Salience Theory and Stock Prices: Empirical Evidence*

Mathijs Cosemans†
Rotterdam School of Management, Erasmus University

Rik Frehen‡
Tilburg University

First draft: June 2016

This version: July 2017

Abstract

We present empirical evidence on the asset pricing implications of salience theory. In our model, investors overweight salient past returns when forming expectations about future returns. Consequently, investors are attracted to stocks with salient upsides, which are overvalued and earn low subsequent returns. Conversely, stocks with salient downsides are undervalued and yield high future returns. We find strong empirical support for these predictions in the cross-section of U.S. stocks. The salience effect is stronger among stocks with greater limits to arbitrage and during high-sentiment periods and not explained by common risk factors and proxies for lottery demand and investor attention.

Keywords: salience theory, probability weighting, asset pricing, return predictability

JEL classification: D03, G11, G12, G14

---

*For helpful comments and suggestions, we thank Dion Bongaerts, Pedro Bordalo, Mathijs van Dijk, Sebastian Ebert, Nicola Gennaioli, David Hirshleifer, Yigitcan Karabulut, Sebastian Müller, Daniel Schmidt, Oliver Spalt, Marta Szymanowska, Wolf Wagner, Baolian Wang, and seminar participants at Erasmus University, Tilburg University, the 2016 Research on Behavioral Finance Conference in Amsterdam, the 16th Colloquium on Financial Markets in Cologne, the 2017 FMA European Conference in Lisbon, the 2017 CEPR European Summer Symposium in Financial Markets in Gerzensee, and the 2017 SFS Cavalcade North America in Nashville.

†Corresponding author: Mathijs Cosemans, Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, 3062 PA Rotterdam, Netherlands, E-mail: mcosemans@rsm.nl, Phone: +31-10-4089095.

‡Tilburg University, Warandelaan 2, 5000 LE Tilburg, Netherlands, E-mail: r.g.p.frehen@uvt.nl, Phone: +31-13-4664070.

1 Introduction

Whereas traditional asset pricing theory assumes investors to be fully rational and to use all available information when choosing between risky assets, a large body of research finds their attention and processing power to be limited (e.g., Kahneman (1973)).[1] Bordalo, Gennaioli, and Shleifer (2012), henceforth BGS, argue that because of these cognitive limitations, decision makers' attention is drawn to the most unusual attributes of the options they face. These salient attributes are consequently overweighted in their decisions and non-salient attributes are neglected. BGS (2012) propose a novel theory of choice under risk that formalizes such salient thinking and demonstrate that salience can account for fundamental puzzles in decision theory, such as the Allais paradox.

In this paper, we present empirical evidence on the asset pricing implications of salience theory. Specifically, we test, for the cross-section of stock returns, the predictions of the salience-based asset pricing model of Bordalo, Gennaioli, and Shleifer (2013a), in which the demand for risky assets is influenced by the salience of their payoffs in different states of the world. Salience is defined in the psychology literature as "the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments" (Taylor and Thompson (1982)).

A key premise of the salience model is that choices are made in context, which means that investors evaluate each risky asset by comparing its payoffs with those of the available alternatives. This context dependence is motivated by a large body of experimental evidence that shows preferences to depend on the context in which choices are presented.[2] A stock's most salient payoffs are therefore those that stand out relative to the payoffs of other stocks in the market. Because investors focus their attention on salient payoffs, they are attracted to stocks with salient upsides. The excess demand for these stocks results in overvaluation and lower future returns, whereas stocks with salient downsides become undervalued and earn higher subsequent returns.

Any application of salience theory requires a specification of the states of the world that can occur. Following Barberis, Mukherjee, and Wang (2016), we assume that investors making a trading

[1] Hirshleifer (2015) provides a recent overview of this literature.
[2] See Camerer (1995) for a comprehensive survey of this literature.

decision mentally represent a stock by the distribution of its past returns, viewed as a proxy for its future return distribution. Investors thus infer the set of possible future return states from the set of past return states. Because these past returns have been realized, their objective probabilities are known. Investors who engage in salient thinking form a context-dependent representation of each stock by replacing the objective probabilities with decision weights that depend on the salience of the stock's past returns. Specifically, we suggest that investors form expectations about future returns by extrapolating salience-weighted daily returns over the past month. Intuitively, investors attach more weight to a 5% stock return on a day when the market is flat than on a day when the market is also up by 5%. Salience weights not only depend on the distance between stock and market returns but also on their level. For example, when a stock outperforms the market by 3%, this outperformance stands out more on a day when the market return is 0% than when it is 10%.

Motivated by our theoretical framework, we define the salience theory (ST) value of a stock as the distortion in return expectations caused by salient thinking. ST is positive when the forecast of salient thinkers exceeds the forecast computed using objective probabilities, which occurs when a stock's highest past returns are salient. Investors then focus on the upside potential of a stock, thereby effectively acting as risk seekers and accepting a negative risk premium. When a stock's lowest past returns stand out, investors overemphasize downside risk and ST is negative. Investors then exhibit risk-averse behavior and demand a positive risk premium for holding the stock.

Because salience distortions stem from cognitive limitations, salient thinkers are assumed to engage in narrow framing: when evaluating a stock, they do not think about its contribution to the return of their portfolio. The salience of a stock's return is therefore determined only by its relative difference from the market return and does not depend on investor-specific characteristics. Consequently, salience-driven demand for stocks will be correlated across investors and can exert pressure on prices, given limits to arbitrage that prevent rational investors from correcting mispricing. We thus expect the predictive power of the salience theory variable for future returns to be stronger among stocks for which arbitrage is more costly. We further predict the salience effect to be more pronounced among stocks with greater ownership by individual investors, typically assumed to be less sophisticated than professional investors and therefore more prone to salient thinking.

Our empirical results provide strong support for the predictions of the salience model. First, we show that stocks with salient upsides earn lower future returns than stocks with salient downsides. A univariate portfolio analysis indicates that the return difference between stocks in the highest and lowest ST deciles is statistically significant and economically large. The average excess return for the zero-cost strategy that buys high-ST stocks and shorts low-ST stocks ranges from -1.91% per month for the equal-weighted portfolio to -0.80% per month for the value-weighted portfolio. These return differences are not explained by standard market, size, value, momentum, and liquidity factors, with five-factor alphas ranging from -2.04% (EW) to -1.01% (VW) per month.

To ensure that the salience effect we identify is not just a repackaging of existing return anomalies, we construct double-sorted portfolios and perform firm-level Fama-MacBeth regressions. Our salience theory measure retains significant explanatory power for returns after controlling for a long list of firm characteristics known to explain cross-sectional variation in returns. Further tests confirm that the relation between ST and future returns is also robust to alternative specifications of salience, different portfolio weighting schemes, controls for industry salience, other definitions of the state space, and alternative estimation methods. The results also hold for different subperiods and across various subsamples that exclude penny stocks, NASDAQ stocks, and illiquid stocks.

Second, we find a stronger cross-sectional relation between salience and future returns among stocks with higher retail ownership and greater limits to arbitrage. We also find that the impact of salience is greater during high-sentiment periods when unsophisticated investors are more likely to participate in the market. Further analyses show that the salience effect is detected only when the salience measure is constructed using conventional close-to-close returns and not when using open-to-open returns that are usually not observed by retail investors. Collectively, these findings lend support to a behavioral interpretation of the relation between salience and future returns.

Third, we find support for the prediction that salience-induced mispricing arises because returns on other stocks in the market distort investors' perception of a stock's future return distribution. Specifically, we show that the ability of ST to explain cross-sectional differences in future returns weakens when the salience of a stock's past returns is defined in isolation rather than in the context of all available stocks. Changes in context affect the predictive power of ST because they induce changes in salience and, consequently, in investors' return expectations and trading decisions.

We explore three alternative explanations for the negative relation between ST and future returns. We consider first the possibility that ST picks up short-term reversal. Common behavioral explanations for short-term reversal are based on overreaction to company news (Subrahmanyam (2005)) or over-extrapolation of past returns (Greenwood and Shleifer (2014)). Salience theory differs from these existing theories because it predicts that investors' reaction to information is context-dependent. In our salience model, investors overweight past stock returns only if they stand out relative to the overall market return and underweight non-salient returns. Salience-induced distortions in return expectations therefore do not arise from overreaction to past returns but from biases in the perception of these returns. Since ST is defined as the *difference* between salience-weighted and equal-weighted daily returns, it does not capture reversal but the incremental effect of salience distortions on return expectations, conditional on investors using past returns to forecast future returns. Empirically, we differentiate the salience effect from reversal by controlling for last month's stock return in the bivariate portfolio sorts and Fama-MacBeth regressions, by including a short-term reversal factor in the model used to compute alphas of the high-low ST portfolio, and by skipping a month between the construction of ST and the measurement of subsequent returns. The evidence shows that controlling for reversal does not eliminate the predictive power of ST.

A second potential concern is that our salience measure proxies for lottery demand. Several theoretical models predict that investors are attracted to lottery-like assets, either because they overweight the small probability of a large gain these assets offer (Barberis and Huang (2008)) or because they have a preference for skewness (Mitton and Vorkink (2007)). In the salience model, however, extreme stock returns are only overweighted if they are salient relative to the aggregate stock market return. Moreover, the asset pricing implications of salience theory are derived without assuming that investors have lottery preferences. Consistent with these theoretical differences, we find that the return-forecasting power of salience is not subsumed by measures of lottery demand used in the literature, such as a stock's idiosyncratic skewness and maximum daily return.

A third potential explanation for our findings is the attention-induced price pressure hypothesis of Barber and Odean (2008), which posits that the search problem implicit in choosing stocks induces individual investors to buy attention-grabbing stocks. An increase in attention is therefore expected to result in temporary positive price pressure. In salience theory, attention is drawn to salient return states rather than to salient stocks. Salience affects prices by distorting decision weights and return expectations, not by narrowing the set of stocks investors consider for purchase. We distinguish between these theories by exploiting their opposite predictions for stocks with salient downsides. The attention hypothesis predicts that such stocks become overpriced because both positive and negative attention-grabbing events lead to net buying by individual investors. Salience theory predicts that they become underpriced because investors focus on their downside risk. Our finding that stocks with salient downsides earn higher future returns supports the salience theory interpretation. Moreover, the salience effect remains large and statistically significant when we control for a number of attention proxies using bivariate sorts and Fama-MacBeth regressions.

Our work adds to the growing literature on the asset pricing implications of behavioral choice theories, most of which focuses on the prospect theory of Kahneman and Tversky (1979). At the aggregate level, Benartzi and Thaler (1995) and Barberis, Huang, and Santos (2001) demonstrate that prospect theory can account for the equity premium puzzle. In the cross-section, there is considerable empirical support for the prediction of Barberis and Huang (2008) that lottery-type assets earn lower returns.[3] In their prospect theory framework, investors care about gains and losses at the *portfolio* level. In contrast, Barberis, Mukherjee, and Wang (2016) assume that investors derive utility from *stock*-level gains and losses and overvalue stocks whose historical return distributions are appealing under prospect theory. We contribute to this literature by providing empirical evidence on the pricing implications of a novel theory of choice under risk in which preferences are driven by the psychologically motivated mechanism of salience.

Our paper also adds to a large literature that examines the consequences of limited attention for asset prices. Studies show that investors underreact to news when distracted (e.g., DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009)) and that returns are predictable when investors neglect specific types of information (e.g., Peng and Xiong (2006), Cohen and Frazzini (2008), Da, Gurun, and Warachka (2014)). Prior work has also studied the impact of attention-grabbing events

[3]Examples include Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), Boyer and Vorkink (2014), Conrad, Kapadia, and Xing (2014), and Eraker and Ready (2015).

on stock prices and trading behavior. Da, Engelberg, and Gao (2011) find support for the attention hypothesis of Barber and Odean (2008) and Hartzmark (2015) argues that investors tend to sell the best- and worst-ranked stocks in their portfolio because extreme positions are more likely to enter their consideration set. Our work complements these papers by examining the impact of salience on the actual choice between stocks in the consideration set in the final stage of the decision process.

Lastly, our paper contributes to the rapidly expanding literature on the impact of salience on individual decision making. Recent papers demonstrate that salience theory can account for evidence on decision making in a wide range of fields including consumer choice (Bordalo, Gennaioli, and Shleifer (2013b)), judicial decisions (Bordalo, Gennaioli, and Shleifer (2015b)), tax effects (Chetty, Looney, and Kroft (2009)), corporate policy choices (Dessaint and Matray (2016)), and education choice (Choi, Lou, and Mukherjee (2016)). To the best of our knowledge, our paper is the first to provide empirical evidence on the asset pricing implications of salience.

The paper proceeds as follows. Section 2 summarizes salience theory and discusses its implications for stock prices. Section 3 describes the data and Section 4 presents empirical evidence on the cross-sectional relation between salience and future stock returns. Section 5 explores the role of the choice context in the salience model. Section 6 considers alternative explanations for our findings and Section 7 reports results for additional robustness checks. Section 8 concludes.

2 Salience Theory and Stock Prices

In this section, we discuss the conceptual framework that relates salience to stock prices. In Section 2.1, we review salience theory and highlight differences with prospect theory. In Section 2.2, we explain how salience distorts decision weights. In Section 2.3, we summarize the salience-based asset pricing model of BGS (2013a). Section 2.4 describes the construction of our salience measure.

2.1 Salience Theory

A key premise of salience theory (ST) is that decision makers' attention is directed to the most salient payoffs of the lotteries available for choice. This distorted attention allocation leads agents to overweight the states of the world in which these salient payoffs occur. Also central to ST is that choices are made in context, i.e., agents compare each lottery's payoffs to the payoffs of the available alternatives. A lottery's salient payoffs are therefore those that differ most from the payoffs of other lotteries, motivated by the observation of Kahneman (2003) that differences are more accessible to decision makers than absolute values. The salience model of BGS (2012) combines the ideas of endogenous attention allocation and context-dependent choice by specifying a context-dependent weighting function that transforms objective state probabilities into decision weights.

An important implication of the weighting function in salience theory is that payoffs in the tails of the distribution are only overweighted if they are salient. In contrast, in the cumulative prospect theory (CPT) of Tversky and Kahneman (1992), state probabilities are distorted by a fixed weighting function, which implies that tail events are always overweighted. In other words, whereas in prospect theory the distortion of probabilities is determined by the rank of payoffs, in salience theory the magnitude of payoffs and the choice context matter. BGS (2012) demonstrate that, by adopting a context-dependent weighting function, salience theory can account for many violations of expected utility theory, such as the instability of risk preferences across choice sets. Salience can explain most of these anomalies without requiring a value function that is concave for gains and convex for losses. Decision makers exhibit risk-seeking behavior when a lottery's upsides (i.e., the highest payoffs) are salient and are risk averse when the downsides stand out.

The differences between probability weighting in ST and CPT can be illustrated with a simple example. Assume that an agent must choose between two correlated lotteries, L_1 and L_2:

Probability	0.10	0.30	0.60
Payoff L_1	\$2000	\$0	\$1000
Payoff L_2	\$2000	\$300	\$850

In both lotteries, the highest payoff of \$2000 occurs in the low-probability state. In CPT, the low probability associated with this high payoff is overweighted because the decision maker is assumed to treat the lotteries as independent. In ST, context dependence implies that the low-probability state is non-salient because both lotteries yield the same payoff. Instead of being overweighted, the state cancels out in the salient thinker's evaluation of the two lotteries and does not affect choice.

Recent experimental evidence on lottery choices provided by Mormann and Frydman (2016) confirms that risk taking is systematically affected by the correlation structure between lotteries. The context-dependent weighting function of salience theory can explain much of the observed variation in risk taking. In contrast, the choice data is inconsistent with all parameterizations of expected utility and cumulative prospect theory. The evidence also supports salience theory's prediction that risk taking is greater (smaller) when a risky lottery's upside (downside) is salient.

2.2 Salience-Based Probability Weighting

To measure the salience of the payoff x_{is} of lottery i in state s, BGS (2012) propose the function:

$$\sigma(x_{is}, \bar{x}_s) = \frac{|x_{is} - \bar{x}_s|}{|x_{is}| + |\bar{x}_s| + \theta}, \tag{1}$$

where $\theta > 0$ and $\bar{x}_s = \sum_i^N x_{is}/N$, with N denoting the number of lotteries.

The salience function in Equation (1) satisfies four conditions: (i) ordering; (ii) diminishing sensitivity; (iii) reflection; and (iv) convexity. The ordering property implies that the salience of state s for lottery i increases in the distance between its payoff and the average payoff in state s of all lotteries in the choice set. Diminishing sensitivity implies that salience decreases as absolute payoff levels rise uniformly for all lotteries. Put differently, differences in payoffs are perceived less intensely when they occur at higher payoff levels. According to reflection, salience depends not on the sign, but only on the magnitude of payoffs. In other words, reflecting gains into losses does not change the salience of a state because perception is sensitive to differences in absolute values. Convexity implies that diminishing sensitivity weakens as absolute payoff levels increase.[4] A smaller value of the parameter θ in Equation (1) increases the convexity of the salience function. More importantly, θ controls the salience of states in which a lottery has a zero payoff. If θ were excluded, zero-payoff states would have maximal salience, regardless of the average payoff level $\bar{x}_s$.

Given the salience function in Equation (1), the salient thinker ranks each lottery's payoffs and

[4]Formally, assume two states, s and s', and two lotteries, i and j. Let x_s^{min} and x_s^{max} denote the lowest and highest payoff in s. Ordering implies that if the interval $[x_s^{min}, x_s^{max}]$ is a subset of $[x_{s'}^{min}, x_{s'}^{max}]$, then $\sigma(x_{is}, x_{js}) < \sigma(x_{is'}, x_{js'})$. Diminishing sensitivity implies that if $x_{is}, x_{js} > 0$, then for any $\epsilon > 0$, $\sigma(x_{is} + \epsilon, x_{js} + \epsilon) < \sigma(x_{is}, x_{js})$. Reflection implies that if $x_{is}, x_{js}, x_{is'}, x_{js'} > 0$, then $\sigma(x_{is}, x_{js}) < \sigma(x_{is'}, x_{js'}) \Leftrightarrow \sigma(-x_{is}, -x_{js}) < \sigma(-x_{is'}, -x_{js'})$. Convexity implies that if $x_{is}, x_{js} > 0$, then for any $\epsilon, z > 0$, $\sigma(x_{is} + z, x_{js} + z) - \sigma(x_{is} + z + \epsilon, x_{js} + z + \epsilon)$ decreases with z.

replaces the objective state probabilities with lottery-specific decision weights, given by:

$$\tilde{\pi}_{is} = \pi_s \cdot \omega_{is}, \tag{2}$$

where ω_{is} is the salience weight:

$$\omega_{is} = \frac{\delta^{k_{is}}}{\sum_{s'} \delta^{k_{is'}} \cdot \pi_{s'}}, \qquad \delta \in (0, 1], \tag{3}$$

where k_{is} is the salience ranking of payoff x_{is}, which ranges from 1 (most salient) to S (least salient). S denotes the set of states, where each state s occurs with probability π_s, such that $\Sigma_{s=1}^{S} \pi_s = 1$. The decision weights are normalized to sum to 1, i.e., the expected distortion is zero ($\mathbb{E}[\omega_{is}] = 1$).

The parameter δ in Equation (3) captures the degree to which salience distorts decision weights and proxies for the decision maker's cognitive ability. When $\delta = 1$, there are no salience distortions and decision weights are equal to objective probabilities ($\omega_{is} = 1$ for all $s \in S$). This case corresponds to the rational decision maker. When $\delta < 1$, the decision maker is a salient thinker who overweights salient states ($\omega_{is} > 1$) and underweights non-salient states ($\omega_{is} < 1$). When $\delta \to 0$, the salient thinker considers only a lottery's most salient payoff and neglects all other payoffs.

2.3 Salience-Based Asset Pricing Model

The salience-based asset pricing model proposed by Bordalo, Gennaioli, and Shleifer (2013a) illustrates how salience affects trading decisions and stock prices. BGS (2013a) start from a two-period consumption-based model with a measure one of identical investors. Each investor has linear utility over current (t=0) and future (t=1) values of consumption and there is no time discounting.[5] Each investor is endowed with wealth w_0, as well as a holding of one unit of each of the N available stocks. Stock i has a current price p_i and yields a payoff x_{is} in state s at $t = 1$. At $t = 0$, the

[5] Linear utility is assumed to illustrate how the mechanism of payoff salience can generate shifts in risk attitudes without relying on an S-shaped value function. The implications of salience theory for stock prices can also be derived in a mean-variance framework with risk-averse investors, analogous to the approach taken by Barberis, Mukherjee, and Wang (2016) to study the implications of prospect theory. In this alternative framework, traditional mean-variance investors hold the tangency portfolio, whereas salient thinkers adjust the tangency portfolio by tilting their holdings towards stocks with salient upsides and away from stocks with salient downsides. The main prediction derived from this model coincides with the key prediction of the consumption-based model of BGS (2013a), namely, that stocks with salient upsides (downsides) earn lower (higher) future returns.

investor trades an amount α_i of each stock i to maximize expected utility:

$$\begin{aligned}\max_{\{\alpha_i\}} \quad & u(c_0) + \mathbb{E}[\omega_{is} u(c_{1,s})], \\ \text{s.t.} \quad & c_0 = w_0 - \sum_i^N \alpha_i p_i, \\ & c_{1,s} = \sum_i^N (\alpha_i + 1) x_{is}.\end{aligned} \tag{4}$$

The first-order condition for a solution to this problem is:

$$p_i u'(c_0) = \mathbb{E}[\omega_{is} x_{is} u'(c_{1,s})] = \sum_s^S \pi_s \left(\omega_{is} x_{is} u'(c_{1,s})\right), \quad \forall i \in N. \tag{5}$$

Except for using distorted state probabilities, the investor's valuation of payoffs is standard. Compared to an expected utility maximizer who evaluates stocks using undistorted probabilities, a salient thinker wants to buy more (less) shares of stock i when its upside (downside) is salient.

The pricing implications of salience-driven demand for stocks can be derived by combining the optimal trading decisions of all investors with the market clearing condition, i.e., $\alpha_i = 0$ for all i. In equilibrium, all investors hold the market portfolio and stock prices are given by:[6]

$$p_i = \mathbb{E}[\omega_{is} x_{is}] = \mathbb{E}[x_{is}] + \text{cov}[\omega_{is}, x_{is}], \quad \forall i \in N. \tag{6}$$

The first term on the right-hand side of Equation (6) shows that, in the absence of salience distortions, the price of a stock is equal to the expected value of its future payoff, where the expectation is calculated using objective probabilities. The second term captures the impact of salient thinking on stock prices. When a stock's highest payoffs are the salient ones, i.e., $\text{cov}[\omega_{is}, x_{is}] > 0$, the stock is overvalued because investor's attention is drawn to its upside potential. When a stock's lowest payoffs are the salient ones, i.e., $\text{cov}[\omega_{is}, x_{is}] < 0$, the investor focuses on its downside risk and is willing to hold the stock only when it is priced below the rational price $\mathbb{E}[x_{is}]$.

[6] To see this, recall that $\mathbb{E}[\omega_{is}] = 1$ and for a linear utility function $u'(c_1)/u'(c_0) = 1$.

Dividing both sides of (6) by p_i yields the implications of salience for expected returns:

$$\mathbb{E}[r_{is}] = -\text{cov}[\omega_{is}, r_{is}] \equiv -\text{ST}_i, \quad \forall i \in N, \tag{7}$$

where ST_i stands for stock i's salience theory value. Equation (7) captures the main prediction of the salience-based asset pricing model: stocks with salient upsides (positive ST) have lower future returns than stocks with salient downsides (negative ST). When investors are rational ($\delta = 1$), there are no salience distortions and all states are equally salient. In this case, $\text{cov}[\omega_{is}, r_{is}] = 0$ and the expected return is also zero, since investors are risk-neutral and do not discount the future.

2.4 Construction of Salience Measure

To test the prediction that a stock's salience theory value negatively predicts its future returns, we need to specify the states of the world that can occur and their objective probabilities. In an experimental setting in which subjects are asked to choose between lotteries, the payoffs and their probabilities are given. In an empirical application, however, the definition of the state space is less clear. Following Barberis, Mukherjee, and Wang (2016), we suggest that, when choosing between stocks, investors mentally represent each stock by the distribution of its past returns and infer the set of future return states from past states. In our analysis, we assume that the state space is formed by the daily returns over the past month. Since each of these past returns has been realized, its probability is known and equal to the inverse of the number of trading days in the month.

We compute ST over a one-month window for two reasons. First, in our empirical analysis, we predict one-month-ahead stock returns.[7] Because a one-month window of past returns matches the one-month forecasting horizon, the number of past states is approximately equal to the number of future states. Second, because the selective attention that distorts decision weights stems from cognitive limitations, salient thinkers may recall only the most recent returns.[8] In Section 6.1, we

[7] Strictly speaking, given the daily state space, $\mathbb{E}[r_{is}]$ in (7) is the expected daily return in the next period. We predict monthly rather than daily returns to facilitate comparison of our results with the results in the literature that predicts monthly returns. Results are similar when predicting the average daily return over the next month.

[8] Consistent with a shorter memory span, Greenwood and Shleifer (2014) find that expectations of individual investors are more sensitive than those of professional investors to the most recent past returns. Bordalo, Gennaioli, and Shleifer (2015a) develop a theory of consumer choice that combines salience theory with a model of limited recall.

examine the robustness of our results to alternative choices of window length and return frequency.

The salience of a stock's return on day s (r_{is}) depends on its distance from the average return across all stocks in the market on that day ($\bar{r}_s$), i.e., Equation (1) becomes:[9]

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{|r_{is}| + |\bar{r}_s| + \theta}. \tag{8}$$

The following example illustrates the measurement of salience. Suppose that on day s, the return on stock i is 10% and the market return is 5%. On another day s', the stock return is 5% and the market return is 0%. Although the difference between stock and market returns is the same on both days, the stock's return is more salient to the investor on day s' because of diminishing sensitivity, captured by the denominator in Equation (8). Intuitively, the stock's outperformance of 5% stands out more on a day when the market is flat than on a day when the market goes up.

Equation (8) implies that salience is determined by an individual stock's return relative to the market return, independent of investor-specific characteristics.[10] This form of "narrow framing" implies that a stock return salient to one investor will be salient to all other investors. Consequently, salience-driven demand for stocks will be correlated across investors and can exert pressure on stock prices, given limits to arbitrage that prevent rational investors from correcting mispricing.

For each stock, we rank the daily returns in each month in descending order of salience and calculate the corresponding salience weights ω_{is} using Equation (3). To compute salience weights, we need to specify values for the parameters θ and δ. Our implementation uses the values calibrated by BGS (2012) to match experimental evidence on long-shot lotteries, namely, $\theta = 0.1$ and $\delta = 0.7$. We then obtain ST by computing the covariance between salience weights and daily returns.

Our salience measure ST has an intuitive interpretation. To see this, write ST as:

$$\text{ST}_{i,t} \equiv \text{cov}[\omega_{is,t}, r_{is,t}] = \sum_{s}^{S_t} \pi_{s,t}\omega_{is,t}r_{is,t} - \sum_{s}^{S_t} \pi_{s,t}r_{is,t} = \mathbb{E}^{ST}[r_{is,t}] - \bar{r}_{is,t}, \tag{9}$$

[9] In Section 5, we explore other definitions of the choice context with respect to which salience is measured.

[10] The assumption that investors engage in stock-level narrow framing is common in the literature that studies the impact of mental accounting on trading decisions and asset prices (e.g., Barberis and Huang (2001), Barberis, Huang, and Thaler (2006), Ingersoll and Jin (2013), and Barberis, Mukherjee, and Wang (2016)). Notable exceptions are Barberis and Huang (2008) and Hartzmark (2015), who consider framing of gains and losses at the portfolio level.

where the second equality follows from $\mathbb{E}[\omega_{is}] = 1$ and the last equality follows from $\pi_{s,t} = 1/S_t$, where S_t is equal to the number of trading days in month t. Equation (9) shows that ST is equal to the difference between salience-weighted and equal-weighted past returns. ST thus measures the distortion in return expectations caused by salient thinking.[11] When a stock's highest (lowest) past returns are salient, investors raise (lower) their expectation about its future return and push its price above (below) the fundamental value, lowering (increasing) future realized returns.

3 Data

Our data come from CRSP and Compustat and consist of the daily and monthly return, book and market value of equity, and trading volume for all firms listed on the NYSE, AMEX, and NASDAQ for the period January 1926 to December 2015. A stock is included in the analysis for a given month if a minimum of 15 daily return observations is available in that month to compute ST and if historical data is available to compute each of the firm characteristics used as control variables.

We control for a large set of characteristics known to explain cross-sectional variation in returns. We measure firm size (ME) as the log of the market value of equity and book-to-market (BM) as the ratio of the book and market value of equity. Following Fama and French (1992), we calculate book-to-market using accounting data from Compustat as of December of the previous year and exclude firms with negative book equity. Because Compustat does not have book common equity (BE) data for the first part of our sample period, we obtain BE data from Kenneth French's data library for the period 1926-1953.[12] Momentum (MOM) is measured as the cumulative return over the 11 months prior to the current month. Amihud (2002) illiquidity (ILLIQ) is computed as the absolute daily return divided by the daily dollar trading volume, averaged over all trading days in a month. Short-term reversal (REV) is defined as the stock return in the previous month.

We also account for different measures of risk. Market beta (BETA) is estimated from a re-

[11] The rational benchmark here is the expected return computed using undistorted, objective probabilities. Note that we do not claim that the use of past returns to forecast future returns is rational. In fact, given the low serial correlation in returns, predicting future returns based on past returns may not be optimal. What matters, however, is that in practice individual investors do extrapolate past returns (e.g., Greenwood and Shleifer (2014)). Conditional on investors using past returns, we examine the incremental effect of salience distortions on return expectations.

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

gression of daily excess stock returns on the daily excess market return over a one-month window. Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals from this regression. Downside beta (DBETA) is estimated from a regression of daily excess stock returns on the daily excess market return over a one-year window, using only days on which the market return was below the average daily market return during that year, as in Ang, Chen, and Xing (2006). Coskewness (COSKEW) is defined as the coskewness of daily stock returns with daily market returns over a one-year window, computed using the approach of Harvey and Siddique (2000).

Lastly, we construct several measures of lottery demand. MAX (MIN) is a stock's maximum (minimum) daily return within a month, as in Bali, Cakici, and Whitelaw (2011). The prospect theory (TK) value of a stock is constructed using a five-year window of monthly returns, following the approach of Barberis, Mukherjee, and Wang (2016). Skewness (SKEW) is the skewness of daily stock returns, and idiosyncratic skewness (ISKEW) is defined as the skewness of the residuals from a Fama and French (1993) three-factor model regression, as in Boyer, Mitton, and Vorkink (2010). Following Bali, Cakici, and Whitelaw (2011), we compute the skewness measures using daily returns over a one-year period and require a minimum of 200 valid daily return observations within the estimation period. All variables are winsorized at the 1st and 99th percentiles.

4 Cross-Sectional Relation Between Salience and Stock Returns

In this section, we test the main prediction of the salience model outlined in Section 2: stocks with salient upsides (high ST) will earn lower subsequent returns than stocks with salient downsides (low ST). We perform univariate and bivariate portfolio analyses in Sections 4.1 and 4.2 and estimate firm-level Fama-MacBeth regressions in Section 4.3. In Sections 4.4 and 4.5, we conduct conditional analyses that examine the impact of limits to arbitrage and investor sentiment on the strength of the cross-sectional relation between salience and future stock returns.

4.1 Univariate Portfolio Sorts

We begin our empirical analysis with univariate portfolio sorts. Each month, we sort stocks into decile portfolios based on their salience theory value and calculate the equal-weighted (EW) and value-weighted (VW) portfolio returns over the next month. Table 1 reports the time series average of the one-month-ahead excess portfolio return, the four-factor alpha obtained from the Carhart (1997) model, and the five-factor alpha obtained from the Carhart (1997) model extended with a liquidity factor, constructed as the innovation in the VW average of the Amihud (2002) illiquidity measure across all stocks in the CRSP universe.[13] The last row reports returns and alphas for the zero-cost strategy that buys high-ST stocks (decile 10) and shorts low-ST stocks (decile 1).

The results in Table 1 provide strong support for our prediction that future returns are lower for stocks with salient upsides than for stocks with salient downsides. The first column shows that average EW returns decline nearly monotonically across the ST decile portfolios. Differences in the performance of high- and low-ST stocks are not only statistically significant but also large in economic terms. The average excess return on the EW high-low ST portfolio is -1.91% per month, with a Newey and West (1987) t-statistic of -13.13. This return difference is not explained by market, size, value, momentum, and liquidity factors, with four- and five-factor alphas of -2.07% and -2.04% and corresponding t-statistics of -14.37 and -14.41, respectively.

The right-hand panel of Table 1 shows that the return difference between the highest and lowest ST deciles is also significant for the value-weighted (VW) portfolios. As expected, the results are less pronounced than for the EW portfolios because large stocks tend to have lower retail ownership and smaller limits to arbitrage. The effect of salience on VW portfolio returns is nevertheless sizeable, with a return spread of -0.80% per month (t-stat = -5.24). Again, we find no evidence that this return difference is driven by differences in factor exposures. The four- and five-factor alphas of the VW high-low ST portfolio are close to -1% per month and significant at the 1% level.[14]

To get a better understanding of the composition of the ST-sorted portfolios, we compute the cross-sectional average of various characteristics of the stocks in each decile. Table 2 reports the time series mean of the characteristics across all months in the sample for the EW (panel A) and VW (panel B) portfolios. Panel A shows that the portfolio sort generates a substantial spread in

[13] Our results are robust to using the Pastor and Stambaugh (2003) liquidity factor. We employ the Amihud (2002) liquidity factor because the Pastor and Stambaugh (2003) factor is available only from 1968 onwards.

[14] We also construct gross-return-weighted portfolios to correct for a potential bias in EW returns induced by noise in stock prices, as suggested by Asparouhova, Bessembinder, and Kalcheva (2013). Unreported results show that the return-weighted excess returns and alphas on the ST portfolios are similar to their EW counterparts in Table 1.

ST, ranging from -3.26 for the decile of stocks with lowest ST to 6.26 for those with highest ST. We relate this variation in ST to variation in firm characteristics in the other columns. We observe that stocks in the extreme ST deciles have lower market capitalization on average. Small stocks are more likely to have salient returns (positive or negative) because they have higher idiosyncratic volatility. High- and low-ST stocks are also more illiquid and have a higher market beta. ST is positively associated with the contemporaneous monthly stock return (REV) because an extreme positive (negative) daily stock return that drives monthly returns up (down) will be salient if the market return on that day is moderate. We further explore the relation between salience and short-term reversal in Section 6. As expected, total and idiosyncratic skewness also increase with ST because positively (negatively) skewed stocks are more likely to have salient upsides (downsides). We observe similar, albeit less pronounced, patterns for the VW portfolios in panel B.

To summarize, the univariate analysis provides preliminary evidence of a strong negative relation between a stock's ST value and its return in the next month, consistent with the predictions of the salience-based asset pricing model described in Section 2. The return difference between the high- and low-ST deciles is economically large and statistically significant and is not explained by standard risk factors. However, a potential concern is that ST is related to a number of firm characteristics that have been shown to explain variation in returns. Below, we examine whether the negative relation between ST and future returns is robust to controlling for these characteristics.

4.2 Bivariate Portfolio Sorts

In this section, we construct double-sorted portfolios to control for firm characteristics correlated with ST. Each month, we sort stocks into deciles based on one of the control variables and, within each decile, further sort stocks into deciles based on ST, such that a total of 100 portfolios is created. We record for each of these portfolios the realized return over the next month and average the returns of the salience theory deciles across the different deciles of the control variable.

Table 3 provides the results of the bivariate sorts. We report the average monthly excess return for each of the ST-sorted deciles on both an EW (panel A) and VW (panel B) basis. The bottom rows present the differences in monthly returns and alphas between decile 10 (high ST) and decile

1 (low ST). We find that the salience effect remains economically large and statistically significant after accounting for each of the firm characteristics. For the EW portfolios, the return spread between the high- and low-ST deciles ranges from -0.61% to -1.78% per month and is significant at the 1% level in all cases. As before, the portfolio returns decrease nearly monotonically across the ST deciles, which indicates that the negative relation between ST and subsequent returns is not driven solely by the stocks in the highest and lowest ST deciles. Differences in five-factor alphas range from -0.70% to -1.86% per month and are also statistically significant at the 1% level.

Comparing the results of the bivariate portfolio analysis to the univariate results in Table 1 shows that most firm characteristics have only limited impact on the magnitude of the return spread between high- and low-ST stocks. This result is not surprising given the (inverse) U-shaped relation between ST and a number of the characteristics (see Table 2). For instance, both high- and low-ST stocks tend to be those of relatively small firms. Because of their limited variation, these characteristics cannot explain the large return spread between the extreme ST deciles. We observe a larger reduction in the magnitude of the return and alpha differences when we control for characteristics, such as short-term reversal and MAX, that do vary substantially across high- and low-ST stocks. Nevertheless, the average return and alpha of the high-low ST portfolio remains economically sizeable and statistically significant, even for the value-weighted portfolios.

4.3 Firm-Level Fama-MacBeth Regressions

An important benefit of the portfolio analysis above is that it does not assume a specific functional form for the relation between ST and future returns. However, aggregating stocks into portfolios leads to a loss of information because it conceals differences across firms in characteristics other than those used for sorting. In this section, we therefore estimate firm-level Fama and MacBeth (1973) regressions that enable us to control for a large number of characteristics simultaneously.[15]

We estimate predictive cross-sectional regressions of excess stock returns in month $t+1$ on a

[15]Estimating panel regressions with time fixed effects and double-clustered standard errors yields similar results and shows that the predictive ability of ST for future returns is robust to the use of alternative estimation methods.

firm's ST value and a vector of control variables W_{it} measured at the end of month t:

$$r_{it+1} = \lambda_{0t} + \lambda_{1t} ST_{it} + \lambda_{2t} W_{it} + \upsilon_{it}. \tag{10}$$

In the most general specification, W_{it} includes size (ME), book-to-market (BM), momentum (MOM), illiquidity (ILLIQ), market beta (BETA), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), minimum daily return (MIN), prospect theory value (TK), skewness (SKEW), coskewness (COSKEW), idiosyncratic skewness (ISKEW), and downside beta (DBETA).

Table 4 reports the results of the Fama-MacBeth regressions. Consistent with the results of the portfolio sorts, we find that ST negatively predicts one-month-ahead stock returns. The coefficient on ST in the univariate regression in column 1 is statistically significant at the 1% level (t-stat = -13.57). The slope is also economically significant, with a one-standard-deviation increase in ST predicting a decrease in next month's stock return of -0.64%. Column 2 shows that the inclusion of the beta, size, book-to-market, and momentum characteristics hardly affects the coefficient estimate on ST. Although controlling for short-term reversal reduces the magnitude of the ST coefficient, salience continues to have strong predictive power. After accounting for reversal, adding proxies for lottery demand (IVOL, MAX, SKEW, and ISKEW) has little impact on the predictive ability of ST. When we include all 14 characteristics simultaneously, a one-standard-deviation increase in a stock's ST value is associated with a decrease in next month's return of 0.23%.

Harvey, Liu, and Zhu (2016) emphasize in a recent paper that multiple testing should be accounted for in assessments of statistical significance in asset pricing tests. The ST variable used in our analysis is directly motivated by the salience model in Section 2, and the parameter values used to construct ST are taken from BGS (2012). These theoretical underpinnings should alleviate any data mining concerns. Moreover, all t-statistics in Table 4 easily clear the more stringent hurdle of 3.0 proposed by Harvey, Liu, and Zhu (2016) to correct for multiple testing.

4.4 Impact of Limits to Arbitrage

In the model of BGS (2013a), all investors are assumed to be salient thinkers. In reality, investors differ in their cognitive abilities and therefore likely vary in the degree of salient thinking. Some investors may act as expected utility maximizers who evaluate stocks using objective probabilities. In the absence of limits to arbitrage, these rational investors can correct the mispricing induced by salient thinkers by buying stocks with salient downsides and shorting stocks with salient upsides. We therefore expect the salience effect to be stronger among stocks with greater limits to arbitrage.

We test this hypothesis by interacting ST with five proxies for limits to arbitrage: firm size, illiquidity, idiosyncratic volatility, institutional ownership, and analyst coverage. Arbitrage is more costly and risky for small stocks, illiquid stocks, and stocks with high idiosyncratic risk (see, e.g., Brav, Heaton, and Li (2010)). Low institutional ownership can impede arbitrage by reducing the supply of lendable stocks in the short-selling market (see, e.g., Nagel (2005)). Low institutional ownership can also strengthen the salience effect because it is likely that retail investors are particularly prone to salient thinking. Low analyst coverage has been associated with higher arbitrage risk because it signals that less information is available about a firm, which increases valuation uncertainty (Zhang (2006)). Institutional ownership (IO) is defined as the fraction of shares outstanding held by institutional investors, available from the Thomson Reuters Institutional Holdings (13F) database from 1980 onwards and lagged by one quarter to avoid any look-ahead bias. Analyst coverage (NOA) is measured as the log of one plus the number of analysts covering a firm, available from the Institutional Brokers' Estimate System (I/B/E/S) data set from 1976 onwards. Because IO and NOA are strongly correlated with firm size, we follow Conrad, Kapadia, and Xing (2014) in computing the residuals from a regression of each of these variables on firm size and time dummies.

Table 5 reports the results of Fama-MacBeth regressions that include interaction terms between ST and each of the proxies for arbitrage costs. The estimates support our conjecture that the salience effect is most pronounced among stocks with greater limits to arbitrage. The negative relation between ST and future returns is particularly strong among small stocks, illiquid stocks, and stocks with high idiosyncratic risk, low institutional ownership, and low analyst coverage.

4.5 Salience and Investor Sentiment

Having found evidence that the magnitude of the salience effect varies across firms, we now examine whether the predictive power of ST varies with time. This analysis is motivated by studies that link the strength of cross-sectional return anomalies to investor sentiment and limits to arbitrage. Miller (1977), for example, argues that short-sale impediments render stocks more likely to be overpriced than underpriced. Building on this work, Stambaugh, Yu, and Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2016) show overpricing to be most prevalent during high-sentiment periods when unsophisticated investors tend to be overly optimistic and more likely to participate in the market. Because unsophisticated investors are more prone to engage in salient thinking, we expect the impact of salience on stock prices to increase during high-sentiment periods.

We test this hypothesis by computing the returns on ST-sorted portfolios separately for high- and low-sentiment periods. Following Stambaugh, Yu, and Yuan (2012), we define high-sentiment months as those in which the Baker and Wurgler (2006) sentiment index in the previous month is above the median value for the sample period. Low-sentiment months are those with below-median values. The sentiment index is available from July 1965 onwards. The results in Table 6 confirm that high sentiment strengthens the negative relation between ST and subsequent stock returns. The monthly return on the EW high-low ST portfolio equals -2.16% following high sentiment and -1.63% following low sentiment. The difference of -0.53% is significant at the 5% level. The return spread between the VW high- and low-ST deciles increases by 0.83% (t-stat = 2.41) after periods of high investor optimism.[16] The five-factor alphas in the last row of Table 6 exhibit similar patterns.

Collectively, the evidence from the conditional analyses in Tables 5 and 6 is consistent with a behavioral interpretation of the negative relation between a stock's salience and future returns. Stocks with salient upsides become overpriced and earn lower subsequent returns, and this negative relation is stronger among stocks with greater limits to arbitrage and after periods of high sentiment.

5 Role of Choice Context

The crucial feature that sets salience theory apart from alternative models of choice under risk, such as prospect theory, is the context-dependence of the probability weighting function. In our implementation of salience theory, the investor's trading decision is modeled as a choice problem

[16] Alternative tests, in which we regress the return spread between high- and low-ST deciles on the *level* of the lagged sentiment index, confirm that the spread increases with sentiment. The standardized coefficient on sentiment ranges from -0.30 (t-stat = -2.25) for the EW high-low ST portfolio to -0.51 (t-stat = -2.96) for the VW portfolio.

defined by (i) the choice context, i.e., the set of stocks available to the investor, and (ii) the state space, i.e., the set of states of the world. In this section, we explore alternative specifications of the context with respect to which salience is defined and in the next section we consider variations in the state space. Changes in the context used to evaluate stocks, because they affect the salience of a stock's past returns, will lead to changes in investors' return expectations and trading behavior. We therefore expect the return-forecasting ability of salience to depend on the context.

Following BGS (2013a), we have thus far assumed that investors evaluate a stock in the context of all available stocks in the market. We measure salience by comparing stock returns to the overall market return instead of making pairwise comparisons between individual stock returns because salience generally changes across pairwise comparisons, which may lead to intransitivities (see BGS (2012)). We use the equal-weighted CRSP index as our proxy for the market index because equal-weighting preserves the ordering, diminishing sensitivity, and reflection properties of the salience function. Apart from these theoretical considerations, the market is an appropriate context in our setting because we seek to explain the cross-section of returns on all stocks in the CRSP universe.

To examine the impact of the index weighting scheme, we measure salience by contrasting stock returns with the return on the value-weighted CRSP index and run Fama-MacBeth regressions with the resulting ST variable. To facilitate comparison of results across the different ST specifications, we standardize all independent variables to have zero mean and unit variance. Estimation results for the VW CRSP index in column 2 of Table 7 indicate that the predictive power of ST is not sensitive to the index weighting scheme. The slope on ST is identical in magnitude to the coefficient on the original ST variable constructed using the EW index and significant at the 1% level.

Instead of considering all available stocks in the market, investors may focus on a subset of stocks. For instance, it is possible that some investors evaluate a stock in the context of other stocks in the same industry. We therefore construct an alternative salience measure by contrasting a stock's return to its industry return, i.e., we replace $\bar{r}_s$ in Equation (8) with the value-weighted or equal-weighted industry return. We classify stocks into 48 industries following the classification of Fama and French (1997).[17] The results in columns 3 and 4 indicate that the predictive power

[17] Results are similar when classifying stocks into the 10 or 30 industries available in Kenneth French's data library.

of ST further increases when salience is defined relative to a firm's industry return. The larger magnitude of the salience effect is consistent with stocks becoming mispriced because investors' expectations about their returns are distorted by the returns on other stocks in the same industry. An alternative explanation is that by measuring salience relative to a stock's industry return, we effectively control for industry momentum. Moskowitz and Grinblatt (1999) show that the industry momentum effect is particularly strong at the one-month horizon and suggest that it is driven by underreaction to public information. In our original salience specification that compares a stock's returns to the overall market return, firms may have salient upsides because of positive news about their industry. The salience model predicts these stocks to earn lower returns over the next month. However, if part of the positive industry information is incorporated in stock prices with a one-month lag, leading to industry momentum, the salience effect will be harder to detect. In Section 6.1 we present empirical evidence that is consistent with this alternative explanation.

We next compute the salience of stock returns relative to the risk-free rate, i.e., we replace $\bar{r}_s$ in Equation (8) with the one-month T-bill rate. This setting corresponds to an investor choosing between investing in a stock or the risk-free asset instead of choosing between different stocks. If a stock truly becomes mispriced because investors' return expectations are influenced by other stocks in the market, as predicted by the salience model, then ST measures that assume a different context than the market should be less capable of predicting differences in returns across stocks.[18] Column 4 confirms that the predictive power of ST weakens when the context is given by the risk-free asset. Although the coefficient on ST remains statistically significant, it drops from -0.23 to -0.14.

Lastly, we explore the consequences of ignoring the choice context when defining salience. This setting corresponds to evaluating each stock in isolation, essentially comparing the stock to the alternative of not investing at all, i.e., of earning a zero return for sure. Ignoring context thus implies that the salience function can be reduced to $\sigma(r_{is}) = |r_{is}|$.[19] In words, salience increases in the absolute value of the stock return. Column 6 reports estimation results for the ST measure

[18] For instance, a stock that has a salient downside when evaluated in the context of the aggregate stock market can have a salient upside when compared to the risk-free asset if the risk-free rate is lower than the market return.

[19] To see this, note that when stock returns are contrasted with zero, the salience function in Equation (8) reduces to $\sigma(r_{is}) = \frac{|r_{is}|}{|r_{is}|+\theta}$. For $\theta > 0$, $\sigma(r_{is})$ increases in $|r_{is}|$. Because $\sigma(r_{is})$ is used only to determine the salience *ranking* of a stock's returns, the salience function can be further simplified to $\sigma(r_{is}) = |r_{is}|$.

computed without considering the choice context. Although the slope on ST is still significant, it is almost 50% smaller in magnitude than the coefficient on the original ST variable in column 1.

We draw two conclusions from the evidence in Table 7. First, the salience effect is robust to alternative choices of the market index with respect to which salience is defined and robust to controlling for industry salience. Second, our finding that the predictive power of ST weakens when the choice context is given by the risk-free asset rather than by the market, or is ignored altogether, is consistent with the salience model's prediction that stocks become mispriced because investors' perception of their return distribution is distorted by the returns on other stocks in the market.

6 Alternative Explanations for the Salience Effect

Although our empirical evidence is consistent with the predictions of salience theory, there might be other explanations for the negative relation between our salience measure and future returns. In this section, we present additional tests to differentiate the salience effect from existing anomalies. In Section 6.1, we perform further empirical analyses to rule out that the salience effect merely captures short-term reversal. Section 6.2 discusses conceptual and empirical differences between salience theory and the investor attention theory of Barber and Odean (2008).

6.1 Salience and Short-Term Reversal

We consider first the possibility that our salience measure ST picks up the short-term return reversal effect documented by Jegadeesh (1990) and Lehmann (1990). A common behavioral interpretation of short-term reversal is that investors overreact to company news, which implies that high or low one-month stock returns are subsequently reversed (e.g., Subrahmanyam (2005)). Moreover, recent survey evidence indicates that investors over-extrapolate past returns when forming expectations about future returns (Greenwood and Shleifer (2014). Salience theory differs from these existing behavioral theories because it predicts that investors' reaction to information is context-dependent.

In our salience model, investors also use information about past returns to form expectations about future returns. However, they overweight a stock's past returns only if they stand out relative to the returns on other stocks in the market and underweight its non-salient returns. Salience-induced distortions in expectations therefore do not arise from overreaction to past returns but from biases in the perception of these returns.[20] More specifically, we define ST as the difference between the salience-weighted and equal-weighted daily stock return in a given month (see Equation (9)). ST therefore does not pick up reversal but the incremental effect of salience distortions on return expectations, conditional on investors using past returns to forecast future returns. A high one-day stock return pushes up the EW daily return and the overall return over that month (REV). Salience theory predicts that if the market is flat or down, the high stock return stands out and is overweighted when investors form expectations about future returns, thereby increasing ST. In contrast, if the market is up sharply, the stock's high return is less likely to catch investors' attention and receives less weight. As a result, the high one-day return leads to a smaller increase in the salience-weighted daily return than in the equal-weighted return, thereby lowering ST.

An important implication of the conceptual differences between salience theory and behavioral theories of reversal is that they yield different predictions for stocks with similar one-month returns but different one-day returns. Despite having similar one-month returns, these stocks can have very different ST values depending on the market return on the days when their highest and lowest returns occur. The salience model predicts that stocks with salient upsides have lower future returns than stocks with salient downsides, even if they have the same one-month return. The results of the sequential sort on reversal and ST in Table 3 support this prediction. We find that among stocks with similar one-month returns, high-ST stocks earn significantly lower future returns than low-ST stocks. The results of the Fama-MacBeth regressions in Table 4 provide further evidence that the negative relation between ST and future returns is robust to controlling for reversal.

In this section we perform three additional analyses to differentiate the salience effect from reversal. First, we augment the five-factor model with the Fama-French short-term reversal factor when computing alphas of the ST-sorted deciles in the univariate portfolio analysis. The results in panel A of Table 8 show that the alpha of the zero-cost strategy that buys high-ST stocks and shorts low-ST stocks remains economically large and statistically significant after controlling for the

[20]Barberis, Greenwood, Jin, and Shleifer (2015) develop a consumption-based model in which some investors hold rational beliefs and others form expectations about future stock market returns by extrapolating past price changes. Extending this model to an economy with multiple risky assets, in which investors extrapolate salience-weighted past returns, is an important direction for future work but beyond the scope of this paper.

short-term reversal factor. When measuring salience relative to the aggregate market index, alphas range from -1.77% per month for the EW portfolio to -0.74% per month for the VW portfolio. When salience is defined in an industry context, alphas range from -1.83% (EW) to -0.88% (VW).

We next consider variations in the state space used to define salience. Our baseline salience specification assumes that investors infer the set of possible future returns from the daily returns realized over the past month. We choose a relatively short window because salient thinkers, due to their cognitive limitations, may recall only the most recent returns. Investors may also deliberately weight distant returns less because they believe them to be less representative of future returns. Either way, we expect the relation between ST and future returns to gradually weaken when extending the window. However, if the salience effect is just a repackaging of the one-month reversal effect, we expect it to vanish abruptly when salience is measured over intermediate (quarterly or annual) horizons at which returns typically exhibit momentum rather than reversal.

We test this hypothesis by comparing the predictive ability of ST measures computed using daily returns over the past month, quarter, or year. Because some investors may only observe monthly stock returns, we also construct ST based on one-year and five-year windows of monthly returns. Panel B reports Fama-MacBeth results for the ST measures defined on alternative state spaces. The estimates confirm our expectation that the predictive power of salience gradually weakens when more distant returns are used to construct ST. When salience is measured in the context of the overall stock market, the standardized coefficient on ST ranges from -0.19 for the quarterly ST variable based on daily returns to -0.12 for the five-year ST measure based on monthly returns.[21] When a firm's industry is used as benchmark to define salience, coefficient estimates range from -0.28 (quarterly horizon) to -0.15 (five-year horizon). Most importantly, however, regardless of the window length, the coefficient on ST is always negative and significant at the 1% level.

Although the relative impact of last month's return decreases with the horizon used to measure ST, it may still have a disproportionate effect on the predictive power of ST. We therefore also run Fama-MacBeth regressions in which all ST variables are lagged by an additional month. Specifically, we use ST measures computed with data up to month $t-1$ to forecast returns in month $t+1$. The

[21] In the regressions with five-year ST, we include the cumulative return from the start of month $t-60$ to the end of month $t-13$ as an additional control to ensure that ST does not merely capture the long-term reversal effect.

results in panel C show that all ST measures retain significant predictive power after skipping a month between their construction and the measurement of subsequent returns, providing further evidence that the salience effect is distinct from one-month reversal. The one-month lag leads to only a small drop in the economic magnitude of the salience effect. The main exception is the slope on the one-month ST variable constructed using a stock's industry return as benchmark, which falls (in absolute value) from -0.42 to -0.25. This drop is consistent with the explanation given in the previous section that measuring salience in the context of a firm's industry takes out the industry momentum effect that obfuscates the salience effect. Because industry momentum is strongest at the one-month horizon, controlling for this effect sharply increases the magnitude of the coefficient on the one-month ST variable in panel B. When lagging ST by an additional month (panel C), industry momentum plays a smaller role and the coefficients on the ST variables defined in the context of a firm's industry are similar to those on the ST measures defined relative to the market.

Lastly, we construct an ST measure based on a monthly window of daily open-to-open returns. Because (retail) investors usually observe daily returns measured from close-to-close, we expect the predictive power of ST to be weaker when using opening returns. However, if the perception of returns plays no role and our results are driven by overreaction to news about firm fundamentals, the significance of ST should be unaffected by the definition of daily returns. We construct open-to-open returns following the method of Amihud and Mendelson (1987) that accounts for stock splits and dividends. Opening prices are available from CRSP from July 1992 onwards. For comparison, we also report results for the same subperiod for the one-month ST measure based on close-to-close returns. Consistent with our hypothesis, we find in panel D that the coefficient on the open-to-open ST variable is small (0.05) and insignificant (t-stat = 0.92). In contrast, the slope on the close-to-close ST measure is economically large (-0.35) and statistically significant (t-stat = -4.78). We observe a similar difference when salience is defined in an industry context. These differences are hard to reconcile with explanations based on risk or overreaction to news and lend further support to our salience-based interpretation of the predictive relation between ST and future returns.

6.2 Salience and Investor Attention

Another explanation for our findings is offered by the attention theory of Barber and Odean (2008). Their attention hypothesis predicts that retail investors are net buyers of attention-grabbing stocks because when buying, they must choose from the large universe of stocks. Due to cognitive limitations, investors may consider only stocks that have caught their attention. When selling, retail investors do not face such search problems because they can sell only stocks they already own, as they usually do not sell short. Hence, investors are more likely to buy rather than sell attention-grabbing stocks, which leads to positive price pressure in the short run and subsequent reversal.

Attention also plays an important role in salience theory, but the underlying mechanism differs. In the salience model, investor attention is drawn to salient return states rather than to salient stocks. Salience affects trading decisions and stock prices by distorting decision weights and return expectations, not by narrowing the set of stocks investors actively consider for purchase.[22] An important consequence of these different mechanisms is that salience and attention yield opposite predictions for stocks with attention-grabbing downsides. Salience theory predicts that such stocks become underpriced and earn higher future returns because investors focus on their downside risk. The attention hypothesis predicts them to become overpriced because both positive and negative attention-grabbing events lead to net buying by retail investors.[23]

We perform three additional tests to distinguish between the salience- and attention-based explanations for our results. First, we construct double-sorted portfolios by sorting stocks into deciles based on an attention proxy and, within each of the attention portfolios, further dividing the stocks into deciles based on the salience measure ST. We rebalance the portfolios monthly and average the returns of the ST deciles across the different deciles of the attention variable.

We consider four proxies for investor attention that are available for the full sample period: (i) the maximum absolute abnormal daily return within each month (MAX |ABN DRET|); (ii)

[22] If investors consider only stocks that grab their attention, the consideration set is smaller than the actual choice set. In the salience model of BGS (2012), the choice set is equated with the consideration set by assuming that, before evaluating lotteries, decision makers edit the choice set by discarding the lotteries they are not considering.

[23] Specifically, Barber and Odean (2008) argue that "if big price changes catch investors' attention, then we expect that those investors whose buying behavior is most influenced by attention will tend to purchase in response to price changes - both positive and negative."

the absolute abnormal monthly return (|ABN RET|); (iii) the maximum abnormal daily trading volume within each month (MAX ABN DVOL); and (iv) the abnormal monthly trading volume (ABN VOL). Extreme returns and abnormal trading volume have been used as proxies for investor attention by, among others, Gervais, Kaniel, and Mingelgrin (2001) and Barber and Odean (2008). We define abnormal returns as the difference between stock returns and market returns.[24] Abnormal daily (monthly) trading volume is calculated as a stock's daily (monthly) dollar trading volume divided by its average daily (monthly) dollar volume over the twelve months prior to month t.

Panel A of Table 9 reports the results of the bivariate portfolio sorts. We find that the return difference between the high- and low-ST deciles is statistically significant at the 1% level, regardless of the attention proxy used for sorting. Although controlling for the two return-based attention measures reduces the return on the high-low ST portfolio, its economic magnitude remains sizeable, ranging from an average of -1.25% per month for the EW portfolios to -0.72% for the VW portfolios. The two volume-based proxies have almost no effect on the return of the high-low ST portfolio. Differences in five-factor alphas are also economically and statistically significant in all cases.

We next include the attention proxies as additional controls in the Fama-MacBeth regressions. The results in panel B of Table 9 show that the cross-sectional relation between ST and one-month-ahead returns remains negative and statistically significant at the 1% level in the presence of the attention measures. The magnitude of the coefficient on ST also remains largely the same.

Lastly, we split ST into positive and negative parts to test the opposing predictions of the salience model and the attention hypothesis for stocks with salient downsides. ST POS is equal to ST when ST is positive, and zero otherwise. ST NEG equals -ST when ST is negative, and zero otherwise. We take the negative of ST so that higher values of ST NEG correspond to more negative values of ST. Both ST components are included as separate regressors in the Fama-MacBeth regressions in the last three columns of panel B. The signs of the estimated coefficients provide additional support for the salience model. The negative coefficient on ST POS implies that stocks with positive upsides tend to earn lower future returns. Most importantly, we find that the coefficient on ST NEG is significantly positive, which means that the more negative ST, the higher

[24]We obtain similar results when using raw returns or characteristic-adjusted abnormal returns computed following Daniel, Grinblatt, Titman, and Wermers (1997).

the future return. The opposite impact of positive and negative ST on future returns is consistent with the predictions of salience theory but cannot be explained by the attention hypothesis.

In sum, we find that the negative relation between ST and future stock returns is robust to controlling for measures of investor attention. Although our empirical evidence is consistent with salience theory, we believe that both attention and salience can influence trading decisions and stock prices. Attention plays an important role in the formation of the consideration set in the first stage of the choice process by narrowing the list of available stocks. Salience affects the actual choice between the remaining stocks in the next stage by influencing investors' return expectations.

7 Additional Robustness Tests

In this section, we perform additional tests to verify the robustness of our results. Section 7.1 considers alternative salience specifications that vary in terms of functional form and parameter values. In Section 7.2, we estimate Fama-MacBeth regressions over different subperiods and various subsamples of stocks. Section 7.3 considers alternative specifications of the control variables.

7.1 Alternative Salience Specifications

We now examine the predictive power of alternative salience specifications, beginning with an alternative specification of the salience function analogous to that in BGS (2013a):

$$\sigma(R_{is}, \bar{R}_s) = \frac{|R_{is} - \bar{R}_s|}{R_{is} + \bar{R}_s}, \tag{11}$$

where R_{is} and $\bar{R}_s$ denote the *gross* return on stock i and the market on day s. We apply (11) to gross, rather than net, returns because this alternative function is defined only for positive values.

Table 10 reports Fama-MacBeth regression results for this alternative specification. Estimates in column 1 are for the ST measure based on the original salience function in Equation (8). Column 2 shows that the negative relation between a stock's salience theory value and its one-month-ahead return becomes even stronger when we use the alternative ST measure based on the salience function in (11). The slope estimate is statistically significant (t-stat = -7.24) and economically large, with a one-standard-deviation increase in gross ST predicting a decrease in next month's return of -0.29%.

We next check the robustness of our results to different values of the θ and δ parameters in Equations (8) and (3). Recall that θ affects the convexity of the salience function, and δ measures the degree to which salience distorts decision weights. The baseline values used to construct the ST variable in column 1 are those suggested by BGS (2012), namely, $\theta = 0.1$ and $\delta = 0.7$. In columns 3 and 4, we set θ equal to 0.05 and 0.15, respectively, while keeping δ fixed at 0.7. Varying the value of θ has little impact on the predictive power of ST, which remains strong and statistically significant. In columns 5 and 6, we set δ equal to 0.6 and 0.8, respectively, while keeping θ fixed at 0.1. Again, the coefficient on ST remains largely similar in magnitude and statistical significance.

Based on the evidence in Table 10, we conclude that our results are not particularly sensitive to the values of the θ and δ parameters. Although we believe it is reasonable to assume that investors give more weight to salient returns, the degree of overweighting is hard to pin down and likely varies across investors. We therefore find it reassuring that the ability of ST to predict cross-sectional variation in returns depends mainly on the overweighting of salient past returns per se and less on the precise extent to which salience distorts decision weights.

7.2 Subsample Analyses

The Fama-MacBeth results presented thus far are obtained from regressions estimated over the full sample of NYSE/AMEX/NASDAQ stocks and the full sample period from 1931 to 2015. We now check whether our results also hold in various subsamples. We first estimate the regressions over two subperiods, January 1931 to June 1963 and July 1963 to December 2015. We break the sample in July 1963 because this is the starting point of many empirical asset pricing papers. The results in Table 11 show that ST has significant return-forecasting power in both subperiods.

To ensure that our results are not driven by microstructure effects, we next repeat the regressions for three subsets of stocks. The first excludes from the sample all stocks with a price less than \$5 (column 4), the second all NASDAQ stocks (column 5), and the third the top decile of illiquid stocks based on the Amihud (2002) measure (column 6). The evidence in Table 11 confirms that the salience effect is not confined to penny stocks, NASDAQ stocks, or illiquid stocks.

7.3 Alternative Construction of Control Variables

The existing literature uses various window lengths to compute some of the control variables included in the Fama-MacBeth regressions. Here, we check whether our results are robust to variations in the time horizon used to construct the prospect theory and skewness variables.

We begin by computing the prospect theory (TK) variable of Barberis, Mukherjee, and Wang (2016) over a one-month window of daily returns instead of a five-year window of monthly returns. This alternative definition allows for a more direct comparison between TK and our one-month salience measure ST. In line with the theoretical differences between prospect theory and salience theory outlined in Section 2.1, the Fama-MacBeth results in column 1 of Table 12 show that the one-month TK variable does not subsume the predictive power of ST.

We next construct skewness, coskewness, and idiosyncratic skewness measures using a monthly window of daily returns instead of the annual window used in the main analysis. We also compute a measure of expected idiosyncratic skewness (EISKEW) using five years of monthly returns following the method of Boyer, Mitton, and Vorkink (2010). We find that the predictive ability of ST is robust to controlling for these alternative skewness measures.

8 Conclusion

We provide empirical evidence on the asset pricing implications of a model in which investors focus their limited cognitive resources on a stock's most salient returns, defined as those that stand out relative to the returns of other stocks in the market. In our framework, investors overweight these salient past returns when forming expectations about future returns. Because of the salience-induced distortions in attention allocation, investors are attracted to stocks with salient upsides. The excess demand for these stocks leads to overvaluation and lower future returns, whereas stocks with salient downsides become undervalued and earn higher subsequent returns.

We find strong empirical support for these predictions in the cross-section of U.S. stocks. Univariate portfolio analyses show that stocks whose highest daily returns in the past month are salient earn lower returns in the next month than stocks whose lowest past returns stand out. The return difference between the high- and low-salience deciles is economically large and statistically significant and cannot be explained by standard risk factors. Bivariate portfolio analyses and firm-level Fama-MacBeth regressions confirm that the negative cross-sectional relation between salience and future stock returns remains significant after controlling for a long list of firm characteristics.

Consistent with a behavioral interpretation of our results, we find that the predictive power of salience for future returns is stronger among stocks with greater limits to arbitrage and higher retail ownership. Our evidence further shows that the salience effect is larger during periods of high investor sentiment when unsophisticated investors are more likely to enter the market. We also find support for the prediction that salience-induced mispricing arises because returns on other stocks in the market distort investors' perception of a stock's future return distribution.

Although our evidence is consistent with salience theory, salience and other theories of decision making need not be mutually exclusive. For instance, elements from prospect theory, such as loss aversion, can be readily incorporated into the salience model. Experiments like those conducted by Mormann and Frydman (2016) can be helpful in testing the mechanism that generates context-dependent shifts in risk preferences in each of these models. Examining the pricing implications of salience theory for other assets, such as options, provides another fruitful avenue for future work.

References

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

——— , and H. Mendelson, 1987, Trading mechanisms and stock returns: An empirical investigation, *Journal of Finance* 42, 533–553.

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

Antoniou, C., J. Doukas, and A. Subrahmanyam, 2016, Investor sentiment, beta, and the cost of equity capital, *Management Science* 62, 347–367.

Asparouhova, E., H. Bessembinder, and I. Kalcheva, 2013, Noisy prices and inference regarding returns, *Journal of Finance* 68, 665–714.

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

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

Barber, B., and T. Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer, 2015, X-CAPM: An extrapolative capital asset pricing model, *Journal of Financial Economics* 115, 1–24.

Barberis, N., and M. Huang, 2001, Mental accounting, loss aversion, and individual stock returns, *Journal of Finance* 56, 1247–1292.

——— , 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

——— , and T. Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1–53.

Barberis, N., M. Huang, and R. Thaler, 2006, Individual preferences, monetary gambles, and stock market participation: A case for narrow framing, *American Economic Review* 96, 1069–1090.

Barberis, N., A. Mukherjee, and B. Wang, 2016, Prospect theory and stock returns: An empirical test, *Review of Financial Studies* 29, 3108–3139.

Benartzi, S., and R. Thaler, 1995, Myopic loss aversion and the equity premium puzzle, *Quarterly Journal of Economics* 110, 73–92.

Bordalo, P., N. Gennaioli, and A. Shleifer, 2012, Salience theory of choice under risk, *Quarterly Journal of Economics* 127, 1243–1285.

——— , 2013a, Salience and asset prices, *American Economic Review: Papers & Proceedings* 103, 623–628.

——— , 2013b, Salience and consumer choice, *Journal of Political Economy* 121, 803–843.

——— , 2015a, Memory, attention and choice, Working Paper, University of Oxford.

——— , 2015b, Salience theory of judicial decisions, *Journal of Legal Studies* 44, S7–S33.

Boyer, B., T. Mitton, and K. Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.

Boyer, B., and K. Vorkink, 2014, Stock options as lotteries, *Journal of Finance* 69, 1485–1527.

Brav, A., J. Heaton, and S. Li, 2010, The limits of the limits of arbitrage, *Review of Finance* 14, 157–187.

Camerer, C., 1995, Individual decision making, in J. Kagel, and A. Roth, ed.: *Handbook of Experimental Economics* . pp. 587–703 (Princeton University Press: Princeton, N.J.).

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

Chetty, R., A. Looney, and K. Kroft, 2009, Salience and taxation: Theory and evidence, *American Economic Review* 99, 1145–1177.

Choi, D., D. Lou, and A. Mukherjee, 2016, The effect of superstar firms on college major choice, Working Paper, Chinese University of Hong Kong.

Cohen, L., and A. Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.

Conrad, J., R. Dittmar, and E. Ghysels, 2013, Ex-ante skewness and expected stock returns, *Journal of Finance* 68, 85–124.

Conrad, J., N. Kapadia, and Y. Xing, 2014, Death and jackpot: Why do individual investors hold overpriced stocks?, *Journal of Financial Economics* 113, 455–475.

Da, Z., J. Engelberg, and P. Gao, 2011, In search of attention, *Journal of Finance* 66, 1461–1499.

Da, Z., U. Gurun, and M. Warachka, 2014, Frog in the pan: Continuous information and momentum, *Review of Financial Studies* 27, 2171–2218.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

DellaVigna, S., and J. Pollet, 2009, Investor inattention and Friday earnings announcements, *Journal of Finance* 64, 709–749.

Dessaint, O., and A. Matray, 2016, Do managers overreact to salient risks? Evidence from hurricane strikes, *Journal of Financial Economics*, Forthcoming.

Eraker, B., and M. Ready, 2015, Do investors overpay for stocks with lotter-like payoffs? An examination of the returns on OTC stocks?, *Journal of Financial Economics* 115, 486–504.

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

——— , 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fama, E., and J. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 71, 607–636.

Gervais, S., R. Kaniel, and D. Mingelgrin, 2001, The high-volume return premium, *Journal of Finance* 56, 877–919.

Greenwood, R., and A. Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Hartzmark, S., 2015, The worst, the best, ignoring all the rest: The rank effect and trading behavior, *Review of Financial Studies* 28, 1024–1059.

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

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

Hirshleifer, D., 2015, Behavioral finance, *Annual Review of Financial Economics* 7, 133–159.

———, S. Lim, and S. Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance* 64, 2289–2325.

Ingersoll, J., and L. Jin, 2013, Realization utility with reference-dependent preferences, *Review of Financial Studies* 26, 723–767.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

Kahneman, D., 1973, *Attention and Effort* (Prentice Hall: Englewood Cliffs, NJ).

———, 2003, Maps of bounded rationality: Psychology for behavioral economics, *American Economic Review* 93, 1449–1475.

———, and A. Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

Lehmann, B., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1–28.

Miller, E., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151–1168.

Mitton, T., and K. Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255–1288.

Mormann, M., and C. Frydman, 2016, The role of salience and attention in choice under risk: An experimental investigation, Working Paper, University of Miami.

Moskowitz, T., and M. Grinblatt, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.

Nagel, S., 2005, Short sales, institutional investors, and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

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

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

Peng, L., and W. Xiong, 2006, Investor attention, overconfidence, and category learning, *Journal of Financial Economics* 80, 563–602.

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

Subrahmanyam, A., 2005, Distinguishing between rationales for short-horizon predictability of stock returns, *Financial Review* 40, 11–35.

Taylor, S., and S. Thompson, 1982, Stalking the elusive vividness effect, *Psychological Review* 89, 155–181.

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

Zhang, X., 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105–136.

Table 1: **Returns on ST-Sorted Portfolios**

This table reports raw excess returns and alphas for decile portfolios formed on the salience theory variable ST. At the end of each month, stocks are sorted into decile portfolios based on their ST value, constructed using the procedure explained in the text. Portfolio 1 (10) contains the stocks with the lowest (highest) ST value. Portfolios are rebalanced at the end of the next month and their realized return is recorded. For each decile portfolio, we report the equal-weighted (EW) and value-weighted (VW) average monthly excess return, four-factor alpha obtained from the Carhart (1997) model, and five-factor alpha obtained from the Carhart (1997) model augmented with the Amihud (2002) liquidity factor. The last row reports differences in monthly returns and alphas between decile 10 (high ST) and decile 1 (low ST). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015.

	EW Portfolios			VW Portfolios		
Decile	Raw Return	4F Alpha	5F Alpha	Raw Return	4F Alpha	5F Alpha
Low ST	1.73	0.85	0.82	0.89	0.14	0.11
2	1.11	0.32	0.31	0.82	0.18	0.16
3	0.95	0.22	0.21	0.75	0.14	0.14
4	0.90	0.17	0.16	0.73	0.11	0.11
5	0.87	0.14	0.14	0.65	0.03	0.04
6	0.92	0.15	0.16	0.64	0.00	0.00
7	0.86	0.05	0.06	0.71	0.03	0.03
8	0.73	-0.16	-0.15	0.57	-0.20	-0.20
9	0.57	-0.35	-0.34	0.65	-0.17	-0.18
High ST	-0.18	-1.22	-1.22	0.10	-0.89	-0.90
High-Low	-1.91	-2.07	-2.04	-0.80	-1.03	-1.01
t-stat	(-13.13)	(-14.37)	(-14.41)	(-5.24)	(-6.20)	(-6.13)

Table 2: **Characteristics of ST-Sorted Portfolios**

This table reports characteristics for decile portfolios formed on the basis of ST. At the end of each month, we sort stocks into decile portfolios based on their ST value and compute the equal-weighted (panel A) and value-weighted (panel B) averages of various firm characteristics. The table reports the time-series averages of these monthly characteristics for each ST decile. ME is the log of a firm's market capitalization (in \$). BM is the book-to-market ratio. MOM is the cumulative stock return over the 11 months prior to the current month. ILLIQ is the Amihud (2002) illiquidity measure, averaged over all trading days in a month. BETA is the market beta, estimated from a regression of daily excess stock returns on the daily excess market return over a one-month window. IVOL is the idiosyncratic volatility obtained from these monthly regressions. REV is the stock return over the previous month. MAX (MIN) is a stock's maximum (minimum) daily return within a month, as in Bali, Cakici, and Whitelaw (2011). TK is the prospect theory value of a stock, constructed using a five-year window of monthly returns, as in Barberis, Mukherjee, and Wang (2016). SKEW is the skewness of daily stock returns, calculated over a one-year window. COSKEW is the coskewness of daily stock returns with daily market returns over a one-year window, calculated following Harvey and Siddique (2000). ISKEW is the skewness of the residuals from a Fama and French (1993) three-factor model regression estimated over a one-year window of daily returns, as in Boyer, Mitton, and Vorkink (2010). DBETA is the downside beta, estimated from a regression of daily excess stock returns on the daily excess market return over a one-year window, using only days on which the market return was below the average daily market return during that year, as in Ang, Chen, and Xing (2006). All variables are winsorized at the 1st and 99th percentiles. The sample period is January 1931 to December 2015.

	Panel A: EW Portfolios														
Decile	ST	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
Low ST	−3.26	17.03	1.63	11.48	12.83	1.07	2.91	−10.98	5.38	−8.87	−0.07	0.26	−4.95	0.49	1.09
2	−1.46	17.73	1.24	13.17	6.16	0.88	2.15	−5.21	4.52	−5.86	−0.06	0.29	−3.97	0.46	0.96
3	−0.79	18.03	1.15	13.37	5.07	0.79	1.87	−2.69	4.22	−4.79	−0.06	0.30	−3.45	0.46	0.88
4	−0.30	18.09	1.11	13.66	4.59	0.76	1.77	−1.08	4.24	−4.25	−0.06	0.32	−3.37	0.51	0.85
5	0.11	17.95	1.12	13.01	4.48	0.75	1.74	0.14	4.49	−3.97	−0.06	0.33	−3.43	0.56	0.85
6	0.56	18.03	1.14	14.19	5.54	0.87	2.02	0.93	5.61	−4.39	−0.06	0.34	−3.82	0.54	0.93
7	1.08	17.91	1.19	14.40	6.78	0.97	2.25	2.62	6.65	−4.69	−0.06	0.37	−3.97	0.58	0.99
8	1.73	17.70	1.29	14.32	9.51	1.10	2.62	4.83	8.10	−5.18	−0.06	0.41	−4.49	0.65	1.06
9	2.76	17.33	1.43	13.03	13.61	1.25	3.21	7.89	10.50	−6.04	−0.07	0.46	−5.16	0.77	1.13
High ST	6.26	16.68	1.84	7.12	27.99	1.55	4.51	14.91	16.89	−8.70	−0.07	0.51	−5.91	0.97	1.21

	Panel B: VW Portfolios														
Decile	ST	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
Low ST	−2.76	19.73	0.82	19.30	1.54	1.28	2.18	−8.89	4.06	−7.24	−0.05	0.09	−1.98	0.13	1.18
2	−1.42	20.39	0.74	16.70	0.55	1.02	1.55	−4.23	3.32	−4.59	−0.05	0.15	−0.80	0.21	1.03
3	−0.78	20.66	0.73	15.20	0.37	0.88	1.28	−1.84	2.98	−3.48	−0.05	0.16	−0.48	0.24	0.92
4	−0.30	20.76	0.74	15.43	0.30	0.82	1.18	−0.02	2.92	−2.95	−0.05	0.18	−0.38	0.27	0.88
5	0.12	20.74	0.71	16.05	0.30	0.85	1.20	1.03	3.19	−2.82	−0.05	0.19	−0.51	0.30	0.89
6	0.55	20.72	0.72	16.51	0.38	0.95	1.30	2.37	3.75	−2.91	−0.05	0.20	−0.52	0.31	0.95
7	1.06	20.59	0.72	17.33	0.51	1.08	1.49	4.28	4.57	−3.13	−0.05	0.24	−0.56	0.37	1.03
8	1.71	20.32	0.74	18.78	0.95	1.25	1.82	6.54	5.88	−3.57	−0.05	0.30	−0.88	0.45	1.13
9	2.68	19.87	0.77	20.40	1.94	1.46	2.34	9.88	8.05	−4.25	−0.04	0.41	−1.55	0.60	1.24
High ST	5.30	19.07	0.88	20.50	5.89	1.73	3.40	17.25	13.18	−5.83	−0.04	0.54	−3.01	0.87	1.34

Table 3: **Returns on Double-Sorted ST Portfolios**

This table reports raw excess returns and alphas for double-sorted portfolios formed on the basis of a control variable and a stock's ST value. Stocks are first sorted into decile portfolios based on one of the 14 control variables defined in the caption of Table 2 (ME, BM, MOM, ILLIQ, BETA, IVOL, REV, MAX, MIN, TK, SKEW, COSKEW, ISKEW, and DBETA). Next, within each decile portfolio, stocks are further sorted into deciles based on ST, such that a total of 100 portfolios is created. All portfolios are rebalanced at the end of the next month and their realized return is recorded. Returns of the ST deciles are then averaged across the different deciles of the control variable. Portfolio 1 (10) corresponds to the average return on the 10 portfolios that contain the stocks with the lowest (highest) ST value. For each of the ST-sorted decile portfolios, we report the equal-weighted (EW, panel A) and value-weighted (VW, panel B) average monthly excess return. The bottom rows report differences in monthly returns between decile 10 (high ST) and decile 1 (low ST) and in the four-factor alphas obtained from the Carhart (1997) model and five-factor alphas obtained from the Carhart (1997) model augmented with the Amihud (2002) liquidity factor. Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015.

	Panel A: EW Portfolios													
Decile	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
Low ST	1.63	1.69	1.77	1.56	1.65	1.62	1.09	1.73	1.54	1.85	1.73	1.73	1.77	1.75
2	1.25	1.24	1.19	1.30	1.14	1.24	0.95	1.14	1.23	1.30	1.17	1.13	1.19	1.18
3	1.09	1.07	1.03	1.13	1.01	1.04	0.96	0.89	1.14	1.18	1.00	1.04	1.01	0.99
4	1.01	1.01	0.97	1.01	0.97	1.00	0.91	0.95	1.03	1.05	0.92	0.90	0.96	0.92
5	0.96	0.97	0.92	0.98	0.86	0.83	0.95	0.76	0.96	1.02	0.89	0.90	0.93	0.96
6	0.93	0.95	0.87	0.91	0.86	0.78	0.87	0.73	0.89	0.97	0.88	0.87	0.91	0.89
7	0.80	0.93	0.78	0.82	0.77	0.66	0.86	0.69	0.77	0.96	0.83	0.82	0.85	0.81
8	0.65	0.69	0.66	0.60	0.74	0.54	0.82	0.63	0.61	0.83	0.67	0.70	0.66	0.76
9	0.35	0.52	0.47	0.44	0.55	0.50	0.84	0.55	0.39	0.69	0.51	0.52	0.48	0.57
High ST	-0.15	-0.09	0.17	-0.06	0.04	0.35	0.48	0.42	-0.03	0.27	-0.01	-0.03	0.00	-0.05
H-L Return	-1.78	-1.78	-1.60	-1.62	-1.61	-1.28	-0.61	-1.31	-1.57	-1.58	-1.74	-1.76	-1.77	-1.79
t-stat	(-13.23)	(-13.50)	(-11.69)	(-12.98)	(-13.14)	(-10.79)	(-5.66)	(-8.78)	(-13.32)	(-13.16)	(-13.85)	(-13.89)	(-14.33)	(-13.77)
H-L 4F α	-1.86	-1.89	-1.81	-1.72	-1.73	-1.28	-0.70	-1.25	-1.70	-1.72	-1.85	-1.88	-1.85	-1.89
t-stat	(-14.67)	(-14.63)	(-13.31)	(-14.38)	(-13.66)	-(11.64)	(-8.51)	(-9.71)	(-15.71)	(-15.05)	(-14.51)	(-14.81)	(-14.98)	(-14.55)
H-L 5F α	-1.84	-1.86	-1.78	-1.69	-1.71	-1.24	-0.70	-1.22	-1.68	-1.69	-1.82	-1.85	-1.83	-1.86
t-stat	(-14.90)	(-14.83)	(-13.37)	(-14.38)	(-13.65)	(-11.70)	(-8.53)	(-9.66)	(-16.08)	-(14.98)	(-14.44)	(-14.71)	(-14.79)	(-14.51)

Table 3: **Returns on Double-Sorted ST Portfolios (continued)**

	Panel B: VW Portfolios													
Decile	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
Low ST	1.57	1.27	1.01	1.36	1.00	1.01	0.85	0.94	1.08	1.23	1.10	1.07	1.18	1.09
2	1.23	1.04	0.94	1.12	0.87	0.84	0.83	0.75	0.93	1.11	0.91	0.91	0.98	0.89
3	1.05	0.96	0.84	1.00	0.82	0.70	0.83	0.61	0.78	0.95	0.84	0.86	0.83	0.80
4	1.00	0.88	0.67	0.85	0.75	0.68	0.81	0.79	0.75	0.85	0.75	0.71	0.78	0.76
5	0.93	0.86	0.65	0.83	0.69	0.55	0.80	0.66	0.66	0.78	0.72	0.76	0.68	0.76
6	0.89	0.80	0.59	0.75	0.71	0.64	0.80	0.58	0.63	0.74	0.73	0.67	0.76	0.72
7	0.78	0.79	0.45	0.65	0.62	0.57	0.73	0.56	0.61	0.74	0.70	0.67	0.75	0.60
8	0.62	0.68	0.42	0.43	0.59	0.46	0.77	0.52	0.44	0.67	0.56	0.63	0.57	0.66
9	0.33	0.54	0.30	0.27	0.51	0.39	0.66	0.47	0.37	0.65	0.52	0.52	0.52	0.51
High ST	-0.19	0.09	0.13	-0.21	0.16	0.36	0.45	0.36	-0.01	0.35	0.13	0.17	0.18	0.11
H-L Return	-1.76	-1.17	-0.87	-1.58	-0.84	-0.65	-0.41	-0.59	-1.07	-0.88	-0.97	-0.90	-1.00	-0.98
t-stat	(-13.07)	(-9.27)	(-7.13)	(-12.75)	(-6.86)	(-5.63)	(-3.02)	(-3.87)	(-8.02)	(-7.69)	(-7.95)	(-7.21)	(-7.46)	(-8.41)
H-L 4F α	-1.84	-1.28	-1.10	-1.72	-1.01	-0.67	-0.51	-0.57	-1.20	-1.04	-1.11	-1.03	-1.10	-1.11
t-stat	(-14.50)	(-10.04)	(-8.90)	(-14.08)	(-7.58)	(-5.90)	(-4.35)	(-4.59)	(-9.21)	(-9.27)	(-8.61)	(-8.18)	(-7.90)	(-9.11)
H-L 5F α	-1.82	-1.26	-1.07	-1.70	-0.99	-0.63	-0.52	-0.54	-1.19	-1.02	-1.08	-1.00	-1.10	-1.08
t-stat	(-14.74)	(-10.11)	(-8.95)	(-14.00)	(-7.50)	(-5.88)	(-4.41)	(-4.46)	(-9.32)	(-9.15)	(-8.63)	(-8.11)	(-7.85)	(-9.06)

Table 4: **Firm-Level Fama-MacBeth Regressions**

This table reports Fama-MacBeth estimates for the cross-section of stocks listed on the NYSE, AMEX, and NASDAQ. Monthly cross-sectional regressions are run of excess stock returns in month $t+1$ on a firm's ST value and a vector of control variables W_{it} measured at the end of the previous month t:

$$r_{it+1} = \lambda_{0t} + \lambda_{1t} ST_{it} + \lambda_{2t} W_{it} + v_{it}.$$

In the most general regression specification in column 10, W_{it} includes the firm characteristics market beta (BETA), size (ME), book-to-market (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), maximum daily return (MAX), minimum daily return (MIN), idiosyncratic volatility (IVOL), prospect theory value (TK), skewness (SKEW), coskewness (COSKEW), idiosyncratic skewness (ISKEW), and downside beta (DBETA). Reported coefficients on BETA, ME, BM, MOM, ILLIQ, SKEW, COSKEW, ISKEW, and DBETA are multiplied by 100. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ST	-0.18	-0.19	-0.09	-0.09	-0.09	-0.07	-0.07	-0.06	-0.06	-0.07
	(-13.57)	(-16.34)	(-6.85)	(-7.10)	(-6.83)	(-5.94)	(-4.93)	(-4.71)	(-4.86)	(-5.25)
BETA		0.02	0.01	0.01	0.04	0.04	0.05	0.05	0.05	0.05
		(0.69)	(0.45)	(0.41)	(1.63)	(1.64)	(2.15)	(2.03)	(2.05)	(2.66)
ME		-0.12	-0.08	-0.07	-0.11	-0.13	-0.12	-0.13	-0.13	-0.13
		(-2.83)	(-1.99)	(-1.92)	(-3.21)	(-4.62)	(-4.74)	(-5.03)	(-5.06)	(-4.98)
BM		0.24	0.21	0.18	0.17	0.16	0.13	0.13	0.13	0.13
		(5.64)	(5.05)	(4.64)	(4.57)	(4.45)	(3.93)	(3.93)	(3.99)	(4.04)
MOM		0.90	0.91	0.97	0.95	0.94	0.94	0.96	0.99	0.99
		(4.92)	(4.56)	(4.85)	(4.73)	(4.53)	(5.21)	(5.28)	(5.45)	(5.60)
REV			-0.06	-0.06	-0.06	-0.06	-0.07	-0.07	-0.07	-0.07
			(-9.85)	(-10.17)	(-11.86)	(-11.88)	(-13.09)	(-13.13)	(-13.29)	(-14.57)
ILLIQ				0.03	0.04	0.04	0.03	0.03	0.03	0.03
				(2.48)	(3.56)	(3.82)	(3.11)	(2.97)	(3.00)	(3.07)
MAX					-0.01	-0.00	-0.00	0.00	-0.01	-0.01
					(-1.01)	(-0.56)	(-0.04)	(0.23)	(-0.70)	(-1.03)
MIN					0.07	0.06	0.06	0.06	0.07	0.07
					(6.75)	(5.99)	(6.33)	(6.35)	(6.50)	(6.58)
IVOL						-0.16	-0.11	-0.11	-0.11	-0.11
						(-3.10)	(-2.06)	(-2.12)	(-2.12)	(-2.37)
TK							-0.04	-0.04	-0.04	-0.04
							(-2.94)	(-2.99)	(-2.93)	(-3.03)
SKEW								-0.11	-0.01	0.01
								(-2.90)	(-0.22)	(0.29)
COSKEW								0.00	0.00	0.00
								(0.42)	(0.19)	(0.40)
ISKEW									-0.09	-0.10
									(-3.47)	(-4.39)
DBETA										-0.01
										(-0.10)

Table 5: **Fama-MacBeth Regressions: Limits to Arbitrage**

This table reports results of a Fama-MacBeth analysis of the impact of limits to arbitrage on the relation between a stock's salience theory value and future return. Monthly cross-sectional regressions are run of excess stock returns in month $t+1$ on a firm's ST value and on interaction terms between ST and proxies for limits to arbitrage constructed at the end of the previous month t:

$$r_{it+1} = \lambda_{0t} + \lambda_{1t} ST_{it} + \lambda_{2t} ST_{it} \times Z_{it} + \lambda_{3t} Z_{it} + \lambda_{4t} W_{it} + \upsilon_{it},$$

where Z_{it} is one of five firm-level proxies for limits to arbitrage: size (ME), Amihud illiquidity (ILLIQ), idiosyncratic volatility (IVOL), residual institutional ownership (IO), and residual analyst coverage (NOA). Residual IO and NOA are the residuals from a regression of each of these variables on firm size and time dummies. W_{it} is a vector of controls that includes the full set of firm characteristics defined in Table 2. The coefficients on ME, ILLIQ, IO, NOA, and the interaction terms involving these variables are multiplied by 100. Coefficients on the control variables are not reported for brevity. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015, except for the regression specifications that include institutional ownership and analyst coverage, which start in 1980 and 1976, respectively, due to data availability.

	(1)	(2)	(3)	(4)	(5)
ST	-0.82	-0.02	0.09	-0.07	-0.08
	(-11.70)	(-1.78)	(4.54)	(-4.94)	(-6.34)
ST×ME	4.66				
	(10.86)				
ST×ILLIQ		-0.83			
		(-3.64)			
ST×IVOL			-3.91		
			(-5.05)		
ST×IO				1.43	
				(3.22)	
ST×NOA					1.73
					(1.88)
ME	-0.15	-0.13	-0.13	-0.08	-0.12
	(-5.41)	(-4.85)	(-4.88)	(-2.51)	(-3.79)
ILLIQ	0.03	0.04	0.03	0.02	0.02
	(3.70)	(3.88)	(3.68)	(2.48)	(2.87)
IVOL	-0.19	-0.19	-0.16	-0.12	-0.17
	(-3.97)	(-4.07)	(-3.33)	(-1.65)	(-2.67)
IO				0.10	
				(4.00)	
NOA					0.20
					(5.87)
Controls	YES	YES	YES	YES	YES

Table 6: **Returns on ST-Sorted Portfolios During Periods of High and Low Sentiment**

This table reports excess returns and alphas for ST-sorted decile portfolios following periods of high and low sentiment. High-sentiment (low-sentiment) months are defined as those in which the investor sentiment index of Baker and Wurgler (2006) in the previous month is above (below) the median value for the sample period. At the end of each month, stocks are sorted into decile portfolios based on their ST value. Portfolio 1 (10) contains the stocks with the lowest (highest) ST value. Portfolios are rebalanced at the end of the next month and their return is recorded. For each of the ST-sorted decile portfolios, we report the equal-weighted (EW) and value-weighted (VW) average monthly excess return. The last rows show the differences in monthly returns between decile 10 (high ST) and decile 1 (low ST) and in the five-factor alphas obtained from the Carhart (1997) model augmented with the Amihud (2002) liquidity factor. Differences in returns and alphas on the high-low ST portfolio between periods of high and low sentiment are shown in bold. Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is July 1965 to December 2015 as the sentiment index starts in July 1965.

	EW Portfolios			VW Portfolios		
Decile	High Sent	Low Sent	High-Low Sent	High Sent	Low Sent	High-Low Sent
Low ST	0.54	1.55	-1.01	0.30	0.67	-0.38
2	0.51	0.95	-0.45	0.66	0.66	0.00
3	0.57	0.83	-0.26	0.78	0.51	0.28
4	0.50	0.83	-0.32	0.72	0.50	0.22
5	0.44	0.76	-0.32	0.60	0.49	0.11
6	0.54	0.83	-0.29	0.52	0.43	0.09
7	0.36	0.81	-0.45	0.46	0.61	-0.15
8	0.10	0.78	-0.68	0.30	0.74	-0.44
9	-0.37	0.60	-0.97	0.13	0.75	-0.62
High ST	-1.62	-0.09	-1.53	-0.70	0.50	-1.21
H-L Return	-2.16	-1.63	**-0.53**	-1.00	-0.17	**-0.83**
t-stat	(-8.90)	(-8.12)	**(-1.98)**	(-3.90)	(-0.77)	**(-2.41)**
H-L 5F α	-2.27	-1.85	**-0.42**	-1.07	-0.40	**-0.67**
t-stat	(-8.70)	(-8.76)	**(-1.73)**	(-3.97)	(-1.73)	**(-2.10)**

Table 7: **Fama-MacBeth Regressions for Alternative Choice Contexts**

This table reports results of Fama-MacBeth regressions that explore the impact of the context in which stocks are evaluated on the relation between the salience theory variable ST and future stock returns. Column 1 reports results for the original ST specification, in which the context is described by the equal-weighted CRSP index. Columns 2 to 5 correspond to several variations in choice context. Specifically, salience in Equation (8) is computed by adopting as context the value-weighted CRSP index (column 2), equal-weighted industry portfolio (column 3), value-weighted industry portfolio (column 4), or risk-free asset (column 5) or by defining no choice context at all (column 6). Industry portfolios are created by classifying stocks into 48 industries as in Fama and French (1997). For each ST measure, monthly cross-sectional regressions are run of excess stock returns in month $t+1$ on ST and a set of controls constructed at the end of the previous month t. All independent variables are standardized to have mean zero and standard deviation 1, and reported coefficients are multiplied by 100. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015.

Context	Market	Market	Industry	Industry	Risk-free	None
Index Weighting	EW	VW	EW	VW	-	-
Specification	(1)	(2)	(3)	(4)	(5)	(6)
ST	-0.23	-0.23	-0.42	-0.41	-0.14	-0.12
	(-5.25)	(-4.96)	(-12.02)	(-11.72)	(-3.26)	(-2.71)
BETA	0.13	0.14	0.14	0.14	0.14	0.14
	(2.66)	(2.66)	(2.74)	(2.79)	(2.81)	(2.79)
ME	-0.29	-0.29	-0.28	-0.28	-0.28	-0.29
	(-4.98)	(-4.92)	(-4.85)	(-4.91)	(-4.94)	(-4.95)
BM	0.30	0.30	0.30	0.30	0.30	0.30
	(4.04)	(3.99)	(4.08)	(4.08)	(4.00)	(4.00)
MOM	0.58	0.57	0.57	0.58	0.58	0.58
	(5.60)	(5.48)	(5.60)	(5.58)	(5.51)	(5.55)
REV	-1.03	-1.04	-0.97	-0.99	-1.05	-1.06
	(-14.57)	(-14.49)	(-13.73)	(-13.99)	(-14.77)	(-14.85)
ILLIQ	2.55	2.49	2.43	2.50	2.49	2.48
	(3.07)	(3.01)	(3.00)	(3.02)	(3.04)	(3.04)
MAX	-0.08	-0.08	-0.02	-0.02	-0.04	-0.08
	(-1.03)	(-1.02)	(-0.28)	(-0.27)	(-0.56)	(-0.98)
MIN	0.39	0.37	0.56	0.54	0.35	0.33
	(6.58)	(6.22)	(8.63)	(8.45)	(5.71)	(5.38)
IVOL	-0.19	-0.18	-0.11	-0.12	-0.18	-0.18
	(-2.37)	(-2.31)	(-1.39)	(-1.47)	(-2.25)	(-2.31)
TK	-0.14	-0.14	-0.13	-0.14	-0.14	-0.14
	(-3.03)	(-3.10)	(-2.98)	(-3.07)	(-3.06)	(-3.06)
SKEW	0.01	0.01	0.02	0.02	0.01	0.01
	(0.29)	(0.29)	(0.88)	(0.66)	(0.30)	(0.27)
COSKEW	0.06	0.07	0.02	0.04	0.07	0.07
	(0.40)	(0.46)	(0.14)	(0.28)	(0.49)	(0.48)
ISKEW	-0.12	-0.12	-0.13	-0.13	-0.12	-0.12
	(-4.39)	(-4.40)	(-4.59)	(-4.42)	(-4.35)	(-4.34)
DBETA	-0.01	-0.01	-0.01	-0.00	-0.01	-0.01
	(-0.10)	(-0.11)	(-0.13)	(-0.07)	(-0.12)	(-0.13)

Table 8: **Salience and Reversal**

This table reports results of univariate portfolio analyses and firm-level Fama-MacBeth analyses of the relation between a stock's salience theory (ST) value and future return, using various controls for short-term reversal. Panel A reports raw excess returns and six-factor alphas for portfolios formed by sorting stocks into deciles based on their ST value. In the first four columns the salience of a stock's returns is defined with respect to the equal-weighted CRSP index. In the last four columns salience is measured by contrasting stock returns with the equal-weighted industry return. All portfolios are rebalanced at the end of the next month and their realized return is recorded. Portfolio 1 (10) corresponds to the average return on the 10 portfolios that contain the stocks with the lowest (highest) ST value. For each of the ST-sorted decile portfolios, we report the equal-weighted (EW) and value-weighted (VW) average monthly excess return and six-factor alpha obtained from the Carhart (1997) model augmented with the Amihud (2002) liquidity factor and the short-term reversal factor available from Kenneth French's data library. The last row reports differences in monthly returns and alphas between decile 10 (high ST) and decile 1 (low ST). Panels B to D report results of Fama-MacBeth regressions of stock returns in month $t+1$ on alternative ST measures defined on different state spaces and a set of control variables constructed at the end of the previous month t. In Panel B we consider ST measures computed using monthly, quarterly, and annual windows of daily returns and annual and five-year windows of monthly returns. In Panel C all ST variables are lagged by one month, i.e, returns in month $t+1$ are regressed on ST variables constructed with data up to month $t-1$. In Panel D ST is constructed using daily open-to-open returns in month t, which are available from July 1992 onwards. For comparison, we also report results over the same subperiod for the baseline ST specification based on a monthly window of daily close-to-close returns. In each regression, we include the full set of control variables defined in Table 2. In the regressions with five-year ST, we further include the cumulative return from the start of month $t-60$ to the end of month $t-13$ to control for long-term reversal. Coefficients on the control variables are not reported for brevity. All independent variables are standardized to have mean zero and standard deviation 1, and reported coefficients are multiplied by 100. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015 in Panels A to C and July 1992 to December 2015 in Panel D.

Panel A: Returns on ST-Sorted Portfolios - Controlling for Short-Term Reversal Factor								
	Context: Market				Context: Industry			
	EW		VW		EW		VW	
	Raw Return	6F Alpha	Raw Return	6F Alpha	Raw Return	6F Alpha	Raw Return	6F Alpha
Low ST	1.73	0.58	0.89	0.07	1.78	0.70	0.97	0.03
2	1.11	0.17	0.82	0.17	1.24	0.31	0.94	0.16
3	0.95	0.10	0.75	0.23	1.05	0.20	0.88	0.17
4	0.90	0.09	0.73	0.17	0.96	0.20	0.73	0.14
5	0.87	0.06	0.65	0.07	0.82	0.09	0.63	0.01
6	0.92	0.16	0.64	-0.01	0.85	0.06	0.60	-0.03
7	0.86	0.08	0.71	-0.09	0.80	-0.03	0.58	-0.09
8	0.73	-0.02	0.57	-0.14	0.72	-0.10	0.60	-0.08
9	0.57	-0.30	0.65	-0.34	0.50	-0.39	0.52	-0.21
High ST	-0.18	-1.19	0.10	-0.67	-0.22	-1.13	-0.05	-0.85
High-Low	-1.91	-1.77	-0.80	-0.74	-2.00	-1.83	-1.02	-0.88
t-stat	(-13.13)	(-12.59)	(-5.24)	(-4.43)	(-14.49)	(-14.38)	(-5.91)	(-4.86)

Table 8: **Salience and Reversal (continued)**

Panel B: Fama-MacBeth Regressions										
Context	Market	Market	Market	Market	Market	Industry	Industry	Industry	Industry	Industry
Window	Month	Quarter	Year	Year	5-Year	Month	Quarter	Year	Year	5-Year
Frequency	Daily	Daily	Daily	Monthly	Monthly	Daily	Daily	Daily	Monthly	Monthly
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ST_t	-0.23	-0.19	-0.17	-0.14	-0.12	-0.42	-0.28	-0.23	-0.29	-0.15
	(-5.25)	(-4.44)	(-3.72)	(-4.26)	(-2.52)	(-12.02)	(-6.78)	(-5.60)	(-8.54)	(-4.11)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel C: Fama-MacBeth Regressions - Additional ST Lag										
Context	Market	Market	Market	Market	Market	Industry	Industry	Industry	Industry	Industry
Window	Month	Quarter	Year	Year	5-Year	Month	Quarter	Year	Year	5-Year
Frequency	Daily	Daily	Daily	Monthly	Monthly	Daily	Daily	Daily	Monthly	Monthly
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ST_{t-1}	-0.22	-0.17	-0.15	-0.12	-0.10	-0.25	-0.20	-0.19	-0.22	-0.13
	(-8.14)	(-4.56)	(-3.57)	(-3.92)	(-2.18)	(-8.37)	(-5.52)	(-5.07)	(-6.70)	(-3.30)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel D: Fama-MacBeth Regressions - ST Constructed using Open-to-Open Returns				
Context	Market	Market	Industry	Industry
Window	Month	Month	Month	Month
Frequency	Daily	Daily	Daily	Daily
Returns	Opening	Closing	Opening	Closing
Specification	(1)	(2)	(3)	(4)
ST_t	0.05	-0.35	-0.05	-0.52
	(0.92)	(-4.78)	(-1.36)	(-6.09)
Controls	YES	YES	YES	YES

Table 9: **Salience and Investor Attention**

This table reports results of bivariate portfolio analyses and firm-level Fama-MacBeth analyses of the relation between a stock's salience theory value and future return, controlling for measures of investor attention. We consider four proxies for attention: (i) the maximum absolute abnormal daily return within each month (MAX |ABN DRET|); (ii) the absolute abnormal monthly return (|ABN RET|); (iii) the maximum abnormal daily volume within each month (MAX ABN DVOL); and (iv) the abnormal monthly trading volume (ABN VOL). Abnormal returns are calculated as the difference between stock returns and market returns. Abnormal daily (monthly) trading volume is calculated as a stock's daily (monthly) dollar trading volume divided by its average daily (monthly) dollar volume over the twelve months prior to month t. Panel A reports raw excess returns for portfolios formed by first sorting stocks into decile portfolios based on one of the four attention proxies and, within each of the attention portfolios, further dividing the stocks into deciles based on the salience theory measure ST. All portfolios are rebalanced at the end of the next month and their realized return is recorded. Returns of the ST deciles are then averaged across the different deciles of the attention variable. Portfolio 1 (10) corresponds to the average return on the 10 portfolios that contain the stocks with the lowest (highest) ST value. For each of the ST-sorted decile portfolios, we report the equal-weighted (EW) and value-weighted (VW) average monthly excess return. The last rows show the differences in monthly returns between decile 10 (high ST) and decile 1 (low ST) and in five-factor alphas obtained from the Carhart (1997) model augmented with the Amihud (2002) liquidity factor. Panel B reports results of the Fama-MacBeth analyses. Column 1 corresponds to regression specification (10) in Table 4 that does not include attention proxies. Results in the next five columns correspond to regressions of excess stock returns in month $t+1$ on a firm's ST value and the attention proxies constructed at the end of the previous month t. In the last three columns, ST is split into positive and negative parts. ST POS equals ST when ST is positive, and zero otherwise. ST NEG equals -ST when ST is negative, and zero otherwise. In each regression, we include the full set of control variables defined in Table 2. The coefficients on MAX ABN DVOL and ABN VOL are multiplied by 100. Coefficients on the control variables are not reported for brevity. All t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015.

Panel A: Returns on Portfolios Sorted on Attention and ST								
	MAX |ABN DRET|		|ABN RET|		MAX ABN DVOL		ABN VOL	
Decile	EW	VW	EW	VW	EW	VW	EW	VW
Low ST	1.70	1.11	1.35	0.97	1.74	1.02	1.75	1.10
2	1.25	0.83	1.19	0.92	1.20	0.98	1.26	0.95
3	1.03	0.70	1.05	0.81	1.06	0.86	1.10	0.84
4	0.91	0.66	1.02	0.81	0.97	0.75	0.91	0.70
5	0.80	0.61	0.88	0.69	0.91	0.70	0.93	0.64
6	0.70	0.56	0.82	0.59	0.83	0.67	0.89	0.59
7	0.70	0.55	0.73	0.56	0.86	0.69	0.85	0.65
8	0.55	0.42	0.72	0.66	0.72	0.58	0.73	0.50
9	0.45	0.38	0.61	0.64	0.55	0.58	0.56	0.38
High ST	0.33	0.29	0.26	0.34	-0.08	0.10	-0.10	-0.13
High-Low Return	-1.37	-0.82	-1.09	-0.62	-1.82	-0.92	-1.85	-1.24
t-stat	(-10.72)	(-5.82)	(-10.49)	(-5.46)	(-14.27)	(-7.60)	(-14.13)	(-9.70)
High-Low 5F α	-1.35	-0.82	-1.21	-0.80	-1.90	-1.06	-1.93	-1.34
t-stat	(-12.31)	(-6.36)	(-13.11)	(-7.25)	(-15.20)	(-8.60)	(-14.99)	(-11.15)

Table 9: **Salience and Investor Attention (continued)**

	Panel B: Fama-MacBeth Regressions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ST	-0.07	-0.07	-0.06	-0.06	-0.06	-0.06			
	(-5.25)	(-5.26)	(-4.35)	(-4.71)	(-4.82)	(-4.67)			
MAX |ABN DRET|		-0.04				-0.06			
		(-3.03)				(-4.94)			
|ABN RET|			0.02			0.01			
			(5.47)			(3.48)			
MAX ABN DVOL				0.04		-0.03			
				(6.89)		(-4.51)			
ABN VOL					0.50	0.61			
					(11.98)	(13.17)			
ST POS							-0.04		-0.04
							(-2.20)		(-2.27)
ST NEG								0.09	0.09
								(4.75)	(4.85)
Other Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: **Fama-MacBeth Regressions for Alternative Salience Specifications**

This table reports results of Fama-MacBeth regressions of future stock returns on alternative specifications of the salience theory measure ST. Column 1 corresponds to the original ST variable based on the salience function in Equation (8), using the baseline parameter values from Bordalo, Gennaioli, and Shleifer (2012), $\theta = 0.1$ and $\delta = 0.7$. Column 2 reports results for the alternative specification of the salience function in Equation (11) applied to gross returns. Columns 3 and 4 are based on alternative choices of the θ parameter in Equation (8). Columns 5 and 6 report results for ST measures constructed using different values of δ in Equation (3). For each ST measure, monthly cross-sectional regressions are run of excess stock returns in month $t+1$ on ST and a set of controls constructed at the end of the previous month t. All independent variables are standardized to have mean zero and standard deviation 1, and reported coefficients are multiplied by 100. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015.

Returns	Net	Gross	Net	Net	Net	Net
θ	0.1	-	0.05	0.15	0.1	0.1
δ	0.7	0.7	0.7	0.7	0.6	0.8
Specification	(1)	(2)	(3)	(4)	(5)	(6)
ST	-0.23	-0.29	-0.23	-0.23	-0.21	-0.24
	(-5.25)	(-7.24)	(-5.09)	(-5.08)	(-4.83)	(-5.21)
BETA	0.13	0.14	0.14	0.14	0.14	0.14
	(2.66)	(2.68)	(2.63)	(2.68)	(2.66)	(2.67)
ME	-0.29	-0.29	-0.29	-0.29	-0.29	-0.28
	(-4.98)	(-4.97)	(-4.94)	(-4.90)	(-4.93)	(-4.92)
BM	0.30	0.30	0.30	0.30	0.30	0.30
	(4.04)	(3.94)	(3.96)	(3.98)	(3.98)	(3.98)
MOM	0.58	0.55	0.55	0.55	0.55	0.55
	(5.60)	(5.45)	(5.42)	(5.39)	(5.39)	(5.38)
REV	-1.03	-1.01	-1.03	-1.03	-1.05	-1.01
	(-14.57)	(-14.35)	(-14.65)	(-14.49)	(-14.86)	(-14.02)
ILLIQ	2.55	2.36	2.48	2.48	2.46	2.49
	(3.07)	(2.87)	(3.02)	(3.01)	(3.01)	(3.02)
MAX	-0.08	-0.13	-0.08	-0.08	-0.07	-0.06
	(-1.03)	(-1.63)	(-1.05)	(-1.02)	(-0.95)	(-0.84)
MIN	0.39	0.44	0.37	0.38	0.37	0.36
	(6.58)	(7.37)	(6.04)	(6.29)	(6.38)	(6.17)
IVOL	-0.19	-0.17	-0.19	-0.18	-0.19	-0.18
	(-2.37)	(-2.06)	(-2.43)	(-2.27)	(-2.39)	(-2.30)
TK	-0.14	-0.14	-0.14	-0.14	-0.14	-0.14
	(-3.03)	(-3.11)	(-3.09)	(-3.09)	(-3.09)	(-3.09)
SKEW	0.01	0.01	0.01	0.01	0.01	0.01
	(0.29)	(0.27)	(0.32)	(0.30)	(0.28)	(0.29)
COSKEW	0.06	0.05	0.06	0.07	0.06	0.06
	(0.40)	(0.36)	(0.42)	(0.48)	(0.40)	(0.41)
ISKEW	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
	(-4.39)	(-4.30)	(-4.44)	(-4.40)	(-4.41)	(-4.39)
DBETA	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-0.10)	(-0.11)	(-0.10)	(-0.11)	(-0.10)	(-0.10)

Table 11: **Fama-MacBeth Regressions: Subsample Analyses**

This table reports results of Fama-MacBeth regressions of future stock returns on the salience theory variable ST estimated over various subsamples. Results in column 1 are for the baseline Fama-MacBeth regression estimated over the full sample of NYSE/AMEX/NASDAQ stocks and the full sample period from January 1931 to December 2015. Columns 2 and 3 report results for two subperiods, January 1931 to June 1963 and July 1963 to December 2015. The analysis in column 4 excludes all penny stocks, defined as stocks with a price less than $5. Column 5 excludes all NASDAQ stocks and column 6 the top decile of illiquid stocks in each month, based on the Amihud (2002) illiquidity measure. For each subsample, monthly cross-sectional regressions are run of excess stock returns in month $t+1$ on ST and a set of control variables constructed at the end of the previous month t. All independent variables are standardized to have mean zero and standard deviation 1, and reported coefficients are multiplied by 100. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags.

Sample Period	Full	1931-1963/06	1963/07-2015	Full	Full	Full
Penny stocks(< $5)	Included	Included	Included	Excluded	Included	Included
NASDAQ stocks	Included	Included	Included	Included	Excluded	Included
Illiquid stocks	Included	Included	Included	Included	Included	Excluded
Specification	(1)	(2)	(3)	(4)	(5)	(6)
ST	-0.23	-0.22	-0.23	-0.18	-0.21	-0.20
	(-5.25)	(-2.66)	(-4.58)	(-3.98)	(-4.17)	(-4.36)
BETA	0.13	0.23	0.08	0.10	0.17	0.13
	(2.66)	(2.03)	(1.87)	(2.36)	(3.04)	(2.50)
ME	-0.29	-0.37	-0.23	-0.29	-0.31	-0.32
	(-4.98)	(-3.67)	(-3.36)	(-5.46)	(-5.35)	(-5.77)
BM	0.30	0.11	0.42	0.27	0.25	0.28
	(4.04)	(1.29)	(3.96)	(3.23)	(3.31)	(3.36)
MOM	0.58	0.54	0.56	0.62	0.54	0.59
	(5.60)	(2.44)	(6.00)	(7.16)	(5.04)	(5.85)
REV	-1.03	-1.34	-0.84	-0.79	-0.99	-0.82
	(-14.57)	(-11.42)	(-10.77)	(-12.59)	(-12.73)	(-12.60)
ILLIQ	2.55	1.39	3.15	-0.59	2.58	3.12
	(3.07)	(1.93)	(2.52)	(-0.65)	(2.73)	(0.87)
MAX	-0.08	-0.03	-0.04	-0.07	-0.03	-0.04
	(-1.03)	(-0.24)	(-0.48)	(-0.88)	(-0.33)	(-0.61)
MIN	0.39	0.19	0.49	0.43	0.36	0.50
	(6.58)	(1.62)	(9.04)	(7.06)	(5.52)	(8.63)
IVOL	-0.19	-0.20	-0.17	-0.14	-0.20	-0.13
	(-2.37)	(-1.39)	(-1.91)	(-1.92)	(-2.35)	(-1.67)
TK	-0.14	-0.12	-0.16	-0.12	-0.12	-0.13
	(-3.03)	(-1.55)	(-2.96)	(-2.89)	(-2.69)	(-2.98)
SKEW	0.01	0.01	0.01	0.01	0.02	0.02
	(0.29)	(0.28)	(0.30)	(0.29)	(0.52)	(0.50)
COSKEW	0.06	0.22	-0.02	0.19	0.15	0.12
	(0.40)	(0.70)	(-0.30)	(1.27)	(0.91)	(0.64)
ISKEW	-0.12	-0.12	-0.11	-0.12	-0.12	-0.13
	(-4.39)	(-4.42)	(-4.10)	(-4.31)	(-4.36)	(-4.74)
DBETA	-0.01	-0.08	0.02	0.02	0.03	0.01
	(-0.10)	(-0.70)	(0.36)	(0.30)	(0.45)	(0.14)

Table 12: **Fama-MacBeth Regressions: Alternative Definitions of Control Variables**

This table reports results of Fama-MacBeth regressions of future stock returns on the salience theory variable ST and alternative specifications of the control variables. For comparison, column 1 repeats the estimation results for the regression specification that includes the original control variables. In column 2, the prospect theory variable TK is computed over a one-month window of daily returns. Columns 3 to 5 correspond to regression specifications that include measures of skewness, coskewness, and idiosyncratic skewness calculated over a one-month window of daily returns. Expected idiosyncratic skewness (EISKEW) in column 6 is calculated using five years of monthly data following the approach of Boyer, Mitton, and Vorkink (2010). In each regression specification, all other control variables are defined as in the caption of Table 2. All independent variables are standardized to have mean zero and standard deviation 1, and reported coefficients are multiplied by 100. The *t*-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is January 1931 to December 2015, except for the regression that includes EISKEW, which starts in January 1988 due to data availability.

Control variable	Original	TK	SKEW	COSKEW	ISKEW	EISKEW
Window	-	Month	Month	Month	Month	5-Year
Specification	(1)	(2)	(3)	(4)	(5)	(6)
ST	-0.23	-0.24	-0.24	-0.23	-0.25	-0.26
	(-5.25)	(-5.29)	(-5.24)	(-4.97)	(-5.39)	(-5.37)
BETA	0.13	0.13	0.14	0.14	0.14	0.06
	(2.66)	(2.60)	(2.77)	(2.46)	(2.67)	(1.19)
ME	-0.29	-0.29	-0.29	-0.29	-0.29	-0.23
	(-4.98)	(-4.93)	(-4.95)	(-5.05)	(-4.92)	(-2.96)
BM	0.30	0.34	0.30	0.30	0.30	0.42
	(4.04)	(4.23)	(4.01)	(3.99)	(3.96)	(3.72)
MOM	0.58	0.51	0.58	0.58	0.55	0.54
	(5.60)	(4.60)	(5.60)	(5.55)	(5.36)	(4.64)
REV	-1.03	-0.94	-1.02	-1.02	-1.02	-0.90
	(-14.57)	(-10.52)	(-14.16)	(-14.45)	(-14.17)	(-10.24)
ILLIQ	2.55	2.50	2.58	2.59	2.50	1.29
	(3.07)	(3.01)	(3.09)	(3.15)	(3.05)	(2.96)
MAX	-0.08	0.14	-0.01	-0.04	-0.03	0.14
	(-1.03)	(1.64)	(-0.11)	(-0.62)	(-0.35)	(1.70)
MIN	0.39	0.48	0.34	0.38	0.31	0.50
	(6.58)	(6.71)	(4.68)	(6.21)	(5.20)	(8.73)
IVOL	-0.19	-0.23	-0.19	-0.18	-0.19	-0.17
	(-2.37)	(-2.66)	(-2.41)	(-2.24)	(-2.43)	(-1.94)
TK	-0.14	-0.19	-0.13	-0.14	-0.14	-0.15
	(-3.03)	(-2.01)	(-2.97)	(-3.04)	(-3.06)	(-2.38)
SKEW	0.01	0.01	0.08	0.01	-0.07	0.00
	(0.29)	(0.32)	(2.71)	(0.39)	(-3.20)	(0.02)
COSKEW	0.06	0.05	0.03	-0.09	0.07	-0.02
	(0.40)	(0.39)	(0.22)	(-0.49)	(0.55)	(-0.22)
ISKEW	-0.12	-0.12	-0.12	-0.12	0.09	-0.10
	(-4.39)	(-4.40)	(-5.29)	(-4.32)	(4.77)	(-2.85)
DBETA	-0.01	-0.03	-0.01	-0.02	-0.02	-0.01
	(-0.10)	(-0.44)	(-0.17)	(-0.33)	(-0.30)	(-0.07)
EISKEW						-0.06
						(-0.62)