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Salience theory on four financial instruments: Empirical evidence on currencies, bonds, indices and commodities

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PREFACE AND ACKNOWLEDGEMENTS

I have written this thesis with much joy, as it represents the final piece of my studies. I'd like to thank my parents for always supporting me during my studies, my supervisor for his immaculate flexibility, my friend Bram for fixing my excel modelling problem in five minutes and my close friends with whom I could discuss all my thesis struggles and frustrations throughout the process.

ABSTRACT

The study assesses the impact of salience, measured by covariance of daily salience and returns over 21 days, on asset classification. Utilising tertiles, assets are grouped, with the most salient shorted and the least salient taken long in the subsequent month. Results reveal significant positive returns for the overall sample and individual asset classes, supported by OLS regressions with salience and salience-sorted portfolios showing statistical significance on future returns. Robustness tests confirm the efficacy of the salience measure, with quartile, quintile, and decimal portfolios demonstrating superior returns. Notably, extreme salience rankings yield the highest returns. The study underscores salience's independent influence on future returns and suggests potential for practical application in portfolio management, albeit with acknowledgment of limitations regarding trading costs and risks.

Keywords: Salience, Asset pricing, market anomaly, behavioural finance

JEL Classification: G11, G12, G14, G41

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1.0 Introduction

In everyday life, individuals often encounter situations troubled with uncertainty. Uncertainty arises when both the outcomes and the probabilities are unknown. Alternatively, individuals may find themselves weighing various scenarios with known likelihoods, a circumstance referred to as "choice under risk."

Expected utility theory, a staple of classical economics, endeavours to predict individuals' choices by suggesting that they seek to maximise their expected utility. This theory, popularised by Briggs (2014), operates on the assumption that individuals select options yielding the highest expected utility when combined with their respective probabilities. Yet, empirical evidence has shown instances where expected utility theory fails to accurately forecast decision-making behaviours, as illustrated by Allais (1953) and others.

In response to such discrepancies, researchers have explored alternative frameworks, collectively termed "non-expected utility" models. These models diverge from the foundational principles of expected utility theory. Among these models, Kahneman and Tversky's seminal work on "prospect theory" (1979) and its subsequent refinement, "cumulative prospect theory" (Tversky & Kahneman, 1992), stand out. Prospect theory suggests that framing decisions in terms of changes in wealth rather than absolute wealth levels and emphasising losses over gains better captures individuals' decision-making processes.

One such recent addition to the repertoire of non-expected utility models is the "salience theory" proposed by Bordalo, Gennaioli, and Schleifer (2012). Salience, as defined by psychologists Taylor and Thompson (1982), refers to the phenomenon where selectively directing attention to particular aspects of the environment leads to disproportionate weighting of information from those aspects in their subsequent judgments. Salience theory suggests that individuals' inconsistent risk preferences stem from the salient payoffs associated with certain lotteries, causing decision-makers to overweight these lotteries and distort objective probabilities. Furthermore, Bordalo, Gennaioli, and Schleifer (2012) underscore the role of context in shaping decision-making and its ultimate outcomes.

Building upon this theoretical foundation, Bordalo, Gennaioli, and Shleifer (2013) introduced a salience-based asset pricing model aimed at explaining four enduring puzzles in asset pricing. These puzzles encompass preferences for assets offering potentially high returns, the value-growth puzzle, the equity premium anomaly, and counter cyclical variations in risk premia. By incorporating salient thinking and investors' shared trading behaviours, the model of Bordalo et al. (2013) offers explanations for these puzzles within the framework of salience theory.

While theoretical frameworks like salience theory could perhaps help with explaining market phenomena, empirical validation remains crucial. Cosemans and Frehen (2017) provide pioneering empirical evidence on the predictive capacity of salience in the US stock market. Their findings suggest that salience influences stock returns, with investors being attracted towards salient stocks, thus contributing to their overvaluation and subsequent lower returns. Notably, this effect intensifies during periods of higher investor sentiment and when arbitrage constraints are tighter.

Thereby, a closer look at salience's effect was researched by Cakici and Zaremba (2022), in light of the findings from Cosemans and Frehen (2017). The study reveals a negative association between salience theory (ST) and future returns in global markets, particularly affecting the smallest firms. However, the anomaly weakens over longer estimation periods and has diminished in recent decades. It resembles short-term reversal patterns and displays international variation influenced by market development. Moreover, its significance diminishes during stable market conditions. These results shine light on the question of salience's effectiveness in predicting future returns only for stocks, not for other financial instruments. Thus this study will look into this effect for other not yet studied financial instruments. Hence, a compelling research question emerges:

Does salience have predictive capacity for future returns for bonds, stocks, indices and commodities?

In this thesis, the possible predictive capacity of salience on bonds, stocks, indices and commodities is researched. By utilising data from Datastream from 1990-2024, the daily returns of 20 to 26 of the most liquid and high quality variables are taken per asset class. With the daily returns, the monthly salience measure could be calculated, next to momentum, momentum reversal, skewness, maximum and minimum variables. The salience measure is taken from previous papers on the topic (Bordalo, Gennaioli, and Shleifer 2013; Coseman and Frehen 2017). First, the four asset classes are treated as one constituent group to see if salience has predictive capacity on the samples combined. Later all four asset classes are researched independently, as this thesis aims to answer the question of the capacity of salience on all four asset classes separately. With the results from both analyses it will show whether or not this particular group of assets has better results being treated as one financial market or not.
The monthly values of salience are taken for every relevant asset class at the last trading day of the month. Here, they are ranked on the covariance of their daily salience measure and the daily returns

for the past 21 trading days. Based on the value that comes out of that calculation, the assets are divided into subgroups, mostly tertiles throughout this thesis. The most salient tertile is then taken into a short position in the upcoming month and the least salient tertile is taken into a long position in the upcoming month.

1.1 Literature

Asset pricing is a fundamental and intricate field within finance that explores the valuation and determination of asset prices in financial markets. The foundation of asset pricing theory lies in in explaining the behaviour of asset prices and, subsequently, the allocation of resources in financial markets. This field forms the backbone of modern finance and has evolved significantly over the years, guided by prominent financial economists and their seminal contributions. Understanding asset pricing is indispensable for investors, financial analysts, and policymakers, as it offers essential insights into the pricing, risk, and returns of financial assets.

At the core of asset pricing theory is the Efficient Market Hypothesis (EMH), which suggests that asset prices in efficient markets reflect all available information and, therefore, are fairly valued. The EMH has sparked extensive research and debate, leading to the development of three primary forms: the weak form, which asserts that past prices and volumes are already reflected in current prices; the semi-strong form, which suggests that all public information is already factored into prices; and the strong form, which implies that all information, public and private, is incorporated into asset prices. This foundational concept influences various aspects of asset pricing, including the study of anomalies and market inefficiencies.

The introduction of the CAPM model in asset pricing theory was first published by William Sharpe (1964). With his groundbreaking work he provided the field with a framework to capture the expected return on an asset given its systematic risk, or beta to be more specific. Together with the work of his academic peers, Miller (Modigliani and Miller, 1958) and Markowitz (1952), the Nobel prize for economics was presented to them for their efforts in asset pricing theory.

Their theories formed the consensus of asset pricing theory for their time, although the theory never lacked criticism. Even though plenty additional theories were built on top of the CAPM framework that we still find influential in the academic field today. One such highly influential paper by Fama (1970) advocated the efficient market hypothesis (EMH), as stated earlier. On the foundation of the CAPM theories, Fama introduced the theory of a completely efficient financial market. Three years later, another highly influential paper built further on the existing theories. The paper of Merton

(1973) suggested that the intertemporal constraint of consumption should be implemented into CAPM theory, further sharpening the model.

Criticisms on the theory still persisted. One of the first papers to exhibit cracks in the CAPM framework came from Banz (1981). The author found evidence of a size effect, where small stocks tended to outperform large stocks over time. This contradicted the predictions of the EMH and suggested the presence of systemic anomalies. Adding to this, the three factor model of Fama and French (1992) was notably influential in disregarding the CAPM as a flawless model. Although Fama was one of the original proponents of the EMH, this paper introduced the Fama-French Three-Factor Model, which extended the traditional Capital Asset Pricing Model (CAPM) by including two additional factors: size and book-to-market ratio. The findings in this paper suggested that there are systematic patterns in stock returns that go beyond what the EMH would predict.

The systematic breakdown of the theory continued as more and more evidence emerged in the light of market anomalies. One of the most famous examples comes from Jegadeesh and Titman (1993), where they found a momentum factor present in their portfolios. This suggested that, next to size and book-to-market ratio, there now was another anomaly that contradicted the theory of a fully efficient financial market.

Fast forwarding to the present, where many anomalies in the financial markets have been found. Some of these anomalies have been heavily researched, some less than others. In 2012 (Bordalo et al) the anomaly of Salience was found present in financial instruments. The authors propose that individuals overweight salient information, or information that is easily noticeable, in their risk assessments. This psychological bias leads individuals to place excessive weight on highly salient, but not necessarily economically relevant, information when making choices involving risk. The theory suggests that this salience bias affects both individual decisions and market outcomes. The authors present experimental evidence supporting their theory and discuss implications for understanding investor behaviour, market dynamics, and the formation of financial bubbles. The Salience Theory contributes to behavioural economics by highlighting the importance of attention and perception in shaping individuals' risk preferences and decision-making processes.

This theory should not be confused with momentum theory, which is similar to Salience Theory in many aspects, but not all. Asness et al (2013) found momentum to be present in stocks, next to the value factor. Here, the authors suggest that there is a zero weight portfolio possible that in the long run will grant you returns for a combined portfolio of value and momentum measures. The momentum measures overlap in some aspects, as it is alike in framework. The momentum portfolio is constructed by buying the top one-third performing financial instruments as measured from a year

back until last month and shorting the worst one-third performing financial instruments as measured from a year back until last month.
Here, momentum is measured over the span of a year, whereas Salience Theory has a much shorter outlook. Short term momentum can be a part of the salience of a financial instrument, but not fully resemble it. Salience can also be measured by events, news coverage and trends, whereas momentum is just the performance trend of a financial instrument. Most importantly, however, is the difference in cyclicality. With momentum theory it suggests that the performance will continue with the trend, whereas with Salience the theory suggests that the one should bet against the most salient instruments. Thereby, the least salient instruments should be taken into a long position, as they will diverge from their current underperformance.

Recently, Cosemans and Frehen (2021) dove deeper into Salience Theory and profoundly tested the theory on US stocks. They demonstrated that ST has direct implications for empirical asset pricing. They developed a measure that captures the salience of past returns distributions and show that it reliably predicts the cross-section of US stock returns. The high-ST companies significantly underperform their low-ST counterparts.
This paper drew the attention of other academics and swiftly after the publication of the claim that a marketable strategy could be put forth using the salience theory, more research was conducted on the topic. Cakici and Zaremba (2022) found that salience exists only in micro firms (those that made up the bottom 3% of the stock market) in a sample that spans 49 countries. For small and big firms, the effect is small and insignificant. There is nothing there statistically speaking for 97% of the market, the more tradeable part of the market. Also, most of the salience in the micro caps is most profound during extreme market situations, like a big crash. Considering these findings, given that there are also high transaction fees involved with the strategy, the implication of their paper is thus that there is no trading strategy around the salience theory after dividing the stock-listed firms by market capitalization. Thereby, the fact that the paper by Cosemans and Frehen (2021) only incorporated US stock data in their analysis, whereas Cakici and Zaremba (2022) performed their analyses on almost all available and adequate stock data, highlights the importance of incorporating all available data.

2.0 Methodology

A key idea in salience theory is that people make decisions, and when they do they tend to focus more on the outcomes that stand out the most among their options. This can cause them to give too much importance to certain outcomes that catch their attention. Another important aspect of salience theory is that people make decisions by comparing the potential results of each choice they have. The outcomes that stand out the most are the ones that are very different from what other choices offer. This is based on the idea, mentioned by Kahneman (2003), that people find it easier to notice differences rather than exact values.

The salience model, proposed by Bardalo et al (2012), combines these ideas by using a special formula that takes into account both where people naturally pay attention and how they compare different options when making choices. This formula helps translate the probabilities of different outcomes into the importance people give to those outcomes when making decisions.

In this paper, the Salience Theory (ST) value is determined by closely following the examples of Cosemans and Frehen (2021) and Cakici and Zaremba (2022), who based their research also on the contributions of Bardalo et al (2013). It is assumed that an agent's choice should comprise all available financial instruments within the same asset class. This is in place, so that the assessment of an instrument will be done against the performance of all other similar financial instruments. The salience of such an instrument on a day ($r_{i,s}$) is then weighted off against the performance of all other relevant instruments on the market that day in the sample ($\bar{r}_s$). The commonly used formula for the Salience daily payoff measure is formulated as in equation 1:

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

By example of Cosemans and Frehen (2021) and Cakici and Zaremba (2022), the θ is assumed to be 0,1. The average return of $\bar{r}_s$ is derived from the corresponding average of all the other instruments within the respective asset class. This is done as this paper assumes that the investor is looking to invest within that asset class and will thus look to them as the most likely reference point.

In previous literature (Bordalo et al. 2012; Cakici & Zaremba, 2022; Cosemans & Frehen, 2021), the numerator is taken for absolute values. In this research, the formula is copied as in the literature. In another master thesis (Chlorokostas, 2018), a reasonable case is argued for the removal of the absolute values in the numerator, allowing the values to range between -1 and 1 instead of 0 and 1. With this implementation, it becomes possible to see whether the market is overvalued or undervalued. This could help with predicting future market returns. In the robustness section of this research, the disparity in results is shown between the two methods.

In equation 1 the function satisfies the following conditions needed for Salience Theory: ordering; diminishing sensitivity; and reflection.
Ordering means that the Salience σ $(r_i \bar{r}_s)$ increases with the distance between the return of stock i and its cross-sectional average. The second condition, diminishing sensitivity, means that salience rises when the absolute returns uniformly increase for all stocks, or indices and ETF's. I.e. salience is dependent on the difference in returns between the other similar financial instruments and the studied subject. Lastly, reflection implies that the payoffs' sign is irrelevant, and the overall salience depends only on the magnitude of the returns. Investor perception is sensitive to absolute values, thus reflecting gains as losses does not impact a return's salience.

The final ST value is calculated in multiple steps, as pioneered by the previous literature of Cosemans et al (2021) and Cakici and Zaremba (2022). After equation 1 is put in order, the sort of the payoffs r_{is} on their respective salience for the measured period. Ranks $K_{i,s}$ will then be assigned ranging from 1 for the most salient instrument to S for the least salient instrument. S being the number of possible states, depending on the amount of individual data points used in the regression and the amount of trading days within the month. So, every possible return has the same probability π_s so that

$\sum_{s=1}^{S} \pi_s = 1$

Thereby, the salience-weighted probabilities from the returns of $\tilde{\pi}_{i,s}$ are calculated but can be substituted by π_s. Giving us equation 2:

$$\tilde{\pi}_{i,s} = \pi_s * \ \omega_{i,s}$$

Where the salient weight of a security day is as follows in equation 3:

$$\omega_{i,s} = \frac{\delta_{i,s}^{K}}{\sum_{s'} \delta_{i,s}^{K} * \pi_{s'}}$$

The parameter δ is set at 0,7 like the predecessors in this academic field have shown (Cosemans and Frehen, 2021; Cakici and Zaremba, 2022). For the resemblance of a monthly weight, the past 21 trading days are used in this formula.

Finally, the monthly ST value (ST_i) for stock *i*, which we use to predict the subsequent month's return, is computed as the covariance between salience weights and daily returns in equation 4:

$$ST_i = cov[\omega_{i,s}, r_{is}]$$

This equation captures the principal prediction of the salience-based asset-pricing framework. Securities with high ST values are expected to have low future returns while stocks with low ST scores should produce higher future returns. The range of this formula captures the daily return and salience weights for the past 21 trading days, as to mimic the ST of a full trading month. In order to capture the full potential of the salience, the assets will be ranked every month in order of salience and sorted into portfolios of certain thresholds. Then the financial instruments with high salience will be shorted and those with low salience will be taken into a long position, as to capture the respective over- and undervaluation.

3.0 Data

The scope of this thesis is meant to broaden the knowledge of the effects of salience on financial instruments other than stocks. In the literature of this field, the contributions have almost solely focussed on the effects of salience on the stock market. Stocks are the most traded financial instruments and the worldwide stock market accounts for the highest market capitalization of all financial instruments, but financial instruments can vary in usage and elasticity from instrument to instrument. Seeing the gap in research, this thesis will focus on other commonly traded instruments. To be more specific: Bonds, commodities, currencies and indices. With this scope, this thesis can show perspective on the perseverance of salience in these specific markets, on top of the current knowledge of salience on the stock market.

The data of these bonds, commodities, currencies and indices will be retrieved from Eikon Datastream. The platform allows for access to accurate historical data that goes as far back as it can be accurately traced, providing this thesis with an adequate dataset to conduct research upon. For these financial instruments certain risks are involved during research. Following the example of Fama and French (2012, 2017) all prices are calculated and displayed in the currency of US dollars. The data is downloaded on daily values from 15 January 1990 – 15 January 2024 and will be displayed as monthly values throughout this research. This data range was chosen because it grants an adequate 30 years of data going through multiple booms and busts, while it is also important to note that most financial instruments used in this research have their data start around that time as well, although some start later. The monthly value is taken at every end of the month, not taking into account the trading days for every unique month. For convenience's sake the average of 21 trading days is used for all months. In table 1, the number of datapoints per asset class is given. Every asset class has at least 20 variables, although not all start at the same date.

Table 1. An overview of all financial asset in the dataset

Type	Freq.	Percent	Cum.
Currencies	7643	22.71	22.71
Bonds	7685	22.83	45.54
Indices	10205	30.32	75.85
Commodities	8129	24.15	100.00
Total	33662	100.00	

The bond market:

Most tradeable and long-term liquid bonds in the market are governmental bonds. This is reflected in the bonds data sample as almost all are 10 year running governmental bonds from various nations around the world, with one Euro corporations' bond in the sample. The data ranges from 1990-2024 for most of this panel, starting anywhere from 1990 until the data becomes available. In table 2 the 20 bonds are displayed.

Here we see the running governmental bonds of many western nations or those with good quality data, except for the Euro corporate, FTSE, JSE and Ibox bonds, namely: Australia, Belgium, Bulgaria, China, Spain, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Austria, Sweden, the UK and the US. The frequency displays the number of months the instruments have within the sample.

Table 2. Overview of the bond data

Asset	Freq.	Percent	Cum.
AUSTRALIA10Y	359	4.67	4.67
BELGIUM10Y	406	5.28	9.95
BULGARIA10Y	406	5.28	15.24
CHINA10Y	359	4.67	19.91
ESPANA10Y	396	5.15	25.06
EUCORPORATE10Y	299	3.89	28.95
FINLAND10Y	387	5.04	33.99
FRANCE10Y	406	5.28	39.27
FTSECVGH	359	4.67	43.94
GERMANY10Y	406	5.28	49.23
IBOXGBP10Y	311	4.05	53.27
IRELAND10Y	406	5.28	58.56
ITALY10Y	392	5.10	63.66
JAPAN10Y	406	5.28	68.94
JSEALL10Y	357	4.65	73.58
NETHERLANDS10Y	406	5.28	78.87
OSTEREICHS10Y	406	5.28	84.15
SWEDEN10Y	406	5.28	89.43
UKRAINE10Y	406	5.28	94.72
US10Y	406	5.28	100.00
Total	7685	100.00	

Commodities:

The most liquid commodities will be covered in this research as to allow for adequately tradable instruments, where a potential trading strategy could be hypothesised on. The most commonly traded commodities include metals, energy products, and agricultural products. In table 3 the full list of the 21 commodities is displayed, where the variety of frequencies tells the availability of the data for this particular panel. Only crude oil and gold have accurate data on all the months of the date range of January 1990-2024, the less frequency a commodity has, the later it starts.

Table 3. An overview on the commodity data

Asset	Freq.	Percent	Cum.
ALUMINIUM	406	4.99	4.99
BARLEY	317	3.90	8.89
BRENT	406	4.99	13.89
CATTLE	406	4.99	18.88
COFFEE	404	4.97	23.85
COPPER	406	4.99	28.85
CORN	406	4.99	33.84
CRUDEOIL	406	4.99	38.84
COTTON	406	4.99	43.83
GOLD	406	4.99	48.83
LEAN HOGS	336	4.13	52.96
LUMBER	322	3.96	56.92
OATS	324	3.99	60.91
PALLADIUM	406	4.99	65.90
PLATINUM	406	4.99	70.89
RHODIUM	339	4.17	75.06
SILVER	406	4.99	80.06
SOY	406	4.99	85.05
SOYBEANOIL	406	4.99	90.05
SUGAR	406	4.99	95.04
WHEAT	403	4.96	100.00
Total	8129	100.00	

Currencies:

The exchange rates between 20 currencies are taken into this dataset. All are shown as exchanging their native currency into a US dollar. The full list is: Argentine pesos, Australian dollars, Brazilian reals, Canadian dollars, Chilean dollars, Egyptian pounds, Euro’s, Great British Pounds, Hong Kong dollars, Indonesian rupiah, Japanese Yen, Mexican pesos, Indian Rupee’s, Swedish Krona, Swiss Francs, Taiwanese dollars, Turkish Lira’s, South Korean Wons and Chinese Yuan, which later becomes Renminbi’s. All these variables are shown in table 4.

Table 4. An overview on the currency data

Asset	Freq.	Percent	Cum.
ARGUSD	357	4.67	4.67
AUSUSD	359	4.70	9.37
BRAUSD	394	5.16	14.52
CANUSD	359	4.70	19.22
CHILUSD	407	5.33	24.55
EGYUSD	375	4.91	29.45
EURUSD	406	5.31	34.76
GBPUSD	406	5.31	40.08
HNGUSD	405	5.30	45.37
INDOUSD	360	4.71	50.09
JPYUSD	406	5.31	55.40
MEXUSD	401	5.25	60.64
RUPUSD	360	4.71	65.35
SARUSD	359	4.70	70.05
SWEUSD	407	5.33	75.38
SWIUSD	406	5.31	80.69
TAIWUSD	400	5.23	85.92
TURUSD	359	4.70	90.62
WONUSD	359	4.70	95.32
YUANUSD	358	4.68	100.00
Total	7643	100.00	

Indices:

The most traded and most liquid indices in the world were taken from DataStream for this research, including national indices, sector indices and world region indices. In table 5, the 26 equities are shown. Most indices represent their national indices, though broader indices like the MSCI world and Eurostoxx 600 are also present in the sample. Compared to the other asset classes, the indices has a multitude of accessible data points available on Datastream, hence the higher number of variables compared to the other assets. Additionally, compared to the other asset classes, almost all indices also start directly at the beginning of the timespan in this analysis: 1990.

Table 5. An overview of the indices data

Asset	Freq.	Percent	Cum.
AEX	406	3.98	3.98
ASX300	359	3.52	7.50
BEL20	406	3.98	11.47
BIST100	359	3.52	14.99
DAX	406	3.98	18.97
EU600	406	3.98	22.95
EUR50	406	3.98	26.93
FRA40	406	3.98	30.91
FTSE100	406	3.98	34.88
FTSE250	406	3.98	38.86
FTSEALL	406	3.98	42.84
HANGSENG	359	3.52	46.36
IBEX35	406	3.98	50.34
JSEALLSHARE	341	3.34	53.68
KORCOMP	359	3.52	57.20
MSCIEAF	406	3.98	61.18
MSCIEM	406	3.98	65.15
MSCIEU	406	3.98	69.13
MSCIPAC	406	3.98	73.11
MSCIWORLD	406	3.98	77.09
NASDAQ	406	3.98	81.07
NIFTY50	359	3.52	84.59
SHANGHAI	359	3.52	88.10
SP500	406	3.98	92.08
TAIWAN	402	3.94	96.02
TOPIX	406	3.98	100.00
Total	10205	100.00	

Control variables:

Without stocks in the data sample, the amount of control variables required is significantly less than in the previous literature. With the sample containing currency exchanges, bonds, indices and commodities, the control variables are based on price fluctuations, as the salience is also calculated using only historic price movements of the instruments. With that, many characteristics that explain the return on financial instruments can be accounted for.

The first control variable that is within the dataset is momentum. This phenomenon is the instrument's return over the past year up until one month before the time of measuring, month t – 12 up until month t – 2, as presented in Carhart (1997). The last month is ejected in this timeframe, to account for a possible momentum reversal (momreverse). It is constructed by taking the return of an instrument from the month before, with the hypothesis the return of the month before will negatively correlate with the return in the upcoming month. Skewness of the returns could potentially influence salience and the future returns of the instruments in the upcoming month.

Therefore, skewness (skew) is introduced as a control variable, constructed by taking the skewness of the daily returns from the last month. The maximum (max) is the highest one-day return within last month, as supposed by Bali, Cakici and Whitelaw (2011). These authors also suggested that the minimum return (min), of the previous month should be taken into account. Salience is measured as described in chapter 2. Raw returns imply the monthly return of an instrument in the upcoming month. The excess return variable is constructed by taking the return of an instrument in the upcoming month, minus the return of the respective benchmark. In this case, the benchmark is the same as with the construction of the salience variable, the average return of all assets in that asset class. Another excess return variable was constructed using not the asset class's average return as benchmark, but that of the whole sample. When this benchmark is used, it will be deliberately stated. In an analysis to see if the four asset classes as a whole would show an effect of salience on future returns, then the excess return needs to be relevant to the whole sample. In most instances regarding the research of excess returns in financial literature, the US T-bill is commonly used as a 'risk-free' investment, but as this instrument is an integral part of the dataset, alongside many other nation's government bonds this cannot be the case here, hence the need to construct the sample wide average as a benchmark. 'Tertiles' is the constructed tertile portfolio, based on the salience rankings of all instruments. This will later be repeated per asset class. All return variables are winsored with 1 percent at the edges if used for regressions, as to make OLS less sensitive to the outliers.

In table 6 the correlations of all variables are displayed. Momentum and reversal momentum have considerable correlation, which is explanatory knowing that they are very similar measurements of the same indicator. Tertiles and salience also overlap to an extensive degree, which is to be expected as Tertiles is built using salience as a rank. Tertiles is later used to show the returns of different portfolios, it is not a control variable. The minimum and maximum score of the return of an instrument in the previous month is also highly correlated. This can be expected as higher returns, either negative or positive are associated with more volatile instruments. Both also display higher levels of correlation with raw return, excess return and salience. These findings are similar to previous studies done by Barberis et al (2016), where instead of salience theory, prospect theory is researched, where the mathematical foundation for salience is partly derived from. In their study, prospect theory correlates moderately with the control variables.

Table 6:
correlation table of all variables

The table below shows the correlation between the dependent variable as measured by the raw return of next month (7) and the excess return of the following month when compared to the assets' average return (8), the independent variable Salience as the numeric Salience measure (10) and as in its sorted tertiles (9), as well as all control variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Momentum	1.000									
(2) Minimum	0.167	1.000								
(3) Maximum	0.135	0.719	1.000							
(4) Skewness	0.066	-0.000	-0.007	1.000						
(5) Momentum reverse	0.167	0.010	-0.005	0.044	1.000					
(6) Raw return	0.164	-0.017	0.021	0.058	0.073	1.000				
(7) Return next month	0.044	-0.127	0.127	0.077	0.012	0.067	1.000			
(8) Excess return next month	0.037	-0.067	0.112	0.075	0.014	0.037	0.833	1.000		
(9) Tertiles	0.007	-0.085	0.122	0.044	0.009	0.061	0.249	0.331	1.000	
(10) Salience	0.011	-0.055	0.121	0.140	0.005	0.096	0.333	0.419	0.599	1.000

4.0 Hypotheses:

Hypothesis 1) Does Salience predict future market returns for bonds, currencies, indices and commodities?

Here we look for a statistically significant effect of salience on future market returns. In an OLS regression the two salience measures will be tested on their ability to predict future returns, that is the return of the asset in the upcoming month. In chapter two, the methodological approach to calculate the numeric salience measure is portrayed. The other salience measure that this thesis will test is called 'tertiles'. The financial instruments will be ranked based on their covariance between daily salience and daily return every month and put into different portfolios based on these ranks. The portfolios will be constructed roughly into tertiles. The top 30% salience instruments go into tertile 1, the tertile 30% instruments into tertile 3 and the middle 40% will enter portfolio 2. Every month these portfolios will be updated.

Hypothesis 2) Is it possible to construct a market timing strategy based on salience?

If there is no predictive capacity of salience on future market returns, as hypothesised above in hypothesis 1, then the answer will be a simple no, but tested anyway. If there is a predictive capacity within salience on future market returns, however, then the question becomes whether this is significant enough to be made into a market strategy. Based on the salience sorted tertiles as above mentioned, the hypothesis will be tested using a tabulation of the average return per tertile. This is done for the future raw returns as well as the future excess returns. For the tertiles, the most salient tertile is forecasted to have an overvalued aspect to it, whilst the least salient tertile is hypothesised to be undervalued. Hence in the upcoming month the most salient tertile is shorted and the least salient tertile is taken into a long position. Utilising this long-short strategy, the investment should have been 'zero cost', when not taking into account any trading costs or risks.

Hypothesis 3) Does Salience survive after controlling for momentum and volatility factors?

This hypothesis is just like hypothesis 2, only relevant for further research if with the testing of hypothesis 1 the predictive capacity of salience is found present. If not, the answer to this question will also be negative. In the case there is predictive capacity in salience, however, then it should be tested whether this predictive capacity could have come from other factors like momentum, reverse momentum, the maximum and minimum daily results within the previous month and the skewness of the financial instrument over the last month. To test this two OLS regressions are performed, for both salience measures as independent variables together with all control variables. If the outcomes show a statistically significant coefficient for the salience measure, the predictive capacity of the variable will likely not be just a proxy of other variables, but a strong indicator in its own right.

Hypothesis 4) Does the possible Salience's effect on future market returns differ among the asset classes?

This research focuses on currencies, bonds, indices and commodities, which are all asset classes with their own unique characteristics. One is more liquid than the other, more volatile, more capital intensive, which is why there is likely to be a spread in the results of the effects of salience on future returns. Hypotheses 1 to 3 will be performed on the sample of assets as a whole. The idea is to test whether the asset classes together will provide interesting results for a strategy to be built upon, next to the tests of the asset classes individually. The grouping of the assets is bound to deliver different results. Since the asset groups themselves contain from 20 to 26 individual assets, it could be that this number is not extensive enough to deliver significant results, hence the grouping together. Perhaps the results of the whole sample will even outperform the individual asset classes as the long-short portfolio contains the top salient and bottom salient assets from multiple asset classes, enlarging the extremes.

To test the asset classes individually, a table will lay the tertile portfolio's results out for the returns of every asset class. Next to the results showcased in the long-short portfolios, the regression from hypothesis 3 will also be performed on all four asset classes individually. An OLS regression with all control variables for both salience measures shall indicate whether the predictive capacity of salience is strong on its own or likely to be a proxy of other variables.

5.0 Results

In this chapter the results of the tables and regressions will be shown to answer the stated hypotheses. Section 5.1 will provide results on the effect of salience on future market returns for all asset types. Regressions on the effects of salience on the returns and excess returns for the upcoming months will show the explanatory capacity of salience and salience sorted portfolios. In section 5.2 the salience sorted portfolios will be tabulated into their tertiles to show their average effect on the return and excess return of the following month. In section 5.3 the control variables enter the regression fray and will determine if the salience effect on the returns of the following month holds, or is mostly due to other factors. Tables showing the results of the excess returns and normal returns of regressions with all control variables utilised, as well as the effects of the salience sorted portfolios for all the financial instruments. In section 5.4 all of the above is repeated but for asset sorted portfolios. Instead of conglomerating all currencies, bonds, indices and commodities into one portfolio, all will be regressed and tabulated separately.

5.1 First hypothesis

Table 7 shows salience regressed by the winsorized return of the instrument in the upcoming month in regression 1 and the excess return regarding the average return of the asset class it belongs to in regression 2. The results of the first two regressions make it evident that the salience measure to a certain degree is able to proxy future returns.

The third and fourth regressions show use the tertile portfolio instead of the salience measure as an independent variable to measure salience. The results here indicate that the portfolio is an adequate measure of salience, although some predictive value gets lost with the construction of tertile portfolios. The coefficients for the tertiles are also significantly smaller than that for the salience measure itself, this could be attributed to the fact that there are three portfolios numbered 1, 2 and 3, whereas the salience measure can range between -1 and 1, but in reality never reaches values near the edges and thus stays a very small number. All results are statistically significant for the 1% margin and show that with an increase in salience, an increase in future returns can be expected. The coefficient, however, will not be interpreted without the control variables. The sign and significance are enough to answer the first hypothesis.

As the salience measure was found to be normally distributed, no robust regression was needed. This leads to the regression displaying considerably high T-values.

Table 7.

Regressions of salience and salience sorted tertiles on the return or excess return of the next month

VARIABLES	(1) Return next month	(2) Excess return next month	(3) Return next month	(4) Excess return next month
Salience	2.861***	2.919***		
	(61.27)	(80.88)		
Tertiles			0.0201***	0.0215***
			(48.25)	(66.31)
Constant	0.00437***	-0.000306	-0.0352***	-0.0427***
	(13.76)	(-1.25)	(-39.60)	(-61.67)
Observations	33,850	33,850	33,850	33,850
R-squared	0.100	0.162	0.064	0.115

T-values in parentheses

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

5.2 Second hypothesis

In this section, the portfolios will be constructed around the predictive capacity of salience in tertile portfolios for all financial instruments in the sample. In table 8 the raw and excess returns of the next month is displayed for all tertiles of the salience sorted portfolio. 'Excess return' stands for excess market returns where the market is defined as the average of that specific asset. The portfolio sorts are ranked from the least salient instruments (pf1), to the most salient instruments (pf3), with pf(2) being the middle 40% of salient instruments. The mean of the portfolios on the excess market returns shows that the 30% least salient instruments have an average expected excess return of 2,3% in the following month, where the middle 40% of the salient instruments show -0,1% excess return. The most salient instruments, however, display a negative excess 2,1% return in the upcoming month.

Table 8 shows that the average return across the tertiles does differ between the most salient instruments also on raw returns. As the most salient tertile showed a negative excess market return in the bottom of the table, it shows again a lower average expected future monthly return. Going short in the most salient tertile would result in a raw return of 1,5% and going long in the least salient tertile would result in 2,6% return in the upcoming month. Thus, combined in a 'zero cost' long-short portfolio, the salience strategy would return 4,1% on average each month. This is of course without taking any trading costs or risks into consideration.

Table 8.
The raw and excess returns in the upcoming month for the salience sorted tertile portfolio

Variable	Obs	Mean	Std.Dev.	Min	Max
Return next month (1)	10,468	-0.015	0.064	-0.715	0.453
Return next month (2)	13,324	0.004	0.045	-0.435	1.012
Return next month (3)	10,058	0.026	0.077	-0.351	1.239
Long-short		0.041			
Excess return next month (1)	10,468	-0.021	0.050	-0.575	0.430
Excess return next month (2)	13,324	-0.001	0.033	-0.384	0.926
Excess return next month (3)	10,058	0.023	0.063	-0.330	1.191
Long-short		0.044			

5.3 Third hypothesis

In this section, the control variables are introduced into the regression. As hypothesis 3 poses, the question is whether the found effects of salience and salient sorted tertile portfolios will hold after the controls for momentum and volatility are put into place. Here the whole sample of currencies, bonds, indices and commodities is still used and are morphed into monthly tertile portfolios based on their salience ranking. It could very well be that salience is just a proxy for other variables, but underperforms in comparison to them. To find out, an OLS regression is performed with all variables, salience and salience sorted tertiles on both raw return in the next month and excess returns in the upcoming month.

Table 9 shows that the additional control variables do not invalidate the statistical significance of the capacity to predict the future return by salience. The T-values are slightly lower, however, the end results are as statistically significant as those in table 6 in section 5.1. What is interesting is that tertiles showcase much higher T-values than salience is in this table. It becomes evident that salience and salience sorted tertile portfolios have a predictive capacity on future return by 1% statistical significance, ceteris paribus.

Interestingly enough, apart from momentum reverse and skewness in the second regression, all variables show a highly significant effect on the future market returns, though the coefficients vary wildly in size. Maximum, minimum, momentum and skewness results in the last 21 trading days seem to predict the future market returns to some degree, where reverse momentum does not. For both the return variables, the dependent variables, the winsorized version was used as this was an OLS regression where outliers can affect the accuracy of the results.

Table 9.

A robust regression of salience or salience sorted tertiles and all control variables on future returns or future excess returns

VARIABLES	(1) Return next month	(2) Excess return next month	(3) Return next month	(4) Excess return next month
Salience	2.176***	2.610***		
	(10.72)	(10.69)		
Skewness	0.00174***	0.000609	0.00303***	0.00208***
	(4.69)	(1.63)	(7.92)	(5.92)
Momentum reverse	0.00948	0.0101	0.00838	0.00846
	(1.09)	(1.37)	(0.95)	(1.13)
Maximum	2.68e-06***	1.22e-06***	2.81e-06***	1.28e-06***
	(36.69)	(16.86)	(47.71)	(27.05)
Minimum	-2.87e-06***	-1.21e-06***	-2.96e-06***	-1.23e-06***
	(-38.32)	(-16.48)	(-48.94)	(-25.17)
Momentum	3.36e-07***	1.79e-07***	3.33e-07***	1.73e-07***
	(10.26)	(6.76)	(9.97)	(6.33)
Tertiles			0.0131***	0.0183***
			(28.20)	(49.85)
Constant	0.00125*	-0.00361***	-0.0250***	-0.0402***
	(1.83)	(-6.32)	(-20.97)	(-41.08)
Observations	33,398	33,398	33,398	33,398
R-squared	0.184	0.189	0.155	0.145

T-values in parentheses

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

This begs the question, how a salience sorted portfolio compares against portfolios that are sorted by the other control variables. Seeing that most control variables in table 8 display a highly statistically significant predictive capacity on future returns, it is interesting to compare the results of those against one another. In table 10, the raw future returns are displayed by tertiles per control variable, as well as salience itself. As seen in table 8, here too the Salience measure's tertile generates a long-short portfolio of 4,1% return per month. Next in the column is the maximum return of an asset in the last month, sorted in tertiles. The most salient maximum tertile displays an average return of -

0,5% per month and the least salient tertile has an average raw return of 1,5% per month. A long-short portfolio for this indicator would suggest a raw return of 2% per month, again not taking into account any trading costs or risk. The minimum return per month shows flipped returns for its most and least salient tertiles when compared to all other tested variables. The rationale behind this is that the tertile with the highest negative returns in the last month will likely be undervalued and for the lowest negative return tertile it is vice versa. The Long-short portfolio suggests that a negative return would be made, which is a wrong display of the opportunity it offers. Just as the positive and negative returns are swapped around with this variable, the long and short positions need to be swapped to actually exploit the possible returns the minimum sorted tertiles offer. A monthly updated long position in the most salient minimum tertile and a short position in the least salient tertile would grant a positive return of 1,4% on average, not taking into account any trading costs or risks.
Now it must be noted that the salience is still measured by taking the covariance of the salience weight and raw daily returns for the past month, whereas the maximum and minimum results are just one number. This will undoubtedly result in a lower explanatory capacity for those variables as just one daily return speaks for their measure in an entire trading month.
The remaining variables in the table, momentum, momentum reversal and skewness respectively, have been measured over the whole past month just as salience was. This would expect one perhaps to grant them more accurate results in attempting to predict future results of the financial asset. This is, however, not the case. Momentum's long-short portfolio grants a 0,7% return per month on average, where momentum reversal returns only an underwhelming 0,1% and the skewness sorted tertiles net a 0,9% raw return. For all three of these variables the highest tertile is positive, though lower than the lowest tertile. This portrays perhaps a different picture than the other variables, salience included, where there is a clear discrepancy between the top and bottom tertiles, contributing to the mediocre results of the long-short portfolios.

Table 10.
Overview of the returns of tertiles sorted portfolios by salience and every control variable individually

Variable	Salience	Max	Min	Momentum	Mom. reversal	Skewness
Return next month (1)	-0.015	-0.005	0.011	0.001	0.005	0.001
Return next month (2)	0.004	0.004	0.006	0.005	0.003	0.004
Return next month (3)	0.026	0.015	-0.003	0.008	0.006	0.010
Long-short PF	0.041	0.020	-0.014	0.007	0.001	0.009

5.4 Fourth hypothesis

In this section, the asset classes of currency exchanges, running bonds, indices and commodities will be separately tested for their salience' effect on future market returns, as well as future excess market returns when compared to their own respective asset's average return. The results of all four asset classes are portrayed in table 11, for both return measures. As with the previous subsections of chapter five, the benchmark of the salience calculation is from their own respective asset's daily average. Though, no winsorized variables were used in the formation of this table, as there was no OLS involved in making it and the outliers were thus not of a threat to the integrity of the results.

Table 11.
All four asset classes on the returns of their salience sorted tertile portfolios

Variable	Bonds	Indices	Currencies	Commodities
Return next month (1)	-0.003	-0.015	-0.004	-0.035
Return next month (2)	0.002	0.006	0.003	0.007
Return next month (3)	0.006	0.030	0.018	0.052
Long-Short PF	0.009	0.045	0.022	0.077
Excess next month (1)	-0.005	-0.020	-0.010	-0.041
Excess next month (2)	0.001	0.001	-0.003	0.000
Excess next month (3)	0.004	0.025	0.014	0.046

Bonds

In the first results column in table 11 the excess future market returns are displayed for every salient sorted bond tertile. Here it becomes evident that the salient tertiles have much less correlation with future market excess returns when compared to the sample average in table 8. A long-short portfolio of going long in the least salient 30% of the bonds' sample and short in the most salient 30% would grant you on average 0,9% per month. The excess returns display a similar story, only the most and least salient tertiles display on average a more negative return. This table shows that the salience tertiles grant a zero cost portfolio that returns 0,9% per month, when not taking into account any trading costs or risk measures. The result is interesting, as one would not characterise the bond market as one where salience would play a significant role. Though, the results are only preliminary, as the trading costs and turnover are not yet taken into account.

Indices

In the second column of table 11, the raw and excess future returns for the indices are displayed by tertile portfolios. Here the results show that the future excess and raw returns exhibit quite some disparity in returns between the most and least salient tertiles. For raw returns, a long-short portfolio would grant a monthly return of 4,5% on average, taking into account no additional trading costs or any trading risks. This staggering return is above the sample average shown in table 8. This category enjoys more observations in comparison to the other three, making the results statistically slightly more significant, though this addition from 7500 or 8000 to 10000 observations is only a marginal upgrade. The results indicate that the market for indices could be very well suited for a salience determined strategy, in theory.

Currencies

In the third row of table 11 the raw and excess future returns of the currency exchanges salience sorted tertile portfolios are tabulated. The results show a clear pattern across the tertiles, as the top 30% most salient and least salient currency exchanges show negative and positive results respectively. This result shows a lesser return than in table 8, where the results of the whole sample are tabulated. This result suggests that a market beating strategy would be to take short positions in the top 30% most- and a long position in the 30% least salient currency exchange rates.
The bottom half of the table shows us the excess returns of the tertile portfolios. Here it becomes evident that the return for a long-short portfolio is almost the same as that of the raw returns. The main difference comes from the disparity between the most and least salient returns. Where the most salient tertile has -.4% return per month on average, the excess has -1%. This is balanced out by the fact that the least salient tertile has more modest excess returns than raw returns. As one would expect the currency market to be more macro-economically shaped, it is interesting to find results that would indicate that a strategy based on salience could grant a substantial monthly return, on average, without taking into account any trading costs or risks.

Commodities

In the last row of table 11, the excess future returns for commodity tertile portfolios are displayed. Here the results show that positive future excess returns can be obtained by the salience sorted portfolios in the commodity market. The least salient tertile displays a positive mean of 4,6% monthly excess return on the commodity market on average over the timespan of this sample. Thereby, the most salient tertile indicates a negative excess market return of minus 4,1% a month. In contrast to the results for the previous three markets, it seems that the salience sorted tertile portfolios have a relatively high predictive ability on future market returns. A long-short portfolio in these tertiles would result in a staggering 7,7% return per month on average, not taking into account any trading costs or risks.

All previous results shown in the tables and figures have encompassed the sample as a whole with the intent to show the predictive capacity of salience on future market returns. All tests have thus far proved the effect of all four assets combined, instead of proving isolated effects. In the appendix, the regressions from 5.3 are also shown on the isolated assets. Tables A.1, A.2, A.3 and A.4 show the statistical significance of the coefficients for salience and the salience sorted tertiles for all four asset classes separately. These tables show for all four asset classes respectively that the salience sorted tertiles enjoy more explanatory capacity on future market returns than the numeric salience measure itself. All tertile variables have statistically significant coefficients, with 1% significance, except for the bond market. With the bond market, the numeric salience measure does not have a statistically significant coefficient, not even weakly significant. The tertiles, however, are weakly significant for this asset class. This result is counterintuitive as table 11 showed that a long-short portfolio with the salience sorted bonds resulted in a 0,9% raw return per month, not taking into account any trading costs or risks. A 0,9% return per month translates into 11,35% return on a yearly basis, which beats the average market return, if we take the global indices as the market. The bottom half of the table reports the excess future returns. For every tertile it shows what the average return is, subtracted from the sample average. Normally, this would be done using a 'risk-free' investment, here it is found in the same asset class. As explained in chapter 2, the idea is that one seeks to invest within that asset class's market. It shows that the most salient tertile further underperforms compared to the rest of the sample. Moreover, the raw returns in the following month of the least salient tertiles are in significant excess of the sample's average.

Despite the salience measure not being a statistically significant predictor of future market returns, a simple salience based strategy still would result in relatively large returns. In table A.5 in the appendix, two more regressions are displayed for the bond market. The table shows the regressions of the effect of salience and salience sorted tertiles on raw future market returns. Even though the salience measures are not statistically significant with all control variables in the regression, without them they are. Both the salience and salience sorted tertiles have coefficients with 1% statistically significance. These results suggest that although salience itself might not be an accurate predictor for future market returns, it might be an adequate proxy. This would explain the relatively large results for the long-short portfolio for the bond market in table 11, in the light of the contrasting evidence found of the predictive capacity of the salience measures in table A.3.

6.0 Additional tests

So far, all tests on the future raw return generative capacity of salience have been focussed on tertile portfolios. This, however, excludes a plethora of other obvious candidates to exploit the predictive capacity of salience. In table 12 three more portfolios are tabulated. In the first row, the tertile portfolio from table 8 is shown for comparison purposes. The second row shows a portfolio where salience was sorted into quartiles, for all assets combined. All assets are combined here to make a better comparison to the other results found previously with the same methodological approach. In the third row, the salience measure is sorted into quintiles of 20% each. The fourth row displays decimal portfolios. The most salient group is always located at the second row where the returns start to be displayed at 'Return next month (1)'. From there, descending with every row the salience declines, ending with the least salient sort at the bottom of the list. For tertiles this bottom is (3), for quartiles it's (4), (5) for quintiles and (10) for decimals.
At the right of the table, in the last column, the decimal portfolio for only the commodities is displayed. This was chosen because commodities showed the highest returns in a long-short portfolio out of all four assets and would make an interesting case to see how a small dataset would perform on small salience sorted groups.

The table shows that the average raw future monthly returns increase for the long-short portfolios with every portfolio when more groups are added. The tertile portfolio still shows an average raw future monthly return of 4,1%, when the most salient sort is shorted and a long position is taken in the least salient tertile. Moving one column to the right, the quartile portfolio generates a higher return with averaging 4,8% per month. Moving further right, to the quintile portfolio, the long short portfolio of the salience sorted quintiles generates an even higher return with a remarkable 5,6% per month. Still not done rising, moving one column further to the right in table 12, the decimal portfolios top the last three portfolios with its average return. Here, the decimal portfolio showcases an average monthly return of 8,3%. Again, all these returns are raw returns of the upcoming month, there will be trading costs and risk involved when this portfolio would be put into practice. Thereby, the more subsets within a portfolio, the less assets in it and thus less trading costs would be involved when going long or short in the respective assets.
To the furthest right in table 12 the commodities of this dataset are put into decimal sorts. The commodities displayed substantial returns for the salience sorted tertile long-short portfolio, however, that result is dwarfed by the decimals. Going short in the most salient decimal sort of the commodities and long in the least salient commodity decimal grants the portfolio holder an average monthly result of an abnormal 13%, taking into account no trading costs or risks. Thereby, the commodity sample consists of 21 commodities. So, the most and least salient groups are merely two

assets each. This would suggest that trading costs are of little concern in this example dataset. It would, however, raise the trading risk, as holding such a small number of assets increases the asset specific risks, as well as the volatility.

All portfolio sorts show a clear pattern of increasing return from the most salient group up to the least salient group. Beginning with a negative return and ending with a positive return. In the more spread out groups, like decimals and quintiles, it becomes evident that the highest returns are located at the edges. The stepwise return change increases the more the group is at the edge. For example, the two most salient decimal groups return on average -3,3% (1) and -0,8% (2) per month, whereas the middle two groups return on average 0,4% (5) and 0,3% (6) per month. The same holds true for the least salient two groups at the bottom of the column. The disparity in returns between the groups at the edges and in the middle hints at a parabolic relationship between salience and return. If so, the more salience sorted groups one makes, the more potential for return, not taking increased exposure and trading costs or risk in account.

Table 12.

An overview of portfolio sorts and their respective future returns, for all assets combined and commodities in the last row.

Variable	Tertiles all assets	Quartiles all assets	Quintiles all assets	Decimals all assets	Commodity decimals
Return next month (1)	-0.015	-0.018	-0.021	-0.033	-0.056
Return next month (2)	0.004	0.002	-0.000	-0.008	-0.025
Return next month (3)	0.026	0.006	0.003	-0.002	-0.014
Return next month (4)		0.030	0.009	0.001	-0.008
Return next month (5)			0.035	0.004	0.002
Return next month (6)				0.003	0.014
Return next month (7)				0.007	0.018
Return next month (8)				0.010	0.037
Return next month (9)				0.021	0.048
Return next month (10)				0.050	0.074
Long-short	0.041	0.048	0.056	0.083	0.130

As stated in chapter 2, the measure of salience is calculated using formula 1. Here the numerator is in absolute brackets, so that the difference between the asset's return and the benchmark's return is taken as a positive value. This leads, however, to the measure only ranging from 0 to 1. In the case of Chlorokostas (2017), the case was made for a removal of the absolute bracket in the numerator so that the salience value could range from -1 to 1, allowing assets to be under- and overvalued. This was previously tested on stocks, though not on other financial instruments. In table 13, the salience sorted tertiles' future monthly raw returns are shown per group.

Here it becomes clear that this measurement of salience is in fact inferior to the one used throughout this thesis. The most salient group has an average return of 0,3% per month, where in table 7 the return was -1,5%. When performing a long-short portfolio on this strategy, the return will be negative from shorting this most salient group (1) instead of being a net-positive investment. Thereby, the least salient group (3) returns 0,9% per month when taking a long position, where it was 2,6% in table 8. The measurement of salience with the absolute brackets in formula 1 is evidently a much better estimate of salience.

Table 13.

The raw future returns of the salience sorted tertiles using no absolute signs on the salience numerator

Variable	Obs	Mean	Std.Dev.	Min	Max
Return next month (1)	10,468	0.003	0.041	-0.341	1.012
Return next month (2)	13,324	0.003	0.050	-0.421	0.365
Return next month (3)	10,058	0.009	0.094	-0.715	1.239
Long-short		0.006			

7.0 Discussion

After seeing the bare results as well as the additional robustness test, they shall be further analysed and discussed in this section. They will be discussed in the sequence of the hypotheses, just like the subsections of chapter five were divided to accommodate the answers to every hypothesis. As the results are discussed and remarks are made, the final subsection of this chapter will dive a little further into the shortcomings and robustness of the results of this thesis.

7.1 First hypothesis

The first hypothesis begs the question whether salience has predictive capacity on future market returns for currencies, bonds, indices and commodities. In the total sample where all four all present, the regression shows that salience has statistically significant predictive capacity over future market returns and salience sorted tertile portfolios were a great predictor of excess- and raw future market returns. Though salience itself had much higher T-values than the salience sorted tertiles, it promised interesting results for as possible salience strategy for future returns. The whole sample was chosen here as it would shine light on the possibility that this combination would outperform the asset classes independently. Later on, in section 5.4 all four asset classes underwent the same research as the whole sample, to show all results and answer the main research question for each asset class. All four combined, however, could have provided more robustness and perhaps better results. The question of the first hypothesis was straightforward and so is its answer: Salience and salience sorted tertile portfolios seem to have the capacity to predict future market returns. The coefficients in table 7 showed that both regressions were statistically significant for 1%, with quite high T-values to show for it. Though, these T-values are also bolstered by the fact that the regression was not a robust one, since the salience variable was found to be normally distributed.

7.2 Second hypothesis

In the second hypothesis, the question was posed whether the found predictive capacity in 5.1 would translate into a marketable strategy for investment purposes. Table 8 shows that the previous results translate into a profit making strategy by sorting the assets on salient ranking into tertiles. Taking raw returns and not taking into account any trading costs or risks, a long-short portfolio in the least- and most salient tertiles returns on average 4,5% per month, ceteris paribus. The choice to not dive deeper into the trading costs is intentional, as the portfolios here are quite small in nature, thus any trading costs would be marginal. Thereby, the dataset contains 20 currencies, 20 bonds, 21 commodities and 26 indices, so any tertile encompasses only around 28 to 29 assets at any given time. Knowing that the trading costs are mostly a couple cents per trade, this would not steal enormous amounts of return from the strategy. Thereby, the turnover would likely not be a full 100%, driving the amount of trades per month further down for this strategy. What is more important to the actual return is the spread of the assets. This would likely be the highest cost driver in this strategy. As this data is not available for all assets, it was not further researched within this thesis, although it would make its results much more robust. Moreover, the intent of this paper is to research the possible predictive capacity salience has on future returns, not to construct the best possible market beating strategy using salience. I.e. The research has to be within the scope of the paper.

7.3 Third hypothesis

The third hypothesis is shaped into existence to test the robustness and accuracy of the found effect of salience on future returns. It could well be that the found effect thus far has been a proxy of other variables, which could mean that the returns found in 5.2 could be more accurately predicted by using the very variables that salience possibly proxies. In the regressions where salience and the salience sorted tertiles are calculated together with all the control variables, the found evidence for the first two hypotheses is further strengthened. In table 8, the salience measure and salience sorted tertiles still exhibit a strong correlation with future returns. Other variables, namely maximum and minimum results from that month, also display strong correlations with future returns. The interpretation of the coefficients is of lesser importance, as it is the crafting of the performance of the strategy using the effects of those variables on the future returns that matters. It becomes evident that salience and the salience sorted tertiles possess strong predictive capacity on future market returns, which bolsters the findings in 5.2 where the salience sorted tertiles return 4,5% raw return per month on average, not taking any trading costs or risks into account.
To further convince one of the usage of salience as a marketable strategy, the comparison is drawn to all other variables in the dataset. In table 9, all control variables' returns are displayed using the same tertile strategy that was previously used for salience. The results indicate that among all these portfolios, salience was the best indicator of future market returns. Other variables also showed promising results, though none came close to the results of a long-short portfolio using salience. This suggests that for the case of using tertile portfolios as a strategy, salience delivers the highest return among the tested options.

7.4 Fourth hypothesis

In the last subsection of chapter five, the results are recalculated for every individual asset class as opposed to the sample as a whole. The breakdown of the sample at large showcases the different nature of all four markets, as well as whether or not a combination of all four asset classes bolstered the returns of the tertile portfolio strategy. In table 11 the main results are exhibited. Here it becomes evident that the long-short portfolio of the whole sample was more of an average for all four asset classes combined, as opposed to increasing the returns by enlarging the sheer sample size. The table showcases that out of all four asset classes bonds have the least return on their long-short portfolio, averaging 0,9% per month. The same long-short strategy returned 2,2% for currencies, 4,5% for indices and 7,7% for commodities, not taking into account any trading costs or risks.
The bottom part of the table explains for every sorted tertile the return's difference from the sample average. For every tertile it shows what the average return is, subtracted from the sample average. Normally, this would be done using a 'risk-free' investment, here it is found in the same asset class. In most literature, it is standard to use the US-T bill, only here that runs into a problem: this thesis researches the bond market too and the US-T bill is an asset in the data there. To compare one bond's return to another is like comparing apples to apples, quite literally. As almost all bonds in the sample are from either broad corporate bond indices or mostly stable economies, all of these bonds could individually be considered a 'risk-free' investment for comparisons in the other three asset classes. In order to stick to the same narrative in the methodology per asset class, the sample's average is chosen with the argument that investors seek to invest within that particular asset class.

Returning back to the results of table 11, it manifests that salience has different magnitudes of explanatory capacity on future returns. Where salience seems to flourish in its ability to do so for the commodity market, it's results for bonds is underwhelming. On the other hand, the bond market is a market tainted with stability and a lack of volatile returns. Therefore, to achieve 0,9% raw return on a monthly basis in a long-short portfolio is noteworthy.

The previously staggering result of 7,7% monthly return on a long-short commodity tertiles portfolio almost gets dwarfed by the results shown in table 12. In order to test the robustness and relative performance of the tertile portfolio that thus far had been standardised in this thesis, a test was performed using multiple portfolio sorts. The tertile portfolio's results are compared against those using quartiles, quintiles and decimals. The results clearly indicate that the returns increase by every increase in the amount of subgroups within the portfolios. Not only does the return of the least salient group increase with every step towards more subgroups, the negative return of the most salient groups also increases. Ranging from 4,1% to 8,1% return, the results of the whole sample are impressive. On top of those astonishing results, a commodity long-short portfolio for salience sorted decimals is the zenith of the results in this thesis with a monthly raw return of 13,0%. For every return mentioned, again, there are no trading costs or risks weighed in the evaluation.

7.5 Further limitations

The result of this decimal long-short portfolio has some notes, though. It uses just a futile amount of four variables out of the sample of 21 commodities. Although the timespan of the findings confines a total of almost 34 years, the limited amount of variables in the commodity dataset raises some doubts. The most commonly traded commodities that also had qualitative data available on Datastream were chosen for this research. Undoubtedly the actual commodity market boasts a rich plethora of instruments compared to this small sample, with much less liquid commodities as well. To incorporate all the actual commodities would likely impact the results. On the other hand, with at most four assets traded every month, the turnover costs would likely be minimal. Nevertheless, these results invite in possible further research on this topic. Since the scope of this research is to find evidence on the possibility of salience having a correlation with future returns, establishing the perfect trading portfolio strategy with the found results is to be delegated to further research.
To help that possible future research on its way, the results in table 11 suggest that the highest returns are to be made at the very edges of the salience sorts. As aforementioned, the results increase with every step towards more subgroups within a portfolio split. On top of this, the results do not linearly increase, but seem to exponentially increase as the disparity between the subgroups in the decimal portfolios clearly finds its extreme differences at the most- and least salient edges. So, it would be interesting to perform a similar research on a bigger sample with a higher portfolio subgroup split. Thereby, it would have been interesting to see the same OLS regressions as in section 5.1 be performed with a parabolic function on the numeric measure of salience.

To elaborate on the point of having just 21 commodity variables, this extends also to the other three markets in this thesis. For currencies and bonds it’s 20 variables each, whereas indices data comprises 26 variables. Over the timespan of 30 years, this is close to the most you can retrieve from Datastream given the timespan of the analysis before one starts to accidently add the same variable in a different currency. To complement these results, it would be interesting to see an analysis with more variables for every market and perhaps a different timespan so that a more accurate reflection of all four asset classes is presented. This would either further cement the findings of this research, question them, or at least enunciate them.

A point on the return variable must also be made, as raw returns in the upcoming month are easy to grasp whilst future excess returns are more subjective. The benchmark against which the returns are compared differs from portfolio to portfolio. For this thesis, the benchmark has been the asset's class average for comparison purposes. In order to achieve a more robust conclusion, different benchmarks could have been implemented. Subtracting the return with the return of the US-T bill for currencies, indices and commodities would have generated excess market returns. For stocks, the literature is rich with measurements of return. Take the four-factor model from Carhart (1997) for example, which explains the stock returns with market risk, size, value and momentum. Not all of these indicators work for these three markets unfortunately, hence the practical usage of excess returns to its own asset's average.

On a last discussion point, there seems to be a relationship between the volatility of a market and the performance of salience in predicting future returns. In previous literature of salience and stock returns (Cakici and Zaremba 2022; Cosemans and Frehen 2017; Sun, Wang and Zhu 2023) it would have been interesting to see the results in market conditions where the VIX or any other volatility indicator would have been above a certain threshold. In this case, the volatility in the commodity market seems to have enabled the salience measure to adequately predict which commodities would do well in the upcoming month and which would perform poorly. An average monthly return of 13% for a plain long-short decimal portfolio is not neglectable.

8.0 Conclusion

This thesis investigates the predictive capacity of salience on bonds, stocks, indices, and commodities using Datastream data from 1990 to 2024. Based on the salience groundwork from Bordalo et al (2013), the salience measure was constructed in the same way as previous studies (Cakici and Zaremba 2022; Cosemans and Frehen 2017). Daily returns of 20 to 26 high-quality variables per asset class are analysed alongside other variables such as momentum and skewness. Monthly salience values are then ranked based on covariance with daily returns over the past 21 days, followed by the assets being grouped into tertiles. The most salient tertile is shorted while the least salient tertile is taken long for the upcoming month, aiming to detect whether treating these assets collectively or separately yields better predictive outcomes. All asset classes are treated collectively at first, followed by separate analyses to assess salience's impact on each class individually.

The OLS regressions returned statistically significant coefficients for salience as well as the salience sorted tertile portfolios on their coefficients that indicated their predictive capacity of future monthly returns, even when all control variables were added. Thus, it shows that salience was not a proxy for other variables' effect on return, only that of itself. The results further indicate that this 'zero cost' long-short portfolio returns impressive positive returns for the whole sample as well as the asset classes individually. The 'zero cost' being purely the long-short portfolio, not taking into account any trading costs or risks. With this evidence of salience on future returns found present for the dataset, some robustness tests were performed. Among these tests, a different measurement for salience was taken which led to underwhelming results, thus further cementing the present formula of salience as the leading measurement. Also, different portfolios were constructed apart from the tertile portfolio. These quartile, quintile and decimal portfolios had even better returns, as it turned out that the most returns can be obtained on the extremes of the salient rankings. For the future returns, the raw return of the portfolio in the upcoming month was used, not taking into account any trading costs or risks. All results taken into account, the presented evidence points in a singular direction: the salience measure has great predictive capacity on the future returns of all four asset classes combined into one sample, as well as the individual asset classes of currencies, indices, commodities and to a lesser degree also bonds.

The analysis acknowledges several limitations. Firstly, the study's focus on 20 to 26 assets within each class, selected based on availability of qualitative data, raises concerns about representativeness. The limited sample size might not fully capture the diversity of the commodity market, potentially affecting the generalizability of findings. Also, the study's reliance on raw returns as opposed to excess returns introduces subjectivity, suggesting consideration of alternative benchmarks for a more robust conclusion. Thereby, the scope of this study was limited to finding evidence for the predictive capacity of salience on future returns. To establish a trading strategy that takes into account all different costs and risks, like turnover costs, average spread, optimal portfolio allocation is not within the scope. For a more practical analysis of salience, this would be necessary. For a more theoretical analysis of salience that dives deeper into the topic than this thesis it would be interesting to: take a larger dataset for all asset classes, take a wider timeframe and do analyses on different timeframes within that span, use different benchmarks in the salience measure as well as different benchmarks for returns so to get a return more similar to a that of a four factor model, look into the relationship between market volatility and salience efficiency and finally to look at the likely parabolic shape of salience's returns as the returns at the edges are exponentially increasing.

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Appendix

A.1

A robust OLS regression of salience and salience sorted tertiles on future raw returns, with all control variables, for the commodity market.

VARIABLES	(1) Return next month	(2) Return next month
Salience	2.966***	
	(19.45)	
Skewness	0.00137**	0.00328***
	(2.48)	(5.71)
Momentum reverse	0.00358	0.00483
	(0.27)	(0.35)
Maximum	2.16e-06***	2.14e-06***
	(16.02)	(16.25)
Minimum	-2.30e-06***	-2.28e-06***
	(-15.63)	(-15.97)
Momentum	1.88e-07**	1.72e-07*
	(2.16)	(1.95)
Tertiles		0.0345***
		(27.98)
Constant	0.00503*	-0.0614***
	(1.71)	(-15.62)
Observations	8,140	8,140
R-squared	0.233	0.201

T-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.2

A robust OLS regression of salience and salience sorted tertiles on future raw returns, with all control variables, for the currencies market.

	(1)	(2)
VARIABLES	Return next month	Return next month
Salience	1.044**	
	(2.30)	
Skewness	0.00119***	0.00159***
	(2.60)	(2.80)
Momentum reverse	0.181***	0.175***
	(4.47)	(4.36)
Maximum	1.76e-06***	1.80e-06***
	(10.71)	(13.96)
Minimum	-1.30e-06***	-1.27e-06***
	(-7.78)	(-8.73)
Momentum	2.79e-07***	2.68e-07***
	(5.63)	(5.31)
Tertiles		0.00548***
		(8.37)
Constant	-0.00438***	-0.0155***
	(-4.73)	(-8.94)
Observations	7,586	7,586
R-squared	0.163	0.147

T-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3

A robust OLS regression of salience and salience sorted tertiles on future raw returns, with all control variables, for the bond market.

VARIABLES	(1) Return next month	(2) Return next month
Salience	0.239	
	(1.11)	
Skewness	0.00136	0.00138
	(1.45)	(1.46)
Momentum reverse	-0.0385***	-0.0383***
	(-2.62)	(-2.61)
Maximum	2.10e-06***	2.09e-06***
	(26.81)	(26.81)
Minimum	-2.33e-06***	-2.32e-06***
	(-28.29)	(-28.05)
Momentum	2.32e-07***	2.32e-07***
	(5.41)	(5.40)
Tertiles		0.000927*
		(1.90)
Constant	0.000761	-0.00109
	(0.74)	(-0.77)
Observations	7,587	7,587
R-squared	0.162	0.162

T-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4

A robust OLS regression of salience and salience sorted tertiles on future raw returns, with all control variables, for the indices market.

VARIABLES	(1) Return next month	(2) Return next month
Salience	1.480***	
	(6.99)	
Skewness	0.00374***	0.00402***
	(2.81)	(2.99)
Momentum reverse	-0.0261**	-0.0258**
	(-2.34)	(-2.33)
Maximum	3.85e-06***	3.75e-06***
	(36.50)	(36.15)
Minimum	-5.28e-06***	-5.13e-06***
	(-54.25)	(-55.07)
Momentum	3.17e-07***	3.12e-07***
	(5.03)	(4.98)
Tertiles		0.0128***
		(14.93)
Constant	0.0249***	-0.000866
	(10.59)	(-0.29)
Observations	10,085	10,085
R-squared	0.228	0.235

T-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5

Regression of salience and salience sorted tertiles on future market returns for the bond market

VARIABLES	(1) Return next month	(2) Return next month
Tertiles	0.00463***	
	(9.06)	
Salience		1.405***
		(7.95)
Constant	-0.00767***	0.00161***
	(-7.04)	(4.05)
Observations	7,685	7,685
R-squared	0.011	0.008

T-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1