Gambling, Risk Appetite and Asset Pricing*

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Abstract

A measure of the propensity to gamble in casinos constructed without any asset price data provides relevant information for asset pricing. This measure of risk appetite improves the fit of conditional asset pricing models such as the conditional CAPM, explains cross-sectional differences in future returns for portfolios sorted on various characteristics, and helps forecast market and portfolio excess returns. The relationship between risk appetite and asset prices appears to be mainly explained by simultaneous changes in risk and risk premia.

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1 Introduction

Many asset pricing studies argue that the relationship between expected returns and risk varies over time, implying predictable market expected returns and a dependence of the cross-section of expected returns on the state of the economy.[1] Depending on the approach, relevant state variables could be (unobservable) time-varying risk aversion or non-tradable labor income, or yet other variables that could be summarized by a consumption-wealth ratio.[2] Hence, the state of the economy that matters for investment decisions would be generally dependent on variables such as risk aversion and non-tradable risks. An alternative to this "risk-based view" poses that expected returns may fluctuate even in the absence of changes in risks due to variation in investor sentiment.[3] These two views share in common the fact that the relationship between expected returns and risk varies over time, and potentially across assets, owing to changes in investor attitudes towards risk – something we refer to broadly as "risk appetite".

In this paper, we postulate that risk appetite affects not only the demand for risky assets, but also the propensity to take other risks, such as gambling.[4] If so, aggregate data on gambling activity should convey relevant information on the pricing of various portfolios and on market predictability. We use a long time series of aggregate gambling activity in the US to construct measures of risk appetite that vary over time at a quarterly frequency. Unlike other approaches in the literature, our baseline risk appetite measure is constructed without any asset price data.

We first employ our measures of risk appetite in an empirical specification that can speak to both risk-based and investor sentiment channels, as the two may co-exist. Following the approach

[1]On the theoretical side, changes in expected returns in the overall market and across assets could be justified by changes in risk aversion (e.g., Campbell and Cochrane [1999] in the context of a habit formation model), changes in market risk (e.g., Bansal and Yaron [2004] in the case of their long-run risk model), or yet by changes in other risks. In equilibrium, measures such as the dividend yield and the consumption-wealth ratio would capture these changes and thus vary over time. Many papers have shown that these measures are useful in forecasting market excess returns (see Cochrane [2001] for a textbook treatment), but some have also raised econometric issues against these results (e.g. Welch and Goyal [2008]).

[2]For instance, Campbell and Cochrane [1999], Jagannathan and Wang [1996], Lettau and Ludvigson [2001a] and Lettau and Ludvigson [2001b].

[3]For instance, Baker and Wurgler [2006] propose a measure of investor sentiment and provide evidence that this measure affects the cross-section of stock returns.

[4]Even though gambling is not consistent with expected utility preferences, variations in gambling may correlate with variations in other types of risk taking. Barsky et al. [1997], for example, use survey responses to show that risk tolerance in general is positively related to risky behavior across individuals in a variety of arguably unrelated settings. For instance, it predicts both smoking and holding stocks.

of Baker and Wurgler [2006], we find evidence that the relationship between risk appetite and asset prices is explained mainly by simultaneous changes in risk and risk appetite.[5] We further explore the risk channel by estimating cross-sectional regressions with portfolios sorted on various firm characteristics. We find that using our risk appetite measures as conditioning variables improves the fit of traditional asset pricing models, such as the conditional CAPM. All results point to meaningful time-variation in betas that can partially explain the cross-section of stock returns.

We also show that our gambling-based measures help forecast market excess returns both in sample and out of the sample, providing information that is not already contained in standard predictors used in the literature, such as the dividend yield and the consumption-wealth ratio.

Our baseline risk appetite measure is the residual of the cointegrating relationship between real casino gambling expenditures and key determinants – namely, real aggregate income, inflation-adjusted airline fares, and a measure of the size of the gaming industry. Hence, our measure is akin to an "adjusted gambling-to-income ratio". The idea is to control for other variables that affect gambling demand and supply, but are arguably unrelated to risk taking in general, so as to extract a measure of the propensity to gamble. While our baseline measure is constructed without any asset price data, we also consider a version that controls for wealth effects by including an aggregate stock price index in the cointegrating system.

We also construct measures of risk appetite based on total gambling activity, which includes lotteries and pari-mutuel. However, we emphasize a measure constructed solely with casino gambling data for several reasons. First, the reward-risk trade-off remains constant over time for most casino games, such as blackjack and roulette.[6] Second, as opposed to sports betting or racing, the rewards to many casino games do not depend on information. Third, as opposed to other lotteries' bettors, the socio-economic characteristics of the typical casino gambler are more likely to reflect the marginal investor in the stock market.[7] Fourth, casino payoffs are less skewed

[5]In the Appendix, we consider longer investment horizons and find that the sentiment channel appears to play a role in explaining returns of value-based portfolios.

[6]As jackpots and number of bettors vary over time, expected returns in state lotteries, for instance, also vary over time.

[7]Although direct evidence on differences between socio-economic characteristics of different types of gamblers is scant, Sproston et al. [2000] report that households in higher social classes are less prone to gambling overall, but

than those of most lotteries. Finally, since the early 1980s, casino gambling is the dominant form of gambling in the U.S., currently accounting for roughly 75% of total gambling expenditures in the National Income and Product Accounts (NIPA).

Our paper relies on the idea that gambling is connected to stock market activity. Other papers in the literature have explored this connection, but our approach and research question are both very different from theirs. Kumar [2009], Kumar et al. [2011] and Chen et al. [2016], for instance, argue that propensity to gamble in lotteries is positively associated with investor demand for stocks with "lottery-like" characteristics (i.e., low price, skewed and volatile).[8] Markiewicz and Weber [2013] show that propensity to gamble predicts stock trading. Dorn et al. [2015] and Gao and Lin [2015] document a negative relationship between jackpots in local lotteries and trading activity, suggesting that individual investors see investing in the stock market and gambling as substitutes. In a recent paper about the low-risk effect, Asness et al. [2017] find a connection between profits earned by casinos in the U.S. and the returns of idiosyncratic risk factors. They conclude that "lottery demand" partially explains the low-risk effect. Our paper explores the connection between gambling activity and the cross-section of stock returns for a broad range of portfolios in a conditional asset pricing setting.

Other papers have used disaggregated consumption data and related measures to study asset prices. Ait-Sahalia et al. [2004] use consumption of luxury goods in an unconditional Consumption CAPM framework. Savov [2011] explores garbage data instead. In the Appendix, we also explore a conditioning variable constructed with luxury goods consumption data, and find that our measures of risk appetite do better at pricing assets.

Our paper also adds to the literature that infers risk preferences from observed (or surveyed) behavior. Most of these papers try to measure risk aversion. Although related, our measure of risk appetite is not a proxy for risk aversion. Risk appetite, as defined here, and risk aversion would only coincide if other non-tradable risks remained constant over time, and if investor

gamble more in casinos than those in lower social classes, who tend to bet more on lotteries and other gambling activities.

[8]Brunnermeier et al. [2007] and Barberis and Huang [2008] propose models of demand for lottery-like stocks. Barberis [2012] develops a model of casino gambling. Luo and Subrahmanyam [2016] propose a model in which agents derive gambling-like utility from trading, and show that it may affect the cross-section of stock returns.

sentiment did not play a role. Nevertheless, changes in risk aversion might be an important contributor to variations in risk appetite. One approach in the literature relies on surveys with hypothetical lotteries at particular points in time. Barsky et al. [1997], Kimball et al. [2009] and Sahm [2012], for instance, develop a framework to map hypothetical gambles introduced in surveys to measures of risk tolerance. Alternatively, Chiappori et al. [2012] develop a structural econometric method to recover the distribution of risk aversion from aggregate betting data on horse races. A strand of the literature also explores time variation in risk aversion. Guiso et al. [forthcoming], for example, combine portfolio choices and survey-based measures to claim that risk aversion increased after the Great Recession. Bliss and Panigirtzoglou [2004] estimate the risk aversion implied in option prices, while Dew-Becker [2012] measures the implied time-varying risk aversion in a model with habit formation.

Before we proceed, a few caveats are in order, even though some of them are mitigated by our use of casino gambling data. First, gambling has negative expected payoff.[9] Second, the skewness and other high-order moments of gambling payoffs might differ from those of market and portfolio returns. Third, the socio-economic characteristics of gamblers might be different from investors, and might change over time. Finally, our risk appetite measure is noisy, as the cointegrating residual may encapsulate information on other determinants of gambling consumption. Despite these caveats, it is reassuring that our measure improves the fit of conditional asset pricing models and also helps predict market and portfolio excess returns.

The remainder of the paper is organized as follows. First, we define our conditioning variable and show how we estimate it. Second, we present evidence that our risk appetite measure is relevant in explaining the cross-section of asset returns. Finally, we show that this conditioning variable does provide useful predictive information both in-sample and out-of-sample. We also provide additional material, results and robustness analyses in a number of appendices.

[9]Therefore, we implicitly need to assume that (some) investors that choose to gamble realize non-pecuniary utility gains, making the subjective expected return positive. Alternatively, we may also assume alternative preferences that are not globally concave and that derive utility from positive skewness in the spirit of Friedman and Savage [1948].

2 Risk Appetite and Gambling

We define risk appetite broadly as a state variable that governs investors attitudes when facing risk-return trade-offs. If risk appetite is high (low), investors are willing to take more (less) risk for a given expected return. Changes in risk appetite may be rational to the extent that they reflect changes in the degree of risk aversion (i.e. market-wide willingness to take risk) and/or background risk (i.e. volatility of non-tradeable income). But they may also reflect changes in investor sentiment, defined as the propensity to speculate in the stock market or the degree of optimism about stocks in general (see Baker and Wurgler [2006]).

In this section we describe how we use long time-series of gambling activities in the US to construct proxies for risk appetite that vary over time at a quarterly frequency. Our crucial assumption is that risk appetite not only governs how investors behave when faced with the trade-off between risk and return in financial markets, but also affects the decision to take non-market risks such as casino gambling (and gambling in general).

2.1 Casino Gambling Activity and Risk Appetite

We consider long time-series data on both casino and overall gambling activities. Although we favor data on casino gambling, throughout the paper we also present some robustness analysis with the total gambling. For brevity, we focus the remainder of this section on how we use data on casino gambling to extract a measure of risk appetite, and in the Appendix we present details on how we construct another such measure using data on total gambling expenditures.

Data on casino and total gambling expenditures are from the NIPA tables for Personal Consumption Expenditures (codes DCASRC0 and DGAMRC0, respectively). In addition to casino gambling, total gambling also includes lotteries and pari-mutuel. We considered other possibilities, such as measures of casino revenues or profits. However, balance sheet information was only available for publicly listed companies.[10] We also entertained using data from the Consumer Expenditures Survey, but the sample is shorter and there are no data on casino expenditures.

[10] In addition, revenues and profits of publicly listed US casino companies are also affected by their overseas operations, and do not cover the US activities of foreign casino companies that operate in the US.

NIPA data have the clear benefits of being representative of aggregate US gambling activities, and of accounting for gaming expenditures only, excluding other expenses that also affect casino revenues, such as food and accommodation.

Our baseline risk appetite measure (*rap*) is the cointegrating residual of the relationship between the log of real casino gambling expenditures per capita in the US (CASINO) and key determinants of gambling activity. The idea is to factor out lower-frequency movements in gambling activity that are arguably unrelated to risk in general. Hence, our cointegrating system includes aggregate income measured by the log of real GDP per capita (GDP), the log price index associated with air transportation (deflated by the CPI) obtained from the BEA (AIRFARES), and the number of states in which casino gambling is legal (STATES).[11] Besides income effects, our specification captures the effects on gambling activity over time of the steady decline of airfares after the deregulation of the airline industry in 1978, as well as the increasing number of states over time where casino gambling became legal.

As we argued previously, one of the main advantages of our baseline measure of risk appetite is the fact that it does not rely on asset prices. Nonetheless, one may argue that our cointegrating system does not properly account for wealth effects. To address this potential criticism, we consider an alternative specification in which we add the CRSP stock market price index to the cointegrating system. We refer to this alternative risk appetite measure as *rapa*. By construction, all risk appetite measures have zero mean. In addition, for ease of interpretation of our results, we normalize them to have unit standard deviation.

[11]Under US federal law, gambling is legal, and it is up to each state to regulate its practice within its borders. Nevada was the first state to legalize casino gambling in 1931. Since then, several states have legalized some kind of casino gambling, but restrictions differ across states and within states over time. For example, only Nevada and Louisiana allow casino gambling statewide. In other states, casino gambling restricts to small geographic areas, or to American Indian reservations. In addition, some states only permit casinos in riverboats. To construct the variable STATES, we consider the quarter following the date when casino gambling was legalized or the date when a relevant flexibilization took place in any of the fourteen states where data used to compute CASINO come from. The following states started to count after some kind of casino gambling was legalized: Nevada in March 1931, New Jersey in November 1976, Minnesota in October 1989, Illinois in January 1990, Mississipi in March 1990, Connecticut in May 1991, Louisiana in July 1991, Washington in September 1991, Indiana in July 1993, Michigan in November 1993 and New Mexico in February 1995. In addition, South Dakota and Colorado started to count after November 2000 and November 2008, respectively, when the maximum bet changed from five to one hundred dollars, although casino gambling was legalized in these states before. Finally, Missouri started to count after November 1998, when the restriction that riverboat casinos must be cruising was no longer required. Results are robust to alternatives coding of STATES.

NIPA data on gambling expenditures begin in 1959Q1. However, there are historical as well as statistical reasons to start our baseline sample with casino gambling in the early 1980s. During the 1960s and 1970s, casinos were not the dominant form of gaming in the US. In the 1960s, casino gambling expenditures corresponded to approximately 26 percent of total gambling expenditures, whereas lotteries and pari-mutuel corresponded to one percent and 72 percent, respectively. During the 1970s, the relevance of casinos and lotteries increased substantially at the expense of pari-mutuel. During the 1980s, casino gambling became the preferred form of gaming in the US, surpassing 50 percent of total gambling expenditures in 1981 – at which time the share of lotteries was around 17 percent. The casino industry reached its mature stage during the 1990s, something McGowan [2001] called "the triumph of casino gaming", as it became more accepted as a legal form of entertainment in the American society. The author attributes this rise in casino gaming to three factors. First, during the 1980s, Las Vegas and Atlantic City, the two largest markets for casino gambling in the US, turned into family-oriented vacation cities with megaresorts. Second, riverboat gambling became popular in the 1990s, with Iowa being the first state to allow it in 1989, followed by Louisiana, Illinois, Indiana, Mississippi and Missouri. Finally, in 1988, Congress allowed Indian casino gaming operations, with Foxwoods in Connecticut being the leading example of success. As a result, after the 1990s, casino activity increased at a much slower pace. After the mid-2000s the shares of casino gambling and lotteries stabilized at around 75 percent and 21 percent of total gambling expenditures, respectively. Over time, pari-mutuel became a minor form of gaming. To capture its earlier relevance, the alternative risk appetite measure based on total gambling expenditures covers a longer sample.[12] All samples end in 2015Q3.

This historical narrative suggests that the relationship between casino gambling and its key determinants might have become more stable sometime after the 1970s. Absent a clear landmark date to start the baseline sample, we resort to structural break tests. In particular, we run a series of Gregory and Hansen [1996] tests of cointegration subject to regime shifts.[13] We analyze

[12]Results using the alternative risk appetite measure are presented in Section 3 on the cross-section of expected returns. In the Appendix, we also consider proxies for risk appetite constructed solely with data on lotteries and pari-mutuel expenditures.

[13]Its null hypothesis is no cointegration, while the alternative hypothesis is cointegration with a single shift in

both the baseline cointegrating system and the version that allows for wealth effects. The tests point to regime shifts between 1980Q3 and 1982Q1, depending on the version and test statistic. Hence, we begin our baseline sample in 1982Q1, and verify that results are robust to starting the sample a few quarters earlier or later.[14] We run the same tests on the cointegrating system that uses data on total gambling expenditures, and find no evidence of regime shifts.

We follow Engle and Granger [1987] and estimate the cointegrating system by ordinary least squares (OLS),[15] which yields the following cointegrating residual:

$$\epsilon_t^{rap} = \text{CASINO}_t + 8.46 - 1.35 \times \text{GDP}_t + 0.39 \times \text{AIRFARES}_t - 0.073 \times \text{STATES}_t.$$

The estimated coefficient on GDP is consistent with the view that casino gambling is a luxury good. In addition, as expected, the coefficient on AIRFARES is negative and the coefficient on STATES is positive. All coefficients are statistically significant at the 1% level. Our baseline risk appetite measure is obtained by standardizing the cointegrating residual ϵ_t^{rap}.

The top panel of Figure 1 plots the evolution over time of CASINO, along with the other variables that comprise the baseline cointegrating system. All variables are demeaned and normalized. The bottom panel of Figure 1 compares the evolution of *rap* with the consumption-wealth ratio measure (*cay*) from Lettau and Ludvigson [2001a] and Lettau and Ludvigson [2001b] and the investment sentiment measure (*is*) from Baker and Wurgler [2006], which were shown by these prominent contributions to explain and predict stock returns. Both series were obtained at their respective authors' personal webpages.[16]

coefficients at an unknown date.

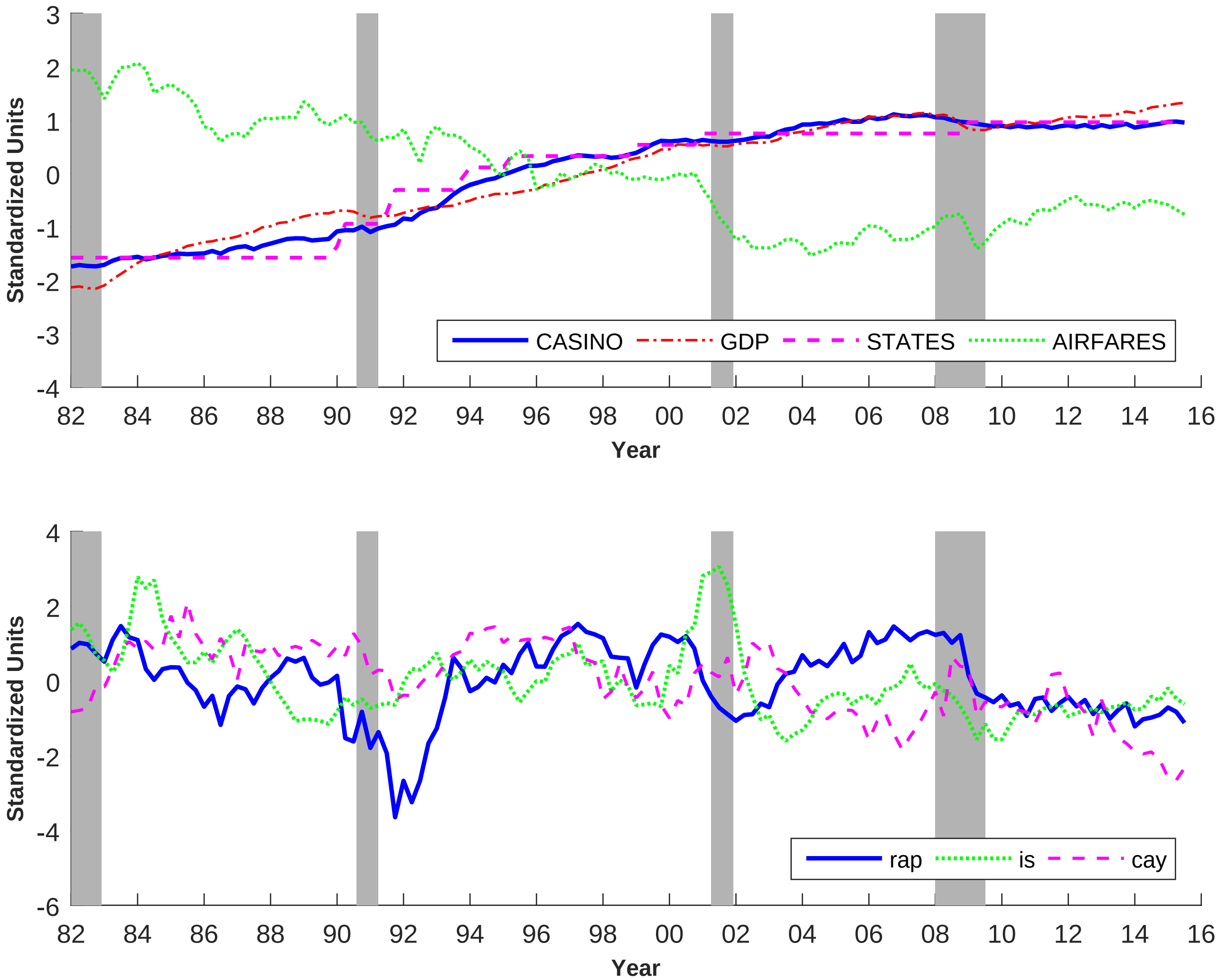
[14] Johansen [1988] tests reject the null of no cointegration and indicate the existence of one cointegration restriction in our baseline sample and specification. All time series econometric results are available upon request.

[15] Results are robust to estimation by dynamic OLS with lags and leads varying from zero to eight quarters.

[16] At the time this version of the paper started to circulate, the *is* measure was available up to 2015Q3.

Figure 1: Evolution of CASINO, GDP, AIRFARES, STATES, *rap*, *cay* and *is*

The top panel plots the evolution of the log of real casino gambling expenditures per capita in the US (CASINO), the log of real GDP per capita (GDP), the log price index associated with air transportation deflated by the CPI (AIRFARES) and the number of states in which casino gambling are legalized (STATES) from 1982Q1 to 2015Q3. The bottom panel plots the evolution of risk appetite (*rap*) over the same period, which is the residual of the cointegrating relationship between CASINO, GDP, AIRFARES and STATES, as well as the evolution of the consumption-wealth ratio measure (*cay*) from Lettau and Ludvigson [2001a] and Lettau and Ludvigson [2001b] and the investment sentiment measure (*is*) from Baker and Wurgler [2006]. *cay* and *is* were obtained at Martin Lettau's and Jeffrey Wurgler's personal websites, respectively. Series are demeaned and normalized. Shaded areas indicate NBER recessions.



Our risk appetite measure (*rap*) displays interesting business cycle fluctuations. In the early 1990s and early 2000s, *rap* falls before the beginning of the recession, and recovers after the recession ends. In the Great Recession, *rap* remains relatively stable until 2008Q3, when it drops precipitously.[17] According to our measure, risk appetite remains at low levels ever since.[18] Al-

[17]The significant decline in *rap* in the Great Recession is in line with the evidence in Guiso et al. [forthcoming], who elicited measures of risk aversion from a sample of clients of an Italian bank in 2007 and 2009.

[18]The behavior of our casino-based measure in the recent past might be affected by the growth of online

though periods with below-average *rap* do not systematically lead, coincide or lag US recessions, most of them occur around these episodes. This is in line with previous research claiming that worse macroeconomic conditions are associated with lower degrees of risk tolerance (e.g., Barsky et al. [1997]).

We also estimate a version of the baseline cointegrating system augmented with the log CRSP stock market price index (CRSP), leading to the following cointegrating residual:

$$\epsilon_t^{rapa} = \text{CASINO}_t + 5.57 - 1.05 \times \text{GDP}_t + 0.46 \times \text{AIRFARES}_t - 0.069 \times \text{STATES}_t - 0.074 \times \text{CRSP}_t.$$

Finally, in the Appendix we present a similar strategy to extract measures of risk appetite from data on total gambling expenditures over the period 1965Q3 to 2015Q3 – thus starting the sample when the investment sentiment measure from Baker and Wurgler [2006], a variable we use in some exercises, becomes available. The cointegrating system includes log total gambling expenditures per capita in the US (TOTALG), GDP, AIRFARES, STATES, and a series of the number of states (weighted by their GDP) in which lotteries are legal (LSTATES).[19] The standardized cointegrating residual of this system, which we name *rapt*, is an alternative measure of risk appetite that we use for robustness purposes. The correlation between *rap* and *rapt* in our baseline sample (1982Q1-2015Q3) is approximately 0.65. Finally, we also considered a version of *rapt* that accounts for wealth effects, constructed as the standardized residual of the cointegrating system that includes TOTALG, GDP, AIRFARES, STATES, LSTATES, and CRSP. Since the coefficient on CRSP is economically small and statistically insignificant, results based on this measure are similar to those obtained using *rapt*, and are hence omitted for conciseness.

2.2 Relationship to Other Variables

In this section we show how our risk appetite measures based on casino gambling (*rap* and *rapa*) correlate with other variables that are used in Section 4 as ground for comparison regarding

gambling options – something that future research might be able to investigate.

[19] In this case, states are weighted by GDP because demand for lotteries is arguably local, whereas demand for casino gambling goes beyond state borders.

predictive ability. In particular, we assess whether *rap* and *rapa* help predict excess market returns ($R_m - R_f$), where R_m is the return on the value-weighted CRSP Index and R_f is the return associated with the three-month US Treasury bill.

Following Welch and Goyal [2008], we compare the performance of *rap* and *rapa* with other measures used in the literature. The dividend yield (d/p) is the ratio of the sum of dividends (d) over the course of the previous twelve months that accrue to stocks in the CRSP cap weighted index (p). We also consider the aggregate (private nonresidential) investment-to-capital ratio (i/k) as proposed by Cochrane [1991], as well as the book value (b/m), which is the book-to-market value of the Dow Jones Industrial Average, explored by Kothari and Shanken [1997] and Pontiff and Schall [1998]. Also, we consider the risk-free rate proxied by the Treasury-bill rate (*tbl*), the long-term yield (*lty*), and the terms spread (*tms*) meaning the spread of the *lty* over the *tbl*. These variables were studied, for example, in Campbell [1987], Fama and French [1989] and Hodrick [1992]. Moreover, we include the default yield spread (*dfy*), defined as the spread of BAA over AAA corporate bonds, emphasized by Keim and Stambaugh [1986] and Fama and French [1989], among others. Furthermore, the CPI inflation rate in the US (*infl*) as evaluated by Lintner [1975], Fama [1981] and Campbell and Vuolteenaho [2004]. We refer to Welch and Goyal [2008] for more details on how these variables are constructed. Finally, we consider the consumption-wealth ratio (*cay*) proposed by Lettau and Ludvigson [2001a] and Lettau and Ludvigson [2001b], as well as the investor sentiment measure (*is*) proposed by Baker and Wurgler [2006].[20]

[20] *cay* is the cointegrating residual of aggregate consumption, aggregate wealth and aggregate income, whereas *is* is the principal component of closed-end fund discount, NYSE share turnover, number of IPOs, average first-day returns, share of equity issues in total issuance and dividend premium. We refer the reader to the original papers for more details. Note, however, that given the way these series are constructed, every monthly update changes the entire series.

Table 1: Summary Statistics: *rap*, *rapa* and Other Variables from 1982Q1 to 2015Q3

The top panel of this table displays the autocorrelations with lags varying from one to eight quarters for market excess returns ($R_m - R_f$), our risk appetite measures (*rap* and *rapa*), consumption-wealth ratio (*cay*), investor sentiment (*is*), dividend yield (*d/p*), investment to capital ratio (*i/k*), book-to-market value (*b/m*), Treasury-bill rate (*tbl*), long-term yield (*lty*), terms spread (*tms*), default yield spread (*dfy*) and CPI inflation rate (*infl*). Details are presented in the text. The bottom panel displays the correlations between these variables. Data are from 1982Q1 to 2015Q3.

Statistics	lags	$R_m - R_f$	rap	$rapa$	cay	is	d/p	i/k	b/m	tbl	lty	tms	dfy	$infl$
Autocorrelations	1	0.04	0.90	0.89	0.89	0.92	0.97	0.98	0.98	0.98	0.98	0.87	0.84	0.08
	2	-0.04	0.81	0.80	0.83	0.80	0.94	0.93	0.96	0.95	0.95	0.73	0.65	0.01
	3	-0.07	0.73	0.71	0.78	0.63	0.91	0.87	0.93	0.92	0.94	0.59	0.51	0.13
	4	-0.03	0.60	0.58	0.71	0.46	0.89	0.80	0.90	0.88	0.92	0.43	0.41	0.00
	5	0.02	0.51	0.48	0.64	0.31	0.87	0.72	0.89	0.85	0.90	0.28	0.34	0.12
	6	0.01	0.41	0.38	0.58	0.21	0.85	0.64	0.88	0.80	0.90	0.16	0.31	0.17
	7	-0.11	0.30	0.26	0.53	0.14	0.83	0.56	0.87	0.76	0.89	0.05	0.27	0.06
	8	0.04	0.23	0.19	0.46	0.10	0.81	0.49	0.87	0.72	0.90	-0.06	0.24	0.06

Correlations		$R_m - R_f$	rap	$rapa$	cay	is	d/p	i/k	bm	tbl	lty	tms	dfy
	rap	-0.03											
	$rapa$	-0.08	0.99										
	cay	-0.10	0.09	0.11									
	is	-0.15	0.15	0.13	0.30								
	d/p	-0.07	-0.16	-0.10	0.37	0.14							
	i/k	-0.09	0.57	0.51	0.19	0.45	-0.43						
	bm	-0.02	-0.02	0.03	0.17	0.26	0.87	-0.29					
	tbl	-0.02	0.33	0.32	0.51	0.50	0.54	0.40	0.58				
	lty	-0.00	0.15	0.15	0.58	0.53	0.68	0.18	0.72	0.91			
	tms	0.03	-0.48	-0.44	0.04	-0.05	0.19	-0.59	0.17	-0.43	-0.03		
	dfy	-0.14	0.06	0.12	0.04	0.10	0.54	-0.27	0.62	0.14	0.25	0.21	
	$infl$	0.04	0.06	0.06	0.15	0.07	0.19	0.07	0.20	0.38	0.37	-0.11	-0.21

Table 1 provides summary statistics for *rap*, *rapa*, and the aforementioned variables in our baseline sample. Our risk appetite measures display fairly less persistence than *d/p*, *i/k*, *b/m*, among other variables. Hence, our results are less susceptible to the criticism that inference might be problematic because any highly persistent variable has the potential to spuriously explain asset returns (e.g., Boudoukh et al. [2008]). Our measures also display weak correlations with most of these variables, except *i/k*, *tms*, and *tbl*. Hence, they contain information that is not present in other common variables used in the literature, such as *cay* or *is*. Finally, *rap* and *rapa* are highly correlated.

3 Cross-Sectional Implications

In this section, we present evidence that our measure of risk appetite based on the propensity to gamble in casinos helps explain the cross-section of stock returns.[21]

We consider two alternative channels, associated with risk or investor sentiment. Our risk appetite measure may capture information on future returns of different portfolios as it provides conditional information about changing risks and risk aversion (risk channel). Alternatively, changes in risk appetite may have different effects on different portfolios, since some of them may be harder to value or more difficult to arbitrage – as argued by Baker and Wurgler [2006] with respect to investor sentiment (sentiment channel). Moreover, we entertain the possibility that both may be at play simultaneously. For instance, a deterioration in economic conditions may reduce the willingness to take risks and simultaneously change the risk of each portfolio (i.e., their betas). This effect could interact with changes in investor sentiment induced by the same changes in economic conditions, which may have larger effects on portfolios that are more difficult to price.

These two channels can be represented by the following equation:

$$E_t[R_{i,t+1} - R_{0,t+1}] = \alpha_i + \underbrace{b_i rap_t}_{\text{investor sentiment}} + \underbrace{\lambda(rap_t)\beta_i(rap_t)}_{\text{conditional risk}},$$

where $R_{i,t+1}$ and $R_{0,t+1}$ are the returns of asset i and the zero beta portfolio, respectively. In addition, $\beta_i(rap_t)$ represents the beta for asset i with respect to the chosen priced factor and $\lambda(rap_t)$ represents the respective risk premium. We postulate that both are conditional on risk appetite, as otherwise the effect of *rap* would not impact unconditional moments. If they indeed

[21] We also entertained unconditional models, but results are not supportive and thus, for brevity, not reported.

depend on risk appetite, a conditional risk model is appropriate. The coefficient b_i captures the direct impact of risk appetite on expected returns, consistent with the investor sentiment channel. In the following subsections, we consider various tests of these alternative views.

3.1 Conditional Characteristic Models: Sentiment vs Risk

As argued by Baker and Wurgler [2006], some stocks may be harder to value or more difficult to arbitrage than others. Hence, portfolios with different characteristics could be exposed differently to changes in risk appetite in the economy, independently of their risk (i.e., betas). If so, risk appetite should contain information on future returns that goes beyond the cross-sectional predictability implied by conditional risk models.

To assess the presence of this investor sentiment channel – above and beyond the risk channel – we follow Baker and Wurgler [2006] and run regressions of long-short portfolio returns on: i) lagged risk appetite, ii) market returns, and iii) the interaction of both.

Tables 2 and 3 present the results for a series of portfolios with one-quarter horizon, while longer horizons are discussed in the Appendix. Table 2 considers our baseline measure, *rap*, whereas Table 3 considers the measure that accounts for wealth effects, *rapa*. Panel A shows estimates of market beta just for comparison. Panel B allows for market betas that are conditional on risk appetite. Panel C tests whether risk appetite behaves as an investor sentiment measure, by allowing for alphas that are conditional on risk appetite. Lastly, Panel D considers both conditional alpha and conditional beta channels. We use long-short portfolios based on value, size and investment. For each case, we consider three different versions of long-short portfolios based on the same firm characteristic. In the case of value, we use the traditional HML factor, a factor that compares the usually ignored medium portfolio with the low book-to-market portfolio (M-L), and a factor that only uses the extreme deciles ranked solely on book-to-market (H-L). We follow the same logic for size and investment. Additionally, we consider portfolios where firms are sorted on two characteristics simultaneously. For instance, we use the 25 portfolios sorted on both size and book-to-market to construct SH-BL, a portfolio where we go long the extreme small-value portfolio (SH) and short the extreme big-growth portfolio (BL). We do the same for the other two combinations.

In order to test whether alphas and betas are conditional on risk appetite, we use three dummies, $high(rap_t)$, $medium(rap_t)$ and $low(rap_t)$, that assume unit value when rap is high (good state), medium or low, respectively. A good (bad) state is a quarter t when rap_t is among the 33% highest (lowest) levels and the medium state lies in between. We use dummies to allow for a non-linear relationship between alphas, betas and the conditioning variables. In particular, the coefficients represent the average alpha or beta in each of the three states.[22]

Tables 2 and 3 show that rap and $rapa$, respectively, seem to be more relevant via the conditional risk channel, i.e. through its effect on betas associated with the term that interacts market return with risk appetite. Panel B shows that the conditional risk channel may be relevant to explain returns when the sentiment channel is ignored, as betas are lower when risk appetite is higher in almost all cases. Panel C reveals that there is no clear pattern in conditional alphas. Lastly, Panel D shows that the risk channel remains statistically significant only for size and investment factors when we introduce the direct sentiment channel.[23]

For long-short portfolios based on value, we find that none of the channels appear to be significant. We find significance regarding the value dimension only when we use double-sorted portfolios on both value and size.

[22]For completeness, in the Appendix we present the linear version of the same test. Although weaker in a statistical sense, results are consistent with those based on the specification with dummy variables. We also consider a specification in which Baker and Wurgler [2006]'s investor sentiment is the sole driver of variation in alphas, and find the same conclusions regaring the effect of rap on conditional betas.

[23]In the next section, we analyze this case in more detail using all firm characteristics simultaneously as standard in cross-sectional asset pricing tests.

Table 2: Time-Series Regressions of Portfolio Returns: Sentiment vs Risk

This table presents regressions of long-short portfolio returns based on single characteristics over the next quarter ($h = 1$) on market excess returns ($R^e_{m,t:t+h}$), conditioning variables, and interactions. HML, SMB and CMA are cumulative excess returns over the next quarter, based on value, size and investment from Ken French's library. Other columns such as M-L, M-B and C-M consider comparisons to the usually excluded middle portfolios on the same sorts. H-L, S-M and C-A are based on the extreme deciles only. HS-LB, HC-LA and SC-BA combine two dimensions at the same time, using 25 portfolios sorted on both characteristics. For instance, HS-LB is long small-value and short big-growth. For conditioning variables, we use three dummies that equal unity when risk appetite (*rap*) is high (good state), medium, or low. A good state is a quarter when *rap* is among the top one-third highest values, while the bad state is the symmetric opposite. This table reports OLS time-series regression coefficients. Standard errors are Newey-West adjusted. $\bar{R}^2$ denotes the adjusted R^2 statistic. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

	Book-to-Market			Size			Investment			Combined		
	HML	M-L	H-L	SMB	M-B	S-B	CMA	C-M	C-A	HS-LB	HC-LA	SC-BA
Panel A: Market Model												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01***	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.08	-0.17*	0.14	-0.19	0.31***
	[0.13]	[0.09]	[0.13]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.12]
$\bar{R}^2$	0.06	0.04	-0.01	0.16	0.14	0.10	0.11	0.04	0.09	0.01	0.02	0.06
Panel B: Conditional Beta												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01**	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h} * low(rap_t)$	-0.12*	-0.08	0.05	0.31***	0.20***	0.29***	-0.09	0.12***	-0.06	0.24***	0.09	0.52***
	[0.06]	[0.08]	[0.08]	[0.06]	[0.03]	[0.05]	[0.10]	[0.05]	[0.10]	[0.09]	[0.14]	[0.12]
$R^e_{m,t:t+h} * medium(rap_t)$	-0.10	-0.04	0.07	0.22***	0.12***	0.24***	-0.17*	0.13	-0.13*	0.27	-0.16	0.27
	[0.16]	[0.09]	[0.21]	[0.06]	[0.03]	[0.07]	[0.10]	[0.08]	[0.08]	[0.20]	[0.25]	[0.18]
$R^e_{m,t:t+h} * high(rap_t)$	-0.32	-0.19	-0.15	0.13**	0.08	0.11	-0.25**	-0.01	-0.31*	-0.07	-0.50	0.12
	[0.24]	[0.17]	[0.22]	[0.06]	[0.05]	[0.08]	[0.11]	[0.09]	[0.17]	[0.24]	[0.42]	[0.17]
$\bar{R}^2$	0.07	0.05	0.00	0.16	0.15	0.10	0.12	0.06	0.12	0.01	0.04	0.07
Panel C: Conditional Alpha												
$low(rap_t)$	0.01	0.01	0.00	0.00	0.00	-0.00	0.01**	0.00	0.01*	0.01	0.01	0.01
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]
$medium(rap_t)$	0.01**	0.01	0.01	-0.00	-0.00	-0.00	0.01***	0.00	0.01**	0.02	0.03**	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.02]	[0.01]	[0.02]
$high(rap_t)$	0.01	-0.00	0.00	-0.01	-0.00	-0.01	0.01	-0.00	0.01	-0.00	0.02	-0.00
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.02	0.22***	0.13***	0.21***	-0.17**	0.08	-0.17*	0.13	-0.19	0.30***
	[0.12]	[0.08]	[0.12]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.21]	[0.11]
$\bar{R}^2$	0.04	0.03	-0.03	0.14	0.13	0.08	0.09	0.02	0.07	-0.00	-0.00	0.04
Panel D: Conditional Alpha and Beta												
$low(rap_t)$	0.01	0.01	0.00	-0.00	0.00	-0.00	0.01*	0.00	0.01*	0.01	0.00	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.02]	[0.02]	[0.02]
$medium(rap_t)$	0.01	0.00	0.00	-0.00	-0.00	-0.00	0.01**	-0.00	0.01	0.01	0.03**	0.00
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
$high(rap_t)$	0.01	-0.00	0.00	-0.01	-0.00	-0.01	0.01	-0.00	0.01	-0.00	0.02	-0.00
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.03]	[0.02]
$R^e_{m,t:t+h} * low(rap_t)$	-0.11	-0.09	0.05	0.30***	0.19***	0.29***	-0.08	0.11***	-0.05	0.22**	0.12	0.52***
	[0.07]	[0.08]	[0.09]	[0.06]	[0.03]	[0.05]	[0.10]	[0.05]	[0.10]	[0.10]	[0.16]	[0.12]
$R^e_{m,t:t+h} * medium(rap_t)$	-0.11	-0.05	0.07	0.21***	0.12***	0.23***	-0.18*	0.14*	-0.13	0.24	-0.21	0.26*
	[0.16]	[0.08]	[0.21]	[0.06]	[0.03]	[0.06]	[0.10]	[0.08]	[0.08]	[0.18]	[0.23]	[0.15]
$R^e_{m,t:t+h} * high(rap_t)$	-0.32	-0.18	-0.15	0.14**	0.08	0.11	-0.25**	-0.01	-0.31*	-0.06	-0.51	0.12
	[0.24]	[0.17]	[0.22]	[0.07]	[0.06]	[0.09]	[0.12]	[0.09]	[0.18]	[0.24]	[0.44]	[0.18]
$\bar{R}^2$	0.05	0.03	-0.02	0.15	0.13	0.08	0.10	0.04	0.10	-0.00	0.03	0.05

Table 3: Time-Series Regressions of Portfolio Returns: Sentiment vs Risk

This table presents regressions of long-short portfolio returns based on single characteristics over the next quarter ($h = 1$) on market excess returns ($R^e_{m,t:t+h}$), conditioning variables, and interactions. HML, SMB and CMA are cumulative excess returns over the next quarter, based on value, size and investment from Ken French's library. Other columns such as M-L, M-B and C-M consider comparisons to the usually excluded middle portfolios on the same sorts. H-L, S-M and C-A are based on the extreme deciles only. HS-LB, HC-LA and SC-BA combine two dimensions at the same time, using 25 portfolios sorted on both characteristics. For instance, HS-LB is long small-value and short big-growth. For conditioning variables, we use three dummies that equal unity when wealth-effect-adjusted risk appetite ($rapa$) is high (good state), medium, or low. A good state is a quarter when rap is among the top one-third highest values, while the bad state is the symmetric opposite. This table reports OLS time-series regression coefficients. Standard errors are Newey-West adjusted. $\bar{R}^2$ denotes the adjusted R^2 statistic. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

	Book-to-Market			Size			Investment			Combined		
	HML	M-L	H-L	SMB	M-B	S-B	CMA	C-M	C-A	HS-LB	HC-LA	SC-BA
Panel A: Market Model												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01***	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.08	-0.17*	0.14	-0.19	0.31***
	[0.13]	[0.09]	[0.13]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.12]
$\bar{R}^2$	0.06	0.04	-0.01	0.16	0.14	0.10	0.11	0.04	0.09	0.01	0.02	0.06
Panel B: Conditional Beta												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01**	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h} * low(rapa_t)$	-0.22***	-0.12*	-0.07	0.31***	0.19***	0.29***	-0.16	0.14***	-0.09	0.18*	-0.08	0.43***
	[0.06]	[0.07]	[0.11]	[0.06]	[0.04]	[0.05]	[0.10]	[0.04]	[0.10]	[0.10]	[0.14]	[0.12]
$R^e_{m,t:t+h} * medium(rapa_t)$	-0.04	-0.01	0.13	0.19***	0.11***	0.21***	-0.11	0.03	-0.14*	0.27*	-0.06	0.35**
	[0.12]	[0.06]	[0.16]	[0.04]	[0.03]	[0.06]	[0.08]	[0.08]	[0.08]	[0.15]	[0.20]	[0.16]
$R^e_{m,t:t+h} * high(rapa_t)$	-0.29	-0.20	-0.10	0.14*	0.08	0.12	-0.24*	0.04	-0.30	-0.05	-0.48	0.10
	[0.27]	[0.20]	[0.24]	[0.07]	[0.06]	[0.09]	[0.13]	[0.08]	[0.21]	[0.27]	[0.51]	[0.20]
$\bar{R}^2$	0.07	0.06	0.00	0.16	0.15	0.09	0.11	0.05	0.10	0.01	0.02	0.06
Panel C: Conditional Alpha												
$low(rapa_t)$	0.01*	0.01	0.00	0.00	0.00	-0.00	0.02***	0.00	0.01**	0.02	0.02	0.01
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]
$medium(rapa_t)$	0.01	-0.00	0.00	-0.00	-0.01	-0.00	0.01***	-0.00	0.00	0.01	0.01	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$high(rapa_t)$	0.02	0.00	0.01	-0.00	-0.00	-0.00	0.02*	-0.00	0.01	0.00	0.03	0.00
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]
$R^e_{m,t:t+h}$	-0.17	-0.11	-0.01	0.22***	0.14***	0.21***	-0.16**	0.08	-0.16*	0.14	-0.17	0.31***
	[0.12]	[0.08]	[0.12]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.11]
$\bar{R}^2$	0.05	0.03	-0.03	0.14	0.13	0.08	0.10	0.03	0.08	-0.01	0.00	0.04
Panel D: Conditional Alpha and Beta												
$low(rapa_t)$	0.01*	0.01*	0.01	-0.00	0.00	-0.00	0.02***	0.00	0.01**	0.02	0.02	0.01
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]
$medium(rapa_t)$	-0.00	-0.01	-0.01	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$high(rapa_t)$	0.02	0.00	0.01	-0.00	-0.00	-0.00	0.02*	-0.00	0.01	0.01	0.03	0.01
	[0.02]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.03]	[0.02]
$R^e_{m,t:t+h} * low(rapa_t)$	-0.23***	-0.14**	-0.08	0.31***	0.19***	0.28***	-0.17*	0.14***	-0.10	0.16*	-0.08	0.41***
	[0.06]	[0.06]	[0.11]	[0.06]	[0.03]	[0.06]	[0.10]	[0.04]	[0.09]	[0.09]	[0.14]	[0.11]
$R^e_{m,t:t+h} * medium(rapa_t)$	0.03	0.03	0.18	0.20***	0.13***	0.22***	-0.07	0.03	-0.10	0.30**	0.03	0.41***
	[0.11]	[0.06]	[0.15]	[0.05]	[0.03]	[0.06]	[0.07]	[0.09]	[0.07]	[0.13]	[0.18]	[0.14]
$R^e_{m,t:t+h} * high(rapa_t)$	-0.30	-0.20	-0.11	0.14*	0.08	0.12	-0.25*	0.04	-0.31	-0.05	-0.50	0.09
	[0.29]	[0.21]	[0.26]	[0.07]	[0.06]	[0.09]	[0.14]	[0.08]	[0.21]	[0.28]	[0.54]	[0.21]
$\bar{R}^2$	0.07	0.05	-0.01	0.14	0.14	0.07	0.11	0.03	0.10	-0.01	0.02	0.05

In the Appendix, we consider longer horizons of up to twelve quarters. Along the value dimension, we find that conditional alphas become more relevant as we extend the horizon. In general, the conditional beta channel is not significant for value-based portfolios.

While these results show evidence that risk appetite may affect asset prices through a risk channel, they do not constitute a formal test of a conditional asset pricing model. The reason is that variation in betas is necessary, but not sufficient to conclude in favor of such models. Betas must also covary with risk premia, something we address in what follows.

3.2 Conditional Risk Models

In this section, we formally test whether our measure of risk appetite is a relevant conditioning variable when pricing assets in the cross section in a risk-based framework. While the core of our analysis focuses on CAPM-related specifications, in the Appendix we also present consumption-based versions.

Our aim is to test whether risk appetite can at least partially explain cross-sectional differences in average returns in stock portfolios. Standard models, such as the CAPM, may hold conditionally in every period, but they may not be testable unconditionally with the same specification if conditional expectations for both betas and risk premia covary. This may happen if they are jointly determined by the same state variable. Many papers have tested conditional asset pricing models with supporting evidence (e.g. Ang and Chen [2007]), while others claim that the required extent of covariation between beta and expected market returns is empirically implausible (e.g. Lewellen and Nagel [2006]).

Nonetheless, we show below that our risk appetite variable does a good job at explaining the cross-section of value- and size-sorted portfolios. This conditioning variable helps improve the fit of the model, even though variation in betas may not be sufficient to fully explain the cross-sectional variation in average returns. These results are robust to the inclusion of other portfolios sorted on additional firm characteristics.

For simplicity, we consider a conditional model with a single risk factor.[24] If portfolio betas

[24] In the Appendix, we review the unconditional implications of conditional models.

are linear in the conditioning variable z_t, i.e. $\beta_i = \beta_{i,0} + \beta_{i,1} z_t$, then unconditional excess returns associated with portfolio i can be written as:

$$E[R_{i,t+1} - R_{f,t+1}] = \lambda_{z,0} + E[\lambda_{factor,t}]\beta_{i,0} + E[\lambda_{factor,t} z_t]\beta_{i,1}, \quad (1)$$

where $\lambda_{z,0}$ is the unconditional difference between the zero-beta rate and the risk-free rate. Unconditionally, each portfolio has two different risk parameters, i.e., betas related to the unconditional and the conditional exposure to the relevant risk factor. The premium associated with the latter part of equation (1) exists only when the factor risk premium $\lambda_{factor,t}$ covaries unconditionally with the conditioning variable. In the case of our conditioning variable, rap_t, this term should be negative, since a high value for risk appetite indicates a good state for the economy.

We test equation (1) by applying the approach proposed in Fama and MacBeth [1973] to two sets of portfolios described below. To compare models and analyze how well they fit the data, we report the R^2 of each cross-sectional regression. In order to determine the statistical significance of the two risk premium terms, we report standard errors of the estimated coefficients λ_0 $(= E[\lambda_{factor,t}])$ and λ_1 $(= E[\lambda_{factor,t} z_t])$. As $\beta_{i,1}$ and $\beta_{i,0}$ are estimated in the first stage of the regression, we use corrected standard errors based on Shanken [1992].

Table 4 presents results for both unconditional and conditional asset pricing models. Regressions in Panel A are based on Fama-French's 25 portfolios sorted on value and size. They are value-weighted returns formed by independently sorting stocks into five size and five book-to-market quintiles constructed with NYSE, AMEX, and NASDAQ stocks. Panel B reports results for a larger set of portfolios based on five characteristics: size, book-to-market, beta, investment and operational profitability. For each characteristic, we obtain ten decile portfolios from Ken French's website, adding up to a total of 50 portfolios.

The first row of each panel shows the performance of the unconditional CAPM, with the CRSP value-weighted excess return, $R^e_{m,t}$, proxying for the market. The risk-premium coefficient is not statistically significant and has a sign that is inconsistent with CAPM theory. The R^2

is the smallest across models.[25] The second model presented in Table 4 is the Fama-French three-factor model as described in Fama and French [1993]. About 55% of the cross-sectional variation in the returns is explained by this model, but the premia on SMB and HML betas are statistically insignificant. Panel B reveals a large decline in goodness of fit once we introduce additional firm characteristics.

The last three rows in each panel of Table 4 present results for the conditional CAPM with *rap* and *cay* as conditioning variables, introduced separately and jointly.[26] As expected, the risk premium associated with the "rap-conditional beta" is negative and statistically significant in both specifications in which *rap* enters solely as a conditioning variable. Interestingly, Panel B shows that, once the 50 portfolios are considered, the specification with *rap* performs as well as the Fama-French model.

The inclusion of *cay* as an additional conditioning variable (last row of panels) does not change these findings for Panel B, but it weakens the statistical significance of the risk premium associated with *rap* in Panel A with 25 Fama-French portfolios. Although *cay* improves the fit of the model in Panel A, the estimates for its risk premium have the wrong sign in all specifications – since a high consumption-wealth is associated with a bad state of the economy, the sign of its premium is supposed to be positive. Finally, in the next subsection, we show that risk premia associated with alternative risk appetite measures remain statistically significant when *cay* is included in all specifications considered.

[25] Although the goodness of fit in this sample is much higher than in previous studies, this should not be seen as evidence in favor of CAPM due to the wrong sign on the risk premium. The R^2 in Panel B declines significantly when we include other portfolio characteristics, such as investment, beta and operational profitability.

[26] In the Appendix, we also present results with the investment sentiment measure from Baker and Wurgler [2006] as a conditioning variable.

Table 4: Risk Premium Estimates in Cross-sectional Regressions with Baseline Risk Appetite Measure

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. The conditioning variables are *rap* and *cay*, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Model	constant	$R^e_{m,t+1}$	SMB_{t+1}	HML_{t+1}	$R^e_{m,t+1} * cay_t$	$R^e_{m,t+1} * rap_t$	$R^2/[\bar{R}^2]$
Panel A: 25 Fama-French Portfolios							
CAPM	4.54***	-1.82					0.25
	[1.34]	[1.44]					[0.22]
Fama-French	5.31***	-3.05**	0.13	0.84			0.56
	[1.14]	[1.32]	[0.42]	[0.52]			[0.49]
rap_t	3.86***	-1.52				-3.59*	0.39
	[1.17]	[1.38]				[1.98]	[0.34]
cay_t	5.18***	-2.65*			-6.71*		0.42
	[1.51]	[1.57]			[3.60]		[0.36]
cay_t, rap_t	4.56***	-2.24			-5.12*	-2.56	0.47
	[1.25]	[1.42]			[3.03]	[1.73]	[0.39]
Panel B: 50 Single-sorted portfolios on 5 characteristics: size, B/M, beta, investment, op profitability							
CAPM	2.68***	-0.34					0.04
	[0.77]	[1.05]					[0.02]
Fama-French	2.47***	-0.24	0.10	0.65			0.27
	[0.79]	[1.06]	[0.41]	[0.53]			[0.23]
rap_t	2.69***	-0.47				-3.09**	0.24
	[0.77]	[1.05]				[1.51]	[0.20]
cay_t	3.13***	-0.82			-1.95		0.09
	[0.92]	[1.13]			[2.14]		[0.05]
cay_t, rap_t	3.00***	-2.24			-5.12	-2.94**	0.26
	[0.89]	[1.13]			[2.03]	[1.41]	[0.21]

3.3 Other Conditioning Variables

Here we consider alternative risk appetite measures. First, we use the version constructed with a longer time-series on total gambling expenditures, *rapt*. Second, we consider the measure based on casino gambling that accounts for wealth effects, *rapa*. We find that results are robust to these alternative measures.

Table 5 presents the same analysis as in Table 4, but now with the measure based on total gambling expenditures, *rapt*. With this longer sample, the R^2 for CAPM is close to zero, but the fit of the Fama-French model improves substantially. In addition, the premium on HML beta is now statistically significant. In the conditional model with *rapt*, the risk premium for its interaction with market excess returns remains statistically significant and with correct sign in both portfolio groups presented in Panels A and B. The inclusion of *cay* does not change results meaningfully.

Table 5: Risk Premium Estimates in Cross-sectional Regressions with Risk Appetite Measure Based on Total Gambling Expenditures

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. The conditioning variables are *rapt* and *cay*, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Model	constant	$R^e_{m,t+1}$	SMB_{t+1}	HML_{t+1}	$R^e_{m,t+1} * cay_t$	$R^e_{m,t+1} * rapt_t$	$R^2/[\bar{R}^2]$
Panel A: 25 Fama-French Portfolios							
CAPM	2.49***	-0.21					0.00
	[0.96]	[1.11]					[-0.04]
Fama-French	3.62***	-1.99*	0.63	1.10***			0.72
	[0.99]	[1.15]	[0.40]	[0.42]			[0.68]
$rapt_t$	1.28	0.36				-7.90***	0.48
	[0.92]	[1.11]				[2.34]	[0.43]
cay_t	4.98***	-3.14***			-10.06***		0.48
	[1.19]	[1.25]			[2.73]		[0.43]
$cay_t, rapt_t$	3.31***	-1.71*			-7.99***	-7.03***	0.60
	[0.74]	[0.95]			[2.21]	[2.32]	[0.55]
Panel B: 50 Single-sorted portfolios on 5 characteristics: size, B/M, beta, investment, op profitability							
CAPM	1.30*	0.47					0.06
	[0.67]	[0.91]					[0.04]
Fama-French	1.93***	-0.34	0.61	0.81*			0.63
	[0.75]	[0.96]	[0.40]	[0.44]			[0.61]
$rapt_t$	1.46**	0.13				-5.63***	0.41
	[0.67]	[0.90]				[1.89]	[0.39]
cay_t	2.03***	-0.35			-3.85***		0.24
	[0.66]	[0.89]			[1.41]		[0.21]
$cay_t, rapt_t$	1.75***	-1.71			-7.99***	-5.32***	0.44
	[0.65]	[0.88]			[1.34]	[1.90]	[0.40]

We have so far focused on measures of risk appetite that are constructed without any asset price data. We now consider a version of our baseline risk appetite measure that accounts for wealth effects, *rapa*. In particular, we include the stock market index as proxy for wealth in the cointegrating system. On one hand, an increase in financial wealth could lead to more consumption and more gambling consequently, distorting our baseline risk appetite measure, *rap*. On the other hand, we believe that our previous measures, *rap* and *rapt*, by being constructed without any asset price data, are less likely to be affected by a criticism that wealth may be driving results.[27]

Table 6 shows cross-sectional tests with *rapa*. It is reassuring that results are robust to the inclusion of financial assets in the cointegrating vector. Indeed, the risk premium associated with *rapa* is statistically significant in both panels, whether *cay* is included or not.[28]

In the Appendix, we also entertain the possibility that other types of gambling (lottery and pari-mutuel) and another specific measure of consumption (luxury goods) could also work in a similar conditional setting. Although these other measures provide relevant information in some cases, our risk appetite measures based on casino and total gambling fare better overall.

[27] Brennan and Xia [2005] suggest the same criticism for the conditioning variable *cay*.

[28] As mentioned previously, results based on total gambling that also account for wealth effects are very close to those in Table 5. This is not surprising, as the coefficient on financial assets in the cointegrating system with total gambling is economically small and statistically insignificant. For brevity, we do not report these results, but they are available upon request.

Table 6: Risk Premium Estimates in Cross-sectional Regressions with Risk Appetite Measure Based on Casino Expenditures - CRSP Adjusted

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. The conditioning variables are *rapa* and *cay*, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Model	constant	$R^e_{m,t+1}$	SMB_{t+1}	HML_{t+1}	$R^e_{m,t+1} * cay_t$	$R^e_{m,t+1} * rapa_t$	$R^2/[\bar{R}^2]$
Panel A: 25 Fama-French Portfolios							
CAPM	4.54***	-1.82					0.25
	[1.34]	[1.44]					[0.22]
Fama-French	5.31***	-3.05**	0.13	0.84			0.56
	[1.14]	[1.32]	[0.42]	[0.52]			[0.49]
$rapa_t$	4.17***	-1.77				-4.03**	0.39
	[1.27]	[1.43]				[1.94]	[0.33]
cay_t	5.18***	-2.65*			-6.71*		0.42
	[1.51]	[1.57]			[3.60]		[0.36]
$cay_t, rapa_t$	4.78***	-2.44			-5.42	-3.06*	0.48
	[1.40]	[1.51]			[3.28]	[1.71]	[0.40]
Panel B: 50 Single-sorted portfolios on 5 characteristics: size, B/M, beta, investment, op profitability							
CAPM	2.68***	-0.34					0.04
	[0.77]	[1.05]					[0.02]
Fama-French	2.47***	-0.24	0.10	0.65			0.27
	[0.79]	[1.06]	[0.41]	[0.53]			[0.23]
$rapa_t$	2.76***	-0.49				-2.51*	0.15
	[0.78]	[1.05]				[1.28]	[0.12]
cay_t	3.13***	-0.82			-1.95		0.09
	[0.92]	[1.13]			[2.14]		[0.05]
$cay_t, rapa_t$	3.17***	-2.44			-5.42	-2.49*	0.20
	[0.92]	[1.14]			[2.14]	[1.29]	[0.15]

4 Market Predictability and Risk Appetite

In this section we assess whether our risk appetite measures (*rap* and *rapa*) help predict excess returns, comparing their performance with standard measures described in Section 2.2.[29] Namely: (i) dividend yield (*d/p*); (ii) aggregate investment-capital ratio (*i/k*); (iii) book-to-market value (*b/m*); (iv) risk-free rate (*tbl*); (v) long-term yield (*lty*); (vi) terms spread (*tms*); (vii) default yield spread (*dfy*); (viii) inflation rate (*infl*); (ix) consumption-wealth ratio (*cay*); and (x) investor sentiment measure (*is*). We consider the sample from 1982Q1 to 2015Q3 and report both in-sample and out-of-sample prediction statistics.

Table 1 in Section 2.2 reports some statistical properties of the aforementioned measures. Recall that *rap* and *rapa* present weak correlations with most variables, except *i/k* (approximately 0.55), *tms* (-0.45) and *tbl* (0.35). Hence, the information content in *rap* or *rapa* is not present in common variables used in the literature, such as *cay* or *is*. In addition, the persistence of *rap* and *rapa* is fairly lower than that of variables such as *d/p*, *i/k*, *b/m* and *lty*. Importantly, recall that our baseline risk appetite measure *rap* is the only variable other than *i/k* and *infl* that does not rely on any asset price information.

In order to compare performance across measures, we run the following set of regressions:

$$R_{m,t:t+h} - R_{f,t:t+h} = \alpha + \beta X_{t-1} + \varepsilon_t, \tag{2}$$

where $R_{m,t:t+h} - R_{f,t:t+h}$ measures excess returns accumulated over h quarters for the value-weighted CRSP Index. The risk-free rate is the return associated with the three-month US Treasury bill. X_{t-1} is the lag of one of the aforementioned predictors. The next subsections analyze in-sample and out-of-sample predictability for our risk appetite measures and the other aforementioned variables. In the Appendix, we also check the in-sample predictive power of *rap* that goes beyond other variables by presenting results from regressions with *rap* and other predictors pairwise.

[29] We select variables that have been shown to predict stock returns with sample size at least as long as ours. For instance, we do not consider option-based measures such as variance risk premium (Bollerslev et al. [2009]) and option-based equity risk premium (Martin [2017]) as they have much shorter samples.

4.1 In-sample Predictability Tests

Table 7 shows in-sample predictability for *rap*, *rapa* and the other aforementioned variables across horizons of one up to six years. For each regression, the table reports OLS estimates of the regressors, Newey-West corrected t-statistics in parentheses, and adjusted R^2 statistics in square brackets. Coefficients on *rap* and *rapa* are always negative, in line with our expectation that high risk appetite is associated with lower future excess.

In congruence with the literature on empirical asset pricing, *d/p*, *i/k* and *tms* perform relatively well at any horizon. This conclusion is based both on the statistical significance of the point estimates (high t-statistics) as well as the fit of the model (high adjusted R^2 statistics). Note, however, that d/p and i/k are highly persistent, which might be a source of inference problems over longer horizons (Boudoukh et al. [2008]). In other words, standard errors might be biased toward finding significant effects for both *d/p* and *i/k*.

Except for these three variables, *rap* performs better over five- and six-year forecasting horizons, whereas *cay* does better over two-, three- and four-year horizons. *rapa* perfoms worse than *rap* at any horizon, although *rapa* is also a relevant predictor over longer horizons. Importantly, these variables are fairly less persistent than *i/k* and *d/p*. For one-year horizon, *cay*, *is* and *infl* also perform well.

In the Appendix, we present forecasting regressions with both *rap* and every other predictor pairwise. The main takeaways are the following. First, *rap* has predictive power that goes beyond *cay*, d/p and b/m, even for shorter horizons. For example, the adjusted R^2 increases substantially at two-, three- and four-year horizons once *rap* is included in a model with either *cay*, d/p or b/m. Second, at a six-year horizon, *rap* helps predict excess returns beyond and above i/k. For four- and five-year horizons, *rap* ceases to be significant once included with i/k. Third, once combined with tms, the fit of the models at five- and six-year horizons improves substantially, but *rap* ceases to be significant at a four-year horizon. Finally, *rap*'s predictive power barely improves once combined with either *is* or $infl$ at any horizon.

Table 7: In-sample Market Return Predictability

This table displays the estimated regression coefficient associated with X_{t-1} in the following equation

$$R_{m,t:t+h} - R_{f,t:t+h} = \alpha + \beta X_{t-1} + \varepsilon_t,$$

for several models and horizons, as well as Newey-West standard errors (in brackets) and adjusted R-squared (in parenthesis). *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The dependent variable is the excess return associated with the value-weighted CRSP Index. The proxy for the risk-free rate is the return associated with the three-month U.S. Treasury bill. In each model we consider a different regressor X_{t-1}. Besides our risk appetite measures (*rap* and *rapa*), we also consider: (i) consumption-wealth ratio (*cay*); (ii) investor sentiment measure (*is*); (iii) dividend yield (*d/p*); (iv) aggregate investment-capital ratio (*i/k*); (v) book-to-market ratio (*b/m*); (vi) risk-free rate (*tbl*); (vii) long-term yield (*lty*); (viii) terms spread (*tms*); (ix) default yield spread (*dfy*); and (x) inflation rate (*infl*). See Section 2.2 on how these regressors are constructed. We consider forecasting horizons ranging from four to twenty four quarters (one to six years). The sample period is from 1982Q1 to 2015Q3.

X_{t-1}:	*rap*	*rapa*	*cay*	*is*	*d/p*	*i/k*	*b/m*	*tbl*	*lty*	*tms*	*dfy*	*infl*
Forecasting horizon: 4 quarters												
$\hat{\beta}$	-0.02	-0.01	0.04*	-0.03	0.15***	-9.86	0.28***	-0.00	0.51	2.39	8.73**	-4.37
[*s.e.*]	[0.02]	[0.02]	[0.02]	[0.02]	[0.06]	[6.44]	[0.11]	[0.83]	[0.94]	[1.67]	[4.15]	[2.99]
($\bar{R}^2$)	1.29	-0.13	3.85	3.18	9.86	3.69	9.77	-0.78	-0.15	2.14	4.56	1.54
Forecasting horizon: 8 quarters												
$\hat{\beta}$	-0.05	-0.03	0.12***	-0.04	0.22*	-23.49*	0.29	-1.29	0.15	7.78***	10.51	-6.45**
[*s.e.*]	[0.04]	[0.04]	[0.05]	[0.04]	[0.12]	[12.82]	[0.21]	[1.10]	[1.52]	[3.04]	[8.07]	[2.95]
($\bar{R}^2$)	3.14	0.73	15.60	1.44	11.19	11.63	4.87	1.51	-0.77	14.41	2.95	1.68
Forecasting horizon: 12 quarters												
$\hat{\beta}$	-0.08	-0.05	0.18***	-0.01	0.33**	-41.04***	0.42	-1.42	1.03	11.63***	13.37	-3.06
[*s.e.*]	[0.06]	[0.05]	[0.07]	[0.05]	[0.14]	[13.41]	[0.26]	[1.87]	[2.27]	[3.71]	[11.74]	[3.47]
($\bar{R}^2$)	4.81	1.66	19.98	-0.65	15.20	21.75	6.32	0.74	-0.15	19.64	2.84	-0.49
Forecasting horizon: 16 quarters												
$\hat{\beta}$	-0.12*	-0.08	0.18*	-0.04	0.47***	-62.25***	0.63**	-1.34	2.36	15.29***	21.42	-3.85
[*s.e.*]	[0.06]	[0.05]	[0.10]	[0.06]	[0.16]	[9.72]	[0.30]	[2.80]	[2.99]	[4.08]	[16.00]	[5.82]
($\bar{R}^2$)	7.83	3.58	13.76	0.18	20.44	33.50	10.00	0.01	1.31	23.09	5.47	-0.51
Forecasting horizon: 20 quarters												
$\hat{\beta}$	-0.18***	-0.14***	0.17	-0.01	0.65***	-80.08***	0.84***	-0.99	3.59	17.82***	36.11*	-6.28
[*s.e.*]	[0.05]	[0.05]	[0.10]	[0.08]	[0.19]	[11.13]	[0.35]	[3.88]	[3.57]	[5.78]	[20.92]	[9.90]
($\bar{R}^2$)	13.70	7.32	7.82	-0.79	27.50	36.04	12.47	-0.58	2.41	20.97	11.67	-0.24
Forecasting horizon: 24 quarters												
$\hat{\beta}$	-0.21***	-0.17***	0.14**	-0.01	0.72***	-96.31***	0.79*	-0.37	4.25	17.47**	34.69	-2.41
[*s.e.*]	[0.06]	[0.07]	[0.06]	[0.07]	[0.22]	[20.38]	[0.42]	[4.07]	[3.67]	[8.20]	[22.96]	[11.04]
($\bar{R}^2$)	18.40	11.72	4.88	-0.89	33.44	43.80	10.59	-0.88	3.34	18.32	10.36	-0.83

4.2 Out-of-sample Predictability Tests

In this section, we follow Campbell and Thompson [2007] and Welch and Goyal [2008], and compute statistics that evaluate models according to their out-of-sample (OOS) forecast errors. The idea of using OOS forecast errors is to compare the predictability of each model considering only information that was available in "pseudo real time",[30] including the residuals, *rap* and *cay*, of their respective cointegrating vectors estimated with pseudo real-time data. We also consider versions in which residuals are computed using cointegrating vectors estimated only once in the whole sample. In this case, residuals, which we denote by *rapc* and *cayc*, are expected to have more predictive power as they might suffer from *look-ahead bias* (see Brennan and Xia [2005]).

The out-of-sample window runs from 1992Q1 to 2015Q3. Hence, we estimate the first set of regressions in (2) for each regressor X_t using the subsample from 1982Q1 to 1991Q4. Then, we use the estimated coefficients to predict future excess returns for various horizons and compute the associated out-of-sample residuals. We proceed iteratively, adding each observation at a time, reestimating the predictive regression, and computing new forecasts. We use these OOS residuals to compute the statistics to evaluate models. As a ground for comparison, we also compute statistics based on in-sample residuals estimated in the whole sample.

Following Welch and Goyal [2008], we report R^2, R^2_{IS} and R^2_{OOS}, which are the R-squared computed with in-sample residuals for the whole sample, in-sample residuals from 1992Q1 to 2015Q3 (i.e., the out-of-sample window) and out-of-sample residuals, respectively.[31] In addition, following Campbell and Thompson [2007], we also report $R^2_{OOS,COEF}$, $R^2_{OOS,PREM}$ and $R^2_{OOS,COEF,PREM}$, which are the R-squared computed with the OOS residuals, obtained after adjusting each regression coefficient to zero whenever its sign is different than expected ($R^2_{OOS,COEF}$), the predicted premium is negative ($R^2_{OOS,PREM}$), and at least one of these cases happens ($R^2_{OOS,COEF,PREM}$).

Table 8 presents the results for *rap*, which performs fairly well at longer horizons, predicting something between 22 and 27 percent of excess returns at five- and six-year horizons. At these

[30]We use the term pseudo real time because some measures use recent vintages of data rather than vintages available at each point in time.

[31]Notice that R-squared computed with in-sample residuals is the same for both *rap* and *rapc*, as well as *cay* and *cayc*. In addition, as opposed to the previous subsection, we consider only data from 1982Q1 on to compute *cay* and *cayc*.

horizons, only *cay-cayc* and i/k perform better than *rap* according to all metrics considered. d/p also performs better if we do not restrict its coefficient to be positive. If we restrict, instead, its OOS predictive power falls considerably due to the fact that both estimated coefficients and predicted premia turn out to have the wrong sign during the mid-nineties.

Table 8: Out-of-sample Market Return Predictability

This table displays the R^2, R^2_{IS}, R^2_{OOS}, $R^2_{OOS,COEF}$, $R^2_{OOS,PREM}$ and $R^2_{OOS,COEF,PREM}$ (see definitions in the text) associated with the following equation

$$R_{m,t:t+h} - R_{f,t:t+h} = \alpha + \beta X_{t-1} + \varepsilon_t,$$

for several models and horizons. The dependent variable is the excess return associated with the value-weighted CRSP Index. The proxy for the risk-free rate is the return associated with the three-month U.S. Treasury bill. In each model we consider a different regressor X_{t-1}. Besides our risk appetite measure (*rap*-*rapc*), we also consider: (i) consumption-wealth ratio (*cay*-*cayc*); (ii) investor sentiment measure (*is*); (iii) dividend yield (*d/p*); (iv) aggregate investment-capital ratio (*i/k*); (v) book-to-market ratio (*b/m*); (vi) risk-free rate (*tbl*); (vii) long-term yield (*lty*); (viii) term spread (*tms*); (ix) default yield spread (*dfy*); and (x) inflation rate (*infl*). See Section 2.2 on how these regressors are constructed. We consider forecasting horizons ranging from four to twenty four quarters (one to six years).The sample period is from 1982Q1 to 2015Q3, whereas the out-of-sample window is from 1992Q1 to 2015Q3.

X_{t-1}	*rap*	*rapc*	*cay*	*cayc*	*is*	*d/p*	*i/k*	*b/m*	*tbl*	*lty*	*tms*	*dfy*	*infl*
Forecasting horizon: 4 quarters													
R^2	2.55	-	10.05	-	4.95	9.55	5.18	9.03	0.01	0.51	2.93	3.89	3.02
R^2_{IS}	4.19	-	13.24	-	12.13	10.90	9.95	6.96	0.14	-0.60	3.17	1.21	5.90
R^2_{OOS}	-1.30	2.19	6.49	9.22	4.19	-1.43	0.89	2.53	-4.07	-4.74	1.46	-1.14	2.48
$R^2_{OOS,COEF}$	-0.66	-0.27	6.49	9.22	-1.72	-1.02	-472.95	2.53	-8.29	-4.74	1.36	-1.14	2.11
$R^2_{OOS,PREM}$	-1.17	2.19	12.26	15.50	4.19	1.01	1.19	2.67	-3.13	-3.26	1.46	-1.14	2.48
$R^2_{OOS,COEF,PREM}$	-0.54	-0.27	12.26	15.50	-1.72	1.41	-2.07	2.67	-3.83	-3.26	1.36	-1.14	2.11
Forecasting horizon: 8 quarters													
R^2	5.48	-	28.93	-	2.81	13.31	14.89	6.38	2.26	0.15	18.78	3.69	2.30
R^2_{IS}	7.35	-	34.34	-	6.88	17.41	21.79	6.88	5.51	-0.45	19.81	3.89	4.08
R^2_{OOS}	1.39	5.18	22.24	27.35	0.57	8.98	11.43	4.05	0.62	-4.71	17.35	2.57	1.42
$R^2_{OOS,COEF}$	0.18	-0.15	22.24	27.35	-2.24	-24.69	-449.63	3.88	0.46	-4.92	17.35	-0.93	1.30
$R^2_{OOS,PREM}$	2.24	5.18	18.34	23.45	0.57	8.79	11.43	4.05	0.62	-4.38	16.58	2.57	1.42
$R^2_{OOS,COEF,PREM}$	1.04	-0.15	18.34	23.45	-2.24	0.91	-3.10	3.88	0.56	-4.59	16.58	-0.93	1.30
Forecasting horizon: 12 quarters													
R^2	7.76	-	43.54	-	0.12	18.83	26.00	8.37	1.67	1.05	25.30	4.44	0.41
R^2_{IS}	11.90	-	53.19	-	0.70	23.07	33.12	7.93	5.14	-0.37	32.97	3.28	1.08
R^2_{OOS}	7.02	7.01	39.74	44.92	-2.15	12.63	24.69	4.95	-2.23	-3.72	26.08	2.51	-1.54
$R^2_{OOS,COEF}$	3.86	-0.53	39.74	44.92	-2.25	-29.13	-140.70	4.76	-0.43	-4.01	26.14	0.13	3.60
$R^2_{OOS,PREM}$	7.02	7.01	31.56	36.76	-2.15	11.64	24.24	4.95	-2.23	-3.58	25.56	2.51	-1.54
$R^2_{OOS,COEF,PREM}$	3.86	-0.53	31.56	36.76	-2.25	-0.37	-8.47	4.76	1.63	-3.87	25.62	0.13	3.60
Forecasting horizon: 16 quarters													
R^2	10.95	-	41.63	-	0.47	24.28	36.94	12.24	0.64	3.28	27.71	7.57	0.34
R^2_{IS}	17.45	-	51.92	-	1.17	28.61	44.58	10.98	2.85	1.06	35.75	5.89	0.96
R^2_{OOS}	13.15	9.79	43.05	42.94	-0.51	17.61	37.47	7.82	-4.07	-1.90	28.59	5.31	-2.07
$R^2_{OOS,COEF}$	9.26	-0.91	43.05	44.00	-1.00	-36.92	24.10	7.70	-1.37	-3.73	28.59	4.18	8.63
$R^2_{OOS,PREM}$	13.15	9.79	40.90	41.76	-0.51	16.61	36.42	7.82	-4.07	-1.88	28.56	5.31	-2.07
$R^2_{OOS,COEF,PREM}$	9.26	-0.91	40.90	42.81	-1.00	-0.09	25.10	7.70	-0.33	-3.70	28.56	4.18	8.63
Forecasting horizon: 20 quarters													
R^2	18.98	-	33.48	-	0.00	32.04	39.11	15.25	0.09	4.76	23.57	13.08	0.29
R^2_{IS}	25.76	-	42.75	-	-0.03	38.08	47.62	14.63	0.97	2.24	30.73	11.73	1.12
R^2_{OOS}	22.97	20.07	39.04	34.42	-1.22	26.78	41.63	11.87	-3.94	0.69	24.56	11.09	-4.18
$R^2_{OOS,COEF}$	22.56	0.50	39.31	40.06	-1.22	-24.38	41.36	11.72	-1.52	-1.77	24.56	9.17	12.23
$R^2_{OOS,PREM}$	22.97	20.07	43.63	39.01	-1.22	26.16	40.71	11.87	-3.94	0.69	24.59	11.09	-3.61
$R^2_{OOS,COEF,PREM}$	22.56	0.50	43.90	44.65	-1.22	4.94	40.44	11.72	-1.52	-1.77	24.59	9.17	12.23
Forecasting horizon: 24 quarters													
R^2	22.65	-	23.62	-	0.11	39.68	47.00	14.93	0.07	6.69	19.94	11.68	0.00
R^2_{IS}	25.38	-	25.97	-	0.29	46.48	51.63	16.38	-0.58	4.57	27.82	13.19	0.10
R^2_{OOS}	26.34	22.99	29.97	23.25	-1.28	38.80	49.56	14.19	-2.15	4.96	20.29	10.92	-6.77
$R^2_{OOS,COEF}$	26.56	0.50	31.11	26.69	-1.08	-174.48	49.56	13.03	0.15	-8.35	20.32	5.41	16.13
$R^2_{OOS,PREM}$	26.34	22.99	33.34	25.94	-1.28	38.78	49.24	14.19	-2.15	4.96	20.30	10.92	-4.98
$R^2_{OOS,COEF,PREM}$	26.56	0.50	34.48	29.38	-1.08	-10.13	49.24	13.03	0.15	-8.35	20.32	5.41	16.13

5 Conclusion

We present evidence that quarterly measures of risk appetite constructed from long time-series data on gambling expenditures provide relevant information for asset pricing. While gambling may not be a rational activity for an expected utility investor, we argue that variations in aggregate gambling correlate with broad risk appetite in the economy.

Our simple measures of risk appetite can at least partially explain cross-sectional differences in future returns for portfolios sorted on various characteristics. Our measures improve the fit of conditional asset pricing models such as the conditional CAPM. Moreover, these conditioning variables also help forecast market and portfolio excess returns both in sample and out of sample, providing information that is not contained in standard variables used in the literature, such as the consumption-wealth ratio and the dividend yield.

The relationship between risk appetite and asset prices appears to be mainly explained by simultaneous changes in risk and risk premia. We find that changes in betas are usually in the expected direction, and that conditional betas matter in the cross-section of a range of portfolios. In quantitative terms, our results are consistent with Lewellen and Nagel [2006], as variation in betas does help explain the cross-section of expected returns, but is not sufficient to fully account for the observed differences.

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Appendix

This Appendix provides additional material, results and robustness analyses. First, we describe how we construct an alternative proxy for risk appetite, *rapt*, based on total gambling expenditures. Second, we report more results exploring the risk and sentiment channels. Third, we briefly review the unconditional implications of conditional asset pricing models. Fourth, we present results for versions of Consumption CAPM. Fifth, we use the investment sentiment measure from Baker and Wurgler [2006] as a conditioning variable. Sixth, we show a conditional model using luxury consumption as conditioning variable and the effect of using alternative gambling measures based solely on lotteries or pari-mutuel expenditures. Finally, we present additional in-sample market predictability results.

A Total Gambling Activity

In this section we explain how we construct *rapt*, our proxy for risk appetite based on total gambling expenditures. Here, *rapt* is the stanzedardized cointegrating residual of the relationship between log of total gambling expenditures per capita in the US (TOTALG), GDP, AIRFARES, STATES and a series on the number of states (weighted by their GDP) in which lotteries are legal (LSTATES). As opposed to STATES, which is simply the number of states in which casino gaming are legalized, LSTATES weights each state by its GDP. The reason is that demand for lotteries is arguably local, whereas demand for casino gambling goes far beyond state borders.

In this case, we consider a longer sample from 1965Q3 to 2015Q3.[32] Again, we estimate the cointegrating system by OLS, which yields the following cointegrating residual:

$$\epsilon_t^{rapt} = \text{TOTALG}_t + 13.11 - 1.62 \times \text{GDP}_t - 0.11 \times \text{AIRFARES}_t - 0.010 \times \text{STATES}_t - 0.024 \times \text{LSTATES}_t.$$

Although the coefficient on AIRFARES does not have the expected sign, it is statistically insignificant and economically small. The coefficients on GDP and LSTATES are significant at

[32]The period was chosen due to the availability of the investment sentiment measure from Baker and Wurgler [2006]. We run Gregory and Hansen [1996] tests on the cointegrating system but do not find evidence of regime shifts. In addition, Johansen cointegration tests reject the null of no cointegration.

one percent level.

In comparison to *rap*, *rapt* is a bit more persistent (0.92 instead of 0.90) and displays more positive correlation with *cay* (0.49 instead of 0.09). Finally, the correlation between *rap* and *rapt* from 1982Q1 to 2015Q3 is approximately 0.65.

Once CRSP is added to account for wealth effects, one obtains:

$$\begin{aligned}\epsilon_t^{rapta} &= \text{TOTALG}_t + 12.73 - 1.57 \times \text{GDP}_t - 0.11 \times \text{AIRFARES}_t - 0.009 \times \text{STATES}_t - \\ &\quad -0.022 \times \text{LSTATES}_t - 0.014 \times \text{CRSP}_t.\end{aligned}$$

Importantly, the coefficient associated with CRSP is statistically insignificant, and the remaining coefficients are similar in terms of magnitude and statistical significance to those in the previous version without wealth effects. Hence, reported results with *rapt* are very similar to their unreported counterpart once wealth effects are accounted for.

B More on Sentiment vs. Risk

In this section, we report additional variations to the analysis in Section 3.1, on the relative importance of the sentiment and risk channels. We consider three changes. First, we consider a different variable to proxy for investor sentiment. Second, we change the investment horizon from one to twelve quarters. Finally, we consider the case where alphas and betas are linear in the conditioning variable.

In Table 9, we use Baker and Wurgler [2006]'s investor sentiment variable to determine the variation of the conditional alpha, but still assume that our measure of risk appetite drives conditional betas. We find that changing the conditional alpha does not modify any of the results related to conditional betas.

Table 10 modifies the investment horizon to twelve quarters. We find that horizon may matter to our conclusions as conditional betas become less important, while conditional alphas become statistically different in low and high risk appetite periods, particularly in the case of value-sorted portfolios. In general, we find that evidence in favor of the sentiment channel is stronger for longer horizons. Results for horizons between one and twelve quarters are available upon request.

Table 9: Time-Series Regressions of Portfolio Returns: Sentiment vs Risk

This table presents regressions of long-short portfolio returns based on single characteristics over the next quarter ($h = 1$) on market excess returns ($R^e_{m,t:t+h}$), conditioning variables, and interactions. HML, SMB and CMA are cumulative excess returns over the next quarter, based on value, size and investment from Ken French's library. Other columns such as M-L, M-B and C-M consider comparisons to the usually excluded middle portfolios on the same sorts. H-L, S-M and C-A are based on the extreme deciles only. HS-LB, HC-LA and SC-BA combine two dimensions at the same time, using 25 portfolios sorted on both characteristics. For instance, HS-LB is long small-value and short big-growth. Underlying conditioning variables are investment sentiment (is) and risk appetite (rap), depending on the specification. We use dummies that equal unity when the underlying conditioning variable is high (good state), medium or low. A good state is a quarter when the underlying conditioning variable is among the top one-third highest values, while the bad state is the symmetric opposite. This table reports OLS time-series regression coefficients. Standard errors are Newey-West adjusted. $\bar{R}^2$ denotes the adjusted R^2 statistic. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

	Book-to-Market			Size			Investment			Combined		
	HML	M-L	H-L	SMB	M-B	S-B	CMA	C-M	C-A	HS-LB	HC-LA	SC-BA
Panel A: Market Model												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01***	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.08	-0.17*	0.14	-0.19	0.31***
	[0.13]	[0.09]	[0.13]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.12]
$\bar{R}^2$	0.06	0.04	-0.01	0.16	0.14	0.10	0.11	0.04	0.09	0.01	0.02	0.06
Panel B: Conditional Beta												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01**	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h} * low(rap_t)$	-0.12*	-0.08	0.05	0.31***	0.20***	0.29***	-0.09	0.12***	-0.06	0.24***	0.09	0.52***
	[0.06]	[0.08]	[0.08]	[0.06]	[0.03]	[0.05]	[0.10]	[0.05]	[0.10]	[0.09]	[0.14]	[0.12]
$R^e_{m,t:t+h} * medium(rap_t)$	-0.10	-0.04	0.07	0.22***	0.12***	0.24***	-0.17*	0.13	-0.13*	0.27	-0.16	0.27
	[0.16]	[0.09]	[0.21]	[0.06]	[0.03]	[0.07]	[0.10]	[0.08]	[0.08]	[0.20]	[0.25]	[0.18]
$R^e_{m,t:t+h} * high(rap_t)$	-0.32	-0.19	-0.15	0.13**	0.08	0.11	-0.25**	-0.01	-0.31*	-0.07	-0.50	0.12
	[0.24]	[0.17]	[0.22]	[0.06]	[0.05]	[0.08]	[0.11]	[0.09]	[0.17]	[0.24]	[0.42]	[0.17]
$\bar{R}^2$	0.07	0.05	0.00	0.16	0.15	0.10	0.12	0.06	0.12	0.01	0.04	0.07
Panel C: Conditional Alpha												
$low(is_t)$	0.01	0.00	0.00	0.00	-0.00	-0.00	0.01***	0.01***	0.01***	0.01	0.03**	0.01
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.02]	[0.01]	[0.02]
$medium(is_t)$	0.00	-0.01	-0.00	-0.00	-0.00	-0.01	0.00	-0.00	-0.00	-0.01	-0.01	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$high(is_t)$	0.03***	0.01**	0.02*	-0.00	-0.00	-0.00	0.02***	0.00	0.02***	0.02	0.04*	0.00
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.03]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.07	-0.17*	0.13	-0.20	0.30***
	[0.12]	[0.08]	[0.13]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.21]	[0.12]
$\bar{R}^2$	0.08	0.08	-0.01	0.14	0.12	0.08	0.14	0.04	0.13	0.00	0.03	0.04
Panel D: Conditional Alpha and Beta												
$low(is_t)$	0.00	0.00	-0.00	-0.00	-0.00	-0.00	0.01***	0.00**	0.01*	0.01	0.02	0.01
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.02]	[0.01]	[0.02]
$medium(is_t)$	0.00	-0.01	-0.00	-0.00	-0.00	-0.01	0.00	-0.00	-0.00	-0.01	-0.01	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$high(is_t)$	0.03***	0.01**	0.02*	-0.00	0.00	-0.00	0.03***	0.00	0.03***	0.02	0.04**	0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]
$R^e_{m,t:t+h} * low(rap_t)$	-0.08	-0.07	0.07	0.30***	0.20***	0.29***	-0.07	0.11**	-0.04	0.26***	0.10	0.51***
	[0.07]	[0.08]	[0.09]	[0.06]	[0.04]	[0.05]	[0.10]	[0.05]	[0.11]	[0.10]	[0.13]	[0.11]
$R^e_{m,t:t+h} * medium(rap_t)$	-0.12	-0.05	0.06	0.22***	0.12***	0.24***	-0.19*	0.13*	-0.15*	0.24	-0.19	0.26
	[0.18]	[0.09]	[0.22]	[0.05]	[0.03]	[0.06]	[0.10]	[0.08]	[0.08]	[0.21]	[0.25]	[0.18]
$R^e_{m,t:t+h} * high(rap_t)$	-0.33	-0.20	-0.16	0.13**	0.08	0.11	-0.26***	-0.01	-0.32**	-0.08	-0.52	0.11
	[0.21]	[0.15]	[0.20]	[0.06]	[0.05]	[0.08]	[0.09]	[0.09]	[0.15]	[0.22]	[0.38]	[0.17]
$\bar{R}^2$	0.10	0.08	0.00	0.14	0.13	0.08	0.16	0.06	0.16	0.01	0.06	0.05

Table 10: Time-Series Regressions of Portfolio Returns, 12-quarter Horizon: Sentiment vs Risk

This table presents regressions of long-short portfolio returns based on single characteristics over the next 12 quarters ($h = 12$) on market excess returns ($R^e_{m,t:t+h}$), conditioning variables, and interactions. HML, SMB and CMA are cumulative excess returns over the next quarter, based on value, size and investment from Ken French's library. Other columns such as M-L, M-B and C-M consider comparisons to the usually excluded middle portfolios on the same sorts. H-L, S-M and C-A are based on the extreme deciles only. HS-LB, HC-LA and SC-BA combine two dimensions at the same time, using 25 portfolios sorted on both characteristics. For instance, HS-LB is long small-value and short big-growth. For conditioning variables, we use three dummies that equal unity when risk appetite (rap) is high (good state), medium, or low. A good state is a quarter when rap is among the top one-third highest values, while the bad state is the symmetric opposite. This table reports OLS time-series regression coefficients. Standard errors are Newey-West adjusted. $\bar{R}^2$ denotes the adjusted R^2 statistic. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

	Book-to-Market			Size			Investment			Combined		
	HML	M-L	H-L	SMB	M-B	S-B	CMA	C-M	C-A	HS-LB	HC-LA	SC-BA
Panel A: Market Model												
constant	0.15*	0.05	0.09	0.08	0.04	0.04	0.21***	0.03	0.17***	0.35	0.27*	0.46
	[0.08]	[0.07]	[0.07]	[0.05]	[0.03]	[0.09]	[0.08]	[0.02]	[0.06]	[0.23]	[0.14]	[0.30]
$R^e_{m,t:t+h}$	-0.14	-0.17	-0.07	-0.22***	-0.15*	-0.30*	-0.31*	-0.04	-0.23	-0.56	-0.34	-0.98
	[0.17]	[0.17]	[0.16]	[0.09]	[0.08]	[0.16]	[0.18]	[0.06]	[0.15]	[0.44]	[0.29]	[0.60]
$\bar{R}^2$	0.04	0.06	-0.00	0.15	0.09	0.11	0.28	0.00	0.15	0.10	0.07	0.21
Panel B: Conditional Beta												
constant	0.14*	0.03	0.07	0.07	0.02	0.01	0.20***	0.01	0.15***	0.31	0.23*	0.43
	[0.08]	[0.07]	[0.07]	[0.05]	[0.03]	[0.08]	[0.08]	[0.02]	[0.06]	[0.22]	[0.13]	[0.30]
$R^e_{m,t:t+h} * low(rap_t)$	-0.07	0.04	0.15	-0.02	0.12	0.11	-0.22	0.23***	-0.04	-0.04	0.19	-0.48
	[0.16]	[0.14]	[0.19]	[0.11]	[0.08]	[0.17]	[0.16]	[0.05]	[0.12]	[0.45]	[0.32]	[0.58]
$R^e_{m,t:t+h} * medium(rap_t)$	-0.08	-0.10	-0.10	-0.33***	-0.23***	-0.48***	-0.31**	-0.11***	-0.24**	-0.71*	-0.48**	-1.23*
	[0.14]	[0.12]	[0.13]	[0.09]	[0.05]	[0.17]	[0.15]	[0.04]	[0.12]	[0.38]	[0.24]	[0.64]
$R^e_{m,t:t+h} * high(rap_t)$	-0.24	-0.40	-0.21	-0.27***	-0.28***	-0.45***	-0.37*	-0.19***	-0.37*	-0.83	-0.61	-1.12*
	[0.26]	[0.29]	[0.29]	[0.09]	[0.09]	[0.15]	[0.22]	[0.07]	[0.22]	[0.55]	[0.37]	[0.63]
$\bar{R}^2$	0.05	0.15	0.04	0.24	0.31	0.26	0.29	0.37	0.22	0.16	0.19	0.24
Panel C: Conditional Alpha												
$low(rap_t)$	0.19***	0.17**	0.22***	0.16**	0.15***	0.21*	0.25***	0.17***	0.27***	0.62***	0.60***	0.63**
	[0.07]	[0.08]	[0.09]	[0.08]	[0.05]	[0.12]	[0.06]	[0.02]	[0.06]	[0.26]	[0.16]	[0.29]
$medium(rap_t)$	0.15*	0.08	0.10	0.04	0.01	-0.02	0.20**	0.01	0.17**	0.27	0.27**	0.45
	[0.08]	[0.09]	[0.10]	[0.07]	[0.04]	[0.12]	[0.09]	[0.02]	[0.08]	[0.26]	[0.12]	[0.39]
$high(rap_t)$	0.12	-0.02	0.03	0.07*	-0.00	-0.00	0.19*	-0.03	0.11	0.27	0.10	0.38
	[0.11]	[0.09]	[0.11]	[0.04]	[0.04]	[0.06]	[0.10]	[0.02]	[0.08]	[0.24]	[0.15]	[0.29]
$R^e_{m,t:t+h}$	-0.17	-0.25	-0.15	-0.25**	-0.20***	-0.37**	-0.33**	-0.11***	-0.29**	-0.68	-0.53**	-1.08*
	[0.16]	[0.18]	[0.17]	[0.10]	[0.08]	[0.17]	[0.16]	[0.04]	[0.14]	[0.43]	[0.24]	[0.60]
$\bar{R}^2$	0.03	0.15	0.06	0.22	0.26	0.22	0.28	0.45	0.24	0.17	0.30	0.21
Panel D: Conditional Alpha and Beta												
$low(rap_t)$	0.22***	0.14***	0.20***	0.09	0.06	0.06	0.23***	0.13***	0.25***	0.57*	0.61***	0.35
	[0.06]	[0.05]	[0.07]	[0.11]	[0.07]	[0.16]	[0.03]	[0.03]	[0.03]	[0.31]	[0.25]	[0.27]
$medium(rap_t)$	0.11	0.03	0.09	0.05	0.01	0.01	0.19**	0.00	0.16**	0.24	0.28***	0.56
	[0.07]	[0.09]	[0.10]	[0.08]	[0.04]	[0.14]	[0.09]	[0.02]	[0.07]	[0.27]	[0.12]	[0.47]
$high(rap_t)$	0.13	-0.01	0.03	0.08*	0.01	0.00	0.19*	-0.03	0.12	0.28	0.09	0.38
	[0.12]	[0.09]	[0.11]	[0.04]	[0.03]	[0.06]	[0.11]	[0.02]	[0.08]	[0.25]	[0.17]	[0.30]
$R^e_{m,t:t+h} * low(rap_t)$	-0.23**	-0.18*	-0.09	-0.06	0.03	0.01	-0.28***	-0.00	-0.24***	-0.55	-0.57	-0.33
	[0.11]	[0.09]	[0.16]	[0.20]	[0.13]	[0.28]	[0.07]	[0.04]	[0.08]	[0.55]	[0.44]	[0.45]
$R^e_{m,t:t+h} * medium(rap_t)$	-0.04	-0.11	-0.13	-0.30**	-0.22***	-0.47*	-0.29*	-0.10**	-0.25**	-0.59	-0.55***	-1.43
	[0.11]	[0.14]	[0.13]	[0.15]	[0.08]	[0.26]	[0.16]	[0.05]	[0.12]	[0.42]	[0.21]	[0.88]
$R^e_{m,t:t+h} * high(rap_t)$	-0.24	-0.38	-0.18	-0.27***	-0.27***	-0.44***	-0.37	-0.17***	-0.35	-0.80	-0.51	-1.08
	[0.28]	[0.28]	[0.28]	[0.09]	[0.08]	[0.14]	[0.24]	[0.06]	[0.22]	[0.59]	[0.41]	[0.66]
$\bar{R}^2$	0.04	0.16	0.04	0.23	0.30	0.24	0.27	0.47	0.24	0.16	0.29	0.23

Finally, Tables 11 and 12 assume that alphas and betas are linear in *rap* for horizons of one and twelve quarters, respectively. For the one-quarter horizon, although conditional alphas and betas have the right signs, results are weaker in a statistical sense. For the twelve-quarter horizon, results are stronger, and conclusions are similar to those from their non-linear counterpart in Table 10.

Table 11: Time-Series Regressions of Portfolio Returns, Linear Case: Sentiment vs Risk

This table presents regressions of long-short portfolio returns based on single characteristics over the next quarter ($h = 1$) on market excess returns ($R^e_{m,t:t+h}$), conditioning variable, and interaction. HML, SMB and CMA are cumulative excess returns over the next quarter, based on value, size and investment from Ken French's library. Other columns such as M-L, M-B and C-M consider comparisons to the usually excluded middle portfolios on the same sorts. H-L, S-M and C-A are based on the extreme deciles only. HS-LB, HC-LA and SC-BA combine two dimensions at the same time, using 25 portfolios sorted on both characteristics. For instance, HS-LB is long small-value and short big-growth. Conditional alphas and betas are linear in risk appetite (rap). This table reports OLS time-series regression coefficients. Standard errors are Newey-West adjusted. $\bar{R}^2$ denotes the adjusted R^2 statistic. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

	Book-to-Market			Size			Investment			Combined		
	HML	M-L	H-L	SMB	M-B	S-B	CMA	C-M	C-A	HS-LB	HC-LA	SC-BA
Panel A: Market Model												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01***	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.08	-0.17*	0.14	-0.19	0.31***
	[0.13]	[0.09]	[0.13]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.12]
$\bar{R}^2$	0.06	0.04	-0.01	0.16	0.14	0.10	0.11	0.04	0.09	0.01	0.02	0.06
Panel B: Conditional Beta												
constant	0.01*	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01**	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.14***	0.21***	-0.17**	0.08*	-0.17*	0.14	-0.19	0.31***
	[0.13]	[0.09]	[0.13]	[0.03]	[0.03]	[0.04]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.12]
$R^e_{m,t:t+h} * rap_t$	-0.05	-0.01	-0.02	-0.07*	-0.05*	-0.04	-0.03	-0.04	-0.07	-0.06	-0.20	-0.09
	[0.11]	[0.09]	[0.11]	[0.04]	[0.03]	[0.04]	[0.08]	[0.05]	[0.11]	[0.11]	[0.21]	[0.10]
$\bar{R}^2$	0.06	0.04	-0.01	0.16	0.15	0.09	0.11	0.04	0.09	0.00	0.03	0.06
Panel C: Conditional Alpha												
constant	0.01**	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01***	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
rap_t	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01	-0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.07	-0.17*	0.13	-0.19	0.30***
	[0.13]	[0.08]	[0.13]	[0.04]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.22]	[0.11]
$\bar{R}^2$	0.06	0.04	-0.01	0.15	0.14	0.09	0.11	0.05	0.08	0.01	0.01	0.06
Panel D: Conditional Alpha and Beta												
constant	0.01**	0.00	0.00	-0.00	-0.00	-0.00	0.01***	0.00	0.01***	0.01	0.02	0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
rap_t	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00*	-0.00	-0.01	-0.00	-0.00
	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
$R^e_{m,t:t+h}$	-0.18	-0.11	-0.01	0.22***	0.13***	0.21***	-0.17**	0.08*	-0.17*	0.13	-0.19	0.31***
	[0.12]	[0.08]	[0.12]	[0.03]	[0.03]	[0.05]	[0.08]	[0.05]	[0.09]	[0.13]	[0.21]	[0.11]
$R^e_{m,t:t+h} * rap_t$	-0.04	-0.00	-0.02	-0.07*	-0.05	-0.03	-0.03	-0.03	-0.06	-0.04	-0.19	-0.08
	[0.12]	[0.09]	[0.12]	[0.04]	[0.03]	[0.04]	[0.08]	[0.05]	[0.11]	[0.11]	[0.23]	[0.10]
$\bar{R}^2$	0.05	0.04	-0.02	0.16	0.15	0.09	0.10	0.05	0.09	0.01	0.02	0.05

Table 12: Time-Series Regressions of Portfolio Returns, 12-quarter Horizon, Linear Case: Sent. vs Risk

This table presents regressions of long-short portfolio returns based on single characteristics over the next 12 quarters ($h = 12$) on market excess returns ($R^e_{m,t:t+h}$), conditioning variable, and interaction. HML, SMB and CMA are cumulative excess returns over the next quarter, based on value, size and investment from Ken French's library. Other columns such as M-L, M-B and C-M consider comparisons to the usually excluded middle portfolios on the same sorts. H-L, S-M and C-A are based on the extreme deciles only. HS-LB, HC-LA and SC-BA combine two dimensions at the same time, using 25 portfolios sorted on both characteristics. For instance, HS-LB is long small-value and short big-growth. Conditional alphas and betas are linear in risk appetite (rap). This table reports OLS time-series regression coefficients. Standard errors are Newey-West adjusted. $\bar{R}^2$ denotes the adjusted R^2 statistic. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

	Book-to-Market			Size			Investment			Combined		
	HML	M-L	H-L	SMB	M-B	S-B	CMA	C-M	C-A	HS-LB	HC-LA	SC-BA
Panel A: Market Model												
constant	0.15*	0.05	0.09	0.08	0.04	0.04	0.21***	0.03	0.17***	0.35	0.27*	0.46
	[0.08]	[0.07]	[0.07]	[0.05]	[0.03]	[0.09]	[0.08]	[0.02]	[0.06]	[0.23]	[0.14]	[0.30]
$R^e_{m,t:t+h}$	-0.14	-0.17	-0.07	-0.22***	-0.15*	-0.30*	-0.31*	-0.04	-0.23	-0.56	-0.34	-0.98
	[0.17]	[0.17]	[0.16]	[0.09]	[0.08]	[0.16]	[0.18]	[0.06]	[0.15]	[0.44]	[0.29]	[0.60]
$\bar{R}^2$	0.04	0.06	-0.00	0.15	0.09	0.11	0.28	0.00	0.15	0.10	0.07	0.21
Panel B: Conditional Beta												
constant	0.13*	0.02	0.06	0.07	0.01	0.00	0.20***	-0.00	0.15**	0.29	0.20	0.42
	[0.08]	[0.07]	[0.08]	[0.05]	[0.03]	[0.08]	[0.08]	[0.02]	[0.06]	[0.22]	[0.13]	[0.30]
$R^e_{m,t:t+h}$	-0.10	-0.10	0.00	-0.18**	-0.09*	-0.22	-0.29*	0.03	-0.18	-0.43	-0.17	-0.90
	[0.16]	[0.13]	[0.13]	[0.08]	[0.05]	[0.14]	[0.17]	[0.04]	[0.13]	[0.41]	[0.26]	[0.59]
$R^e_{m,t:t+h} * rap_t$	-0.13	-0.24*	-0.26*	-0.13***	-0.22***	-0.30***	-0.07*	-0.23***	-0.17**	-0.48***	-0.57***	-0.30*
	[0.09]	[0.13]	[0.14]	[0.05]	[0.05]	[0.07]	[0.04]	[0.03]	[0.08]	[0.13]	[0.13]	[0.16]
$\bar{R}^2$	0.08	0.19	0.11	0.21	0.32	0.24	0.29	0.42	0.24	0.18	0.30	0.22
Panel C: Conditional Alpha												
constant	0.16**	0.08	0.12*	0.09*	0.05*	0.07	0.21***	0.05***	0.18***	0.40*	0.34***	0.48
	[0.07]	[0.06]	[0.06]	[0.05]	[0.03]	[0.09]	[0.08]	[0.01]	[0.06]	[0.23]	[0.11]	[0.30]
rap_t	-0.05	-0.08*	-0.10**	-0.03	-0.06***	-0.08***	-0.02	-0.08***	-0.06**	-0.17***	-0.26***	-0.07
	[0.03]	[0.04]	[0.04]	[0.02]	[0.02]	[0.03]	[0.02]	[0.02]	[0.03]	[0.05]	[0.04]	[0.07]
$R^e_{m,t:t+h}$	-0.17	-0.23	-0.14	-0.25***	-0.19***	-0.37**	-0.32*	-0.10**	-0.27*	-0.69	-0.52**	-1.03*
	[0.16]	[0.16]	[0.15]	[0.09]	[0.07]	[0.16]	[0.16]	[0.04]	[0.14]	[0.42]	[0.24]	[0.58]
$\bar{R}^2$	0.09	0.17	0.12	0.18	0.23	0.19	0.28	0.43	0.24	0.19	0.46	0.21
Panel D: Conditional Alpha and Beta												
constant	0.15***	0.04	0.10	0.07	0.02	0.01	0.20***	0.02	0.16***	0.35	0.32***	0.42
	[0.05]	[0.06]	[0.06]	[0.06]	[0.03]	[0.10]	[0.06]	[0.02]	[0.05]	[0.22]	[0.09]	[0.30]
rap_t	-0.03	-0.03	-0.07	-0.00	-0.01	-0.02	-0.00	-0.05***	-0.03	-0.10	-0.23***	0.01
	[0.06]	[0.04]	[0.04]	[0.03]	[0.03]	[0.05]	[0.04]	[0.01]	[0.04]	[0.11]	[0.10]	[0.13]
$R^e_{m,t:t+h}$	-0.14	-0.14	-0.09	-0.18	-0.10	-0.24	-0.29**	-0.04	-0.23**	-0.56	-0.48***	-0.88
	[0.11]	[0.10]	[0.10]	[0.11]	[0.07]	[0.17]	[0.12]	[0.04]	[0.10]	[0.38]	[0.17]	[0.56]
$R^e_{m,t:t+h} * rap_t$	-0.06	-0.17	-0.12	-0.13	-0.19***	-0.27**	-0.07	-0.13***	-0.10	-0.27	-0.09	-0.32
	[0.16]	[0.16]	[0.16]	[0.09]	[0.06]	[0.13]	[0.11]	[0.03]	[0.11]	[0.31]	[0.25]	[0.36]
$\bar{R}^2$	0.09	0.20	0.13	0.20	0.31	0.23	0.29	0.49	0.25	0.19	0.45	0.22

C Unconditional Implications of Conditional Models

Here we review the unconditional implications of a conditional model. We assume that a factor representation holds conditionally. For the sake of conciseness, we consider that a single-beta model holds at time t, meaning that both beta and risk premium may vary over time but this relation holds conditional on the information available at time t. $R_{i,t+1}$ is the return of asset i, $R_{0,t+1}$ is the return of the zero beta portfolio, $\beta_{i,t}$ is the beta of asset i given the information at time t and $\lambda_{factor,t}$ is the risk premium for period $t+1$ associated with the aforementioned beta risk given the information at time t:

$$E_t[R_{i,t+1} - R_{0,t+1}] = \lambda_{factor,t}\beta_{i,t}.$$

We should emphasize that $\lambda_{factor,t}$ is the conditional expectation at time t of the return of the priced tradable factor (or of the factor-mimicking portfolio return if the factor is not tradable), $\lambda_{factor,t} = E_t[R_{factor,t+1}]$. Even if this single-beta model holds conditionally, we can only guarantee that a similar relationship will be true unconditionally if beta and risk premium are uncorrelated. Indeed,

$$\begin{aligned} E[R_{i,t+1} - R_{0,t+1}] &= E[\lambda_{factor,t}\beta_{i,t}] \\ &= \underbrace{Cov(\beta_{i,t}, \lambda_{factor,t})}_{=\alpha_i} + E[\lambda_{factor,t}]E[\beta_{i,t}]. \end{aligned}$$

Hence, the covariance term could be interpreted as a pricing error α_i with respect to the unconditional model. If the Sharpe-Lintner version of CAPM holds, we should also observe that $R_{0,t+1} = R_{f,t+1}$.

There are multiple ways to test the conditional version of the model. If we assume that beta is linear in the state variable z_t, the unconditional version shows that each asset will be compensated not only by its unconditional average beta to the priced factor, but also by the variation in the beta that depends on the same conditioning variable that determines the time variation in risk premium. We also assume that the difference between the conditional zero-beta rate and the risk-free rate is linear in the conditioning variable. Indeed,

$$\begin{aligned} E_t[R_{i,t+1} - R_{f,t+1}] &= \lambda_{z,0} + \lambda_{z,1} z_t + (b_{i,0} + b_{i,1} z_t)\lambda_{factor,t} \\ &= \lambda_{z,0} + \lambda_{z,1} z_t + \lambda_{factor,t} b_{i,0} + (\lambda_{factor,t} z_t) b_{i,1}, \end{aligned}$$

where the linear term $\lambda_{z,0} + \lambda_{z,1} z_t$ captures the difference between the conditional zero-beta rate and the risk-free rate. Given that the conditioning variables are mean zero, the unconditional expectation becomes:

$$E[R_{i,t+1} - R_{f,t+1}] = \lambda_{z,0} + E[\lambda_{factor,t}] b_{i,0} + E[\lambda_{factor,t} z_t] b_{i,1}. \tag{3}$$

Unconditionally, each portfolio has two different risk parameters, i.e., betas related to the unconditional and the conditional exposure to the risk factor. The premium associated with the latter part of equation (3) exists only when $\lambda_{factor,t}$ and z_t covary unconditionally. If so, that premium will depend on the second moment of the common conditioning variable because the variance of the conditioning variable is one of the determinants of the covariation between beta and risk premium.[33]

D Unconditional and Conditional Consumption CAPM

Now we test the cross-sectional implications of a conditional version of the Consumption CAPM (CCAPM). We find that our risk appetite measure can partially describe the cross-section of portfolio returns. Table 13 reports the same regressions as in Table 4, but for CCAPM frameworks where betas are estimated with respect to log consumption growth (nondurables goods and service excluding shoes and clothing), as measured in Lettau and Ludvigson [2001a]. Here we focus on the 25 Fama-French portfolios. The factors are: current-period consumption growth, lagged conditioning variable (*cay* or *rap*) and consumption growth times lagged conditioning variable.

[33] In the case of a vector of conditioning variables, all parameters in equation (3) become vectors and the second moment becomes the covariance matrix of all conditioning variables.

Table 13: Fama-Macbeth Regression for Consumption Models: Risk Premium Estimates in Cross-sectional Regressions with Casino Gambling

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors (consumption growth and scaled consumption growth) to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. The conditioning variables are *rap* and *cay*, depending on the specification. We present results for the 25 Fama-French portfolios. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Model	constant	dc_{t+1}	$dc_{t+1} * cay_t$	$dc_{t+1} * rap_t$	$R^2/[\bar{R}^2]$
CCAPM	2.42***	0.04			0.00
	[0.74]	[0.15]			[-0.04]
rap_t	3.18***	-0.08		-0.55***	0.22
	[0.81]	[0.13]		[0.23]	[0.15]
cay_t	2.41***	0.05	0.03		0.01
	[0.80]	[0.14]	[0.25]		[-0.09]
cay_t, rap_t	3.11***	-0.07	0.08	-0.56***	0.23
	[0.85]	[0.12]	[0.26]	[0.23]	[0.12]

The unconditional CCAPM has the worst R^2, explaining zero percent of the cross-sectional variation in average returns for the 25 Fama-French portfolios. Similarly, the scaled CCAPM using *cay* as conditioning variable does not perform well in this sample. The remaining models presented in this table are versions of scaled CCAPM with *rap* alone and with both *rap* and *cay* as conditioning variables. These models have the highest R^2 among all CCAPM specifications, explaining nearly twenty percent of the cross-sectional variation in average returns. The coefficients on the *rap*-scaled consumption factor are individually significant, with the correct sign. Therefore, we find that the cross-term beta is important in explaining the cross sectional variation in average returns, but only when our risk appetite measure is used as the conditioning variable.

E Investment Sentiment and the Cross-Section

Tables 14 and 15 are versions of Tables 4 and 5, respectively, in which we use the investment sentiment measure (*is*) from Baker and Wurgler [2006] instead of the consumption-wealth ratio (*cay*) as a conditioning variable. Table 14 (Table 15) focuses on the shorter (longer) sample and the risk appetite measure based on casino (total) gambling, *rap* (*rapt*).

In all cases considered, risk premia associated with our risk appetite measures remain statistically significant when *is* is included. Interestingly, except for the specification based on the shorter sample and Fama-French's 25 portfolios (Panel A in Table 14), the cross-term betas associated with *is* are statistically significant, and also help explain cross-sectional variation in average returns.

Table 14: Risk Premium Estimates in Cross-sectional Regressions with Risk Appetite and Investor Sentiment - Short Sample Based on Casino Gambling Expenditures

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. The conditioning variables are rap and is, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The sample period is from 1982Q1 to 2015Q3.

Model	constant	$R^e_{m,t+1}$	SMB_{t+1}	HML_{t+1}	$R^e_{m,t+1} * is_t$	$R^e_{m,t+1} * rap_t$	$R^2/[\bar{R}^2]$
Panel A: 25 Fama-French Portfolios							
CAPM	4.54***	-1.82					0.25
	[1.34]	[1.44]					[0.22]
Fama-French	5.31***	-3.05**	0.13	0.84			0.56
	[1.14]	[1.32]	[0.42]	[0.52]			[0.49]
rap_t	3.86***	-1.52				-3.59*	0.39
	[1.17]	[1.38]				[1.98]	[0.34]
is_t	3.85***	-1.28			-2.29		0.30
	[1.23]	[1.43]			[2.52]		[0.23]
is_t, rap_t	3.56***	-1.25			-1.73	-3.39*	0.40
	[1.20]	[1.42]			[2.40]	[1.78]	[0.32]
Panel B: 50 Single-sorted portfolios on 5 characteristics: size, B/M, beta, investment, op profitability							
CAPM	2.68***	-0.34					0.04
	[0.77]	[1.05]					[0.02]
Fama-French	2.47***	-0.24	0.10	0.65			0.27
	[0.79]	[1.06]	[0.41]	[0.53]			[0.23]
rap_t	2.69***	-0.47				-3.09**	0.24
	[0.77]	[1.05]				[1.51]	[0.20]
is_t	2.40***	-0.18			-3.23*		0.30
	[0.76]	[1.05]			[1.84]		[0.27]
is_t, rap_t	2.45***	-1.25			-1.73*	-2.60*	0.41
	[0.77]	[1.05]			[1.80]	[1.36]	[0.38]

Table 15: Risk Premium Estimates in Cross-sectional Regressions with Risk Appetite and Investor Sentiment - Long Sample Based on Total Gambling Expenditures

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. The conditioning variables are *rapt* and *is*, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The sample period is from 1965Q3 to 2015Q3.

Model	constant	$R^e_{m,t+1}$	SMB_{t+1}	HML_{t+1}	$R^e_{m,t+1} * is_t$	$R^e_{m,t+1} * rapt_t$	$R^2/[\bar{R}^2]$
Panel A: 25 Fama-French Portfolios							
CAPM	2.49***	-0.21					0.00
	[0.96]	[1.11]					[-0.04]
Fama-French	3.62***	-1.99*	0.63	1.10***			0.72
	[0.99]	[1.15]	[0.40]	[0.42]			[0.68]
$rapt_t$	1.28	0.36				-7.90***	0.48
	[0.92]	[1.11]				[2.34]	[0.43]
is_t	0.79	1.06			-11.14***		0.54
	[0.99]	[1.17]			[3.24]		[0.49]
$is_t, rapt_t$	0.67	0.96			-9.50***	-6.31***	0.62
	[0.99]	[1.17]			[2.93]	[2.04]	[0.57]
Panel B: 50 Single-sorted portfolios on 5 characteristics: size, B/M, beta, investment, op profitability							
CAPM	1.30*	0.47					0.06
	[0.67]	[0.91]					[0.04]
Fama-French	1.93***	-0.34	0.61	0.81*			0.63
	[0.75]	[0.96]	[0.40]	[0.44]			[0.61]
$rapt_t$	1.46**	0.13				-5.63***	0.41
	[0.67]	[0.90]				[1.89]	[0.39]
is_t	0.78	0.85			-5.96***		0.35
	[0.70]	[0.93]			[1.91]		[0.33]
$is_t, rapt_t$	1.16*	0.96			-9.50***	-4.74***	0.45
	[0.68]	[0.91]			[1.67]	[1.81]	[0.42]

F Luxury Goods and Other Measures

We also consider the possibility that our risk appetite measures might capture information on the consumption of the rich. To assess this possibility, we follow the same cross-sectional approach as in Section 3.2, but using personal consumption expenditures on luxury goods. We construct the cointegrating residual of a system with luxury goods consumption per capita, real GDP per capita, and the relative price of luxury goods. Unlike Ait-Sahalia et al. [2004], we do not use luxury good consumption as a new proxy for consumption growth of the marginal investor – rather, we use it as a conditioning variable in a conditional model.

Tables 16, 17 and 18 consider specifications with *rap*, *rapa* and *rapt*, respectively. Hence, Table 18 considers a longer sample than Tables 16 and 17. The second panels of Tables 16 and 17 show that a conditioning variable based on luxury goods does a good job in explaining the cross-section of portfolio returns in the shorter sample. Once *rap* and *rapa* are included additionally as conditioning variables, both risk premia associated with luxury goods and *rap* cease to be statistically significant, but the one associated with *rapa* remains significant. In the longer sample, the sign of the risk premium coefficient associated with luxury goods becomes inconsistent with theory, while the risk premium associated with *rapt* remains statistically significant in all cases reported in the second panel of Table 18.

As previously mentioned, other types of gambling activity may not be as informative of risk appetite. Indeed, analogous measures based on personal consumption expenditures on lottery and pari-mutuel do not deliver satisfactory results.[34] Third and fourth panels of Tables 16 and 17 show that lottery and pari-mutuel are not individually significant in the shorter sample. In addition, Table 16 shows that the risk premium associated with *rap* remains statistically significant once pari-mutuel in included in the model, but the same does not hold for lottery. However, once wealth effects are accounted for, Table 17 shows that our risk appetite measure (*rapa*) remains significant in all specifications.

Finally, in the longer sample, Table 18 shows that the inclusion of lottery or pari-mutuel in

[34] Measures based on lottery and pari-mutuel are the cointegrating residuals of systems with consumption expenditures per capita on those activities and GDP per capita. In the case of lottery, we also control for the number of states where lotteries are legalized weighted by their respective GDP.

regressions with *rapt* does not impact the performance of the risk appetite measure based on total gambling. In addition, the risk premium estimate for the beta associated with the interaction between *rapt* and market excess returns remains significant in all cases. Lottery and pari-mutuel become relevant statistically when we use the longer sample.

Table 16: Risk Premium Estimates in Cross-sectional Regressions with Other Conditioning Variables - Short Sample with *rap*

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. Besides *rap* and *cay*, we also consider other conditioning variables based on expenditures on luxury goods, lottery and pari-mutuel, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The sample period is from 1982Q1 to 2015Q3.

Model	constant	$R^e_{m,t+1}$	$R^e_{m,t+1} * other_t$	$R^e_{m,t+1} * rap_t$	$R^e_{m,t+1} * cay_t$	$R^2/[\bar{R}^2]$
Casino	3.86***	-1.52		-3.59*		0.39
	[1.17]	[1.38]		[1.98]		[0.34]
Luxury	4.94***	-2.43	-6.15*			0.37
	[1.48]	[1.59]	[3.39]			[0.31]
	4.26***	-1.90	-3.64	-2.98		0.41
	[1.31]	[1.49]	[2.79]	[1.90]		[0.33]
	4.52***	-2.19	-2.22	-2.64	-5.18	0.47
	[1.32]	[1.48]	[2.80]	[1.81]	[3.15]	[0.36]
Lottery	4.17***	-1.73	-5.34			0.38
	[1.25]	[1.42]	[3.68]			[0.32]
	3.79***	-1.53	-3.04	-2.21		0.44
	[1.17]	[1.38]	[3.13]	[1.49]		[0.36]
	4.42***	-2.12	-3.84	-2.25	-4.82*	0.47
	[1.13]	[1.34]	[3.42]	[1.51]	[2.63]	[0.37]
Pari-mutuel	2.95**	-0.54	-0.36			0.35
	[1.37]	[1.55]	[0.29]			[0.29]
	3.20**	-0.93	-0.21	-2.84*		0.41
	[1.38]	[1.57]	[0.27]	[1.53]		[0.33]
	4.51***	-2.18	-0.25	-2.53	-5.05**	0.47
	[1.17]	[1.38]	[0.29]	[1.57]	[2.31]	[0.36]

Table 17: Risk Premium Estimates in Cross-sectional Regressions with Other Conditioning Variables - Short Sample with *rapa*

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. Besides *rapa* and *cay*, we also consider other conditioning variables based on expenditures on luxury goods, lottery and pari-mutuel, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The sample period is from 1982Q1 to 2015Q3.

Model	constant	$R^e_{m,t+1}$	$R^e_{m,t+1} * other_t$	$R^e_{m,t+1} * rapa_t$	$R^e_{m,t+1} * cay_t$	$R^2/[\bar{R}^2]$
Casino	4.17***	-1.77		-4.03**		0.39
	[1.27]	[1.43]		[1.94]		[0.33]
Luxury	4.94***	-2.43	-6.15*			0.37
	[1.48]	[1.59]	[3.39]			[0.31]
	4.52***	-2.14	-4.03	-3.17*		0.41
	[1.44]	[1.57]	[3.25]	[1.82]		[0.33]
	4.77***	-2.43	-2.52	-3.10*	-5.46	0.48
	[1.47]	[1.58]	[3.14]	[1.82]	[3.36]	[0.37]
Lottery	4.17***	-1.73	-5.34			0.38
	[1.25]	[1.42]	[3.68]			[0.32]
	3.95***	-1.71	-3.21	-2.53*		0.46
	[1.22]	[1.41]	[3.24]	[1.48]		[0.39]
	4.49***	-2.20	-3.93	-2.60*	-4.78*	0.49
	[1.20]	[1.38]	[3.51]	[1.50]	[2.67]	[0.38]
Pari-mutuel	2.95**	-0.54	-0.36			0.35
	[1.37]	[1.55]	[0.29]			[0.29]
	3.15**	-0.90	-0.23	-3.18**		0.43
	[1.37]	[1.54]	[0.27]	[1.54]		[0.35]
	4.38***	-2.08	-0.27	-2.90*	-4.91**	0.48
	[1.16]	[1.36]	[0.29]	[1.57]	[2.28]	[0.38]

Table 18: Risk Premium Estimates in Cross-sectional Regressions with Other Conditioning Variables - Long Sample with *rapt*

This table presents estimates of the risk premium λ obtained through the Fama-MacBeth procedure. The first stage of the procedure involves a time-series regression of returns on factors to compute the β estimates. The second stage is a cross-sectional regression of the returns on β and delivers the respective λ estimates. Besides *rapt* and *cay*, we also consider other conditioning variables based on expenditures on luxury goods, lottery and pari-mutuel, depending on the specification. We present results for two groups of portfolios: 25 Fama-French portfolios and 50 portfolios which combine 10 single-sorted portfolios separately on five characteristics: size, B/M, beta, investment and operational profitability. The table reports Fama-MacBeth cross-sectional regression coefficients; standard errors for each estimate based on Shanken [1992]'s correction. R^2 denotes the unadjusted cross-sectional R^2 statistic and $\bar{R}^2$ adjusts for degrees of freedom. *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The sample period is from 1965Q3 to 2015Q3.

Model	constant	$R^e_{m,t+1}$	$R^e_{m,t+1} * other_t$	$R^e_{m,t+1} * rapt_t$	$R^e_{m,t+1} * cay_t$	$R^2/[\bar{R}^2]$
Total	1.28	0.36		-7.90***		0.48
	[0.92]	[1.11]		[2.34]		[0.43]
Luxury	1.78**	0.48	4.18**			0.04
	[0.87]	[1.07]	[1.87]			[-0.05]
	1.11	0.54	1.60	-7.85***		0.48
	[0.87]	[1.07]	[1.54]	[2.33]		[0.40]
	3.03***	-1.43	2.43	-6.87***	-8.08***	0.61
	[0.71]	[0.93]	[1.59]	[2.28]	[2.22]	[0.53]
Lottery	2.18**	-0.30	-7.08***			0.38
	[0.94]	[1.11]	[2.44]			[0.33]
	1.47	0.17	-4.79**	-6.70***		0.51
	[0.91]	[1.10]	[2.23]	[2.08]		[0.44]
	3.91***	-2.32**	-6.34***	-5.18***	-8.71***	0.68
	[0.80]	[1.00]	[2.54]	[2.03]	[2.43]	[0.61]
Pari-mutuel	0.08	1.50	-0.78***			0.49
	[1.12]	[1.25]	[0.26]			[0.45]
	0.48	1.08	-0.66**	-5.05***		0.52
	[1.26]	[1.37]	[0.28]	[2.14]		[0.45]
	2.59***	-1.05	-0.65**	-5.00**	-7.27***	0.62
	[1.04]	[1.18]	[0.29]	[2.18]	[1.91]	[0.55]

G Market Predictability: Additional Results

In this section, we report additional results on the in-sample predictive ability of *rap*. Table 19 presents results from regressions with *rap* and every other predictor pairwise. In particular, we consider the following extension of equation (2),

$$excess_{t+h} = \alpha + \beta rap_{t-1} + \gamma X_{t-1} + \varepsilon_t,$$

where X is one of the variables other than *rap* listed in Section 2.2.

For each regression, Table 19 reports the estimated coefficient associated with rap_{t-1}, Newey-West corrected t-statistics in parentheses, and adjusted R^2 statistics in square brackets. The main takeaways, discussed in the text, are: (i) *rap* has predictive power that goes beyond and above *cay*, d/p, b/m and *tms*; (ii) at a six-year horizon, *rap* remains significant once included with i/k, but ceases to be significant at shorter horizons; and (iii) there are not much gains in terms of prediction once *is* or *infl* is combined with *rap*.

Table 19: In-sample Market Return Predictability: Additional Results

This table displays the estimated regression coefficient associated with rap_{t-1} in the following equation

$$R_{m,t:t+h} - R_{f,t:t+h} = \alpha + \beta rap_{t-1} + \gamma X_{t-1} + \varepsilon_t,$$

for several models and horizons, as well as Newey-West standard errors (in brackets) and adjusted R-squared (in parenthesis). *, **, *** indicate significance at the 10, 5 and 1 percent levels, respectively. The dependent variable is the excess return associated with the value-weighted CRSP Index. The proxy for the risk-free rate is the return associated with the three-month U.S. Treasury bill. In each model we consider a different regressor X_{t-1}. Namely: (i) consumption-wealth ratio (cay); (ii) investor sentiment measure (is); (iii) dividend yield (d/p); (iv) aggregate investment-capital ratio (i/k); (v) book-to-market ratio (b/m); (vi) risk-free rate (tbl); (vii) long-term yield (lty); (viii) terms spread (tms); (ix) default yield spread (dfy); and (x) inflation rate ($infl$). See Section 2.2 on how these regressors are constructed. We consider forecasting horizons ranging from four to twenty four quarters (one to six years). The sample period is from 1982Q1 to 2015Q3.

X_{t-1}:	cay	is	d/p	i/k	b/m	tbl	lty	tms	dfy	$infl$
Forecasting horizon: 4 quarters										
$\hat{\beta}$	-0.03	-0.02	-0.02	-0.01	-0.02	-0.03	-0.03	-0.01	-0.03	-0.02
[$s.e.$]	[0.02]	[0.02]	[0.02]	[0.03]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
($\bar{R}^2$)	5.32	3.81	9.98	3.03	10.89	0.72	1.43	1.87	6.35	2.71
Forecasting horizon: 8 quarters										
$\hat{\beta}$	-0.04	-0.05	-0.03	-0.00	-0.05	-0.04	-0.05	-0.00	-0.05	-0.05
[$s.e.$]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
($\bar{R}^2$)	18.15	3.97	12.37	10.91	7.75	3.41	2.45	13.74	6.42	4.75
Forecasting horizon: 12 quarters										
$\hat{\beta}$	-0.06	-0.08	-0.05	0.01	-0.07	-0.07	-0.08	-0.01	-0.08	-0.08
[$s.e.$]	[0.05]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.04]	[0.06]	[0.06]
($\bar{R}^2$)	23.11	4.05	17.25	21.16	10.71	4.51	4.84	19.04	7.95	4.36
Forecasting horizon: 16 quarters										
$\hat{\beta}$	-0.10**	-0.11*	-0.08	0.01	-0.11**	-0.11*	-0.12**	-0.03	-0.12**	-0.12*
[$s.e.$]	[0.05]	[0.06]	[0.05]	[0.06]	[0.05]	[0.06]	[0.06]	[0.04]	[0.06]	[0.06]
($\bar{R}^2$)	19.45	7.63	24.18	32.98	17.14	7.13	9.19	22.90	14.00	7.44
Forecasting horizon: 20 quarters										
$\hat{\beta}$	-0.17***	-0.18***	-0.14***	-0.04	-0.17***	-0.18***	-0.18***	-0.10**	-0.19***	-0.18***
[$s.e.$]	[0.04]	[0.05]	[0.03]	[0.05]	[0.04]	[0.05]	[0.05]	[0.05]	[0.04]	[0.05]
($\bar{R}^2$)	18.88	12.94	34.66	36.03	25.13	12.96	15.72	23.67	26.58	13.63
Forecasting horizon: 24 quarters										
$\hat{\beta}$	-0.20***	-0.21***	-0.16***	-0.06*	-0.21***	-0.22***	-0.21***	-0.15***	-0.22***	-0.22***
[$s.e.$]	[0.06]	[0.05]	[0.04]	[0.04]	[0.04]	[0.06]	[0.05]	[0.06]	[0.05]	[0.06]
($\bar{R}^2$)	20.45	17.64	43.13	44.46	27.88	17.88	20.71	24.82	30.25	17.81