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Salience theory and stock prices: Empirical evidence☆

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ABSTRACT

We present 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 empirical support for these predictions in the cross section of US stocks. The salience effect is stronger among stocks with greater limits to arbitrage and during high-sentiment periods. Our results are not explained by common risk factors, return reversals, lottery demand, and attention-grabbing news events.

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). Bordalo et al. (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 nonsalient 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 implications of salience theory for the cross section of stock returns. We test the predictions of the salience-based asset pricing model of Bordalo et al. (2013a), in which the demand for risky assets is influenced by the salience of their payoffs in different states of the world. A key premise of this model is that choices are made in context, which means that investors evaluate each asset by comparing its payoffs with those of the available alternatives. This context dependence is motivated by experimental evidence that shows that preferences depend on the context in which choices are presented (Camerer, 1995). A stock's most salient payoffs are therefore those that stand out relative to the payoffs of other stocks. Because investors

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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.

Following Barberis et al. (2016), we assume that investors mentally represent a stock by the distribution of its past returns, viewed as a proxy for its future return distribution. 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 beliefs about future returns by extrapolating salience-weighted daily returns over the past month. Following BGS (2013a), we assume that investors evaluate a stock in the context of all available stocks in the market, i.e., the entire Center for Research in Security Prices (CRSP) universe. We therefore measure the salience of a stock's daily return by comparing it to the return on the equal-weighted CRSP index.[1] Intuitively, when forming return beliefs, salient-thinking 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 a stock's salience theory value ST 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 stock's upside potential, thereby effectively acting as risk seekers and accepting a negative risk premium. When a stock's lowest past returns stand out, ST is negative and investors overemphasize its downside risk. 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 institutional investors and therefore more prone to salient thinking.

Our empirical results provide strong support for the predictions of the salience model in the cross section of US stocks with a price above \$5. First, we show that stocks with salient upsides earn lower returns over the next month 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 over the sample period 1931–2015. The average return for the zero-cost strategy that buys high-ST stocks and shorts low-ST stocks ranges from −1.28% per month for the equal-weighted (EW) portfolio to −0.60% per month for the value-weighted (VW) portfolio. These return differences are not explained by standard market, size, value, momentum, and liquidity factors, with five-factor alphas ranging from −1.44% (EW) to −0.80% (VW) per month. The salience effect also cannot be explained by the investment and profitability factors in the Fama and French (2018) six-factor model, with six-factor alphas of −1.32% (EW) and −0.64% (VW).

Second, we find a stronger cross-sectional relation between ST and future returns among stocks with higher retail ownership and greater limits to arbitrage. The predictive power of ST is also stronger during high-sentiment periods when unsophisticated investors are more likely to participate in the market. Further analyses show that the salience effect is much weaker when ST is constructed using open-to-open instead of close-to-close returns, consistent with our conjecture that retail investors make trading decisions based on the close-to-close returns they observe. Since a change in the return definition does not alter the fundamentals of the firm, this finding is hard to reconcile with a risk-based explanation for the salience effect. Collectively, these results lend support to a behavioral interpretation of the relation between the ST measure and future returns.

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, including various proxies for lottery demand. Further tests confirm that the relation between ST and future returns is also robust to alternative parameterizations of the function used to measure the salience of a stock's return and to alternative choices of the market index with respect to which salience is defined.

We explore two alternative explanations for the negative relation between ST and future returns. We consider first the possibility that ST picks up short-term (one-month) return reversals. A common behavioral explanation for one-month return reversals is over-extrapolation of information about past returns when forming beliefs about future returns (Subrahmanyam, 2005; Greenwood and Shleifer, 2014). In contrast to models of return

[1] We use the equal-weighted index because BGS (2012) demonstrate that equal weighting preserves the key properties of the function used to measure salience. Our empirical results are robust to using the value-weighted index.

extrapolation, salience theory predicts that investors' reaction to information is context dependent. Investors overweight a stock's past returns only if they stand out relative to the market return and underweight past returns that are nonsalient. Salience thus determines which returns investors extrapolate when forming return beliefs. Salience-induced distortions in expectations therefore do not arise from overreaction to past returns but from biases in the perception of these returns. ST, defined as the difference between salience-weighted and equal-weighted returns, captures the effect of these distortions on return expectations.

We perform a variety of tests to differentiate the salience effect from one-month return reversal. First, we show that the salience effect remains significant when we skip an extra month between the construction of ST and the measurement of subsequent returns and when we compute ST over horizons longer than one month at which stock returns do not exhibit reversal. Second, we augment the five-factor model with a short-term reversal factor and show that alphas of the high-low ST portfolio remain large and significant after controlling for the reversal factor, ranging from 102 basis points (bps) (t-statistic $= -10.35$) per month for the EW portfolio to 32 bps (t-statistic $= -2.24$) for the VW portfolio. Third, we include a stock's past one-month return in bivariate portfolio sorts and in Fama-MacBeth regressions. Again we find that although controlling for reversal reduces the magnitude of the salience effect, it remains sizable and significant. In the bivariate sorts, the average return spread between the high- and low-ST deciles is 48 bps per month with equal weighting and 22 bps with value weighting. In terms of five-factor alpha, the spreads range from 60 bps (EW) to 30 bps (VW) per month, or equivalently, 7.2% to 3.6% per year. In the Fama-MacBeth regressions, the coefficient on ST is statistically significant at the 1% level (t-statistic $= -6.80$) after controlling for a stock's past one-month return and 13 other firm characteristics. The slope is also economically significant: a two standard deviation increase in ST predicts a decrease in next month's stock return of 26 bps.

As a further robustness check, we repeat our main analysis using stock returns calculated from quote midpoints and show that the salience effect is not attributable to microstructure effects such as the bid-ask bounce. In contrast, short-term reversal weakens by 40% with midpoint returns. Consistent with these results, we also detect diverging time trends in the magnitude of the salience and reversal effects. In line with prior literature, we find that return reversal has weakened substantially in recent decades with improvements in market liquidity. In contrast, the salience effect remains strong and statistically significant. Finally, we show that the return associated with the salience effect is earned entirely intraday, whereas the return on a short-term reversal strategy is earned overnight. These opposite patterns in intraday and overnight returns provide further evidence that the salience and reversal effects are distinct phenomena with different origins.

Another 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 thus 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. Finally, we show that our results are also not attributable to a specific firm-level attention-grabbing event (earnings news) or to market-wide news events that may distract investors.

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 et al. (2001) demonstrate that prospect theory can account for the equity premium puzzle. In the cross section, Barberis et al. (2016) show that investors overvalue stocks whose historical return distributions are appealing under prospect theory. We contribute to this literature by providing empirical evidence on the cross-sectional asset 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 (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009) and that returns are predictable when investors neglect specific types of information (Cohen and Frazzini, 2008; Da et al., 2014a). Prior work also finds support for the prediction of the attention hypothesis of Barber and Odean (2008) that 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 (Da et al., 2011; Hartzmark, 2015). Our work complements these papers by examining the influence of salience on the actual choice between stocks in the consideration set in the final stage of the decision process.

Finally, our paper contributes to the rapidly expanding literature on the impact of salience on individual decision-making. Recent papers demonstrate that salience can account for evidence on decision-making in a wide range of fields including consumer choice (Bordalo et al., 2013b), judicial decisions (Bordalo et al., 2015), tax effects (Chetty et al., 2009), corporate policy choices (Dessaint and Matray, 2017), and education choice (Choi et al., 2019). To the best of our knowledge, our paper is the first to provide empirical evidence on the asset pricing implications of the salience theory of BGS (2012).

The paper proceeds as follows. Section 2 summarizes the asset pricing implications of salience theory. Section 3 describes the data. Section 4 presents empirical evidence on the relation between our salience theory measure and future stock returns. Section 5 elaborates on the differences between salience and reversal. Section 6 examines whether our findings can be explained by the attention hypothesis. Section 7 reports additional robustness tests. Section 8 concludes.

2. Salience theory and stock prices

2.1. Salience theory

A key premise of salience theory 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 salience theory 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 CPT 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, without requiring a value function that is concave for gains and convex for losses.

The differences between probability weighting in salience theory 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 salience theory, context dependence implies that the low-probability state is nonsalient 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 provided by Frydman and Mormann (2018) confirms the prediction of salience theory that risk taking is affected by the correlation structure between lotteries.

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.[2]

The salience function in Eq. (1) satisfies three conditions: (i) ordering, (ii) diminishing sensitivity, and (iii) reflection. Ordering implies that the salience of state s for lottery i increases in the distance between its payoff and the average lottery payoff in state s. Diminishing sensitivity implies that salience decreases as absolute payoff levels rise uniformly for all lotteries, i.e., differences in payoffs are perceived less intensely when they occur at higher payoff levels. Reflection implies that salience only depends on the magnitude of payoffs, not on their sign. Reflecting gains into losses does not change the salience of a state because perception is sensitive to differences in absolute values.

Given the salience function in Eq. (1), the salient thinker ranks each lottery's payoffs and replaces the objective state probabilities with lottery-specific decision weights, given by

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

where $\tilde{\pi}_{is}$ denotes the salience-weighted subjective state probability, π_s is the objective probability, and ω_{is} is the salience weight defined as

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

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 Eq. (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 nonsalient 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] The parameter 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 $\bar{x}_s$.

2.3. Salience-based asset pricing model

The salience-based asset pricing model proposed by Bordalo et al. (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.[3] 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 investor trades an amount α_i of each stock i to maximize expected utility:

$$\max_{\{\alpha_i\}} \quad u(c_0) + \mathbb{E}[\omega_{is} u(c_{1,s})], \tag{4}$$

$$\text{s.t.} \quad c_0 = w_0 - \sum_i^N \alpha_i p_i,$$

$$c_{1,s} = \sum_i^N (\alpha_i + 1) x_{is},$$

where $\alpha_i + 1$ is the endowment of asset i plus any additional amount bought or sold by the investor.

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[4]

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

The first term on the right-hand side of Eq. (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 the 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 $\mathbb{E}[x_{is}]$.

Dividing both sides of Eq. (6) by p_i yields the implications of salience theory for expected returns:[5]

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

where ST_i stands for stock i's salience theory value. Eq. (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.

In summary, salience theory predicts that stocks with salient upsides attract excess demand, which leads to overvaluation and high returns during the period of salience-driven buying, followed by low returns in the next period when the overpricing is corrected. Conversely, because stocks with salient downsides are unattractive to investors, they earn low returns during the period of salience-driven selling, followed by high returns in the next period when the underpricing is corrected. In our empirical analysis we test the prediction of salience theory for returns in the correction period.[6]

2.4. Construction of salience theory 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 et al. (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 objective 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

[3] 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 et al. (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 toward stocks with salient upsides and away from stocks with salient downsides. The predictions for expected returns derived from this model coincide with the predictions derived from the consumption-based model of BGS (2013a).

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

[5] Specifically, after some rearrangements, we obtain $\mathbb{E}[R_{is}] = 1 - \text{cov}[\omega_{is}, R_{is}]$, where $R_{is} = x_{is}/p_i$ denotes the gross return on stock i. Defining net returns as $r_{is} = R_{is} - 1$ yields Eq. (7).

[6] We do not examine the contemporaneous effect of ST on returns during the period of salience-driven trading because that would lead to an endogeneity problem, as our measure of ST is based on the returns in that period.

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]

Salience theory suggests that the context with respect to which salience is defined coincides with the choice set. Following BGS (2013a), we assume that investors' choice set consists of all available stocks in the market, i.e., investors evaluate a stock in the context of all other stocks. The salience of a stock's return on day s (r_{is}) then depends on its distance from the average return across all stocks in the market on that day ($\bar{r}_s$), i.e., Eq. (1) becomes

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

We measure salience by comparing stock returns to the market return instead of making pairwise comparisons between individual stock returns because salience 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. The CRSP index is an appropriate benchmark in our setting because we seek to explain the cross section of returns on all stocks in the CRSP universe, thus implicitly assuming that the choice set consists of all stocks in the market.[9]

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 Eq. (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.

Eq. (8) implies that salience is determined by an individual stock's return relative to the market return, independent of investor-specific characteristics. This form of "narrow framing" implies that a stock return salient to one investor will be salient to all other investors.[10] 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 Eq. (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 theory measure ST has an intuitive interpretation. To see this, write ST as

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

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. Eq. (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, thereby 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 firms listed on the NYSE, Amex, and Nasdaq. The sample period is January 1926 to December 2015. We exclude stocks with a closing price less than \$5 per share at the end of the previous month to mitigate market microstructure effects. 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 are 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

[7] Strictly speaking, given the daily state space, $\mathbb{E}[r_{is}]$ in Eq. (7) is the expected daily return in the next period. We predict monthly rather than daily returns to facilitate the comparison of our results with those 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. In Section 5.1, we show that our results are robust to alternative choices of window length and return frequency.

[9] When performing subsample analyses that restrict the choice set, we redefine the benchmark accordingly to comport with theory. For instance, when restricting the analysis to large-cap stocks, we measure salience by comparing a stock's return to the equal-weighted average return on large-cap stocks.

[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).

[11] The benchmark here is the expected return computed using objective probabilities, i.e., the EW past return. We do not claim that the use of past returns to forecast future returns is rational. Given the low serial correlation in returns, predicting 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 to form beliefs about the future, ST captures the effect of salience distortions on return expectations.

value of equity. Following Fama and French (2008), we calculate book-to-market using accounting data from Compustat as of December of the previous year and exclude firms with negative book equity (BE). Because Compustat does not have book equity data for the first part of our sample period, we obtain BE data from Kenneth French's website for these early years.[12] Momentum (MOM) is measured as a stock's cumulative return over an 11-month period ending two 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 over the prior month.

We also account for different measures of risk. Market beta (BETA) is estimated from a regression 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 et al. (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).

Finally, we construct several measures of lottery demand. MAX (MIN) is a stock's maximum (minimum) daily return within a month, as in Bali et al. (2011). The prospect theory (TK) value of a stock is constructed using a five-year window of monthly returns, following the approach of Barberis et al. (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 et al. (2010). Following Bali et al. (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.[13]

4. Cross-sectional relation between salience and stock returns

4.1. Univariate portfolio sorts

We begin our empirical analysis with univariate portfolio sorts. At the end of each month t, we sort stocks into decile portfolios based on their salience theory value and calculate the EW and VW portfolio returns over the next month $t+1$. Table 1 reports for each portfolio the time-series average of the one-month-ahead excess portfolio return, the four-factor alpha obtained from the Carhart (1997) model, the five-factor alpha obtained from the Carhart (1997) model augmented with a liquidity factor,[14] and the six-factor alpha obtained from the Fama and French (2018) model that extends the Fama and French (2015) five-factor model with a momentum factor.[15] The last row reports monthly 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 return on the EW high-low ST portfolio is −1.28% per month, with a Newey and West (1987) t-statistic of −10.73. This return difference is not explained by market, size, value, momentum, and liquidity factors, with a five-factor alpha of −1.44% (t-statistic = −12.50). The salience effect also cannot be explained by the investment and profitability factors in the Fama and French (2018) six-factor model, with a six-factor alpha of −1.32% (t-statistic = −11.01).

The return spread between the highest and lowest ST deciles is also significant for 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 sizable, with a return spread of −0.60% per month (t-statistic = −4.08).[16] Again, we find no evidence that this return difference is driven by differences in factor exposures. Five- and six-factor alphas are large (−0.80% and −0.64%, respectively) and significant at the 1% level.

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 for the EW portfolios the time-series mean of the characteristics.[17] Stocks in the extreme ST

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

[13] Table A1 in the Online Appendix presents descriptive statistics for the stock characteristics used in our analysis. Panel A reports means, medians, and standard deviations, and panel B reports pairwise correlations.

[14] Following Pastor and Stambaugh (2003), we construct the liquidity factor as the VW return on a portfolio that goes long in the decile of stocks with highest liquidity betas and short in the decile of stocks with lowest betas. For each stock, we estimate its liquidity beta by running a regression of stock returns on the excess market return, SMB, HML, UMD, and innovations in aggregate liquidity, using the most recent five years of monthly data. As in Watanabe and Watanabe (2008), we compute innovations in aggregate liquidity by fitting an AR(2) model to the average Amihud (2002) illiquidity measure across all NYSE and Amex stocks with a price between $5 and $1,000.

[15] We collect data on the investment (CMA) and profitability (RMW) factors in the six-factor model from Kenneth French's data library for the period July 1963 to December 2015. For the period July 1940-June 1963, we retrieve monthly returns on the CMA and RMW factors constructed by Wahal (2019) from the JFE website (http://jfe.rochester.edu/data.htm). For the 1931–1940 period, we use the proxies for investment and profitability defined by Lochstoer and Tetlock (2020) and construct the CMA and RMW factors following Fama and French (2015).

[16] If we exclude stocks with prices below $1 a share instead of stocks with prices below $5, the salience effect increases to −1.80% with equal weighting and to −0.79% with value weighting (see Table A2 in the Online Appendix).

[17] We find similar patterns in the characteristics of the VW portfolios reported in Table A3 in the Online Appendix.

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 Section 2.4. Portfolio 1 (10) contains the stocks with the lowest (highest) ST value. All 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, five-factor alpha obtained from the Carhart (1997) model augmented with a liquidity factor, and six-factor alpha obtained from the Fama and French (2018) model that augments the Fama and French (2015) five-factor model with a momentum factor. The last row reports differences in 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 includes all common stocks listed on the NYSE, Amex, and Nasdaq with a price above $5 a share at portfolio formation. The sample period is January 1931 to December 2015.

	EW portfolios				VW portfolios			
Decile	Raw return	4F alpha	5F alpha	6F alpha	Raw return	4F alpha	5F alpha	6F alpha
Low ST	1.37	0.47	0.47	0.52	0.92	0.16	0.16	0.24
2	1.10	0.30	0.29	0.26	0.80	0.14	0.14	0.10
3	0.98	0.21	0.20	0.14	0.80	0.16	0.16	0.11
4	0.91	0.16	0.16	0.08	0.71	0.08	0.08	0.02
5	0.82	0.11	0.10	0.05	0.65	0.02	0.03	−0.03
6	0.89	0.09	0.09	0.04	0.65	−0.00	−0.00	−0.04
7	0.83	0.00	−0.00	−0.04	0.68	−0.01	−0.01	−0.01
8	0.72	−0.18	−0.19	−0.19	0.56	−0.20	−0.20	−0.19
9	0.56	−0.38	−0.39	−0.35	0.59	−0.24	−0.26	−0.15
High ST	0.09	−0.96	−0.97	−0.80	0.32	−0.63	−0.64	−0.40
High-low	−1.28	−1.43	−1.44	−1.32	−0.60	−0.79	−0.80	−0.64
	(−10.73)	(−12.70)	(−12.50)	(−11.01)	(−4.08)	(−5.24)	(−5.17)	(−3.91)

Table 2
Characteristics of ST-sorted portfolios.
This table reports characteristics for portfolios formed on the basis of the salience theory variable ST. At the end of each month, we sort stocks into decile portfolios based on their ST value and compute the equal-weighted average of various firm characteristics. The table reports for each ST decile the time-series average of these monthly characteristics. PRICE is the stock price (in $). ME is the log of a firm's market capitalization (in $). BM is the book-to-market ratio. Momentum (MOM) is a stock's cumulative return (in %) over the 11-month period ending two 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 (in %) obtained from this regression. REV is the stock return over the previous month (in %). MAX (MIN) is a stock's maximum (minimum) daily return within a month (in %), as in Bali et al. (2011). TK is the prospect theory value of a stock, constructed using a five-year window of monthly returns, as in Barberis et al. (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 et al. (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 et al. (2006). The last row presents the differences in average characteristics between the high- and low-ST deciles. All variables are winsorized at the 1st and 99th percentiles. The sample period is January 1931 to December 2015.

Decile	ST	PRICE	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
Low ST	−2.33	21.16	17.90	1.25	20.42	2.55	1.14	2.18	−8.82	4.56	−7.26	−0.07	0.23	−4.56	0.32	1.15
2	−1.20	26.45	18.34	1.08	17.11	1.82	0.91	1.66	−4.34	3.91	−5.01	−0.06	0.26	−3.61	0.35	0.98
3	−0.66	29.52	18.54	1.01	16.03	1.57	0.81	1.46	−2.10	3.66	−4.14	−0.06	0.27	−3.17	0.37	0.90
4	−0.24	31.24	18.62	0.99	16.49	1.47	0.78	1.38	−0.54	3.58	−3.69	−0.06	0.28	−3.13	0.41	0.87
5	0.12	31.25	18.61	0.98	17.08	1.44	0.80	1.40	0.35	3.87	−3.54	−0.06	0.30	−3.17	0.45	0.88
6	0.50	30.41	18.59	1.00	17.19	1.51	0.87	1.51	1.30	4.59	−3.64	−0.06	0.30	−3.42	0.44	0.93
7	0.93	29.03	18.50	1.01	17.98	1.65	0.97	1.67	2.79	5.39	−3.83	−0.06	0.32	−3.61	0.47	0.99
8	1.44	27.01	18.34	1.04	18.93	1.82	1.10	1.89	4.68	6.43	−4.12	−0.06	0.36	−4.06	0.52	1.08
9	2.16	24.19	18.11	1.10	20.16	2.09	1.26	2.23	7.41	8.06	−4.56	−0.06	0.42	−4.66	0.61	1.18
High ST	3.74	20.05	17.68	1.26	23.35	2.80	1.59	2.98	13.81	11.90	−5.56	−0.06	0.51	−5.52	0.82	1.32
High-low	6.07	−1.11	−0.22	0.01	2.93	0.25	0.45	0.80	22.63	7.34	1.70	0.01	0.28	−0.96	0.50	0.17

deciles are smaller than those in the other deciles. Their average market cap is about one-half that of the average stock in our sample but still sizable ($59.4 million for those in the low-ST decile and $47.7 million for the high-ST decile). Their average trading prices are also lower ($21.16 for the low-ST decile and $20.05 for the high-ST decile), but they are clearly not penny stocks. High- and low-ST stocks are also more illiquid and have higher market beta and idiosyncratic volatility. ST is positively associated with the past one-month stock return (REV) because an extreme positive (negative) daily stock return pushes up (down) one-month returns and is more likely to be salient than a modest daily stock return. Total and idiosyncratic skewness also increase with ST because positively (negatively) skewed stocks are more likely to have salient upsides (downsides).

To summarize, the univariate analysis provides preliminary evidence of a strong negative relation between a stock's ST value and its return over 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 common 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 create double-sorted portfolios to control for characteristics correlated with ST. Each month, we sort stocks into deciles based on one of the characteristics and, within each decile, further sort stocks into deciles based on ST so that a total of 100 portfolios is created. For each portfolio, we record the return over the next month and then compute the difference in returns between the high- and low-ST subdeciles within each decile of the characteristic. This allows us to examine if the salience effect is widespread or concentrated in stocks with extreme characteristics.

Table 3 provides the results of the bivariate sorts. Panel A presents the average high-low ST return spreads for EW portfolios and panel B for VW portfolios.[18] The bottom rows in each panel report the average of these return spreads across all deciles of the characteristic. We find that the salience effect remains economically large and statistically significant after accounting for each of the 14 characteristics. For the EW portfolios, the average return spread between the high- and low-ST deciles ranges from −0.48% to −1.22% per month and is significant at the 1% level in all cases. Differences in five-factor alphas range from −0.60% to −1.37% per month and are also all statistically significant. Importantly, the return spread is large and significant in nine out of ten market cap deciles, which indicates that the salience effect is not confined to the dusty corners of the market.

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 is not surprising given the (inverse) U-shaped relation between ST and the majority of characteristics (see Table 2). For instance, both high- and low-ST stocks tend to have higher idiosyncratic volatility. Because of their limited variation, these characteristics cannot explain the large return spread between the extreme ST decile portfolios. We observe a greater reduction in the magnitude of the average return and alpha spreads when we control for firm characteristics, such as REV and MAX, that do vary substantially between high- and low-ST stocks. Nevertheless, the spreads remain substantial and statistically significant. Accounting for reversal reduces the return spread to 48 bps per month with equal weighting and to 22 bps with value weighting. Five-factor alphas on the high-low ST portfolio are 60 bps (EW) and 30 bps (VW) per month. On an annual basis, this corresponds to alphas of 7.2% and 3.6%, which are still sizable.[19] Overall, the evidence in Table 3 suggests that the salience effect is widespread among stocks and robust to controlling for a large set of characteristics.

The positive correlation between ST and REV and MAX raises the question of whether salience theory helps to explain the reversal or MAX effect. We therefore also conduct bivariate portfolio analyses in which we first sort stocks into decile portfolios based on ST and then sort them into subdeciles based on REV or MAX. Panel A of Table A6 in the Online Appendix shows that controlling for ST reduces the return spread between the high- and low-REV deciles by one-third with equal weighting but has little impact on the spread for VW portfolios. The reversal effect remains economically large and statistically significant in both cases. Controlling for ST leads to a larger reduction in the magnitude of the MAX effect. The average return spread between the high- and low-MAX deciles drops by 60% for the EW portfolios and by 40% for the VW portfolios.[20]

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.

We estimate predictive cross-sectional regressions of excess stock returns in month $t+1$ on a firm's ST variable 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). We standardize each explanatory variable to have a mean of zero and a standard deviation of one in each month. Each regression coefficient therefore measures the effect of a one standard deviation change in the explanatory variable on next month's stock return.

Table 4 reports the results of the Fama-MacBeth regressions. Consistent with the results of the portfolio sorts, we

[18] Alpha spreads in Tables A4 and A5 in the Online Appendix are similar to the spreads in raw returns.

[19] We address the relation between the salience effect and short-term return reversal in detail in Section 5.

[20] Consistent with the results of the portfolio sorts, we find that controlling for ST has little effect on the magnitude of the coefficient on REV in predictive cross-sectional regressions (Table A6, panel B). In contrast, adding ST to the regression leads to a large drop in the coefficient estimate on MAX (Table A6, panel C).

Table 3
Return spreads on double-sorted ST portfolios.
This table reports monthly high-low ST return spreads 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. 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. For each decile of the control variable, we report the average spread in monthly returns between the high- and low-ST subdeciles. Portfolio 1 (10) in the table refers to the decile portfolio that contains the stocks with the lowest (highest) values of the control variable. Panel A presents monthly return spreads for equal-weighted portfolios, and panel B corresponds to value-weighted portfolios. The bottom rows report the number of deciles of the control variable for which the high-low ST return spread is positive or negative at the 10% significance level and the average of the return and alpha spreads across all deciles. Four-factor alphas are obtained from the Carhart (1997) model, and five-factor alphas are obtained from the Carhart (1997) model augmented with a liquidity factor. 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.

	Panel A: EW portfolios													
Decile	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
Low control	−2.59	−0.62	−2.65	0.03	−1.40	−0.22	−0.87	−0.70	−2.43	−1.91	−1.01	−1.70	−1.22	−1.61
	(−12.56)	(−3.60)	(−11.82)	(0.23)	(−6.51)	(−1.98)	(−3.38)	(−4.96)	(−9.53)	(−8.11)	(−6.63)	(−7.71)	(−7.04)	(−10.14)
2	−2.05	−0.75	−1.58	−0.18	−1.01	−0.38	−0.68	−0.76	−1.83	−1.42	−0.65	−1.14	−1.03	−1.21
	(−8.53)	(−4.68)	(−8.68)	(−1.11)	(−6.18)	(−3.40)	(−4.02)	(−5.57)	(−8.99)	(−8.22)	(−4.38)	(−6.28)	(−6.25)	(−6.83)
3	−1.46	−0.72	−1.41	−0.45	−0.69	−0.52	−0.75	−0.73	−1.57	−1.38	−0.98	−1.12	−0.85	−1.00
	(−8.07)	(−4.06)	(−6.71)	(−2.25)	(−4.51)	(−3.79)	(−4.67)	(−5.12)	(−6.51)	(−7.12)	(−5.25)	(−6.62)	(−5.76)	(−5.91)
4	−1.36	−0.79	−0.84	−0.65	−0.70	−0.90	−0.50	−0.72	−1.16	−1.33	−1.01	−1.12	−1.08	−0.94
	(−6.93)	(−4.69)	(−4.73)	(−3.61)	(−5.40)	(−7.34)	(−3.12)	(−4.69)	(−6.94)	(−7.67)	(−6.78)	(−7.31)	(−7.37)	(−6.14)
5	−1.14	−1.23	−0.68	−0.77	−1.02	−0.97	−0.36	−0.68	−1.14	−1.19	−1.55	−0.91	−1.38	−1.18
	(−5.43)	(−6.49)	(−5.45)	(−4.41)	(−6.93)	(−6.65)	(−2.15)	(−4.08)	(−6.85)	(−7.23)	(−8.96)	(−5.70)	(−8.27)	(−6.01)
6	−0.75	−1.26	−0.57	−0.83	−0.92	−0.78	−0.32	−0.81	−0.75	−0.98	−1.03	−1.14	−1.27	−1.18
	(−4.50)	(−7.09)	(−3.73)	(−4.28)	(−5.55)	(−5.17)	(−2.44)	(−5.14)	(−4.71)	(−6.75)	(−5.53)	(−7.32)	(−6.48)	(−5.37)
7	−0.74	−1.37	−0.74	−1.40	−0.95	−0.85	−0.21	−0.72	−0.56	−1.08	−1.17	−0.96	−1.09	−1.19
	(−4.67)	(−8.37)	(−4.44)	(−7.83)	(−7.15)	(−5.84)	(−1.29)	(−4.12)	(−4.22)	(−7.37)	(−6.25)	(−6.27)	(−6.60)	(−7.09)
8	−0.66	−1.58	−0.93	−1.67	−1.12	−0.92	−0.35	−0.38	−0.56	−0.82	−1.45	−0.99	−0.82	−1.14
	(−4.43)	(−10.89)	(−6.19)	(−9.01)	(−6.94)	(−5.19)	(−2.15)	(−2.27)	(−5.22)	(−4.57)	(−7.65)	(−6.45)	(−3.66)	(−6.26)
9	−0.38	−1.80	−0.71	−1.73	−1.11	−1.17	−0.15	−0.69	−0.50	−0.87	−1.40	−1.09	−1.29	−0.87
	(−2.49)	(−9.64)	(−4.93)	(−9.12)	(−6.40)	(−5.80)	(−0.86)	(−4.05)	(−4.51)	(−5.22)	(−7.44)	(−6.61)	(−6.83)	(−4.77)
High control	−0.18	−2.04	−1.07	−2.79	−1.56	−2.13	−0.61	−1.26	−0.27	−1.02	−1.44	−1.52	−2.18	−1.45
	(−1.47)	(−9.22)	(−5.55)	(−15.71)	(−7.69)	(−7.87)	(−2.91)	(−5.50)	(−2.35)	(−6.07)	(−7.89)	(−8.62)	(−9.30)	(−7.57)
# Sign. pos.	0	0	0	0	0	0	0	0	0	0	0	0	0	0
# Sign. neg.	9	10	10	8	10	10	8	10	10	10	10	10	10	10
Mean H-L ret	−1.13	−1.22	−1.12	−1.04	−1.05	−0.88	−0.48	−0.74	−1.08	−1.20	−1.17	−1.17	−1.22	−1.17
	(−10.37)	(−12.35)	(−10.93)	(−10.55)	(−11.63)	(−10.18)	(−4.82)	(−7.79)	(−11.57)	(−11.68)	(−12.05)	(−11.53)	(−12.20)	(−11.49)
Mean H-L 4F α	−1.26	−1.32	−1.30	−1.19	−1.18	−0.95	−0.58	−0.71	−1.23	−1.33	−1.28	−1.30	−1.31	−1.29
	(−11.86)	(−13.31)	(−13.37)	(−12.12)	(−12.68)	(−10.40)	(−6.71)	(−7.95)	(−15.10)	(−13.51)	(−13.73)	(−13.18)	(−13.26)	(−12.36)
Mean H-L 5F α	−1.30	−1.34	−1.32	−1.22	−1.21	−1.00	−0.60	−0.75	−1.25	−1.37	−1.32	−1.34	−1.34	−1.33
	(−12.11)	(−13.48)	(−13.45)	(−12.27)	(−12.89)	(−10.89)	(−6.84)	(−8.45)	(−15.19)	(−13.63)	(−14.04)	(−13.42)	(−13.42)	(−12.64)

(*continued on next page*)

Table 3 (*continued*)

Decile	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
	Panel B: VW portfolios													
Low control	−2.42	−0.66	−1.86	−0.01	−0.63	−0.27	−0.11	−0.45	−1.27	−1.01	−0.38	−0.92	−0.88	−1.30
	(−10.27)	(−2.97)	(−7.19)	(−0.10)	(−2.37)	(−2.09)	(−0.41)	(−2.81)	(−4.54)	(−3.52)	(−1.86)	(−3.62)	(−4.15)	(−5.76)
2	−2.05	−0.58	−1.15	−0.38	−0.62	−0.40	−0.56	−0.52	−1.08	−0.93	−0.10	−0.77	−0.44	−1.22
	(−8.42)	(−2.98)	(−4.79)	(−2.35)	(−3.32)	(−3.11)	(−2.34)	(−3.06)	(−4.04)	(−3.96)	(−0.50)	(−2.97)	(−2.01)	(−5.84)
3	−1.45	−0.41	−1.22	−0.60	−0.45	−0.21	−0.36	−0.32	−1.18	−0.89	−0.49	−0.68	−0.26	−0.73
	(−8.04)	(−1.87)	(−4.96)	(−3.00)	(−2.69)	(−1.32)	(−1.56)	(−1.84)	(−4.63)	(−3.89)	(−2.20)	(−3.59)	(−1.37)	(−3.63)
4	−1.39	−0.43	−0.24	−0.65	−0.48	−0.50	−0.34	−0.40	−0.72	−0.74	−0.40	−0.40	−0.51	−0.41
	(−6.91)	(−2.13)	(−1.30)	(−3.33)	(−2.64)	(−2.92)	(−1.67)	(−2.31)	(−3.09)	(−3.69)	(−1.99)	(−1.84)	(−2.49)	(−2.41)
5	−1.13	−0.77	−0.14	−0.94	−0.35	−0.34	0.01	−0.30	−0.72	−0.50	−0.87	−0.22	−0.89	−0.35
	(−5.43)	(−3.55)	(−0.76)	(−5.06)	(−2.13)	(−1.68)	(0.06)	(−1.69)	(−3.22)	(−2.22)	(−4.00)	(−0.96)	(−4.25)	(−1.62)
6	−0.72	−0.70	−0.19	−0.92	−0.35	−0.29	−0.41	−0.07	−0.36	−0.58	−0.54	−0.90	−0.86	−0.44
	(−4.39)	(−3.27)	(−1.08)	(−4.10)	(−1.58)	(−1.56)	(−2.41)	(−0.34)	(−1.97)	(−2.80)	(−2.22)	(−4.79)	(−3.59)	(−2.10)
7	−0.76	−0.84	−0.27	−1.46	−0.58	−0.55	0.34	−0.30	−0.36	−0.83	−0.46	−0.54	−0.65	−0.50
	(−4.61)	(−3.97)	(−1.35)	(−7.75)	(−3.42)	(−3.23)	(1.72)	(−1.34)	(−2.00)	(−4.54)	(−2.10)	(−2.65)	(−3.23)	(−2.54)
8	−0.65	−1.06	−0.49	−1.75	−0.47	−0.39	−0.31	−0.03	−0.31	−0.61	−0.91	−0.57	−0.31	−0.48
	(−4.36)	(−4.85)	(−2.35)	(−8.37)	(−2.32)	(−1.90)	(−1.70)	(−0.13)	(−2.20)	(−2.96)	(−4.14)	(−2.97)	(−1.32)	(−2.48)
9	−0.40	−1.07	−0.39	−1.77	−0.43	−0.68	0.07	−0.12	−0.32	−0.45	−0.96	−0.09	−0.67	−0.23
	(−2.61)	(−4.21)	(−1.98)	(−8.51)	(−1.66)	(−2.51)	(0.29)	(−0.52)	(−2.11)	(−2.11)	(−3.89)	(−0.51)	(−2.92)	(−0.96)
High control	−0.13	−1.39	−0.72	−2.62	−1.12	−1.45	−0.59	−0.85	−0.21	−0.78	−1.05	−0.96	−1.18	−0.82
	(−1.03)	(−5.56)	(−2.92)	(−12.69)	(−4.50)	(−4.23)	(−2.31)	(−3.08)	(−1.59)	(−3.21)	(−4.73)	(−4.03)	(−4.35)	(−3.40)
# Sign. pos.	0	0	0	0	0	0	1	0	0	0	0	0	0	0
# Sign. neg.	9	10	6	9	9	8	5	6	9	10	9	8	8	8
Mean H-L ret	−1.11	−0.79	−0.67	−1.11	−0.55	−0.51	−0.22	−0.34	−0.65	−0.73	−0.62	−0.61	−0.67	−0.65
	(−9.94)	(−7.24)	(−6.77)	(−11.27)	(−5.53)	(−4.95)	(−2.11)	(−2.98)	(−6.31)	(−6.68)	(−5.93)	(−5.75)	(−6.26)	(−6.61)
Mean H-L 4F α	−1.24	−0.94	−0.87	−1.26	−0.71	−0.58	−0.28	−0.32	−0.83	−0.88	−0.76	−0.77	−0.75	−0.76
	(−11.33)	(−8.21)	(−8.33)	(−12.86)	(−6.57)	(−5.47)	(−2.64)	(−2.97)	(−8.56)	(−7.83)	(−7.00)	(−6.93)	(−6.77)	(−7.15)
Mean H-L 5F α	−1.29	−0.96	−0.88	−1.28	−0.74	−0.62	−0.30	−0.36	−0.85	−0.91	−0.78	−0.80	−0.77	−0.79
	(−11.63)	(−8.29)	(−8.25)	(−12.77)	(−6.71)	(−5.79)	(−2.68)	(−3.36)	(−8.59)	(−7.87)	(−7.01)	(−7.09)	(−6.77)	(−7.31)

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: $r_{it+1} = \lambda_{0t} + \lambda_{1t}ST_{it} + \lambda_{2t}W_{it} + \upsilon_{it}$. 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). All independent variables are defined in Table 2 and are standardized to have zero mean and unit variance in each month. The table presents the time-series averages of the cross-sectional regression coefficients. The 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ST	−0.32	−0.35	−0.17	−0.16	−0.13	−0.12	−0.13	−0.12	−0.13	−0.13
	(−9.47)	(−12.26)	(−6.55)	(−6.65)	(−6.45)	(−6.75)	(−6.78)	(−6.53)	(−6.82)	(−6.80)
BETA		0.03	0.02	0.01	0.06	0.05	0.06	0.06	0.06	0.06
		(0.88)	(0.55)	(0.29)	(2.44)	(2.36)	(2.66)	(2.65)	(2.67)	(3.54)
ME		−0.11	−0.08	−0.12	−0.18	−0.20	−0.20	−0.21	−0.21	−0.20
		(−2.36)	(−1.86)	(−2.56)	(−4.42)	(−5.05)	(−5.08)	(−5.29)	(−5.32)	(−5.22)
BM		0.18	0.16	0.15	0.14	0.13	0.12	0.12	0.12	0.12
		(4.52)	(3.94)	(3.92)	(3.68)	(3.66)	(3.42)	(3.43)	(3.48)	(3.53)
MOM		0.36	0.37	0.37	0.38	0.39	0.41	0.41	0.43	0.43
		(8.12)	(8.13)	(8.11)	(8.55)	(8.67)	(8.96)	(9.06)	(9.24)	(9.81)
REV			−0.35	−0.35	−0.41	−0.41	−0.41	−0.42	−0.41	−0.43
			(−7.73)	(−7.73)	(−9.68)	(−9.76)	(−9.96)	(−10.08)	(−10.04)	(−10.82)
ILLIQ				−0.06	−0.01	−0.00	−0.00	−0.00	−0.00	0.01
				(−2.46)	(−0.51)	(−0.16)	(−0.10)	(−0.13)	(−0.01)	(0.26)
MAX					−0.08	−0.05	−0.05	−0.04	−0.03	−0.03
					(−2.51)	(−1.63)	(−1.60)	(−1.33)	(−0.90)	(−0.98)
MIN					0.22	0.19	0.19	0.20	0.21	0.22
					(7.32)	(6.49)	(6.89)	(6.85)	(6.86)	(7.49)
IVOL						−0.08	−0.08	−0.09	−0.09	−0.08
						(−1.56)	(−1.73)	(−1.85)	(−1.90)	(−1.77)
TK							−0.06	−0.06	−0.06	−0.06
							(−2.23)	(−2.19)	(−2.06)	(−2.28)
SKEW								−0.04	0.02	0.03
								(−2.65)	(0.99)	(1.84)
COSKEW								0.02	0.01	−0.00
								(1.23)	(0.55)	(−0.18)
ISKEW									−0.09	−0.10
									(−4.72)	(−5.51)
DBETA										−0.01
										(−0.25)

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-statistic = −9.47). The slope is also economically significant: a two standard deviation increase in ST predicts a decrease in next month's stock return of 64 bps. Column 2 shows that the inclusion of the beta, size, book-to-market, and momentum characteristics hardly changes the coefficient estimate on ST. Controlling for short-term reversal reduces the magnitude of the ST coefficient by about half, in line with the bivariate portfolio analysis. Nevertheless, the predictive power of ST remains economically large and statistically significant (t-statistic = −6.55). 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 control for all 14 characteristics simultaneously, a two standard deviation increase in a stock's ST value is associated with a decrease in next month's return on the stock of 26 bps.

Harvey et al. (2016) emphasize 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 are above 6.0, thereby easily clearing the more stringent hurdle of 3.0 proposed by Harvey et al. (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, idiosyn-

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); institutional ownership (IO), defined as the fraction of shares outstanding held by institutional investors; and analyst coverage (NOA), defined as the log of one plus the number of analysts covering a firm. W_{it} is a vector of controls that includes the full set of firm characteristics listed in Table 4. ST and all proxies for limits to arbitrage are standardized to have zero mean and unit variance in each month. 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 1980 to December 2015, as data on institutional ownership start in 1980.

	(1)	(2)	(3)	(4)	(5)
ST	−0.15	−0.15	−0.13	−0.15	−0.16
	(−6.15)	(−6.06)	(−5.21)	(−6.11)	(−6.52)
ST×ME	0.06				
	(2.85)				
ST×ILLIQ		−0.06			
		(−3.80)			
ST×IVOL			−0.05		
			(−3.45)		
ST×IO				0.04	
				(2.90)	
ST×NOA					0.06
					(3.55)
ME	−0.22	−0.22	−0.22	−0.23	−0.22
	(−3.48)	(−3.51)	(−3.58)	(−3.82)	(−3.56)
ILLIQ	−0.04	−0.03	−0.04	−0.05	−0.04
	(−1.21)	(−1.06)	(−1.31)	(−1.54)	(−1.31)
IVOL	−0.04	−0.05	−0.04	−0.05	−0.04
	(−0.71)	(−0.78)	(−0.72)	(−0.77)	(−0.72)
IO	0.11	0.11	0.11	0.11	0.11
	(3.19)	(3.25)	(3.16)	(3.14)	(3.21)
NOA	0.06	0.06	0.06	0.06	0.06
	(1.85)	(1.80)	(1.87)	(1.87)	(1.97)
Controls	Yes	Yes	Yes	Yes	Yes

cratic 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 et al., 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 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 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.

Table 5 reports the results of Fama-MacBeth regressions that include interaction terms between ST and each of the proxies for arbitrage costs.[21] The sample period is restricted by the availability of data on institutional ownership to 1980–2015. 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 et al. (2012) and Antoniou et al. (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 et al. (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 onward.[22] 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 −1.41% following high sentiment and −0.88% following low sentiment. The difference of 53 bps is significant at the 5% level. The return spread between the VW high- and low-ST deciles widens by 72 bps (t-statistic = 2.44) after periods of high investor optimism. 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 in-

[21] We create the interaction terms after standardizing all independent variables to have zero mean and unit variance. The slope on ST in each regression therefore measures the effect of a one standard deviation (SD) increase in ST on one-month-ahead returns at the mean value of a proxy for arbitrage costs. For instance, the coefficient estimate on ST in column 3 (−0.13) implies that for a firm with average IVOL, a one SD increase in ST predicts a 13 bps decrease in next month's return. The coefficient on the interaction term ST×IVOL measures the change in the strength of the relation between ST and next month's return for a one SD increase in IVOL. For instance, the slope of −0.05 in column 3 means that for a firm with IVOL one SD above the cross-sectional mean of IVOL in that month, a one SD increase in ST predicts a decrease in next month's stock return of $(-0.13 \times 1) + (-0.05 \times 1 \times 1) = -0.18\%$.

[22] We obtain sentiment data from Jeffrey Wurgler's website: http://people.stern.nyu.edu/jwurgler.

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 and five-factor alphas between decile 10 (high ST) and decile 1 (low ST). Five-factor alphas are obtained from the Carhart (1997) model augmented with a 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	0.96	1.30	−0.34	0.56	0.64	−0.08
2	0.88	0.96	−0.08	0.73	0.62	0.11
3	0.73	0.81	−0.08	0.77	0.57	0.20
4	0.73	0.77	−0.04	0.76	0.40	0.36
5	0.69	0.71	−0.02	0.58	0.45	0.13
6	0.70	0.79	−0.09	0.55	0.50	0.05
7	0.63	0.77	−0.14	0.52	0.51	0.01
8	0.44	0.76	−0.32	0.32	0.65	−0.33
9	0.16	0.60	−0.44	0.13	0.69	−0.56
High ST	−0.45	0.42	−0.87	−0.09	0.71	−0.80
H-L return	−1.41	−0.88	**−0.53**	−0.65	0.07	**−0.72**
	(−6.24)	(−5.10)	**(−1.99)**	(−2.50)	(0.37)	**(−2.44)**
H-L 5F α	−1.45	−1.05	**−0.40**	−0.68	−0.18	**−0.50**
	(−7.21)	(−6.13)	**(−1.60)**	(−2.95)	(−0.95)	**(−1.80)**

terpretation of the negative relation between a stock's ST value and its future return. 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.

4.6. Alternative definition of daily returns

Up until this point, we construct ST by measuring the salience of a stock's daily close-to-close returns, implicitly assuming that investors form return expectations and make trading decisions based on close-to-close returns. In this section, we compute an alternative ST measure based on daily open-to-open returns. Salience theory implies that the salience effect arises from distortions in the perception of the past returns used by investors to form expectations about future returns. We therefore expect the predictive power of ST to weaken when using opening returns that investors are less likely to perceive or use than closing returns.[23] On the other hand, if the return spread between high- and low-ST stocks is caused by differences in fundamental risk, it should be unaffected by a change in the definition of returns, as this does not alter the underlying fundamentals of the firm.

We test these predictions by repeating our main analysis with the ST measure based on open-to-open returns.[24] We conduct the analysis for the full sample of stocks as well as three size-based subsamples. Following Fama and French (2008), at the end of each month we allocate stocks to three groups based on their market cap: microcaps, small stocks, and big stocks. The breakpoints are the 20th and 50th percentiles of market cap for NYSE stocks. The analysis across size groups addresses issues with EW and VW portfolios constructed using the full sample of stocks.[25]

The results of the portfolio sorts in panel A of Table 7 provide strong empirical support for the salience model. We find that the return spread between the high- and low-ST deciles drops by almost 50% (from 90 bps to 47 bps per month) when constructing ST based on opening returns. The difference of 43 bps is significant at the 1% level. This stark difference in the results for the open-to-open and close-to-close ST variables is present in all three size groups, suggesting that it is unlikely to be driven by microstructure issues.

Panels B and C present results for Fama-MacBeth regressions of one-month-ahead returns on the open-to-

[23] Because the open-to-open and close-to-close ST measures are positively correlated (0.66), we do not expect the salience effect to vanish entirely with the open-to-open ST measure, i.e., open-open ST is not a classic placebo.

[24] We construct open-to-open returns following the method of Amihud and Mendelson (1987) that accounts for stock splits and dividends. Daily opening prices are available from CRSP from July 1992 onward. For comparison, we also report results for the period 1992–2015 for the original ST measure based on close-to-close returns.

[25] EW long-short portfolios that use all stocks can be dominated by stocks that are plentiful but tiny. Conversely, VW portfolios can be dominated by a few very big stocks, again providing an unrepresentative picture of the significance of an anomaly. A separate analysis for each of the size groups addresses these problems.

Table 7
Salience effect: open-to-open versus close-to-close returns.
This table reports results of portfolio sorts and Fama-MacBeth regressions that explore the impact of measuring a stock's salience theory (ST) value using open-to-open returns on the relation between ST and future stock returns. Panel A presents results for a univariate portfolio analysis in which at the end of each month, stocks are sorted into deciles based on their ST value. ST is constructed using a one-month window of daily close-to-close returns or a one-month window of daily open-to-open returns. Portfolios are rebalanced at the end of the next month, and their equal-weighted realized return is recorded. We conduct the portfolio analysis for the full sample of stocks as well as three size-based subsamples. Stocks are assigned to three groups (microcaps, small stocks, and big stocks) based on their market cap at the end of the previous month. The breakpoints are the 20th and 50th percentiles of market cap for NYSE stocks. For each size group, we report the difference in the average monthly return and five-factor alpha between the highest and lowest ST deciles. Five-factor alphas are obtained from the Carhart (1997) model augmented with a liquidity factor. The last rows show the differences in returns and alphas on the high-low portfolios constructed using the close-to-close and open-to-open ST measures. Panel B reports results for univariate Fama-MacBeth regressions of excess stock returns in month $t+1$ on a firm's ST value measured at the end of the previous month t. Panel C reports Fama-MacBeth estimates for multivariate regressions that include the full set of control variables listed in Table 4. Panel D includes the open-to-open and close-to-close ST measures jointly in the regressions. The last rows report the differences in coefficients on the close-to-close and open-to-open ST measures. All independent variables are standardized to have zero mean and unit variance in each month. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags. The sample period is July 1992 to December 2015, as daily open-to-open returns are available from July 1992 onward.

Panel A: Portfolio sorts								
	High-low raw return				High-low 5F alpha			
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
ST close-to-close	−0.90	−1.17	−0.68	−0.42	−0.97	−1.27	−0.74	−0.40
	(−3.46)	(−4.75)	(−2.35)	(−1.56)	(−5.14)	(−5.76)	(−3.11)	(−1.86)
ST open-to-open	−0.47	−0.67	−0.28	−0.14	−0.59	−0.78	−0.41	−0.19
	(−2.03)	(−2.95)	(−0.93)	(−0.53)	(−3.57)	(−4.49)	(−1.83)	(−0.93)
Difference	−0.43	−0.50	−0.40	−0.28	−0.38	−0.49	−0.33	−0.21
	(−5.08)	(−4.68)	(−2.91)	(−2.96)	(−4.90)	(−4.47)	(−2.44)	(−2.29)
Panel B: Univariate Fama-MacBeth regressions								
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
ST close-to-close	−0.24	−0.31	−0.16	−0.13				
	(−3.46)	(−4.00)	(−1.72)	(−1.70)				
ST open-to-open					−0.12	−0.17	−0.07	−0.06
					(−1.67)	(−2.33)	(−0.74)	(−0.77)
Controls	No	No	No	No	No	No	No	No
Panel C: Multivariate Fama-MacBeth regressions								
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
ST close-to-close	−0.17	−0.25	−0.07	−0.11				
	(−4.46)	(−4.68)	(−1.56)	(−3.01)				
ST open-to-open					0.04	0.02	0.06	0.03
					(1.07)	(0.53)	(1.57)	(0.79)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel D: Fama-MacBeth regressions: ST close-to-close versus ST open-to-open								
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
ST close-to-close	−0.26	−0.34	−0.20	−0.19	−0.20	−0.29	−0.12	−0.15
	(−5.05)	(−6.31)	(−3.10)	(−2.91)	(−4.54)	(−5.03)	(−2.21)	(−3.12)
ST open-to-open	0.05	0.06	0.07	0.08	0.10	0.11	0.13	0.08
	(0.86)	(0.85)	(0.92)	(1.29)	(2.47)	(2.03)	(2.62)	(2.02)
Difference	−0.31	−0.40	−0.27	−0.27	−0.30	−0.40	−0.25	−0.23
	(−4.22)	(−4.63)	(−2.59)	(−2.86)	(−3.90)	(−4.25)	(−2.79)	(−3.39)
Controls	No	No	No	No	Yes	Yes	Yes	Yes

open and close-to-close ST variables. The univariate results in panel B are in line with the portfolio sorts and show that the salience effect weakens by about 50% when ST is measured using opening returns. After adding control variables (panel C), the coefficient on the close-to-close ST measure remains negative (−0.17) and statistically significant at the 1% level, consistent with the predictions of the salience-based asset pricing model. In contrast, the slope on open-to-open ST is close to zero (0.04) and insignificant (t-statistic = 1.07). Because the open-open and close-close ST measures are positively correlated, we also include them jointly in the regressions. Panel D shows that the coefficient on close-close ST remains strongly negative and statistically significant in the presence of open-open

ST. In contrast, the slope on open-open ST is positive and insignificant in the bivariate regressions.[26] These stark differences in the results for the open-to-open and close-to-close ST measures seem hard to reconcile with a risk-based explanation for the salience effect and lend further support to a behavioral interpretation of the relation between ST and future returns.

5. Salience and short-term reversal

Although our empirical evidence is consistent with the predictions of salience theory, there might be other explanations for the negative relation between our ST variable and future returns. We consider first the possibility that ST picks up one-month return reversals. Starting with Lehmann (1990) and Jegadeesh (1990), a large literature shows that high (low) one-month returns tend to be followed by low (high) returns over the next month. Since an extreme positive (negative) one-day return drives up (down) a stock's one-month return and is more likely to be salient than a modest one-day return, ST and REV are positively correlated.[27] Thus far, we have controlled for return reversals by performing sequential sorts on a stock's one-month return (REV) and ST and by including REV as a control variable in the Fama-MacBeth regressions. In this section we perform various additional tests to rule out that the salience effect is a rediscovery of the reversal effect.

5.1. Alternative state space specifications

In this section, we exploit variations in the state space on which salience is defined to further differentiate the salience effect from reversal. 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 a repackaging of the one-month reversal effect, we expect it to vanish abruptly when salience is measured over intermediate horizons at which returns do not exhibit 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 a five-year window of monthly returns. Panel A of Table 8 reports for each of these ST measures the monthly return and alpha on the zero-cost strategy that buys high-ST stocks and shorts low-ST stocks. As expected, the return and alpha spreads between the high- and low-ST deciles gradually decrease when ST is computed over longer horizons. Raw returns on the long-short portfolios constructed using the one-year and five-year ST measures are smaller due to the confounding effect of momentum.[28] Five-factor alphas show that once we account for momentum, the salience effect is also economically large and statistically significant when ST is measured over one- and five-year horizons. We further report alphas obtained from a seven-factor model that extends the five-factor model with the Fama-French short-term and long-term reversal factors. For each ST measure, alphas on the long-short portfolios remain large and significant after controlling for the reversal factors, both with equal weighting and value weighting. For the portfolio created using the one-month ST measure, seven-factor alphas range from 102 bps (t-statistic $= -10.35$) per month for the EW portfolio to 32 bps (t-statistic $= -2.24$) for the VW portfolio.

Panel B reports Fama-MacBeth results for the ST measures defined on alternative state spaces. The estimates show that the predictive power of the ST measures gradually weakens when more distant returns are used to construct ST. The coefficient on ST drops from -0.13 for the one-month ST variable to -0.09 for the quarterly ST measure and to -0.07 for the one- and five-year ST variables. Most importantly, however, the salience effect remains significant at the 1% level when we compute ST over horizons longer than one month at which stock returns do not exhibit reversal.

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 results on the right-hand side of panel B show that all ST measures retain significant predictive power after skipping a month between their construction and the measurement of subsequent returns, providing direct evidence that the salience effect is distinct from one-month reversal.

5.2. Time trends in salience and reversal effects

Next, we compare historical trends in the magnitude of the salience and reversal effects. Previous literature (e.g., Kaniel et al., 2008; Hameed and Mian, 2015) has shown that the short-term return reversal effect has weakened substantially over time since the publication of the early work on reversal by Lehmann (1990) and Jegadeesh

[26] The positive coefficient on open-open ST becomes significant after adding the control variables. We interpret the significance of this slope with some caution because the correlation between close-close and open-open ST, although far from one, may cause some collinearity issues that affect the magnitude and significance of the coefficient estimate.

[27] Table A1 shows that the correlation between ST and REV is positive but far from perfect (0.65).

[28] Stocks with salient daily upsides (downsides) during the past year are more likely to have a high (low) cumulative return over that year. As a result, ST constructed using daily returns over the past year is positively correlated (0.30) with a stock's MOM characteristic. Since past winners (losers) tend to have salient upsides (downsides), salience theory predicts them to earn low (high) future returns. However, momentum implies that future returns of winners (losers) continue to be high (low). The momentum effect therefore obfuscates the salience effect at the one-year horizon. The long-short portfolio based on the five-year ST measure also loads positively on the momentum factor.

Table 8
Salience and reversal: alternative state space specifications.
This table reports results of portfolio analyses and firm-level Fama-MacBeth analyses of the relation between a stock's salience theory (ST) value and its future return, using alternative specifications of the state space on which salience is defined. We consider ST measures computed using monthly, quarterly, and annual windows of daily returns and a five-year window of monthly returns, all ending in month t. Panel A presents results for a univariate portfolio analysis in which stocks are sorted into deciles at the end of each month based on their ST value. Portfolios are rebalanced at the end of the next month, and their realized return is recorded. For each ST measure, we report the difference in the average monthly return, five-factor alpha, and seven-factor alpha between the high- and low-ST deciles. Five-factor alphas are obtained from the Carhart (1997) model augmented with a liquidity factor. Seven-factor alphas are obtained by augmenting the five-factor model with a short-term reversal factor and a long-term reversal factor. Panel B presents estimates for Fama-MacBeth regressions of excess stock returns in month $t+1$ on the alternative ST measures computed using data up to month t. We also estimate regressions in which these ST measures are lagged by an additional month, i.e, returns in month $t+1$ are regressed on ST variables constructed with data up to month $t-1$. In each regression we include the full set of control variables listed in Table 4. 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. All independent variables are standardized to have zero mean and unit variance in each month. 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.

Panel A: Portfolio sorts

	EW portfolios				VW portfolios			
Window	Month	Quarter	Year	5-year	Month	Quarter	Year	5-year
Frequency	Daily	Daily	Daily	Monthly	Daily	Daily	Daily	Monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
H-L return	−1.28	−0.68	−0.35	−0.20	−0.60	−0.40	−0.21	−0.09
	(−10.73)	(−5.23)	(−2.12)	(−2.01)	(−4.08)	(−2.49)	(−1.10)	(−0.68)
H-L 5F α	−1.44	−1.05	−0.81	−0.46	−0.80	−0.84	−0.79	−0.35
	(−12.50)	(−9.31)	(−7.60)	(−5.79)	(−5.17)	(−5.81)	(−5.73)	(−3.27)
H-L 7F α	−1.02	−0.77	−0.82	−0.43	−0.32	−0.56	−0.83	−0.35
	(−10.35)	(−6.38)	(−6.91)	(−4.91)	(−2.24)	(−3.62)	(−4.87)	(−2.77)

Panel B: Multivariate Fama-MacBeth regressions

Window	Month	Quarter	Year	5-year	Month	Quarter	Year	5-year
Frequency	Daily	Daily	Daily	Monthly	Daily	Daily	Daily	Monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ST_t	−0.13	−0.09	−0.07	−0.07				
	(−6.80)	(−4.66)	(−2.35)	(−3.32)				
ST_{t-1}					−0.10	−0.07	−0.06	−0.07
					(−5.94)	(−2.69)	(−2.59)	(−3.28)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(1990) and the improvements in market liquidity and efficiency.[29] If our findings are a rediscovery of return reversal, we should expect to observe a similar downward trend in the magnitude of the salience effect in recent decades.

To examine changes in the strength of both effects, we perform portfolio sorts and firm-level regressions over various subperiods: 1931–1963/06, 1963/07–1979, 1980–1999, and 2000–2015. The evidence in Table 9 confirms that the short-term reversal effect has weakened over time. The portfolio sorts in panel A show that the average return on the high-low REV decile portfolio monotonically decreases from 227 bps during the 1931–1963/06 period to 193 bps during 1963/07-1979, 80 bps during 1980–1999, and to 54 bps during 2000–2015. Importantly, reversal is no longer significant among small caps and large caps in recent decades, consistent with large improvements in market liquidity over this period that mitigate microstructure issues like the bid-ask bounce. In contrast, although the salience effect is also strongest in the early part of the sample, it does not show signs of weakening during the most recent subperiod. The return spread between the high- and low-ST deciles slightly increases from 92 bps during 1980–1999 to 98 bps during 2000–2015. Moreover, the salience effect remains sizable and significant among small- and large-cap stocks.

The Fama-MacBeth regressions in panel B yield similar conclusions. The slope on REV decreases (in absolute value) from −0.51 in the 1963–1979 period to −0.24 during 1980–1999 and to −0.16 during 2000–2015. The coefficient on ST also decreases from the 1963–1979 period (−0.37) to the 1980–1999 period (−0.24) but remains stable during 2000–2015 (−0.26) and significant at the 1% level.[30]

[29] Subrahmanyam (2005) and Da et al. (2014b) compute returns using quote midpoints and find that microstructures issues such as the bid-ask bounce do not completely explain the reversal effect. An alternative interpretation of reversal is that investors overreact to information, which implies that high or low one-month stock returns are subsequently reversed (e.g., Subrahmanyam, 2005). Consistent with this interpretation, survey evidence indicates that investors over-extrapolate past returns when forming expectations about future returns (Greenwood and Shleifer, 2014). We therefore control for a stock's past-month return in our bivariate portfolio sorts and Fama-MacBeth regressions. In Section 7.1 we also rule out that our results are driven by overreaction to company news.

[30] We estimate univariate Fama-MacBeth regressions to detect time trends in the raw reversal and salience effects. Multivariate results re-

Table 9
Salience and reversal: historical trends.
This table presents an analysis of historical trends in the magnitude of the salience effect and the short-term return reversal effect. We conduct portfolio sorts and estimate firm-level regressions over the full sample period and four subperiods (1931/01–1963/06, 1963/07–1979/12, 1980/01–1999/12, and 2000/01–2015/12). We perform the subperiod analyses for the full sample of stocks as well as three size-based subsamples. Stocks are assigned to three groups (microcaps, small stocks, and big stocks) based on their market cap at the end of the previous month. The breakpoints are the 20th and 50th percentiles of NYSE market cap. Panel A presents results for a portfolio analysis in which stocks are grouped into deciles at the end of each month based on their one-month return (REV) or ST value. Portfolios are rebalanced at the end of the next month, and their equal-weighted return is recorded. For each subperiod and size group, we report the average return spread between the high- and low-REV deciles and the high- and low-ST deciles. Panel B shows results for univariate Fama-MacBeth regressions of excess stock returns in month $t+1$ on a firm's REV or ST value measured at the end of month t. REV and ST are standardized to have zero mean and unit variance in each month. The t-statistics in parentheses are based on Newey and West (1987) standard errors with 12 lags.

Panel A: Portfolio sorts

	Reversal effect				Salience effect			
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
1931/01 - 2015/12	−1.53	−2.33	−1.62	−0.88	−1.28	−1.97	−1.15	−0.62
	(−9.25)	(−9.25)	(−6.77)	(−5.46)	(−10.73)	(−11.73)	(−7.71)	(−5.79)
1931/01 - 1963/06	−2.27	−3.44	−2.89	−1.45	−1.55	−2.54	−1.48	−0.80
	(−7.73)	(−6.15)	(−6.70)	(−5.30)	(−8.87)	(−7.98)	(−6.09)	(−5.45)
1963/07 - 1979/12	−1.93	−2.96	−1.53	−1.02	−1.50	−2.49	−1.26	−0.70
	(−7.15)	(−8.55)	(−4.49)	(−4.40)	(−7.71)	(−10.67)	(−6.73)	(−4.06)
1980/01 - 1999/12	−0.80	−1.18	−0.65	−0.46	−0.92	−1.21	−0.72	−0.34
	(−3.40)	(−5.16)	(−2.15)	(−1.45)	(−4.43)	(−6.08)	(−2.43)	(−1.41)
2000/01 - 2015/12	−0.54	−0.95	−0.36	−0.11	−0.98	−1.22	−0.88	−0.52
	(−1.86)	(−3.24)	(−0.94)	(−0.29)	(−3.48)	(−3.76)	(−2.40)	(−1.75)

Panel B: Univariate Fama-MacBeth regressions

	Reversal effect				Salience effect			
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
1931/01 - 2015/12	−0.39	−0.66	−0.46	−0.24	−0.32	−0.54	−0.33	−0.17
	(−8.03)	(−5.47)	(−9.28)	(−5.15)	(−9.47)	(−13.45)	(−7.92)	(−5.38)
1931/01 - 1963/06	−0.54	−0.93	−0.77	−0.36	−0.37	−0.65	−0.41	−0.19
	(−5.73)	(−3.04)	(−9.07)	(−4.53)	(−7.06)	(−11.44)	(−6.24)	(−4.04)
1963/07 - 1979/12	−0.51	−0.96	−0.48	−0.28	−0.37	−0.75	−0.35	−0.16
	(−6.55)	(−11.04)	(−5.89)	(−3.93)	(−4.73)	(−9.32)	(−4.74)	(−3.17)
1980/01 - 1999/12	−0.24	−0.31	−0.21	−0.18	−0.24	−0.32	−0.25	−0.12
	(−3.22)	(−4.89)	(−2.79)	(−2.38)	(−3.47)	(−4.62)	(−2.81)	(−2.02)
2000/01 - 2015/12	−0.16	−0.26	−0.11	−0.03	−0.26	−0.34	−0.23	−0.18
	(−2.26)	(−2.36)	(−0.75)	(−0.22)	(−3.09)	(−4.02)	(−2.40)	(−1.98)

The diverging trends in the strength of both effects provide preliminary evidence that the salience effect is not driven by liquidity shocks that induce short-term return reversal. In Section 7.2 we directly control for the bid-ask bounce by repeating our analysis using quote midpoint returns.

6. Salience and investor attention

We next examine whether our findings can be explained by the attention theory of Barber and Odean (2008). The 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 usually sell only stocks they already own. Investors are thus more likely to buy rather than sell attention-grabbing stocks, which leads to positive price pressure in the short run and subsequent reversal.

We perform three 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 then further dividing the stocks into subdeciles based on ST. We consider four proxies for attention: (i) the maximum absolute abnormal daily return within each month (ABNRETD), (ii) the absolute abnormal monthly return (ABNRETM), (iii) the maximum abnormal daily trading volume within each month (ABNVOLD), and (iv) the abnormal monthly trading volume (ABNVOLM). Extreme returns and abnormal volume have been used as proxies for investor attention by, among others, Gervais et al. (2001) and Barber and Odean (2008).[31] We define abnormal returns as the difference between a stock's returns and the market return. Abnormal daily (monthly) volume is calculated as a stock's daily (monthly) dollar trading volume divided

ported in panel A of Table A13 confirm that the salience effect remains economically large (ST coefficient = −0.15) and statistically significant (t-statistic = −3.60) in the most recent period 2000–2015.

[31] In Section 7.1.1 we examine the sensitivity of our results to a specific attention-grabbing event (earnings news).

by its average daily (monthly) dollar volume over the previous one year.[32]

Table 10 reports the results of the bivariate portfolio sorts. 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. Controlling for the return-based attention measures reduces the return on the high-low ST portfolio by about one-third (panel A), but its economic magnitude remains sizable, even among large-cap stocks. The volume-based attention proxies in panel B hardly affect our results.

We next include the attention proxies as additional controls in the Fama-MacBeth regressions. The results in panel C 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.

Finally, we test the opposite predictions of the salience model and the attention hypothesis for stocks with attention-grabbing downsides. Specifically, in the salience model, attention is drawn to salient return states rather than to salient stocks. Salience thus affects trading decisions and stock prices by distorting return expectations, not by narrowing the set of stocks investors consider for purchase.[33] Because of these different mechanisms, salience and attention yield opposite predictions for stocks with salient downsides. Salience theory predicts that negative ST stocks become underpriced and earn higher future returns because investors focus on their downside risk. In contrast, the attention hypothesis predicts them to become overpriced and earn lower future returns because both positive and negative attention-grabbing events lead to net buying. For stocks with negative ST values, salience theory thus predicts a negative slope in a regression of one-month-ahead returns on ST, whereas the attention hypothesis predicts a positive slope.[34]

We test these opposite predictions by splitting ST into positive and negative parts. ST POS equals ST when ST is positive and zero otherwise, and ST NEG equals ST when ST is negative and zero otherwise. Both ST components are included as separate regressors in panel C. The coefficient on ST NEG in column 6 is negative (−0.11) and significant (t-statistic = −5.82), which means that stocks with larger salient downsides in month t tend to earn higher returns in month t+1. This finding supports the prediction of salience theory and 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 evidence is consistent with salience theory, we believe that both attention and salience can influence trading decisions and stock prices. Visibility plays an important role in the first stage of the choice process by determining which stocks grab investors' attention and thereby enter their consideration set. Salience affects the actual choice between these stocks in the second stage of the decision process by determining which returns catch investors' attention, thereby influencing investors' expectations about future stock returns.

7. Additional robustness tests

7.1. Salience and news

7.1.1. Firm-specific news

An alternative explanation for our findings is that they are driven by investor overreaction to firm-specific news (Subrahmanyam, 2005). In this section, we explore this possibility by examining the impact of earnings announcements on the magnitude of the salience effect. If the salience effect is driven by increased attention to stocks that announce earnings or by overreaction to these announcements, we should expect the effect to be greater in months with earnings announcements.

We test these predictions in several ways. We first retrieve quarterly earnings announcements dates from I/B/E/S and rerun the Fama-MacBeth regressions excluding a stock/month observation if there is an earnings announcement for the stock in that month. Table A8 shows that excluding announcement months hardly changes the magnitude and significance of the coefficient on ST. Next, to study the effect of salient returns around announcements more directly, we construct an alternative ST measure that excludes the returns on the day of the announcement and the day before and after the announcement. We control for the announcement premium documented by Frazzini and Lamont (2007) by including a dummy variable that takes on a value of one if there is an announcement for firm i in month t and zero otherwise. We also include the interaction between this dummy and ST to test if the strength of the salience effect changes in announcement months. We further account for the post-earnings announcement drift (PEAD) by adding the cumulative abnormal return over the days -1 to +1 around the earnings announcement date to the regressions.

We find that after controlling for the announcement premium and the PEAD, the coefficient on the alternative ST measure (−0.18) is almost identical to the baseline estimate in column 1 (−0.17). Moreover, the slope on the interaction term between ST and the announcement

[32] For robustness, we consider alternative measures of abnormal volume: (i) the average abnormal daily volume in month t and (ii) the maximum and average standardized abnormal daily volume in each month, with standardized abnormal volume defined as the difference between volume on day s and average volume over the prior 252 trading days divided by the standard deviation of volume over the prior 252 days. We also construct variations of these measures computed by comparing volume on day s in month t to average volume over the 252 days prior to the start of month t. All measures of abnormal volume yield very similar results (see Table A7 in the Online Appendix).

[33] If investors consider only stocks that grab their attention, the consideration set is smaller than the 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.

[34] For stocks with negative ST values, a negative (positive) coefficient on ST implies a positive (negative) return in the next month. Note that for stocks with positive ST values, both the salience model and the attention hypothesis predict overvaluation and low future returns, i.e., both models imply a negative coefficient on ST. We therefore focus on stocks with negative ST values for which salience theory and the attention hypothesis yield different predictions.

Table 10
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 various measures of investor attention. We consider four attention proxies: (i) the maximum absolute abnormal daily return within each month (ABNRETD), (ii) the absolute abnormal monthly return (ABNRETM), (iii) the maximum abnormal daily volume within each month (ABNVOLD), and (iv) the abnormal monthly trading volume (ABNVOLM). Abnormal returns are calculated as the difference between a stock's returns and the market return. Abnormal daily (monthly) trading volume is calculated as a stock's daily (monthly) dollar trading volume divided by its average daily (monthly) trading volume over the previous one year. Panels A and B report results for bivariate portfolio analyses in which stocks are first sorted into decile portfolios based on one of the abnormal return (panel A) or abnormal volume (panel B) measures and then, within each decile portfolio, are further divided into deciles based on the salience theory measure ST. All portfolios are rebalanced at the end of the next month, and their equal-weighted return is recorded. Returns on the ST deciles are then averaged across the different abnormal return or volume deciles. We conduct the portfolio analysis for the full sample of stocks as well as three size-based subsamples. Stocks are assigned to three groups (microcaps, small stocks, and big stocks) based on their market cap at the end of the previous month. The breakpoints are the 20th and 50th percentiles of NYSE market cap. For each size group, we report the difference in the average monthly return and five-factor alpha between the highest and lowest ST deciles. Five-factor alphas are obtained from the Carhart (1997) model augmented with a liquidity factor. Panel C reports results of the Fama-MacBeth analyses. Results in columns 2 to 5 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. We use the logarithmic transformation of the abnormal volume variables. In column 6, 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 listed in Table 4. All independent variables are standardized to have zero mean and unit variance in each month. 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.

Panel A: Bivariate portfolio sorts: controlling for abnormal return								
	ABNRETD				ABNRETM			
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
High-low return	−0.86	−1.19	−0.68	−0.52	−0.84	−1.31	−0.79	−0.44
	(−10.49)	(−10.89)	(−6.43)	(−6.65)	(−8.43)	(−10.26)	(−6.13)	(−5.09)
High-low 5F α	−0.95	−1.20	−0.75	−0.58	−1.01	−1.36	−0.99	−0.56
	(−11.13)	(−10.30)	(−6.56)	(−6.54)	(−11.32)	(−11.67)	(−8.17)	(−6.52)
Panel B: Bivariate portfolio sorts: controlling for abnormal volume								
	ABNVOLD				ABNVOLM			
Firm size	All	Micro	Small	Big	All	Micro	Small	Big
High-low return	−1.28	−2.09	−1.18	−0.63	−1.39	−2.05	−1.20	−0.68
	(−13.60)	(−14.52)	(−8.95)	(−6.70)	(−14.32)	(−14.26)	(−9.47)	(−7.74)
High-low 5F α	−1.44	−2.18	−1.44	−0.79	−1.49	−2.15	−1.36	−0.78
	(−15.40)	(−15.18)	(−11.03)	(−8.04)	(−15.41)	(−14.85)	(−10.92)	(−8.63)
Panel C: Multivariate Fama-MacBeth regressions								
	(1)	(2)	(3)	(4)	(5)	(6)		
ST	−0.13	−0.13	−0.11	−0.12	−0.12			
	(−6.80)	(−6.95)	(−6.37)	(−6.68)	(−6.85)			
ABNRETD		−0.04						
		(−0.84)						
ABNRETM			0.09					
			(4.02)					
ABNVOLD				0.22				
				(9.30)				
ABNVOLM					0.34			
					(11.88)			
ST POS						−0.04		
						(−2.35)		
ST NEG						−0.11		
						(−5.82)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes		

dummy is zero. We obtain similar results after accounting for a direct measure of the earnings surprise and after controlling for abnormal volume patterns around announcements. In summary, the evidence in Table A8 suggests that the salience effect cannot be explained by overreaction to earnings news.

7.1.2. Market-wide news

Next, we examine the relation between the salience effect and market-wide news events such as economic crises. In times of crisis, investors' attention to the stock market might be heightened or muted due to other distractions. We study the impact of crisis episodes and other distracting events on the strength of the salience effect in two ways. First, we estimate separate Fama-MacBeth regressions for contractions and expansions as defined by the National Bureau of Economic Research (NBER). The results in columns 1 and 2 of Table A9 show that the salience effect is large and significant both in booms and in recessions.

To investigate the impact of distractions on the magnitude of the salience effect more directly, we perform a second test that exploits the distracting news events identified by Peress and Schmidt (2020). Specifically, we obtain data on a variable called “news pressure” that indicates how much newsworthy material is available on a given day.[35] News pressure is defined by Eisensee and Strömberg (2007) as the median number of minutes that US news broadcasts devote to the first three news segments. Following Peress and Schmidt (2020), we focus on spikes in daily news pressure, defined as the 10% of business days with the highest news pressure in each year. They find that on days with a spike in news pressure (distraction days), trading activity, liquidity, and volatility decrease, particularly among small stocks owned predominantly by retail investors, and interpret these results as evidence that noise traders are distracted by sensational news events.

We study the relation between distracting news events and the salience effect by constructing an alternative ST measure that excludes distraction days. Salience theory predicts that investors’ attention is drawn to the days in a month on which a stock’s return stands out most from the returns on other stocks in the market. However, if investors are distracted by a sensational news story on day s and pay no attention to the stock market, that day is essentially nonsalient for all stocks. In that case, we expect that excluding distraction day s removes noise from ST and therefore strengthens its predictive power. On the other hand, if investors pay attention to the stock market but are subject to even greater attention constraints than usual due to the attention-grabbing news event on day s, salience may play an even larger role than usual. We then expect the relation between ST and future returns to weaken when excluding distraction days.

Table A9 presents regression results for the alternative ST measure that excludes distraction days (column 3) and the regular ST measure constructed using all days (column 4). The coefficient on ST is smaller when distraction days are excluded, but the difference is small (−0.12 versus −0.13).[36] We conclude that our results are not attributable to sensational news events that distract investors.

[35] We obtain daily news pressure for the period August 1968 to December 2015 from David Strömbergs website: http://perseus.iies.su.se/~dstro.

[36] Since Peress and Schmidt (2020) find that distraction events matter most for small stocks mainly held by retail investors, we also estimate separate regressions for microcaps. The ST coefficients in columns 5 (−0.17) and 6 (−0.21) suggest that salience plays a larger role when investors are distracted by sensational news events. However, the effect of distraction shocks on the magnitude of the salience effect remains quite limited, even in the microcaps subsample.

7.2. Market microstructure effects

Thus far we have addressed concerns that our results may be driven by market microstructure effects by excluding stock/month observations if a stock’s month-end price is below \$5 a share and by controlling for past one-month returns and the Amihud (2002) illiquidity measure in our regressions. In this section, we perform an additional robustness check by repeating our main analysis using stock returns calculated from end-of-day quote midpoints to further alleviate concerns that our findings may be affected by the bid-ask bounce. We compute the daily quote midpoint from TAQ data as the average of the daily closing national best bid and offer (NBBO).[37]

In panel A of Table A10, we sort stocks into decile portfolios based on the ST measure computed using daily midpoint returns and report the midpoint return for each decile over the next month. The difference in raw returns between the high- and low-ST deciles (82 bps per month) is significant and similar to the return spread obtained when using closing transaction prices (89 bps).

For comparison, panel B reports results for portfolios sorted on past-month midpoint returns. In line with Nagel (2012), we find that short-term reversal is much weaker with midpoint returns. The return spread between the high- and low-REV deciles drops by 40%, from 70 bps using transaction returns to 42 bps using midpoint returns, and is no longer significant in terms of alpha.

Panel C reports results for Fama-MacBeth regressions of one-month-ahead midpoint returns on ST computed using daily midpoint returns. The slope on this alternative ST measure (−0.22, t-statistic = −5.99) is similar to the slope on the original ST measure constructed using transaction returns (−0.19, t-statistic = −5.71). In contrast, we observe a sharp drop in the slope on the REV variable computed from midpoint returns (from −0.25 to −0.15). Overall, the results in Table A10 show that the salience effect is not attributable to the bid-ask bounce.[38]

We further control for a potential microstructure bias in EW portfolio returns using the method of Asparouhova et al. (2013). Specifically, we calculate portfolio returns by weighting each individual stock return by the gross return on the stock in the prior month. Panel A of Table A11 shows that the return-weighted raw returns and alphas on the ST portfolios are very similar to their EW counterparts, again suggesting that any microstructure bias is small.

Finally, we account for the impact of days on which a stock’s return is zero by constructing an alternative ST measure excluding days with zero returns. Panel B of Table A11 shows that returns on portfolios formed on this ST measure are very similar to those obtained with the original ST.

[37] The sample period is restricted by the availability of TAQ data to 1993–2013. To mitigate noise, we follow Nagel (2012) and require that the ratio of bid to quote midpoint is not smaller than 0.5 and the one-day return based on quote midpoints minus the return based on closing prices is not less than −50% and not higher than 100%.

[38] We also repeat our baseline regression excluding the top decile of illiquid stocks based on the Amihud measure. The evidence in panel A of Table A13 confirms that the salience effect is not confined to the most illiquid stocks.

7.3. Overnight-intraday decomposition of salience and reversal returns

In this section, we extend our analysis by decomposing the salience effect and the reversal effect into intraday and overnight return components. This analysis is motivated by recent work of Lou et al. (2019), who show that the return on a short-term reversal strategy is earned entirely overnight, i.e., stocks with low returns in the previous month earn significantly higher overnight returns than stocks with high past returns. In contrast, other anomalies not based on past returns, such as the value premium, only show up in intraday returns.

The authors attribute these differences to a tug of war across the two periods between different investor clienteles. In particular, their evidence suggests that retail investors make trades that tend to execute when markets open, consistent with them adjusting their portfolios in the evening. In contrast, institutional investors are shown to trade mostly during the day and especially near the close because of greater liquidity. Because these clienteles prefer to trade at different times, overnight returns tend to be driven by retail trading, whereas intraday returns are strongly affected by institutional trading. These patterns and the finding of Kaniel et al. (2008) that individuals tend to be contrarian can explain why the reversal effect shows up in overnight returns. Specifically, retail investors buy stocks with low past-month returns, pushing up their price and overnight return (as their trades tend to execute at the open), and sell stocks with high past-month returns, driving down their price and overnight return. As a result, the reversal strategy that goes long in past-month losers and short in past-month winners earns a positive overnight return.

In contrast, we expect the salience effect to be mainly an intraday phenomenon because institutions are likely less prone to biases in perception than individuals.[39] In particular, we expect institutional investors to correct in month t+1 the salience-induced mispricing caused by retail trading in month t. Institutions sell the overpriced high-ST stocks (driving down their price and intraday return because institutions tend to trade during the day) and buy the underpriced low-ST stocks (pushing up their price and intraday return). We thus expect the intraday return on high-ST stocks in month t+1 to be lower than the intraday return on low-ST stocks.

We test these predictions by computing the monthly intraday and overnight returns for decile portfolios formed on either ST or REV.[40] Panel A of Table A12 reports the average spread in raw returns and alphas between the decile 10 (high ST or REV) and decile 1 (low ST or REV) portfolios. We confirm that the profit on the short-term reversal strategy is earned entirely overnight.[41] In stark contrast, the return associated with the salience effect is earned entirely intraday. Whereas the difference in the intraday returns of the high- and low-ST deciles is large (86 bps per month) and significant (t-statistic = −4.54), the spread in overnight returns is close to zero and insignificant. We observe this striking pattern in all three size groups, both in raw returns and in alphas.

Panels B and C report results for Fama-MacBeth regressions of overnight and intraday stock returns in month $t+1$ on the REV and ST variables measured at the end of the previous month t. Consistent with the portfolio sorts, the univariate results in panel B show that one-month return reversal occurs entirely overnight, whereas the salience effect is purely an intraday phenomenon.[42] We find similar intraday and overnight patterns after including the full set of controls (panel C).

In summary, the overnight-intraday return decomposition in Table A12 provides further evidence that the salience effect and the short-term reversal effect are distinct phenomena. More work on the trading strategies of different investor clienteles and on the timing of their trades is needed to fully understand the causes of these intraday and overnight return patterns.

7.4. Alternative choice contexts

Following BGS (2013a), we have thus far assumed that investors evaluate a stock in the context of all available stocks in the market and therefore measured the salience of a stock's daily return by comparing it with the return on the EW CRSP index. In this section, we explore alternative specifications of the context with respect to which salience is defined.

We start by examining the impact of the index weighting scheme on the predictive power of ST. Specifically, we measure salience by contrasting stock returns with the return on the VW CRSP index and run regressions with the resulting ST variable. Panel B of Table A13 shows that the predictive ability of ST is not sensitive to the index weighting scheme. Because in practice, investors may use more visible benchmarks as proxies for the market, we also measure salience relative to the S&P 500. Again we find that the strength of the salience effect remains unchanged.

Instead of considering all stocks in the market, investors may focus on a subset of stocks. For instance,

[39] Barber and Odean (2008) show empirically that institutional investors are less prone to engage in attention-driven stock purchases, presumably because they are less subject to cognitive limitations than retail investors. For instance, institutions have more resources to monitor continuously the returns on a wider range of stocks. We therefore expect that their return expectations and trading decisions are not based on only the most salient past returns on a stock.

[40] We construct intraday and overnight returns following the method of Lou et al. (2019) that assumes that dividend payments and stock splits occur overnight. The analysis starts in July 1992 when open prices are available.

[41] The short-term reversal strategy in Lou et al. (2019) goes long in the low past one-month return decile and short in the high past one-month return decile. In contrast, all our portfolio analyses are based on going long in decile 10 (high) and short in decile 1 (low). The positive overnight return on the reversal strategy reported by Lou et al. (2019) is therefore consistent with the negative overnight return we report in Table A12.

[42] The coefficients in the regressions using intraday and overnight returns do not sum exactly to the coefficients in the regressions using closing returns due to an interaction term between overnight and intraday returns. This interaction term arises mechanically because the daily close-to-close return on a stock is the product (not the sum) of its daily overnight return and its daily intraday return. This discrepancy is minor and does not affect our conclusions.

investors may evaluate a stock in the context of other stocks in the same industry. We therefore construct an alternative ST measure by contrasting a stock's return to its industry return, i.e., we replace $\bar{r}_s$ in Eq. (8) with the EW or VW industry return. We group stocks into 48 industries following the classification of Fama and French (1997). Coefficients on the industry-specific ST variables are similar to the slope on the regular ST measure.

Finally, we explore the consequences of defining salience relative to a random choice context. In particular, we compute the salience of a stock's return on day s in month t relative to a market return that is randomly drawn without replacement from the set of daily market returns in t. We expect the predictive power of ST to weaken when specifying a random choice context because a random benchmark return alters the salience of a stock's return, thereby adding noise to ST. The results in Table A13 confirm that the forecasting ability of ST weakens when salience is defined relative to a random context. The slope on ST drops from −0.13 to −0.09 but remains significant.

7.5. Alternative salience specifications

We next 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, defined as 1 plus the net return, e.g., a net return of 5% corresponds to a gross return equal to 1.05. We apply Eq. (11) to gross, rather than net, returns because this alternative function is defined only for positive values.

Panel C of Table A13 reports regression results for the ST measure based on the salience function in Eq. (11). As expected, the coefficient on this alternative ST variable is smaller than the slope on the regular ST measure (−0.09 versus −0.13), since investors usually observe net rather than gross returns. Nonetheless, the salience effect remains statistically significant at the 1% level (t-statistic = −4.91).

Finally, we check the robustness of our results to different values of the θ and δ parameters in Eqs. (8) and (3). The baseline values used to construct the ST measure 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. In columns 5 and 6, we set δ equal to 0.6 and 0.8, respectively, while keeping θ fixed at 0.1. Varying the values of θ and δ has little impact on the predictive power of ST, which remains strong and statistically significant in all cases.

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 US 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 spread between the high- and low-salience deciles is economically large and statistically significant and cannot be explained by common risk factors. Bivariate portfolio analyses and firm-level Fama-MacBeth regressions confirm that the negative relation between our salience theory measure 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. 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. Examining the pricing implications of salience theory for other assets, such as options, provides another fruitful avenue for future work.

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