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“Effect of the salience theory in asset pricing in a context of uncertainty: US evidence”

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1. Introduction

There are a lot of studies about the effect of behavioral elements on financial issues. On the theoretical front one of the most important contributions is Prospect Theory (Kahneman and Tversky, 1979), where the authors postulate that investors derive their utility from gains and losses relative to some reference or benchmark value.

According to Bordalo et al. (2012), the Prospect Theory incorporates the assumption that the probability weights people use to make choices are different from objective probabilities. Bordalo et al. (2012) suggest that these weights depend on the actual payoff and their salience. Bordalo et al. (2013) proposed an asset pricing model based on this idea.

The present study will test the model presented by Bordalo et al. (2013), in the context of the US stocks and considering the effect of uncertainty.

We employ an approach similar to the one used by Coseman and Frehen (2020) in their study about the effect of the Salience Theory in the US stocks.

The main difference between the present study and Cosemans and Frehen (2020), is the incorporation of uncertainty as a key element to understand salience effects.

About uncertainty, it can be seen that Bachmann et al. (2013) in a study use confidential micro data of the German IFO Business Climate Survey to compare a disagreement-based measure of uncertainty with a qualitative index of the forecast error variance of production expectations, and found that both uncertainty measures are positively correlated.

So, the using of non-standard criteria in evaluate the business climate seems to be more important, in relative terms, in a context of high uncertainty.

As long as the increase in the relative importance of non-standard criteria would be associated to an increase in the relative importance of behavioral biases in asset evaluation (according to Cosemans and Frehen (2020), investors differ in their cognitive abilities; so the behavioral biases would not act always in the same intensity for different individuals); then more uncertainty could increase the effect of behavioral biases.

Then, more uncertainty could increase the effect of other behavioral biases such as the Salience Theory.

Moreover, Kumar (2009) and Zhang (2006) found that higher uncertainty increase the effect of some behavioral biases such as the overconfidence and the underreaction to new information.

So, it would be important to measure the effect of uncertainty over different behavioral biases in order to understand better the nature of some distortions over pricing that may influence in some important financial issues as the overvaluation or undervaluation of financial assets.

The paper proceeds as follows. Section 2 shows literature about uncertainty and the Salience Theory. Section 3 analyze in detail the Salience Theory. Section 4 describes the data used in the studio. Section 5 shows how the Salience Theory variable is built. Section 6 explains the other variables that are included, putting emphasis on uncertainty measures. Section 7 explains the models used. Section 8 shows the results of the study. And section 9 concludes.

2. Literature review

According to Knight (1921), uncertainty is defined as individual's inability to forecast the likelihood of events happening.

Following that definition, there are some ways to try to measure the uncertainty. By one hand, there are some measures that are based on some effects of the uncertainty as the VIX (according to Whaley (2009), a market-based measure), or the measures of disagreement in surveys (a consequence of uncertainty), as the measures developed by Bachmann et al. (2013) and Sheen & Wang (2017).

According to Bekaert, Hoerova, and Duca (2012), VIX has a large component that appears driven by factors associated with time-varying risk-aversion rather than economic uncertainty.

Another way to try to measure the uncertainty is by the EPU index proposed by Baker et al. (2016), a newspaper coverage based index. This measure, is oriented to some sources of uncertainty (this measure, try to proxy the news that generate uncertainty).

About the measures based on surveys, Sheen & Wang (2017) indicates that two potential problems with uncertainty measures using survey data are that: (1) they are typically based on one particular survey and, (2) very often rely on one specific economic indicator in the survey, thus making it hard to generalize to the aggregate economy.

The effect of uncertainty on behavioral finance is documented in some studies, as in Kumar (2009), where the author found that more uncertainty increase both the overconfidence and disposition biases. Also, Zhang (2006) found that higher uncertainty increase the underreaction to new information. Moreover, Hirshleifer (2001) and Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) posit that psychological biases are increased when there is more uncertainty.

So, following the idea of test the effect of uncertainty over behavioral finance, the study will analyze the effect of the uncertainty over the Salience Theory.

Following Taylor and Thompson (1982), “salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments".

According to Bordalo et al. (2012), Prospect Theory incorporates the assumption that the probability weights people use to make choices are different from objective probabilities. Bordalo et al. (2012) suggest that these weights depend on the actual payoff and their salience.

Then, Coseman and Frehen (2020) study the effect of the Salience Theory in the US stocks, in order to analyze this idea in an empirical context. They found significative results in a sense that, according to their study, Salience Theory actually has an effect on stock pricing.

3. The Salience Theory

Cosemans and Frehen (2020) said that the first key premise of Salience Theory is that decision makers direct their attention to the most salient payoffs lotteries available for choice.

Moreover, according to Bordalo et al. (2012), psychologists view salience detection as a key attentional mechanism enabling humans to focus their limited cognitive resources on a relevant subset of the available sensory data.

Then Prospect Theory incorporates the assumption that the probability weights people use to make choices are different from objective probabilities (Bordalo et al., 2012).

So, salience is a cognitive mechanism that implies the existence of a subset of observations (the salient observations) which are more relevant in the cognitive process than other observations.

Then, if these observations receive more attention than others, they are more relevant in the assessment of a situation.

If we compare the Salience Theory with the Prospect Theory, we can see that according to Cosemans and Frehen (2020), in the weighting function in Salience Theory, the payoffs in the tails of the distribution are only overweighted if they are salient.

While in Cumulative Prospect Theory of Tversky and Kahneman (1992), decision weights are distorted by a fixed weighting function, which implies that tail events are always overweighted.

In this line, according to Cosemans and Frehen (2020), a key premise of the salience model is that choices are made in context, which means that investors evaluate each risky asset by comparing its payoffs to those of the available alternatives.

Moreover, Cosemans and Frehen (2020) indicates that in the salience model, the extreme stock returns are overweighted not because they have small probabilities but because they are salient relative to the market return.

4. Data

The data of the firm-specific variables will be obtained from Thomson Reuters Eikon Datastream; the data is from January 2001 to December 2019, and contains information of the companies listed on NYSE or NASDAQ. By other hand, the data of uncertainty will be obtained from some links[1].

Some data is daily and other data is monthly. By one hand, prices, volume and the value of the market index (S&P 500 is used) are registered as daily variables; and by other hand, price to book, market cap, uncertainty, number of analysts and sentiment are registered as monthly values.

As in Cosemans and Frehen (2020), an stock will be included in the analysis for month “t" if it satisfies the following criteria: First, there should be a minimum of 15 daily return observations within the given month to compute ST. Second, historical data should be available to compute each of the firm characteristics that are used as control variables.

In Table 1, the descriptive statistics can be seen.

[1] https://www.policyuncertainty.com/ for EPU; and http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data for VIX.

5. The measure of Salience Theory

The measure of Salience Theory will be the same as in the study of Coseman & Frehen (2020). In their study, they define that the space of possible states is given by the daily returns that had the share "i" in the month "t".

Then, is assumed that the individuals see these possible states (which happened in the past), as possible states of the share in the future.

Then, the salience of the state "s" for the share "i", depends on the difference among the share's return for this state (r_{is}) and the average return of all the shares for this state ($\bar{r}_s$).

So, it can be obtained the following salience function:

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{|r_{is}| + |\bar{r}_s| + \theta} \qquad (1)$$

Where, following Coseman & Frehen (2020), θ has a value of 0.1.

Then, the following functions are defined:

$$\tilde{\pi}_{is} = \pi_s * \omega_{is} \qquad (2)$$

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

Where, following Coseman & Frehen (2017), δ has a value of 0.7.

ω_{is} is the salience weight, which depends on the ranking of salience (k_{is}) of the state "s" for the share "i"(k_{is} can take discrete values from 1 to S, where S is the number of possible states; k_{is} ranks the results obtained by the salience function $\sigma(r_{is}, \bar{r}_s)$). k_{is} takes a value of 1 in the case of the highest salience, and takes a value of S in the case of the lowest salience.

ω_{is} are normalized so that they sum to 1; then the expected distortion is zero ($E(\omega_{is}) = 1$).

By other hand, π_s is the objective probability of the state "s", which is equal to 1/S (where S, is equal to the number of trading days in the month).

Then, it can be obtained the following measure of salience:

$$ST_{it} \equiv \mathrm{cov}[\omega_{ist}, r_{ist}] = \sum_{s}^{S} \pi_{st} * \omega_{ist} * r_{ist} - \sum_{s}^{S} \pi_{st} * r_{ist} = E^{ST}[r_{ist}] - \bar{r}_{ist} \qquad (4)$$

So, ST measures the distortion of the return expectations, caused as a consequence of the salient thinking.

6. Control variables

The study will include the uncertainty as a control variable in order to analyze the influence of the uncertainty over the effect of Salience Theory.

By other hand, the firm-specific variables included in Coseman & Frehen (2020) as control variables, will be included.

6.1 Uncertainty

Knight (1921) defines uncertainty as individual's inability to forecast the likelihood of events happening.

One of the measures that try to reflect the uncertainty is the EPU index proposed by Baker et al. (2016). This variable is based on newspaper coverage; moreover, according to Baker et al. (2016), for the case of US, this measure reflects the frequency of articles in 10 leading US newspapers that contain the following triple: “economic" or “economy"; “uncertain" or “uncertainty"; and one or more of “congress", “deficit", “Federal Reserve", “legislation", “regulation" or “White House".

Another variable used to measure uncertainty is the S&P 500 volatility index VIX. According to Whaley (2009), VIX is implied by the current prices of S&P 500 index options and represents expected future market volatility over the next 30 calendar days.

Baker et al. (2016) says that VIX index is the most commonly used proxy for overall economic uncertainty.

Also, according to Bekaert, Hoerova, and Duca (2012), VIX has a large component that appears driven by factors associated with time-varying risk-aversion rather than economic uncertainty.

In the present study, both uncertainty measures will be used.

Another kind of variable that measures uncertainty, are the measures of disagreement in surveys, as the index developed by Bachmann et al. (2013) and Sheen & Wang (2017).

The index developed by Bachmann et al. (2013), use micro data of the German IFO Business Climate Survey to measure disagreement. By other side, Sheen & Wang (2017) use the Michigan Survey of Consumers, the Survey of Professional Forecasts, and the Livingston Survey in order to measure disagreement.

According to Sheen & Wang (2017), two potential problems with uncertainty measures that use survey data are that: (1) they are typically based on one particular survey and, (2) very often rely on one specific economic indicator in the survey, thus making it hard to generalize to the aggregate economy.

6.2 Firm-specific factors

This study also will include the firm-specific variables used in Cosemans and Frehen (2020). These variables are the following:

-Firm size (ME), measured as the log of the market value of equity. This is a variable used in Fama & French (1993), in order to explain asset returns.

-Book-to-market (BM), as the ratio of the book and market value of equity (following Fama & French (1993), the Book-to-market is calculated using accounting data of December of the previous year and exclude firms with negative book equity). This is also a variable used in Fama & French (1993), in order to explain asset returns.

-Momentum (MOM), as the cumulative return over the 11 months prior to the current month. This is a variable used in Carhart (1997), in order to explain asset returns.

-Amihud (2002), illiquidity (ILLIQ), as the absolute daily return divided by the daily dollar trading volume, averaged over all trading days within the month. This variable was used by Amihud (2002) as an explanatory variable of stock returns.

-Market beta (BETA), which is estimated from a regression of daily excess stock returns on the daily excess market return over a one-month window.

-Idiosyncratic volatility (IVOL), as the standard deviation of the residuals from this last regression. This variable is used following that Ang et al. (2009) found that stocks with recent past high idiosyncratic volatility tend to have much lower returns than stocks with recent past low idiosyncratic volatility.

-Short-term reversal (REV), as the stock return in the previous month t-1. The Short-term return reversal effect on stock return was documented by Jegadeesh (1990) and Lehmann (1990).

-The maximum (MAX) and the minimum (MIN) daily return on a stock within each month. This variables are added following that Bali et al. (2011) found an important role of that variables in order to explain asset returns.

-The Prospect Theory (TK) value of a stock. This variable is constructed using a five-year window of monthly returns following the approach of Barberis et al. (2016). The Prospect Theory variable is analyzed in Kahneman and Tversky (1979), where the authors said that investors derive their utility from gains and losses relative to some reference or benchmark value.

-The Skewness (SKEW) is the skewness of daily stock returns, a variable that according to Kraus and Litzenberger (1976) influence the investor's preferences. Following Bali et al. (2011), total skewness, coskewness, and idiosyncratic skewness are computed using daily returns over a one-year period in order to have sufficient observations to adequately capture skewness.

-The Coskewness (COSKEW), a variable important in explaining the asset returns according to results found by Harvey and Siddique (2000). This variable is defined as the coskewness of daily stock returns with daily market returns, computed using the approach of Harvey and Siddique (2000).

-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. (2009). According to Kumar (2005), this variable has a role on explanation of asset returns.

-The downside beta (DBETA), a variable that has influence on asset returns according to Ang et al. (2006). This variable 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).

All variables are winsorized at the 1st and 99th percentiles.

7. Models used to analyze the relation between salience and stock returns

As in Cosemans and Frehen (2020), firm-level Fama-MacBeth regressions will be ran; the impact of limits to arbitrage in the results, also will be analyzed, as a way to check for the robustness of the results.

7.1 Fama-Macbeth regressions

As in Coseman & Frehen (2017), some firm-level Fama and MacBeth (1973) regressions will be ran in order to control for multiple characteristics simultaneously.

The regression equation used by Coseman & Frehen (2017) is (r_{it+1} is the excess stock return in month t+1):

$$r_{it+1} = \lambda_0 + \lambda_1 ST_{it} + \lambda_2 W_{it} + v_{it} \qquad (5)$$

Where 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).

To analyze the potential influence of different levels of uncertainty on the effect of ST on returns, we incorporate thresholds in our empirical analysis[2]. Consequently, the following regression will be estimated:

[2] See Ma et.al. (2018) for an application threshold analysis and uncertainty in the context of forecasting

$$r_{it+1} = \lambda_0 + \lambda_1 ST_{it} I(U_t \leq \gamma) + \lambda_2 ST_{it} I(U_t > \gamma) + \lambda_3 I(U_t \leq \gamma) + \lambda_4 W_{it} + v_{it} \quad (6)$$

Where, U_t is the level of uncertainty (can be EPU or VIX), and γ is the median of the uncertainty levels observed in the sample.

The Fama and MacBeth (1973) regressions will include Newey-West (1987) Standard Errors with 12 lags.

7.2 Impact of limits to arbitrage

According to Cosemans and Frehen (2020), investors differ in their cognitive abilities and therefore 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 could correct the mispricing induced by salient thinkers by buying stocks with salient downsides and shorting stocks with salient upsides.

Therefore, using Fama-Macbeth regressions based on the regressions used by Cosemans & Frehen (2020), the results will be controlled by limits to arbitrage in order to check for the robustness of the results.

Following Cosemans and Frehen (2020), four proxies for limits to arbitrage will be considered: firm size, illiquidity, idiosyncratic volatility, and analyst coverage (measured by the Number of Analysts, NOA).

Cosemans and Frehen (2020) said that arbitrage is more costly and risky for small stocks, illiquid stocks, and stocks with high idiosyncratic risk. Also, they said that low analyst coverage has been associated with higher arbitrage risk because it signals that less information is available about the firm.

According to Cosemans and Frehen (2020), NOA is strongly correlated with firm size; then, following Conrad et al. (2014), the residuals from a regression of this variable on firm size and time dummies are computed.

8. Results

As in Cosemans and Frehen (2020), the coefficients associated to Salience Theory are negative and statistical significative.

In Table 2 and 3, it can be seen that there is an important difference between the coefficient associated to ST under low uncertainty and ST under high uncertainty. So, this tables indicates that uncertainty influences the effect of Salience Theory both using VIX or EPU as an uncertainty measure.

Kumar (2009) and Zhang (2006) indicates that uncertainty strengthen some behavioral biases. So, the results in Table 2 and 3 are in line to these studies, as in this tables it can be seen that uncertainty strengthen a behavioral bias as the Salience Theory.

By other hand, according to Cosemans and Frehen (2020), investors differ in their cognitive abilities and therefore vary in the degree of salient thinking. Then, when there are no limits to arbitrage, the investors with less salient thinking could correct in some measure the effect caused by the investors that have high salient thinking.

In Table 4 and 5, it can be seen that the results of controlling by limits to arbitrage are similar to the results of Table 2 and 3 respect the differences between the coefficient associated with ST under low uncertainty and ST under high uncertainty. So, the results show that uncertainty has some influence over the effect of the Salience Theory on stock returns, even controlling by limits to arbitrage.

Is interesting to analyze the differences between results obtained by using one measure of uncertainty or another.

In Fama-MacBeth regressions that does not include controls by limits to arbitrage, the VIX index is associated to more relevant differences between salience under high uncertainty and salience under low uncertainty.

In Fama-MacBeth regressions that include controls by limits to arbitrage, the EPU index is associated to more relevant differences between salience under high uncertainty and salience under low uncertainty.

A possible explanation to that results could be that VIX not only measures effects of more uncertainty, because more risk (known risk) could increase the VIX.

EPU, by other hand, could be less oriented to known risks than VIX, and then EPU could be more oriented to uncertainty (as a consequence of the nature of EPU, an index that is based on news coverage; then EPU could be more oriented to new and less known issues that generates variations in the economic outputs).

So, in one case, the threshold could be based on uncertainty measured in a cleaner way than in the other threshold, and as controls by limits to arbitrage could reduce better the arbitrage effects of known risks, then limits to arbitrage could affect more the results found in an analysis where the uncertainty measure would be measure using VIX.

Then, because VIX index include also known risks, then added to the effect of the uncertainty in the Salience Theory, it could be seen the effects of other variables over the Salience Theory if VIX index is used instead of EPU index (for the case that doesn't include limits to arbitrage).

Also, according to Bekaert, Hoerova, and Duca (2012), VIX has a large component that appears driven by factors associated with time-varying risk-aversion rather than economic uncertainty.

So, the possible explanation of the differences between the results of using different index could be explained by the nature of the index, in a sense of the influence of both known risks and risk-aversion, in VIX index.

It would be interesting to test this hypothesis related to using one proxy for uncertainty or another, in future studies.

9. Conclusions

As in Cosemans & Frehen (2020), it can be found that the coefficient associated to Salience Theory is negative and statistically significative.

And following the results observed in Kumar (2009) and Zhang (2006), that higher uncertainty increase some behavioral variables, in the present study it can be found that Salience Theory (another behavioral variable) is increased when the uncertainty is higher.

The higher effect of the Salience Theory also can be found by controlling for limits to arbitrage.

The mentioned results vary between different proxies for uncertainty. Specifically, in Fama-MacBeth regressions that include controls by limits to arbitrage, the EPU index is associated to more relevant differences between salience under high uncertainty and salience under low uncertainty (in comparation to using VIX index as a proxy to uncertainty).

Meanwhile, in Fama-MacBeth regressions that doesn't include controls by limits to arbitrage, the VIX is associated to more relevant differences in the role of Salience Theory.

A possible explanation could be the nature of the proxies of uncertainty. VIX index could be oriented more to both known risks and risk-aversion than EPU index, so arbitrage could have a more important role around VIX index.

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Table 1: Descriptive Statistics

	Obs	Mean	Std. Deviation
ST	220,813.0	0.002	0.02
TK	137,740.0	-0.1	0.1
EPU	220,814.0	133.3	48.6
VIX	200,741.0	17.5	6.8
Downside beta	204,200.0	1.0	0.6
Skewness	204,200.0	-0.04	1.3
Coskewness	204,200.0	-6.9	17.8
Iskew	204,200.0	-0.007	1.5
Book to Market	220,572.0	0.6	0.6
Min return	220,814.0	-0.1	0.049
Max return	220,814.0	0.1	0.1
Short term reversal	217,704.0	-0.002	0.1
Idiosyncratic volatility	220,814.0	0.024	0.02
Illiquidity	220,814.0	0.0006	0.0026
Momentum	220,801.0	1.1	0.5
Beta	220,814.0	0.9	1.1
Market Cap	220,814.0	5,728.8	15,925.6

Table 2: Fama-Macbeth regressions with EPU, and Newey and West (1987)-adjusted standard errors with 12 lags.

	(1)	(2)	(3)	(4)
Salience Theory X Low-EPU	-0.040*	-0.049*	-0.039	-0.009
	[-1.884]	[-1.973]	[-1.607]	[-0.263]
Salience Theory X High-EPU	-0.042	-0.034	-0.094***	-0.088***
	[-0.320]	[-0.501]	[-3.580]	[-2.624]
Low-EPU	-0.005*	-0.001	-0.005***	-0.005***
	[-1.801]	[-0.730]	[-2.791]	[-3.312]
TK		0.052	0.072**	0.042
		[1.251]	[1.975]	[1.275]
Skewness		0.002	0.009	-0.002*
		[0.420]	[0.754]	[-1.866]
Coskewness		0.000**	0.000**	-0.000
		[2.006]	[2.029]	[-0.063]
Iskew		-0.001	-0.010	0.000
		[-0.419]	[-0.818]	[0.083]
Book to Market			-0.001	0.010***
			[-0.062]	[7.178]
Market Cap			-0.000	0.000
			[-0.962]	[0.998]
Beta				0.001
				[0.409]
Downside Beta				0.003
				[0.689]
Min Ret				-0.046
				[-0.884]
Max Ret				0.051
				[1.577]
Short-term Reversal				0.018
				[1.547]
Idiosyncratic Volatility				-0.599***
				[-3.545]
Illiquidity				1.599***
				[4.231]
Momentum				-0.001
				[-0.170]
Constant	0.003	0.001	0.004	-0.006
	[0.779]	[0.377]	[0.973]	[-0.553]
Observations	218,971	136,453	136,356	136,356

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Fama-Macbeth regressions with VIX, and Newey and West (1987)-adjusted standard errors with 12 lags.

	(1)	(2)	(3)	(4)
Salience Theory X Low-VIX	0.076	0.032	-0.028	-0.035
	[0.642]	[0.465]	[-1.370]	[-1.588]
Salience Theory X High-VIX	-0.158***	-0.115***	-0.105***	-0.063*
	[-2.827]	[-3.589]	[-3.407]	[-1.666]
Low-VIX	-0.001	-0.002	-0.001	-0.011
	[-0.191]	[-0.853]	[-0.172]	[-0.997]
TK		0.052	0.072**	0.042
		[1.251]	[1.975]	[1.275]
Skewness		0.002	0.009	-0.002*
		[0.420]	[0.754]	[-1.866]
Coskewness		0.000**	0.000**	-0.000
		[2.006]	[2.029]	[-0.063]
Iskew		-0.001	-0.010	0.000
		[-0.419]	[-0.818]	[0.083]
Book to Market			-0.001	0.010***
			[-0.062]	[7.178]
Market Cap			-0.000	0.000
			[-0.962]	[0.998]
Beta				0.001
				[0.409]
Downside Beta				0.003
				[0.689]
Min Ret				-0.046
				[-0.884]
Max Ret				0.051
				[1.577]
Short-term Reversal				0.018
				[1.547]
Idiosyncratic Volatility				-0.599***
				[-3.545]
Illiquidity				1.599***
				[4.231]
Momentum				-0.001
				[-0.170]
Constant	-0.002	0.002	-0.001	0.000
	[-0.483]	[0.600]	[-0.141]	[0.123]
Observations	218,971	136,453	136,356	136,356

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Fama-Macbeth regressions with EPU, Limits to Arbitrage, and Newey and West (1987)-adjusted standard errors with 12 lags.

	(1)	(2)	(3)	(4)
Salience Theory X Market Cap	0.000			
	[1.001]			
Salience Theory X Illiquidity		-7.093		
		[-0.639]		
Salience Theory X Idiosyncratic volatility			-1.605	
			[-1.217]	
Salience Theory X Number of Analyst				0.001
				[0.094]
Salience Theory X Low-EPU	0.004	-0.005	-0.028	-0.001
	[0.122]	[-0.105]	[-0.644]	[-0.017]
Salience Theory X High-EPU	-0.086***	-0.061**	0.033	-0.084***
	[-2.682]	[-2.154]	[0.592]	[-2.719]
Low-EPU	-0.004**	-0.003	-0.002	-0.004**
	[-2.336]	[-1.561]	[-1.595]	[-2.209]
Market Cap	-0.000	0.000	0.000	0.000
	[-1.006]	[0.997]	[0.998]	[1.000]
Idiosyncratic Volatility	-0.540***	-0.521***	-0.539***	-0.540***
	[-2.945]	[-2.967]	[-2.876]	[-2.945]
Illiquidity	1.683***	1.817***	1.683***	1.683***
	[4.123]	[4.796]	[4.221]	[4.123]
Number of Analyst	-0.000	-0.000	-0.000	-0.000
	[-1.001]	[-1.001]	[-1.001]	[-1.001]
Constant	0.005	-0.007	-0.008	-0.006
	[1.582]	[-0.718]	[-0.771]	[-0.610]
Observations	128,894	128,894	128,894	128,894

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Fama-Macbeth regressions with VIX, Limits to Arbitrage, and Newey and West (1987)-adjusted standard errors with 12 lags.

	(1)	(2)	(3)	(4)
Salience Theory X Market Cap	0.000			
	[1.001]			
Salience Theory X Illiquidity		-7.093		
		[-0.639]		
Salience Theory X Idiosyncratic Volatility			-1.605	
			[-1.217]	
Salience Theory X Number of Analyst				0.001
				[0.094]
Salience Theory X Low-VIX	-0.025	-0.026	-0.001	-0.038
	[-1.073]	[-1.056]	[-0.045]	[-1.607]
Salience Theory X High-VIX	-0.056*	-0.040	0.006	-0.046
	[-1.681]	[-1.199]	[0.140]	[-1.455]
Low-VIX	-0.001	-0.011	-0.012	-0.012
	[-0.865]	[-0.997]	[-1.151]	[-1.118]
Market Cap	-0.000	0.000	0.000	0.000
	[-1.006]	[0.997]	[0.998]	[1.000]
Idiosyncratic Volatility	-0.540***	-0.521***	-0.539***	-0.540***
	[-2.945]	[-2.967]	[-2.876]	[-2.945]
Illiquidity	1.683***	1.817***	1.683***	1.683***
	[4.123]	[4.796]	[4.221]	[4.123]
Number of Analyst	-0.000	-0.000	-0.000	-0.000
	[-1.001]	[-1.001]	[-1.001]	[-1.001]
Constant	0.002	0.000	0.002	0.001
	[0.497]	[0.095]	[0.541]	[0.363]
Observations	128,894	128,894	128,894	128,894

*** $p<0.01$, ** $p<0.05$, * $p<0.1$