI.B and Table IA20 of the Internet Appendix, we show that alternative versions of the FMAX factor calculated using MAX measured as the average of the k highest daily returns in month t for $k \in \{1,2,3,4,5\}$, produce similar results.

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respectively). When the BAB factor is added to the 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 returns generated by the FMAX factor are not explained by the BAB factor.[11]

Although we interpret the ability of the FMAX factor to explain the returns of the high–low β portfolio and BAB factor as evidence that lottery demand explains the beta anomaly, we do not consider the FMAX factor to be a *risk* factor in the traditional sense. Specifically, we do not suggest that sensitivity to the FMAX factor explains the cross section of returns.[12] The FMAX factor should be viewed, therefore, as a diagnostic tool used to demonstrate that lottery demand explains the beta anomaly.

VI. Lottery Demand Price Pressure

Having demonstrated that the beta anomaly is in large part driven by lottery demand, we now further examine the channel by which lottery demand affects the relation between beta and expected stock returns. 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, we demonstrate that the beta anomaly exists only 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.

A. Correlation between β and MAX

We begin by examining 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 provide preliminary evidence that this is the case. Here, we further investigate this relation.

Each month t, we calculate the cross-sectional Pearson product–moment correlation between β and MAX, which we denote $\rho_{\beta,\text{MAX}}$. β and MAX are highly cross-sectionally correlated, as the average (median) value of $\rho_{\beta,\text{MAX}}$ is 0.30 (0.29). Values of $\rho_{\beta,\text{MAX}}$ range from −0.03 to 0.84, with only 4 of the 593 months in the sample period generating a negative cross-sectional correlation between β and MAX. Consistent with our hypothesis, in most months, lottery

[11]In Section IA-VI.C and Table IA21 of the Internet Appendix, we demonstrate that our results are robust using an alternative version of the BAB factor designed to account for differences in the samples used in our analyses and by Frazzini and Pedersen (2014).

[12]In unreported empirical analyses, we find that stock-level sensitivity to the FMAX factor does not explain the cross section of expected returns.

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stocks are predominantly high-beta stocks. Price pressure exerted by lottery demand therefore falls disproportionately on high-beta stocks, thereby generating the beta anomaly.

B. The Beta Anomaly and $\rho_{\beta,\mathrm{MAX}}$

The driving force behind our explanation for why lottery demand generates the beta anomaly 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 betweenβ 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 about the role that lottery demand plays in producing the beta anomaly is correct, the beta anomaly should be particularly strong in months after the 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- and high-beta stocks, the beta anomaly is expected to be substantially weaker. To test this hypothesis, we divide our sample into the months with high and low cross-sectional correlation between β and MAX ($\rho_{\beta,\mathrm{MAX}}$) and analyze the 1-month-ahead returns of the β-sorted decile portfolios in each subset. High-$\rho_{\beta,\mathrm{MAX}}$ (low-$\rho_{\beta,\mathrm{MAX}}$) months are those with values of $\rho_{\beta,\mathrm{MAX}}$ greater than or equal to (less than) the median $\rho_{\beta,\mathrm{MAX}}$.

We run univariate portfolio analyses of the relation between β and future stock returns for high- and low-$\rho_{\beta,\mathrm{MAX}}$ months. The results, shown in Table 7, show that in high-$\rho_{\beta,\mathrm{MAX}}$ months, the high–low β portfolio generates an economically large, albeit statistically insignificant, average monthly return of -0.68%. The FFC4 (FFC4+PS) alpha of -0.72% (-0.72%) per month is highly statistically significant, with a t-statistic of -2.86 (-2.61). After accounting for the FMAX factor, the alpha of this portfolio relative to the FFC4+FMAX (FFC4+PS+FMAX) model of 0.09% (0.04%) per month is statistically indistinguishable from 0, with a t-statistic of 0.54 (0.20).

In low-$\rho_{\beta,\mathrm{MAX}}$ months, the average high–low β portfolio return is -0.01% per month (t-statistic $= -0.02$), the FFC4 alpha is only -0.26% per month (t-statistic $= -0.86$), and the FFC4+PS alpha is -0.20% per month (t-statistic $= -0.61$). Similarly, the FFC4+FMAX alpha is 0.07% per month (t-statistic $= 0.26$) and the FFC4+PS+FMAX alpha is 0.10% per month (t-statistic $= 0.35$). Thus, in low-correlation months, the average return and all alphas of the high–low β portfolio are small and statistically indistinguishable from 0.

Consistent with the hypothesis that the beta anomaly is a manifestation of disproportionate lottery demand price pressure on high-beta stocks, the beta anomaly is strong in months in which the cross-sectional relation between MAX and β is high. When these two variables are not strongly related, the high–low β portfolio fails to generate economically important or statistically significant abnormal returns. However, even in months when the beta anomaly is strong (high-$\rho_{\beta,\mathrm{MAX}}$ months), the lottery demand factor FMAX captures the returns of the high–low β portfolio. This is strong evidence that lottery demand is an important driver of the beta anomaly.

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TABLE 7

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

Table 7 presents the results of portfolio analyses using subsets of the sample period corresponding to high-$\rho_{\beta,\mathrm{MAX}}$ and low-$\rho_{\beta,\mathrm{MAX}}$ months. We split our sample into months t for which the cross-sectional correlation between β and MAX ($\rho_{\beta,\mathrm{MAX}}$) is at or above its median value of 0.29 (high-$\rho_{\beta,\mathrm{MAX}}$ months) and those in which $\rho_{\beta,\mathrm{MAX}}$ is below its median (low-$\rho_{\beta,\mathrm{MAX}}$ months). At the end of each month t in each subperiod, all stocks are sorted into ascending β (MAX) decile portfolios. Panel A (Panel B) presents the time-series means of the monthly equal-weighted values of β (MAX), 1-month-ahead excess returns (R), FFC4 alphas (FFC4 α), FFC4+PS alphas (FFC4+PS α), and in Panel A, FFC4+FMAX alphas (FFC4+FMAX α) and FFC4+PS+FMAX alphas (FFC4+PS+FMAX α) for each of the β-sorted (MAX-sorted) decile portfolios, as well as for the high–low β (MAX) portfolio. Excess returns and alphas are reported in percentages per month. t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis of a 0 mean excess return or alpha, are shown in parentheses. The bolded results highlight the finding that including the FMAX factor explains the betting against beta phenomenon.

Panel A. Portfolios Sorted on β

Value	β 1 (Low)	β 2	β 3	β 4	β 5	β 6	β 7	β 8	β 9	β 10 (High)	High–Low β
$\rho_{\beta,\mathrm{MAX}}$: 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)
FFC4+PS α	0.26	0.30	0.30	0.24	0.27	0.11	0.06	−0.03	−0.23	−0.45	−0.72
	(1.84)	(2.35)	(3.10)	(2.48)	(2.91)	(1.31)	(0.56)	(−0.30)	(−1.70)	(−2.47)	(−2.61)
FFC4+FMAX α	**0.05**	0.06	0.04	0.00	0.12	−0.06	−0.02	−0.02	0.04	**0.14**	**0.09**
	(0.42)	(0.62)	(0.71)	(0.05)	(1.48)	(−0.68)	(−0.22)	(−0.22)	(0.36)	**(1.28)**	**(0.54)**
FFC4+PS+FMAX α	**0.08**	0.08	0.05	0.02	0.09	−0.05	−0.04	−0.01	0.03	**0.12**	**0.04**
	(0.63)	(0.78)	(0.83)	(0.24)	(1.07)	(−0.50)	(−0.39)	(−0.10)	(0.25)	**(1.04)**	**(0.20)**
$\rho_{\beta,\mathrm{MAX}}$: 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)
FFC4+PS α	0.17	0.17	−0.01	−0.07	−0.11	−0.16	−0.18	−0.20	−0.17	−0.03	−0.20
	(1.01)	(1.09)	(−0.05)	(−0.67)	(−1.29)	(−2.01)	(−2.66)	(−2.67)	(−1.74)	(−0.15)	(−0.61)
FFC4+FMAX α	0.10	0.06	−0.13	−0.17	−0.21	−0.22	−0.21	−0.20	−0.11	0.17	0.07
	(0.64)	(0.45)	(−1.21)	(−2.00)	(−3.05)	(−2.60)	(−3.22)	(−2.82)	(−1.24)	(1.07)	(0.26)
FFC4+PS+FMAX α	0.09	0.06	−0.13	−0.20	−0.21	−0.25	−0.23	−0.22	−0.12	0.19	0.10
	(0.52)	(0.39)	(−1.16)	(−2.21)	(−2.81)	(−3.00)	(−3.32)	(−2.82)	(−1.26)	(1.14)	(0.35)

Panel B. Portfolios Sorted on MAX

Value	MAX 1 (Low)	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10 (High)	High–Low MAX
$\rho_{\beta,\mathrm{MAX}}$: 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)
FFC4+PS α	0.29	0.57	0.50	0.46	0.38	0.27	0.19	0.01	−0.40	−1.44	−1.72
	(2.06)	(5.12)	(5.27)	(5.33)	(4.22)	(2.89)	(2.17)	(0.19)	(−3.65)	(−8.11)	(−6.73)
$\rho_{\beta,\mathrm{MAX}}$: 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)
FFC4+PS α	0.15	0.24	0.18	0.10	0.08	−0.02	−0.01	−0.15	−0.32	−0.84	−1.00
	(1.24)	(2.35)	(1.99)	(1.20)	(0.96)	(−0.23)	(−0.13)	(−2.13)	(−3.63)	(−6.30)	(−5.11)

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To demonstrate that lottery-demand-based price pressure persists in both high-$\rho_{\beta,\text{MAX}}$ and low-$\rho_{\beta,\text{MAX}}$ months, we perform a univariate portfolio analysis of the relation between MAX and 1-month-ahead excess stock returns for each subset of months. In high-$\rho_{\beta,\text{MAX}}$ months, the average high–low return of -1.55% per month and FFC4 (FFC4+PS) alpha of -1.76% (-1.72%) per month are economically large and highly statistically significant. In months in which $\rho_{\beta,\text{MAX}}$ is low, the relation remains strong, as 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 FFC4 alpha of -1.05% per month (t-statistic $= -5.77$) and FFC4+PS alpha of -1.00% per month (t-statistic $= -5.11$). The results demonstrate that the effect of lottery demand on prices exists in both high-$\rho_{\beta,\text{MAX}}$ and low-$\rho_{\beta,\text{MAX}}$ months.

C. Institutional Holdings and the Beta Anomaly

Our final analysis demonstrating that the abnormal returns associated with the beta anomaly are in large part driven by lottery-demand-based price pressure examines the strength of the beta anomaly among stocks with differing levels of institutional ownership. An implication of the leverage constraints explanation for the beta anomaly proposed by Frazzini and Pedersen (2014) is that the effect is strongest for stocks with the greatest degree of institutional ownership (stocks owned predominantly by pension funds and mutual funds), as these investors are expected to face the most serious margin constraints. Consistent with previous work showing that individual investors exhibit behavioral tendencies (Barber and Odean (2000), (2001)), Kumar (2009) and Han and Kumar (2013) demonstrate that lottery demand is prominent among individual investors but not among institutional investors. If the beta anomaly is in fact driven by lottery demand, the alpha of the high–low β portfolio is expected to be concentrated in stocks with low institutional ownership and to be weaker in stocks predominantly owned by institutions. To measure a stock's institutional holdings, we define month t INST to be the fraction of total shares outstanding that are owned by institutional investors as of the end of the last fiscal quarter during or before month t. Values of INST are available for Jan. 1980 through Dec. 2012.

To examine the strength of the beta anomaly among stocks with differing levels of institutional ownership, we use a bivariate portfolio analysis. At the end of each month t, 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 averages of the 1-month-ahead 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 beta anomaly is very strong among stocks with low institutional ownership but insignificant among stocks with high institutional ownership. The magnitudes of the average returns and FFC4 alphas of the high–low β portfolios are decreasing (nearly monotonically) across the deciles of INST. For decile 1 through decile 5 of INST, the average returns and FFC4 alphas of the high–low β portfolios are negative, economically large, and highly statistically significant. For INST deciles

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TABLE 8

Bivariate Portfolio Analyses: β, MAX, and INST

Table 8 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 INST. At the end of each month t, all stocks in the sample are sorted into decile groups based on an ascending sort of INST. Within each INST 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 averages of the equal-weighted 1-month-ahead excess returns for each of the portfolios. The section labeled High–Low β Portfolios (High–Low MAX Portfolios) in Panel A (Panel B) presents results for portfolios that are long the β (MAX) decile 10 portfolio and short the β (MAX) decile 1 portfolio within each decile of INST. The rows labeled R, FFC4 α, and FFC4+PS α present the average return, FFC4 alpha, and FFC4+PS alpha of the high–low portfolios, respectively. Excess returns and alphas are reported in percentages per month. The numbers in parentheses are t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis that the mean monthly return or alpha is equal to 0. The section labeled Percentage of Total Market Capitalization in Panel A presents the time-series average of the percentage of the total market capitalization of all stocks in the sample that are in each INST decile.

	INST 1	INST 2	INST 3	INST 4	INST 5	INST 6	INST 7	INST 8	INST 9	INST 10
Panel A. Portfolios Sorted on INST Then β										
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 β Portfolios										
R	−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)
FFC4+PS α	−1.90	−1.85	−1.21	−1.12	−0.90	−0.72	−0.16	−0.04	0.15	0.45
	(−6.78)	(−5.84)	(−3.49)	(−3.15)	(−3.01)	(−2.62)	(−0.55)	(−0.12)	(0.45)	(1.27)
Percentage of Total Market Capitalization										
	1.11%	1.55%	2.94%	5.02%	10.16%	13.69%	15.92%	16.77%	17.53%	15.33%
Panel B. Portfolios Sorted on INST Then MAX										
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 MAX Portfolios										
R	−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)
FFC4+PS α	−2.76	−2.16	−1.55	−1.71	−1.09	−1.26	−0.80	−0.61	−0.67	−0.09
	(−9.25)	(−8.40)	(−5.00)	(−6.35)	(−3.84)	(−4.46)	(−2.76)	(−2.15)	(−2.40)	(−0.36)

7 through 10, the returns and alphas of the high–low β portfolios are statistically insignificant. The high–low β portfolio, therefore, generates large abnormal returns when implemented on stocks with low institutional holdings but not when implemented on stocks with only high institutional holdings. The FFC4+PS alphas indicate a similar pattern. The results are consistent with our hypothesis that demand for lottery is an important driver of the beta anomaly.

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Individual investors are known to overweight small-market-capitalization stocks in their portfolios. Because the beta anomaly exists only in the bottom 6 deciles of INST, it is possible that the segment of the market driving the beta anomaly is small relative to the size of the entire market. To examine this possibility, in the last row of Panel A in Table 8, we present the time-series average of the percentage of the total market capitalization of the stocks in our sample that fall into each INST decile. Consistent with previous work, the results show that stocks with low values of INST tend to have small market capitalizations. The first decile of INST, where the beta anomaly is strongest, accounts for only 1.11% of the total market capitalization of our sample. However, the lowest 6 INST deciles make up 34.47% of the sample's total market capitalization. Our results therefore indicate that while the beta anomaly exists in 60% of the stocks in the sample, these stocks comprise just slightly more than one-third of the total sample market capitalization, a nontrivial but also not predominant segment of the market.

To ensure that it is in fact individual investors that drive the lottery demand phenomenon, we repeat the bivariate portfolio analysis, this time sorting on INST and then MAX. As shown in Panel B of Table 8, the magnitudes of the returns, FFC4 alphas, and FFC4+PS alphas of the high–low MAX portfolios are 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 is an important driver of the beta anomaly. 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 high–low β 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 beta anomaly is weak (strong). Finally, we show that the beta anomaly is strongest in stocks that are most susceptible to lottery demand price pressure, namely, stocks with low institutional ownership.

VII. MAX as Lottery Demand

The analyses presented throughout this article use MAX calculated in month t to predict returns in month $t+1$. Our interpretations of these results as indicating that lottery demand explains the beta anomaly are based on 2 implicit assumptions. The first is that, as claimed by Bali et al. (2011), MAX measures the lottery qualities of a stock. The second is that MAX measured in month t is indicative of a stock's month $t+1$ lottery qualities. In this section, we explicitly test these assumptions.

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A. MAX Measures Lottery Demand

As discussed in Kumar ((2009), p. 1891), "investors perceive low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness as lotteries." We therefore examine whether these qualities accurately characterize the stocks we claim are high-lottery demand stocks, namely, high-MAX stocks, by examining the average price, idiosyncratic volatility, and idiosyncratic skewness of the stocks in each of the MAX decile portfolios. Panel A of Table 9 presents contemporaneously measured average MAX, price (PRICE), idiosyncratic volatility (IVOL), and idiosyncratic skewness (ISKEW) for stocks in each

TABLE 9

Characteristics of MAX-Sorted Portfolios

Table 9 presents the characteristics of portfolios formed by sorting on MAX. At the end of each month t, all stocks are sorted into ascending MAX decile portfolios. Panel A (Panel B) presents the time-series means of the monthly average month t (month $t+1$) values of MAX, PRICE, IVOL, and ISKEW for stocks in each of the MAX decile portfolios. The column labeled High–Low MAX presents results for the difference in average stock characteristics between the decile 10 portfolio and the decile 1 portfolio. t-statistics, adjusted following Newey and West (1987) using 6 lags, testing the null hypothesis of a zero average difference are shown in parentheses. Panel C presents the distribution of the pooled month $t+1$ stock returns for stocks in the decile 10 (High-MAX) and the decile 1 (Low-MAX) portfolios.

Value	MAX 1 (Low)	MAX 2	MAX 3	MAX 4	MAX 5	MAX 6	MAX 7	MAX 8	MAX 9	MAX 10 (High)	High–Low MAX
Panel A. Contemporaneous Portfolio Characteristics											
MAX	0.66	1.25	1.69	2.09	2.49	2.91	3.41	4.04	4.98	7.62	6.96
											(40.99)
PRICE	70.76	49.56	41.76	34.49	28.79	28.40	23.30	20.25	18.41	14.99	−55.77
											(−5.90)
IVOL	0.94	1.20	1.37	1.52	1.71	1.94	2.22	2.57	3.08	4.58	3.64
											(33.64)
ISKEW	−0.17	0.04	0.07	0.09	0.14	0.19	0.25	0.33	0.43	0.69	0.86
											(33.67)
Panel B. Future Portfolio Characteristics											
MAX	1.65	2.06	2.33	2.55	2.79	3.06	3.35	3.68	4.09	4.83	3.17
											(31.39)
PRICE	72.27	50.01	42.26	34.87	29.13	28.62	23.57	20.52	18.76	15.38	−56.89
											(−5.89)
IVOL	1.35	1.48	1.60	1.71	1.86	2.04	2.24	2.46	2.75	3.31	1.96
											(33.41)
ISKEW	0.21	0.19	0.17	0.17	0.18	0.19	0.20	0.22	0.23	0.26	0.05
											(3.51)

					Percentile								
MAX	Mean	Median	Std. Dev.	Skew	P1	P5	P10	P25	P50	P75	P90	P95	P99
Panel C. Distribution of Month $t+1$ Returns													
Low	1.16	0.51	9.25	1.24	−23.15	−11.92	−7.76	−2.74	0.51	4.55	10.5	15.56	30.27
High	−0.04	−1.32	18.79	2.89	−42.26	−25.97	−19.35	−10.17	−1.32	8.24	20.37	30.26	56.83

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MAX decile portfolio.[13] By construction, the average values of MAX increase across the portfolios from 0.66 for MAX decile 1 to 7.62 for MAX decile 10. The average price of stocks in the MAX decile portfolios decreases monotonically from \$70.76 for stocks in the lowest MAX decile to \$14.99 for stocks in the highest MAX decile. The average price difference between stocks in the high-MAX and low-MAX deciles of −\$55.77 is not only economically very large (approximately double the price of the average stock) but also highly statistically significant with a t-statistic of −5.90. Average IVOL increases monotonically across the MAX deciles from 0.94 for decile 1 to 4.58 for decile 10. The average difference of 3.64 is economically important and highly statistically significant (t-statistic = 33.64). Average ISKEW also increases monotonically from −0.17 for low-MAX stocks to 0.69 for high-MAX stocks. The difference in average ISKEW of 0.86 (t-statistic = 33.67) is once again economically important and highly statistically significant.

Although the contemporaneous price, idiosyncratic volatility, and idiosyncratic skewness of stocks in the MAX decile portfolios indicate that high-MAX stocks have exhibited lottery-like behavior in the past, when making investment decisions, lottery demanders are likely to be more concerned about whether their investments will exhibit lottery characteristics in the future. We therefore examine the average 1-month-ahead MAX, PRICE, IVOL, and ISKEW for stocks in each of the MAX decile portfolios. Panel B of Table 9 shows that MAX is highly persistent, as the average month $t+1$ MAX values increase from 1.65 for the low-MAX portfolio to 4.83 for high-MAX portfolio. Importantly, the pattern in the month $t+1$ average values of PRICE, IVOL, and ISKEW are very similar to those of the contemporaneously measured values.

To further examine whether MAX effectively captures the lottery properties of the distribution of future stock returns, Panel C of Table 9 presents the distribution of 1-month-ahead returns for stocks in the low-MAX and high-MAX decile portfolios. The results show that the high-MAX portfolio holds stocks whose future returns are much more volatile and more positively skewed than the returns of stocks in the low-MAX portfolio. The results therefore demonstrate that stocks in the high-MAX portfolio are much more lottery-like, both contemporaneously and in the future, than stocks in the low-MAX portfolio.

B. Persistence of MAX

The results in Panels B and C of Table 9 provide evidence supporting our implicit assumption that MAX measured in month t captures lottery demand that persists into month $t+1$. To further test this assumption, we examine the persistence of MAX using a portfolio transition matrix indicating the probability that a stock in the ith month t MAX decile portfolio will be in the jth month $t+1$ MAX decile portfolio. The transition matrix, shown in Table 10, demonstrates that 31% (66%) of stocks in the highest month t MAX decile portfolio remain in the highest (3 highest) decile portfolio(s) of MAX in month $t+1$. Similarly, 40% (70%) of

[13]ISKEW is calculated following Boyer, Mitton, and Vorkink (2010) as the skewness of the residuals from a regression of excess stock returns on MKTRF, SMB, and HML using 1 month of daily return data.

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TABLE 10
Transition Matrix for MAX-Sorted Portfolios

Table 10 presents the transition matrix for MAX-sorted portfolios. At the end of each month t, all stocks are sorted into ascending MAX decile portfolios. For each month t MAX decile, the table presents the time-series averages of the percentage of stocks in the given month t MAX decile portfolio that fall in each month $t+1$ MAX decile portfolio.

	MAX_{t+1} 1	MAX_{t+1} 2	MAX_{t+1} 3	MAX_{t+1} 4	MAX_{t+1} 5	MAX_{t+1} 6	MAX_{t+1} 7	MAX_{t+1} 8	MAX_{t+1} 9	MAX_{t+1} 10
MAX_t 1 (Low)	40%	19%	11%	7%	6%	5%	4%	3%	3%	2%
MAX_t 2	19%	21%	16%	12%	9%	7%	5%	4%	3%	3%
MAX_t 3	11%	17%	17%	15%	12%	9%	7%	5%	4%	3%
MAX_t 4	8%	12%	15%	15%	14%	11%	9%	7%	5%	4%
MAX_t 5	6%	9%	12%	14%	14%	13%	11%	9%	7%	4%
MAX_t 6	5%	7%	10%	12%	13%	14%	13%	11%	9%	6%
MAX_t 7	4%	5%	7%	10%	12%	13%	14%	14%	12%	8%
MAX_t 8	3%	4%	6%	7%	10%	12%	14%	16%	15%	12%
MAX_t 9	3%	3%	4%	5%	7%	10%	13%	16%	19%	18%
MAX_t 10 (High)	3%	3%	3%	4%	5%	7%	10%	14%	21%	31%

stocks in the lowest month t MAX decile portfolio remain in the lowest (3 lowest) month $t+1$ MAX decile portfolio(s). Furthermore, the probability that a stock is in the same MAX decile portfolio in month $t+1$ as in month t is greater than 10% for all month t MAX deciles. In Section IA–VII.A and Table IA22 of the Internet Appendix, we present the 2-, 3-, 6-, and 12-month MAX transition matrices. The results indicate that MAX is highly persistent. Twenty-three percent (57%) of stocks in the high-MAX portfolio remain in the high-MAX portfolio (top 3 deciles of MAX) 12 months in the future. Similarly, 33% (63%) of stocks in the month t low-MAX portfolio remain in the low-MAX portfolio (bottom 3 deciles of MAX) in month $t+12$. These results provide strong evidence that MAX measured in month t captures future lottery demand.

C. Patterns in Beta Anomaly and Lottery Demand Returns

In addition to identifying characteristics attributed to lottery demand stocks, previous work has documented return patterns related to lottery demand. We therefore investigate whether these return patterns hold when using MAX as a measure of lottery demand. Because these results have been documented in previous work, to save space, detailed discussions and tabulated results are given in the Internet Appendix (relevant sections, tables, and figures are indicated in parentheses below).

Consistent with Kumar et al. (2011) and Doran et al. (2011), who demonstrate that the lottery effect is stronger in January, we find that the return of the high–low MAX portfolio is approximately twice as large in Januaries as it is in other months (Table IA23 of Section IA-VII.B). We also find that lottery demand explains the beta anomaly both in Januaries and in other months (Table IA24 of Section IA-VII.B).

Next, we examine 2 sets of stocks, the first (second) containing stocks in the lowest (highest) quintile of price, the highest (lowest) quintile of idiosyncratic volatility, and the highest (lowest) quintile of idiosyncratic skewness. Consistent with Han and Kumar (2013), we find that both the beta anomaly and lottery demand phenomenon are strong among the first set of stocks but nonexistent among

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the second set. We also find that after controlling for lottery demand, the beta anomaly does not exist in either set of stocks (Table IA2 of Section IA-VII.C).

Kumar (2009), Kumar et al. (2011), and Doran et al. (2011) show that time variation in lottery demand plays a role in the relation between lottery demand and expected stock returns. We find similar results in our sample. Specifically, defining aggregate lottery demand to be the average value of MAX across all stocks, we find that aggregate lottery demand exhibits substantial time-series variation (Figure IA1 of Section IA-VII.D). We then demonstrate that the negative relation between MAX and stock returns is much stronger in months following above-median aggregate lottery demand than in months following below-median aggregate lottery demand (Table IA26 of Section IA-VII.D).

Kumar (2009) demonstrates that lottery demand is strongest in bad economic states. We therefore examine whether the ability of lottery demand to explain the beta anomaly persists across different economic states. We find that our results hold in all economic states (Table IA27 of Section IA-VII.E).[14]

Finally, we investigate how retail investors identify lottery stocks. We focus on retail investors by examining only stocks in the bottom tercile of INST (retail stocks). Using analyst coverage (CVRG) as a proxy for investor attention (see Hirshleifer and Teoh (2003), Hirshleifer et al. (2013), and Bali, Peng, Shen, and Tang (2014)), we examine the strength of the beta anomaly and lottery demand effect among high-CVRG and low-CVRG retail stocks. Consistent with the hypothesis that analyst coverage grabs retail investors' attention, thereby helping them identify lottery stocks, we find that among retail stocks, both the beta anomaly and lottery demand effects are stronger among stocks with high investor attention than stocks with low investor attention (Table IA28 of Section IA-VII.F).

VIII. Conclusion

In this article, we propose that demand for lottery-like assets, a phenomenon documented by Kumar (2009) and Bali et al. (2011), plays an important role in generating the beta anomaly. Lottery demanders exert upward price pressure on stocks with high probabilities of large up moves. Because 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.

Measuring lottery demand using MAX, defined as the average of the 5 highest daily returns over the past month, we find strong and robust evidence in support of our hypothesis. Bivariate portfolio analyses demonstrate that the abnormal returns of the high–low β portfolio disappear when the portfolio is constructed to be neutral to MAX. A univariate portfolio analysis that sorts stocks on the portion of beta that is orthogonal to MAX fails to detect a pattern in returns. FM (1973) regressions show that market beta is positively related to future stock returns when the regression specification includes MAX. When our lottery demand factor, FMAX, is included in factor models, the abnormal returns associated with

[14]We use the Chicago Fed National Activity Index to define economic state.

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the beta anomaly become economically small and statistically indistinguishable from 0. In all of our analyses, the economic and statistical significance of the lottery demand phenomenon persists after controlling for the beta anomaly. Our results are robust to using different sample periods and empirical approaches.

Finally, we show that the channel by which lottery demand affects the beta anomaly is disproportionate lottery demand price pressure on high-beta stocks. In an 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. When this correlation is low (high), the beta anomaly is not detected (is strong), indicating that disproportionate lottery-demand-based price pressure on high-beta stocks is an important driver of the beta anomaly. Consistent with previous evidence that lottery demand is attributable to individual, not institutional, investors, we show that the beta anomaly is concentrated among stocks that have low institutional ownership.

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