UNIVERSIDAD DE CANTABRIA

FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES
DEPARTAMENTO DE ADMINISTRACIÓN DE EMPRESAS

TESIS DOCTORAL INTERNACIONAL

EL AFECTO, LAS DECISIONES FINANCIERAS Y LOS MERCADOS FINANCIEROS

Robert P. Merrin

Dirigida por:
Profesor Dr. Francisco Javier Martínez García
Profesor Dr. Lázaro Rodríguez Ariza
Profesor Dr. Guillermo Maraver Tarifa

Santander, 2015

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PRESENTADA POR EL DOCTORANDO

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DIRIGIDA POR LOS DOCTORES

D. Francisco Javier Martínez García

D. Lázaro Rodríguez Ariza

D. Guillermo Maraver Tarifa

Santander, 2015

à mes chers parents,

Claude et Susan

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To my parents, Claude and Susan, and my sister, Catherine, thanks for setting an example of tenacity and perseverance, for your continued support, understanding, and encouragement. I missed you the whole way through. I am also very thankful to my in-laws Julia, Antonio, Pepe, and Arantza for their incredible kindness that has made me feel like part of the family.

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Table of Contents

LIST OF TABLES XV

LIST OF FIGURES XVII

SHORT NOTICE CONCERNING AFFECTIVE TERMINOLOGY XIX

BREVE NOTA RELATIVA A LA TERMINOLOGÍA SENTIMENTAL XXI

ABSTRACT XXIII

RESUMEN XXV

INTRODUCTION CHAPTER 1

1. Introduction to Affect, Financial Decision Making, and Financial Markets 1
2. The Road to Behavioral Finance: Historical Background of Affect and the Social Sciences 6
3. Problem, Motivation, Research Questions, and Contribution to Behavioral Finance 14
    - 3.1. Chapter 1 16
    - 3.2. Chapter 2 18
    - 3.3. Chapter 3 19
    - 3.4. Concluding chapter 21

CHAPTER 1: INVESTOR SENTIMENT AND THE CROSS-SECTION OF STOCK RETURNS: AFFECT AND THE BOTTOM-UP APPROACH 23

Abstract 23

1. Investor sentiment: a short introduction 24
    - 1.1. Approaches to the study of investor sentiment 24
    - 1.2. Limitations of the bottom-up approach and the synchronization problem 25
    - 1.3. Addressing the synchronization problem: the Affect Hypothesis 26
    - 1.4. Testing the Affect Hypothesis 27
    - 1.5. Takeaways: the contribution of this study 28

2. Placing the study: context and background 30
2.1. The "Top-to-Bottom" conceptual model of investor sentiment 31
2.1.1. The top-down approach 31
2.1.2. The bottom-up approach 35
a. Investor Decisions 37
b. Cognitive Biases 37
c. Affect 38
d. Physiology 38
e. The Environment 39
2.2. Affect: empirical, theoretical, and practical considerations 39
2.2.1. Definition of affect 39
2.2.2. Theory 40
2.2.3. Empirics 41
2.2.4. Practical Considerations 41
3. Research design 43
3.1. Data collection and descriptive statistics 43
3.1.1. Investor Affect 43
3.1.2. Stock market outcomes and their historical circumstance 51
3.2. Methodology 59
3.2.1. The conditional characteristics model 59
3.2.2. The sentiment seesaw 62
4. Results 65
4.1. Parametric results: the conditional characteristics model 65
4.1.1. Levels and subsequent corrections 65
4.1.2. Changes and contemporary overreactions 67
4.2. Non-parametric results: cross-sectional graphs conditional on affect 70
5. Conclusion and Discussion 78

CHAPTER 2: OF TRIGGERS AND TARGETS: RISK-BASED AFFECT IN A DOUBLE-HURDLE MODEL OF RETAIL COMMON STOCK TRADING DECISIONS 81

Abstract 81

1. Introduction ... 82
2. Literature review ... 84
3. Data collection and descriptive statistics ... 87
    3.1. Affective risk behavior ... 87
    3.2. Risk exposure ... 94
    3.3. Trading decisions ... 95
4. Methodology ... 97
    4.1. The Double-Hurdle model ... 98
5. Results ... 101
    5.1. Purchase decisions ... 101
        5.1.1. Hurdle 1: Participation decisions ... 101
        5.1.2. Hurdle 2: Degree of riskiness ... 105
    5.2. Sale decisions ... 107
        5.2.1. Hurdle 1: Participation decisions ... 107
        5.2.2. Hurdle 2: Degree of riskiness ... 109
6. Discussion and Conclusion ... 110

CHAPTER 3: MANAGING MARKET-BASED ASSETS: CUSTOMER SATISFACTION AS A BUFFER AGAINST SENTIMENTAL STOCK PRICE MOVEMENTS ... 113

Abstract ... 113

1. Introduction ... 114
2. Literature Review ... 115
    2.1. The benefits of managing market-based assets ... 115
    2.2. Managing firm exposure to investor sentiment ... 116
    2.3. Customer satisfaction and the stock market: a review ... 118
3. Descriptive Statistics ... 121
    3.1. Customer Satisfaction ... 123
    3.2. Investor Sentiment ... 124
    3.3. Monthly Stock Returns ... 124
4. Methodology and Results ... 125
    4.1. Non-parametric approach ... 125

4.2. Parametric approach 128
5. Robustness Check: Repeating the Analysis with Corporate Social Responsibility .. 130
5.1. Introduction to CSR: a Determinant of Customer Satisfaction 130
5.2. Data and descriptive statistics of the Robustness Check 132
5.2.1. CSR Scores 133
5.2.2. Investor Sentiment 133
5.2.3. Stock Returns 133
5.3. Methodology and results of the Robustness Check 133
5.3.1. Non-Parametric Approach 134
5.3.2. Parametric Approach 135
6. Discussion and conclusion 137

CONCLUSION CHAPTER 140

1. Summary and Concluding Remarks 140
2. Limitations of this Research 145
3. Considerations for Future Research 148

BIBLIOGRAPHY 153

APPENDICES 175

Appendix A. Spanish translation of Introduction Chapter to opt for the International Doctorate 179

Appendix B. Spanish translation of Conclusion Chapter to opt for the International Doctorate… 205

List of Tables

Table 1.1: Top-down measures of investor sentiment 33
Table 1.2: Bottom-up measures of investor sentiment 36
Table 1.3: Scales of SMA, RP, and RA, their survey items and factor analysis 45
Table 1.4: Summary statistics of the monthly survey responses for SMA, RA, and RP 48
Table 1.5: Summary statistics and correlation of monthly of SMA, RA, and RP 50
Table 1.6: Common stock characteristics: measurement and relation to riskiness 54
Table 1.7: Summary statistics of returns and characteristics data 57
Table 1.8: The conditional characteristics model: lagged monthly levels of SMA, RA, RP, and aggregate affect on long-short portfolios of the ASX, April 2008-April 2009........ 66
Table 1.9: The conditional characteristics model: monthly levels of SMA, RA, RP, and aggregate affect on long-short portfolios of the ASX, April 2008-April 2009 69
Table 2.1: Yearly summary statistics of Dutch retail investors responding to the surveys, and their trades, April 2008 to April 2009........ 88
Table 2.2: Definition and interpretation of risk behavior factors, adapted from Pennings and Wansink (2004) 89
Table 2.3: Factor survey items, their scales, and the results of the factor analysis 91
Table 2.4: Summary statistics of the monthly survey results, April 2008-April 2009 92
Table 2.5: Common stock characteristics: measurement and relation to riskiness 93
Table 2.6: Average monthly stock deciles traded, purchased, and sold by the sample of Dutch Retail Investors, April 2008-2009 96
Table 2.7: Double-hurdle model of factors influencing the common stock purchase decisions of individual investors 103
Table 2.8: Double-hurdle model of factors influencing the common stock sale decisions of individual investors........ 108
Table 3.1: Descriptive statistics: returns, ACSI, and investor sentiment, January 1994 to December 2010........ 122
Table 3.2: Portfolio returns for ACSI-sorted portfolios in periods of high and low investor sentiment........ 128
Table 3.3: Summary Statistics for the Corporate Social Responsibility Data 134
Table 3.4: Conditional characteristics model regression results........ 137

List of Figures

Figure A.1: The heterogeneity of emotions 4
Figure 1.1: The top-to-bottom conceptual model of investor sentiment 30
Figure 1.2: Monthly levels of SMA, RA, and RP and the AEX Dutch Stock Index, April 2008 to April 2009 46
Figure 1.3: Monthly changes of SMA, RA, and RP, and the AEX Dutch Stock Index, April 2008 to April 2009 52
Figure 1.4: Monthly returns of the shares in our sample of the AEX Dutch Stock Index, April 2008 to April 2009 53
Figure 1.5: Theoretical cross-section of stock returns conditional on investor sentiment…...63
Figure 1.6: RA sentiment seesaws: monthly returns portfolios, ASX-listed volatility-sorted shares, April 2008 to April 2009 71
Figure 1.7: RP sentiment seesaws: monthly returns portfolios, ASX-listed volatility-sorted shares, April 2008 to April 2009 72
Figure 1.8: RA-changes sentiment seesaws: monthly returns portfolios, ASX-listed volatility-sorted shares, April 2008 to April 2009 75
Figure 1.9: RP-changes sentiment seesaws: monthly returns portfolios, ASX-listed volatility-sorted shares, April 2008 to April 2009 76
Figure 3.1: The American Customer Satisfaction Index model (ACSI), adapted from Fornell et al. (1996) 119
Figure 3.2: S&P 500, ACSI, and investor sentiment from January 1994 to December 2010 123
Figure 3.3: Theoretical effects of investor sentiment on stocks sorted by customer satisfaction, adapted from Baker and Wurgler (2006) 126
Figure 3.4: Cross-section of ACSI returns conditional on levels of investor sentiment in the previous month 127
Figure 3.5: Cross-section of CSR returns conditional on levels of investor sentiment in the previous month 135

SHORT NOTE CONCERNING AFFECTIVE TERMINOLOGY

The focus of this thesis is what can collectively be called “affect” as it applies to various financial topics. However, the scientific study of affect spans many disciplines and has been performed in many languages – especially because it exhibits a long and storied history. For this reason, it is easy to confuse terms that refer to passions, attitudes, feeling states, moods, the process that is responsible for emotions, the results of emotions, and the way that each of these is referred to in various languages, various disciplines, and even time periods (what once was called passion came to be understood as emotion, and is now called affect).

Given that this thesis is interdisciplinary and tries to bring the affective terminology from various fields together, it has been a challenge to reconcile the various terms from each discipline: finance, marketing, accounting, management, psychology, and neuroscience. Each discipline has become comfortable using its own specific terminology, but this has not brought any order to the overall nomenclature. Instead of lexicographical harmonization in the domain of affect (i.e. using the same words to refer to the same things), we are currently experiencing an explosion in affective neologisms including terms such as: “fast and slow thinking,” “hot and cold cognition”, and “emotional intelligence.” The growing diversity in affective wording is encouraging because it attests to the vast interest in affect, but it can make it quite challenging to ensure that words being used are specific enough to refer to that which is meant.

The challenge is great when reaching across disciplines, but also when reaching across cultures. This thesis was written in an international context where readers with native proficiencies in Greek, Spanish, French, Dutch, German, and English have made valid points concerning the specificity and appropriateness of each individual term in the affective lexicon used in this dissertation: it turns out that from a cultural standpoint, the affective lexicon exhibits strong implicit definitions that are specific to different regions (and this despite their often common Greek and Latin etymology).

Hence, here are some definitions to help curb any misunderstandings that may arise from the chosen wording:

- **Affect:** (from marketing, psychology, and neuroscience) the physiological processes in the nervous system that are responsible for emotions and feeling states.

- **Investor Sentiment (or “Market Sentiment”, or simply “Sentiment”):** (from Finance) the difference between the theoretical ideal price and the actual market price.
- **Attitude:** (from psychology and marketing) an expression of favor or disfavor toward a person, place, thing, or event (the attitude object).
- **Emotion:** (from psychology) a subjective, conscious experience characterized primarily by psychophysiological expressions, biological reactions, and mental states. Emotion is often associated and considered reciprocally influential with mood, temperament, personality, disposition, and motivation.
- **Mood:** (from psychology) differs from emotions in that they are less specific, less intense, and less likely to be triggered by a particular stimulus or event. Moods generally have either a positive or negative valence.
- **Feeling State:** (from psychology and neuroscience) synonym of emotion.

BREVE NOTA SOBRE LA TERMINOLOGÍA SENTIMENTAL

Esta tesis se centra en lo que en conjunto se puede denominar “afecto” ya que atañe a varios temas financieros. Sin embargo, el estudio científico del afecto es multidisciplinar y se ha realizado en muchos idiomas ya que presenta una larga y variada historia. Por este motivo, es fácil confundir no solo los términos con los que nos referimos a las pasiones, actitudes, sentimientos, estados de ánimos, los procesos responsables de las emociones y los resultados de esas emociones sino también a la manera de referirnos a cada uno de estos términos en varios idiomas, disciplinas e incluso períodos temporales (así, por ejemplo, lo que una vez se llamó pasión fue entendido más tarde como emoción y ahora es llamado afecto).

Dado que esta tesis es interdisciplinar e intenta aunar la terminología de varios campos, ha sido todo un desafío armonizar los diferentes términos de cada disciplina: economía, marketing, contabilidad, administración y dirección de empresas y neurociencia. Cada una de las disciplinas anteriores usa su propia terminología específica, lo que ha fomentado que no exista una nomenclatura común e unitaria. En lugar de una armonización lexicográfica con respecto al dominio del afecto, es decir, que se usen los mismos vocablos para referirse a las mismas entidades, estamos experimentando ahora mismo una explosión de neologismos afectivos que incluyen términos como por ejemplo: “pensar rápido y despacio”, “pensar en caliente y en frío” e “inteligencia emocional”. La creciente diversidad de la nomenclatura afectiva es motivadora ya que pone de manifiesto el vasto interés que existe por el afecto pero, a su vez, puede llegar a resultar desafiante cuando intentamos asegurarnos de que los vocablos que usamos sean lo suficientemente específicos parar hacer referencia a lo que queremos decir.

El desafío es aún mayor cuando se trabaja con distintas disciplinas y también cuando se trabaja con diferentes culturas. Esta tesis ha sido escrita dentro de un contexto internacional en el que diferentes lectores con un dominio lingüístico nativo de griego, español, francés, holandés, alemán e inglés han expresado observaciones muy acertadas con respecto a la especificidad y grado de propiedad de cada término individual del léxico afectivo usado en este trabajo: desde un punto de vista cultural, el léxico afectivo muestra fuertes definiciones implícitas que son específicas según las diferentes regiones, y esto a pesar de su frecuente etimología común griega y latina.

Por esto, más abajo se muestran algunas definiciones con el objetivo de no dar pie a ningún malentendido que pueda ocasionar la nomenclatura elegida:

- **Afecto:** (en marketing, psicología y neurociencia) diferentes procesos fisiológicos del sistema nervioso responsables de las emociones y los sentimientos.
- **Sentimiento inversor (o "sentimiento de mercado" o sencillamente "sentimiento"):** (en economía) la diferencia entre el precio teórico ideal y el precio de mercado real.
- **Actitud:** (en psicología y marketing) expresión a favor o en contra de una persona, lugar, objeto o situación (el objeto actitudinal).
- **Emoción:** (en psicología) experiencia subjetiva, consciente caracterizada principalmente por expresiones psicofisiológicas, reacciones biológicas y estados mentales. Las emociones con frecuencia se asocian y se considera que tienen una influencia recíproca con los estados de ánimo, el temperamento, la personalidad, la disposición y la motivación.
- **Estado de ánimo:** (en psicología) difiere de las emociones en que es menos específico, menos intenso y tiene menos probabilidades de ser desencadenado por un estímulo o situación particular. Los estados de ánimo tienen normalmente una valencia positiva o negativa.
- **Sentimiento:** (en psicología y neurociencia) sinónimo de emoción.

ABSTRACT

Affect refers to the physiological processes in the nervous system that are responsible for emotions and feelings. This dissertation studies the relationship between affect and three aspects of financial markets. The first chapter examines affective influences in the stock market as a whole. The second chapter zooms in and studies the relationship between market participants' affect and their trading decisions. Finally, the third chapter takes the perspective of another kind of market participant, the publically traded firm, and studies how affect influences corporate financial policy. These three empirical studies contribute to a broader research effort to develop a structured and comprehensive theory of behavioral finance based on findings from neuroscientific studies. Each study in this dissertation provides novel evidence that specific affective factors exhibit distinct relationships with the cross-section of stock returns, are each relevant to different investor trading decisions, and can help corporations improve their price performance with regards to stock market crashes. Implications of this research suggest that affect-based measurement of investor sentiment can help improve arbitrage and reduce the incidence, as well as the virulence, of price bubbles. Opportunities for future research on this topic are widespread – for finance scholars, but also for accounting and marketing scholars – as is discussed in the concluding chapter.

RESUMEN

Los procesos fisiológicos que tienen lugar en el sistema nervioso y que son responsables de las emociones y los sentimientos a menudo son referidos en la literatura del campo científico de la neurociencia como “emociones” –en inglés, *affect*. Mediante tres estudios empíricos, esta tesis doctoral estudia la relación que se establece entre las emociones y tres aspectos de los mercados financieros. El primer capítulo examina de forma global la influencia de las emociones en el mercado bursátil. Por su parte, los capítulos segundo y tercero abordan dos áreas específicas de dicha influencia. Por una parte, el segundo capítulo estudia la relación que se establece entre las emociones de quienes participan en el mercado bursátil y sus decisiones comerciales. Por otra parte, el tercer capítulo se centra en la perspectiva de empresas cotizadas y documenta cómo influyen las emociones en su política financiera. El objetivo de estos tres capítulos es contribuir a un mayor entendimiento de las finanzas conductuales a partir de los hallazgos alcanzados en el campo de la neurociencia contemporánea. A la luz de los resultados que arrojan estos estudios se puede concluir que distintas emociones exhiben distintas relaciones con el corte transversal de los retornos accionarios esperados en el mercado, desencadenan distintas decisiones de inversión, y pueden ayudar a las corporaciones a mejorar la actuación de sus precios durante crisis financieras. Las implicaciones de esta investigación sugieren que una herramienta de medida del “sentimiento del inversor” que se base en las neurociencias afectivas puede ayudar a mejorar el arbitraje y a reducir la incidencia, así como la virulencia, de las burbujas de precios. Como se recoge en el capítulo de conclusiones, esta tesis doctoral abre una amplia prospectiva investigadora no solo para los estudiosos en finanzas, sino también para académicos en las áreas de contabilidad y de marketing.

Introduction Chapter

1. Introduction to Affect, Financial Decision Making, and Financial Markets

As science gains a better understanding of how the brain works and how decisions are made, it provides fresh wherewithal to improve the existing financial model. Many interesting breakthroughs have come to show that affect drives behavior more than previously thought and should hold a central role when studying humans, their organizations, and their societies. Due to the complex, heterogeneous, and latent nature of affect, social science researchers have tended to leave affect out of their analyses. They have instead favored the use of so-called "rational" models of behavior that rely on simplified rules and describe automatons rather than actual decision behavior.

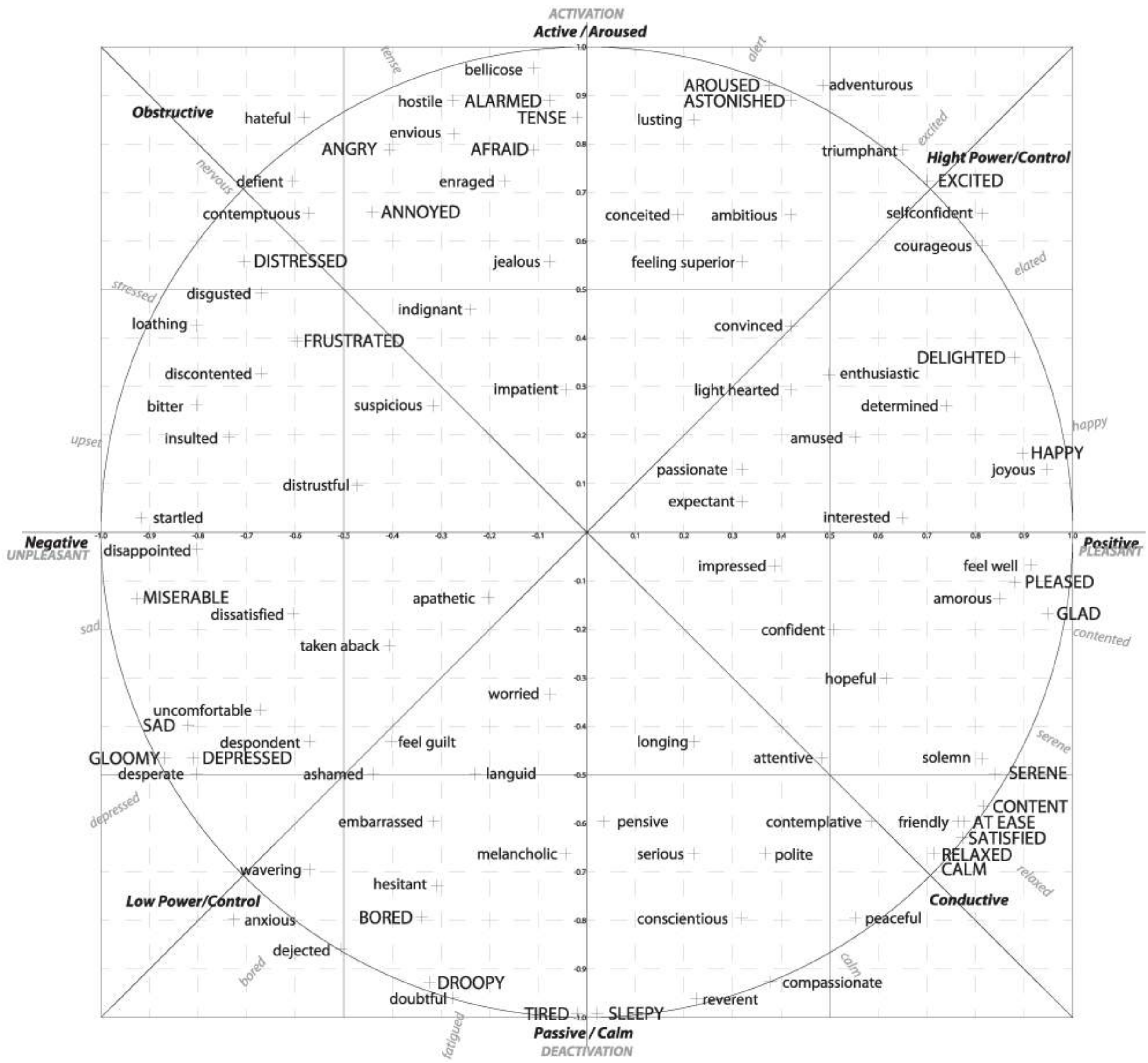
Thanks to the maturation of neuroscience, rational models have become controversial: we now know that the very part left out of rational models – affect – is fundamental to the functioning of the brain. Affect has thus come to hold a unique position in social sciences in general, and in finance in particular: it is the most neglected and yet the most important piece to the puzzle of behavior. This state of affairs represents a great opportunity for researchers: a large gap exists between current models of decision-making and the models of behavior that would incorporate affect.

Each discipline has taken upon itself to adopt affect at its own pace; some fields have integrated the related neuroscientific findings very quickly, others are rather resistant to do so. In economics, two disciplines represent the tail ends of this spectrum. On one hand, marketing scholars have been very quick to update their models of agent behavior to incorporate affect, perhaps even competing with psychology in terms of their focus on affective topics. On the other hand, finance scholars have been more resistant to incorporate affect in formal models, even though finance practitioners widely recognize its importance. This is partly due to the fact that the methodologies of financial research are successful enough to have rooted the development of the modern financial system, which has become an important set of institutions for any developed economy.

Comparing finance and marketing provides an interesting example in terms of showing how a discipline that incorporates affect uses it to provide effective affect-based solutions to its practitioners, whereas the other struggles with problems that are widely recognized to be caused by affect. Research in marketing has theoretically and empirically embraced affective processes; the drivers of affect are commonly studied and their consequences for behavior and marketing practice are widely documented and used in industry. Despite vast progress in behavioral finance, finance theory still considers behavior to be secondary to "rationality" and has resisted incorporating affect, especially as a primary driver of decision behavior. Instead, standard finance theory considers behavior to be a source of error rather than an objective piece of the financial puzzle. It is hardly surprising then, that stock bubbles remain one of financial economics' main unresolved questions; it is broadly acknowledged that popping stock bubbles result from affectively rooted manias and panics. It results that the standard analytical methods rule out affect as a fundamental part of the mechanics of a price bubble, and that the intuitive cause of stock bubbles goes unexamined.

Although finance scholars have made tremendous progress in understanding price bubbles, the explanation of bubbles that has received the least empirical attention has been affect. The reason may be because of practical research design issues: affect is hard to define and measure. Behavioral finance, the sub-discipline that specializes in behavioral explanations of price formation, has explored many alternatives to measuring affect. One successful approach has been the post-hoc analysis of financial data, the patterns of which do not fit rational financial predictions. Another approach is to document the consequences of many cognitive biases for market participants' decisions, portfolio performance, and price behavior. Behavioral finance has implicitly attempted to proxy for affect using financial data, which provided the additional benefit of real-time behavioral inference. However, the important drawback of this approach is that it only concerns aggregate affect – such proxies are unable to capture the defining characteristics of affect that are the diversity and heterogeneity of affective factors and their effects. Proxy-based approaches that address affective diversity and heterogeneity (surveys, semantic analysis, etc.) have rarely been used in research, and are mainly used practitioners. The few cases of research using these methods have earned recognition as plinths for future behavioral finance research, but where the measures are borrowed from practitioners there is an unfortunate lack scientific rigor, despite their interesting findings.

While implicit and general references to affect are common in behavioral finance, few measurements, methodologies, and theory treat affect directly, or even draw from the affective sciences proper (e.g. affective neuroscience, psychometrics, consumer behavior…). Specifically, such references to affect often consider market participants to only exhibit two opposing feeling states (e.g. “positive and negative” or “greed and fear”). While it may be summarized as such, the true empirical nature of affect is diverse and heterogeneous (see Figure A.1, below). Each particular emotional sensation is on a scale of its own, and they operate conjointly. Specifically, this dissertation shows new evidence that different affective factors - whether positive, neutral, or negative - exhibit individual relationships to the stock market and the underlying investment decisions.



From: Georgios Paltoglou, Michael Thelwall, "Seeing Stars of Valence and Arousal in Blog Posts," IEEE Transactions on Affective Computing, vol. 4, no. 1, pp. 116-123, Jan.-March 2013, doi:10.1109/T-AFFC.2012.36

Figure A.1: The Heterogeneity of Emotions

The heterogeneity of emotions is quite impressive: in addition to specifying the emotions shown in this figure, it is also possible to measure them as targeted towards objects, as well as the intensity of each affective factor. For example, at the same time, a person may be disappointed about one aspect of an event, but delighted about another, both at the same time. These feelings may interact when exerting an influence on judgment and decision making, providing for even more complexity and heterogeneity. Approaches that measure emotion by valence (positive vs. negative) or arousal (active vs. calm) alone thus leave out large amounts of information.

As an example, instead of considering fear and greed to be opposite points on the same scale with opposite effects on the stock market, a more accurate and descriptive way of conceptualizing greed and fear is to consider that fear is one affective factor and that greed is another. They would thus each be measured on a scale, and may both have positive and negative valences or be neutral. Greed and fear may thus effectively influence different trading decisions in different ways and at the same time. By conceptualizing each affective factor as its own driver of behavior, researchers will be thus able to examine a more accurate and nuanced set of relationships between affective processes and financial markets.

Finance is only just beginning to take heed of the ongoing affective revolution in the social sciences, and the perspectives are broad and exciting. Access to the technologies necessary to study affective topics (such as big data, social media, and medical imagery) is becoming widespread. For the first time, reliable, longitudinal, and direct measurements of affect are possible and accessible. This means that researchers who are interested in studying how affect is responsible for price bubbles can now open that black box. We now have the ability to paint a detailed picture of the latent mechanics of a price bubble. This set of circumstances is exciting because our financial system will benefit greatly from the better information we will have, that will make markets more efficient, and allow for better regulation, monitoring, and investor performance. The situation is also a little off-putting because affective information is of a personal nature and a disconcertingly good predictor of behavior. The changes to the financial system will be inevitable because the typical measures of utility and wealth will be complemented (perhaps even replaced) by distinct affective factors, which can be specifically related to physical processes in the brain. Indeed, the purpose of the financial system is to ensure that resources and capital are efficiently distributed and used; the success of this process is measured today by economic growth or returns. One may imagine a not so distant (and somewhat Orwellian) future where the success of capital distribution may also be directly measured by subjective states of wellbeing.

Indeed, when economists measure the success of a financial system with metrics of economic size and growth, the implied purpose is to estimate to what degree people are better off. In this sense, economic indicators are proxies for the subjective experiences of the people of which the economic system consists. It follows that determining what affect is, how to measure it, and how variation in affective factors is related to financial decisions are the next logical steps to improve our understanding of the financial system, its latent mechanics, and its participants. This research is effectively using finance as a testing ground for a new, modern, and innovative set of tools to eventually help tackle tough economic problems that continue to confound researchers and policy-makers: price bubbles, excessive wealth-distribution inequality, and economic growth. It is too early to see where this research will lead us, but the prospects are exciting and full of promise.

Well before research of affect in finance matures to the point of being able to address the larger macroeconomic problems, it is important to determining what affect *is* and to grasp the depth and scale of the revolution caused by neuroscientific advances at the microeconomic level. As a result, this dissertation focuses on defining and measuring affect, and testing its influence on the financial system in terms of price formation, trading decisions, and corporate financial policy. The rest of this introductory chapter consists of a summary of the history of affect from its earliest conceptualizations until the development of the social sciences, and ultimately the role it has played in framing behavioral finance. This provides broader context for the research performed in in this dissertation in terms of understanding why we think the way we do about emotions. Subsequently, we specify the motivation and research questions of each study.

2. The Road to Behavioral Finance: Historical Background of Affect and the Social Sciences

Speaking of emotions in the context of behavior is common throughout the history of the study of humanity, before anyone even knew what affect was, or even that it originated in the brain. Discussing some of the more influential ideas that have framed the contemporary perception of what affect is can provide helpful context for understanding the motivation for the research in this dissertation. Many of the important thinkers that laid the roots for Western thought have discussed emotions and have consequently framed the contemporary discussion on emotions, what they are, and how they drive behavior. In particular, it helps to explain why affect has taken so long to integrate finance, and why there has been so much resistance in the academic financial community to incorporate affect into a standard financial model. This is especially surprising when public discourse so obviously refers to affect in financial markets be it by regulators (e.g. Greenspan's famous reference to "irrational exuberance"), or by practitioners on any financial news network.

There is a historical reason for why, at least among Western thinkers, there is resistance to the idea that emotions drive behavior, and a propensity to believe that emotions are implicitly responsible for "bad" behavior. At first, emotions were objectively considered to be part of the process that resulted in behavior. Plato and Aristotle (IIIrd B.C.) provided a surprisingly accurate picture of emotions by portraying them as part of an interactive relationship with the process responsible for conscious, analytical thought. Some of their disagreements would be the subject of debate for over 2000 years, and would represent significant hurdles to the incorporation of emotions into any consensus among thinkers concerned with behavior and society. On one hand, Plato posited that this interaction was brought about by a mind that pre-existed the body; Aristotle, on the other, felt the whole mechanism is derived from physical processes.

During much of the Middle Ages, thinkers tended to draw from Plato more than from Aristotle on questions of emotion and behavior – making emotions somewhat of an immeasurable metaphysical concept beyond the grasp of scientific inquiry. Thomas Aquinas (XIIIth c.), for example, argued explicitly against the Aristotelian view and would lay influential groundwork for subsequent thinkers in the realm of emotions. In particular, he is responsible for formulating the idea that animals can be classified as "rational," and essentially stating that the only rational animals were humans. Although rationality as described by Thomas Aquinas resembles cognition in many ways, his description does not preclude a role for emotions in human decision making. Aquinas' idea that rationality is what separates man from beast would be perpetuated by later scholars who posed the question of emotions' role with respect to rationality. In particular, René Descartes (XVIIth c.) would be the philosopher to become most known for his discussion of emotions, and is the first thinker to explicitly address emotions and their consequences for decisions. The consecration of "rationality" and the perception that emotions were bad decision drivers (as opposed to just being relevant, as is thought today) would come from Descartes – and believable if only because he was arguably the father of the modern scientific method.

Descartes’ influence on science and philosophy is still felt today: some of his contributions include the Cartesian graphing system, analytical geometry, infinitesimal calculus, and his philosophical writings represent one of the foundations for Western philosophical thought. His revolutionary piece, the *Passions of the Soul* (1649), would set the stage for examination and analysis of emotions and behavior for at least the next 400 years. In his philosophy, he posited that the world consisted of both tangible and intangible matter, and that the human body was made from the former, and the soul (i.e. interpretable here as the “mind”), an inherently rational device, consisted of the latter. Despite how outlandish his model might sound by today’s standards, it is effectively the first ever dual-process model; a successful class of models of behavior built on cognition and affect that are still used to this day.

Descartes even targeted, albeit incorrectly, the place in the brain (i.e. the pineal gland), where interactions between the soul and animal spirits would occur – putting, in very avant-garde fashion, the brain in the center of his explanation of behavior. The sensations that arose from these interactions are what Descartes would call passions, and would eventually come to be called emotions. Descartes’ discussion of passions would be the basis for the understanding of emotions until modern neuroscience’s growing interest in emotions would take the helm in the end of the twentieth century. While other influential thinkers would immediately build upon Descartes’ analysis of emotions, the recurring assumption has since been that emotions hampers “rationality” and the ability to make successful decisions. The part of the philosophy that was so hard to uproot from conventional scientific thought about behavior, was that human behavior was primarily driven by the rational part, but was intermittently subject to the emotional part. The reality however, is that affect is the primary driver of behavior, and that reasoning only occurs intermittently, due to its high cost in terms of physiological resources.

The social sciences would thus consider emotions to be a passing and suboptimal decision mechanism. It was assumed that if people wanted to behave optimally, they would ignore their emotions, broadly defined, and would behave rationally. In this view, the normative models based on rationality would not diverge greatly from real behavior, which made them seem accurate, effective, and practical. For this reason, disciplines like sociology or anthropology, or even geography, had largely ignored possible affective explanations for phenomena in favor of ones that were supported by rational behavior. However, in addition to being inaccurate, modeling humans as strictly rational agents can have negative consequences when moving from social science theory to organizational practice – precisely because affective effects are ignored. Affective effects condemn rational theories' usefulness and can cause extensive monetary and social costs as a result: first, by putting the "rational" idea into practice, only to subsequently discover that it does not work, and then by having to undo what had been put in place. It results that social science models must include affect if they are to be used to create and administer social organizations and institutions.

This dissertation argues that including the theoretical and empirical study of affect in finance will improve financial institutions, decisions, and policy. In order to convey why this topic is important and how it fits cutting-edge scientific trends, it is helpful in the context of this section to offer a historic example of how a rational theory put into practice would backfire for the lack of incorporating the study of affect. Here, the analogy with finance concerns another social science discipline in its own right: geography. Geography realized the importance of affect after the rise and fall of the rational urban planning movement (1890-1960). Just like rational finance (1900-1980), the rational urban planning movement formed as a result of the generalization of quantitative techniques (in terms of measurement and predictive modeling, for example) that were brought about by the industrial revolution.

In the case of urban planning these techniques used important spatial characteristics such as exposure to direct sunlight, movement of vehicular traffic, standardized housing units, and proximity to green-space. The list brings to mind the common variables used in rational financial research: returns, volatility, size, liquidity, volume, book-to-market ratio... Neither discipline's measurements concern subjective preferences of the people involved – the potential residents in the case of urban planning or the market participants in the case of finance – both fields effectively ignored affect.

In order to apply quantitative techniques to these factors, urban planners had to hire highly specialized technicians including architects, urban designers, and engineers. Similarly, the advanced quantitative techniques in rational finance required development by mathematicians, computer scientists, engineers, and physicists. Rational planning was an inherently top-down approach, because the technicians would impose a particular urban plan based on rational characteristics onto a population, as influenced by government officials and private developers. This would subject rational planning to the eventual critique of being elitist and socially insensitive; its limits would become clear when, sometimes just after being built, many housing projects around the world would fail and be dismantled at great cost. Rational finance is also an inherently top-down discipline, studying aggregate market characteristics and drawing conclusions about what is in effect a diverse and heterogeneous set of market participants. Finance has also been criticized of being elitist, and although markets have not been dismantled, the financial crises subsequent fallout are very costly, and were blamed on the financial community.

The rational urban planning movement ended because it had lost touch with the public it was building the housing projects for. The rational model of behavior they were based on assumed that exposure to direct sunlight, movement of vehicular traffic, standardized housing units, and proximity to green-space were characteristics that would make residents happy, but something important had been left out. From the subsequent bottom-up urban planning movements, we now know that residents feel very strongly about many intangible characteristics that were ignored in rational planning such as social cohesion, the preservation of local culture, and sustainability. These characteristics satisfy affective needs of residents, and were a necessary condition in order to improve on rational planning: the majority of subsequent urban planning movements favored bottom-up planning. This approach meant measuring the agents first, and would focus on public participation, communication, and consensus to establish preferences and what important affective characteristics needed to be addressed.

The experience of urban planning is informative because it is a historical example of the transformation that the social sciences are going through, forced by the consequences they face as a result of ignoring affective processes in the social agents they study. This example provides a narrative to the motivation of this dissertation; many financial institutions today reflect a similar situation to rational urban planning because they, too, have been developed based on rational models of behavior. Financial institutions are not designed to take affect into account; they therefore have no policy towards affect, which leaves them vulnerable to problems originating with affective processes. The symptom for this type of problem is the stock market bubble: investors' "animal spirits" push prices up, despite all evidence to the contrary, to unsustainable levels. Eventually, the market panics and subsequently crashes causing damage to the financial system and economic growth. Studies have provided many rational causes for stock market bubbles, such as excessive credit or loose monetary policy, and while these causes are a part of the bubble problem, they do not preclude the role of affective events like manias and panics. Indeed, many researchers have tended to study affect-related processes to explain financial crises rather than affect itself.

"Animal spirits" has become a popular term for the collective effects of many non-rational decision behaviors that have emerged from psychology since the 1970s, and explain economic phenomena that do not conform to rational models of the economy. Psychologists have provided a long list of cognitive biases, named for their divergence from rational behavior, which can be integrated into rational models of the economy with relative ease. In terms of model parsimony however, each non-rational adjustment to an economic model makes the model increasingly complex. Often, economic models can only account for two or three cognitive biases at a time, but nonetheless are generally accompanied by improved model performance over the original rational model. The most famous case is the replacement of Von Neumann and Morgenstern's rational expected utility model with use of Kahneman and Tversky's prospect theory – it is possible to swap the first for the second in any expected utility model to make it a behavioral model that relies on empirically determined decision routines rather than rationally theorized ones. The success of prospect theory's adaptation by economists ended up being a seminal event in economics that would spawn many models based on cognitive biases, and generalize the acceptance of behavioral approaches to economic problems.

The emergence of behavioral finance in the 1980s was encouraged by the recognition that behavioral techniques could improve economic modeling procedures by making them more descriptive. For example, the movement of stock prices was found to exhibit a greater volatility than could be explained by rational models alone, so it became clear that behavior would come fill that gap. Behavioral finance would primarily draw from psychology to understand the judgment and decision making mechanisms that cause prices to behave the way they do. Throughout the 1990s, behavioral finance would propose two theories to explain why prices behavior deviated from rational expectations: the first is called investor sentiment, which states that markets over- and under-react; the second is called limited arbitrage, which states that markets fail to "apply the brakes," and that market participants who are supposed to correct unsustainable prices do not act to do so (sometimes even exacerbating the problem). Many behavioral explanations for the extra volatility in price behavior would thus be documented: herding, overtrading, overconfidence, positive feedback trading, the disposition effect (i.e. holding losing stocks too long, and winners not long enough), and the expression of preferences. Even though it is implicit that emotions play a role in the manifestation of such behavioral explanations of price behavior, the role of affect is not explicitly examined: the study of investor sentiment has yet to focus on the study of actual sentiments.

Investor sentiment is a term that behavioral economists have borrowed from finance practitioners that originally referred to the feelings of the market participants that practitioners would speak with. As such, the original use of the term explicitly referred to their instinctive understanding of market participants' affect, but since the development of behavioral finance, it refers instead to the collection of documented psychological effects on prices. One reason for the shift in semantics comes from the fact that when behavioral finance came into existence in 1980, an important debate in psychology about affect remained unresolved. The aftermath of that discussion would prove to be an important turning point in the way that psychology would influence other social sciences, and would foreshadow the empirical results of future neuroscientific studies. The debate concerned which of the three categories of the mind: cognitive (e.g. reflection and analysis), affective (e.g. feeling states), and conative (e.g. impulse behavior), was the first system in the brain to respond to stimuli. The original view, inherited from Descartes, assumed that cognitive mechanisms reacted first and that affect would interrupt. Throughout the 1970s, researchers influenced by Pavlov and Skinner would instead argue that affect was the primary stimulus-response mechanism.

The scientific trend that placed affect as the primary motivator of behavior would provide evidence contradicting the concept that humans were primarily rational beings. By the 1980s, the discussion leaned heavily in favor of the primacy of affect, which would eventually incorporate conation and be considered in the end as a prerequisite for cognition. The neuroscientific evidence for this would emerge during the second half of the 1990s in the form of the somatic marker hypothesis, and is described in a book by the neuroscientist Antonio Damásio and entitled "Descartes' Error." Damásio's book notably refers to the natural experiment arising in cases of patients who after brain injuries underwent a personality changes. The particular parts of the brain that were damaged were related to emotional processes. As Damásio explains, the changes in personality were due to the fact that even though emotional parts of the brain were damaged, the patients could not perform what would normally be considered rational tasks. He concludes based on observing the brain that cognition and affect are inherently linked at a neurological level, and that neither one can function without the presence of the other. As far as the structure of the brain is concerned, the separation of emotion and reason is an illusion of consciousness.

In the late 2000s, once the discovery that activation of cognitive function in the brain happens in concert with affective activation achieved broader acceptance of neuroscientific findings across the social sciences, economic disciplines began studying financial topics related to affect. This dissertation concerns the discipline of finance proper, but in terms of incorporating affect it was a relatively late adopter. Marketing scholars had been keeping up to date concerning research about affect, they did not wait for the breakthrough discovery to incorporate affective research. Behavioral finance is now benefitting from the research performed by marketing researchers, their results, and their methodologies. Finance scholars are finding that the approach to questions of consumer behavior, which relies on extensive affect-related research, is easily translatable to issues of value-creation, trading behavior, and preferences in finance. Other disciplines fueling the affective revolution in finance include psychology and neuroscience, which are motivating the trend for financial research in the 2010s. Financial research on affective topics during this period also reflects a reaction to the subprime crisis, which involved manias, panics, and the management of specific affective sensations in the public (e.g. trust, confidence, and optimism), by central banks for example, despite having no established measurements or policy towards affective effects.

This dissertation thus fits in the early stages of the trend in behavioral finance that explicitly focuses on affect. In particular, it focuses on the most important sign that policies towards affect do not exist which are the lack of a standard measurement framework and the recognition of heterogeneity among affective factors (as opposed to the typical dichotomies used to measure investor sentiment, e.g. positive vs. negative, active vs. calm, greed vs. fear). We examine these themes in the context of financial markets, financial decision making, and financial policy design. We are thus able to contribute to the literature in behavioral finance about price bubbles, their effects, how they arise, and how to manage them. Below we lay out the motivation and research questions for this research.

3. Problem, Motivation, Research Questions, and Contribution to Behavioral Finance

The present collection of studies approaches the problem of price bubbles from three directions: the relationship between affect and prices, the relationship between affect and the trading decisions, as well as how this knowledge can inform corporate financial policy. By examining these three points of view with regard to affect's relationship to financial markets we are able to contribute evidence to the literature on how to conceptualize, measure, and address the incidence of bubbles. The overarching motivation of this dissertation, however, is essentially about measurement: testing a new measurement methodology with the purpose of creating an affect-based measurement framework that can provide relevant informational content about stock bubbles. For the purposes of this study "relevant" means that a relationship exists between affect and price behavior, between affect and trading decisions, and between affect and organizational decision making. Measurements that satisfy these conditions represent the first step in constructing a measurement framework that is useful for all market participants – traders, arbitrageurs, regulators, and researchers - to understand, identify, analyze, and prepare for price bubbles.

The existing standard financial model does not directly treat the existence of price bubbles, but the purpose of behavioral finance is to incorporate a bubble-theory into an all-encompassing model of finance. As of today, all approaches to this problem are controversial in some way. It results that behavioral finance has yet to propose a comprehensive a model, even though it is widely agreed that an uncontroversial answer lies somewhere in the sphere of the study of behavior. For lack of a more specific way to refer to the mechanics of a price bubble, behavioral finance currently rests on the consensus that two forces interact when bubbles occur: investor sentiment and limited arbitrage. Being more specific than just using these two concepts is a thorny affair. There are many competing behavioral explanations for overreacting stock markets that are each controversial in some way; the explanations stretch from the weather to hormones to any number of cognitive biases.

Given the recent turbulence of financial markets, being more specific about the mechanics and drivers of bubbles is necessary, despite its thorniness. Although many causes for investor sentiment have been recognized and can be measured, identifying and correcting price bubbles remains ineffective – they have occurred almost continuously around the world since the 1970s. One reason bubbles are so persistent may be the fact that investor sentiment is poorly measured. The fact that supports this claim is that investor sentiment is also vaguely defined as a result of so many competing explanations. In the case of the stock market, explanations of stock price bubbles are not taken into account. Even if financial data reflects the advent of a bubble, it still does not say anything about the related, latent, non-financial equity valuation process that is occurring amongst investors. As the underlying cause for bubbles, that latent non-financial process requires its own measurement approach. The current picture drawn by traditional accounting- and economics-based measurement and reporting practices does treat the latent valuation of investors, and thus does not make the onset of a price bubble obvious enough for practitioners and policy makers to take pre-emptive action. It is possible to affirm this because the bubbles keep occurring, which is a strong signal that existing measurement and reporting practices, with regard to bubbles at least, require improvement.

By seeking to understand affect and its relation to financial decisions and financial markets, this research poses the question of how to improve current financial measurement and reporting practices such that proactive procedures can be taken with respect to price bubbles. The existing system, based on accounting, obliges public corporations to be transparent in public financial reports and standardizes financial measurements so that corporations can be compared to each other and themselves through time. This helps determine which firms are risky and allows investors to separate them from the safe firms. The shortcoming of such a system is that determining the riskiness of an asset also depends on the relative judgments of other market participants. This is in effect Keynes' famous "beauty contest," and ultimately the point of measuring investor sentiment - to quantify what the rest of the market thinks.

So far, such efforts to quantify investor sentiment have resembled a search for the "holy grail" of sentiment indicators, the one that impeccably predicts the average judgment of the aggregate market. Indeed, the usual view of investor sentiment is that it is driven by a multitude of behavioral factors, but that it is measured on a single “catch all” dimension. It is typically considered to be positive, neutral, or negative, and denotes the average level of excitation of the market. It assumes that excited markets are risk seeking and subject to price bubbles, whereas passive markets are risk averse and underperform their potential. In reality, there is no perfect price indicator, and it is likely that investor judgment and decision making is too complex to be summarized by one direct measurement or proxy. The research performed in this dissertation is novel in its approach in the sense that it argues that rather than one measure, a multidimensional framework for measuring investor sentiment must be developed. Such a framework will complement standard financial reporting measures and provide context for them. This dissertation thus investigates what the best way is to develop such a framework with discussions of theory and empirical evidence.

3.1. Chapter 1

The first step to establishing the relevance of affect for investor sentiment is addressed in Chapter 1. It is a study of the relationship between affect and the cross section of stocks returns: do different affective factors measured using the same methodology exhibit different relationships to the cross-section of stock returns? This research question is fundamental to establish the measurability and relevance of affect in price behavior for two reasons. First, it allows for the comparison between results derived from the affective measurements and those derived from existing investor sentiment measures. Second, by comparing investor sentiment measures with affective measures, it is also possible to determine if using multiple dimensions of affect provide additional information about the market. By proving that it is possible to use affective measures to reproduce the relationships we already know investor sentiment exhibits in the cross section of stock returns, and then by proving that using different dimensions of affect to portray differing relationships, Chapter 1 effectively shows that there is great potential for a measurement framework based on affect.

The potential for such a measurement framework is rooted in the fact that affect-based measurements exhibit the necessary empirical and theoretical conditions: empirically it is possible to reproduce existing studies, and theoretically there is a palatable explanation for why we can reproduce existing studies. In the latter case, the explanation specifically concerns the primacy of affect, which is the recognition that affect is the first process to respond to stimuli. These are important arguments because they allow the study to support the view that affect-based measurements can explain all other valid approaches to explaining and measuring investor sentiment. As such, the chapter aims to assert that affect-based measurements exhibit a high “return on investment” in the sense that they are relatively cheap methodologies to put in place given the wealth of relevant information that they are able to collect. Indeed, they are the most relevant measures in terms of explaining pricing with behavior because they explain all other behavioral explanations for pricing.

Chapter 1 explicitly addresses the theoretical discussion that offers the basis for stating that affect drives other drivers of investor sentiment. It provides a unique and parsimonious theoretical model of the chain of events from the informational stimulus up through the order in which behavioral patterns occur when a trading decision is being made. This is important because currently many measures of investor sentiment compete, yet are fundamentally different in terms of the different parts of the decision making chain of events they target. For example, sunny weather, positive emotional states, the use of heuristics, high levels of testosterone, and changing skin conductance are all competing measures of investor sentiment. However, when the sun is out, people tend to be happier, meaning they use more heuristics, experience higher levels of testosterone, and exhibit changes in skin conductance: each documented cause for investor sentiment is in effect a link in the same chain from stimulus to decision that results in the sentimental market outcome. The important question therefore concerns choosing a universally acceptable way to measure the entire process that causes sentimental market outcomes, so that everyone agrees on what a bubble is, and how to deal with it.

The implications of Chapter 1 are far reaching in particular for arbitrageurs. It is unlikely that arbitrageurs can unite in the face a large bubble because their tools are limited by a poor definition of investor sentiment, and a plethora of measures to choose from. This means that two arbitrageurs using different measurements to quantify sentiment may not execute complementary strategies. The fact that arbitrageurs do not help each other can be problematic if the price bubble in question is so large that no one arbitrageur will take the risk of betting against the bubble. This is especially the case if they are unclear about the measurements that will drive other arbitrageurs trading decisions. Clear definition and measurement of investor sentiment will help synchronize arbitrageurs, which can in turn decrease the intensity and incidence of price bubbles. Because different affective factors exhibit different relationships to the stock market, are measured with the same methodology, and can be structured into a specific framework it suggests that it would offer arbitrageurs a more flexible, more specific, and easily communicable set of tools to better undertake the endeavor of correcting large bubbles.

3.2. Chapter 2

Chapter 2 picks up where Chapter 1 leaves off. From Chapter 1 we know that affect is measurable, is multidimensional, and exhibits statistically and economically significant relationships to the cross-section of stock returns. The next step in terms of providing evidence that affect serves as a better option to measure investor sentiment than existing alternatives is to show that in addition to relationships with price behavior, affect also exhibits a relationship to the very decisions that drive prices: trading decisions. The theory provided by the primacy of affect suggests that affective measures drive decisions and the purpose of Chapter 2 is to provide the empirical evidence. To show that measures of affect also drive trading decisions provides an opportunity to corroborate the findings in Chapter 1, but also to strengthen the argument that affect is a better measure of investor sentiment. Indeed, if measures of affect can explain prices, but can also explain the decisions that drive the prices, then the argument in favor of affect becomes even more tenable. This is especially the case if it is shown that different affective factors are relevant for different trading decisions – such evidence effectively shows that affective-based measures of investor sentiment are capable of doing what other measures of investor sentiment cannot: address issues of latent heterogeneity in behavior.

Chapter 2 thus shifts its focus from the aggregate stock market to the trading decisions of individuals, and thus enlarges the perspectives of measuring affect in order to explain investor sentiment. In particular, Chapter 2 asks the following research question: are different affective factors related to different trading decisions? Understanding what affective factors drive decisions informs us about the behavior of pricing, but also describes the decision-making processes of market participants. Affective factors can subsequently be traced to risk behaviors, to the use of cognitive biases and heuristics, to physiological changes such as skin conductance and hormones, and thus provide a far more detailed picture of how investment decisions are being made. Chapter 2 turns out to find that one set of affective factors influences retail investors' purchases of common shares, and that a different set influences their sales.

The implications of findings in Chapter 2 are far reaching. Research from the affective sciences has documented that affect is malleable; this means that an individual's particular levels of affect can be influenced by third parties. Chapter 2 identifies specific affective factors that are involved in the purchase and sale decisions of retail investors. This suggests that by influencing the affective factors specifically responsible for purchase or sale decisions, it is possible to increase and decrease purchases and sales. Central banks and corporations make use of this finding in their daily operations. Central banks typical use monetary policy to influence markets, cooling them down if they are too hot – or stimulating growth if they feel it is warranted. Another tool they use is their communication with the public – central bank announcements are dissected and heeded by their audiences: this research suggests that the discourse, depending if they wish to encourage buying or selling, should be oriented towards influencing certain affective factors. In the same vein, corporations' investor relations departments can construct a reliable communication policy based on the malleability of the right affective factors.

3.3. Chapter 3

Chapters 1 and 2 showed that affect is related to prices and to the underlying trading decisions. Chapter 3 brings this dissertation full circle; it tests whether there are any immediate applications of this research for practitioners. Chapter 3 studies whether the informational content of affect-based sentiment measures can improve corporate price performance and poses the following research question: does including affect-based investor sentiment in corporate financial policy improve stock price performance? If affect-based investor sentiment measures contain useful information for understanding prices and trading decisions, then this information must also be useful when designing the corporate financial policies, and investor relations policies in particular.

A corporation faced with a stock price bubble, may see its stock prices fall for no other reason than because all other stock prices are falling in a market panic. In such a case, firms will want to protect themselves against such an event - which is ultimately an event that is out of their control. To measure affect, this study collects the customer satisfaction levels of publically traded firms, and analyzes the cross-section of stock returns, conditional on high or low levels of investor sentiment. As such, the study shows how the affect of market participants towards the market can be tempered by the affect of market participants towards individual firms. The study finds that firms with happy customers exhibit smaller corrections than firms with unhappy customers when stock markets are in a relative panic.

Thus this dissertation makes contributions on both theoretical and empirical levels. From a theoretical perspective, it provides the most comprehensive discussion of affective theory in finance, offering the groundwork for a comprehensive model of behavioral finance. Empirically, this dissertation shows that affect is related to price formation, to trading decisions, and to corporate financial policy. In addition, the studies show that different affective factors have different effects on prices and trading decisions. The perspectives for future research are thus quite ample. In particular, building a taxonomy of the various affective factors and their effects on the various parts of the financial system would represent a large step forward in the study of affect and finance. From a practical perspective, this dissertation recasts the importance of measuring affect, not only because it is a fundamental process for behavior, but also because it is more practical to quantify than other drivers of sentiment - providing the most informational content with the least effort, and enough flexibility to capture many complexities of decision behavior that existing measures of investor sentiment simply cannot. The evidence in this dissertation shows that affect-based measurement is capable of being structured into a consistent, comparable, reliable, and valid framework that is at least informative about price behavior, investor decisions, and corporate financial policy.

The approach described in this thesis is helpful for any social science, yet it is fundamental for finance. This is because so much individual welfare depends on financial institutions and policies. A financial crisis can cause many years of political and economic instability, and prolonged suffering amongst large portions of the population. “Affect-proofing,” the act of adapting financial institutions and policies to deal with affective effects of the agents they are meant to serve, can help identify and pre-empt financial crises and thus ensure long-term growth, efficient distribution of capital, and a more stable, sustainable society.

3.4. Concluding chapter

The concluding chapter provides a summary and a holistic discussion about the results of this dissertation for researchers, practitioners, and regulators. It begins by reminding us that investor sentiment is a convoluted term, the theory behind the concept is vague, and that the measurement is, as a result, also convoluted – investor sentiment means many things to many different people. The three studies approach the problem methodically first by defining the term, then by looking for adequate measurements, and then by testing the measurements in various contexts. This approach has identified how the recasting of investor sentiment into a structured theory with specific measurements and definitions can help arbitrageurs, investors, and corporations. Taken together, the studies suggest that markets may work better if such techniques could be refined and applied by various market participants. Nonetheless, the chapter also discusses that despite the exciting results presented here, much work remains to be done, and these studies only scratch the surface of what is truly an immense topic. In any case, the application of affect to finance, and to business economics in general (at least beyond disciplines like marketing) should be transformative and much work remains to be done in the future.

The concluding chapter also discusses perspectives for future research, and what can be expected in terms of findings, as well as their consequences in the long run. One of the main points of this thesis is that affect is the primary driver of behavior, and that it is a very good predictor of behavior. As multidisciplinary research clarifies how affect works and improves measurement methodologies, it is plausible to imagine a world where affect will be integrated in a variety of practices and technologies that people will use. This integration will likely also address many business and economics fields, and in particular finance – in large part because of the intuitive role that emotions play in financial markets. The first step to advance in this direction in finance is to taxonomize affective factors and their importance for the financial system. This means that the heterogeneity of affective factors can be elucidated, and that the latent heterogeneity of market participants can be examined, allowing for improved profiling techniques. Such techniques would help specify the best practices for investor relations officers, help identify the profiles that relate to performance, and allow researchers to test these profiles over time, to determine if they are dynamic or conditional on the environment.

From an interdisciplinary point of view, these perspectives for future research mean that accounting and reporting will also have to adapt to this new environment. Accounting is a discipline that focuses on such topics as auditing, measurement, and reporting. Practitioners and researchers often talk about the softer aspects of these topics that involve affective topics, such as hubris, overconfidence, and the measurement of intangibles. Future research in affect and finance will provide relationships and measurements that accountants may consider as topics for their own studies in reporting. If affective information truly is relevant and complements the traditional financial accounting information, then it may be worthwhile to ask whether public reporting of affective factors is a constructive effort in terms of improving the financial system. The chapter concludes that in effect, money and economic growth are the most convenient proxies to measure individual welfare. Individual welfare however, is an affective construct that can be measured. This suggests that the future of economics will be to measure welfare directly, thus superseding important measures such as monetary returns or GDP growth. Indeed, this thesis is about the infancy of such a movement, and determining the feasibility and palatability of moving economics in this direction. So far the results are promising.

Chapter 1

Investor Sentiment and the Cross-Section of Stock Returns: Affect and the Bottom-Up Approach

Abstract: The Affect Hypothesis (Statman, Fisher, and Anginer 2008) states affect is related to the behavior of stock prices in general, and in particular is a driver of investor sentiment. After reviewing this literature, this chapter performs the first direct and comprehensive test of the Affect Hypothesis. We study the cross-sectional effects of three affective constituents of top-down sentiment (TDS) on stock market returns: Stock Market Attitude (SMA), Stock Market Risk Attitude (RA), and Stock Market Risk Perception (RP). We provide parametric evidence confirming the prediction that bottom-up measurements of investor sentiment exhibit the same relationship to returns as TDS (i.e., *changes* in affect are related to contemporary stock market *overreactions* and *levels* of TDS are related to subsequent stock market *corrections*) (Baker and Wurgler 2006). Although non-parametric evidence also supports the Affect Hypothesis, we show that different affective constituents exhibit different relationships to market overreactions: in particular we find that SMA and RA reproduce the sentiment seesaw (Baker and Wurgler 2007) but RP does not. This finding highlights a standard and recurrent problem in the investor sentiment literature: no consensus exists

concerning its nature or required measurement framework. We conclude that this state of affairs is a cause for the synchronization problem (Abreu and Brunnermeier 2003), where arbitrageurs are unable to synchronize their arbitrage efforts to effectively correct stock price bubbles. This occurs because they cannot agree about the causes and effects of investor sentiment. We discuss why affect will be at the center of future research in this direction.

1. Investor sentiment: a short introduction

Behavioral finance relies on two fundamental assumptions (Baker and Wurgler 2006, 2007). The first, called investor sentiment, states that stock price behavior reflects a variety of psychological, physiological, and evolutionary factors inherent to the natural behavior of market participants (Arthur 1999, Shiller 2003, Lo 2004). Investor sentiment implies that stock prices are susceptible to investor overreaction (De Bondt and Thaler 1985), which may lead to stock price bubbles, and the problematic aftermath of stock market crashes. The natural market mechanism that corrects stock price bubbles relies on arbitrageurs, the traders who can theoretically identify stock price bubbles due to their specific knowledge, and trade against them in order to profit from the subsequent price corrections. The second assumption, limited arbitrage, states that such traders may exhibit reasons to not take action (e.g. limited wealth, see Shleifer and Vishny 1997) thus allowing stock price bubbles to grow unsustainably and become hazardous to the financial system. Identifying stock price bubbles is thus important for two reasons: it creates profit opportunities for traders and it serves as a signal for an impending threat to the financial system.

1.1. Approaches to the study investor sentiment

Researchers have relied on two categories of analysis to support their findings on investor sentiment (Baker and Wurgler 2006, 2007). The first, called the top-down approach, uses exchange-level data to approximate levels of aggregate investor overreaction and studies its relationship with stock price behavior. The purpose of the top-down approach is to test for aggregate investor overreaction using exchange-level variables and to quantify its effects. The top-down approach theorizes that when levels of investor sentiment are high, investors are more likely to be overreacting, and shows that these effects can be measured with stock market variables such as price volatility, trading volume, and implied option volatility (Whaley 2000, Bandopadhyaya and Jones 2008). Baker and Wurgler (2006) maximize the informational content and minimize the error of this measurement approach by using the principal component of several exchange-level variables to estimate levels of investor sentiment. Relying on the assumption that stock-market variables reflect investor overreaction, they show that the cross-section of stock returns exhibits a systematic relationship to levels of investor sentiment. Measures of investor sentiment thus provide investors with specific knowledge that helps identify and correct sentimental price inefficiencies.

The second category of analysis, called the bottom-up approach, relies on a variety of measures drawn from behavioral explanations of investor overreaction, such as heuristics or physiology. While the top-down approach is meant to test for the existence of investor sentiment and measure its effects, it is not designed to make statements on the processes that drive investor overreaction. Bottom-up analysis includes a wealth of theory and empirical measurements that explain how and why investors overreact, as well as consequences for stock price behavior. The multiplicity of studied behavioral explanations for investor overreaction has yet to crystallize into a comprehensive theory of investor sentiment; consequently, no consensus has arisen concerning the nature of investor sentiment aside from the fact that investor sentiment exists and that it has many behavioral drivers. The lack of consensus surrounding the behavioral drivers of investor overreaction is observable from the fact that no uncontroversial measure of investor sentiment currently exists (Baker and Wurgler 2006, 2007).

1.2. Limitations of the bottom-up approach and the synchronization problem

Market participants' ability to make informed trading decisions concerning levels of investor overreaction in the marketplace relies on effective measurement. However, the multiplicity among existing theoretical explanations of investor sentiment hinders the development of a consistent, comparable, and theoretically valid framework for direct measurement of investor overreaction. This is problematic because the natural stock market mechanism that prevents stock price bubbles relies on arbitrageurs' ability to identify and correct sentimental mispricing patterns. Unless arbitrageurs are able to agree what processes cause sentimental patterns, they will be unable to work in unison to correct stock price rallies unjustified by existing information. Without a clear signal for traders that stock prices are overvalued, there is no reason any individual arbitrageur will bear the risk of short-selling overvalued stocks that may continue to increase in value, and thus result in large losses. This explanation for limited arbitrage has been identified in the literature and is called the *Synchronization Problem* (Abreu and Brunnermeier 2003). It occurs because arbitrageurs do not make their bearish trades at the same time, and since small groups of arbitrageurs cannot single-handedly correct a price bubble, no particular arbitrageur has the incentive to take action.

1.3. Addressing the synchronization problem: the Affect Hypothesis

Building consensus surrounding the driving mechanics of investor sentiment can help synchronize arbitrageurs. Understanding how and why investors overreact provides the theoretical wherewithal for a reliable, valid, comparable, and consistent measurement framework that market participants can agree and rely on. The literature has made significant progress in identifying how and why the sentimental pricing process works. From the bottom-up literature, we are able to identify 5 levels of sentimental drivers that influence stock prices: trading decisions, behavioral biases, affect, physiology, and the environment. Affect's central role is almost always, implicitly and explicitly, discussed by studies at each level of sentimental drivers. The reason is because of the profound impact stock market bubbles and crashes have on market participants' feelings. While prices grow investors get progressively more excited until they achieve a state of extremely positive affect (Shiller 2000, 2003, Kindleberger and Aliber 2005). Eventually, they panic and a crash occurs, accompanied by extremely negative subsequent affect. Manias, panics, and ensuing economic troubles are extreme examples of how affect can influence asset prices (and vice-versa), but affective processes also contribute to price formation in less severe cases. This is the premise of the *Affect Hypothesis* (Statman, Fisher, and Anginer 2008), which states that stock prices continuously reflect market participants' affective states.

1.4. Testing the Affect Hypothesis

The *Affect Hypothesis* relies on research in psychology and neuroscience that demonstrates the fundamental function affect performs in the decision-making mechanisms of investors. The affective sciences provide a robust framework for the direct measurement of many affective factors, but in the interest of conservatism, we focus on three that reflect investor affect toward the stock market and stock market risk. First, Stock Market Attitude (SMA) reflects whether investors like or dislike how the stock market makes them feel. Second, Risk Attitude (RA) reflects investor predisposition to stock market risk (e.g. risk preference). Third, Risk Perception (RP) reflects investors' subjective interpretation of the probability to be exposed to stock market risk (the level of risk to which they feel exposed). A good measure of investor sentiment will serve as a leading indicator of price behavior for investors, but will also exhibit contemporary relationships to price bubbles. In order to validate each affective factor as a driver of stock price bubbles, we analyze their relationships to both concurrent stock market overreactions and subsequent stock market corrections.

Our analysis consists of adapting two top-down methodologies: the conditional characteristics model and the sentiment seesaw (Baker and Wurgler 2006, 2007). The former is a regression model that tests the relationship between a sentiment indicator and the difference between the returns of safe, easy-to-arbitrage stocks and risky, hard-to-arbitrage stocks. Examining the difference between safe and risky returns allows us to determine if variation in the sentiment indicator is related to stock market corrections (when the difference between the returns of risky and safe firms shrinks), or stock market overreactions (when this difference grows). The second method, the sentiment seesaw, is a cross-sectional graph of stock market returns conditional on sentiment. It shows how stocks sorted by characteristic-based measures of riskiness are more or less sensitive to sentimental price effects. Adapting top-down analyses for a bottom-up study of investor sentiment provides the benefit of guiding our expectations concerning the relationship between affect and the cross-section of stock returns.

The top-down approach, exemplified in Baker and Wurgler (2006, 2007), displays several facets of the relationship between levels of Top-Down investor Sentiment (hereafter TDS) and the cross-section of stock returns. First, TDS exhibits less influence on the prices of safe, easy-to-arbitrage stocks than on risky, hard-to-arbitrage stocks. Second, high levels of TDS are shown to precede periods of lower than average returns for safe stocks, and higher than average returns for risky stocks. The opposite relationship exists for low levels of TDS, which are found to precede periods of relatively low returns for risky shares, and relatively high returns for safe shares. As a result, if TDS increases, risky shares overreact and subsequently correct more than safe shares. This results in an increase and subsequent decrease in the difference between the returns of safe and risky shares. Baker and Stein (2004) have shown that top-down and bottom-up measures of sentiment are highly correlated, even though they do not stem from a similar measurement frameworks. Hence, using a single affect-based measurement framework, we expect levels of SMA, RA, and RP to exhibit the same cross-sectional patterns as TDS with respect to overreactions and subsequent corrections in stock returns. This is equivalent to breaking down the aggregate measure of sentiment that is TDS into specific affective factors and determining which ones exert the greatest influence.

1.5. Takeaways: the contribution of this study

Our results show that two facets of affective factors that drive investor sentiment. The first confirms existing theory because SMA, RA, and RP are related to contemporary overreactions and subsequent corrections, and show that safe shares are less sensitive to affective influences than risky shares. The second facet of our results shows that SMA, RA, and aggregate affect influence the cross section of returns in the same way that TDS influences the cross-section of returns: that high levels of SMA, RA, and aggregate affect precede periods of lower than average returns for safe stocks, and higher than average returns for risky stocks and low levels of SMA, RA, and aggregate affect precede periods of relatively low returns for risky shares, and relatively high returns for safe shares. RP does not exhibit this relationship to the cross section of returns, and instead we find that high levels of RP precede relatively low returns regardless of riskiness, and that low levels of RP exhibit relatively high returns, regardless of riskiness. The fact that different affective factors can support existing theory on investor sentiment, but still exhibit novel patterns vis-à-vis the cross section of returns is an important finding, because it shows that investors who use different bottom-up measures of investor sentiment, may not be measuring the same process, which on a large scale leads to the synchronization problem.

The research provides three takeaways: the first is that directly measured affective factors, namely SMA, RA, and RP, contain relevant information about equity prices beyond what is contained in TDS. Second, SMA, RA, and RP contain relevant information about the behavior of market participants, providing a measurable and specifically defined explanation for why they are overreacting, in addition to a reason why TDS exists in the first place. Current official reporting systems either do not consider sentimental information relevant (traditional financial reporting) or do not adhere to a behaviorally-based theoretical framework when measuring sentimental information (see e.g. the European Commission's European Sentiment Index). The conclusion of this study is that it would be beneficial to the financial system if affect were reliably measured and publically reported; the information provided by specific affect-based measures of investor sentiment would help market participants identify arbitrage opportunities and prevent stock price bubbles. In terms of the *Synchronization Problem*, arbitrageurs tend to synchronize when there is an unmistakable signal of a market correction – generally observed by a market-wide panic (extremely negative affect) – yet determining such a signal before the market panic itself is no easy task, especially without a common framework. Observed levels of affect during periods of panic can identify thresholds at which investor overreaction is problematic. These may serve as a public warning that investors are taking too many risks, that stock markets are highly overvalued, and that current pricing levels are likely unsustainable. This would encourage arbitrageurs to correct the bubble instead of riding it, thus preventing investor mania, subsequent investor panic, and would avoid significant stress to the financial system.

The following section and lays out the 5-level "top-to-bottom" conceptual model of investor sentiment, reviews the top-down and bottom-up literature, and places the current study. Section 3 discusses the research design of the study, including the data collection procedure, the descriptive statistics, and the methodology used to test the affect hypothesis: the conditional characteristics model and the sentiment seesaw. Section 4 presents the results of the analysis and Section 5 concludes, discusses the implications of this research for the *Synchronization Problem*, and considerations for future research that will help develop an uncontroversial measurement framework for investor sentiment.

2. Placing the study: context and background

Existing research provides many explanations for investor overreaction and its consequences for equity pricing. In order to place this study in the literature, we provide a framework that classifies the causes of investor overreaction into a six-link chain-of-events called the "top-to-bottom" model of investor sentiment. Figure 1.1 shows that sentimental price outcomes at the top are the result of five underlying levels of sentimental price drivers, classified by their chronological proximity to market outcomes: investor decisions, behavioral biases, affect, physiology, and the environment.

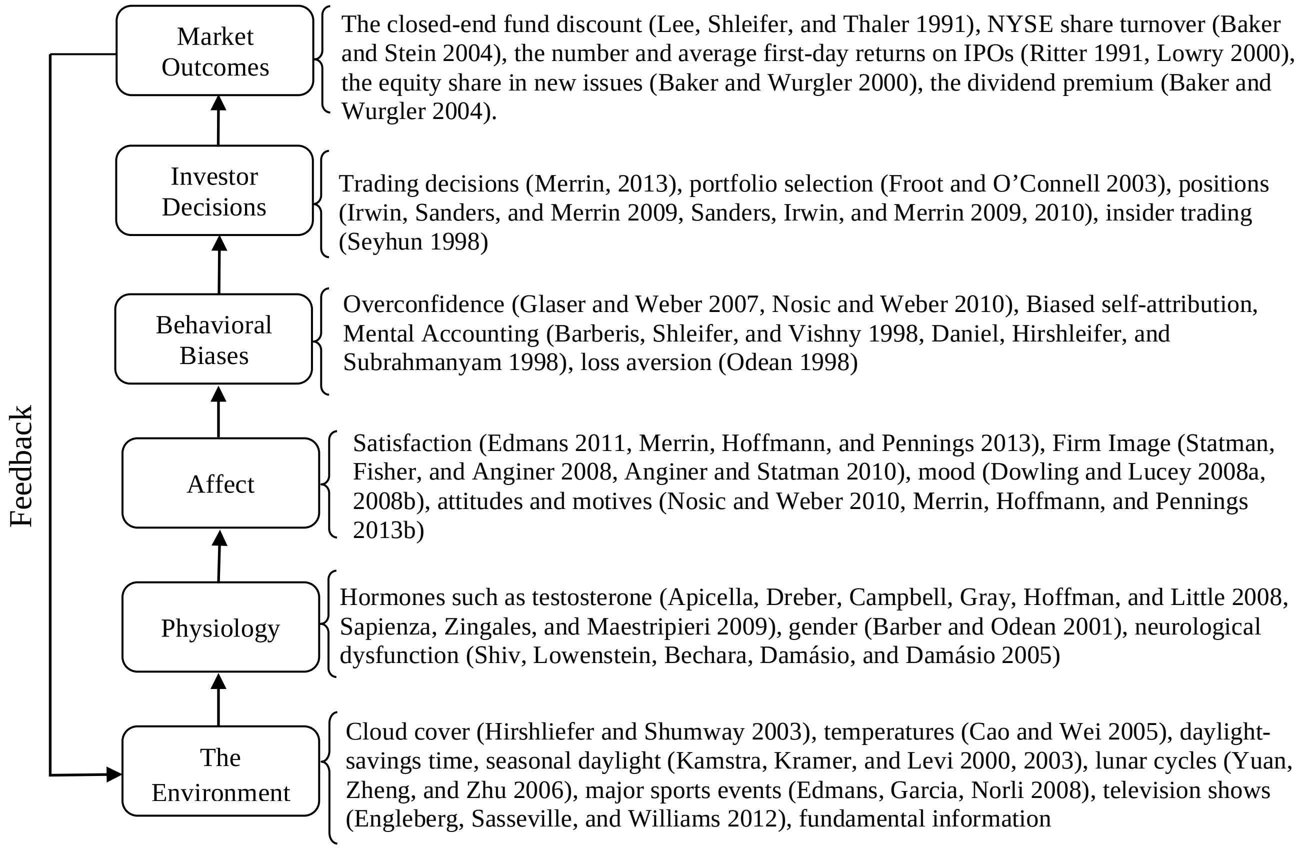


Figure 1.1: The Top-to-Bottom Conceptual Model of Investor Sentiment

Below we review the literature concerning each link the sentimental chain of events. We begin by discussing the top-down literature and work our way down the chain and review the five levels of drivers of investor overreaction identified by the bottom-up literature. The review then focuses on existing research on affect in economics and finance, and why affect is the best link in the top-to-bottom chain of events upon which a sentimental measurement framework should be based.

2.1. The "Top-to-Bottom" conceptual model of investor sentiment

The top-to-bottom model of investor sentiment provides a practical system to classify behavioral studies into top-down and bottom-up categories of research. Top-down analyses can be recognized by their use of market outcomes to explain market outcomes and consider anything below market outcomes (i.e. the drivers of investor sentiment) to be a black box. Bottom-up research includes studies that involve explaining that black box and use underlying drivers of investor sentiment to explain market outcomes.

2.1.1. The top-down approach

Shiller (1981) and De Bondt and Thaler (1985) wrote two seminal top-down studies that paved the way for the subsequent research in behavioral finance. Shiller (1981) provides evidence of excess volatility in equity prices as compared to dividends, which vary too little to explain observed price movements, and thus presuppose the existence of "irrational" factors. De Bondt and Thaler (1985) subsequently advance that investor overreaction is at the root of anomalous price patterns, and test their hypothesis with the residual returns of portfolios compared with the returns produced with the CAPM. The empirical evidence of stock market overreaction provided by these analyses of volatility and returns was followed up by research efforts to identify the other exchange-level expressions of investor overreaction.

Table 1.1 provides a non-exhaustive summary of top-down metrics used to identify the symptoms of investor overreaction in stock markets. When market participants are overreacting many exchange-level variables tend to be higher (or lower) than average and signal an excited, overreacting market. Investors are more likely to go public with their companies, denoted by high rate of IPO issuances (Lowry 2000) and their underperformance in the long-run (Stigler 1964, Ritter 1991). Firms also issue higher levels of equity during these periods (Baker and Wurgler 2000, Derrien and Kecskés 2007). Excited markets display high levels of trading volumes (Scheinkman and Xiong 2003, Baker and Stein 2004), low demand for large dividend paying firms (Baker and Wurgler 2004), and high rates of net redemptions of mutual funds (Neal and Wheatley 1998). While these examples are directly equity-related, other symptoms have been detected in associated markets: option markets (Whaley 2000, Bandopadhyaya and Jones 2008), the market for NYSE seats (Keim and Madhavan 2000), as well as bond markets (Lashgari 2000).

Top-Down Measure	Description	Study
Closed-End Fund Discount	Y/E, value weighted average discount on closed-end mutual funds	Lee, Shleifer, and Thaler (1991), Neal and Wheatley (1998), Baker and Wurgler (2006)
RIPO	Average annual first-day returns on IPOs	Stigler (1964), Ritter (1991), Baker and Wurgler (2006)
IPO Volume	Rate of issues per month	Lowry (2003), Baker and Wurgler (2006)
Share Turnover	Reported share volume divided by average number of shares	Scheinkman and Xiong (2003), Baker and Stein (2004), Baker and Wurgler (2006)
Equity Issuance	Annual equity issued divided by gross annual debt and equity issued	Baker and Wurgler (2000, 2006), Derrien and Kecskés (2007)
NYSE Seat Prices	Seat trading volume or quoted bid-ask-spread	Keim and Madhavan (2000)
Market Volatility Index (VIX)	Implied volatility of options on the S&P100, a.k.a. "the Fear Gauge"	Whaley (2000), Bandopadhyaya and Jones (2008)
Dividend Premium	The log difference of the market-to-book ratios of dividend payers and non-payers ($P^{(D-ND)}$)	Baker and Wurgler (2004)
Net Mutual Fund Redemptions	Ratio of redemptions less fund sales over total fund assets.	Neal and Wheatley (1998)
Odd-Lot Sales Ratio	Ratio of odd-lot share sales to purchases (traditionally)	Neal and Wheatley (1998)
Put/Call Ratio	Puts outstanding divided by calls outstanding	Dennis and Mayhew (2002), Bandopadhyaya and Jones (2008)
Barron's Confidence Index	The difference between high rated bond yields	Lashgari (2000)
TED Spread	T-bill future yield minus Eurodollar futures yield	Lashgari (2000)
Accruals	Total accruals vs. current accruals	Ali and Gurun (2009)
Dividend Returns	Returns at dividend announcements	Sankaraguruswamy and Mian (2008)
Daily Mutual-Fund Flows	Estimation of a sentiment factor as a linear combination of mutual fund category flows	Brown, Goetzmann, Hiraki, Shirishi, and Watanabe (2003), Beaumont, van Daele, Frijns, Lehnert, and Muller (2008)

Table 1.1: Top-down measures of investor sentiment

The relatively large number of indicators in Table 1.1 shows that investor sentiment has various effects on the stock market, but also shows how persuasive the theory behind investor sentiment is. Intuition, anecdote, and theory have kept researchers interested in the measurement of investor sentiment for nearly 20 years, yet the fact that each measure is meant to quantify the same process shows that competition and controversy still surround the topic. Although no measure of investor sentiment is definitive or uncontroversial (Baker and Wurgler 2006), consensus does exist surrounding the basis of top-down indicators, namely the variation in demand brought about by behavioral factors (Thaler 1999, Brown, Goetzmann, Hiraki, Shirishi, and Watanabe 2003, Baker and Wurgler 2006, Fama and French 2007). From the top-down perspective, the term "behavior" includes a vast amount of complex processes considered to be exogenous to pricing but that can justify the study of many top-down indicators. Baker and Wurgler (2006, 2007) choose six such indicators[1], and perform a principal component analysis to minimize measurement error. The resulting composite top-down indicator is based on the common variance of several measures supported by empirical evidence, and is the least controversial top-down approach.

Top-down research has made vast contributions to the finance literature concerning the existence and effects of investor sentiment: it has identified overreaction in markets, has found that behavior is the cause, and has refined the theory to show that cross-sectional variation exists in sentimental effects. Firm characteristics, for example, determine their sensitivity to overreaction: small, young, high volatility, unprofitable, non-dividend-paying, and distressed stocks exhibit higher sensitivity to sentimental effects than firms with opposite (safer) characteristics (Baker and Wurgler 2006, 2007). While top-down research identifies the symptoms of investor sentiment in markets, its main drawback as a measurement framework is that makes assumptions about the drivers of the variation in demand that causes investor sentiment. We identify and review the metrics of these drivers below.

[1] The TDS measurement constructed by Baker and Wurgler (2006) for the NYSE consists of: the closed-end fund discount (Lee, Shleifer, and Thaler 1991), NYSE share turnover (Baker and Stein 2004), the number

2.1.2. The bottom-up approach

The purpose of the bottom-up approach to investor sentiment is to identify the causes of the variation in demand that results in investor overreaction. We discuss these causes and their measures in the context of the five categories shown in Figure 1.1. Many measures have been used to gauge the causes of investor sentiment; Table 1.2 provides a non-exhaustive summary of bottom-up metrics. Most methodologies are based on surveys, though many surveys are unclear in terms of the specific process they intend to measure, opaque in terms of their methods, and are branded for commercial purposes. Solt and Statman (1988) perform one of the first bottom-up studies, and though the results did not support the usefulness of the studied sentiment index, they note the large appeal such measures have among the investing public.

Survey measures of investor sentiment rely on various measurement strategies (those based on affective sciences are discussed in section 2.2). Some surveys establish their reliability by asking individuals with assumed specific knowledge for their opinions and expectations about the economy. Such individuals include institutional investors (AAII), analysts (Investors' Intelligence, Merrill Lynch, CTAs), and managers (ZEW, European Commission). Other surveys target the opinions of retail investors' (UBS/Gallup, ING Investor Barometer, RAI), the trading activity of which has been shown to be a contrarian indicator (Barber and Odean 2000, Kumar and Lee 2006, Kaniel, Saar, and Titman 2008). While little theory exists to supports the validity of informational content based on market participants' expectations (in particular concerning overreaction), empirical evidence shows that the indices built thereupon[2] exhibit high correlations to top-down measures (Brown and Cliff 2004). These surveys quantify opinions and expectations, but are not based on a scientific understanding of behavior.

[2] In many cases, the raw data of branded surveys are not released, nor are the index calculation methodologies.

Bottom-Up Measure	Description	Study
Investors' Intelligence Survey	Weekly survey of newsletter writers	Solt and Statman (1988), Fisher and Statman (2000), Brown and Cliff (2005)
Merrill Lynch Survey	Surveys Wall Street sell-side analysts.	Bernstein and Pradhuman (1994), Fisher and Statman (2000)
Market Vane Bullish Consensus Survey	Tracks the buy and sell recommendations of leading market advisors	Sanders, Irwin, and Leuthold (2000), Qiu and Welch (2004), Brown and Cliff (2005)
Insider Trading	Executive portfolio decisions	Seyhun (1998)
American Association of Institutional Investors Survey	Weekly survey of AAII members	Fisher and Statman (2000, 2003)
Risk Appetite Index (RAI)	Survey of individual investors	Kumar and Persaud (2002), Gai and Vause (2006)
State Street Investor Confidence Index	Changes in levels of risk contained in retail investor portfolios	Froot and O'Connell (2003)
Michigan Consumer Confidence Index	survey of economic, household, and personal finances	Fisher and Statman (2003), Qiu and Welch (2004)
UBS/Gallup Index (ING Investor Barometer in BE and NL)	Phone interviews of individuals concerning the economy	Fisher and Statman (2003), Qiu and Welch (2004), no existing studies of ING measure.
Sentiment Extraction from the Web and Media	Examination of the affective content of semantics	Tetlock (2007), Das and Chen (2007)
Fortune 500 Surveys	Measures the positive and negative images fortune 500 firms.	Staman, Fisher, and Anginer (2008), Anginer and Statman (2010)
Physiological Factors	genes, hormones, gender, the brain	Kuhnen and Chiao (2009), Barber and Odean (2001), Apicella et. al. (2008), Kuhnen, Samanez-Larkin, and Knutson (2011)
ZEW, European Sentiment Index of the European Commission	Monthly survey of manager expectations about the economy	Menkhoff and Rebitzky (2008), Gelper and Croux (2010)
Customer/Employee Satisfaction	Customer and Employee	Edmans (2011), Fornell, Mithas, Morgeson III, and Krishnan (2006)
Environment	Cloud cover, temperature, lunar cycles, sports, television, fashion	Kamstra, Kramer, and Levi (2000, 2003), Hirshleifer and Shumway (2003), Edmans, Garcia, and Norli (2007), Englebert, Sasseville, and Williams (2012)

Table 1.2: Bottom-up Measures of Investor Sentiment

Measurements of investor sentiment that rely on techniques other than opinion and expectation surveys are based on a specific understanding of behavior. Figure 1.1 classifies these measurements according to their chronological proximity to the market outcomes they influence: decisions being the closest events, the environment being the furthest. The classification summarizes the broad themes of research in investor sentiment, and represents the chain of events behavioral finance has come to identify as responsible for investor overreactions: outcomes are driven by decisions, which are influenced by cognitive biases, which are regulated by affect, which relies on physiology, which is stimulated by the environment.

a. Investor Decisions

Market outcomes are the direct result of investor decisions. Due to the immediate proximity of investor decisions to market outcomes, they represent the highest level in the bottom-up approach to investor sentiment. Analyzing investor decisions allows researchers to deduce investor states and the occurrence of economically significant events. For example, Froot and O'Connell (2003) examine investor confidence and risk preference from the changes in portfolio riskiness. Insider trading (Seyhun 1998, Lakonishok and Lee 2001) as well as stock option exercises (Carpenter and Remmers 2001) contain useful information and can be traced back to events that have occurred and caused the insider decisions to be made. In addition, decisions are often practical to study because they are recorded.

b. Cognitive Biases

The second level of bottom-up analysis concerns behavioral biases. These consist of a large collection of information processing shortcuts that have, as a result of their help to survival, evolved to be hard-wired processes that influence decisions. Some effects of biases include non-linear psychophysics of chance (Kahneman and Tversky 1979), the differences in perceptions between actors and observers (Jones and Nisbett 1971), the tendency to overestimate how much people agree with them (Ross, Greene, and, House 1977), and the preprogrammed recognition of snakes and spiders (LeDoux 1998). In finance, herding (Nofsinger and Sias 1999), overconfidence (Nosić and Weber 2010), biased self-attribution

(Daniel, Hirshleifer, and Subrahmanyam 1998), conservatism, representativeness (Barberis, Shleifer, and Vishny 1998), and mental accounting (Thaler 1999) are commonly referenced as causes for market under- and overreaction. It is difficult to measure the incidence of behavioral biases in real time because it is necessary to collect databases of decisions first, and look for biases post-hoc.

c. Affect

Affect is the third level of bottom-up drivers of investor sentiment. It exerts influence on decision making by regulating the use of energy dedicated to cognition. Excited affective states signal the use of low energy decision systems in the brain (e.g. the biases mentioned above), whereas calm affective states signal the use of high energy decision systems (e.g. quantitative analysis and reasoning)[3]. Affect is a fundamental determinant of preferences, beliefs, judgments, and decisions, which has been shown in particular for financial decisions (Kuhnen and Knutson 2011). Affect is implicit to all bottom-up studies of investor sentiment, and has been explicitly measured using surveys (Statman, Fisher, and Anginer 2008), skin conductance, blood volume pulse (Lo and Repin 2002), and event-related fMRI (Kuhnen and Knutson 2005). As of yet, no study has performed direct measurements of stock market and risk-based affective factors. Affect is the focus of our study, and is discussed in more detail in section 2.2 below.

d. Physiology

Physiological factors are the fourth bottom-up driver of investor sentiment. Physiological factors are the canvas on which the rest of behavior is painted: affective reactions to information and cognitive biases are determined by an individual's physiology, hence consequently so are decisions, and market outcomes. Research has shown that an individual's

[3] The nature of the dichotomy between affective states that signal the use of high and low energy decision mechanisms has multiple nomenclatures: "thinking, fast and slow" (Kahneman, 2011), "hot and cool cognition" (Abelson 1979). Traditionally, "reason and passion" and "rational and irrational" have described this dichotomy; the contemporary terms differ from the traditional ones because they describe a spectrum, rather two states of decision behavior.

physiology impacts their risk behavior: genes (Kuhnen and Chiao 2009), gender (Barber and Odean 2001), hormones (Apicella, Dreber, Campbell, Gray, Hoffman, and Little 2008; Sapienza, Zingales, and Maestripieri 2009), and the brain (Camerer, Loewenstein, and Prelec 2004, Kuhnen and Knutson 2005, Kuhnen, Samanez-Larkin, and Knutson 2011).

e. The Environment

The lowest level of bottom-up drivers of investor sentiment is separate from the market participants themselves: it concerns the events that cause market participants to overreact. This includes fundamental information such as corporate earnings announcements (Zarowin 1989), as well as rumors about fundamental information (Zivney, Bertin, and Torabzadeh 1996), and many other events unrelated to markets altogether; the weather (Hirshleifer and Shumway 2003), lunar cycles (Yuan, Zheng, and Zhu 2006), daylight savings time (Kamstra, Kramer, and Levi 2000), hours of sunlight (Kamstra, Kramer, and Levi 2003), major sports events (Edmans, Garcia, and Norli 2007), and fashion trends (Shiller 2000).

The top-to-bottom conceptual model of investor sentiment in Figure 1.1 provides categories for the research in finance that has explained what investor sentiment is, where it comes from, why it occurs, and what its effects are on markets. The model provides the context for affect as a driver of investor sentiment and the background for how it relates to existing research. Below we present the theoretical, empirical, and practical reasons that affect is the category that affords the most promise in terms of measuring and reporting investor sentiment.

2.2. Affect: Empirical, Theoretical, and Practical Considerations

2.2.1. Definition of Affect

Affect is the primary system in the brain to react to stimuli (Zajonc 1980, 1984). It is responsible for providing content to the human experience, and serves as a translator from the signals captured by the five senses into a comprehensive experience that spans beyond conscious activity, influencing even unconscious decisions (Damásio 1994, Shiv, Loewenstein, Bechara, Damásio, and Damásio 2005, Kahneman 2011). The experience afforded to individuals by their limbic systems has been theorized to consist of at least four determinants: motives, moods, attitudes, and emotions (Davidson, Scherer, and Goldsmith 2003). The motive of interest for researchers in finance is often the profit motive, although others exist, such as social motives (Hong, Kubic, and Stein 2005, Hong and Kacperczyk 2009) and environmental motives (Geczy, Stambaugh, and Levin 2005). Research has also examined the financial effects of moods (Dowling and Lucey 2008a, 2008b), which are background feelings that last for long periods of time (up to years). Attitudes are feelings towards an attitude object, such as investors' feelings towards a company or brand (Statman, Fisher, and Anginer 2008, Anginer and Statman 2010). Affective experiences are complex, and categorizing each type of sensation is difficult: the term emotion may thus refer to all sensations caused by neurological activation of affective systems at different levels of circuitry (Damásio 2003).

2.2.2. Theory

Affect is a central concept of many recent economic models and are based on individual experience, psychological, and neuroscientific research. The most prevalent classes of these models are called dual-process models and include both cognition and affect as determinants of judgment and decision making. *Risk as feelings*, for example, builds on traditional cognitive and consequentialist models of decision making that either ignore affect, or portray it as a consequence of cognition. Instead, risk as feelings is a model where affect and cognition are parallel processes that interact (Loewenstein, Weber, Hsee, and Welch 2001). *The affect heuristic* models affective response as the quality of 'goodness' or 'badness' of a stimulus and its consequence for judgments, such as insensitivity to probabilities and proportion dominance (Slovic, Finucane, Peters, and MacGregor 2007). *The somatic marker hypothesis* uses a neural approach to model economic decision behavior, and states that conscious knowledge is not enough to make advantageous decisions: emotions help when they are integral to the task, but do not help when they are unrelated (Bechara and Damásio 2005). Another model, the *adaptive markets hypothesis* implicitly includes affect, because affective systems are the basis for the adaptive behavior of humans (Lazarus 1991). The model suggests that market participants who can adapt to the emergence of new information remain in the market by limiting losses and accumulating gains, but those who do not adapt are knocked out due to the losses they accrue (Lo 2004, 2005). The development of economic models based on affect coincides with vast evidence of affective effects in stock prices.

2.2.3. Empirics

Empirical analysis of affect has relied on multiple measurement techniques. Semantic analysis, for example, examines the affective content of text to deduce the emotions of those expressing themselves. In finance, researchers have used this technique in several media outlets such as newspapers (Tetlock 2007) and forum posts on the web (Das and Chen 2007). They find that affect reflected by semantics is related to subsequent abnormal returns, high volumes, and high volatility. Another technique involves the measurement of affect using signs of psychological and physical arousal (Lo and Repin 2002), which respond to market events and high volatility. Surveys remain the most common measurement methodology: surveys have been used to measure such affective factors as investors' attitudes towards firms (Statman, Fisher, and Anginer 2008), retail investor optimism, retail investor confidence (Hoffmann, Post, and Pennings 2013), consumer confidence (Fisher and Statman 2003), employee satisfaction (Edmans 2011), and customer satisfaction (Fornell, Mithas, Morgeson III, and Krishnan 2006).

2.2.4. Practical Considerations

Surveys are the most common and practical tool to measure affect because of their relative low cost, ease of use, flexibility, and appeal among their end users. The specific survey approach used in this study is based on multiple-item scales, a standard methodological framework (psychometrics, see e.g. Nunnally and Bernstein 1994) used in many disciplines that study affect. Marketing is a discipline in particular that has compiled a voluminous catalogue of affective measures, scales used to quantify them, and summaries of their effects on preferences, beliefs, and behavior[4]. This is a fact worthy of note because it highlights a stark contrast between scholars of marketing and scholars of finance in terms of studying affective effects on behavior. “Marketeers” consider that affect is a primary driver of behavior and consists of any number of feelings each of which has different effects on decision outcomes. Meanwhile, “financiers” consider that affect is secondary to fundamental analysis, and that aggregate measures of affect (e.g. consisting of two states: positive and negative) suffice to explain over- and under-reactions in decision outcomes. Indeed, Baker and Stein (2004) note that top-down and bottom-up measures of sentiment are highly correlated.

Consequently, when it comes to measuring investor sentiment, finance scholars have assumed that one all-encompassing measure is enough to characterize the behavioral effects detected in pricing; a sort of “5th factor” that measures behavioral effects and determines overreaction in markets. However, the fact that so many individual affective factors have been documented suggests multiple measures are necessary to capture the complex variation in pricing caused by affect. An important question therefore arises: do all affective factors exhibit the same relationship to pricing? If affect is relevant to price formation and is complex, then different measures of affect will yield different relationships to pricing. It would thus require a measurement system, as opposed to a single measurement, to characterize it. Multiple measures would have to fit together in a structured manner to avoid a cacophonous collection of unrelated, overlapping, and unreliable sentimental metrics. Developing and cataloguing affective factors and their effects on pricing would also add to our understanding of the nature of investor sentiment. The first step in answering this question is to determine to what extent affective measures are different from each other and from TDS. For this reason, and as we describe in the next section, we choose to study a conservative set of affective factors based on the stock market and stock market risk.

This research is thus designed to identify the relationship of specific affective factors with stock price overreactions and subsequent corrections to compare them with predictions

[4] The so-called Marketing Scales Handbook consists of 6 published volumes, the latest of which (Bruner II 2012) compiles reviews of 682 scales studied from 2006 to 2009.

made by the top-down literature. The next section discusses the research design and details data collection, displays descriptive statistics, and describes the two methodologies of analysis used: the conditional characteristics model, and the sentiment seesaw.

3. Research design

In order to assess affective factors' relationship to stock market bubbles this study relies on the bottom-up adaptations of two top-down methodologies central to the study of investor sentiment and the cross-section of stock returns. First, we adapt the conditional characteristics model based on Daniel and Titman (1997), and used by Baker and Wurgler (2006) to regress top-down investor sentiment on subsequent period stock price corrections. Second, we adapt a non-parametric methodology called the sentiment seesaw (Baker and Wurgler 2007), which is a graph that displays the cross-section of stock returns conditional on high and low levels of sentiment.

The analysis draws from two sources of data: direct measurements of retail investors' affect and publically available exchange-level data. A survey of Dutch retail investors, monthly, from April 2008 to April 2009 resulted in 2038 observations of specific stock market-based affective factors. We relate the affective factors to the price behavior of shares traded on the Amsterdam Stock Exchange (ASX). In addition to collecting monthly stock prices, we also collect the characteristics of all the reporting stocks in the sample. The characteristics of each stock determine how risky each firm is, and allow us to classify firms into portfolios according to their riskiness which serve to construct the cross-section of stocks. We are thus able to construct a unique data set of investor affect with which to perform an analysis of affect on the cross-section of stock returns.

3.1. Data Collection and Descriptive Statistics

3.1.1. Investor Affect

The independent variables in this study consist of measures of three sensations caused by the stock market and stock market risk – a conservative set of affective factors given the breadth of existing measurement scales. Stock Market Attitude (SMA) is a measure of the degree of positive or negative sensations caused by thinking of the stock market; Risk Attitude (RA) measures the extent to which investors like or dislike stock market risk and Risk Perception (RP) is their subjective perception of the stock market risk to which they feel exposed. The validity and reliability of RA and RP survey measures have been verified in multiple economic decision making contexts: channel contract behavior (Pennings and Wansink 2004), hedging behavior (Pennings and Garcia 2004, Pennings Garcia 2010), trading behavior (Pennings 2002), and disaster response behavior (Pennings, Wansink, and Meulenberg 2002, Pennings and Grossman 2008). Here, RA and RP are adapted for the stock market domain from the scales used in Pennings and Smidts (2000) and Pennings and Wansink (2004). SMA is a novel scale developed for the purposes of this study. The scales are shown in Table 1.3 and follow the standard measurement methodology (see e.g. Edwards (1983), Nunnally and Bernstein (1994), Hair, Black, Babin, and Anderson (2010)).

To collect the data, monthly web-based surveys were sent to the retail investors of a large Dutch online brokerage firm from April 2008 to April 2009[5]. The surveys consist of multiple an effective way of measuring each affective factor (see e.g. Weber and Milliman 1997). Table 1.3 also displays Cronbach's alpha (1951) for each scale, which is a gauge of reliability. Alphas for SMA, RA, and RP are beyond the 0.80 threshold established by the literature, and confirm that the measurements are consistent.

[5] Clients of the online brokerage firm were encouraged to participate by offering to include them in a raffle for an Apple iPod if they answered at least 6 of the 13 monthly surveys. In order to reduce sample selection bias, several surveys were developed for different asset classes and randomly sent out to participants each month. The surveys used here are the stock market version.

Stock Market Attitude (SMA, α = 0.95) Survey Items (each item for this affective factor has its own scale)	Factor Loadings
• When I think of the stock market, I feel: Bad (-3) – Neutral (0) – Good (+3)	0.92
• When I think of the stock market, I feel: Positive (-3) – Neutral (0) – Negative (+3)	0.93
• When I think of the stock market, I feel: Unpleasant (-3) – Neutral (0) – Pleasant (-3)	0.95
• When I think of the stock market, I feel: Happy (-3) – Neutral (0) – Sad (-3)	0.93
Risk Attitude (RA, α = 0.84) Survey Items Scale: Completely Agree (-3) – Neutral (0) – Completely Disagree (+3)	**Factor Loadings**
• This month, with respect to the stock market, I prefer financial certainty to financial uncertainty.	0.63
• This month, I am taking higher financial risks in order to realize higher average returns in the stock market.	0.59
• With respect to the stock market, I avoid risks this month.	0.83
• In terms of investing in the stock market this month, I prefer certainty to uncertainty.	0.81
• This month, I am NOT taking financial risks in the stock market.	0.85
• This month I am NOT “playing it safe” in the stock market.	0.61
• This month, I am NOT taking more risks in the stock market to achieve higher returns.	0.66
Risk Perception (RP, α = 0.83) Items Scale: Completely Agree (-3) – Neutral (0) – Completely Disagree (+3)	**Factor Loadings**
• This month, investing in stocks is risky for me.	0.79
• This month, stocks are a safe investment for me.	0.72
• For me, investing in stocks is dangerous this month.	0.80
• For me, investing in stocks leads to a small amount of risk.	0.77

n.b. To construct each measure, items are recoded such that low levels of each decision driver are on the left side of the scale (negative) and high levels on the right (positive). Each decision driver is then calculated by taking the mean of average item scores.

Table 1.3: Scales of SMA, RP, and RA, their Survey Items and Factor Analysis

Table 1.4 shows the descriptive statistics for SMA, RA, and RP individual survey responses collected for each month from April 2008 to April 2009. We take the means of the monthly responses to calculate 13 monthly measures of each affective factor (see Table 1.5), which we use as the independent variable to explain market outcomes. We collected a little over 150 responses per month, the most responses occurring in July and October of 2008 (263 and 281), and the least responses were collected in March 2009 (32). Several possibilities explain the variation of the response rate. One explanation for the variation in the response rate is that investors are motivated at first by the incentive but the novelty wears off because of the repetitiveness of the survey. Another explanation is that the participants answered their minimum quota early in the process, and decided not to waste energy on responding more than they had to. Another explanation is that respondents preferred to answer the survey as they were coping with the crisis, but as soon as the economic situation started to improve (in March 2009), then they felt less inclined to express themselves.

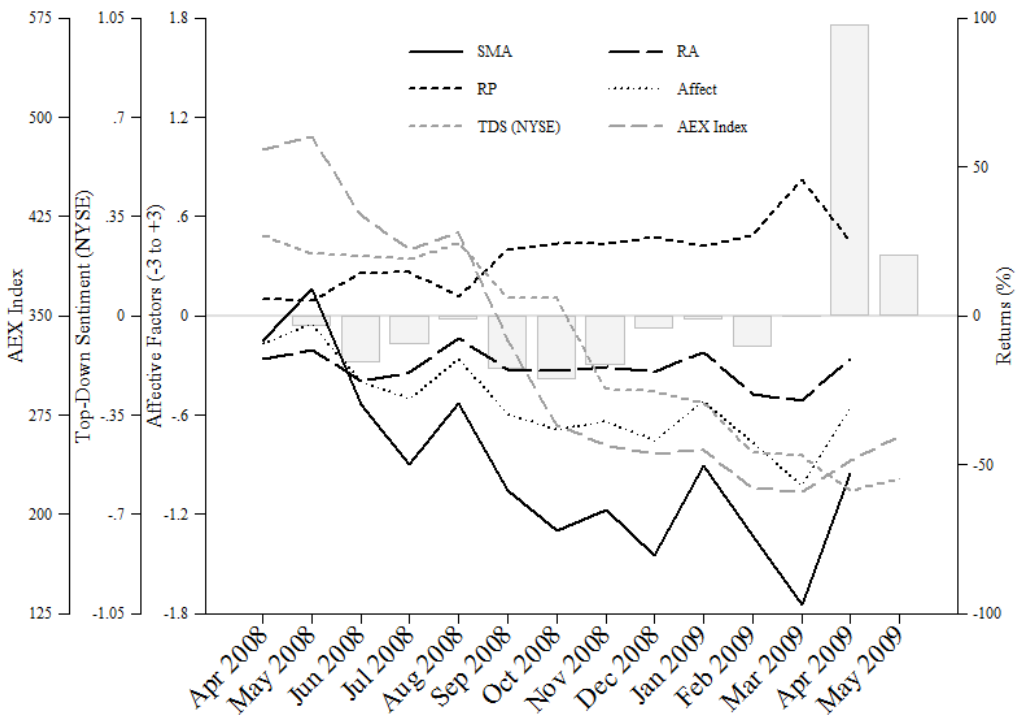


Figure 1.2: Monthly levels of SMA, RA, and RP, and the AEX Dutch Stock Index, April 2008 to April 2009

Responses for SMA covered the whole scale range (the minimum of -3 to the maximum of +3) in every month, while responses for RA only cover the whole range in the first half of the sampling period, and shows that in the second half, no respondents liked stock market risk to the maximum measurable extent. In addition, respondents express the fact that they always feel exposed to stock market risk, as expected, because the minimum RP measured is never -3. Average monthly levels of SMA and RA are negative, which shows that investors dislike the stock and stock market risk, which coincides with the positive average levels of RP show that investors feel they are exposed to stock market risk; this is what we would intuitively expect during a crisis period. Aggregate affect, which consists of the sum of mean SMA, RA, and negative RP[6], is a general measure of the valence of investors' feelings (i.e. positive vs. negative), and is negative for the examined period.

[6] Aggregate affect is calculated with negative RP because RP is negatively correlated with generalized affect, i.e. when individuals feel good, they perceive little risk, and vice-versa (Johnson and Tversky 1983).

	2008 Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	2009 Jan	Feb	Mar	Apr	Overall Sample
Panel A: SMA_{it}														
N	208	166	156	263	114	192	281	106	136	124	151	32	109	2038
Mean	-0.15	0.16	-0.54	-0.90	-0.53	-1.06	-1.30	-1.17	-1.45	-0.91	-1.33	-1.74	-0.95	-0.86
St.Dev.	1.31	1.24	1.26	1.33	1.24	1.30	1.29	1.27	1.31	1.47	1.25	1.41	1.32	1.39
Min	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00
Max	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Skew	0.14	0.14	0.02	0.58	-0.10	0.56	0.54	0.53	0.94	0.44	0.58	1.65	0.21	0.37
Kurt	2.70	2.93	2.90	3.34	2.96	3.36	2.99	3.27	3.77	2.71	3.44	5.52	2.88	2.81
Panel B: RA_{it}														
N	208	166	156	263	114	192	281	106	136	124	151	32	109	2038
Mean	-0.26	-0.21	-0.39	-0.34	-0.14	-0.33	-0.33	-0.31	-0.34	-0.22	-0.47	-0.51	-0.26	-0.31
St.Dev.	1.14	1.00	1.07	1.04	1.12	1.08	1.03	1.03	1.10	1.04	0.98	1.27	1.02	1.09
Min	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00	-3.00
Max	3.00	3.00	2.80	3.00	3.00	3.00	3.00	2.79	3.00	2.60	2.07	2.00	1.80	3.00
Skew	0.09	0.03	-0.11	-0.14	-0.34	-0.11	-0.04	0.21	-0.30	-0.47	-0.47	-0.13	-0.66	-0.14
Kurt	3.25	3.15	3.11	3.49	3.52	3.37	2.80	3.62	3.19	3.37	3.36	2.78	3.55	3.29
Panel C: RP_{it}														
N	208	166	156	263	114	192	281	106	136	124	151	32	109	2038
Mean	0.10	0.09	0.26	0.26	0.12	0.40	0.44	0.43	0.48	0.42	0.49	0.82	0.45	0.33
St.Dev.	0.96	0.77	0.80	0.99	1.00	1.20	1.16	1.11	1.21	1.23	1.09	1.51	1.12	1.07
Min	-2.00	-1.33	-1.67	-2.00	-3.00	-3.00	-2.50	-2.25	-2.75	-2.75	-2.50	-2.00	-2.50	-3.00
Max	2.33	2.00	2.67	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Skew	0.19	0.23	0.39	0.43	0.05	0.11	0.15	0.24	0.06	0.30	0.26	-0.32	0.37	0.30
Kurt	2.84	2.48	2.93	2.84	3.71	2.82	2.51	2.76	2.66	2.82	3.14	1.83	3.08	2.98
Panel D: Aggregate Affect ($SMA_{it} + RA_{it} – RP_{it}$)														
N	208	166	156	263	114	192	281	106	136	124	151	32	109	2038
Mean	-0.17	-0.05	-0.40	-0.50	-0.26	-0.60	-0.69	-0.64	-0.75	-0.51	-0.76	-1.02	-0.55	-0.50
St.Dev.	0.73	0.70	0.74	0.84	0.88	0.95	0.91	0.88	0.89	0.96	0.88	1.02	0.83	0.88
Min	-2.58	-2.33	-2.38	-2.53	-3.00	-2.86	-2.80	-2.47	-2.92	-3.00	-2.82	-2.67	-3.00	-3.00
Max	1.86	1.68	1.42	2.58	2.00	3.00	1.55	1.57	1.82	2.20	2.03	1.43	1.83	3.00
Skew	-0.07	-0.17	-0.43	0.21	-0.24	0.25	0.04	0.11	0.01	-0.09	0.06	0.67	-0.35	-0.08
Kurt	3.17	3.00	3.17	3.32	3.80	3.72	2.65	2.53	2.96	3.07	3.47	3.03	3.51	3.11

Table 1.4: Summary Statistics of the Monthly Survey Responses for SMA, RA, and RP

Figure 1.2 shows monthly levels of SMA, RA, and RP from April 2008 to April 2009, as well as contemporaneous market outcomes; monthly levels of the AEX[7] (the primary Dutch stock index), top-down sentiment for the NYSE[8], and the un-weighted average monthly market-adjusted return for all stocks on the ASX. The sample covers an emotionally

[7] The AEX is a value-weighted index of the returns of the 15 most capitalized firms on the ASX.
[8] Top-down sentiment for the NYSE (Baker and Wurgler 2006) is a available from the website of Jeffrey Wurgler: http://people.stern.nyu.edu/jwurgler/

intense period for market participants - the brunt of the subprime mortgage crisis - as shown by the collapse of the AEX by over 60% during the year, from 550 points to just above 200. The period includes powerful events such as the short sale ban in July 2008 and the collapse of Lehman Brothers in September 2008 - after which the steepest drop in the history of the AEX occurs, and highlights an episode of investor panic (Sorkin 2012). The period is ideal to study investor affect and its effect on stock price bubbles because of the long and painful stock market correction that occurs, and that market participants will remember for the extreme affective sensations they experienced at the time. Taken together, the levels of specific affect in September 2008 may thus serve as approximate average thresholds for investor panic in the Netherlands: SMA of -1, RA of -0.30, and RP of 0.40 (on a scale from -3 to +3).

The additional informational content from measuring three affective factors beyond a single aggregate measure of investor sentiment is apparent from Figure 1.2. The plot shows that the three specific measures of affect exhibit three different patterns over time. Aggregate affect, SMA, and the AEX all have negative slopes during this period, yet RA shows a slope of approximately 0, and RP shows a positive slope. These descriptive statistics support the validity of the measures because as the AEX changes, we can see how investors feelings change accordingly: investors like the stock market less over time, but as they feel exposed to greater risks, their taste for stock market risk changes very little over the course of the year. The correlation coefficients in Table 1.5 confirm this observation: the AEX exhibits the highest correlation with SMA and aggregate affect (0.89), and a high negative correlation with RP (-0.88). RA exhibits the lowest correlation to the AEX, and is insignificantly different than zero.

	Descriptive Statistics								Correlation Table										
	N	Mean	Median	St.Dev.	Min	Max	Skew	Kurt	SMA_t	RA_t	RP_t	$Affect_t$	AEX_t	TDS	ΔSMA_t	ΔRA_t	ΔRP_t	$\Delta Affect_t$	ΔAEX_t
SMA_t	13	-0.91	-0.95	0.53	-1.74	0.16	0.52	2.59	1.00										
RA_t	13	-0.32	-0.33	0.10	-0.51	-0.14	-0.28	2.60	0.67[b]	1.00									
RP_t	13	0.37	0.42	0.20	0.09	0.82	0.44	3.20	-0.91[a]	-0.72[a]	1.00								
$Affect_t$	13	-0.53	-0.55	0.27	-1.02	-0.05	0.16	2.61	0.99[a]	0.76[b]	-0.96[a]	1.00							
AEX_t	13	324.89	267.69	101.01	216.98	485.52	0.44	1.56	0.89[a]	0.47	-0.88[a]	0.88[a]	1.00						
TDS_t	13	-0.09	0.06	0.33	-0.62	0.28	-0.31	1.53	0.63[a]	0.43	-0.81[a]	0.72[a]	0.89[a]	1.00					
ΔSMA_t	12	-0.32	-0.23	1.49	-4.34	2.09	-1.44	5.97	0.16	0.48	-0.09	0.19	-0.08	-0.19	1.00				
ΔRA_t	12	-0.15	-0.03	0.65	-1.39	0.60	-0.86	2.44	0.22	0.61[b]	-0.19	-0.28	-0.06	-0.03	0.58[b]	1.00			
ΔRP_t	12	0.34	0.05	0.90	-0.55	2.39	1.41	3.70	-0.09	-0.44	0.14	-0.15	0.14	0.23	-0.70[b]	-0.82[a]	1.00		
$\Delta Affect_t$	12	-0.69	-0.17	2.24	-7.61	0.73	-2.72	9.00	-0.13	0.35	0.10	-0.06	-0.30	-0.30	0.93[a]	0.54[c]	-0.70[b]	1.00	
ΔAEX_t	12	-0.05	-0.04	0.10	-0.20	0.11	0.12	2.02	0.26	0.45	-0.09	0.26	0.01	-0.33	0.52	0.76[a]	-0.67[b]	0.42	1.00
ΔTDS_t	12	-0.43	-0.03	1.51	-5.11	0.58	-2.78	9.23	0.08	-0.06	-0.05	0.06	0.13	0.05	-0.07	-0.05	-0.01	-0.08	0.10

Table 1.5: Summary Statistics and Correlation of the Monthly Measures of SMA, RA, and RP

Figure 1.2, shows that affective factors exhibit different levels of sensitivity to the emergence of new information in each month. The “bumps” in the curves of each factor in the plot occur at the same time, but to different degrees. As shown in Table 1.5, SMA exhibits the greatest standard deviation of each factor (0.53), ahead of RP (0.20), and RA (0.10). These statistics suggest that each affective factor concerns a different time horizon: SMA is a short term affective factor and reacts the most to new information, while RP is a mid-term factor, and RA, which varies the least, is a long term factor. Affective factors that change little during an even such as a financial crisis may signal that they are determined by stable physiological factors such as age, gender, or genetics and are only slightly influenced by the emergence of new information. Figure 1.3 shows the graph of percent changes in SMA, RA, RP, and aggregate affect (in the filled boxes) and changes in market outcomes (in the outlined boxes). It shows that stock market outcomes are positively related to changes in SMA, RA, and aggregate affect, and negatively related to changes in RP. This is also shown by the correlation coefficients in Table 1.5, although changes in SMA and aggregate affect exhibit an insignificant correlation to the AEX. The descriptive statistics thus suggest that when RA increases and RP decreases, overreactions are likely to occur.

The descriptive statistics support the reliability and the validity of the measures of SMA, RA, RP, and aggregate affect. They behave throughout the crisis period as theory and intuition would have us expect and can thus be considered accurate measure of affective factors. The next section describes the data collection and descriptive statistics of the stock market outcomes we study to determine the influence of affect on stock market bubbles and corrections.

3.1.2. Stock Market Outcomes and their Historical Circumstance

Ideally, studying stock price bubbles involves determining the extent to which stock prices are deviating from fundamental values. However, knowing the ideal stock price is not possible and prevents a direct study of price overreaction. To circumvent this problem, Baker and Wurgler (2006) show that investor over- and under-reactions can be identified by the extent to which the difference between the returns from risky (hard-to-value, hard-to-arbitrage) firms and safe (easy-to-value, easy-to-arbitrage) firms grows or shrinks. Because speculative and hard-to-arbitrage stocks are more susceptible to investor overreaction than safe, easy-to-arbitrage stocks, they will also exhibit larger overreactions and subsequent corrections. Hence, the level of investor sentiment will thus be reflected by the difference between the returns of safe and risky stocks. The extent to which any given firm is safe or risky is determined using the characteristics of each firm. In order to characterize stock returns according to their riskiness, we must therefore collect stock prices as well as characteristic data for each firm in the sample.

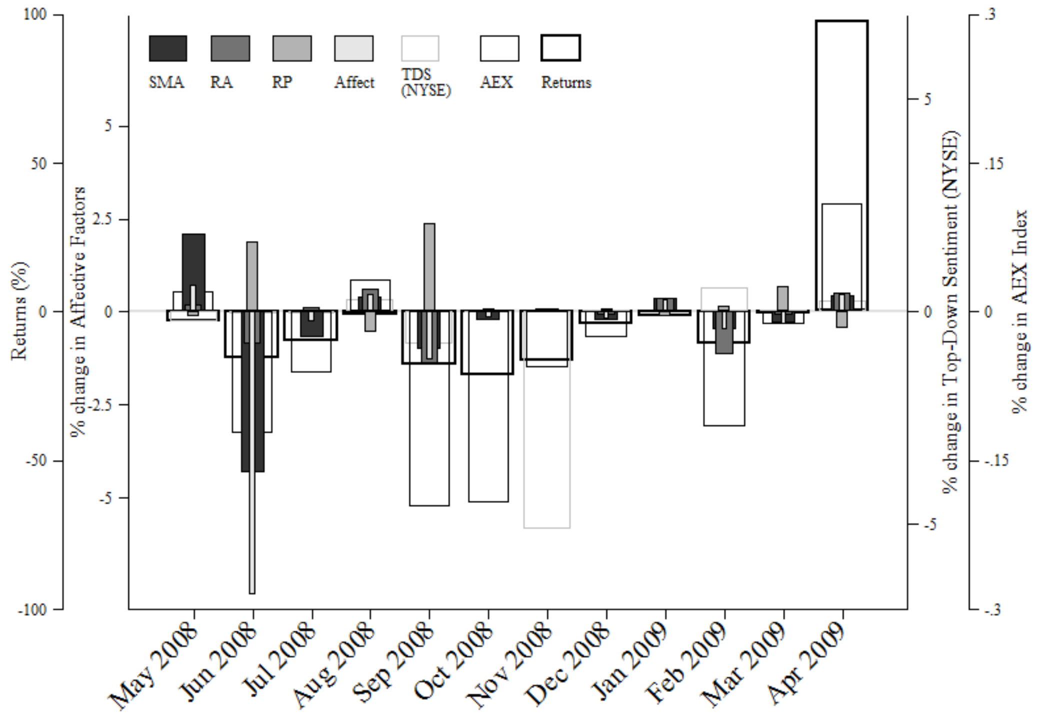


Figure 1.3: Monthly changes of SMA, RA, and RP, and the AEX Dutch Stock Index, April 2008 to April 2009

We collect monthly stock prices for all reporting firms quoted in the Amsterdam Stock Exchange (ASX) from April 2008 to April 2009, and collect firm characteristics from their respective financial reports in the previous year (i.e. the reports investors would have had access to at the time – see Figure 1.4). As shown in Table 1.6, we use 12 characteristics (measures) to assess how speculative and hard-to-arbitrage each stock is in every month of our study: volatility (standard deviation of returns), momentum (returns of last 11 months), size (market capitalization in million EUR), firm age (years since IPO), popularity (trading volume), profitability (earnings over book value), dividend policy (payer vs. non-payer), tangibility (property plant and equipment over total assets), intangibility (other intangibles over total assets), book-to-market (book value over market capitalization), external financing (change in total assets minus change in retained earnings, scaled over total assets), and sales growth (change in sales over total assets). Table 1.6 describes the which levels of the characteristics are safe and risky. The breadth of characteristics examined provides a comprehensive portrait of all the firms on the ASX.

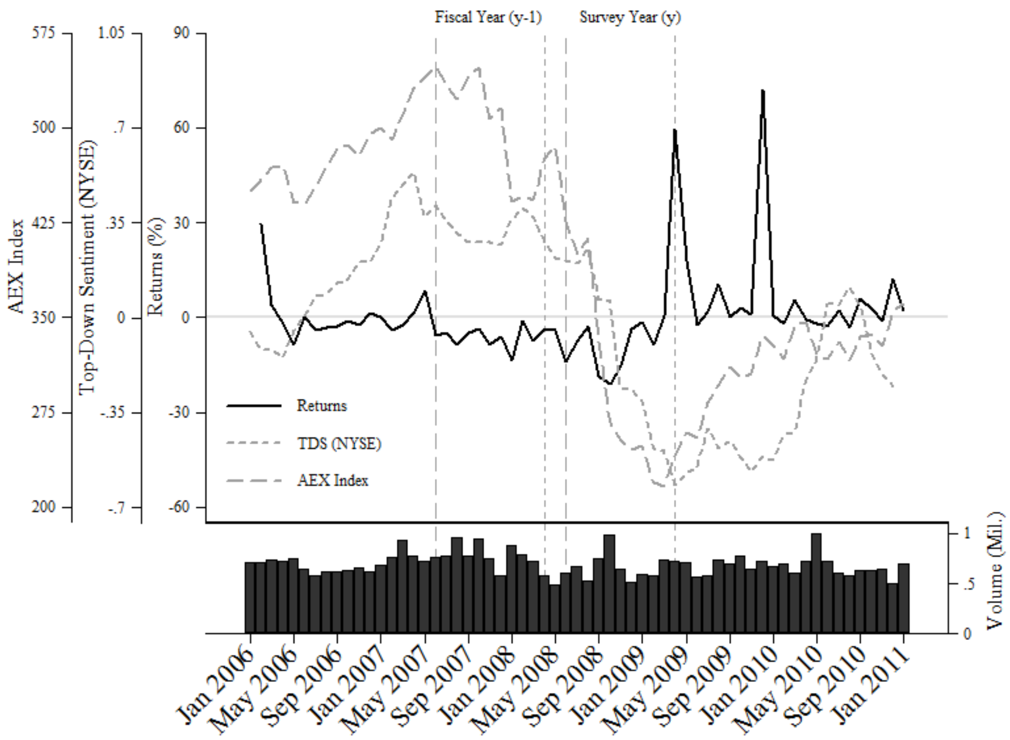


Figure 1.4: Monthly Returns of the Shares in our Sample, and the AEX Dutch Stock Index, April 2008 to April 2009

The process of characterizing returns according to their firm characteristics involves sorting the firms that generate them into three portfolios based on levels of each characteristic[9]; the bottom portfolio (quantile 1) contains the third of firms with the lowest level of a characteristic and the top portfolio (quantile 3) contains the third of firms with the highest level of a characteristic. For example, in the case of size, quantile 1 contains the 33% firms with the smallest market capitalization in that month, while quantile 3 contains the 33%

[9] Firm characteristics are reported in fiscal years, whereas returns are monthly.

of firms with the largest market capitalization. Our monthly dependent variable consists of taking the difference between the average monthly returns of firms in quantile 1 and those in quantile 3. The extent of this difference informs us regarding whether or not the stock market is overreacting or correcting in a given month. If the difference between risky and safe portfolio returns grows, the market is overreacting; if the difference between risky and safe returns shrinks, the market is correcting.

Characteristic	Measure	Risky	Safe
Volatility	Standard Deviation of Returns	Volatile *(high quantile)*	Stable *(low quantile)*
Momentum*	Sum of returns from previous 11 months	Negative Momentum *(low quantile)*	Positive Momentum *(high quantile)*
Size	Market Capitalization	Small *(low quantile)*	Large *(high quantile)*
Firm Age	Years since IPO	Young *(low quantile)*	Established *(high quantile)*
Popularity	Trading Volume	Popular *(high quantile)*	Unopular *(low quantile)*
Profitability	Earnings over Book Value	Zero Profitability *(low quantile)*	High Profitability *(high quantile)*
Dividend Policy	Payers vs. Non-Payers	Non-Payers *(low quantile)*	Payers *(high quantile)*
Tangibility	Property Plant and Equipment over Total Assets	Intangible *(low quantile)*	Tangible *(high quantile)*
Intangibility	Intangible Assets over Total Assets	Intangible *(high quantile)*	Tangible *(low quantile)*
		Both Safe and Risky	
Book-to-Market	Book Value over Market Cap.	Undervalued or Distressed *(low quantile)*	Overvalued or Growth *(high quantile)*
External Financing	Change in Total Assets Minus Change in Retained Earnings Over Total Assets	Internally Financed or Distressed *(low quantile)*	Externally Financed or Growth *(high quantile)*
Sales Growth	Percent change in net sales	Low Sales Growth (or undervalued) *(low quantile)*	High Sales Growth (or overvalued) *(high quantile)*

* In the case of momentum, positive trends and negative trends tend to persist, meaning that negative momentum is riskier than positive momentum. The most “stable” firms are in the middle quantiles and are the safest of the three categories.

Table 1.6: Common Stock Characteristics: Measurement and Relation to Riskiness

Some characteristics however are not straightforward about the riskiness they characterize in a given firm. These characteristics are identified in Table 1.6: momentum, book-to-market ration, external financing, and sales growth. These characteristics ambiguously express the riskiness of the firms they represent. As pointed out by Baker and Wurgler (2006), they may carry multiple hats. Momentum, for example is the most stable in the middle quantiles, which may be considered the safest. However, momentum tends to persist, in this case positive momentum firms are the most likely to make positive returns and negative momentum firms are most likely to earn negative returns, suggesting that high momentum firms are the safest. On the other hand, momentum may also be a signal for a reversal, suggesting that positive momentum is risky, and negative momentum is safe. The book-to-market ratio may indicate distress when high, growth when low, and may act as a indicator of general mispricing. Similarly, sales growth and external finance have at least two interpretations: when low, they may indicate distress, and when high, they may indicate growth. External financing may also behave as an indicator of misevaluation.

Because we study both the contemporary relationship between affect changes and stock prices as well as the lagged effect of affect levels on stock prices, we use characteristics of the studied firms at two different time periods to construct the quantile portfolios. Concerning the lagged effect of affect on stock prices, we are interested in constructing portfolios based on the reported characteristics of the firms that the investors had access to at the time[10]: these were published in the previous fiscal year's financial reports (i.e. June 2007-June 2008, *y-1*), and their descriptive statistics are displayed in Table 1.7 Panel A. In terms of the contemporaneous effects of affect on stock prices, the characteristics used to construct the portfolios are those at the time of the measurements of affect (i.e. April 2008-2009, *y*), and are displayed in Panel B of Table 1.7. Table 1.7 thus shows descriptive statistics of monthly returns and firm characteristics data for June 2007 to June 2008 in Panel A, when firms were reporting at the height of the subprime bubble (labeled as "Fiscal Year" in Figure 1.4). The firm characteristics undergo changes due to the crisis period, which is seen in the descriptive statistics for the period from April 2008 to April 2009 in Panel B of Table 1.7 (labeled the "Survey Year" in Figure 1.4).

[10] As in Fama and French (1992), and Baker and Wurgler (2006).

Table 1.7 Panel A, shows the returns and characteristics data for the 1335 firms listed on the ASX between June 2007 and June 2008. The negative monthly un-weighted market adjusted returns and negative momentum reflect the early crisis period; their median values are -5.45% and -39.13, respectively. The average size of a firm in the June 2007-2008 period is a 3.10 billion-Euro company that issued its IPO 38.75 years ago, and exhibits earnings averaging 14.60% of book value; its total assets consist of 19.70% tangible assets (property, plant, and equipment) and 23% intangible assets; 16.38% of total assets are accounted for as brand value (goodwill) and 6.61% represents other intangibles. The median book-to-market (means are distorted by firms near bankruptcy) describes a firm that has a market value about twice the size of its book value, and is arguably healthy, supported by the fact that about 79.62% of the 1335 firms in the sample are profitable, and about half are dividend payers.

Characteristic:	Measure	N	Mean	Median	St.Dev.	Min	Max	Skew	Kurt
				Panel A: June 2007- June 2008 (y-1)					
Returns*	R_{t-12}	1335	-0.04	-0.05	0.68	-0.78	22.71	29.91	968.66
St. Dev.	σ_{t-12}	1335	0.16	0.09	0.57	0.02	6.58	10.20	111.75
Momentum	$\Sigma\, R_{t-13}$ to R_{t-24}	1264	-0.21	-0.39	1.92	-2.05	22.41	9.64	106.75
Market Cap.	(€Billion)	1335	3.10	0.42	8.98	0.00	82.30	5.17	34.58
Firm Age	(Years)	1118	38.75	25.00	33.77	0.00	107.00	0.77	2.07
Trading Volume	(Million)	1324	0.79	0.57	2.22	0.00	16.30	4.27	22.41
Profitability (%)	*E+/BE*	1335	14.60	13.73	16.94	0.00	167.29	5.12	45.30
Profitable (%)	*E>0*	1335	79.62	1.00	40.29	0.00	1.00	-1.47	3.16
Div. Payers (%)	*Div>0*	1335	49.44	0.00	50.01	0.00	1.00	0.02	1.00
Tangibility (%)	*PPE/TA*	1335	19.70	15.17	17.27	0.00	74.80	0.93	3.05
Intangibles (%)	*INT/TA*	1335	21.38	17.30	19.71	0.00	92.51	0.94	3.25
Book/Market (%)	*BE/ME*	1335	3550.51	43.32	43164.34	0.00	570441	12.59	161.74
External Fin. (%)	*ΔTA-ΔRE/TA*	1335	2.02	2.57	47.78	-478.77	163.03	-6.60	70.20
Sales Growth (%)	*%Δ Net Sales*	1335	61.89	8.24	566.37	-100.00	6909.09	11.93	144.23
				Panel B: April 2008 - April 2009 (y)					
Returns*	R_t	1250	-0.01	-0.07	2.24	-0.68	78.99	35.00	1233.29
St. Dev.	σ_t	1250	0.22	0.12	1.30	0.04	22.86	16.83	291.23
Momentum	$\Sigma\, R_{t-1}$ to R_{t-11}	1249	-0.91	-0.87	0.39	-2.60	0.37	-0.62	4.41
Market Cap.	(€Billion)	1250	2.24	2.12	7.33	0.00	92.50	7.29	73.37
Firm Age	(Years)	1072	39.47	26.00	33.35	0.00	107.00	0.80	2.12
Trading Volume	(Million)	1239	0.78	0.04	2.09	0.00	17.70	4.20	22.86
Profitability (%)	*E+/BE*	1250	9.89	6.82	10.70	0.00	53.48	1.24	4.70
Profitable (%)	*E>0*	1250	69.44	1.00	46.08	0.00	1.00	-0.84	1.71
Div. Payers (%)	*Div>0*	1250	45.12	0.00	49.78	0.00	1.00	0.20	1.04
Tangibility (%)	*PPE/TA*	1250	19.98	15.45	17.14	0.00	66.43	0.90	2.91
Intangibles (%)	*INT/TA*	1250	23.95	20.22	20.62	0.00	92.51	0.77	2.82
Book/Market (%)	*BE/ME*	1250	115.96	70.71	238.09	-274.65	3173.39	7.86	79.47
External Fin. (%)	*ΔTA-ΔRE/TA*	1250	-5.36	1.67	26.73	-89.21	163.03	1.67	13.83
Sales Growth (%)	*%Δ Net Sales*	1250	4.26	0.35	34.72	-100.00	243.40	3.02	21.20

*N.B.: The returns in Panel A are descriptive of the fiscal year from which characteristics are drawn. The returns in Panel B are used calculate the long-short portfolios in the regression analyses performed in this study.

Table 1.7: Summary statistics of returns and characteristic data

The returns and characteristics data from the April 2008 to 2009 period is shown in Table 1.7 Panel B. From the previous period, the sample size drops by to about 1250 firms that enter bankruptcy or are bought out (e.g. Corporate Express, Hagemeyer, Goudavuurfast). The median returns and momentum for this period reflect the acceleration of the stock market crisis, shown by lower median returns (-7.28) than the previous year and twice the negative median momentum (-86.88). Other signs of a crisis accelerating are present in the characteristics of the firms such as the decrease in the proportion of profitable firms in the sample by 10%, and the large decrease in the median firm profitability as a proportion of book value of 50% from 13.73% to 6.82%. In addition, the median book-to-market ratio increases by 63% from 43.32% to 70.71%; this is driven by large drops in market value as the tangible assets change little, and write-downs occur amongst intangible assets. Additional distress is shown by the 35% decrease in median external financing between the two periods (from 2.57% to 1.67%), and the switch, in terms of mean external financing, from external (2.02% in y-1) to internal financing (-5.36% in y). Distress is also shown by the impressive decrease in sales growth: 95.75% in terms of medians (from 8.24% to 0.35%) and 93.11% in terms of means (from 61.89% to 4.26%).

Figure 1.4 puts the aforementioned statistics into context by plotting the average monthly returns of all stocks reporting firms in the ASX as well as the level of the AEX over the period June 2006 to January 2010. The wider time frame in the figure provides the context of our sample period, shown in the graph by the two dotted lines at April 2008 and April 2009. The graph depicts the collapse of the subprime bubble and includes the highs of the AEX (June 2007), the nationalization of Northern Rock (February 2008), the market panic caused by Lehman Brothers (September 2008), the bottoming out of the AEX (March 2009), and the ensuing economic recovery (April 2009). The sample period of this study covers the most important events of the collapse: the first short sale ban in July 2008, the purchase of Merrill Lynch by Bank of America and the Lehman Brothers bankruptcy in September 2008, and the subsequent market panic leading to a drop in the AEX of 60%. The measurements of affect we collect thus reflect a busy period with powerful events that no investor could have ignored.

The historical context of the period provides depth to the characteristics and affective factors we measure and helps interpret the data. The regulatory reaction to market panic was extreme in the sense that never before had such a collection of policies been enacted so quickly and in contradiction to the traditional efforts of the U.S. government to intervene in the economy as little as possible – in the two final weeks of September 2008, the Federal Reserve and U.S. financial regulators effectively cooperated with central banks around the world to purchase troubled assets, broker mergers and acquisitions, provide exceptionally low-cost liquidity, introduce legislation to facilitate government intervention, and ban short-selling of financial institutions[11]. This portrait of the subprime crisis and the identification of the Lehman Brothers panic event provide evidence for two observations. First, by the time Lehman Brothers files for bankruptcy protection on September 15th 2008, the systemic threat of the popping price bubble has become inevitable: the Federal Reserve Board and the U.S. Treasury Department are forced to take extreme measures on the following day to prevent a systemic collapse (Sorkin 2010). Second, it provides a time frame for establishing when dormant arbitrageurs awaken and synchronize their trading behavior: at the earliest in June 2008 - which the last significant monthly increase in the AEX before the economic recovery - and at the latest in September 2008, when the panic caused by the bankruptcy of Lehman Brothers occurred.

The historical context of the collapse of the subprime bubble and description provided by the data lay a solid groundwork for the analysis of SMA, RA, and RP on stock market overreactions and corrections. Below we illustrate the two methodologies used to test the affect hypothesis and identify differences between affective factors in terms of their relationship to stock prices.

3.2. Methodology

3.2.1. The Conditional Characteristics Model

The bottom-up conditional characteristics model is adapted from the top-down version by Baker and Wurgler (2006), is based of the characteristics model of expected returns (Daniel

[11] The St. Louis Federal Reserve provides a detailed timeline of the subprime mortgage crisis: http://timeline.stlouisfed.org/index.cfm?p=timeline

and Titman 1997) and is shown equation (1.1) below. We adapt the model by replacing the TDS parameter *T* with one measure of *SMA*, *RA*, *RP*, and aggregate affect at a time. In equation (1.1) *X* is the vector of the characteristics for firm *i* at time *t*:

$$E_{t-1}[R_{it}] = a + a_1 T_{it-1} + b'_1 X_{it-1} + b'_2 T_{jt-1} X_{it-1} + u_{it} \tag{1.1}$$

The difference between returns is then calculated in order to capture the extent to which the market is overreacting or correcting: we take the difference between the returns of the portfolios with high and low levels of each characteristic (constructed from the previous fiscal year, y-1). This results in the empirical model[12] shown in equation (1.2), which regresses the lagged monthly affective factor (AF) on stock price corrections, and controls for the known explanations of stock price behavior: the risk free rate (*RMKT*), size (*SMB*), value (*HML*), and momentum (*UMD*) effects. Standard errors are adjusted for small sample sizes (Imbens and Kolesar 2012):

$$R_{X_{y-1}=High,t} - R_{X_{y-1}=Low,t} = c + dAF_{t-1} + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + u_t \tag{1.2}$$

The *d* coefficient in equation (2) measures the relationship between each affective factor on subsequent period stock price corrections, and provides the following testable hypothesis:

$\mathrm{H1}_0$: $d = 0$, where nonzero effects represent rational compensation for systematic risk.

$\mathrm{H1}_\mathrm{A}$: $d \neq 0$, where nonzero effects represent a systematic cross-sectional relationship between the affective factor and subsequent sentimental price changes.

The model shown in equation (1.2) allows us to determine if SMA, RA, and RP will exhibit a relationship with the subsequent cross-section of stock returns by testing the significance of the *d* coefficient. The *d* coefficient is interpreted as the percent change in the

[12] See Baker and Wurgler (2006) for the arithmetic.

difference between high and low characteristic returns per one unit increase in the affective factor (which is equivalent to a one standard deviation increase, because the measures are standardized).

To corroborate the findings concerning affect and corrections, we also analyze the contemporary effects of affect on stock price behavior. Following established theory, if the lagged effect of positive affect is expected to cause the difference between returns of risky, hard-to-arbitrage and safe, easy-to-arbitrage firms to shrink (e.g. a negative *d* coefficient in equation (1.2)), then the contemporary effect of changes in affect should be one where the difference between risky and safe firms' returns grows (e.g. a positive *d* coefficient in equation (1.2)). To test for contemporary effects, we need a slightly different parameterization of the model in equation (1.2): specifically, the portfolios must be based on contemporary characteristics, and the regressor must consist of contemporary changes in affective factors (*ΔAF)*:

$$R_{X_y=High,t} - R_{X_y=Low,t} = c + d'\Delta AF_t + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + u_t \tag{1.3}$$

The *d'* coefficient in equation (1.3) measures the relationship between changes in each affective factor on same period stock price corrections, and provides another testable hypothesis H2 to corroborate our tests of H1:

$H2_0$: $d' = 0$, where stock prices do not reflect contemporary changes in the affective factor.

$H2_A$: $d' \neq 0$, where a systematic cross-sectional relationship exists between changes in the affective factor and contemporary price changes.

Testing the *d'* coefficient in equation (1.3) allows us to determine if changes in SMA, RA, and RP coincide with contemporary cross-sectional overreactions of stock returns. The *d'* coefficient is interpreted as the percent change in the difference between high and low characteristic returns per one percent increase in the affective factor (changes in affective factors are calculated as percent changes). This parameterization is meant to detect initial overreactions, thus we expect opposite signs from the parameterization in equation (1.2), which is meant to detect the subsequent corrections.

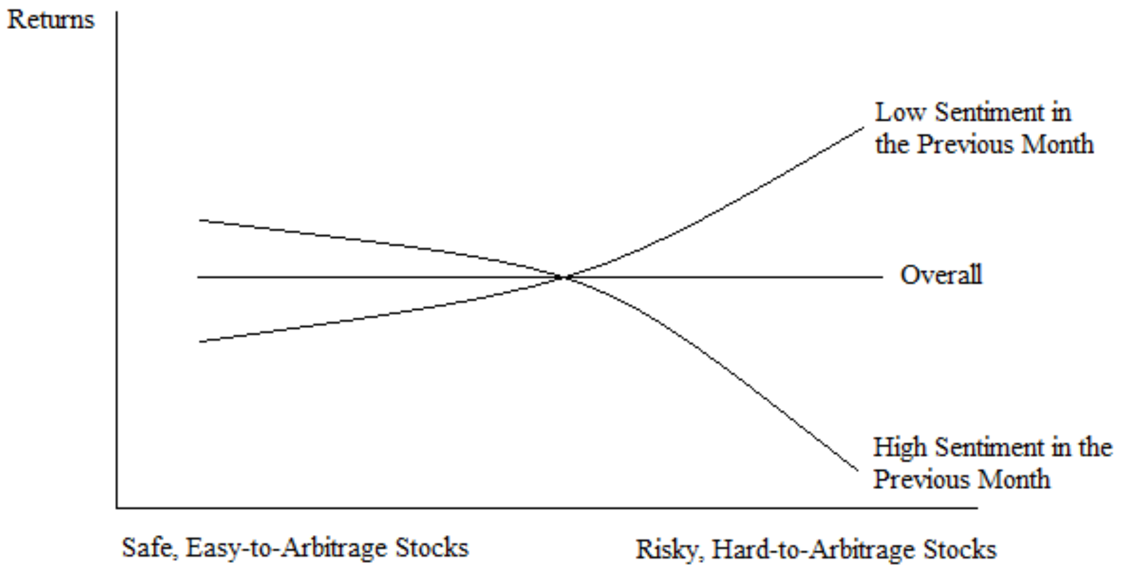
These parametric methods provide evidence that affective factors influence the cross-section of stock returns, and fit within the expectations of the theory of investor sentiment developed by using TDS. Because of our small sample size, it is helpful to complement the inferential results with a picture of the data conditional on affect; this is the purpose of the sentiment seesaw.

3.2.2. The Sentiment Seesaw

The sentiment seesaw is a cross-sectional graph of mean stock returns across levels of firm riskiness and conditional on high and low levels of investor sentiment in a previous period (see Figure 1.5 Panel A) . The methodology is first presented by Baker and Wurgler (2007) and is a parsimonious non-parametric approach that highlights the differences between portfolio returns for high and low levels of sentiment. The first step to constructing the graph consists of building the cross-section of stock market returns. This is done by sorting the firms into characteristic-based portfolios, which separates middle-ground firms from those with risky characteristics (e.g. high volatility or small firms) and safe characteristics (i.e. low volatility or large firms). The average returns of each portfolio are then plotted and show the cross-section across a given characteristic of stock market returns.

Panel A: Cross-Section of Returns Conditional on Prior Period Levels of Investor Sentiment

(The Seesaw)



Panel B: Cross-Section of Returns Conditional on Contemporary Changes in Investor Sentiment

(The Trumpet)

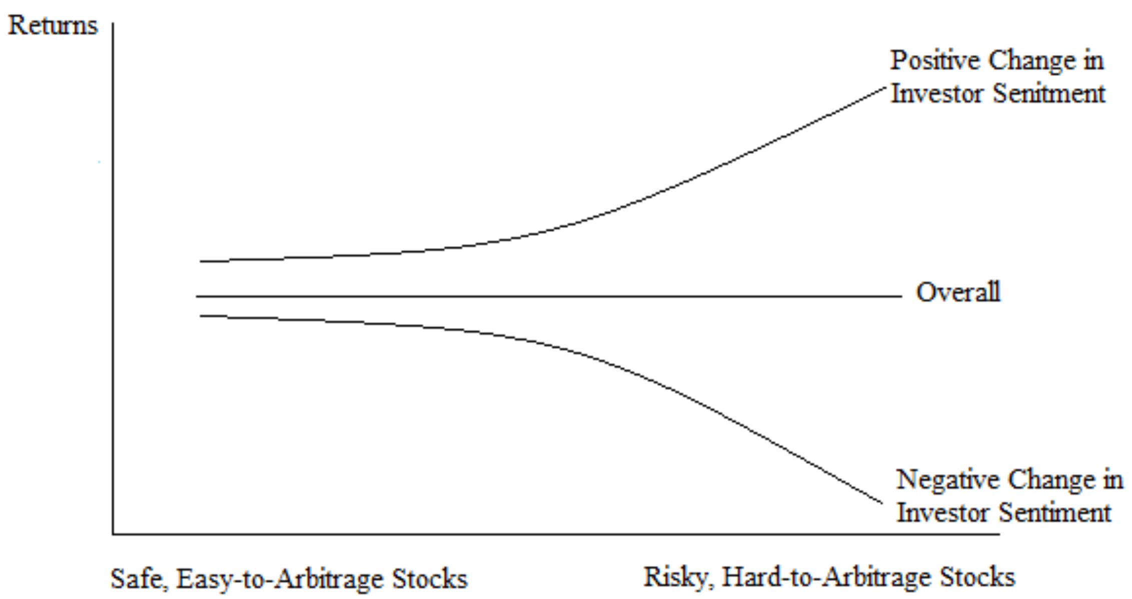


Figure 1.5: Theoretical Cross-Section of Stock Returns Conditional on Investor Sentiment

Once the average returns of the cross-section of stock market returns are plotted, each portfolio is divided into the returns exhibited when sentiment in the previous period was high and when it was low. The two resulting lines represent returns conditional on high sentiment and low sentiment13. They may be interpreted as two states of the average cross-section of stock returns. When sentiment is high, the line representing average stock returns pivots like a seesaw in one direction (safe returns are relatively higher, and risky returns are lower). When sentiment is low the pivot occurs in the opposite direction (safe returns are relatively lower, and risky returns are relatively higher). The graph is thus called the “sentiment seesaw” because it shows that as TDS increases and decreases, the line representing the cross-section of stock returns pivots around the middle.

This study plots the seesaws using previous levels of SMA, RA, RP, and aggregate affect, using the same approach as Baker and Wurgler (2007), which is meant to capture stock market corrections. It plots the returns that arise for the cross-section of stock returns in a month after the levels of sentiment were high or low. If stock returns correct after periods of high or low sentiment, then we expect to find evidence that stock markets overreact to contemporary changes in investor sentiment. If changes in investor sentiment are positive, then we expect the contemporary cross-section of stock returns to increase, and if changes in investor sentiment are negative, then we expect the cross-section of stock returns to decrease. Thus, instead of a seesaw that pivots around the middle, we expect the cross-section of stock returns condition on contemporary changes to pivot around the safe end of the cross-section, thus resulting in a trumpet-like shaped conditional graph (see Figure 1.5 Panel B). When changes in sentiment are positive, the cross-section of stock returns will overreact and produce relatively high returns, but safe stocks will overreact less than risky stocks. Conversely, when changes in sentiment are negative, the cross-section of stock returns will produce relatively lower returns, but safe stocks will overreact less than risky stocks.

[13] In this study, high and low are defined as higher and lower than the sample average.

4. Results

4.1. Parametric Results: The Conditional Characteristics Model

4.1.1. Levels and Subsequent Corrections

Table 1.8 shows the results for the empirical model shown in equation (1.2), which regresses prior period levels of SMA, RA, RP, and aggregate affect on long-short portfolios of high and low levels of each characteristic. For each affective factor, the table displays the expected sign of the coefficient of interest, d, the size of the coefficient, and the robust standard errors adjusted for the small sample size. Overall, Table 1.8 confirms the Affect Hypothesis: as affect is more positive, subsequent periods exhibit greater corrections.

$$R_{X_{y-1}=High,t} - R_{X_{y-1}=Low,t} = c + dAF_{t-1} + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + u_t$$

		AF = SMA			AF = RA			AF = RP			AF = Aggregate Affect		
Characteristic	Long-Short Portfolio	Exp. Sign *d*	*Coef. d*	*Robust St.Err. d*	Exp. Sign *d*	*Coef. d*	*Robust St.Err. d*	Exp. Sign *d*	*Coef. d*	*Robust St.Err. d*	Exp. Sign *d*	*Coef. d*	*Robust St.Err. d*
Volatility	High-Low	-	-0.05^{b}	(0.02)	-	-0.04^{b}	(0.01)	+	0.09^{b}	(0.03)	-	-0.06^{c}	(0.02)
Momentum	UMD	+	0.08^{a}	(0.02)	+	0.04	(0.03)	-	-0.11^{b}	(0.03)	+	0.08^{a}	(0.02)
Mkt. Cap	SMB	-	-0.04^{b}	(0.01)	-	-0.00	(0.01)	+	0.06^{b}	(0.02)	-	-0.04^{b}	(0.02)
Years IPO	High-Low	+	0.03	(0.02)	+	0.04^{b}	(0.01)	-	-0.07^{c}	(0.03)	+	0.05^{c}	(0.02)
Volume	High-Low	-	-0.02	(0.01)	-	-0.02^{b}	(0.01)	+	0.04^{b}	(0.01)	-	-0.03^{b}	(0.01)
Profitability	High-Low	+	0.03	(0.02)	+	0.03^{b}	(0.01)	-	-0.05^{c}	(0.02)	+	0.04^{c}	(0.02)
Div. Payer	>0 - =0	+	0.03^{b}	(0.01)	+	0.01	(0.01)	-	-0.04^{c}	(0.02)	+	0.03^{b}	(0.01)
Tangibility	High-Low	+	0.05^{b}	(0.02)	+	0.01	(0.02)	-	-0.06^{c}	(0.03)	+	0.05^{c}	(0.02)
Intangibility	High-Low	-	-0.03	(0.02)	-	-0.02	(0.01)	+	0.05	(0.03)	-	-0.04^{c}	(0.02)
BE/ME	HML	+/-	-0.05^{b}	(0.01)	+/-	-0.00	(0.02)	+/-	0.06^{b}	(0.02)	+/-	-0.05^{b}	(0.02)
Ext. Fin.	High-Low	+/-	-0.03^{c}	(0.02)	+/-	-0.01	(0.01)	+/-	0.05^{b}	(0.02)	+/-	-0.03	(0.02)
Sales Growth	High-Low	+/-	-0.01	(0.02)	+/-	-0.00	(0.01)	+/-	0.04^{c}	(0.02)	+/-	-0.02	(0.02)

The superscripts designate statistical significance at the ^{a}1% ^{b}5% ^{c}10% level.

Table 1.8: The Conditional Characteristics Model: Lagged Monthly Levels of SMA, RA, RP, and Aggregate Affect on Long-Short Portfolios of the ASX, April 2008-April 2009

Volatility, the flagship characteristic measure of firm riskiness, is shown in the first row. The table shows that as SMA is inversely related to the difference between high and low volatility portfolios. As SMA increases by one unit in the previous month, the difference between high volatility and low volatility returns decreases by 0.05%. RA, which is highly correlated to SMA, is shown to exhibit a similar relationship, although with a smaller coefficient size: a one standard deviation increase in RA results in a 0.04% decrease in the difference between high and low volatility returns. RP, which is negatively correlated to SMA and RA, exhibits a positive relationship to subsequent long-short volatility portfolio returns, which increase by 0.09 percent for change of one standard deviation.

Of the affective factors studied, RP exhibits the largest effects on subsequent corrections, followed by SMA, and RA. This finding suggests that RP is the most important constituent of investor sentiment studied here. It is likely to drive the results found for aggregate affect as well. However, it is interesting to note that SMA, RA, and RP are significantly different than zero for different portfolio sorts. In particular, the coefficients of SMA on long-short portfolios based on age, volume, and profitability are insignificantly different than zero, whereas the coefficient for RA in these cases is statistically different than zero. The particularities of statistical significance with respect to different portfolio sorts suggest that different affective factors are related to different firm characteristics. This is the first evidence we show that indicates that a single measure of investor sentiment may not be enough to characterize the complexity of the holistic effect on the multiple characterizations of the cross section of stock returns. In addition, the coefficient sizes of the affective factors studied here are only a fraction (about one tenth) of the TDS coefficients found by Baker and Wurgler (2006), suggesting that more factors are required to explain the additional variation.

4.1.2. Changes and Contemporary Overreactions

Table 1.9 shows the results for the regression shown in (1.3), which regresses contemporary levels of SMA, RA, RP, and aggregate affect on long-short portfolios of high and low levels of each characteristic. For each affective factor, the table displays the expected sign of the coefficient of interest, *d'*, the size of the coefficient, and the robust standard errors adjusted for the small sample size. Overall, Table 1.9 confirms the Affect Hypothesis: positive contemporary changes in affect relate to contemporary stock price overreactions.

The flagship characteristic for riskiness, volatility, is shown in the first row. The table shows that SMA increases by 1 percentage point, the difference between high and low volatility portfolio returns by 0.01%. In terms of coefficient sizes, this is a large effect given that the mean change for SMA during the sample period is -32 percentage points (from Table 1.5). RA displays an even larger effect of 0.06%, but also exhibits a lower average monthly change (a mean change of -15 percentage points). For a 1 percentage change in RP, the volatility sorted long-short portfolio decreases by 0.05%. The average monthly change in RP is 34 percentage points, thus the size of the RP coefficient is quite large. Aggregate affect also exhibits a positive coefficient: as aggregate affect increases by 1 percentage point, the difference between high and low volatility returns increases by 0.01%. The average change in aggregate affect is -69 percentage points, thus the effect is quite large. The coefficients show that as investors like the stock market and stock market risk more the market concurrently overreacts. The same effect occurs when investors feel less exposed to stock market risk.

$$R_{X_y=High,t} - R_{X_y=Low,t} = c + d'\Delta AF_t + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + u_t$$

		ΔAF = ΔSMA			ΔAF = ΔRA			ΔAF = ΔRP			ΔAF = Aggregate Affect		
Characteristic	Long-Short Portfolio	Exp. Sign d'	*Coef. d'*	*Robust St.Err. d'*	Exp. Sign d'	*Coef. d'*	*Robust St.Err. d'*	Exp. Sign d'	*Coef. d'*	*Robust St.Err. d'*	Exp. Sign d'	*Coef. d'*	*Robust St.Err. d'*
Volatility	High-Low	+	0.01^{b}	(0.00)	+	0.06^{c}	(0.03)	-	-0.05^{a}	(0.01)	+	0.01^{b}	(0.00)
Momentum	UMD	-	-0.01^{c}	(0.00)	-	-0.02	(0.02)	+	0.01	(0.02)	-	-0.00	(0.00)
Mkt. Cap	SMB	+	0.00	(0.01)	+	0.02	(0.03)	-	-0.01	(0.02)	+	0.00	(0.01)
Years IPO	High-Low	-	0.01^{a}	(0.00)	-	-0.05^{a}	(0.00)	+	0.03^{a}	(0.00)	-	-0.01^{b}	(0.00)
Volume	High-Low	+	0.01	(0.01)	+	0.03^{c}	(0.01)	-	-0.02^{c}	(0.01)	+	0.00	(0.00)
Profitability	High-Low	-	-0.01^{a}	(0.00)	-	-0.02	(0.02)	+	0.02	(0.01)	-	-0.01^{b}	(0.00)
Div. Payer	>0 - =0	-	-0.01^{b}	(0.00)	-	-0.02	(0.01)	+	0.01^{b}	(0.00)	-	-0.01^{b}	(0.00)
Tangibility	High-Low	-	-0.01^{c}	(0.00)	-	-0.03	(0.04)	+	0.02	(0.03)	-	-0.01	(0.01)
Intangibility	High-Low	+	0.00^{c}	(0.00)	+	0.02	(0.01)	-	-0.01	(0.01)	+	0.00	(0.00)
BE/ME	HML	+	0.00	(0.01)	+	0.03	(0.02)	-	-0.02^{c}	(0.01)	+	-0.01	(0.01)
Ext. Fin.	High-Low	+	0.00	(0.00)	+	0.01	(0.02)	-	-0.01	(0.01)	+	0.00	(0.00)
Sales Growth	High-Low	+	0.01	(0.01)	+	0.00	(0.03)	-	0.01	(0.02)	+	0.01^{b}	(0.00)

The superscripts designate statistical significance at the [a]1% [b]5% [c]10% level.

Table 1.9: The Conditional Characteristics Model: Monthly Levels of SMA, RA, RP, and Aggregate Affect on Long-Short Portfolios of the ASX, April 2008-April 2009

Taken together, the regression results in tables 8 and 9 show that 3 specific affective factors have provide evidence to support the Affect Hypothesis. This is the first study that has directly measured affective factors and studied their relationship to a comprehensive set of stock market characteristics. We find that while SMA, RA, RP, and aggregate affect all exhibit an effect on stock prices, we also find that the coefficient sizes are different, which supports the hypothesis that each specific affective factor exhibits a different effect on prices.

4.2. Non-Parametric Results: Cross-Sectional Graphs Conditional on Affect

There are two sets of graphs of the cross-section of stock returns conditional on affective factors: the first set is conditional on prior period levels of affect, and the second is based on contemporary changes in affect. Because of the extreme similarity between the SMA, RA, and aggregate affect graphs and in order to conserve space, we only display the plots for RA and RP. The graphs provide several interesting findings: first, the conditional graphs based on prior period levels of SMA, RA, and aggregate affect exhibit the expected seesaw pattern; second, the conditional graphs based on prior period levels of RP do not exhibit the expected seesaw, but rather the aforementioned trumpet; and finally we show that this approach can help determine whether the levels of ambiguous characteristics such as momentum, book-to-market, external financing, or sales growth are risky or safe during a given period according to how the returns they characterize are influenced by affective factors.

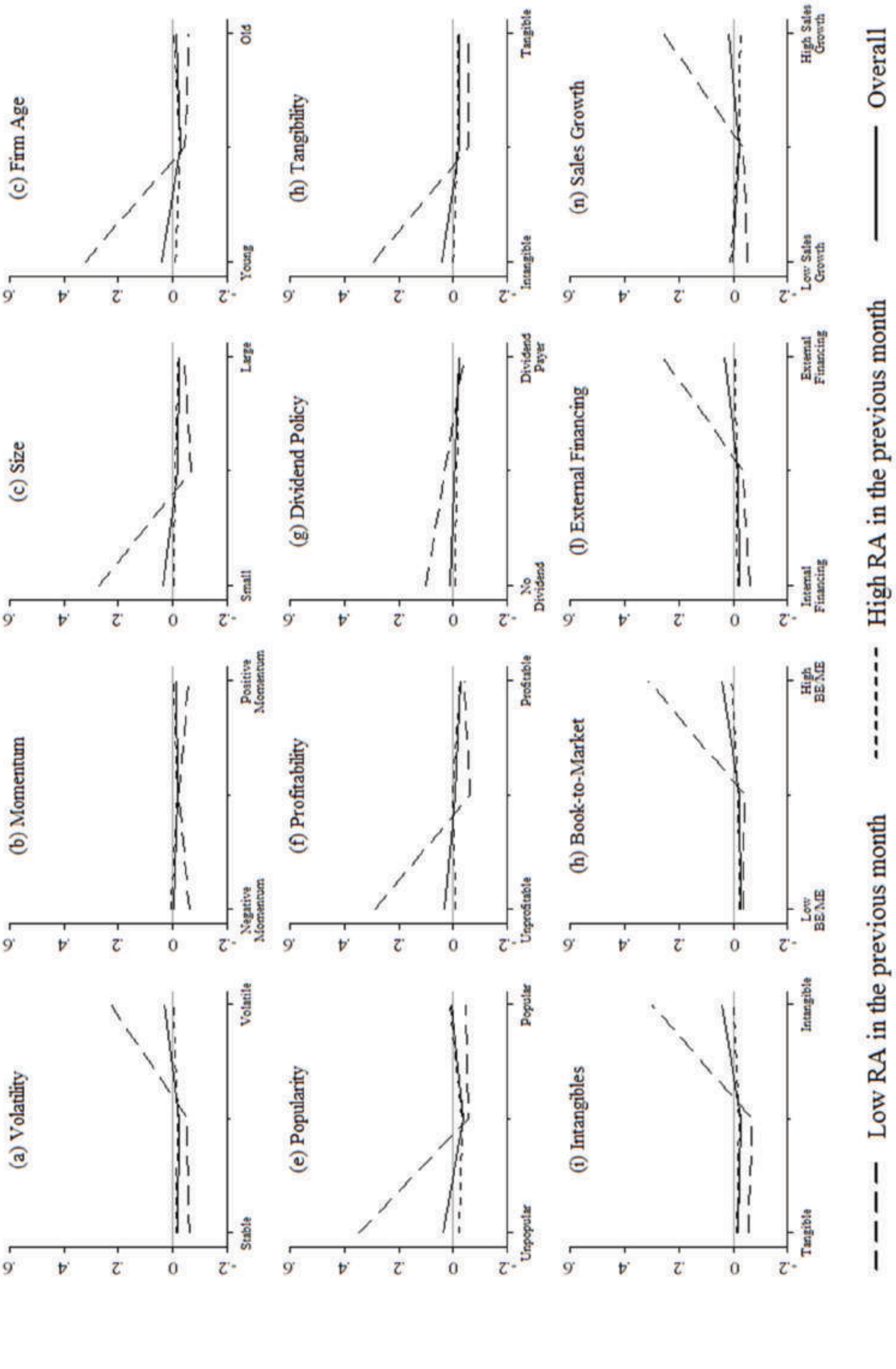


Figure 1.6: RA Sentiment Seesaws: Monthly Returns Portfolios, ASX-listed Volatility-sorted Shares, April 2008 to April 2009

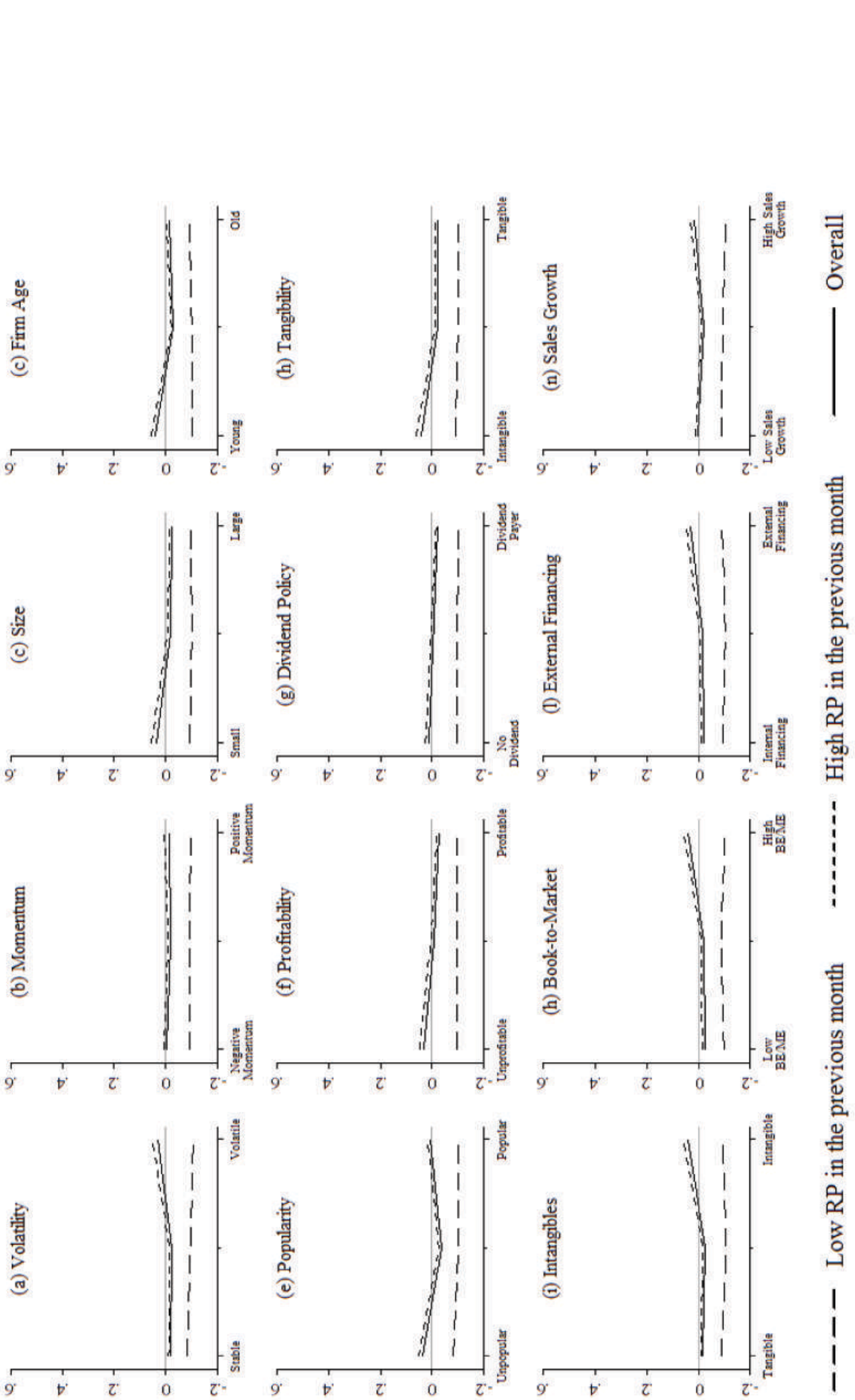


Figure 1.7: RP Sentiment Seesaws: Monthly Returns of Volatility-sorted Portfolios, ASX-listed Shares, April 2008 to April 2009

In terms of the graphs conditional on prior period levels of SMA, RA, and aggregate affect levels exhibit the seesaw pattern, as expected. This is shown in Figure 1.6, which displays the RA graphs for each characteristic. Risky firms exhibit higher sensitivity to levels of RA in the previous period, as evidenced by the large difference between returns of risky firms during high and low levels of RA. Safe firms exhibit relatively little difference between the two. In addition, high RA in the previous period, which designates risk seeking behavior, shows that safe firms make relatively higher returns while risky firms make relatively lower returns. Conversely, when RA is low (i.e. when the seesaw tilts in the other direction and investors are risk averse), safe firms earn relatively low returns and risky firms earn relatively high returns.

As can be seen in Figure 1.7, the cross-sectional graphs conditional on prior period levels of RP exhibit a trumpet pattern, which is contrary to expectations. The graphs show that high levels of RP result in relatively high returns for the whole cross section of stocks, indiscriminately of the level of characteristics. Conversely, low RP, which is when bubbles would be more likely to form, the subsequent period exhibits relatively low market wide returns. The graphs are thus strongly suggestive of a market correction. When people do not feel exposed to stock market risks in a given month, they overreact and cause prices in that month to be too high; this results in low returns in the subsequent month (the long dash in Figure 1.7). Conversely, when they feel exposed to high levels of stock market risk, they under-react and cause an upwards market correction in the subsequent month (the short dash in Figure 1.7). As evidenced by a slight trumpet shape, risky firms still exhibit a slightly higher sensitivity the high and low levels of RP (i.e. the seesaw pivot is now around the save quantile instead of the middle quantile), which explains why the parametric results are as expected even though the non-parametric results shown here are not.

The finding is important because it shows that at least one affective factor does not exhibit the same conditional relationship to the cross-section of stock returns as TDS. This means that arbitrageurs conceptualizing investor sentiment as RA (or SMA, or aggregate affect) and those conceptualizing it as RP will disagree as to the effects investor sentiment exhibits on pricing. We find further evidence for the difference in pricing effects between RA (or SMA, or aggregate affect) and RP when plotting the cross-section of returns conditional on contemporary changes in RA (Figure 1.8) and RP (Figure 1.9). Figure 1.8 shows that changes in RA exhibit the trumpet pattern with respect to contemporary returns: when RA increases the cross-section of returns is relatively high, and when RA decreases returns are relatively low. Safe stocks are still found to be less sensitive to these changes than risky stocks in Figure 1.8. In Figure 1.9, RP also displays a trumpet shape but differs from the RA graph by the complete sensitivity of safe shares to positive or negative changes in RP. Risky shares, on the other hand, exhibit a very strong sensitivity to RP: safe stocks do not react to changes in RP, but risky stocks exhibit relatively high returns when RP decreases and relatively low returns when RP increases. The main difference between the graphs is that while the entire cross-section of stock returns reflects changes in RA (risky stocks more than safe stocks), only risky shares reflect changes in RP.

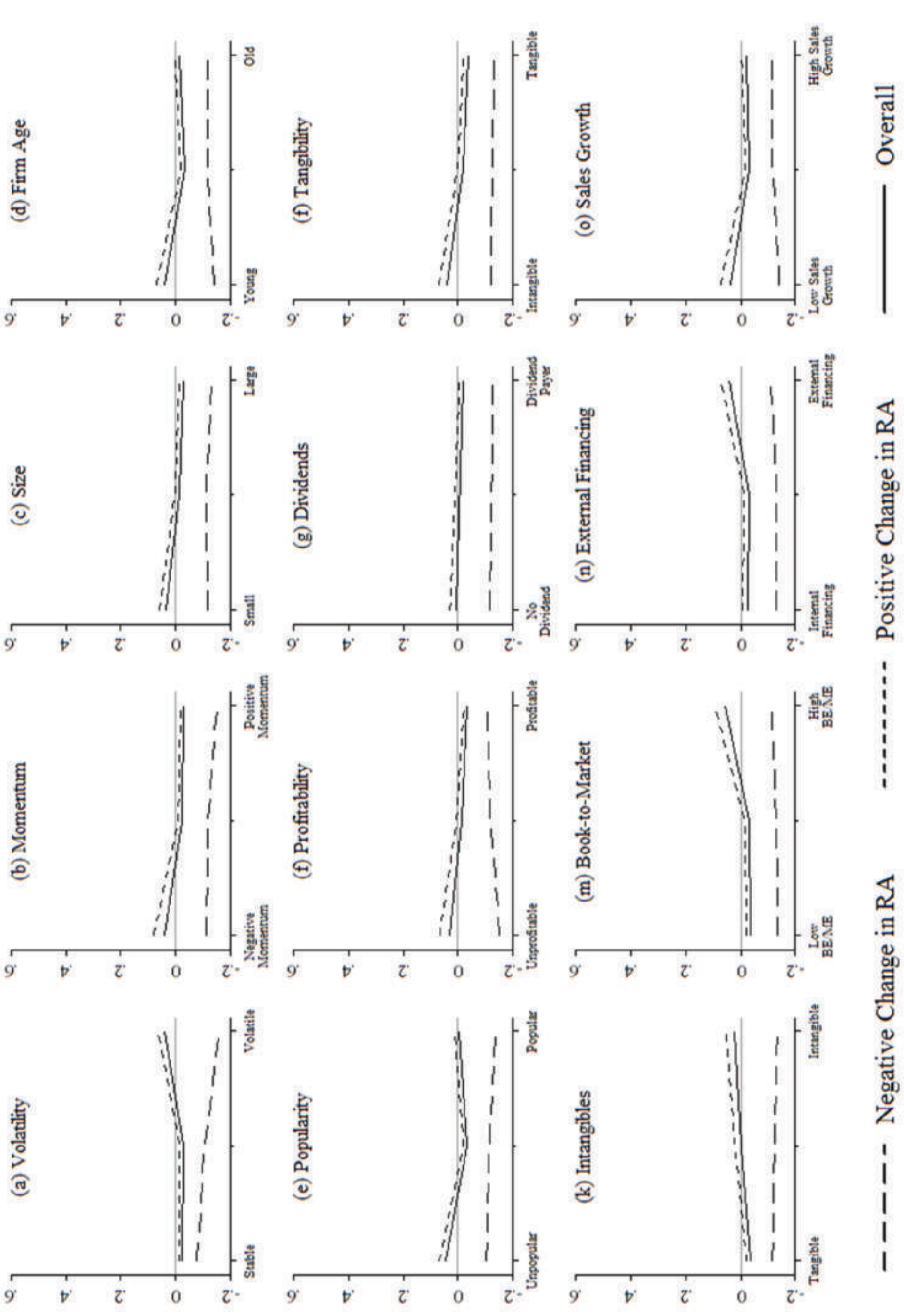


Figure 1.8: RA-changes Sentiment Seesaws: Monthly Returns of Volatility-sorted Portfolios, ASX-listed Shares, April 2008 – April 2009

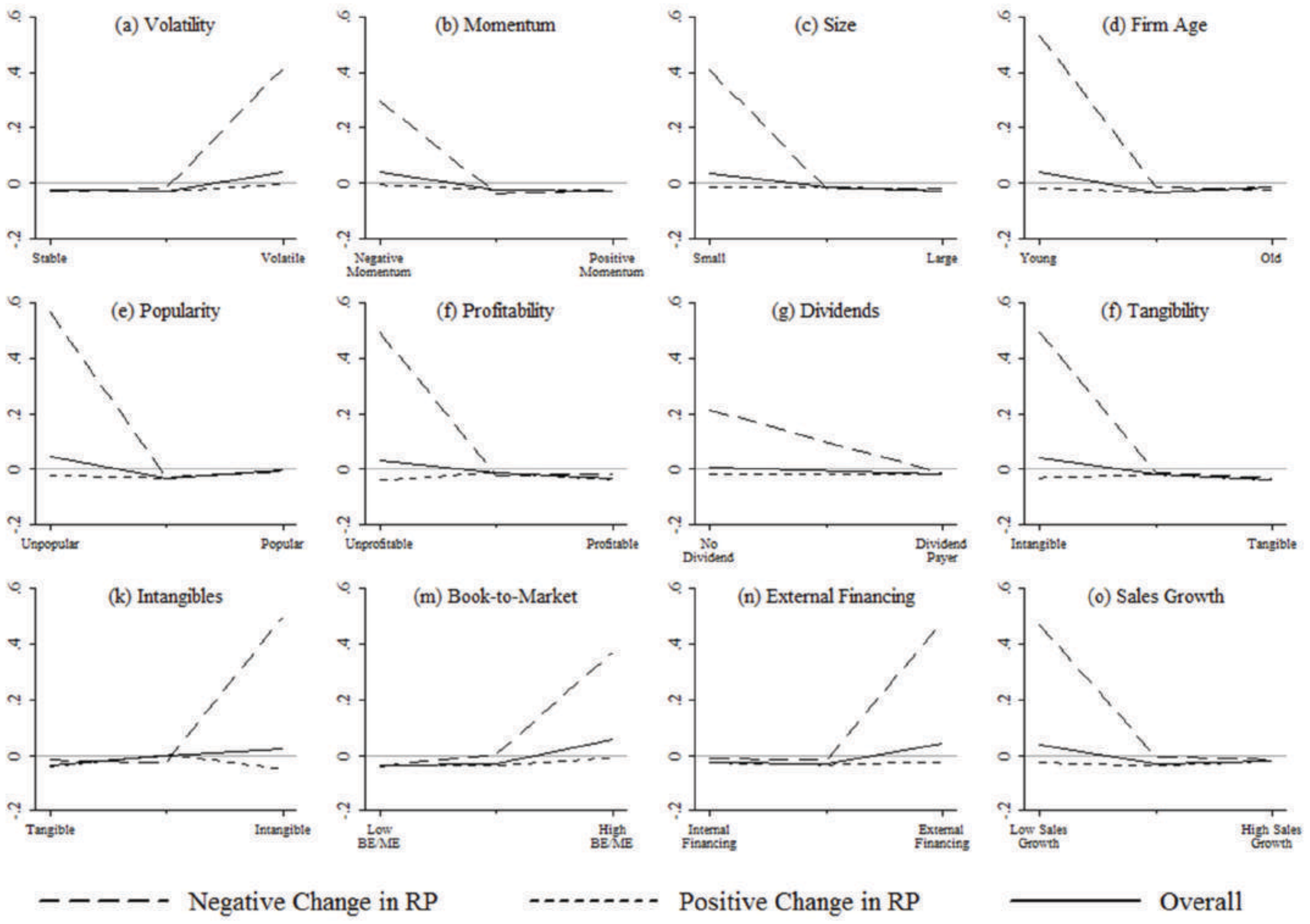


Figure 1.9: RP changes Sentiment Seesaws: Monthly Returns of Volatility-sorted Portfolios, ASX-listed Shares, April 2008 – April 2009

The figures portray the cross-section of stock returns across a variety of characteristics. Four characteristics in particular catch out attention: momentum, book-to-market, external financing, and sales growth. As discussed above, high and low levels of these characteristics do not necessarily represent straightforward measures of riskiness. In a descriptive context, it is possible to determine the riskiness of the various levels of a firm characteristic given the multiple interpretations it may have (as displayed in Table 1.5). By comparing the plots of ambiguous characteristics to those that exhibit a straightforward relationship to risk (such as volatility), it is possible to determine which hat the multifaceted characteristics are wearing during the sample period: the characteristic based quantile portfolio that is sensitive to affective effects exhibits a large difference in returns between high and low affect, and can be considered the risky level of the characteristic. The insensitive quantile portfolio will exhibit a small difference between high and low affect, and can be considered the safe level of the characteristic. In addition, we find that the riskiness of high or low levels of ambiguous characteristics can change depending on whether we examine overreactions or corrections. Two characteristics display this tendency, momentum and sales growth: in Figure 1.6, middle momentum is safe and high sales growth is risky; in Figure 1.8, positive momentum is safe and low sales growth is risky.

The graphs taken together paint an interesting picture of the relationship between the 3 affective factors we study and the dynamics of stock market overreactions and corrections. It provides the basis for imagining how the cross-section of stock returns behaves during two hypothetical cases: when investors get excited to the point of mania, and after they panic. When a price bubble is forming SMA and RA increase pushing the entire stock market up; the concurrent decrease in RP pushes risky shares up even more. When levels of SMA and RA are too high, it predicts the correction of the risky shares and levels; when levels of RP are too low, it predicts a market wide correction. In the case of a market panic, SMA and RA decrease pushing the entire stock market lower; the simultaneous increase in RP pushes risky shares down even more. When levels of SMA and RA are too low they predict a recovery among risky shares; the simultaneously high levels of RP predict the recovery of the entire stock market. When affective factors are aggregated, the subtleties of the effects of each factor are not perceptible, and provide a less specific description of the influence of affect on stock prices.

5. Conclusion and Discussion

This chapter provides an overview of the investor sentiment and the two approaches used to measure and study it: the top-down and the bottom-up approach. We show how these two approaches are related by a chain of events that consists of information from the environment, three steps of processing (physiology, affect, and cognitive biases), decisions, and market outcomes. The top link in the chain, the market outcome, is the focus of top-down methods to analyze investor sentiment and have shown that investor sentiment exists and exerts influence on aggregate market outcome variables (volume, volatility, and prices). The top-down approach, however, is not designed to explain why investor sentiment exists; this is the purpose of the bottom-up approach. The bottom-up approach offers many explanations for why sentimental effects exist in prices based on a scientific understanding of behavior. Although we are able to categorize the causes into three categories based on physiology, affect, and cognitive biases, the existing literature exhibits a myriad of measures that quantify behavior. This has led to confusion surrounding the nature of investor sentiment and poses a problem for market participants.

The natural market mechanism that keeps investor sentiment from causing stock market bubbles is called arbitrage. Arbitrageurs make use of their specific knowledge to identify prices that are too high or too low and apply pressure to correct them. Price bubbles occur when arbitrageurs exhibit a reason not to take the risk of correcting them. Even with specific knowledge, it can be very difficult to identify when a stock price bubble will reverse. Arbitrageurs may not possess the resources to withstand an unpredictably protracted positive price trend. Consequently, arbitrageurs exacerbate the problem of a price bubble by riding the trend while they wait for the price reversal (Shleifer and Vishny 1990 the noise trader approach to finance, Brunnermeier and Nagel, 2004, Griffin, Harris, Shu, and Topaloglu 2011, Zouaoui, Nouygirat, and Beer 2011). This is called the synchronization problem (Abreu and Brunnermeier, 2003) because arbitrageurs do not apply downward pressure to stock prices in concert, and thus contribute to market wide excitation at the prospect of greater wealth because of continuously increasing stock prices.

This chapter argues that by measuring the degree to which investors are in a mania will help identify the price reversal before the market panic that occurs when investors realize that prices are unsustainable. To do this, we cannot rely on the top-down approach to measure investor sentiment because this approach defines sentiment as the deviation of actual prices from fundamental prices, which says nothing about the affect of market participants. We must therefore rely on the bottom-up approach; however, physiology does not change fast enough to explain the variation in prices, and measuring cognitive biases is only possible post-hoc once trading decisions have been recorded and collected. Physiology and cognitive biases are thus not practical for measuring real-time causes of investor sentiment. Hence one option remains: affect. Affect changes rapidly enough to explain changes in pricing, it has exhaustively been documented as a driver of decisions, preferences, and risk behavior. In addition, it is more practical to measure affect in a way that is consistent, comparable, reliable, and valid than other measures of causes for investor sentiment.

This study thus performs the first direct and comprehensive test of the affect hypothesis (Statman, Fisher, and Anginer, 2008), which states that investor affect exhibits an influence on price formation. We select three affective factors based on the stock market and stock market risk: Stock Market Attitude (SMA), stock market Risk Attitude (RA), and stock market Risk Perception (RP) and test their relationship to the cross-section of stock returns. We find that all three factors support the affect hypothesis, and mesh well with existing theory based on top-down studies from the investor sentiment literature (Baker and Wurgler 2006 2007). Our most impressive finding is that SMA and RA exhibit the same cross-sectional pattern to the cross-section of stock returns as TDS, but that RP exhibits a unique pattern. This finding is important because it shows that at least one affective factor does not exhibit the same pattern as TDS and suggests that investor sentiment is composed of a collection of affective factors, that must all be measured in order to characterize it correctly. In terms of the synchronization problem, our findings allow us to make the following prediction: if arbitrageurs conceptualize investor sentiment as RA, their trading behavior will not synchronize with arbitrageurs who conceptualize investor sentiment as RP.

The implications of this research suggest that it may be possible to solve the synchronization problem by identifying the relevant affective factors, standardizing their measurement, and reporting their levels. The research presented here suggests that the asynchronous behavior of arbitrageurs may be caused by the fact that no uncontroversial conceptualization or measure of investor sentiment exists. Consequently, there is no framework upon which arbitrageurs can agree they are measuring the same pricing processes, and no universal signal for market participants to stop positive feedback trading and/or enter short positions until it's too late. This study addresses this issue by providing a classification of the causes of investor sentiment, and showing that measurement based on one such class, affect, is reliable and valid, and that 3 factors therein show how specific market feelings influence pricing individually. We also show that this approach can help determine whether less traditional characteristics are risky or safe (such as customer satisfaction, see Merrin, Hoffmann, and Pennings 2013) given their sensitivity to affective factors.

Finding the unmistakable signal of a market crash before the panic of the crash is a complex task. The panic itself, however, underlines the importance of affect as key driver of investor behavior and its central role in the mechanics of price bubbles. Affect is a vast and complex subject matter. Many other affective factors exist beyond those shown here that likely influence the decision behavior of investors, and provides a wide space for future research. A taxonomy of relevant affective factors would provide arbitrage traders set of tools to measure investor sentiment based on common methodological and theoretical frameworks. Before arbitrageurs can synchronize to correct bubbles, they must first agree about the causes of bubbles and how to measure them. A catalogue of affective factors could help foster a consensus among arbitrageurs, thus allowing them to focus on the interpretation of each measure, instead of worrying about the reliability and validity of each measure. Further research on affective factors and stock markets can help determine if affective effects deserve regulatory attention in terms of measurement and reporting standards to help arbitrageurs synchronize, and fight the incidence of stock price bubbles.

Chapter 2

Of Triggers and Targets: Risk-Based Affect in a Double-Hurdle Model of Retail Common Stock Trading Decisions

Abstract: Research in behavioral finance has focused on the study of investor behavior and its consequences for aggregate market outcomes and portfolio performance. The study of investment decisions proper has received less attention, and has mostly been performed in experimental settings. This study contributes to the literature by concentrating on the retail investment decision in its natural context by pairing 1658 monthly measurements of risk-based affect with the trading records of retail investors. The risk-based affective measurements consist of a psychometric adaptation of the Pratt-Arrow framework: risk attitude (RA), risk perception (RP), and their interaction (IRAP), which represents the Pratt-Arrow coefficient. Using these measures of risk behavior, we explain the investment decision with a double-hurdle model, which fits the implicit and simultaneous two-step investment decision: the decision to trade, and the degree of risk to undertake given the decision to trade. We study purchase and sale decisions separately, and measure investor risk exposure using stock six characteristics of the stocks they trade: volatility, momentum, size, firm age, brand value, and external financing. We find that purchases and sales are driven by different components of risk- behavior: purchases are driven by RA and IRAP, while sales are driven by RP. The influence of RA, RP, and IRAP exhibit no discernible pattern across the six

studied firm characteristics on the degree of risk to undertake. These results suggest that affective reactions to stock market risk, as measured by RA, RP, and IRAP, drive investors' decision to "pull the trigger," but not what they target.

1. Introduction

Trading decisions are a fundamental part of the market mechanism. Documenting the drivers of trading decisions can help investors use data about their trading decisions to make better trades, help brokerage firms profile the needs of their clients, and help regulators adapt policy decisions to descriptive accounts of investor behavior. Risk behavior in particular is an important determinant of investor trading decisions, because of the many risks investing involves. Although the literature on investor behavior extensively documents the effects of risk behavior on prices and performance, few studies focus on investors' decision making mechanism proper. As such, a formal empirical test of risk behavior's impact investor decisions has yet to be performed. Using a unique data set that combines monthly affective measures of risk behavior and the common stock trading records of 1648 retail investors, this study analyzes the relationship between measures of investors' risk behavior and their trading decisions.

In this study, investor risk behavior is composed of affective determinants based on the Pratt-Arrow framework (Pratt 1964, Arrow 1971) and shown in Table 2.1: risk attitude (RA), risk perception (RP), and their interaction (IRAP). The first determinant, RA, informs us of how decisions are influenced by the extent investors like or dislike stock market risk. The second determinant, RP, shows us how decisions are influenced by the extent to which investors feel exposed to stock market risk. The third determinant, IRAP, sheds light on how the intent of investors to cope with stock market risk (e.g. by increasing or decreasing risk exposure) influences trading. Each determinant is measured monthly using a standard psychometric approach based on surveys sent to investors through their brokerage firm. Measuring risk behavior in this fashion permits us to draw conclusions about actual traders' behavior in their natural trading environment.

Trading securities implies being exposed to risk and uncertainty. When investors decide to trade a stock, it is in effect a two-step process; they must simultaneously decide to make the trade, as well as how much risk exposure they wish to undertake. Investors looking for high risk exposure, for example, will trade firms with risky characteristics (e.g. high stock price volatility, low market capitalization…) as opposed to safe characteristics (e.g. low stock price volatility, high market capitalization…), which would cater to investors looking for low risk exposure. The two-step nature of this decision exhibits a structure that fits nicely into a class of corner solution models called the "double-hurdle" model (Cragg 1971). The double-hurdle model integrates a probit regression and a tobit regression, which are designed to analyze a participation decision and a degree decision, respectively. Thus the dependent variables in this study consist of the probability of making a trade (in the first hurdle), and the degree of riskiness undertaken by investors, conditional on making the trade (in the second hurdle).

The analysis reveals that different determinants of risk behavior are related to different trading decisions. In terms of the first step of the trading decision, the extent to which investors like or dislike stock market risk (measured by RA) and their intent of investors to cope with stock market risk (measured by IRAP) are strongly related to investors' decisions to purchase common stocks. In addition, the extent to which investors feel exposed to stock market risk (measured by RP) is found to have a strong relationship with common stock sale decisions. In terms of the second step, however, findings show that the relationship between risk behavior and the choice of risk exposure depended on the characteristics chosen to quantify stocks' riskiness. The study also finds that the major stock index (in this case the AEX) is related to both hurdles of trading decisions, while demographics such as age, gender, and income do not exhibit economically significant influence.

The findings can be interpreted as evidence that risk behavior determines whether investors trade or not, but is unrelated to the choice of what they will trade. This implies that the decision of what to trade is determined by processes that are not directly related to stock market related risk behavior, but rather to investor preferences. Traditional, normative research in financial markets states that trading behavior is based on a given stock is due to its risk-return traits. This normative approach has traditionally downplayed the importance of other characteristics that differentiate firms in the eyes of investors, and have since been shown to exert an influence: brand image (Statman, Fisher, and Anginer 2008), customer satisfaction (Fornell, Mithas, Morgeson III, and Krishnan 2006), social norms (Hong and Kacperczyk 2009), the influence of peers (Hong, Kubik, and Stein 2004), and corporate social responsibility (Luo and Bhattacharya 2006). Such characteristics specifically cater to investor affect and drive investors' preferences and choices, though may not be explicitly related to risk behavior as it has been traditionally theorized. In sum, our analysis shows that risk behavior measured by RA, RP, and IRAP can help determine when traders "pull the trigger," but does not help determine what their target is.

The rest of this chapter is organized as follows: section 2 provides a short survey of the literature on investor behavior; section 3 addresses the data collection procedure and descriptive statistics; section 4 explains the empirical model and the results of our analysis; and section 5 discusses the findings and concludes.

2. Literature Review

Since the late 1990s researchers in finance have increasingly dedicated their focus and efforts to examine the effects of behavior on financial markets because the normative models do not explain reality (Fama and French 2007). Since research in finance has traditionally focused on market outcome variables the behavioral research on financial topics has followed suit, and also focuses variables such as returns, volume, and volatility. This natural progression was necessary to accumulate evidence that would make the divergences between the normative results (of traditional financial research) and descriptive results (of the subsequent behavioral studies) apparent. The divergence between the theoretical and observed levels of market outcome variables is the basis of the literature on "investor sentiment," and is one of the fundamental assumptions of behavioral finance. The relevance and effects of investor sentiment are now widely recognized because the related research has produced evidence from aggregate market outcomes, on portfolio performance, and on decisions in an experimental context. However, no study has yet examined investor decisions as the dependent variable of their study, such variables tend to remain in the traditional realm of risk, return, and performance.

There is a vast collection of explanations for investor sentiment that examines aggregate market behavior. Researchers have shown that environmental factors influence aggregate market outcomes: sunlight (Hirshleifer and Shumway 2003), cloud cover (Kamstra, Kramer, and Levi 2003), as well as lunar cycles (Yuan, Zheng, and Zhu 2006). Beyond celestial and weather related events, human induced occurrences have also been shown to influence aggregate market outcomes, even though they are seemingly unrelated to economic events. Such examples include the loss of sleep from daylight savings time (Kamstra, Kramer, and Levi 2001), the excitement of worldwide sports events (Edmans, Garcia, and Norli 2007), and mediatic attention (Engelberg, Sasseville, and Williams 2010). Shiller (2000, 2003) argues that investor fads and fashions have a large impact on aggregate stock market outcomes, leading to stock market bubbles and crashes. Another prevalent explanation advanced for behavioral effects in markets are cognitive biases such as overconfidence and myopic loss aversion (Barberis, Shleifer, and Vishny 1998, Daniel, Hirshleifer, and Subrahmanyam 1998, Shefrin 2005). The extensive documentation of the causes of investor sentiment in aggregate market outcomes shows that affect and behavior hold a noteworthy place in financial research. Nonetheless, the investor sentiment literature is much less prolific concerning the analysis of investor sentiment and it relation to specific investor decisions.

The largest stream of research that examines behavioral effects on investor decision making has done so by studying performance at the portfolio level. Although this is equivalent to looking at market outcome variables, studying individual investors' performance and portfolio selection allows researchers to make statements about what investor characteristics drive their investment decisions. Researchers have shown, for example, that investors are prone to herding behavior (Grinblatt, Titman, and Wermers 1995, Nofsinger and Sias 1999) and that physiological factors such as gender (Barber and Odean 2001) express themselves in statistically different trading outcomes. In addition, short term price trends tend to cause buying and selling (De Long, Shleifer, Summers, and Waldmann 1990, Dhar and Kumar 2001), even though investors are frequently reminded that "past performance does not guarantee future results." Investor income has also been shown to influence portfolio choice; Kumar (2009) shows that lower income investors are more likely to gamble and purchase lottery-like stocks. Although the portfolio choice and performance approach to study investor decisions has contributed to our understanding of behavior and performance, specific decisions are seldom the examined dependent variables.

The stream of research that specifically examines investor decision does so in an experimental context. While experiments do not always examine real decision-makers in their natural decision making habitat, they can result in important discoveries concerning economic decision making. The classic example of such as result is prospect theory (Kahneman and Tversky 1979), which shows that the psychophysics of chance is non-linear: individuals are risk-averse in situations of certainty, but risk-seeking when confronted with losses (see Odean 1998, for the evidence from portfolio analysis). Experiments have since shown that hormones (testosterone in particular) influence financial risk behavior (Apicella, Dreber, Campbell, Gray, Hoffman, and Little 2008, Sapienza, Zingales, and Maestripieri 2009), which have provided additional evidence for the physiological basis of decision making. The most promising research about the physiological mechanics of decision making concerns the central role played by the brain. Experiments examining economic decision making have shown this by comparing normal patients to patients with neural dysfunction, and found that their decision making differed (Shiv, Loewenstein, Bechara, Damásio, and Damásio 2005). More specifically, they identified affect as the part in the brain that was responsible for the investment decisions in the study (and that related neural dysfunction resulted in more advantageous investor decisions).

This study contributes to the literature on investor behavior and decision making by analyzing the direct measurements of risk-based affect of investors in their natural habitat. In addition, we use specific decisions as dependent variable instead of the outcomes of decisions, and thus study the investment decision mechanism proper, instead of the consequences of the decisions on a given market or portfolio. The approach is a psychometric adaptation of the Pratt-Arrow (Pratt 1964, Arrow 1971) previously used by Pennings and Wansink (2004) to examine channel contract relationships. Here we adapt the methodology to examine the investment decision, modeled as a two-step process, simultaneously consisting of a participation decision (whether to trade) and a degree decision (how much risk to undertake).

We specifically target the effect of risk-based affect on investor decisions because investing is inherently risky and because of the importance of the role of risk in behavioral economics. The measurement and quantification of risk is fundamental to the study of financial markets, and while objective measures of risk (such as volatility) are considered the standard, subjective measures of risk are more relevant to the behavior of individuals, as their subjectivity is likely to drive their behavior (Weber, Shafir, and Blais 2004, Dorn and Huberman 2005, Klos, Weber, and Weber 2005, Nosic and Weber 2010). Further, studying RA and RP at the same time, allows for the study of their interaction (IRAP), which is the basis for our psychometric adaptation of the Pratt-Arrow coefficient (see Pennings and Wansink (2004) for the full arithmetic). Consequently, drawing from marketing methodologies, economic theory, and the financial domain, we are able to perform an interdisciplinary and novel study about investor behavior and the role of RA, RP, and IRAP in investment decision making.

3. Data Collection and Descriptive Statistics

This study benefits from a unique dataset that allows us to examine retail investor trading decisions in their natural habitat. Three sources are used to construct the dataset: survey measures of investors' risk behavior, trading records documenting their trading decisions, and public financial data that characterizes the riskiness of the stocks purchased.

3.1. Affective Risk Behavior

The data on risk behavior is collected using repeated monthly survey measures from April 2008 to April 2009. Participants in the study are individual investors at a large Dutch online retail brokerage firm. The brokerage firm contacted respondents by email and asked if they would like to participate in a study in exchange of a chance to win a prize in a subsequent raffle. The data collection program attracted 1509 investors. In order to reduce sample selection bias, several surveys were developed and randomly sent out to participants each month. The survey response rates are shown in Table 2.1.

The surveys used in this study focused on common stocks and were sent to 595 individuals, who each answered between 1 and 10 monthly iterations. This resulted in an average response rate of 2.77 monthly observations per participant and a total of 1648 monthly responses. This study focuses on common stocks. Of the 595 participants in the study, 335 do not make any common stock transactions, while 260 make at least one common stock transaction, 166 make at least one purchase, and 94 make at least one sale. From Table 2.1 Panel C, we can see that participants who make common stock transactions answer more surveys (3.45) than do participants who do not transact (2.23)[14], which, when regressing transactions on survey responses, may be a source of bias as a result of endogeneity (the correction for which is discussed further in the methodology section 4.2).

	Investors	Mean	SD	Min	Max	Skew	Kurt
Panel A: Participant Demographics							
Age (years)	595	49.60	14.75	10	80	-0.18	2.13
Gender (% male)	595	0.92	0.27	0	1	-3.18	11.11
Income(Thousands)	595	19.71	0.39	10.40	90.90	5.29	76.10
Panel B: Trades per Participant							
Total	595	4.10	12.90	12.90	126	5.89	44.03
Traders	260	9.38	18.22	18.22	126	3.92	20.37
Buyers	166	5.76	10.07	10.07	71	4.34	24.60
Sellers	94	5.37	10.23	10.23	76	4.51	27.61
Panel C: Survey Responses per Participant							
Total	595	2.77	1.97	1	10	1.41	5.01
Non-Traders	335	2.23	1.49	1	9	1.41	5.15
Traders	260	3.45	2.28	1	10	1.05	3.69
Buyers	166	3.54	2.31	1	10	1.02	3.67
Sellers	94	3.30	2.22	1	10	1.10	3.71

Table 2.1: Yearly Summary Statistics of Dutch Retail Investors Responding to the Surveys and their Trades, April 2008 to April 2009

The sample consists of a large majority of men (92%) around the age of 50. Of the 595 individual investors participating in the study, 260 make at least one common stock transaction, 166 make at least one purchases, and 94 make at least one sale. The average number of trades per transacting respondent is 9.38. The most active respondent trades 126 times, spread out over the 13 month length of the sample. Some children are registered under the names of their parents, explaining the minimum age of 10 years.

Table 2.2 displays the definitions of the risk-based measures of affect we use as constituents of risk behavior: RA, RP, and IRAP. RA is defined as the general disposition of investors towards stock market risk. It is the extent to which an investor likes or dislikes

[14] An unpaired *t*-test shows the difference between these two is significant at the 1% level.

stock market risk. Attitudes are a constituent of affect (Davidson, Scherer, and Goldsmith 2003), and in this case the attitude object is stock market risk. RP is investors' subjective interpretation of the probability to be exposed to stock market risk. It is the extent to which investors feel exposed to stock market risk. Finally, we calculate IRAP as the product of RA and RP, which measures the motive of the investor. Motives are also a constituent of affect, and in this case measures the intent of an investor to cope with stock market risks, as well as the risks his or her own actions might generate. Coping with stock market risk involves purchasing or selling stocks to increase or decrease their exposure to risk. The basis for IRAP is provided in Pennings and Wansink (2004) and is the psychometric adaptation of the Pratt-Arrow coefficient of risk aversion.

Determinant	Definition and Interpretation
Risk Attitude (RA)	The general disposition of investors towards stock market risk. It is the extent to which an investor likes or dislikes stock market risk.
Risk Perception (RP)	Investors' subjective interpretation of the probability to be exposed to stock market risk. It is the extent to which an investor expects to encounter stock market risk.
The interaction of RA and RP (IRAP)	The intention of the investor to cope with risks in the stock market, along with the risks his or her own actions generate.

Table 2.2: Definition and Interpretation of Risk Behavior Factors, adapted from Pennings and Wansink (2004)

RA and RP are measured using an online survey with multiple-item Likert scales, adapted from previous research (Pennings and Garcia 2001, Pennings and Wansink 2004). The items are displayed in Table 2.3; summated scales for RA, RP, and IRAP are constructed by taking the average of the responses for each construct. This approach to creating measures is parsimonious and effective in the face of more complex alternatives (Weber and Milliman 1997). RA is coded such that negative designates risk averse (e.g. a scale end point of -3), zero designates risk neutral (e.g. the scale middle point), and positive designates risk seeking (e.g. scale end point of +3). RP is coded from 0 to 6, where the scale end point 0 means the investor does not feel exposed to stock risk, and where the scale end point 6 means the investor feels strongly exposed to stock market risk. This means that negative IRAP (e.g. a scale end point of -18), which is the interaction of risk aversion with strong perceptions of risk results in the motivation to decrease risk exposure. Likewise, positive IRAP (e.g. a scale end point of +18), which is the interaction of risk seeking behavior with strong perceptions of risk, results in the intent to increase risk exposure (see Pennings and Wansink (2004) for a graphic representation). Risk neutrality (when RA is zero) or no perception of risk (when RP is zero) results in a zero IRAP and represents investor motives that are independent from stock market risk.

We performed several steps to ensure the construct validity and reliability of RA, RP, and IRAP. We conducted a confirmatory factor analysis on the scales and dropped those with factor loadings below .50 to maximize construct validity (Hair, Black, Babin, and Anderson 2010). Construct reliability was measured using Cronbach's alpha and was found to be above 0.80 for RA and RP, thus indicating high reliability of each measurement instruments (Hair, Black, Babin, and Anderson 2010).

Existing research supports the use of RA, RP, and IRAP in explaining economic behavior and decision making of individual market participants. Pennings and Wansink (2004), for example, use RA and RP to explain the contracting behavior of producers, processors, and wholesalers. Pennings and Garcia (2004, 2010) also use RA and RP to examine the latent heterogeneity that determines derivative usage and hedging decisions. Willebrands, Lammers, and Hartog (2012) use RP and RA to examine the success of entrepreneurs and managers, and Pennings, Wansink, and Meulenberg (2002) and Pennings and Grossman (2008) use this methodology to discuss the modeling reactions to crises. This study thus benefits from using constructs that have shown to be valid and reliable instruments of behavioral research.

Risk Attitude (RA, α = 0.84) Survey Items Scale: Completely Agree (-3) – Neutral (0) – Completely Disagree (+3)	Factor Loadings
• This month, with respect to the stock market, I prefer financial certainty to financial uncertainty.	0.63
• This month, I am taking higher financial risks in order to realize higher average returns in the stock market.	0.59
• With respect to the stock market, I avoid risks this month.	0.83
• In terms of investing in the stock market this month, I prefer certainty to uncertainty.	0.81
• This month, I am NOT taking financial risks in the stock market.	0.85
• This month I am NOT “playing it safe” in the stock market.	0.61
• This month, I am NOT taking more risks in the stock market to achieve higher returns.	0.66
Risk Perception (RP, α = 0.83) Items Scale: Completely Agree (0) – Neutral (3) – Completely Disagree (+6)	**Factor Loadings**
• This month, investing in stocks is risky for me.	0.79
• This month, stocks are a safe investment for me.	0.72
• For me, investing in stocks is dangerous this month.	0.80
• For me, investing in stocks leads to a small amount of risk.	0.77

n.b. To construct each measure, items are recoded such that low levels of each decision driver are on the left side of the scale (negative) and high levels on the right (positive). Each decision driver is then calculated by taking the mean of average item scores.

Table 2.3: Factor Survey Items, their Scales and the Results of the Factor Analysis

Items recoded where necessary. In order to select the items and scales to measure each factor, we drew from previous research (Pennings and Wansink 2004) and proceeded to test the validity and reliability of each scale using confirmatory factor analyses and calculating the Cronbach’s alphas. Items with factor loading of less than 0.50 were dropped and all factors exhibited alphas above 0.80, supporting validity and reliability of each measure (Hair, Black, Babin, and Anderson 2010).

	N	Mean	SD	Min	Max	Skew	Kurt
			Panel A: All Participants				
RA	1648	-0.28***	1.14	-3	3	-0.13	3.16
RP	1648	3.36***	1.09	0	6	0.29	2.93
IRAP	1648	-1.15***	4.30	-18	14.48	-0.62	4.81
			Panel B: Non-Traders				
RA	1195	-0.38***	1.10	-3	3	-0.17	3.14
RP	1195	3.35***	1.05	0.50	6	0.34	2.96
IRAP	1195	-1.42***	4.14	-18	13	-0.68	4.76
			Panel C: Traders – *Overall*				
RA	453	-0.04	1.19	-3	3	-0.16	3.12
RP	453	3.41***	1.17	0.25	6	0.20	2.72
IRAP	453	-0.47**	4.62	-18	15	-0.62	4.91
			Panel D: Traders - *Purchases*				
RA	286	0.03	1.21	-3	3	-0.09	2.99
RP	286	3.42***	1.23	0.25	6	0.20	2.63
IRAP	286	-0.27	4.85	-18	15	-0.57	5.03
			Panel E: Traders - *Sales*				
RA	167	-0.16**	1.15	-3	3	-0.36	3.27
RP	167	3.40***	1.06	0.25	6	0.18	2.78
IRAP	167	-0.81***	4.19	-15	10	-0.81	4.26

Nota: Different than zero at the *10%, **5%, and ***1% level

Table 2.4: Summary Statistics of Monthly Survey Results, April 2008-April 2009

This table presents the summary statistics of the survey responses for risk attitude (RA), risk perception (RP), and displays the interaction of the two (IRAP), which is the psychometric adaptation of the Pratt-Arrow coefficient. This table paints the portrait of the average investor's affective state vis-à-vis stock market risk during the period April 2008 to April 2009. The table shows that non-traders' RA (Panel B) differs from that of respondents who do trade in a given month (Panel C). In addition, we find differences between the RA of respondents who purchase (Panel D) and respondents who sell (Panel E). The table shows that investors with different levels of risk-based affect also behave differently. To include respondents who purchased and sold in a given month we use the average of all trades performed by that respondent in that month. Stars denote significance of difference from zero.

Table 2.4 Panel A shows the overall summary statistics of the risk behavior surveys. The RA scores show that investors dislike risk only slightly, displaying an average RA slightly below the scale midpoint of zero (RA = -0.28), exhibiting slight risk aversion on average. The RP score indicates that they also perceive stock market risk to be above the scale midpoint of three (RP = 3.36). RP and RA responses included both maximums and minimums at the extreme of each scale, meaning that the dispersion among the risk behaviors of the investors is spread between the scale endpoints, and is suggestive of a large degree of heterogeneity. In terms of IRAP, the average investor in the sample is looking to decrease risk exposure, as made evident by the negative mean IRAP (-1.15). The descriptive statistics in Table 2.4 represent the affective picture of investors during the financial crisis that was ongoing during the sample period, April 2008 to April 2009: they expressed a dislike for stock market risk, they felt exposed to risk, and they intended to cope with this risk by decreasing their risk exposure.

Characteristic and Measure	**Risky**	**Safe**
Volatility (Stock Return Standard Deviation)	Volatile (high decile)	Stable (low decile)
Momentum (Sum of returns from 11 months)	Negative Momentum (low decile)	Positive Momentum (high decile)
Size (Market Capitalization)	Small (low decile)	Large (high decile)
Firm Age (Years since IPO)	Young (low decile)	Established (high decile)
Brand Value (Goodwill over total assets)	Low Brand Value (low decile)	High Brand Value (high decile)
External Financing (*ΔTot.Assets-ΔRet.Earn./Tot.Assets*)	Distressed Firm (low decile)	Growth Firm (high decile)

Table 2.5: Common Stock Characteristics: Measurement and Relation to Riskiness

Table 2.6 also shows respondents' risk behavior in conditional on their trading behavior in that month. Panel B shows that non-traders RA and IRAP (-1.42) is lower than that of trading participants shown in Panel C (-0.47). This difference stems from the lower RA of non-traders (-0.38) compared to that of traders (-0.04). The RP of non-traders (3.35), however, is relatively closer to that of traders (3.42). This result suggests that the difference in trading behavior between the two stems from attitude towards stock market risk, instead of being caused by differences in stock market risk they feel. When, further dividing traders into purchasers and sellers, additional differences in RA and IRAP appear, while RP remains quite similar. Respondents who purchased when they answered the survey exhibit slight risk seeking behavior (i.e. a positive RA of 0.03), while sellers exhibited risk averse behavior (i.e. a negative RA of -0.16). The average IRAP for purchasers is -0.27, which shows that their average intent to decrease their exposure to risk is lower than that of sellers, who exhibit a more negative IRAP of -0.81.

3.2. Risk Exposure

An investor who wishes to cope with changes in stock market risk can do so by modifying their exposure to the stock market. In terms of trading common stocks, several possibilities are at their disposal; investors may both purchase and sell common stocks with varying levels of risk in order to influence the overall riskiness of their common stock holdings. Purchases of risky shares, for example, will increase the average riskiness of the investors' portfolio, and thus increase their risk exposure. On the other hand, purchasing safe stocks would then decrease the average riskiness of the investors' common stock holdings, and thus also decrease their risk exposure. Following the same reasoning, investors may also use sales to modify their risk exposure: selling safe stocks increases risk exposure, and selling risky stocks decreases risk exposure.

To quantify the riskiness of the shares purchased and sold by participants in the study, we rely on six characteristics – volatility, momentum, firm size, firm age, brand value, and level of external financing. We sort all reporting firms listed on the Amsterdam Stock Exchange (ASX) according to each of their characteristics exhibited during each month of the April 2008-April 2009 sample period. We classified the firms into deciles numbered from 1 (low levels of the characteristic) to 10 (high levels of the characteristic). The decile numbers for each characteristic are then used as six different quantifications of the riskiness of each firm. Table 2.5 shows how each characteristic relates to the riskiness of the firm. Volatile, negative momentum, small, low brand value, low external financing firms are riskier and harder to arbitrage than stable, positive momentum, large, high brand value, high external financing firms. These characteristics are an effective way to determine the relative riskiness of firms using their publicly reported financial data (Daniel and Titman 1997, Baker and Wurgler 2006) and are related to the various preferences of investors (Fama and French 2007). Below we discuss the characteristics of the stocks traded in the sample.

3.3. Trading Decisions

Using the trading records of the survey participants, we collect the common stocks' characteristics-based riskiness scores that have been purchased or sold. This allows us to catalogue decisions of investor to participate (or not) in the stock market, and the degree of riskiness of the investment or divestment choices. Table 2.6 shows the descriptive statistics of the decile riskiness scores. A high decile score (above 5) designates that the level of the characteristic is above the ASX median in a given month and a low decile score shows that the level of the characteristic is below the ASX median in a given month. Considering purchases and sales together in Table 2.6 Panel A, the average stock traded by survey participants was a high volatility (7), negative momentum (3.67), large (7), established firm (8), with above average brand value (6.67), and in a position of distress (3). The decile scores reflect the historical context of the market (high volatility, negative momentum, and firm distress), as the data was collected during the brunt of the subprime crisis.

Decile	N	Median	Mean	SD	Min	Max	Skew	Kurt
Panel A: Average Stock Deciles Traded								
Volatility	453	7	6.22	2.79	1	10	-0.32	1.97
Momentum	453	3.67	3.85	2.46	1	10	0.65	2.63
Size	453	7	6.69	2.01	1	10	-0.66	2.92
Firm Age	453	8	6.32	3.76	1	10	-0.62	1.89
Brand Value	453	6.67	4.97	4.14	1	10	-0.20	1.27
External Financing	453	4	3.45	3.04	1	10	0.13	1.61
Panel B: Average Stock Deciles Purchased								
Volatility	286	7	6.64	2.68	1	10	-0.43	2.13
Momentum	286	3	3.50	2.37	1	10	0.80	2.99
Size	286	7	6.69	2.06	1	10	-0.78	3.10
Firm Age	286	8	6.05	3.99	1	10	-0.48	1.62
Brand Value	286	5	4.47	4.13	1	10	0.04	1.25
External Financing	286	3	3.22	3.16	1	10	0.32	1.68
Panel A: Average Stock Deciles Sold								
Volatility	167	6.33	5.56	2.95	1	10	-0.08	1.71
Momentum	167	4	4.40	2.59	1	10	0.42	2.20
Size	167	7	6.70	2.05	1	10	-0.49	2.48
Firm Age	167	7.5	6.47	3.54	1	10	-0.69	2.20
Brand Value	167	7	5.36	4.21	1	10	-0.36	1.31
External Financing	167	4	3.58	2.97	1	9	-0.01	1.56

Table 2.6: Average Monthly Stock Deciles Traded, Purchased, and Sold by the Sample of Dutch Retail Investors, April 2008-April 2009

This table shows the summary statistics of the average characteristic-based decile scores of the stocks traded in by survey respondents in a given month. The decile scores denote the relative level of the characteristics of the stocks traded compared to all stocks listed on the Amsterdam Stock Exchange: a decile score of 1 designates the bottom 10% of that characteristic in the stock market, whereas a decile score of 10 the top 10% of the stock market. A score of 5 means the characteristic at the median level of the stock market. This table shows that more purchases were made than sales, and that the characteristics of the shares purchased and sold are very similar, although the shares sold are slightly riskier than the shares purchased. The latter is evidence of loss aversion (the AEX trend during this period is overwhelmingly negative due to the subprime crisis).

Table 2.6 Panels B and C exhibit the risk scores of purchases and sales. The panels show that individuals made more purchases than sales, which during the examined period of decreasing stock prices, supports existing evidence that they are reluctant to realize their losses (Odean 1998). In addition, the panels show that mean and median risk scores of the stocks purchased and sold are very similar. This echoes previous findings by researchers studying portfolio choice, who find that retail investors tend to herd their trading behavior around the same stocks (Barber and Odean 2008, Strahilevitz, Odean, and Barber 2011). Also interesting, is that investors in the sample consistently purchase stocks with higher risk scores than the stocks they sell; this is in agreement with prospect theory where investors faced with ever increasing losses take ever larger risks (Tversky and Kahneman 1979, Odean 1998, Shu, Yeh, Chiu, and Chen 2005). The fact that the investors in the sample purchase riskier stocks than they sell shows they are increasing the riskiness of their common stock holdings.

A comparison between RA, RP, and IRAP in Table 2.4 and the riskiness of the trading decisions from Table 2.6 show an interesting and novel picture of the individual investor. From Table 2.4, we can see that traders and non-traders, as well as purchasers and sellers exhibit different levels of RA, RP, and IRAP – in particular, purchasers exhibit higher levels of RA (seek more risk) and sellers exhibit lower levels of RA (are more risk averse). The risk behavior measurements coincide with the fact that purchasers are in effect seeking risk by purchasing riskier than median common stocks, and that sellers are avoiding risk by selling riskier than median shares. Thus, not only are these market actors behaving differently, they are also thinking differently. It is impressive that repeated monthly survey measures reflect this, and is a strong argument for their use.

4. Methodology

The decision to invest implies choosing the riskiness of the stocks one will trade. As a result investors are confronted with separate but simultaneous and interdependent choices. They must make a participation decision (i.e. participate in the stock market, purchase or sell) and concurrently make a degree decision (i.e. the degree of risk to undertake). The nature and structure of investment decisions thus fits the “two-tier” or “double-hurdle” regression model, specifically developed for this type of two-step decision.

4.1. The Double-Hurdle Model

The double hurdle model was first proposed by Cragg (1971) and serves as an alternative to the tobit model (Lin and Schmidt 1984, Blundell and Meghir 1987), a censored regression model which applies when the dependent variable is partly continuous and partly categorical (Tobin 1958). A common example of censored data is called top coding, where a survey inquiring about respondent incomes may include an option for "$200,000 or above," which groups all incomes of $200,000 and above in the same category, thus 'censoring' the useful information of incomes above this level (Wooldridge 2010). Although the tobit is an extension of the probit model, thus taking into account binary categorical responses (i.e. participation), but it is not designed for the analysis of the degree to which an observation is not equal to zero. Probit class models can be used to analyze whether a decision is being made, but cannot be used to analyze the degree to which it is being made. The double hurdle-model is thus advantageous in many such situations because it integrates a probit for the binary participation with a tobit for the degree of the decision.

Models of the Cragg type are useful because many processes involving both a binary and a degree component. The application of the double hurdle model to an investment context stands out from the literature because most studies using double hurdle models examine consumer behavior and consumption decisions. Applications of the double-hurdle model include a double-hurdle model to UK household meat expenditure (Burton, Dorsett, and Young 1996), to US food expenditure away from home (Jensen and Yen 1996), and to US household consumption of cheese (Yen and Jones 1997). The tobit model which ignores the participation decision has often been the benchmark for the double-hurdle model; researchers have consistently found double hurdle models to outperform tobit models in participation-consumption situations (Jones 1989, Labeaga 1999, Katchova and Miranda 2004). This study thus uses the double hurdle model to analyze investing as a consumption decisions, as has been advocated by finance scholars, in order to take investor preferences into account (see e.g. Fama and French 2007)

The double hurdle proposes making a change to the tobit likelihood function such that both the binary nature and the degree of the decision are taken into account. The likelihood function proposed by Tobin (1958) is as follows:

$$\boldsymbol{f(y|x)} = \left\{\mathbf{1} - \boldsymbol{\Phi}\left(\frac{\boldsymbol{x_1\beta}}{\boldsymbol{\sigma}}\right)\right\}^{\mathbf{1}(y=\mathbf{0})} \left[\boldsymbol{2\pi}^{-\frac{1}{2}}\boldsymbol{\sigma}^{-\mathbf{1}}\boldsymbol{e}^{\frac{-(y-x_1\beta)^2}{2\sigma^2}}\right]^{\mathbf{1}(y>\mathbf{0})} \tag{2.1}$$

where $\boldsymbol{\Phi}$ is the standard normal cumulative distribution function and exponential indicator functions are $\mathbf{1(y=0)}$ and $\mathbf{1(y>0)}$. The four values of interest after fitting the tobit model are: for any observation $\mathbf{i}$, the probability that $\mathbf{y}$ is zero, $\mathbf{P(y_i = 0|x_i)}$, the probability that $\mathbf{y}$ is positive, $\mathbf{P(y_i > 0|x_i)}$, the expected value of $\mathbf{y}$, conditional on $\mathbf{y}$ being positive, $\mathbf{P(y_i|y_i > 0, x_i)}$, and the unconditional expected value of $\boldsymbol{y}$, $\mathbf{E(y_i|x_i)}$. This information allows for the estimation of the effect of explanatory variables on the probability that $\mathbf{y > 0}$, and captures the binary nature of the process.

In order to capture the degree hurdle of the process, Cragg (1971) proposes the following likelihood function, an extension of equation (2.1):

$$\boldsymbol{f(w,y|x_1,x_2)} = \{\mathbf{1} - \boldsymbol{\Phi(x_1\gamma)}\}^{\mathbf{1}(w=\mathbf{0})} \left[\boldsymbol{\Phi(x_1\gamma)(2\pi)}^{-\frac{1}{2}}\boldsymbol{\sigma}^{-\mathbf{1}} \frac{\boldsymbol{e}^{\frac{-(y-x_2\beta)^2}{2\sigma^2}}}{\boldsymbol{\Phi}\left(\frac{\boldsymbol{x_2\beta}}{\boldsymbol{\sigma}}\right)}\right]^{\mathbf{1}(w=\mathbf{1})} \tag{2.2}$$

where $\boldsymbol{w}$ is a binary indicator equal to 1 if $\boldsymbol{y}$ is positive and 0 otherwise. In Cragg's model the probability of $\boldsymbol{y > 0}$ and the value of $\boldsymbol{y}$, given $\boldsymbol{y > 0}$, are determined by different mechanisms than in the tobit model, designated by the $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ coefficients. Nonetheless, the tobit model (eq. 1) is nested within the Cragg version (eq. 2). This becomes apparent if $\boldsymbol{x_1 = x_2}$ and $\boldsymbol{\gamma = \beta/\sigma}$, which causes both versions to become identical[15]. The benefit of Cragg's extension is that it places no restrictions on $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$, which allows for the binary and degree steps of the decision to be modeled by different vectors of coefficients ($\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$).

In this study, the $\boldsymbol{\beta}$ vector of coefficients explains the participation component of the trading decision, and quantifies the relationship between X, the vector of risk behavior

[15] See Wooldridge (2010) for a discussion of the double hurdle model as well as other alternatives to the tobit model.

variables (X=[RA, RP, IRAP]), and the probability of making a trading decision. The $\boldsymbol{\gamma}$ vector of coefficients explains the degree component of the trading decision, and quantifies the relationship between Z, the vector of behavioral and demographic explanatory variables (Z = [RA, RP, IRAP, AGE, SEX, INCOME]), and the degree of riskiness of the participation decision. Kalogeras (2010) reports that the parameterization of the first and second hurdle must be related, but not identical. This condition is satisfied by including the demographic variables only in the second hurdle (see the Z vector), in accordance with the vast marketing literature that verifies the relationship between demographics and consumer preferences.

In addition, survey responses are treated as endogenous using the standard procedures proposed by Mundlak (1978) and Chamberlain (1984) because survey response rates are related to trading frequency, thus causing error terms to correlate with explanatory variables[16]. The resulting model specification is shown below as two hurdles[17]:

Hurdle 1: $\boldsymbol{Pr}(\boldsymbol{y_{it}}|\boldsymbol{X_{it}}, \boldsymbol{AEX}, \boldsymbol{\alpha_i}) = \boldsymbol{\Phi}(\boldsymbol{\beta X_{it}} + \boldsymbol{\alpha_i} + \boldsymbol{\tau}\, \boldsymbol{AEX_t} + \boldsymbol{u_{it}})$

where $\boldsymbol{\alpha_i} = \boldsymbol{\lambda \bar{X}_i} + \boldsymbol{\epsilon_i}$

Hurdle 2: $\boldsymbol{y_{it}} = \boldsymbol{\gamma Z_{it}} + \boldsymbol{\alpha'_i} + \boldsymbol{\mu}\, \boldsymbol{AEX_t} + \boldsymbol{v_{it}}$

where $\boldsymbol{\alpha'_i} = \boldsymbol{\omega \bar{X}_i} + \boldsymbol{\delta_i}$

The dependent variable $\boldsymbol{y_{it}}$ is the monthly censoring dependent variable, equal to the average characteristic-based riskiness score of all traded common stocks by investor i month t, and equal to zero for investors that do not trade. The t scripts are included as a matter of addressing endogeneity, however it should be noted that the model is estimated as a cross-sectional regression, as is shown in (2.2), and not as a time series regression – each “investor month” is treated as an independent observation.

The model is estimated a total of twelve times: once for each of the 6 characteristic-based riskiness scores for investors who decide to participate by way of common stock purchases, and then for each of the 6 characteristic-based scores for investor sales. The

[16] According to the Mundlak-Chamberlain approach, correlation between the error term and the explanatory variables (e.g. endogeneity) can be permitted in a model by assuming a relationship between the error term and the means of the endogenous explanatory variables over time (in our case this is equivalent to which is equivalent to $\boldsymbol{\alpha_i} = \pi \bar{X}_i + \epsilon_i$ and where ϵ_i is independent of X_{it} and of u_{it} for all i, t)

[17] The regressions are run simultaneously using the double hurdle form by including the adjustments for endogeneity in the *X* and *Z* vectors directly.

variables are standardized meaning that coefficients are calculated as changes in the dependent variable per standard deviation of the independent variable. Once the parameter estimates have been computed, we calculate the predicted values for each observation and take their mean to arrive at average partial effects (APEs) for each parameter. However, the standard deviation of these partial predicted effects cannot be used to calculate statistical significance of the APEs because they describe only the data, and not the parameter estimates. For inference, we thus resort to bootstrapping the APEs: re-estimating the model and generating new APEs on a random subsample within the data for 300 iterations. We then use the standard deviation from those subsample APEs as the standard error for the full sample APEs, which allows us to calculate reliable *p*-values.

5. Results

The results for the volatility, momentum, size, age, brand value, and external financing models of the purchase-decision double-hurdle models are shown in Table 2.7, and the equivalent for the sale-decision double-hurdle models are shown in Table 2.8. The tables exhibit the bootstrapped APEs and standard errors the behavioral variables (X = [RA, RP, IRAP]) and the control variable AEX in Hurdle 1, and for the behavioral and demographic variables (Z = [RA, RP, IRAP, AGE, SEX, INCOME]) and the control variable AEX in Hurdle 2. The controls for endogeneity are left out to conserve space.

5.1. Purchase Decisions

5.1.1. Hurdle 1: Participation decision

Table 2.7 Panel A shows that RA and IRAP exhibit large effects on the probability that investors will make a purchase in a given month, but that these effects depend on the characteristic used to quantify the riskiness of the shares purchased. Although, we would expect changes in the AEX to have a large impact on the probability of investor purchases, the size of the APE for the AEX is only economically significant for large changes in the AEX (to the order of 1/100th of a decile for each point change in the AEX), but only exhibits statistical significance for the characteristics associated with stock prices (volatility, momentum, and size by way of market capitalization). Compared to the effects of the AEX, the APEs of RA and IRAP are relatively large and show that small changes in RA and IRAP can lead to relatively large effects on the probability of purchasing in a given month.

		Volatility	Momentum	Size	Firm Age	Brand Value	External Financing
Hurdle 1: Probability of a Common Stock Purchase Decision in a Given Month (probit estimator)							
RA	*coef*	0.15***	0.15***	0.15***	0.09**	0.06**	0.06*
	st.err.	0.04	0.04	0.05	0.04	0.03	0.03
RP	*coef*	-0.00	-0.01	-0.00	0.00	0.01	0.01
	st.err.	0.02	0.02	0.01	0.02	0.01	0.01
IRAP	*coef*	-0.11***	-0.11**	-0.11**	-0.05	-0.03	-0.03
	st.err.	0.04	0.05	0.04	0.03	0.03	0.04
AEX	*coef*	0.00***	0.00***	0.00***	0.00	0.00	0.00
	st.err.	0.00	0.00	0.00	0.00	0.00	0.00
obs		1648	1648	1648	1648	1648	1648
Hurdle 2: Riskiness of Stocks Purchased by Stock Characteristic (truncated normal estimator)							
RA	*coef*	0.22*	-0.16	0.06	0.07	-0.16*	0.15
	st.err.	0.12	0.14	0.10	0.12	0.09	0.09
RP	*coef*	-0.02	-0.02	-0.00	-0.02	-0.00	0.01
	st.err.	0.05	0.04	0.03	0.05	0.03	0.03
IRAP	*coef*	-0.19*	0.15	-0.02	-0.03	0.17*	-0.14*
	st.err.	0.10	0.11	0.08	0.12	0.09	0.08
AEX	*coef*	-0.00***	0.00***	-0.00*	0.00	0.00*	-0.00
	st.err.	0.00	0.00	0.00	0.00	0.00	0.00
Age	*coef*	-0.00	0.00	-0.00	0.00	-0.00	-0.00
	st.err.	0.00	0.00	0.00	0.00	0.00	0.00
Gender	*coef*	-0.12	0.15	0.15	0.31*	-0.01	0.09
	st.err.	0.09	0.15	0.10	0.18	0.09	0.10
Income	*coef*	0.01*	-0.00	-0.01**	-0.01	0.00	0.00
	st.err.	0.00	0.00	0.00	0.01	0.00	0.00
obs		286	286	286	286	286	286
Double-Hurdle Regression Model Statistics							
Sigma		2.57***	3.01***	2.02***	2.74***	2.05***	1.93***
Log-Likelihood		-1384.83	-1310.50	-1325.01	-1182.29	-885.02	-871.21
P>ChiSq		0.00	0.00	0.00	0.00	0.00	0.00
Pseudo R-sq		0.04	0.04	0.03	0.02	0.02	0.03

Table 2.7: Double-Hurdle Model of Factors Influencing the Common Stock Purchase Decisions of Individual Investors

The dependent variable in each column is the characteristic-based riskiness score. The explanatory variables shown are bootstrapped Average Partial Effects and standard errors; the adjustments for endogeneity are included in both hurdles but are not shown. In terms of the first hurdle, which shows the influence of RA, RP, and IRAP on the probability of a purchase in a given month, the table shows that RA influences the probability of a purchase in a given month to the extent of 15% per unit increase for price-based characteristics (volatility, momentum, and size), and slightly smaller effects for firm age, brand value, and external financing. IRAP is also shown to influence the probability of making a purchase to the extent of -11% for price-based characteristics. Hurdle 1 results mean that investors seek more risk by purchasing more, but investors cope with increased stock market risk by purchasing less. The results in hurdle 2 show that RA, RP, and IRAP exhibit no discernible pattern of influence on the riskiness of the purchases.

The estimated APE of a one unit increase in RA increases the probability of purchasing a common stock by 15%, when common stock riskiness is measured using volatility, momentum, or size. When the stocks' riskiness is measured using firm age, brand value, or external financing, a one unit increase in RA will increase the probability of an investor's purchase by 9%, 6%, and 6%, respectively. To put these results into perspective, RA is measured on a 7-point scale, hence, when measuring riskiness using volatility, an investor at the top of the RA scale is 105% more likely to make a common stock purchase than an investor at the bottom of the RA scale *ceteris paribus*. Table 2.7 Panel A also supports the importance of IRAP as a driver of common stock purchase decisions, although the APEs for IRAP are only significant for volatility, momentum, and size. A one unit increase in investor IRAP results in an 11% decrease in the probability of purchasing common stocks in a given month. Given that the IRAP scale is 37 points wide, a high IRAP investor is predicted to be 4 times less likely (407%) than a low IRAP investor to purchase common stocks *ceteris paribus* (if the stocks are characterized by volatility, momentum, or size).

One counterintuitive result is that the APE for RA exhibits the opposite sign than that of IRAP. Table 2.7 Panel A shows that RA is positive, meaning that increases in RA result in the higher probability of a purchase, but IRAP is negative, meaning that increases in IRAP relate to decreases the probability of purchasing. This is counterintuitive because if IRAP (the product of RA and RP) increases, then so should risk seeking behavior. Although RP exhibits no direct effect on the probability of purchasing, the variation in RP may be captured by the IRAP term, thus exerting an indirect effect on the probability of purchasing through its interaction with RA. If this is the case, and IRAP increases lead to decreases in purchases – then how are investors expressing their intent to cope with their increased risk exposure? Two alternative explanations are possible: either investors sell more safe stocks or altogether trade less. From Table 2.8 Panel A, we deduce that investors trade less because RP is negatively related to common stock sales (which we discuss in more detail in section 4.2.2).

5.1.2. Hurdle 2: Degree of Riskiness

Table 2.7 Panel B shows the APEs of RA, RP, IRAP, age, gender, and income on the average riskiness of investors' purchases in a month as measured by volatility, momentum, size, firm age, brand value, and external financing of the shares they purchase. The most notable result is that no consistent pattern is discernible – the influence of behavioral or demographic variables on the riskiness of purchases depends on the characteristic used to measure riskiness. In terms of statistical significance, the variable that exerts the most consistent effect on the riskiness investors' purchase is the AEX. The findings suggest that there is a high degree of heterogeneity amongst the drivers of investor preferences beyond RA, RP, IRAP, age, gender, and income. Below, we examine the variables that do exhibit relationships to the characteristics examined here; below we discuss the results parameter by parameter.

RA exhibits statistically significant APEs for decile risk scores based on volatility and on firm age. The coefficient signs are consistent with what we expect: as RA increases by one unit, the volatility decile purchased increases by 0.22 and the age decile decreases by -0.16. This means that as RA increases and investors become more risk seeking, they purchase more volatile and younger stocks, both of which are considered to be increases in riskiness. These effect sizes are relatively small given that the risk scores are between 1 and 10: the model estimates that an investor with the lowest possible RA (-3) would thus purchase stocks with a volatility score 1.54 points higher, and a firm age score 1.12 points lower than investors with the highest RA (+3).

Although the results show that the APE of RP on the riskiness of shares purchased is not statistically different than zero for any characteristic, the variation in RP exerts an indirect effect on the riskiness of purchases when characterized by volatility, brand value, and external financing. The results show that an increase in IRAP results in a -0.19 point decrease in the volatility decile score, a 0.17 point increase in the brand value score, and a -0.14 point decrease in the external financing score. These APEs are quite large given that the IRAP scale is 37 points long: the difference in volatility, brand value, and external financing scores purchased by the lowest IRAP investors (-18) and highest IRAP investors (+18) is 7.03, 6.29, and 5.18 points respectively. The reported signs of the APEs show that the increase in IRAP does not result in an increase in the riskiness of the characteristics purchased: the volatility score decreases and the brand value score increases – these reflect safer purchases. The external financing score is negatively related to IRAP, which is what we would expect from investors intending to increase their risk exposure.

The APEs reported for the AEX on riskiness also show the contradictory signs, as well as small coefficients. The effect of AEX on riskiness is statistically significant for volatility, momentum, size, and brand value-based scores, but in terms of economic significance, the AEX would have to change by at least 100 points (which would be an approximate[18] change of 30%) for risk scores to increase by 0.10. In terms of APE signs, the results show that when the AEX increases, investors purchase safer stocks in the case of volatility, momentum, and brand value scores. Meanwhile, the AEX is negatively related to purchased size scores, indicating riskier purchases when the AEX increases.

The demographic parameters exhibit very few statistically significant effects, and the effect sizes are small. Age exhibits no effect on the riskiness of stocks purchased, and gender shows a small difference between men and women. Men are shown to purchase firm age deciles 0.31 points higher than women, meaning that in our sample, men purchase slightly older and safer shares than women. Income is the demographic variable that exhibits the most statistically significant effects. When explaining volatility and size risk scores, income exhibits the signs we expect, the effect sizes, however, are negligible. As investor' income increases by 1000 Euros, the volatility scores they purchase increase by 0.01 and the size scores decrease by 0.01, which means that investors with higher incomes purchase slightly riskier shares.

Taken together, it is difficult to generalize any of the results in Table 2.7 Panel B concerning the degree component of the purchase decision. The table suggests that, in terms of the simultaneous hurdles of the purchase decisions, RA and IRAP influence the participation hurdle, but that the examined behavioral and demographic variables do not influence the degree hurdle.

[18] As of March 2013, the AEX stands at 350 points.

5.2. Sale Decisions

5.2.1. Hurdle 1: Participation decision

Table 2.8 Panel A shows that RP exhibits a consistent effect on the probability that investors will make a common stock sale in a given month, regardless of the characteristic used to quantify the riskiness of the shares sold. The estimated APE of a one unit increase in RP decreases the probability of purchasing a common stock by 3%. To put these results into perspective, an investor at the top of the RP scale is 21% less likely to make a common stock purchase than an investor at the bottom of the RP scale *ceteris paribus*. This result means that as investors feel exposed to greater stock market risks, they are less likely to sell common stocks. This result presents more evidence to support the loss aversion documented by Odean (2002) and Tversky and Kahneman (1979) because as investors feel exposed to more risks, they are less likely to sell shares (and thus realize losses).

		Volatility	Momentum	Size	Firm Age	Brand Value	External Financing
Hurdle 1: Probability of a Common Stock Sale Decision in a given month (probit estimator)							
RA	*coef*	0.03	0.04	0.03	0.02	0.00	0.00
	st.err.	0.04	0.04	0.04	0.03	0.03	0.03
RP	*coef*	-0.03**	-0.03**	-0.03**	-0.03***	-0.03**	-0.03***
	st.err.	0.01	0.01	0.01	0.01	0.01	0.01
IRAP	*coef*	-0.02	-0.03	-0.02	-0.02	-0.01	-0.01
	st.err.	0.03	0.03	0.03	0.03	0.02	0.02
AEX	*coef*	-0.00**	-0.00**	-0.00*	-0.00	-0.00	-0.00
	st.err.	0.00	0.00	0.00	0.00	0.00	0.00
obs		1648	1648	1648	1648	1648	1648
Hurdle 2: Riskiness of Stocks Sold by Stock Characteristic (truncated normal estimator)							
RA	*coef*	-0.03	0.13	0.07	-0.04	0.09*	0.10*
	st.err.	0.13	0.13	0.08	0.14	0.05	0.05
RP	*coef*	0.07	-0.07**	-0.01	0.01	-0.00	-0.01
	st.err.	0.05	0.03	0.03	0.03	0.02	0.02
IRAP	*coef*	0.06	-0.22**	-0.05	0.07	-0.05	-0.13**
	st.err.	0.13	0.10	0.07	0.13	0.04	0.05
AEX	*coef*	-0.00*	0.00	0.00	-0.00	0.00	0.00
	st.err.	0.00	0.00	0.00	0.00	0.00	0.00
Age	*coef*	-0.00	0.00**	0.00	0.00	-0.00	0.00
	st.err.	0.00	0.00	0.00	0.00	0.00	0.00
Gender	*coef*	-0.01	-0.00	0.10	-0.08	0.03	-0.01
	st.err.	0.09	0.08	0.07	0.07	0.06	0.06
Income	*coef*	0.00	0.00	0.00	0.00	-0.00	0.00
	st.err.	0.01	0.01	0.00	0.01	0.00	0.00
obs		167	167	167	167	167	167
Double-Hurdle Regression Model Statistics							
Sigma		3.13***	2.76***	2.00***	2.43***	1.50***	1.66***
Log-Likelihood		-922.45	-886.36	-872.66	-793.70	-587.92	-610.10
P>ChiSq		0.01	0.01	0.01	0.00	0.06	0.03
Pseudo R-sq		0.03	0.04	0.03	0.02	0.04	0.03

Table 2.8: Double-Hurdle Model of Factors Influencing the Common Stock Sale Decisions of Individual Investors

The dependent variable in each column is the characteristic-based riskiness score. The explanatory variables shown are bootstrapped Average Partial Effects and standard errors; the adjustments for endogeneity are included in both hurdles but are not shown. In terms of the first hurdle, which shows the influence of RA, RP, and IRAP on the probability of a sale in a given month, the table shows that RP influences the probability of a purchase in a given month to the extent of -3% per unit increase for all examined characteristic-based risk scores. Hurdle 1 results mean that as investors feel subjected to more stock market risk they sell less. This is evidence of loss aversion behavior. The results in hurdle 2 show how RA, RP, and IRAP influence the riskiness of the sales, but no discernible pattern is found, and statistical and economic significance are negligible, with the exception of momentum.

The AEX is shown to exhibit an inverse relationship to the probability of selling, so as the index increases, investors sell less. The size of the APE for the AEX is only economically significant for large changes in the AEX (to the order of 1/100th of a decile for each point change in the AEX), and only exhibits statistical significance for the characteristics associated with stock prices (volatility, momentum, and size).

5.2.2. Hurdle 2: Degree of Riskiness

Just as was the case with the riskiness of purchases, the riskiness of sales shown in Table 2.8 Panel B exhibits no general relationship to risk behavior or demographics. In particular, some explanatory variables relate to the riskiness of common stock sales when measured using momentum, brand value, and external financing-based riskiness scores. RA for example exhibits a positive relationship with the riskiness of shares traded when measured by brand value and external financing; this means that as investors' seek more risk (RA increases), they sell shares with greater brand value and external financing. This is an expected result because selling safe (high brand value, high external financing) firms increases the average riskiness of the portfolio. In terms of effect sizes, as RA increases by one unit, the brand value and external financing scores increase by 0.09 and 0.10 points respectively, which is a difference of 0.63 points and 0.70 points between the lowest and highest RA investors and is a relatively small effect.

Table 2.8 Panel B also shows RP to be negatively related to the momentum decile sold, where a one unit increase in RP results in a 0.07 point lower momentum score - which is a maximum change of 0.49 points from lowest RP to highest RP. Although the effect size is small, it is also in the direction we expect: when investors feel exposed to more stock market risk, the model predicts that they decrease their risk, as measured by momentum. This is also the case with IRAP, which also exhibits a significant effect on the momentum scores of the shares sold. An increase of one unit of IRAP results in a 0.22 point decrease in the momentum decile of stocks sold, or a difference of 8.14 points out of 10 between the scale endpoints of IRAP. However, the model also shows that a one unit increase of IRAP exhibits an APE of -0.13 on the external finance score of shares sold (a difference of 4.81 between highest and lowest IRAP measures). This result means that as investors intend to cope with greater stock market risks, they will sell riskier shares (in terms of external financing), which decreases their risk exposure - thus the sign of the IRAP APE for external financing is contrary to what we would expect. Finally, investor age also exhibits a statistically significant effect, but it is negligible.

The double-hurdle models used to explain the sale of common stocks based on risk behavior and demographics show that RP exhibits a negative relationship to the probability of selling. The other variables exhibit little or no effect (with the exception of momentum).

6. Discussion and Conclusion

This chapter is the first to examine individual investors purchase and sale decisions directly instead of the market outcomes or performance that they result in. By doing so we are able to contribute to the literature by focusing on the decisions proper as well as the investment preferences of investors. The investment decision consists of two simultaneous components: the first is to participate in the market and the second is the degree of risk to undertake. We base our analysis on the psychometric adaptation of the Pratt-Arrow framework, and therefore explain investor purchases with their risk attitude (RA), their risk perception (RP), and the interaction of RA and RP (IRAP) which represents the Pratt-Arrow coefficient of risk aversion. We discover that RA and IRAP drive purchase decisions, and that RP drives sale decisions. In addition, we find that the effect of RA and IRAP on the probability of purchases is much greater than the effect of RP on the probability of purchases. However, we find that no distinct pattern emerges when attempting to explain the degree of risk investors choose to undertake with their trades.

The study is nonetheless faced with several limitations. The first of which is the sample period which is particular because it is in the middle of a financial crisis. Another limitation is that our research design does not take into account assets other than common stocks that investors may own, and use to cope with stock market risk. Another drawback from this research is the low R^2 of the models. Although RA, RP, and IRAP explain purchase and sale decisions well, the poor model fit is due to the fact that RA, RP, IRAP and demographics poorly explain “second-hurdle” degree decisions and leads us to believe that other factors drive this degree decision such as preferences and herding behavior. The takeaway from these results is that investor preferences are driven by other variables – and the vast literature on consumer choice reflects the fact that many different combinations of affective determinants of choice and firm characteristics determine what investors purchase.

The findings have three implications. The first and most important is that the latent behavior behind purchases and sales is different. This is important because many market participants such as brokers, investment advisors, and investment relationship managers must rely on effective communications strategies to exercise their professions. Market participants who wish to communicate recommendations to their clients can take advantage of the findings presented here to effectively communicate to their clients that it is the time to buy or sell. Influencing investors purchase decisions requires a discussion that influences RA. Such a discussion involves changing the investors' attitude towards risk, and thus involves convincing investors that they like risk or that they do not dislike risk, thus the object of discussion is the investor. Convincing an investor they need to sell means influencing their RP, and thus discussing the size of the risks that exist, the topic of discussion must therefore be the risks being perceived. An effective communication strategy thus involves presenting evidence to investors that influences both their RA and RP. This is also valid for regulatory institutions such as central banks that may need to urgently communicate to investors that they must stop buying or stop selling.

The second implication is that investment professions that would like to influence investors' choice of stocks must present evidence beyond the risk related characteristics of the investment products they sell. Firms exhibit many additional qualities than those that are primarily financially related and may cater to the particular preferences of investors. Such qualities may derive from the corporate culture of the firm, which may exhibit a strong sense of corporate social responsibility or promote environmental causes. Some firms are highly associated with innovation and the excitement of developing fashionable new technologies (such as Apple with the iPod, or Google with its Google Glass computerized eyewear). Investors who wish to participate in the stock market are likely to consider purchasing or selling firms that cater to their personal preferences, which may be vast, complex, and dynamic.

The third implication of this study relates to future research: the measurement methodology used in this study relies on a vast literature that supports the relationship between survey-based measurements of affect and decisions. The importance of affect in decision making, combined with the data-rich environment of financial economics provides the perfect environment for making quantitative analyses of judgment and decision behavior. The future of affect thus holds tremendous promise in the field, and supports the development of a public and standardized affective measurement system. We show that RA and RP relate to the “trigger” of the trading decision, but an extended database might help determine which affective factors drive investor “target” of the trading decision.

In conclusion, future research into a ‘soft’ database would greatly complement the ‘hard’ database commonly used by financial economists, which would provide useful information to market participants, researchers, and regulators about the decisions being made in the market place in addition to their outcomes.

Chapter 3

Nuancing Market-Based Assets: Customer Satisfaction vs. CSR in the face of Changing Investor Sentiment

Abstract: Previous research demonstrated that customer satisfaction is a market-based asset that contributes value to the firm. Prior work also shows that, in addition to directly driving a firm's market value, market-based assets influence stakeholders' expectations concerning firm value. This suggests that by managing market-based assets, managers can influence the expectations of their firm's stakeholders. The current study proposes that a particular promising way for firms to strategically manage their market-based assets is to undertake actions to improve customer satisfaction during periods of high investor sentiment. Customer satisfaction is found to provide a buffer of stakeholder expectations that protects a firm's share price from being negatively affected by stock-market corrections. In particular, we find that firms with higher (lower) levels of customer satisfaction exhibit smaller (greater) price corrections and higher returns after periods of high investor sentiment. The research reveals on surprising result however: Corporate Social Responsibility (CSR), a determinant of customer satisfaction may act as a catalyst of a firm's stock price instead of a buffer in the face of popping stock price bubbles.

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1. Introduction

During the 2008 – 2009 financial crisis and subsequent European debt crisis, many firms' stock prices varied without any new fundamental information. The stock price jumps were well received by firm managers, but the following corrections were sometimes precipitous enough to worry shareholders. As a result, managers may wish to take steps that would protect their firm's share price from falling because of sentimental, non-fundamental information. This study documents that firms can use the affective reactions of their customers - customer satisfaction - as a buffer against sentimental price movements that reduces the negative impact of stock-market corrections on a firm's value.

Customer satisfaction is a well-documented intangible asset based. Existing research by Fornell, Mithas, Morgeson III, and Krishnan (2006) shows that firms with satisfied customers have higher returns, yet do not exhibit higher risks. High-return, low-risk assets, such as customer satisfaction, arise from interactions with individuals and entities from the firm's environment and are called market-based assets. Srivastava, Shervani, and Fahey (1998) indicate that such assets may be leveraged to contribute value to the firm, reduce cash-flow volatility, and reduce cash-flow vulnerability. Investments in customer satisfaction lead to greater brand and customer equity, increase a firm's customer base and retention, and thus also increase expected future revenues (Rust, Ambler, Kumar, and Srivistava 2004). Empirical findings generally support the positive relationship between customer satisfaction and good economic performance (Anderson 1996; Anderson, Fornell, and Lehmann 1994; Anderson, Fornell, and Mazvancheryl 2004; Bolton 1998; Fornell 2001; Ittner and Larcker 1998; Rust, Moorman, and Dickson 2002). Hence, Fornell et al. (2006) conclude it is possible for investors to beat the market consistently by investing in firms that score well on the American Customer Satisfaction Index (ACSI). This finding was recently supported and extended by Tuli and Bharadwaj (2009), who provide evidence that customer satisfaction is negatively correlated with a firm's market risk, idiosyncratic risk, and downside risk.

For managers, however, investments in customer satisfaction are typically constrained by resource demands in other areas of the firm. Managers are thus forced to choose whether and when to make investments in customer satisfaction. In this study, we argue and empirically show that strategically timing investments in customer satisfaction can help firms reduce the risk associated with broad waves of investor sentiment. Well-timed customer service investments benefit the firm by improving interactions with customers (in terms of retention and base), but also take advantage of reductions in downside and systematic risk, the very risk that is problematic during periods of high investor sentiment. Customer service investments thus serve to protect firms from drops in firm share prices that result from systematic (market-wide), non-fundamental (sentimental) sources. Such a strategy maximizes the effectiveness and usefulness of firms' customer service investments.

2. Literature Review

2.1. The Benefits of Managing Market-Based Assets

Market-based assets are assets whose value arises from interactions with parties outside the firm such as customers, suppliers, and investors (Srivastava 1998). Recent research supports the active management of these market-based assets, but because of the fluid and intangible nature of such relationships, this is not a straightforward affair (Lev 2001). Nonetheless, regulators, professionals, and investors have recognized the necessity of managing market-based assets and have made this explicit (Hanssens, Rust, and Srivastava, 2009). Investor relations departments have become standard departments that ensure communication and marketing activities and maintain relationships between a firm and its investors. Their importance has been reinforced by legislation (such as Sarbanes-Oxley) and the progression of investor relations professional associations in many countries since the early 2000s (Rao and Sivakumar 1999). In discussing the complexity of managing market-based assets, Srivastava, Shervani, and Fahey (1997) also lay out the resulting benefits including the development of new products, the attraction of new customers, and the increase of product differentiation. Ultimately, these consequences of managing market-based assets lead to increased cash flows, and thus contribute to the value of the firm.

The relative complexity of marketing measures, however, masks the clear link between marketing activities, those that are most closely associated with the management of market-based assets (such as customers, brands, channels, and innovations), and the firm's share price. This link can take two forms (Aksoy, Cooil, Groening, Keiningham, and Yalcin 2008; Gruca and Rego 2005). First, marketing activities can change the expectations of investors in terms of a firm's future cash flows. Second, marketing activities can influence traditional accounting (e.g. margins) and finance metrics of firm value (e.g. book-to-market ratios). The latter link is intuitive because managing customers, brands, channels, and innovations likely creates value for the firm. The former link suggests that managing market-based assets is also capable of influencing the perceptions and interpretations that stakeholders have of the firm (Hanssens et al. 2009). The risk that these perceptions and interpretations change for any reason other than fundamental information is referred to by finance scholars as non-fundamental risk (Shefrin 2008). Market-based assets thus relate to sentimental asset prices because of their ability to influence stakeholder beliefs and expectations.

2.2. Managing Firm Exposure to Investor Sentiment

Investor sentiment is generally defined to encompass market over- and under-reactions to information, causing prices to behave in ways that are not supported by fundamental information. Reasons for investor sentiment have been related to behavioral biases and heuristics as well as to uninformed, excited, and trend-following investors (Shefrin 2008). Overall, investor sentiment represents the forces that push prices away from their efficient fundamental values. Standard theoretical treatments of investor sentiment consider it exogenous to price formation. It is thus often regarded as an external influence on an otherwise independent pricing process. While no uncontroversial measure of investor sentiment exists, investor sentiment remains an important foundation of behavioral finance and recent empirical work shows that periods of abnormally high investor sentiment are typically followed by market corrections (Baker and Wurgler 2006; 2007).

For managers as well as investors, the challenge of sentimental price behavior lies in extracting benefit from the momentous, sentiment-driven increases in stock prices, while protecting oneself from the imminent stock-price corrections. While the investor sentiment literature discusses how investors and investment firms exhibit herd-like behavior (and try to "find the greater fool") (Brunnermeier and Nagel 2004), few studies examine the behavior of managers at firms whose stock prices are subject to sentimental stock price movements. Shleifer and Vishny (2003) relate periods of high investor sentiment to waves of acquisitions, showing that managers are more likely to make an acquisition during periods of high sentiment. Research by Ali and Gurun, (2009) suggests that managers of small firms increase their amount of accruals during periods of high sentiment. These two studies show that management behavior is, for better or worse, affected by sentiment in stock markets. Managers who do not recognize periods of high sentiment may thus risk to be caught off-guard by large stock-market corrections. The classic case of highly sentimental periods, as described by Minsky (in Kindleberger 1989), is that economic actors believe that good times will continue "forever" (i.e., long enough for them to get caught off-guard). For managers who recognize that high periods of investor sentiment are unsustainable, they must take action to protect the firm's share price from an imminent market correction. One standard defensive strategy is to keep relatively large sums of cash on the firm's balance sheet. This provides flexibility to managers who then have resources to act when its share price declines. One example of management actions that benefit from sentimental periods is to sell treasury stock when stock prices are overvalued (e.g., when investor sentiment is highly positive) and repurchase the stock after the market correction. This strategy, however, is risky and depends greatly on the ability of the firm to correctly time such sales and purchases of treasury stock.

As an alternative, firms can manage the characteristics of their firm as appearing in their financial reports. Baker and Wurgler (2006), for example, show that firms with different balance-sheet and income-statement characteristics are affected differently by changes in investor sentiment. For example, firms with a high proportion of external financing, are less exposed to investor sentiment than firms that finance projects internally. Thus, firms have the option to manage their financial structure such that they have a lower susceptibility to sentimental stock price effects. In the case of external financing, managers may decrease the relative proportion of external financing to internal financing. However, effectively managing the relative proportions of a firm's financial structure takes time, and may require sacrificing growth opportunities (e.g., when reducing external financing).

In terms of facing sentimental markets, market-based assets provide a different alternative: firms can manage the subjective expectations of market participants, which constitutes the cause of sentimental pricing to begin with (Shefrin 2008). Customer satisfaction is a direct measure of such subjective (customer) experiences.

2.3. Customer Satisfaction and the Stock Market: A Review

Customer satisfaction's relationship with stock prices is extensively documented thanks to the public availability of the American Customer Satisfaction Index (ACSI). Johnson, Fornell, Anderson, Cha, and Bryant (1996) developed the ACSI framework (shown in Figure 3.1), the drivers of which include three constructs: customer expectations, perceived quality, and perceived value. Customer expectations designate customer repurchase likelihood. Perceived quality is a post-purchase measure directed at quantifying reliability and customization achieved by the company's product. Perceived value gauges customers' quality assessments relative to the product price. Johnson et al. (1996) also show that the customer satisfaction index is positively related to customer repurchase intentions and loyalty. Since their seminal study in 1996, many other studies using the ACSI have been published and represent the core of the large body of work performed on customer satisfaction and its importance to firms in terms of customers (Luo and Bhattarchaya 2006; Gustafsson, Johnson, and Roos 2005), employees (Nishii, Lepak, and Schneider 2008; Evanschitzky, Groening, Mittal and Wunderlich 2011; Luo and Homburg 2007), and investors (Ali and Gurun 2009; Fornell et al. 2006; Anderson and Mansi 2009; Aksoy et al. 2008).

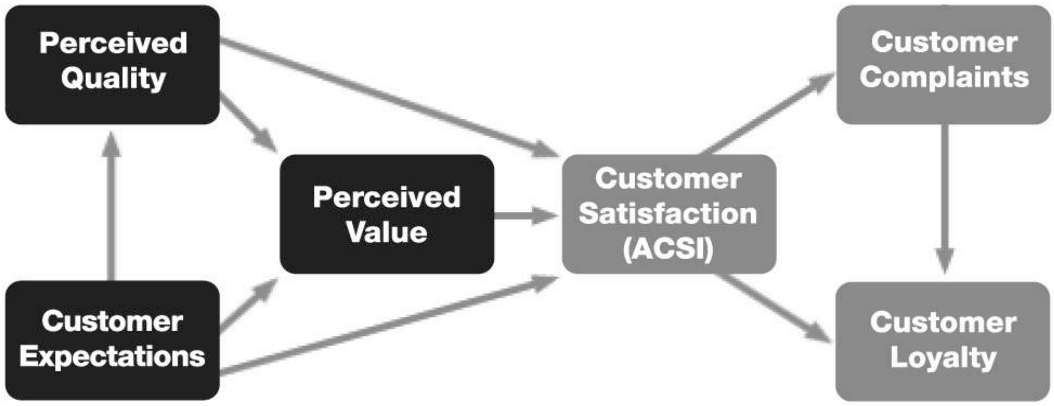

Figure 3.1: The American Customer Satisfaction Index Model (ACSI) adapted from Fornell et al. (1996)

As pointed out by Hanssens, Rust, and Srivastava (2004), market-based assets such as customer satisfaction contribute to firm value in two possible ways. First, they intrinsically create value for the firm. Second, they influence the perceptions of stakeholders, who in turn perceive higher firm value and associate the firm with lower risks. Much of the recent research on customer satisfaction has examined the direct financial payoffs of investments in customer satisfaction. Fornell et al. (2006), for example, show that investments in stocks of companies with high customer satisfaction earn high returns with low risk, contradicting the fundamental notion that higher risks must be compensated by higher returns. Their findings show that an increase of one percent in the ACSI rating translates into a 4.6% increase in market value of the firm, and that investors react to reported changes of customer satisfaction. The authors also report that, for the period 2000 to 2004, a portfolio scoring high on the ACSI measure gained 75%, compared with a loss of 19% for the S&P 500 as a whole. Meanwhile, the beta on such portfolios was reported to be 0.78, which means the ACSI portfolio is less risky than the market.

The question that arises is whether investors are misunderstanding the value of customer satisfaction and are consequently undervaluing these firms, resulting in their subsequently high returns for the betas they exhibit. Using the CAPM, the Fama-French

(1993; 1996) three-factor model, and the Carhart (1997) four-factor model, Aksoy et al. (2008) confirm that trading based on the ACSI information leads to risk-adjusted abnormal returns. The authors confirm that high-satisfaction portfolios perform better than predicted for their levels of risk, and support that investors initially underestimate the value created through satisfying customers and that stock prices adjust over time. Evidence of investors having incorrect reactions to intangible information, such as customer satisfaction, has also been documented by finance scholars such as Daniel and Titman (2006), who argue that investors' reaction to tangible information is efficient, but that intangible information leads to abnormal returns.

Not all literature agrees, however, that firms with high customer service provide abnormal returns. Research by O'Sullivan, Hutchinson, and O'Connell (2009), Jacobson and Mizik (2009), as well as Derwall, Hann, and Kalogeras (2010), for example, provide evidence that customer satisfaction information is efficiently priced into equities. In particular, Derwall et al. (2010) use the errors-in-expectations hypothesis to show that investors correctly price customer satisfaction and that customer satisfaction information is accordingly incorporated into the stock price, suggesting that investors cannot beat the market by strategies investing in companies with superior customer satisfaction. Ittner, Larcker, and Taylor (2009) also provide evidence that mispricing based on customer satisfaction is limited, and that no long-term abnormal returns can be expected from trading based on satisfaction information.

This study proposes that if mispricing arises during a stock-price bubble, increasing customer satisfaction can minimize the effects of a correction, and result in a net increase in firm value. Empirically, this is equivalent to testing if stock-price corrections (after high and low levels of investor sentiment) differ between firms with high and low customer satisfaction. To perform this analysis we use three sources of data: the ACSI, the stock returns of the firms incorporated in the ACSI, and a set of investor sentiment measures.

3. Descriptive Statistics

The sample period of our analysis is from 1994 to 2011, and concerns 209 NYSE-listed firms for which data is available. The firms cover a variety of industries and represent large established firms such as General Electric, Google, Microsoft, Prudential, or Whirlpool. Summary statistics are shown in Table 3.1 and Figure 3.2.

	Obs	Mean	St.Dev	Min.	Max
Monthly Sentiment	204	0.20***	0.57	-0.81	2.32
ACSI (for 209 firms)	1809	75.95***	6.53	49	95
Returns (%):					
Entire Sample	21332	0.00	0.14	-0.89	1.42
Portfolio Deciles:					
1 (low ACSI)	2362	-0.002	0.14	-0.89	1.16
2	2301	0.002	0.10	-0.65	1.05
3	2244	0.002	0.10	-0.78	1.19
4	2235	-0.000	0.11	-0.88	1.20
5	2129	0.006***	0.11	-0.86	1.18
6	1859	-0.000	0.10	-0.53	1.10
7	2100	0.002*	0.11	-0.88	1.15
8	1919	0.00	0.11	-0.86	1.25
9	2192	0.00**	0.10	-0.78	1.38
10 (high ACSI)	1548	0.01***	0.09	-0.63	1.42

Significantly different from zero at *$p > 0.1$, **$p > .05$, ***$p > 0.01$.

Table 3.1: Descriptive Statistics: Returns, ACSI, and Investor Sentiment

January 1994 to December 2010

This table shows descriptive statistics of the data used in this study. Investor sentiment is measured monthly and is given by the principal component of 6 investor sentiment proxies (number of IPOs, IPO first day return, NYSE share turnover, dividend premium, closed-end fund discount, and equity share in new issues) (Baker and Wurgler 2006). The ACSI is a measure of customer satisfaction. The returns in the sample are monthly returns for each of the 209 NYSE-listed firms included in the sample. Monthly returns are sorted into 10 portfolios according to the ACSI level of the firm.

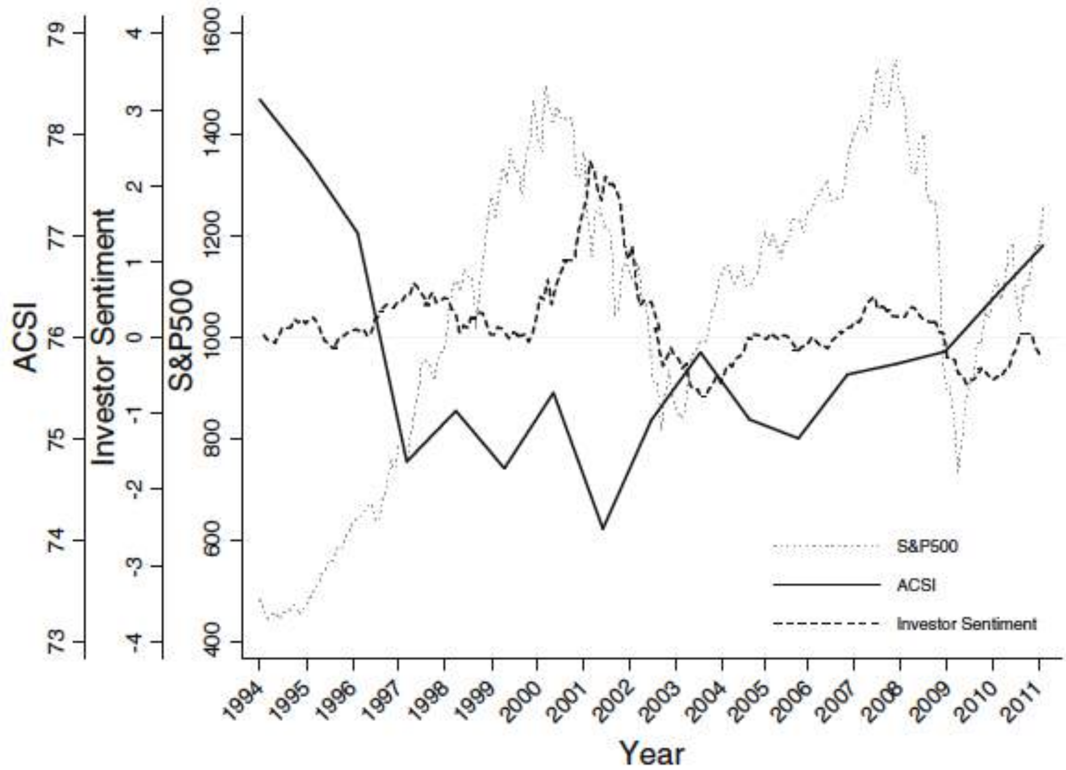

Figure 3.2: S&P 500, ACSI, and Investor Sentiment from January 1994 to December 2010

3.1. Customer Satisfaction

We use the ACSI to operationalize customer satisfaction. The ACSI is an economic indicator based on a model of customer experience developed by Johnson et al. (1996) and shown in Figure 3.1. Every year, the ACSI produces customer satisfaction scores for over 225 firms in 45 different industries and 10 economic sectors.[19] To collect the data, the ACSI contracts a market research firm to collect customer data using surveys, and ensures that the sample is representative of the American customer population. Then, the ACSI produces customer satisfaction scores using structural equation models (Figure 3.1) and publishes the standardized results monthly, on a scale from 0-100 via the ACSI website. The score represents whether the customer feels that the product or service of the firm satisfies (or does

[19] Some ACSI scores concern brands that belong to a parent company. In this case, we take the weighted average of the ACSI for each brand belonging to a same parent company.

not satisfy) them, exceeds (or falls short of) their expectations, and approaches (or fails to compare) to an ideal.

3.2. Investor Sentiment

Investor sentiment data is provided by the study of Baker and Wurgler (2006).[20] The methodology used to construct the sentiment index is described in Baker and Wurgler (2006). Figure 3.2 shows investor sentiment plotted with the S&P 500 and the ACSI. The ACSI displays a negative correlation to investor sentiment and the S&P 500. One possible explanation is that during periods of growth or of high investor sentiment, firms tend to neglect their customer service efforts. Investor sentiment shows a positive correlation with the index.

Baker and Wurgler's measure of investor sentiment is based on six sentiment proxies: the number of IPOs (Lowry 2000), IPO first day returns (Ritter 1991), the share turnover at the NYSE (Baker and Stein 2004), the dividend premium (Baker and Wurgler 2004), the closed-end fund discount (Lee, Shleifer, and Thaler 1991), and the equity share in new issues (Baker and Wurgler 2000). The sentiment index is defined as the first principal component of these variables, which are rescaled in order to ensure unit variance in the sentiment index. High sentiment is defined as "above the long-run average", low sentiment is defined as "below the long-run average."

3.3. Monthly Stock Returns

Returns are calculated using monthly stock prices from Datastream. Table 3.1 shows the mean sample returns, which are not significantly different from zero. Table 3.1 also shows summary statistics of each of 10 portfolios, where the returns of each firm are grouped according to their ACSI levels. While most of the mean returns in each portfolio are not significantly different from zero, the highest non-zero returns come from the highest ACSI portfolio, supporting findings that high-ACSI firms exhibit higher returns. Mean returns by

[20] Available on Jeffrey Wurgler's website: http://people.stern.nyu.edu/jwurgler/.

ACSI-sorted portfolios can also be seen in Figure 3.4, which shows that returns in low-ACSI portfolios are lower than in high-ACSI portfolios. This is consistent with prior findings about the ACSI and stock returns described in Section 2.3.

4. Methodology and Results

This study uses both non-parametric and parametric approaches to examine whether firms with high customer satisfaction are less sensitive to corrections in stock prices after periods of high investor sentiment than firms with low customer satisfaction. The methodology is based on the construction of 10 portfolios based on the ACSI level of each firm, where portfolio 1 contains shares of the firm with the lowest ACSI levels, and portfolio 10 contains shares of the firm with the highest ACSI levels.

4.1. Non-Parametric approach

Monthly returns are sorted into 10 portfolios based on the firms' ACSI score that year. This results in the portfolio returns shown in Table 3.1. Returns are then further classified by separating returns that occurred during periods of high investor sentiment and periods of low investor sentiment. Prices of firms in each portfolio are expected to behave as shown in Figure 3.3. If levels of sentiment are "high" in a given period, we expect prices to be above their fundamental values, when sentiment is "low", we expect prices to be below fundamental values.

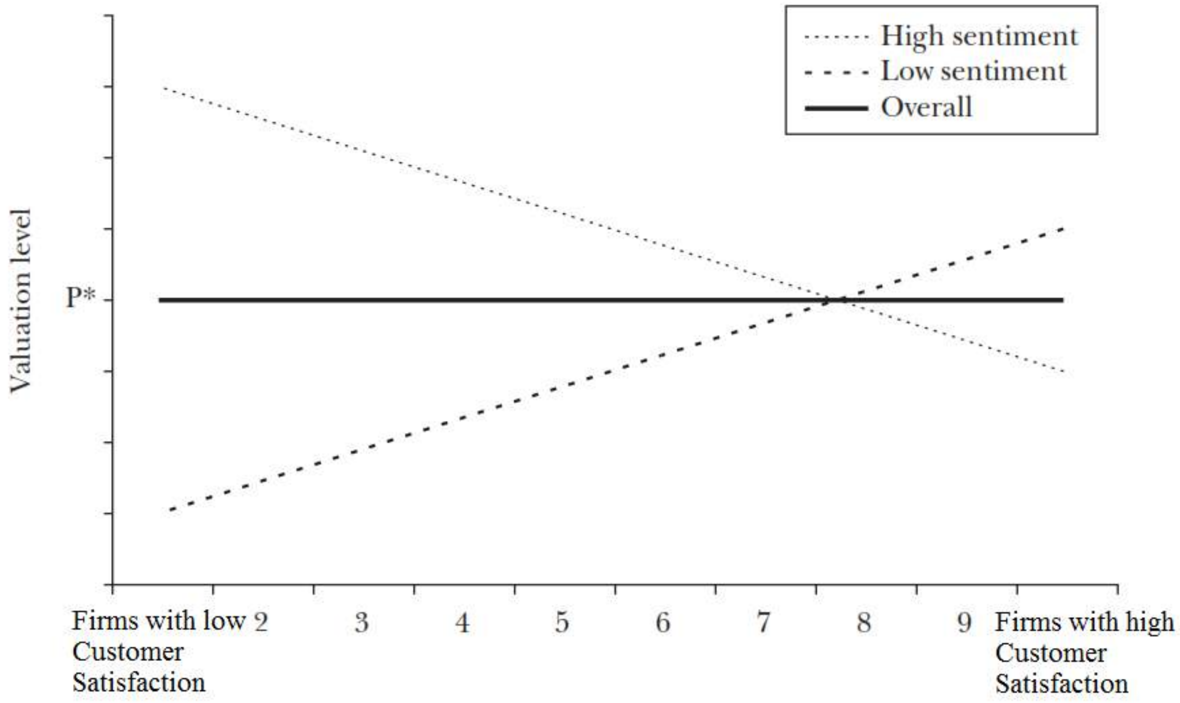

Figure 3.3: Theoretical Effects of Investor Sentiment on Stocks Sorted by Customer Satisfaction, adapted from Baker and Wurgler (2006)

This figure shows the theoretical effects of investor sentiment on the price levels of ACSI-sorted portfolios. The lower the ACSI of the portfolio, the larger the over- and under-reactions caused by high and low levels of investor sentiment.

While Figure 3.3 shows the theoretical behavior of prices, Figure 3.4 displays the empirical returns of each portfolio, sorted from low ACSI on the left, to high ACSI on the right. The figure shows two interesting results. First, the corrections of stock prices of firms with lower ACSI (portfolio 1) are smaller than those with high ACSI (portfolio 10). Figure 3.3 thus supports the proposition that firms with high customer satisfaction resist to price corrections occurring after waves of investor sentiment. This is evident from the positive upward trend in the high sentiment curve of returns. Second, only firms in the highest ACSI portfolio (portfolio 10) exhibit positive returns after a period of high investor sentiment. In Figure 3.3, this is shown by the portion of the high sentiment curve above zero. High-ACSI firms may thus actually see their firms grow in the wake of a stock-market bubble.

Table 3.2 displays the returns of the 10 ACSI-based portfolios after high and low periods of sentiment and the results of *t*-tests; the returns measured for high and low periods of sentiment are effectively different from zero. The table also shows that after a period of low sentiment, high and low ACSI firms still show positive returns. When investor sentiment in the previous period is low, the stocks in the previous period are undervalued (see Figure 3.3). Table 3.2 and Figure 3.4 show that the subsequent correction is positive, thus explaining the exhibited positive returns. The returns that arise after periods of high investor sentiment are consistently and significantly negative, with the exception of the highest ACSI portfolio (10). Hence, when investor sentiment is high in the previous month, investors overvalue low-ACSI stocks (see Figure 3.3) which results in a downward correction of their stock prices, and negative returns. High-ACSI stocks, however, exhibit positive corrections regardless of whether previous period sentiment is high or low, meaning that when a firm satisfies its customers enough, corrections from high and low investor sentiment are positive on average. The returns of high-ACSI firms are positive regardless of whether the previous period sentiment was high or low. The statistical evidence provided in Table 3.2 (and Figure 3.4) supports this: For portfolio 10, returns between high and low periods are not statistically different from each other, but are statistically different from zero.

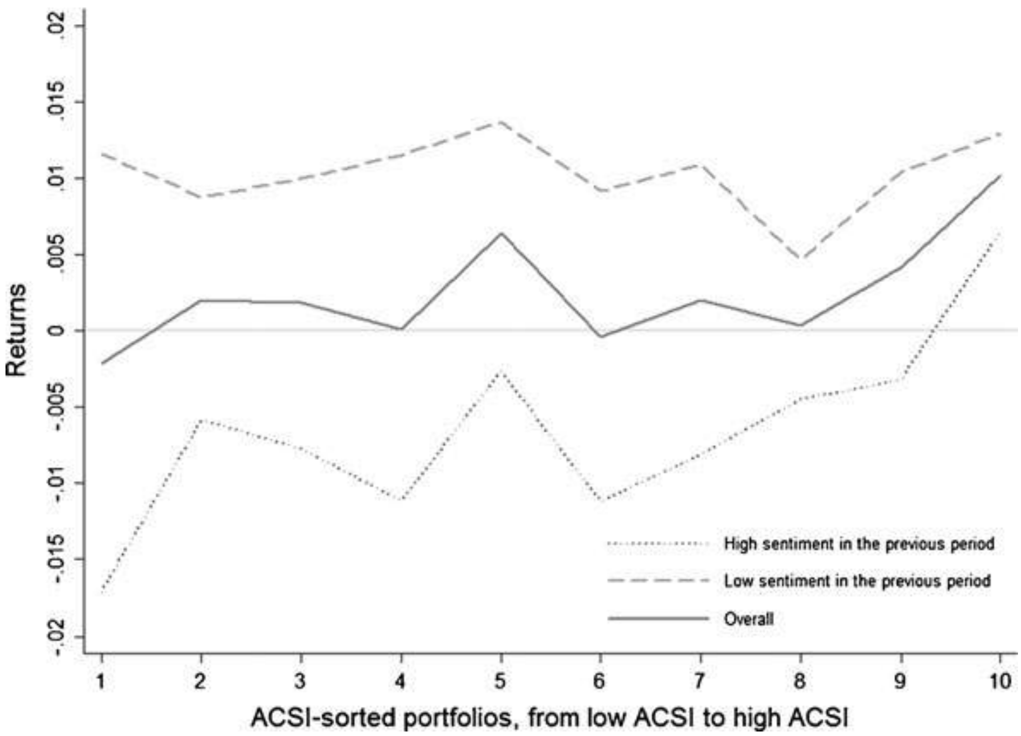

Figure 3.4: Cross-section of ACSI returns conditional on levels of investor sentiment in the previous month

	Low Sentiment in Previous Month			High Sentiment in Previous Month			P-value of
Portfolio	Obs	Mean	St. Dev	Obs	Mean	St. Dev	Difference
Low ACSI	1232	0.011***	0.003	1130	-0.017***	0.005	0.00
2	1240	0.008***	0.002	1061	-0.006***	0.004	0.00
3	1210	0.010**	0.002	1034	-0.008***	0.004	0.00
4	1105	0.011***	0.002	1130	-0.011***	0.004	0.00
5	1178	0.014***	0.003	951	-0.003	0.004	0.00
6	983	0.010***	0.002	876	-0.011***	0.003	0.00
7	1118	0.011***	0.003	982	-0.008**	0.004	0.00
8	1015	0.005**	0.003	904	-0.005*	0.004	0.00
9	1187	0.010***	0.002	1005	-0.003	0.004	0.02
High ACSI	881	0.013***	0.002	667	0.006***	0.004	0.16

Significantly different from zero at $*p > 0.1$, $**p > .05$, $***p > 0.01$.

Table 3.2: Portfolio Returns for ACSI-sorted portfolios in periods of high and low investor sentiment

This table shows the returns of the 10 ACSI-sorted portfolios divided into periods of high and low sentiment. The portfolio returns when sentiment is low in the previous month are significantly positive, and portfolio returns when sentiment in the previous period is high are consistently negative. Portfolio returns are significantly different, as shown by the p-value, with the exception of the high-ACSI portfolio, which shows that returns of high-ACSI firms do not differ in periods of high and low investor sentiment.

4.2. Parametric Approach

The parametric approach used here is based on the conditional characteristics model of expected returns (Daniel and Titman 1997; Baker and Wurgler 2006), and estimates the effects of investor sentiment on the difference between returns of firms with high versus low customer satisfaction. The model is specified as follows:

$$R_{ACSI_t=High,t} - R_{ACSI_t=Low,t} = c + dSENTIMENT_{t-1} + \beta RMRF_t + sSMB_t + hHML_t + mUMD_t + u_t \tag{1}$$

Where $R_{ACSI_{it}=High,t}$ is the average monthly return of firms with high ACSI, $R_{ACSI_{t}=Low,t}$ is the average monthly return of firms with low ACSI. High and low ACSI firms are defined as the firms in the top and bottom three ACSI deciles (as in Baker and Wurgler, 2006). SENTIMENT is the level of investor sentiment in the previous period, measured using the principal component of the aforementioned sentiment proxies (Baker and Wurgler 2006). We include the Fama-French (1993) factors and momentum (Carhart 1997). RMRF, SMB, HML, and UMD are control variables to ensure that the effects of investor sentiment are different than those captured by the Carhart four-factor model. This ensures that the change in the difference between high and low ACSI firms is explained by investor sentiment, and not by market risk, momentum, firm risk, or firm style.

The coefficient of interest is *d,* which provides an estimate of the effect of investor sentiment on the difference between returns of high versus low ACSI firms. A positive non-zero d indicates that investor sentiment in the previous month causes high-ACSI firms' returns to increase and low-ACSI firms' returns to decrease in a given month. The consequence is greater cross-sectional differences between high and low ACSI firms, and represents the size of the correction occurring after the sentimental effects have passed. The hypothesis is thus:

$H_0: d = 0$, where markets are informationally efficient regarding variations in investor sentiment: Investor sentiment is unrelated to differences in returns between high and low ACSI firms. As such, customer satisfaction does not form an effective buffer against sentimental stock price corrections related to investor sentiment.

$H_1: d \neq 0$, where non-zero effects represent cross-sectional patterns in sentimental mispricing: Investor sentiment is related to differences in returns between high and low ACSI firms. As such, customer satisfaction forms an effective buffer against sentimental stock price corrections related to investor sentiment.

The d coefficient is shown in the first row of Table 3.3 for the univariate regression (column 1), the three-factor version (column 2), and the four-factor version (column 3). In all three cases, d is positive and significantly different from zero, thus rejecting the null hypothesis. This is interpreted as follows: When investor sentiment increases in the previous period, the difference between high and low ACSI portfolio returns increases. Thus, when investor sentiment is *high*, the difference between high-ACSI returns and low-ACSI returns is large. Reciprocally, when investor sentiment is *low*, the difference between returns of high-ACSI returns and low-ACSI returns is small. Results in Table 3.3 consistently reject $H_0: d = 0$ and provide inferential evidence that sentimental effects (the d coefficient) affect cross-sectional patterns of price behavior. When sentimental corrections occur, the parametric evidence shows that high-ACSI firms will be less affected. Thus, high-ACSI firms are protected from the consequences of stock-price corrections that arise from investor sentiment, while low-ACSI firms are exposed to the risk of stock-price corrections.

5. Robustness Check: Repeating the Analysis with Corporate Social Responsibility

5.1. Introduction to CSR: a determinant of Customer Satisfaction

Luo and Bhattacharya (2006) show that Corporate Social Responsibility is an antecedent of customer satisfaction, which allows us to hypothesize that CSR can also be undertaken by a firm to protect firm value in the event of a stock price bubble. Results show CSR does not buffer, but instead catalyzes the effects of investor sentiment on firm value. This result is surprising but confirms the work by Luo and Bhattacharya (2006) that that the relationship of CSR to market is moderated by other characteristics of the firm (such as innovativeness capability and product quality). While it does not necessarily disprove the buffering effect customer satisfaction has during stock market crashes, it does provide a nuance for the management of such market-based assets: the implementation of customer satisfaction policies may not necessarily result in the desired effect if they are operationalized using CSR. In terms of managing market-based assets, it results that CSR policies should be undertaken during periods of low investor sentiment, and alternatives to CSR should be undertaken to increase customer satisfaction during periods of high investor sentiment.

Bubbles occur after periods where investor sentiment is high, a sign that markets are overreacting to existing information and that prices are increasing to unsustainable levels. While bubbles are typified by the increase of aggregate market prices, Baker and Wurgler

(2006, 2007) show that firms with different financial characteristics exhibit different reactions to the presence of investor sentiment. In particular, they show that large, established, easy-to-value, and easy-to-arbitrage firms (e.g. blue chip stocks) exhibit a lower sensitivity to investor sentiment than small, young, hard-to-value, hard-to-arbitrage stocks.

The results earlier in this chapter show that nonfinancial characteristics also differentiate firms' reactions to broad waves of investor sentiment. Specifically, they show that firms customer satisfaction can act as a buffer against sentimental price corrections; firms with high levels of customer satisfaction correct less, exhibit higher returns, and have lower volatility in periods after high sentiment than their low-customer satisfaction peers. Indeed, there is a growing literature that shows how customer satisfaction contributes to shareholder value (Anderson, Fornell, and Mazvancheryl, 2004) and how firms that satisfy their customers exhibit relatively higher returns and are relatively less risky than firms that do not (Gruca and Rego, 2005; Fornell, Mithas, Morgeson III, and Krishnan, 2006).

Satisfied customers thus represent an important market-based asset for the firm - they increase shareholder value, enhance and protect cash flows, lower the vulnerability and volatility of cash flows, and increase the residual value of cash flows (Srivastava, Shervani, and Fahey, 1998). In order increase the likelihood of satisfying customers, firms must build deep, committed, and meaningful relationships with their customers. This process involves creating customer intimacy and satisfying the self-definitional needs of customers, allowing customers to identify with the companies they interact with, sometimes even becoming champions of firm brands and firm products (Bhattacharya and Sen, 2003).

One domain in particular where firms can influence customer satisfaction is receiving increasing attention due to its increased importance in practice: Corporate Social Responsibility (CSR). CSR represents a prominent strategic inclination to bolster a firm's market-based assets by attracting talent, improving employee relationships, improving investor relationships, as well as deepening customer relationships (Bhattacharya, Sen, and Korschun, 2008; Sen, Bhattacharya, and Korschun, 2006; Du, Bhattacharya, and Sen, 2007; Luo and Bhattacharya, 2006). In the particular case of customer satisfaction, CSR impacts consumer product responses (Brown, 1998; Brown and Dacin, 1997), customer-company identification (Sen and Bhattacharya, 2001), and customer product attitudes (Berens, van Riel, and van Bruggen, 2005).

Because customer satisfaction has an impact on the value of the firm, and given that CSR is an antecedent of customer satisfaction, it is natural to expect that CSR is also related to the value of the firm. Luo and Bhattacharya (2006) show that indeed, CSR has consequences for the value of the firm, but that the relationship is not unconditional. Some firms are better able to exploit their CSR activities thanks to their internal traits and capacities: execution, support, communication, and exploitation (Brown, 1998; Sen and Bhattacharya, 2001).

As of yet, no study has examined the relevance of CSR for firm value when the stock price is facing the risk of a bursting bubble, yet it is important to understand the role CSR may play when managing market-based assets during the uncertainty of periods of high sentiment. If CSR, as an antecedent of customer satisfaction, provides the same benefits as customer satisfaction when facing high levels of market sentiment, then CSR policies are defensive strategic policies that will help protect financial firm value when stock markets crash. On the other hand, if CSR contributes to customer satisfaction, but does not provide similar benefits during stock bubbles, then CSR is an aggressive strategic policy, that can enhance financial returns at the cost of taking greater risks.

This study provides evidence that CSR engagement catalyzes the effects of investor sentiment on a firm’s stock price: it increases returns but also increases risks. It is thus an aggressive strategic policy that should be undertaken when investor sentiment is low, and the firm is in a strong position and can handle economic headwinds. As such, struggling firms should focus on alternative forms of developing customer satisfaction.

5.2. Data and Descriptive Statistics of the Robustness Check

For the purposes of checking the robustness of the effects perceived above by firms with differing levels of customer satisfaction, it is important to use a similar research design. The sample period for this section of the study thus covers the same period, 1994 to 2012. It concerns 5517 New York Stock Exchange (NYSE)-listed firms for which data are available. The sample is a representative collection of all industries and firm sizes in the American stock market. Table 3.3 shows summary statistics.

5.2.1. CSR Scores

To measure the extent of CSR activities undertaken by each firm, measurements are collected from the KLD research social ratings database at WRDS. The database provides yearly scores for all the socially responsible activities undertaken by each of the firms in the database, divided into seven categories: human rights, environmental activism, community development, employee relations, product quality, diversity, and corporate governance. The CSR score used in this study is the mean score of all activities, and as is shown in Table 3.3, ranges from 0 to 1.05, with a mean of 0.09. This is because usually a firm only undertakes a few CSR activities out of the many accounted for in the KLD scoring system.

5.2.2. Investor Sentiment

The measure of investor sentiment used is the same as in the first part of this chapter: it is taken from Baker and Wurgler (2006). They measure of investor sentiment is a composite index based on the common variation in six underlying proxies for sentiment (see Baker and Wurgler (2006) for details). High investor sentiment is defined as “above the long-run average,” while low sentiment is defined as “below the long-run average.” It is important to use the same

5.2.3. Stock Returns

Returns are calculated using monthly stock-price information from Compustat. Table 3.3 shows the mean sample returns Table 3.3 also shows summary statistics of each of ten portfolios, where the returns of each firm are grouped according to their CSR engagement scores. The highest returns come from the highest CSR portfolio, which is also shown in Figure 3.4.

5.3. Methodology and Results of the Robustness Check

Following the lead of Baker and Wurgler (2006, 2007) and the portion of the study below uses both nonparametric and parametric approaches to test whether CSR protects firms against stock-market corrections.

	Obs.	Mean	St. Dev.	Min.	Max
Yearly Sentiment	17	0.22***	0.61	-0.67	2.12
CSR score	33347	0.09***	0.09	0	1.05
Returns (%):					
Entire Sample	33347	0.04***	0.01	-28.95	293.10
Portfolio Quantile					
1 Low CSR	11129	0.02***	0.04	-9.21	29.76
2	11109	0.02***	0.38	-9.55	16.03
3 High CSR	11109	0.07**	3.50	-28.95	293.10

N.B.: difference between returns of low CSR and high CSR is significant at the 10% level

Table 3.3: Summary Statistics for the Corporate Social Responsibility Data

5.3.1. Non-Parametric Approach

Monthly returns are sorted into three portfolios based on the firms’ CSR score that year. This results in the portfolio returns shown in Table 3.3. Returns are then further classified by separating returns that occurred after periods of high investor sentiment and those that occurred after periods of low investor sentiment. Prices of firms in each portfolio are expected to behave similarly to those in the section above: when sentiment is “high” in the previous period, we expect prices to be lower than average; when sentiment is “low” in the previous period we expect prices to be higher than average. The distance of “high” and “low” returns from the average shows the extent of the corrections in each portfolio.

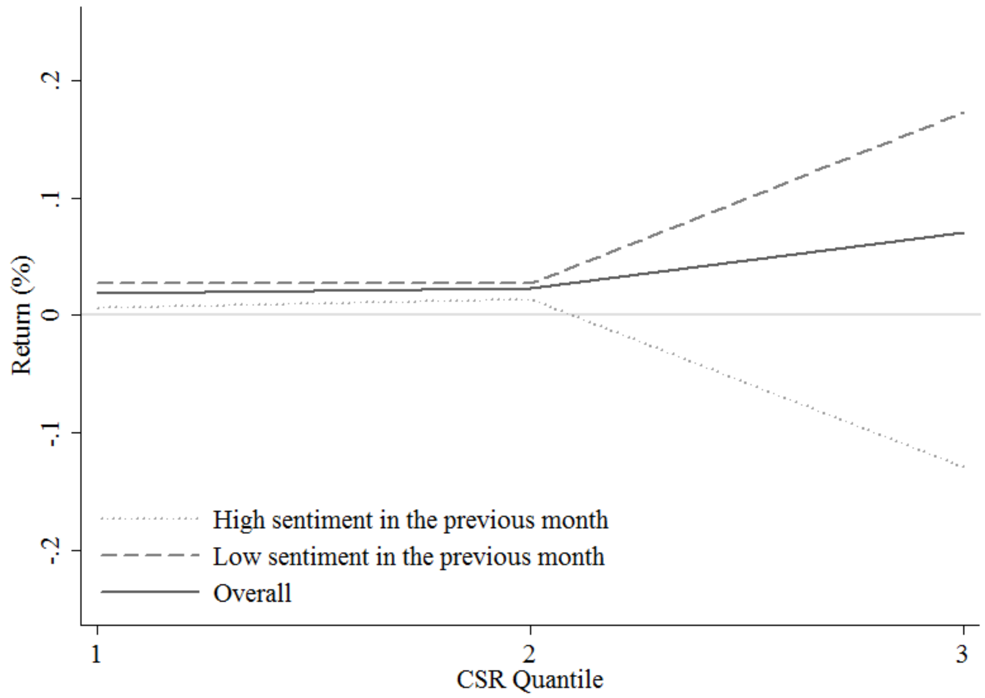

Figure 3.5: Cross-section of CSR returns conditional on levels of investor sentiment in the previous month

Figure 3.4 displays the returns of each portfolio, sorted from low CSR scores on the left to high CSR scores on the right. The figure shows three interesting results. First, the graph exhibits the opposite behavior of shown in chapter 1. Second, the corrections of stock prices of firms with low CSR (portfolio 1) are smaller than those with high CSR (portfolio 3). This means that firms with high CSR are subject to sentimental corrections, and thus riskier on average than firms with low CSR, which are resistant to sentimental corrections. This is evident from the downward trend in the high sentiment curve of returns. Third, the best portfolio performance comes from the highest CSR portfolio (portfolio 3) after periods of low investor sentiment. This result means that High CSR firms grow the most when stock bubbles are in formation.

5.3.2. Parametric Approach

The parametric approach is based on the conditional characteristics model of expected returns (Daniel and Titman, 1997; Baker and Wurgler, 2006) and estimates the effects of investor sentiment on the difference between returns of firms with high versus low levels of CSR. It allows us to verify the findings from Figure 3.4 - that CSR is a catalyst of investor sentiment. The model is specified as follows:

$$R_{CSR=High,t} - R_{CSR=low,t} = c + dSENTIMENT_{t-1} + RMRF_t + SMB_t + HML_t + UMD_t \tag{3.1}$$

Where $\mathrm{R_{CSR=High,t}}$ is the average yearly return of firms with high CSR, and $\mathrm{R_{CSR=low,t}}$ is the average monthly return of firms with low CSR. High and low CSR firms are defined as the firms in the top and bottom CSR deciles, respectively. SENTIMENTt-1 is the level of investor sentiment in the previous period, measured as in Baker and Wurgler (2006). We include the Fama and French (1993) and momentum (Carhart 1997) factors. RMRF, SMB, HML, and UMD are control variables to ensure that the effects of investor sentiment are different from those captured by the Carhart four-factor model. As such, the change in the return difference between high and low CSR firms is explained by investor sentiment, and not by market risk, firm-size characteristics, book-to-market characteristics, or performance persistence (i.e., momentum).

The coefficient of interest is d, which provides an estimate of the effect of investor sentiment on the return difference between high and low CSR firms. Figure 1 has us expect a negative, non-zero d, indicating that investor sentiment in the previous period causes high CSR firms' returns to decrease and low CSR firms' returns to increase in a given period. The consequence is a smaller cross-sectional difference between high and low CSR firms, and this represents the size of the correction occurring after the sentimental effects pass. The hypothesis is thus:

$H_0: d = 0$, where markets are informationally efficient regarding variations in investor sentiment: Investor sentiment is unrelated to differences in returns between high and low CSR firms. As such, CSR is not a catalyst of sentimental stock price corrections.

$H_1: d \neq 0$, where non-zero effects represent cross-sectional patterns in sentimental mispricing: Investor sentiment is related to differences in returns between high and low CSR firms. As such, CSR is catalyst of sentimental stock price corrections.

	Univariate Model		3-Factor Model		4-Factor Model	
	Coef.	St.Dev.	Coef.	St.Dev.	Coef.	St.Dev.
SENTIMENT	-0.16***	0.00	-0.31***	0.00	-0.33***	.00
RMRF			0.13***	0.04	0.29***	0.05
SMB			-6.51***	0.07	-6.65***	0.08
HML			-9.58***	.10	-9.24***	0.11
UMD					0.36***	0.06
Constant	0.08***	0.00	0.15***	0.00	0.14 ***	0.00
R^2	0.07		0.54		0.54	
Wald P	0.00		0.00		0.00	

Significantly different from zero at the *10%, **5%, and ***1% levels.

Table 3.4: Conditional characteristics model regression results

Table 3.4 shows the d coefficients for the univariate (column 1), three-factor (column 2), and four-factor (column 3) regressions of the return difference between high- versus low-CSR firms. In all three cases, d is negative and significantly different from zero, thus rejecting the null hypothesis. This result is interpreted as follows: as investor sentiment in the previous period grows, the return difference between high and low CSR firms is decreases in a given period. As the returns of high CSR firms correct more after periods of high sentiment than those of low CSR firms, CSR acts as a catalyst sentimental stock price effects.

This is the first study to examine the impact of CSR on firm value conditional on investor sentiment. The results indicate that CSR, acts as a catalyst for the effects of investor sentiment on firm value, contrary to customer satisfaction of which it is an antecedent. Hence, corporations looking to manage their market-based assets should resort to CSR strategies when sentiment is low, which is when we find high CSR firms achieve the highest returns.

6. Discussion and Conclusion

Investor sentiment is one of the main assumptions of behavioral finance, which states that investors over- and under-react to information causing temporary periods of mispricing (Baker and Wurgler 2006). When periods of mispricing persist, this leads to stock-price bubbles and high volatility. Overvalued share prices benefit the firm so long as prices increase and there is no correction. When a correction occurs, stock prices drop and returns are low, although a firm's value has not changed in terms of fundamental information. This study proposes that leveraging market-based assets such as customer satisfaction can help to protect firms from the adverse impacts of stock-price corrections that occur after periods of investor overreaction (i.e., sentiment). However, the study also provides a counter-example of how leveraging market-based assets incorrectly may backfire and make the situation worse.

Market-based assets are assets that derive their value from relationships of the firm with individuals and entities in its environment (Srivastava, Shervani, and Fahey 1998). Leveraging market-based assets has been shown to create value for the firm, to decrease cash-flow volatility, and to reduce cash-flow vulnerability. In particular, customer satisfaction is a market-based asset that has been related to several benefits for the firm including good economic performance, higher customer retention, increased brand equity, and consequently higher returns with lower risk (Rust et. al. 2004). In addition, customer satisfaction is negatively correlated with firms' market, idiosyncratic, and downside risk. Nonetheless, as shown by Luo and Bhattacharya (2006), it is necessary to leveraging market-based assets effectively; when attempting to grow customer satisfaction through corporate social responsibility; for example, it is possible that the efforts may backfire if it is not done correctly.

This study shows that firms with high customer satisfaction have positive returns regardless of whether they are made during periods of high investor sentiment (when investors are overreacting) or during periods of low sentiment (when investors are underreacting). Firms with low customer satisfaction, however, exhibit large price corrections as a result of investor over- and under-reaction. Our findings also show that as investor sentiment grows, so does the difference in the returns between firms with high versus low customer satisfaction. Consequently, firms with higher customer satisfaction are not only more protected from investor sentiment, but also increase their returns as investor sentiment increases. However, the opposing results found with corporate social responsibility suggest that the firms that leverage their customer satisfaction do so using other policies than corporate social responsibility.

There are several possible explanations for these findings. First, customer satisfaction contributes to firm value intrinsically (e.g., by increasing customer retention), thus justifying positive nonzero returns. Second, customer satisfaction convinces stakeholders that the firm is a good quality investment because of their attention to customer needs. Investors thus hold the stocks with the subjective expectation that their prices will rebound. Finally, when markets correct after periods of sentimental mispricing, investors may display a flight to quality earnings, transferring their investments from firms with low to firms with high customer satisfaction. This finding is important because it shows that individual firms have the ability to use market-based assets to protect their stock prices from the effects of non-fundamental risk, the risk that arises from changing levels of investor sentiment (Shefrin 2008). Non-fundamental risk is the risk that subjective perceptions of investors change without a change in fundamental information (e.g., financial, macro-economic information), and causes stock price volatility. Market-based assets influence firm value both intrinsically, and by interacting with the subjective expectations of a firm’s stakeholders. The evidence provided by this study shows that firms with high customer satisfaction are able to convince their investors that corrections caused by investor sentiment are not warranted.

Although this study focuses on one market-based asset (e.g., customer satisfaction), many other types of market-based assets exist and may also interact with firm value (e.g., employee or supply-chain relationships). The results presented here are thus to be interpreted as a lower bound of the aggregate effects that market-based assets may have on sentimental stock prices. Existing research calls for the leveraging of market-based assets and promote the low-risk, high-return results of such strategies. However, few sources provide specific strategies to manage market-based assets. This study shows that firms who are concerned with the effects of investor sentiment on their stock prices can use investments in customer satisfaction to alleviate these concerns. Future research holds many opportunities in outlining additional strategies for managing market-based assets, in addition to the customer-related ones examined here. For example, employee and supply-chain satisfaction are two additional market-based assets that are likely to have enduring effects on a firm’s stock-price reaction to investor sentiment, because it seems likely that investors tend to trust firms that treat all their stakeholders well.

Conclusion

1. Summary and Concluding Remarks

This dissertation has presented three chapters on how affect relates to financial markets, financial decision making, and corporate financial policy. The dissertation addresses the criticism of behavioral finance that points out that no comprehensive theory of behavioral finance exists, and that it is instead just a collection of psychological effects on pricing. This is especially applicable to “investor sentiment,” the theory that states that market participants do not behave rationally, and can push prices to levels unjustified by factual information. Normally, unjustified pricing does not last long because market participants can see the resulting profit opportunities and make the trades that push prices back to sustainable levels – a process called arbitrage. The second theory of behavioral finance, “limited arbitrage,” says that sometimes arbitrageurs do not correct prices, letting incorrect pricing persist, grow, and become unsustainable. Price bubbles occur when prices are subject to high levels of investor sentiment are left unchecked by arbitrageurs. In three chapters, this dissertation specifies the shortcomings of investor sentiment as a theory, provides a specific framework for the definition and measurement of investor sentiment based on affect, the primary driver of behavior, and tests whether the aforementioned approach is empirically tenable.

It is no surprise that investor sentiment is a convoluted term, since it originally referred to the hearsay practitioners would come across on the trading floor. Today, in the era of electronic trading, trading floors are disappearing but exchanges still exhibit more brouhaha when traders are excited than on a slow news day. Researchers in behavioral finance have provided many explanations and definitions for the processes that occur in such cases. One common definition of investor sentiment is the difference between observed prices and the prices predicted by a rational financial model. This definition assumes that “something” is occurring that causes prices to deviate from rational values, but makes no statement on what that process is or how to measure it. This definition is the one most used in standard finance, but it considers the causes of investor sentiment to be exogenous to price formation, and thus does not address what exactly investor sentiment is. This makes approaches based on this definition empirically clean and easy to put in place, but sidesteps the issue of what driving mechanics actually actuate during a price bubble.

A subsequent definition is based on psychology. It recognizes the many advances in behavioral finance involving the heuristics and cognitive biases that were found to explain overreacting investors and non-rational pricing. Although this definition is not incorrect, it is not practical because there are over one hundred documented heuristics and biases, and while they are responsible for pricing effects, they can only be measured in experimental settings or post-hoc with investor trading records. As a result, methods based on cognitive biases are rather restrictive in terms of identifying, measuring, and predicting price bubbles. Other causes for investor sentiment based on psychology have been examined and added to the list of cognitive biases; these include bodily and environmental causes alike: hormones, the weather, lunar cycles, skin conductance, and global sporting events. The collection of causes for investor sentiment now consists of a tremendously long list of explanations, which suggests that the critique made of behavioral finance, that it is a “catch-all,” is currently not without justification.

The studies shown here thus attempt to find an innovative alternative to the “catch-all” approach to behavioral finance. They propose that all existing psychological explanations are reflected and measurable in affective processes. To test this proposal, they accumulate evidence about the nature and dynamics of affective measures in financial markets and its actors. The first chapter examines the relationship between affect and the cross-section of stock returns. The second chapter examines the relationship between affect and retail investors’ trading decisions. The third and last chapter examines the relationship between affect and corporate financial policy vis-à-vis stock price bubbles. Each chapter serves both to support the use of such measures in finance by examining how they perform in different contexts, and to build an as of yet missing theoretical background for the role that affect plays in finance. In this sense, this dissertation is a novel and creative contribution to financial research: the discipline has only begun to scratch the surface of the role of affect in finance, and the extant number of finance studies that explicitly refer to affect can be counted on one hand. The work in this thesis helps finance take yet another incremental step in the direction that all social sciences must go: outgrowing outdated rational models of behavior and studying topics with a renewed descriptive understanding of behavior. In particular research has reached into descriptive neuroscientific findings in order to produce the theory and empirics that heavily support the inclusion of affect in the study of financial topics.

Motivated by the practical problem that results from behavioral finance’s failure to remedy the quasi-continuous occurrence of price bubbles across the world, this dissertation has focused on the fact that the theory of investor sentiment is too general, is poorly defined, and is consequently poorly measured. These characteristics of investor sentiment mean that practitioners and regulators have not been able to use the research to find an effective solution to the bubble problem. Drawing from a multidisciplinary approach involving neuroscience and psychometrics, this dissertation proposes to recast investor sentiment in the mold of other affective sciences, such as marketing, that possess the tools to treat and analyze emotions. This dissertation thus intends to take behavioral finance in the direction of affect, the primary system in the brain to react to stimuli; it provides the groundwork for establishing a specific definition for investor sentiment based on affect as well as a reliable and a structured measurement system to quantify and study such affective effects.

The discussion begins with the development of a theory stating that all documented causes of investor sentiment are different moving parts of the same system that drives behavior. These moving parts are serially related, as in a chain; measurements of each driver of sentiment will thus relate to pricing: the environment, including the weather and lunar cycles, influences physiology, which influences affect, which determines the incidence of cognitive biases, which results in a decision, and finally causes an outcome. Thus, the question is not whether investor sentiment exists – it is quite intuitive that it does – the question is instead how to define it. However, defining investor sentiment as the chain of processes from stimulus to market outcome is still too broad to be useful: it provides structure to the documented causes of anomalous price behavior, but is still too much of a catch-all. In addition, it is also redundant: prices that change because of the weather will also be changing because of the physiological changes that the weather causes, as well as the affect that results, and the cognitive biases that are used when investors make decisions. For investors and policy makers to make use of behavioral finance, investor sentiment must be specifically defined in such a fashion that it respects our understanding of the chain of investor sentiment causes, but that is narrow enough that no confusion may arise from the use of the term. This dissertation has argued that affect is the strongest link on which to base the definition of investor sentiment, as well as the most practical for measurement and methodological purposes.

The first chapter of this dissertation develops the discussion of this issue. It distills the many measures and causes of investor sentiment into six categories (environment, physiology, affect, cognitive biases, decisions, and outcomes). The chapter then singles out affect as the most flexible, practical, and informative category from which a specific measurement framework can be developed. Several reasons support this choice: affect can be divided into any number of individual moods, emotions, attitudes, or feelings; it can also be measured in a number of ways (such as surveys, face recognition software, semantic analysis of internet posts), it is intuitive, it is relatable to specific processes in the brain, and it is a tried and tested approach in disciplines that focus on affect (such as marketing and psychology). In order to test whether affect is an effective way to characterize investor sentiment and whether it is a robust theoretical foundation, the chapter examines the relationship between affect and the cross section of stock returns. The findings show that certain affective factors produce the patterns and relationships that the existing theory of investor sentiment predicts (such as *risk attitude* for example). However, the findings also show that other affective factors (such as *risk perception*) exhibit different patterns. The findings show that investor sentiment is not constituted of just one affective factor, but instead is constituted of several factors that each has its own effects on pricing, and their own description of the specific investor sensations that motivate the price effects.

Chapter two provides additional evidence to support this claim. Where chapter one examines the relationship between affect and the cross section of stock returns, chapter two focuses instead on the relationship between affect and the common stock purchase and sale decisions of retail investors. The findings show that certain affective factors (such as *risk attitude*) are related to purchases, while others (such as *risk perception*) are related to sales. The findings also show that interactions among affective factors have an impact on financial decision making. This is an important finding because it supports the findings in the first chapter - that investor sentiment, defined as affect, is not a unitary, homogenous construct. Rather, it is a complex, heterogeneous construct with diverse effects on decisions, as well as prices. As such, this means that investor sentiment is no longer just about predicting price movements, but also about managing market participants' emotions, and consequently their decisions. This research shows that with the adequate affective data, corporations can quantify the dynamic purchasing and selling likelihoods of their investors. In addition, they can enact investor relations strategies that specifically target the affective factors that would increase the likelihood of an investor buying, holding, or selling shares. Another institution that can benefit from this approach is the central bank. Central banks are constantly communicating with the public and especially investors in order to influence their affect: their trust in the financial system, their confidence in the economy, and their optimism for subsequent growth. This chapter successfully identifies two (potentially of many) affective factors that central banks can target with their public relations strategy, which will influence purchases and sales. These fascinating perspectives are further discussed in the section below on future research.

The third chapter is a direct test of the effectiveness of using affective data to manage interactions with the stock market. The study examines the price performance of publicly traded firms conditional on levels of investor sentiment. It shows that the stock prices of firms with high customer satisfaction correct less than the stock prices of firms with low customer satisfaction when investor sentiment is too high (the signal for a subsequent stock market crash). This means that firms that cater to the affective needs of their stakeholders are protected from stock market crashes. The finding is important because it confirms that affective elements are a key part of the bubble bust cycle, and that affective factors can be helpful in terms of identify and managing the onset and aftermath of price bubbles. Indeed, the findings shed light on the power of non-traditional, non-financial measurements to influence financial outcomes. Firms that recognize the usefulness of measuring affective factors, in this case *customer satisfaction*, benefit from that type of additional information. This finding is food for thought because current financial measurement and reporting systems do not consider affective data to be relevant, and thus do not attempt to report it. As Chapter 3 shows, in concert with the findings of the two previous chapters, affective information is useful to all market participants, and would likely make stock markets more efficient.

The three chapters of the dissertation show that affect is a tremendously useful and manifestly relevant type of information for all market participants. Arbitrageurs can improve their ability to correct prices by focusing on specific affective factors. In addition, the potential miscommunication that may arise between arbitrageurs from using the term "investor sentiment" can instead refer to specific causes of sentiment, in particular specific affective factors, thus allowing them to synchronize their efforts in the case of large stock bubbles. Using the affective approach to sentiment described here, firms can specifically estimate how their stock prices will react when one affective factor or another changes, instead of having to rely on the otherwise vague notion of investor sentiment. The measurement of affective information can also allow central banks to analyze the reaction to their public relations policy in terms of the way market affect changes and its subsequent effect on markets. Each group of market participants – investors, corporations, and regulators – can better manage their participation in the financial system with access to affective information. Indeed, this statement brings the study full circle: if market participants are afforded better information, they can make better decisions, and it becomes possible to expect that markets will become more efficient, which will reduce the incidence and degree of price bubbles.

The concluding remark is hence that if stock bubbles occur, it is also because the contemporary financial mechanism, which is an impressive and humbling piece of economic machinery, may have a behavioral working piece that if only shifted or recast, can improve the very high degree of efficiency that already exists. The research presented in this dissertation presents evidence that suggests that this has to do with the role attributed to affective information, its measurement, its dissemination, and its importance in the price formation process. Much more research is necessary to prove beyond a doubt that it is so, and the considerations for future research are vast and exciting. Before discussing future research perspectives, however, we will first visit the limitations of the research presented in this thesis.

2. Limitations of this Research

This dissertation is an attempt to shed light on challenging and important issues in the area of behavioral finance that remain unaddressed and controversial by providing a fresh and novel perspective. Nonetheless, the research faces several important limitations that mostly arise from the fact that the research is in its infancy and still has far to go. These limitations include sampling issues, the choice of modeling frameworks, limited reach in terms of scope, and relying on as-of-yet unproven neuroscientific assumptions.

The first limitation faced by this research concerns sampling and data collection issues. This is due to the nature of behavioral research in economics: the fact that economics cannot be study in a controlled experimental environment, and the fact that affective data is difficult to measure. The research performed in chapters 1 and 2 certainly benefitted from the fact that the sample included the most important substance of the subprime financial crisis. Some of the events present in the sample are the Lehman Brothers collapse, the nationalization of Northern Rock, and the signing into law of economic stimulus legislation. However, the data was only collected monthly for the year starting in April 2008 and ending in April 2009, which is a a less-than-ideal sampling of the period before the crisis as well as its slow build-up that began in February 2007 with the first subprime related press releases from Freddie Mac; the sample from chapters 1 and 2 does not include data from the post-crisis either.

This means that there are two suboptimal characteristics of the sample studied in chapters 1 and 2. On one hand it may miss the “bigger picture” because the pre- and post-crisis variation in affective factors are missing, and would be necessary to correctly interpret agent affect during the crisis period proper. On another hand, and as is particularly the case for chapter 1, the resulting sample size of 13 monthly data points makes the choice of analytical methods extremely restrictive. Although many efforts were made to make the best of the data available, and quantitative modifications were made to adjust for the small sample sizes, it would have been far more reassuring had a complete data set been available. The reason that the ideal data set could not be constructed is because of the highly complex nature of collecting such data: acquire trading records, and then surveying the holders of the trading records requires a high level of commitment and cooperation between a university and a private organization like a bank or a broker. Such a relationship can be difficult to operationalize, especially given the related high pecuniary and non-pecuniary costs. A final note to make about the sampling limitations however is that they are relative: no data set of this type exists so despite its limitations it remains groundbreaking in the field of finance.

The sampling limitations have direct repercussions on the choice of analytical methods. The strength of a regression model is often linked the number of observations it requires. With copious amounts of data, the choice of which model can be used for analysis becomes difficult only because there are many options available; ideally multiple models can be studied using the copious data and conclusions can be drawn from the various perspectives they offer. In the case of this thesis, the initial plan was to use panel models – the data being a longitudinal by design. In practice however, the panel did not have enough time periods to benefit from panel approaches, and the panel ended up being unbalanced because response rates by survey respondents were unpredictable – some respondents would respond multiple times in a month, others would respond intermittently, and others just once. This meant that analytical methodologies had to be adapted to this context; in the interest of parsimony one study settle on a simple time-series model (chapter 1) which adjusted for small sample sizes, and one study settled on a cross-sectional analysis (chapter 2). In this way, the complications of adapting a panel model to the data were avoided in the expectancy that better data would one day be collected for the purpose of running more advanced models.

The scope of this thesis is relatively limited, as is evidenced by the fact that only four affective factors are examined: risk attitude, risk perception, stock market attitude, and customer satisfaction. The reasons echo back to the sampling complications discussed above. Unless the data already exists (as was the case for customer satisfaction), studying more affective factors requires adding more items to the survey. The number of items influences the response rates because respondents are less likely to complete the survey if it takes them too long. Since the surveys used in this research are sent out to respondents every month, it makes the act of responding to the surveys increasingly tedious, and with every subsequent interation the likelihood that the respondent will continue to participate decreases. This meant that this research project had to strike a balance between the number of factors to be studied and the feasibility of the data collection. Owing to conservatism, the project focused on a small number of validated affective factors, sacrificing the opportunity to measure more creative alternatives. Ultimately, because this is the first study to take this approach, future research will offer more opportunities to address the scope of this approach to investor sentiment – in particular by creating a taxonomy, which is discussed in section 3 below.

The final limitation discussed here is that the specific neuroscientific assumptions are relied upon: specifically that specific somatic roots elicit each the different affective factors. This means that if we measure an affective factor with a survey then we are proxying for a neurological process that is specific to that affective factor. The point is that no neuroscientific study has actually shown that risk attitude, or customer satisfaction are affective factors that arise from the their own physiological processes. If such research did exist, then this would bring the sentiment measurement methodology in this dissertation full circle. Nonetheless, the assumption that an affective factor is caused by its own physiological process is not too far-fetched; this has been shown for fear, which is an affective factor, albeit not one studied here. In addition, marketing scholars rarely have neuroscientific corroboration of the affective factors that they document, and they are still able to make progress in their research.

Many of the drawbacks that exist in the research performed in this dissertation are due to practical issues that could not be solved in the time frame of the research project. Nonetheless, they represent propitious springboards for copious future research to be done on the topic. We discuss below.

3. Considerations for Future Research

On one hand, it may seem farfetched to come to the conclusion that feelings can play such a great role in economic and financial institutions that are run by highly trained, highly capable individuals. On the other hand, the deeper understanding of human nature that has slowly emerged is that no matter how much education or training you bestow upon an individual, the decision-making mechanism still primarily relies on affective processes. The implications are far-reaching: the free will of individuals is more limited than previously thought, so when we speak of the “large impact” that discoveries about affect will bring upon finance, we are speaking euphemistically. At the risk of sounding like a futurist, or perhaps a behaviorist, it is becoming a scientific fact that human preferences can be influenced, behaviors programmed, and decisions swayed. Marketing scholars have made such topics their specialty, and the big data revolution has attracted their attention first: they know that if they know everything about you, they cannot just predict what you will do, but they can also cause you to do it.

The world we live in today is a world where individuals volunteer their information to corporations like Facebook, and are constantly monitored by Microsoft and Google, who in turn offer information to governments. In a certain way, we already live in a pale version of the *Brave New World* - but it seems awkward that all that information may be used to sell more or spy on individuals, when a useful application of that information would be to inform markets that a huge price bubble is, like a tsunami after an earthquake, in the process of occurring. Markets that are aware of an intangible, affective earthquake would hopefully prevent or mitigate the subsequent tsunami of a bubble, especially given the wide range of problems a large market crash can cause. From this study, it is clear that the topic deserves further research attention, which would be necessary to establish in greater detail how affective processes influence markets and how an affective measurement framework can be implemented. To provide an idea of how much research remains to be done, consider this: in this dissertation, four affective factors have been examined, when marketing and psychology researchers examine hundreds in a given year.

For finance scholars, there is thus plenty of room to develop a taxonomy of affective factors. In marketing, entire volumes of affective factors have been published that describe how they have been researched and their relevance for various marketing problems and questions. A taxonomy would allow the identification of the affective factors that not only play an important role in the various parts of the financial system, but also how they interact with each other, and how to influence them. The ultimate purpose of developing this taxonomy would be to determine whether affective factors need to be measured and reported to the markets. If it were determined to be so, it would consist in making the first revolutionary improvement to financial reporting standards since the great depression. Affective measures would complement current accounting and economic information with the measurements of the market's propensity to interpret such information. Ultimately, it is plausible that a standardized, consistent, reliable, valid, and public system to measure relevant affective processes could be a piece that would improve the already impressive mechanism that is the global financial system. As such, accounting scholars can also draw from this dissertation to extend their research agendas to the measurement and reporting of affective information.

Making the catalogue of affective factors is certainly an interesting research perspective for finance and accounting scholars, but another aspect of affective research is also important for finance and its related disciplines: the latent heterogeneity of market agents. Financial markets certainly suffer from the herding of its participants, but to summarize them all as members of a herd hides the fact that many of these people exhibit individual intangible characteristics that are relevant to their financial behavior. If we were to measure affect to inform stock markets, it would be interesting to know, for example, if there is heterogeneity among the affect of each category of market participant. It is possible that arbitrageurs, retail investors, and corporate financial policy directors self select into their positions because of their affective make-ups. Alternatively, perhaps being faced with certain decisions as an arbitrageur or as a corporate financial policy director sculpts the affective profile of the person in question. It goes without saying that regardless of the direction of the aforementioned causality, the dynamics of their affective profiles would also be informative as their decisions may differ.

The research perspectives are quite large if only among the topics involving the latent dynamics and heterogeneity of market participants. It would inform researchers who are interested in profiling investors, and whether their findings are generalizable among all market participants or not. This research would also inform the broader topic of decision behavior concerning the relationship between incentives and affective processes. Novel research questions may also concern whether the affective profiles of market participants change according to the market they are participating in, and whether or not such a profile changes if they trade in multiple markets. There are many affective factors, and knowing which affective factors are relevant and in which cases can help refine our understanding of the relationship between specific decisions and specific affect. Purchase and sale decisions of different products may rely on various affective factors that depend on the decision and the market in question.

There is also plenty of space for research on measurement and analysis methodologies. Although this study has drawn from techniques often used in marketing, there are new and interesting approaches that have yet received little attention. Affect is hard to measure, but many new measurement methodologies exist and offer different solutions to capture the variation in affect of market participants. In addition to surveys, textual analysis, facial recognition, and camera-based heart monitoring are all technologies that exist and whose developers are looking for practical and research applications. Dare we imagine, the trading station of the future may include all of these gadgets, putting the trader under tremendous scrutiny for his own information, for the rest of the market, and even for regulators. It is when regulators are mentioned that we come back to the concern surrounding technology, privacy, and the limits of government introspection, especially in terms of the affective space – a space as personal as can be conceived. Hence, future research will also bring up ethical questions and perhaps legal questions as well. Indeed, the point is that society in general is moving in the direction of this *Brave New World*, and that finance will be no exception.

Already we are seeing some “funny” discussions occurring in the public arena that reflect the types of topics addressed in this section. The perspective that people will be tirelessly monitored and their data constantly measured surely sounds uncomfortable. It is however not necessary to assume that this data will be used maliciously – it may even be used for our benefit. Take the example of the discussion of a panel in Europe about the measurement of economic growth and its shortcomings: some economists have suggested that aggregated affective measurements would be an alternative to the existing GDP measures that most economic welfare analyses are based upon. Such economists may sound crazy, or avant-garde by even discussing the topic seriously (as per our cultural tendency to discount the importance of emotions), but a tangible example already exists: they cite the case of the Kingdom of Bhutan, a country where survey measures of Bhutanese subjects’ happiness is considered a serious measure for progress. One possible outcome of pursuing affect in the realm of finance is that it be considered a serious economic measure, and all of a sudden we live in a world where the growth of happiness, instead of GDP, is the measure everyone is trying to improve.

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Chapter 1

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Chapter 2

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Appendices

Appendix A

Spanish translation of Introduction Chapter to opt to the International Doctorate

Introducción

1. Introducción a afecto, toma de decisiones financieras y mercados financieros

A medida que la ciencia comprende cada vez mejor el funcionamiento del cerebro humano y su influencia en la toma de decisiones, nos proporciona unos nuevos medios para mejorar el modelo financiero actual. Muchos interesantes descubrimientos han llegado a demostrar que el afecto –las emociones- influye en el comportamiento más de lo que se pensaba previamente y que debería posicionarse en un eje central en el estudio de los seres humanos, sus organizaciones y sus sociedades. Debido a la naturaleza compleja, heterogénea y latente del afecto, los investigadores de ciencias sociales han tendido a dejar al afecto al margen de sus análisis y han favorecido, sin embargo, el uso de los así llamados modelos de comportamiento “racional” que se basan en reglas simplificadas y describen más el comportamiento de autómatas que el proceso actual de toma de decisiones.

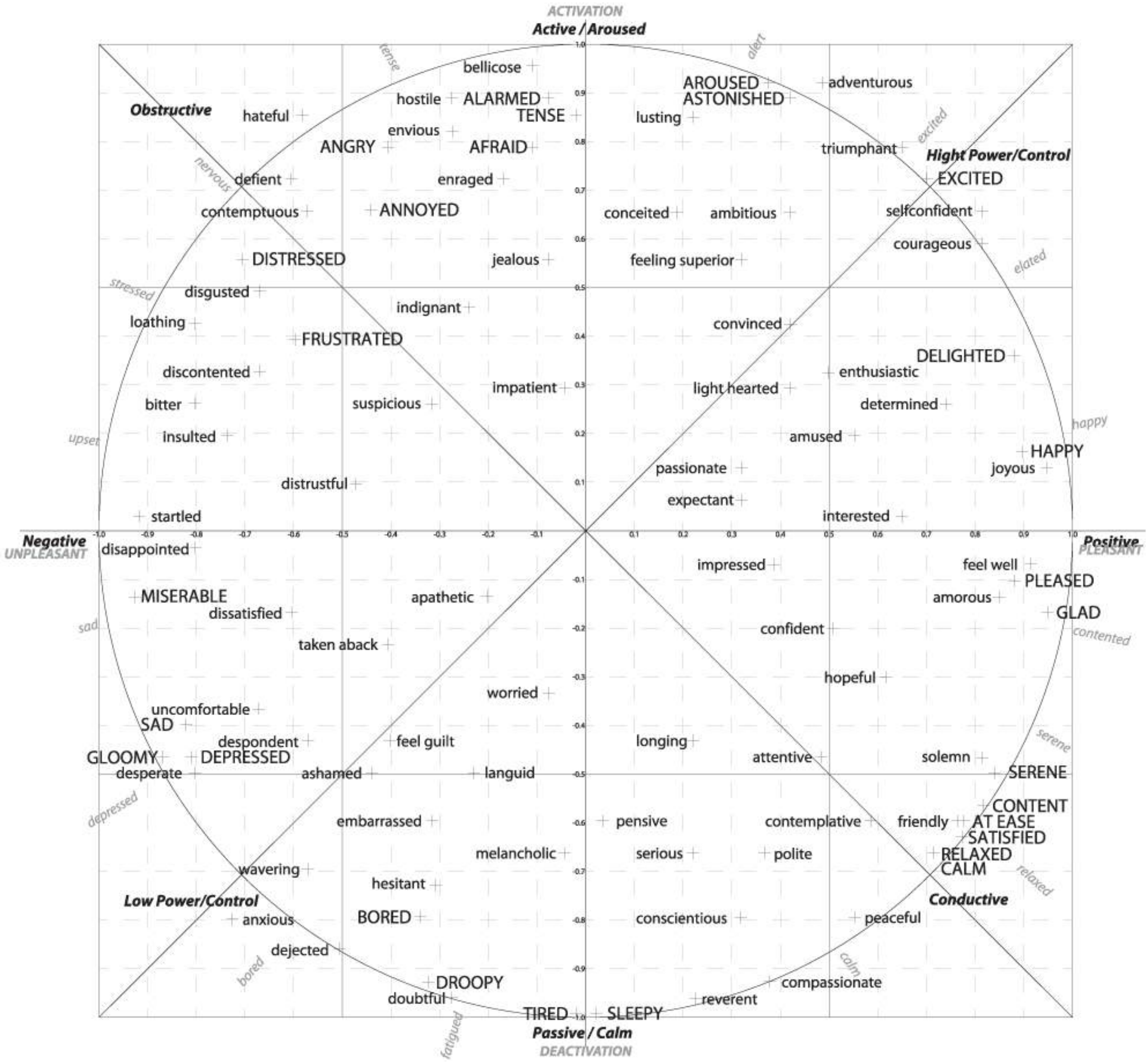
Gracias al desarrollo de la neurociencia, los modelos racionales han llegado a ser bastante polémicos: ahora sabemos que justamente la parte excluida de los modelos racionales – el afecto – es un factor fundamental en el funcionamiento del cerebro. Por lo tanto, el afecto ha acabado manteniendo una posición única entre las ciencias sociales en general y en economía en particular: constituye la pieza más ignorada del rompecabezas del comportamiento y, sin embargo, también la más importante. Esta situación representa una oportunidad única para la investigación pues existe un gran vacío entre los modelos actuales de toma de decisiones y los modelos de comportamiento que incluirían el afecto.

Cada disciplina se ha encargado de adoptar el afecto a su propio ritmo. Algunos campos han incorporado las últimas averiguaciones neurocientíficas muy rápidamente, otros son bastante reacios a hacer lo propio. En economía dos disciplinas representan los polos opuestos de este espectro: por un lado, los investigadores de marketing han sido muy rápidos en adaptar sus modelos de comportamiento de los agentes para incorporar el afecto, quizás incluso compitiendo con la psicología al focalizar su atención en temas de tipo afectivo. Por otro lado, los académicos de economía han sido más reticentes a incorporar el afecto en sus modelos formales, a pesar de que los profesionales reconocen su importancia completamente. Esto se debe en parte al hecho de que las metodologías de investigación financiera son lo suficientemente satisfactorias como para haber asentado el desarrollo del sistema financiero moderno, que se ha convertido en un importante conjunto de instituciones de cualquier economía desarrollada.

La comparación entre economía y marketing nos proporciona un ejemplo interesante al mostrarnos cómo una disciplina que incorpora el afecto lo hace para proporcionar a sus profesionales soluciones efectivas basadas en este, mientras que la otra se debate con problemas comúnmente reconocidos por estar causados por el afecto. La investigación en marketing ha acogido los procesos afectivos teórica y empíricamente: los impulsores del afecto se estudian de forma generalizada y sus consecuencias sobre el comportamiento y el marketing están ampliamente documentadas y son usadas en la industria. A pesar del amplio progreso en las finanzas conductuales, la teoría económica todavía considera al comportamiento en un plano secundario frente a la “racionalidad” y se ha resistido a admitir el afecto, especialmente como motivador primario del comportamiento en la toma de decisiones. En su lugar, la teoría económica estándar considera al comportamiento una fuente de error en vez de una pieza objetiva del rompecabezas financiero. No es de extrañar, por lo tanto, que las burbujas bursátiles sigan siendo una de las principales cuestiones sin resolver de la economía financiera. Es un hecho ampliamente reconocido que el estallido de las burbujas económicas se da como resultado de manías y pánicos arraigados afectivamente. Sin embargo, los métodos analíticos estándar descartan el afecto como parte fundamental de los mecanismos que afectan a una burbuja económica y la causa intuitiva de la burbuja del mercado de valores no se examina.

A pesar de que los académicos de economía han realizado un tremendo progreso en el estudio del funcionamiento de la burbuja económica, la explicación que ha recibido menos atención empírica es el afecto. Esto puede deberse a cuestiones de diseño de investigaciones prácticas: el afecto es difícil de definir y medir. Las finanzas conductuales, subdisciplinas que se especializan en proporcionar explicaciones psicológicas a la formación de los precios, han explorado muchas opciones para medir el afecto. Una estrategia adecuada ha sido el análisis a posteriori de datos financieros, cuyos patrones no encajan con predicciones racionales financieras. Otro enfoque consiste en documentar las consecuencias de muchas preferencias cognitivas de las decisiones de los participantes del mercado, del rendimiento de una cartera y del comportamiento de los precios. La teoría financiera psicológica ha tratado implícitamente de proporcionar un sustituto del afecto usando datos económicos, lo que ha producido el beneficio adicional de la inferencia del comportamiento a tiempo real. Sin embargo, la importante desventaja de este enfoque es que solo se centra en el afecto total: tales sustitutos son incapaces de aprehender las características definitorias del afecto que son la diversidad y heterogeneidad de los factores afectivos y sus efectos. Algunos enfoques basados en sustitutos que se centran en la heterogeneidad y diversidad del afecto han sido usados principalmente por profesionales: hablamos, por ejemplo, de los sondeos y el análisis semántico. Varios casos de investigación usando estos métodos han sido reconocidos como hitos para la investigación futura en la teoría financiera psicológica. Pero, como las medidas se han obtenido de profesionales, desafortunadamente carecen de rigor científico pese que a las conclusiones obtenidas sean realmente interesantes.

Mientras que dentro de las finanzas conductuales las referencias implícitas y generales al afecto son corrientes, escasean las medidas, metodologías y teorías que versen sobre el afecto directamente, o que incluso se basen en las ciencias afectivas propiamente dichas como, por ejemplo, la neurociencia afectiva, la psicometría, el comportamiento del consumidor, etc. Específicamente, tales referencias al afecto consideran con frecuencia que los participantes del mercado solo muestran dos sentimientos opuestos (por ejemplo “positivo y negativo” o “ambición y temor”). Aunque pueda ser sintetizado de esta manera, la naturaleza empírica verdadera del afecto es diversa y heterogénea (véase la ilustración A.1 de más abajo). Cada sensación emocional particular se sitúa en una escala propia y todas ellas funcionan conjuntamente. Específicamente, esta tesis muestra nuevas evidencias de que factores afectivos diversos – ya sean positivos, neutros o negativos – ponen de manifiesto relaciones individuales entre el mercado de valores y las decisiones de inversión subyacentes.



Gráfica A.1: La heterogeneidad de las emociones

La heterogeneidad de las emociones es impresionante: además de especificar las emociones que se muestran en esta gráfica, éstas también se pueden medir en relación a objetos, y se puede medir también la intensidad de cada factor afectivo. Por ejemplo, una persona puede sentirse al mismo tiempo decepcionada sobre un aspecto de un hecho, pero encantada con otro. Además, estos sentimientos pueden interactuar cuando ejerzan una influencia sobre el juicio y la toma de decisiones, produciendo aún más complejidad y heterogeneidad. Por lo tanto, estudios que midan la emoción solamente por medio de valencias (positiva y negativa) o de activación (activo o calmado) omiten una gran cantidad de información.

Por ejemplo, en lugar de considerar al miedo y la ambición como los polos opuestos de la misma escala con efectos antagónicos en el mercado de valores, una manera más precisa y descriptiva de conceptualizarlos consiste en considerar que el miedo es un factor afectivo y la ambición otro. Por ello cada uno podría ser medido en una escala y ambos podrían tener una valencia positiva, negativa o ser neutros. La ambición y el miedo pueden, por lo tanto, influenciar decisiones comerciales diferentes de diversas maneras y, también, al mismo tiempo. Al conceptualizar cada factor afectivo como su propio impulsor de comportamiento, los investigadores serán capaces de examinar un conjunto de relaciones más precisas y con más matices entre los procesos afectivos y los mercados financieros.

La economía está justamente ahora empezando a hacer caso a la revolución “afectiva” que está teniendo lugar en las ciencias sociales y las perspectivas futuras son amplias y apasionantes. El acceso a las tecnologías necesarias para estudiar los temas afectivos como son, por ejemplo, las grandes cantidades de datos, los medios sociales y la visualización somática, está siendo cada vez más amplio. Por primera vez se están pudiendo aplicar y son accesibles medidas fiables, longitudinales y directas del afecto. Esto quiere decir que los investigadores a los que les interese el estudio de la responsabilidad del afecto en las burbujas económicas tienen ahora la posibilidad de abrir esa caja negra. Ahora tenemos la posibilidad de tener una imagen detallada de la mecánica latente de una burbuja económica. Este conjunto de circunstancias resulta fascinante puesto que nuestro sistema financiero se beneficiará enormemente de una mejor información, que hará que los mercados sean más eficaces y permitirá una mejor regulación, supervisión y actuación de los inversores. La situación también resulta un poco desconcertante porque la información afectiva es de naturaleza personal y resulta ser, sorprendentemente, un gran indicador del comportamiento. Será inevitable que haya cambios dentro del sistema financiero porque las medidas típicas de utilidad y riqueza se complementarán (a lo mejor incluso se sustituirán) por factores afectivos diferentes, que pueden estar relacionados específicamente con procesos físicos en el cerebro. De hecho, el propósito del sistema financiero es asegurar que los recursos y el capital se distribuyan y usen eficazmente. El éxito de este proceso se mide hoy por hoy por el crecimiento económico o los beneficios económicos. Podemos imaginarnos un futuro no tan lejano, y en cierto modo orwelliano, en el que el éxito de la distribución del capital pueda estar también medido directamente por los estados subjetivos del bienestar.

De hecho, cuando los economistas miden el éxito de un sistema financiero con medidas de tamaño y crecimiento económico, su propósito implícito es estimar hasta qué punto es más rica la gente. En este sentido, los indicadores económicos son equivalentes a las experiencias subjetivas de la gente de la que está conformado el sistema económico. Por consiguiente, determinar en qué consiste el afecto, cómo puede ser medido y cómo está relacionada la variación de los factores afectivos con decisiones financieras, son los próximos pasos lógicos para mejorar nuestra comprensión del sistema financiero, sus mecánicas latentes y sus participantes. Este estudio se basa en la economía como un laboratorio de pruebas para un conjunto de herramientas nuevas, modernas e innovadoras que con el tiempo ayuden a afrontar los problemas económicos severos que continúan confundiendo a investigadores y legisladores: burbujas económicas, una excesiva desigualdad en la distribución de la riqueza y el crecimiento económico. Todavía es muy pronto para determinar hacia dónde nos dirigirá este estudio pero las perspectivas de futuro que abre son muy emocionantes y vienen cargadas de promesas.

Mucho antes de que la investigación sobre el afecto en la economía madure hasta el punto de poder hacer hincapié en los problemas macroeconómicos mayores, es importante determinar qué es el afecto y comprender la profundidad y escala de la revolución causada por los avances neurocientíficos a nivel microeconómico. Como resultado, esta tesis se centra en definir y medir el afecto y en probar su influencia en el sistema financiero en términos de formación del precio, decisiones comerciales y política corporativa financiera. El resto de este capítulo introductorio consiste en un resumen de la historia del afecto desde sus primeras conceptualizaciones hasta el desarrollo de las ciencias sociales y, finalmente, el papel que ha jugado en enmarcar las finanzas conductuales. Esto proporciona un contexto más amplio a la investigación de esta tesis en cuanto a la comprensión de por qué pensamos de la manera que lo hacemos sobre las emociones. Posteriormente especificaremos la motivación y las preguntas de investigación de cada estudio.

2. El camino hacia las finanzas conductuales: contexto histórico del afecto y las ciencias sociales

Hablar sobre las emociones en el contexto del comportamiento es común a lo largo de la historia del estudio de la humanidad, antes incluso de que nadie supiera lo que era el afecto o incluso que se originaba en el cerebro. Analizar algunas de las ideas más influyentes que han enmarcado la percepción contemporánea de lo que es el afecto, puede proporcionarnos un contexto adecuado para entender la motivación que ha suscitado la investigación de esta tesis.

Muchos de los importantes pensadores que pusieron las primeras piedras del pensamiento occidental hablaron sobre las emociones y, por lo tanto, han enmarcado el debate contemporáneo sobre éstas, qué son y cómo dirigen el comportamiento. En particular, esto ayuda a explicar por qué se ha tardado tanto en incorporar el afecto al estudio de la economía y por qué ha habido tanta resistencia en la comunidad académica económica para incorporar el afecto en un modelo financiero estándar. Esto es especialmente sorprendente cuando el discurso público se refiere tan obviamente al afecto en los mercados financieros ya sea por reguladores (por ejemplo, la referencia famosa de Greenspan a la "exuberancia irracional") o por profesionales de cualquier red de noticias de economía.

Existe una razón histórica por la cual, por lo menos los pensadores occidentales, se resisten a la idea de que las emocionas dirigen el comportamiento y se tiende a pensar que las emociones son implícitamente responsables del "mal" comportamiento. Al principio se consideró objetivamente que las emociones formaban parte del proceso que generaba el comportamiento. Platón y Aristóteles (s. III a. de C.) dieron una descripción sorprendentemente rigurosa de las emociones al presentarlas como parte de una relación interactiva con el proceso responsable del pensamiento consciente y analítico. Algunas de sus discrepancias constituyeron un tema de discusión durante más de 2000 años y representaron auténticos obstáculos para la incorporación de las emociones en cualquier consenso entre pensadores que tuviera que ver con la sociedad y su comportamiento. Platón planteó que dicha interacción estaba provocada por una mente que existía antes que el cuerpo. Aristóteles, por otra parte, pensaba que todo el mecanismo derivaba de procesos físicos.

Durante la mayor parte de la Edad Media, el pensamiento de Platón sobre las emociones y el comportamiento tuvo mayor influencia que el de Aristóteles, haciendo de las emociones un concepto metafísico inconmensurable más allá de la comprensión científica. Santo Tomás de Aquino (s. XIII), por ejemplo, se posicionó explícitamente en contra de la visión aristotélica y su obra influyó notablemente en pensadores posteriores en lo concerniente al ámbito de las emociones. En concreto, es responsable de formular el concepto de que los animales pueden ser clasificados como "racionales" y expuso que, fundamentalmente, los únicos animales racionales eran los humanos. Aunque la racionalidad descrita por Santo Tomás es similar a la cognición en muchas facetas, su descripción no excluye el papel de las emociones en la toma de decisiones humana. Su idea de que la racionalidad es lo que separa al hombre de la bestia sería perpetuada por los pensadores posteriores que se plantearon la pregunta de cuál era el papel de las emociones con respecto a la racionalidad. En concreto, René Descartes (s. XVII) fue el filósofo más famoso por sus disquisiciones sobre las emociones y el primer pensador que abordó explícitamente el tema de las emociones y de sus consecuencias en la toma de decisiones. La consagración de la "racionalidad" y la percepción de que las emociones inducían a tomar decisiones negativas (en oposición a ser simplemente relevantes, como se piensa hoy en día) tuvo lugar con Descartes – y esto se creyó debido a que se le consideró el padre del método científico moderno.

La influencia de Descartes en la ciencia y la filosofía llega hasta nuestros días: algunas de sus contribuciones incluyen, por ejemplo, el sistema de coordenadas cartesianas, la geometría analítica y el cálculo infinitesimal, y sus tratados de filosofía representan uno de los pilares del pensamiento filosófico occidental. Su trabajo revolucionario: *Las pasiones del alma* (1649), preparó el terreno para el examen y análisis de las emociones y el comportamiento durante, por lo menos, los siguientes cuatrocientos años. Según su pensamiento, el mundo estaba formado tanto por materia tangible como intangible: el hombre estaba compuesto por la primera y el alma (interpretable aquí como la "mente"), e inherentemente racional, por la segunda. A pesar de lo extravagante que este modelo pueda parecer actualmente, resulta ser el primero en representar un proceso dual. Comprende una categoría competente de modelos del comportamiento fundamentados en la cognición y el afecto que aún se usa a día de hoy.

Descartes incluso localizó, aunque incorrectamente, el área cerebral (la glándula pineal) en la que ocurrirían las interacciones entre el alma y el espíritu animal, situando de forma pionera, al cerebro en el centro de su explicación del comportamiento. Las sensaciones que se originaban de esas interacciones son lo que Descartes denominó pasiones y, más tarde, serían conocidas como emociones. El estudio de Descartes sobre las pasiones constituiría la base para la comprensión de las emociones hasta que el interés por las emociones de la moderna neurociencia cogiera el timón a finales del siglo XX. Mientras que otros pensadores influyentes se basaron inmediatamente en el análisis de Descartes de las emociones, la asunción recurrente desde entonces ha sido que las emociones obstaculizan la "racionalidad" y la habilidad de tomar decisiones certeras. La parte de la filosofía que fue tan difícil de desligar del pensamiento científico convencional sobre el comportamiento, fue que el comportamiento humano estaba regido primordialmente por la parte racional pero estaba sujeto intermitentemente a la parte emocional. La realidad, sin embargo, es que el afecto es el impulsor primario del comportamiento y el razonamiento solo ocurre intermitentemente, debido a su alto coste en términos de recursos fisiológicos.

Las ciencias sociales consideraban, por lo tanto, que las emociones eran un mecanismo de toma de decisiones pasajero y lejos de ser óptimo. Se asumía que si la gente quería comportarse óptimamente, ignorarían a las emociones, definidas en sentido amplio, y se comportarían de manera racional. De esta manera, los modelos normativos basados en la racionalidad no se diferenciaban considerablemente del comportamiento real, lo que los hacía parecer rigurosos, eficaces y prácticos. Por este motivo, las disciplinas como la sociología o la antropología, o incluso la geografía, han ignorado en gran medida posibles explicaciones concerniendo al afecto de ciertos fenómenos en favor de otras explicaciones respaldadas por el comportamiento racional. Sin embargo, además de no ser preciso, el modelar a los humanos como agentes estrictamente racionales puede tener consecuencias negativas al pasar de la teoría de las ciencias sociales a la práctica organizacional (precisamente porque se han ignorado las consecuencias afectivas). Las consecuencias afectivas condenan la utilidad de las teorías racionales y, como resultado, pueden causar grandes costes monetarios y sociales: primero, al llevar a la práctica la idea “racional”, solo para descubrir más tarde que no funciona, y tener entonces que deshacer lo que se había llevado a la práctica. Por consiguiente, los modelos de ciencias sociales tienen que incluir el afecto si se van a usar para crear y administrar organizaciones e instituciones sociales.

Esta tesis defiende que la inclusión de un estudio teórico y empírico del afecto en economía mejorará las instituciones, decisiones y políticas financieras. Para transmitir la importancia de este tema y cómo se adecua a las ultimas corrientes científicas, nos es de ayuda en esta sección la revisión de un ejemplo histórico de cómo una teoría racional llevada a la práctica no fue un éxito por haber dejado al margen el estudio del afecto. Aquí, la analogía con la economía le concierne a otra disciplina social por pleno derecho: la geografía. La geografía se dio cuenta de la importancia del afecto después del surgimiento y caída del movimiento conocido como urbanismo racionalista (1890-1960). Exactamente igual que con la economía racional (1900-1980), este movimiento se formó como resultado de la generalización de las técnicas cuantitativas (en términos de medidas y modelos predictivos, por ejemplo) que trajo la revolución industrial.

En el caso del urbanismo racionalista, estas técnicas usaban unas características espaciales importantes como la exposición directa a la luz del sol, el movimiento del tráfico de vehículos, unidades de vivienda estándar y la proximidad a espacios verdes. Esta lista nos recuerda las variables comunes usadas en la investigación financiera racional: beneficios, volatilidad, tamaño, liquidez, volumen, paridad bursátil… En ninguna de las dos disciplinas las medidas tienen en cuenta las preferencias subjetivas de la gente involucrada: los residentes potenciales en el caso del urbanismo o los participantes del mercado en el caso de la economía. Los dos campos, de hecho, ignoraron el afecto.

Para aplicar técnicas cuantitativas a estos factores, los urbanistas tuvieron que contratar a técnicos altamente especializados incluyendo a arquitectos, diseñadores de proyectos e ingenieros. De manera similar, las técnicas cuantitativas avanzadas en la economía racional requerían el desarrollo de matemáticos, informáticos, ingenieros y físicos. El urbanismo seguía un modelo de arriba hacia abajo, ya que los técnicos imponían un plan urbano particular basado en características racionales a la población, como indicaban el gobierno y los promotores privados. Esto sometió a este urbanismo a la crítica final de ser elitista y socialmente insensible. Sus límites quedaron claros cuando, algunas veces justamente después de haber sido construidos, muchos proyectos de viviendas en todo el mundo, fracasaron y tuvieron que ser desmantelados a un coste muy elevado. La economía racional también es una disciplina inherentemente de arriba hacia abajo que estudia las características de las cuotas del mercado y saca conclusiones sobre lo que, en realidad, es un conjunto diverso y heterogéneo de participantes del mercado. La economía también ha sido criticada por ser elitista y, aunque los mercados no han sido desmantelados, los efectos secundarios de las últimas crisis económicas han sido muy costosos, y la responsable de esto fue la comunidad financiera.

El urbanismo racionalista finalizó porque perdió de vista al público para el que construía. El modelo racional de comportamiento en el que se basaban asumió que la exposición directa a la luz solar, el tráfico de vehículos, las unidades de vivienda estándar y la proximidad a espacios verdes eran características que harían felices a sus residentes, pero se habían olvidado de algo importante. Desde los últimos movimientos urbanistas de abajo hacia arriba, ya sabemos que los residentes tienen sentimientos muy profundos sobre muchas características intangibles que se ignoraron en el urbanismo racionalista como la cohesión social, el mantenimiento de la cultura autóctona y la sostenibilidad. Estas características satisfacen las necesidades afectivas de los residentes y fueron condición necesaria para mejorar el urbanismo racionalista: la mayoría de los movimientos de urbanismo posteriores favorecieron el modelo de abajo hacia arriba. Este método significó la medición de los agentes al empezar e hizo hincapié en la participación pública, la comunicación y el consenso para establecer ciertas preferencias y las características afectivas importantes que hacía falta considerar.

La experiencia del urbanismo es informativa porque constituye un ejemplo histórico de la transformación que están sufriendo las ciencias sociales, forzadas por las consecuencias a las que se enfrentan al haber ignorado los procesos afectivos en los agentes sociales que estudian. Este ejemplo conforma una base narrativa a la motivación de esta tesis. Hoy por hoy muchas instituciones financieras reflejan una situación parecida al urbanismo racional porque también han sido desarrolladas basándose en modelos racionales del comportamiento. Las instituciones financieras no están diseñadas para tener en cuenta el afecto. Por tanto, no tienen una política con respecto a este, lo que las hace vulnerables a problemas originados por procesos afectivos. El indicador de este tipo de problema es la burbuja bursátil: los "espíritus animales" de los inversores suben los precios, a pesar de cualquier evidencia para hacer lo contrario, hasta niveles insostenibles. Con el tiempo, el mercado entra en pánico y, consecuentemente, se hunde dañando así al sistema financiero y al crecimiento económico. Algunos estudios han proporcionado muchas explicaciones racionales para estas burbujas, como un crédito excesivo o una política monetaria débil. Y mientras que estas causas constituyen una parte del problema de la burbuja, no descartan el papel de los acontecimientos afectivos como manías y pánicos. De hecho, muchos investigadores se han inclinado a estudiar procesos relacionados con el afecto para explicar crisis financieras más que el mismo afecto.

El término "espíritus animales" se ha popularizado para referirse a los efectos colectivos de muchas decisiones de comportamiento no racionales que han aparecido en psicología desde los años 70 y explica los fenómenos económicos que no se ajustan a modelos racionales de la economía. Los psicólogos han catalogado una larga lista de sesgos cognitivos, llamados así por su divergencia con el comportamiento racional, que pueden ser integrados en modelos racionales de la economía con relativa facilidad. Con respecto al principio de parsimonia, sin embargo, cada ajuste no racional que se aplique a un modelo económico lo hace cada vez más complejo. Con frecuencia los modelos económicos solo pueden dar cuenta de dos o tres sesgos cognitivos cada vez, pero, sin embargo, generalmente les acompaña un modelo de actuación mejorado sobre el modelo racional original. El caso más famoso es el de la sustitución del modelo de utilidad esperada racional de Von Neumann y Morgenstern por el uso de la teoría prospectiva de Kahneman y Tversky. Se puede cambiar el primero por la segunda en cualquier modelo de utilidad para convertirlo en un modelo del comportamiento que dependa de rutinas de decisión determinadas empíricamente más que de otras teorizadas racionalmente. El éxito de la adaptación de la teoría prospectiva por los economistas concluyó convirtiéndose en un acontecimiento transcendental en la economía que engendraría muchos modelos basados en sesgos cognitivos y generalizaría la aceptación de los estudios cognitivos en los problemas económicos.

La emergencia de las finanzas conductuales en la década de 1980, fue respaldada por el reconocimiento de que las técnicas conductuales podían mejorar los procedimientos de los modelos económicos al hacerlos más descriptivos. Por ejemplo, se vio que el movimiento del precio de las acciones mostraba una volatilidad más elevada de la que se podía explicar solamente mediante modelos racionales. Así quedó claro que el comportamiento rellenaría ese hueco. Las finanzas conductuales se basaban primordialmente en la psicología para entender los mecanismos de toma de decisiones y de opiniones que hacían que los precios se comportaban de la manera en la que lo hacían. Durante la década de 1990, las finanzas conductuales propusieron dos teorías para explicar por qué el comportamiento de los precios se desviaba de las expectativas racionales: el primero se denomina sentimiento inversor, que implica que los mercados reaccionan exagerada o insuficientemente. El segundo se llama arbitraje limitado, por el cual los mercados no “echan el freno” y los participantes de mercado que se supone que tienen que refrenar unos precios insostenibles no lo hacen (y algunas veces hasta empeoran la situación). También se documentaron muchas explicaciones conductuales sobre el exceso de volatilidad en el comportamiento de los precios: el comportamiento de manada, la sobreinversión, el exceso de confianza, el comercio con resultados positivos, el efecto de la disposición (es decir, mantener acciones que están a la baja durante mucho tiempo y no quedarse durante mucho las que están a la alza) y la expresión de las preferencias. Aunque esté implícito que las emociones juegan un papel en la manifestación de tales explicaciones cognitivas del comportamiento económico, el papel del afecto no ha sido examinado explícitamente: el estudio del sentimiento inversor todavía tiene que prestar atención al estudio de los auténticos sentimientos.

El sentimiento inversor es un término que los economistas conductuales han adoptado de los profesionales de las finanzas y que en origen se refería al sentimiento expresado por los participantes del mercado con quienes hablaban. Así, el uso original del término se refería explícitamente a la comprensión instintiva del afecto de los participantes del mercado, pero desde el desarrollo de las finanzas conductuales, se refiere a la colección de los efectos psicológicos sobre los precios que hay registrados. Un motivo que hay detrás de este cambio semántico radica en que cuando las finanzas conductuales surgieron en 1980, todavía quedaba sin resolver un debate importante en psicología sobre el afecto. El resultado de ese debate demostró ser un importante punto de inflexión en cómo la psicología influiría en otras disciplinas de las ciencias sociales y presagió también los resultados empíricos de los futuros estudios neurocientíficos. En el debate se estudiaba cuál de las tres categorías de la mente: cognitiva (reflexión y análisis), afectiva (estados sentimentales) o conativa (comportamiento impulsivo) es el primer sistema cerebral en responder a un estímulo. El pensamiento original, heredado de Descartes, asumía que los mecanismos cognitivos reaccionaban primero y que el afecto tenía lugar más tarde. Durante la década de 1970, bajo la influencia de Pavlov y Skinner los investigadores mantendrían, sin embargo, que el afecto era el mecanismo primario como respuesta a un estímulo.

La corriente científica que situaba el afecto como el motivador primario del comportamiento proporcionó la evidencia necesaria para contradecir el concepto de que los humanos eran primordialmente seres racionales. En la década de los ochenta, el debate se decantó bastante en favor de la primacía del afecto, que más tarde incorporaría los procesos conativos y se consideraría al final como un prerrequisito para la cognición. La evidencia neurociéntifica para que esto ocurriese emergió durante la segunda mitad de la década de los noventa como la hipótesis de la huella somática y se describe por el neurocientífico Antonio Damásio en un libro titulado *El error de Descartes.* El libro de Damásio se refiere especialmente al experimento natural que se produce en casos de pacientes que, tras un accidente cerebral, sufren cambios de personalidad. Las partes específicas del cerebro que sufrieron daños estaban relacionadas con procesos emocionales. Como Damásio explica, los cambios de personalidad se debían a que, aunque las partes emocionales del cerebro estaban dañadas, los pacientes no podían realizar lo que se consideran normalmente labores racionales. Así, Damásio concluyó, estudiando el cerebro, que los procesos cognitivos y afectivos están inherentemente unidos en el nivel neurológico y que ninguno puede funcionar sin la presencia del otro. Por lo que respecta a la estructura del cerebro, la separación de la razón y de las emociones no es más que una ilusión de la conciencia.

Hacia el final de la primera década del siglo XXI, una vez que el descubrimiento neurocientífico de la activación de la función cognitiva cerebral sucede en concierto con la activación afectiva consiguió una mayor aceptación en las demás ciencias sociales, las disciplinas económicas comenzaron a estudiar temas financieros relacionados con los procesos afectivos. Esta tesis estudia la disciplina de la economía propiamente dicha, pero en términos de incorporar el afecto, fue incluido relativamente más tarde. Los investigadores de marketing se han estado actualizando con respecto a las investigaciones del afecto. Las finanzas conductuales se benefician ahora de la investigación llevada a cabo por estos investigadores, sus resultados y sus metodologías. Estos investigadores están viendo que el estudio de temas como el comportamiento del consumidor, que se basa en un estudio extensivo relacionado con el afecto, se puede extrapolar a temas como la creación del valor, la conducta comercial y las preferencias financieras. Otras disciplinas que alimentan la revolución afectiva en la economía incluyen a la psicología y la neurociencia, que han motivado la línea investigadora en economía durante la década que empezó en 2010. La investigación económica de temas afectivos durante este período también refleja una reacción a la crisis de las hipotecas *subprime,* que comprendió manías, pánico y el control de determinadas sensaciones afectivas en el público (por ejemplo, confianza y optimismo) por los bancos centrales, por ejemplo, a pesar de no tener unas medidas o políticas establecidas sobre los efectos del afecto.

Este estudio, por lo tanto, se enmarca dentro de los estadios tempranos de la investigación sobre finanzas conductuales que se centran explícitamente en el afecto. En particular, se centra en el hecho extremadamente importante de que no existe una normativa sobre el afecto, la falta de un marco de medidas estándar y el reconocimiento de la heterogeneidad entre los factores afectivos (por oposición a las dicotomías típicas usadas para medir los sentimientos de los inversores, por ejemplo positivo/negativo, activo/calmado, ambición/miedo). Examinamos estos temas en el contexto de los mercados financieros, la toma de decisiones financieras y el diseño de políticas financieras. Por todo esto contribuiremos a la literatura de las finanzas cognitivas sobre las burbujas económicas, sus efectos, cómo surgieron y cómo controlarlas. Más abajo especificamos las preguntas de investigación y la motivación de este estudio.

3. Problemática, motivación, preguntas de investigación y contribución a las finanzas conductivas

La presente colección de estudios aborda el problema de las burbujas económicas desde tres puntos de vista: la relación entre el afecto y los precios, la relación entre el afecto y las decisiones de mercado y cómo este conocimiento puede informar a la política corporativa financiera. Examinando estos tres puntos de vista con respecto a la relación del afecto y los mercados financieros, aportamos nuevas evidencias a la literatura sobre cómo conceptualizar, medir y dirigir la incidencia de las burbujas. La motivación dominante de este estudio radica, sin embargo, en la toma de medidas: probar una nueva metodología de medición con el propósito de crear un marco de medidas basado en el afecto que proporcione contenido informativo relevante sobre las burbujas del mercado. Para los propósitos de este estudio, “relevante” quiere decir que existe una relación entre afecto y comportamiento de mercado, entre afecto y decisiones financieras y entre el afecto y la toma de decisiones de las organizaciones. Las medidas que satisfagan estas condiciones representan el primer paso en la construcción de un marco de medidas útil para todos los participantes del mercado - comerciantes, arbitrajistas, reguladores e investigadores – que nos permita entender, identificar, analizar y estar preparados ante las burbujas económicas.

El modelo financiero estándar actual no trata directamente la existencia de las burbujas económicas, pero el propósito de las finanzas conductuales es incorporar una teoría sobre las burbujas en un modelo económico sobrecogedor. Hasta hoy, todos los enfoques sobre este problema son, en cierta medida, polémicos. Las finanzas conductuales tienen todavía que proponer un modelo comprensivo, aunque prevalece la idea generalizada de que una respuesta libre de polémica yace en algún lugar de la esfera del estudio del comportamiento. Ante la ausencia de una forma más específica de referirnos a los mecanismos de una burbuja económica, las finanzas conductuales (han llegado al consenso de que dos fuerzas interactúan cuando se produce una burbuja: el sentimiento inversor y un arbitraje limitado. Usar algún otro término aparte de estos dos es un tema espinoso. Existen muchas explicaciones del comportamiento que compiten para explicar las reacciones desproporcionadas que se dan en los mercados y todas ellas son en cierta forma algo polémicas y se extienden desde explicaciones relacionadas con el tiempo atmosférico, pasando por explicaciones hormonales a cualquier número de sesgos cognitivos.

Dada la reciente turbulencia de los mercados financieros, es necesario que seamos más específicos sobre la mecánica y los agentes impulsores de las burbujas a pesar de que constituya un tema espinoso. Aunque se han reconocido muchas causas del sentimiento inversor y éstas pueden ser medidas, identificar y corregir las burbujas económicas es aún poco efectivo: han ocurrido casi continuamente en todo el mundo desde 1970. Una razón por la que las burbujas son tan persistentes puede radicar en que el sentimiento inversor no se mide correctamente. El hecho que respalda este argumento es que el sentimiento inversor también se define vagamente como el resultado de numerosas explicaciones que compiten entre sí. En el caso del mercado de valores, la explicaciones sobre las burbujas bursátiles no se tienen en cuenta. Incluso si los datos financieros reflejan el advenimiento de una burbuja, todavía no se dice nada sobre el proceso relacionado, latente y no financiero de valoración de las acciones que ocurre entre los inversores. Como causa subyacente de las burbujas, ese proceso latente no financiero requiere su propio método de medición. El panorama actual presentado por la contabilidad tradicional y las medidas basadas en la economía y las prácticas de presentación de la información estudian la evaluación latente de los inversores, y eso no hace que el inicio de una burbuja sea lo suficientemente obvio como para que los profesionales y los responsables políticos tomen ninguna acción preventiva. Hacer esta afirmación es plausible porque las burbujas se siguen sucediendo, señal importante de que, por lo menos por lo que respecta a las burbujas, se tienen que mejorar las medidas existentes y las prácticas de presentación de la información.

En su búsqueda para entender el afecto y sus relación con las decisiones y los mercados financieros, este estudio plantea la pregunta de cómo mejorar las medidas financieras actuales y las prácticas de presentación de la información para que se puedan dar procedimientos proactivos en relación con las burbujas financieras. El sistema actual, basado en la contabilidad, obliga a las corporaciones públicas a ser transparentes en los informes financieros públicos y estandariza las medidas financieras para que las corporaciones puedan ser comparadas, entre ellas y ellas mismas, con el paso del tiempo. Esto ayuda a determinar qué compañías son las arriesgadas y ayuda a los inversores a distinguirlas de las compañías seguras. El defecto de este sistema es que determinar el riesgo de unos activos depende también de los juicios relativos de los otros participantes del mercado. En esto consiste, de hecho, el famoso “concurso de belleza” de Keynes y, básicamente, el punto de medida del sentimiento inversor: cuantificar lo que piensa el resto del mercado.

Hasta ahora el esfuerzo para cuantificar el sentimiento inversor se asimila a la búsqueda del santo grial de los indicadores de sentimiento: ese que predice impecablemente el juicio medio del mercado. De hecho, la concepción habitual del sentimiento inversor es que se mueve por una multitud de factores conductuales, pero se mide en una única dimensión “que lo abarca todo”. Normalmente se considera positivo, neutro o negativo y señala el nivel medio de excitación del mercado. Asume que los mercados agitados buscan el riesgo y están sometidos a burbujas económicas, mientras que los mercados pasivos están en contra de asumir riesgos y rinden por debajo de su potencial. En realidad, no existe un indicador perfecto del precio y es probable que el juicio del inversor y la toma de decisiones sean demasiado complejos para resumirlos con una medida directa o sustituta. El estudio que se lleva a cabo en esta tesis es innovador en el sentido de que expone que en vez de tener una sola medida, debería desarrollarse un estudio multidimensional para medir el sentimiento inversor. Un estudio semejante complementaría las medidas financieras estándar y les proporcionaría un contexto. Esta tesis, por tanto, investiga la mejor manera de desarrollar este estudio respaldada por debates de base teórica y empírica.

3.1. Capítulo 1

El primer paso para establecer la relevancia del afecto en el sentimiento inversor se menciona en el capítulo 1. Consiste en un estudio de la relación entre el afecto y la muestra representativa de beneficios bursátiles: ¿los diferentes factores afectivos medidos usando la misma metodología muestran relaciones diferentes a la muestra representativa de beneficios bursátiles? Esta pregunta de investigación es fundamental para establecer la mensurabilidad y relevancia del afecto en el comportamiento de los precios por dos motivos. Primero, permite la comparación entre los resultados derivados de las comparaciones afectivas y las medidas que existen sobre el sentimiento inversor. Después, al comparar las medidas del sentimiento inversor con las afectivas, también es posible determinar si el uso de dimensiones múltiples del afecto proporcionaría una información adicional sobre los mercados. Al demostrar que es posible usar medidas afectivas para reproducir las relaciones que ya conocemos que muestra el sentimiento inversor en la muestra representativa de beneficios bursátiles, y al demostrar que se usan diferentes dimensiones del afecto para mostrar diferentes relaciones, el capítulo 1 demuestra efectivamente que existe un gran potencial para crear un marco de medidas basado en el afecto.

El potencial para tal marco de medidas está basado en el hecho de que las medidas basadas en el afecto reúnen las condiciones necesarias empíricas y teóricas: empíricamente es posible reproducir estudios existentes y, teóricamente, existe una explicación aceptable por la que podemos reproducir esos estudios existentes. En este último caso, la explicación está específicamente relacionada con la primacía del afecto, que consiste en el reconocimiento de que el afecto constituye el primer proceso en responder a un estímulo. Estos razonamientos son importantes porque permiten que el estudio sostenga la opinión de que las medidas basadas en el afecto puedan explicar otros planteamientos válidos para explicar y medir el sentimiento inversor. Este capítulo pretende afirmar que las mediciones basadas en el afecto muestran un alto "retorno de inversión" en el sentido de que son unas metodologías relativamente baratas de poner en práctica dada la riqueza de información relevante que son capaces de recoger. De hecho, son las medidas más relevantes para explicar la relación de los precios con respecto al comportamiento porque dan cuenta de todas las demás explicaciones sobre los precios.

El capítulo 1 se centra explícitamente en la discusión teórica que ofrece la base para afirmar que el afecto dirige otros motores del sentimiento inversor. Proporciona un modelo único teórico y basado en el principio de parsimonia sobre la cadena de sucesos desde el estímulo informacional hasta el orden en el que los patrones cognitivos se suceden cuando una decisión comercial tiene lugar. Esto es importante ya que en la actualidad muchas mediciones del sentimiento inversor compiten entre ellas, sin embargo son fundamentalmente diferentes debido a las diferentes partes de la cadena de sucesos en la toma de decisiones que cada una tiene como objetivo. Por ejemplo, el buen tiempo atmosférico, los estados emocionales positivos, el uso de la heurística, niveles elevados de testosterona y cambios en la piel son todos medidas del sentimiento inversor que compiten entre sí. Sin embargo, cuando sale el sol la gente tiende a estar más feliz; lo que significa que usan más la heurística, tienen unos niveles más elevados de testosterona y sufren cambios dermatológicos: cada causa documentada del sentimiento inversor constituye en efecto un vínculo dentro de la misma cadena, desde el estímulo a la decisión, que concluye en el resultado de mercado.

Las implicaciones del capítulo 1 son, en particular, de gran interés para los arbitrajistas. Es poco probable que los profesionales del arbitraje puedan unirse ante una gran burbuja porque sus herramientas están limitadas por una definición pobre del sentimiento inversor y por una plétora de medidas de entre las que elegir. Esto sugiere que dos de estos profesionales que usen medidas diferentes para cuantificar sentimientos pueden no llevar a cabo estrategias complementarias. Lo cual puede ser un problema si la burbuja en cuestión es tan grande que ningún otro arbitrajista se arriesgue a apostar en contra de esa burbuja. Una clara definición y medida del sentimiento inversor ayudará a sincronizar a estos profesionales, lo que a su vez puede disminuir la intensidad e incidencia de las burbujas económicas. Ya que diferentes factores afectivos muestran diferentes relaciones con el mercado de valores, se miden siguiendo la misma metodología y pueden ser estructurados dentro de un marco específico, esto ofrecería a los arbitrajistas un conjunto de herramientas más flexible, más específico y más sencillo de comunicar para que lleven a cabo mejor su tarea de corregir burbujas grandes.

3.2. Capítulo 2

El capítulo 2 continúa donde acabó el capítulo 1. En éste averiguamos que el afecto se puede medir, es multidimensional y muestra unas relaciones significativas estadísticas y económicas de la muestra representativa de beneficios bursátiles. El siguiente paso para demostrar que el afecto es una mejor opción para medir el sentimiento inversor que otras alternativas actuales es demostrar que, además de estar relacionado con el comportamiento de los precios, el afecto también está relacionado con las decisiones que regulan los precios: las decisiones de mercado. La teoría proporcionada por la primacía del afecto sugiere que las medidas afectivas regulan las decisiones y el propósito del capítulo 2 es contribuir con evidencia empírica. La demostración de que las medidas del afecto también dirigen las decisiones del mercado, nos proporciona la oportunidad de corroborar las conclusiones del capítulo 1 pero también de afirmar que el afecto es mejor medida que el sentimiento inversor. De hecho, si las medidas del afecto pueden explicar los precios, pero pueden explicar también las decisiones que rigen los precios, el argumento a favor del afecto resulta mucho más sostenible. Esto es así especialmente si se demuestra que factores afectivos diferentes son relevantes en diferentes situaciones de mercado. Tal evidencia demuestra, de hecho, que las medidas del sentimiento inversor basadas en el afecto son capaces de hacer lo que otras no pueden: abordar cuestiones de heterogeneidad latente en el comportamiento.

Así el capítulo 2 deja de centrarse en el mercado bursátil para estudiar las decisiones de mercado de los individuos y agranda así las perspectivas de medir el afecto para explicar el sentimiento inversor. En particular, el capítulo 2 se cuestiona las siguientes preguntas de investigación: ¿están los diferentes factores afectivos relacionados con las diferentes relaciones de mercado? La comprensión de qué factores afectivos dirigen las decisiones nos informa sobre el comportamiento de los precios pero también describe los procesos de toma de decisiones de los participantes del mercado. Los factores afectivos pueden por tanto relacionarse con comportamientos de riesgo; con el uso de sesgos cognitivos y el uso de la heurística; con cambios fisiológicos como el comportamiento de la piel o el hormonal y, por tanto, pueden proporcionar una imagen más detallada de cómo se realizan las decisiones de inversión. El capítulo 2 demuestra que un conjunto de factores afectivos influye en la compra de acciones comunes de los inversores y que un conjunto diferente influye en sus ventas.

Las implicaciones de las averiguaciones del capítulo 2 son de gran repercusión. La investigación de las ciencias afectivas ha documentado que el afecto es maleable. Esto significa que los particulares niveles de afecto de un individuo pueden ser influenciados por terceros. El capítulo 2 identifica factores afectivos específicos relacionados con las decisiones de compraventa de los inversores. Lo que sugiere que, al ejercer cierta influencia en los factores afectivos específicamente responsables de compras o ventas, se pueden incrementar o reducir las compras y ventas. Los bancos centrales y las corporaciones hacen uso de este hallazgo en sus operaciones diarias. Los bancos centrales suelen usar políticas monetarias para influir en los mercados, enfriándolos si están demasiado calientes o estimulando el crecimiento si piensan que está justificado. Otra herramienta que utilizan es la comunicación con el público: los anuncios de los bancos centrales se atienden y diseccionan por el público. Este estudio sugiere que su discurso, dependiendo de si lo que quieren es incentivar las ventas o las compras, debería de estar orientado a influenciar determinados factores afectivos. De la misma manera, los departamentos de las relaciones con el inversor de las corporaciones pueden construir una política de comunicación fiable basada en la maleabilidad de los factores afectivos adecuados.

3.3. Capítulo 3

Después de que los capítulos 1 y 2 demostraran que el afecto está relacionado con los precios y con las decisiones de mercado subyacentes, el capítulo 3 completa el estudio de esta tesis: en él se examina la existencia de aplicaciones inmediatas de este estudio para los profesionales. El capítulo 3 estudia si el contenido informacional de las medidas de sentimientos basados en el afecto pueden mejorar el rendimiento de las corporaciones en lo que respecta a los precios y plantea la siguiente pregunta de investigación: ¿incluir el sentimiento inversor basado en el afecto en la política financiera corporativa mejora la evolución de las cotizaciones? Si las medidas del sentimiento inversor basado en el afecto contienen información útil para entender los precios y las decisiones de mercado, esta información también tiene que ser útil al diseñar políticas financieras corporativas y, en particular, las de relaciones entre inversores.

Una corporación que se enfrente a una burbuja bursátil, puede ver caer la cotización de sus acciones por la sencilla razón de que todas las demás también están cayendo dentro de una ola de pánico del mercado. En tal caso, las empresas querrán protegerse frente a este suceso, que, en última instancia, está fuera de su control. Para medir el afecto, este estudio recoge los niveles de satisfacción de los clientes de compañías que cotizan públicamente y analiza el corte transversal del retorno accionario, condicional en niveles elevados o bajos del sentimiento inversor. Así, este estudio muestra como el afecto de los participantes hacia el mercado se puede temperar por el afecto de estos participantes hacia empresas individuales. El estudio da cuenta de que empresas con clientes satisfechos exhiben correcciones menores que las empresas con clientes insatisfechos cuando los mercados están dentro de un pánico relativo.

Por lo tanto, esta tesis contribuye tanto al plano teórico como al empírico. Desde una perspectiva teórica, proporciona el estudio más comprensivo de la teoría afectiva en economía, ofreciendo el trabajo preliminar de un modelo comprensivo de finanzas conductuales. Empíricamente, esta tesis muestra que el afecto está relacionado con la formación de los precios, las decisiones de mercado y la política financiera corporativa. Además, el estudio demuestra que factores afectivos diversos tienen diferentes efectos en los precios y las decisiones de mercado. Así, las perspectivas que se presentan para futuros estudios son muy amplias. En particular, la construcción de una taxonomía de los distintos factores afectivos y sus efectos en las distintas fases del sistema financiero representaría un gran avance en el estudio del afecto y la economía. Desde un punto de vista práctico, esta tesis reestructura la importancia de medir el afecto no sólo porque es un proceso fundamental en el comportamiento, sino también porque es más práctico de cuantificar que otros motivadores del sentimiento: proporciona el contenido más informacional con el mínimo esfuerzo y suficiente flexibilidad para capturar innumerables complejidades de las decisiones de comportamiento que, sin embargo, otras medidas del sentimiento del inversor simplemente no pueden aportar. La evidencia de este estudio demuestra que la medición basada en el afecto puede estar estructurada en un marco consistente, comparativo, fiable y válido que resulta como mínimo informativo sobre el comportamiento de los precios, las decisiones inversoras y las políticas financieras corporativas.

La estrategia descrita en esta tesis es válida para cualquier ciencia social, y, sin embargo, resulta fundamental para la economía. Esto es así ya que mucho bienestar individual depende de instituciones y políticas financieras. Una crisis económica puede originar años de inestabilidad política y económica y el sufrimiento prolongado entre gran parte de la población. La "protección contra el afecto": la adaptación de las instituciones y políticas financieras para lidiar con los efectos afectivos de los agentes a los que tienen que servir, puede ayudar a identificar y anticipar crisis económicas y, por lo tanto, a asegurar el crecimiento a largo plazo, una distribución eficaz del capital y una sociedad más sostenible y estable.

3.4. Capítulo final

El capítulo final presenta un resumen y una discusión holística sobre el resultado de esta tesis para investigadores, profesionales y reguladores. Comienza recordándonos que el sentimiento inversor es un término complicado, la teoría que hay detrás del concepto es vaga, y que su medición resulta, por lo tanto, también complicada: el sentimiento inversor significa muchas cosas distintas para mucha gente diferente. Los tres estudios se aproximan al problema de manera metódica al definir el término al principio; a continuación buscan las medidas adecuadas y, finalmente, prueban esas medidas en varios contextos. Este estudio ha identificado cómo la reestructuración del sentimiento inversor en una teoría estructurada con medidas y definiciones específicas puede ayudar a los arbitrajistas, inversores y corporaciones. Como conjunto, los estudios sugieren que los mercados podrían trabajar mejor si semejantes técnicas fueran refinadas y aplicadas a varios participantes de mercado. Sin embargo, el capítulo también argumenta que, a pesar de los resultados entusiastas que aquí se presentan, aún queda mucho trabajo por hacer y estos estudios solo arañan la superficie de un tema inmenso. En cualquier caso, la aplicación del afecto en la economía, y en la economía de negocios en general (por lo menos más allá de disciplinas como el marketing) debería ser transformativa y queda mucho trabajo por hacer en el futuro.

El último capítulo también propone perspectivas para la investigación futura y qué se puede esperar en términos de hallazgos, así como sus consecuencias a largo plazo. Uno de los puntos principales de esta tesis es que el afecto es el motivador primario del comportamiento y que es un muy buen indicador del comportamiento. Como las investigaciones multidisciplinares clarifican cómo funciona el afecto y mejoran las metodologías de medición, es posible imaginarse un mundo en el que el afecto esté integrado en una variedad de prácticas y tecnologías usadas por la gente. Esta integración probablemente también estará relacionada con muchos negocios y campos económicos, y en particular las finanzas – en gran parte gracias al papel intuitivo que juegan las emociones en los mercados financieros. El primer paso para avanzar en esta dirección es taxonomizar los factores afectivos y su importancia en el sistema financiero. Esto significa que la heterogeneidad de los factores afectivos puede ser elucidada, y que la heterogeneidad latente de los participantes del mercado puede ser examinada, permitiendo que existan mejores técnicas de evaluación por perfil. Estas técnicas ayudarían a especificar mejores prácticas para los agentes de relaciones de inversión, a identificar los perfiles que están relacionados con el rendimiento, y ayudarían a los investigadores a probar estos perfiles a lo largo del tiempo, a determinar si son dinámicos o si están condicionados al entorno.

Desde un punto de vista interdisciplinar, estas perspectivas de trabajo futuro indican que la contabilidad y la recolección de datos también se tendrán que adaptar a este nuevo entorno. La contabilidad es una disciplina que ahonda en temas como auditorías, mediciones y la recolección de datos. Tanto profesionales como investigadores hablan frecuentemente de los aspectos más suaves de estos temas que incluyen temas afectivos, como la arrogancia, la confianza desmedida y la medición de intangibles. Investigaciones futuras en afecto y economía nos brindarán relaciones y medidas que los contables puedan considerar material de primera calidad en sus propios estudios y transmisión de datos. Si la información afectiva es realmente relevante y complementa la información financiera tradicional, puede ser interesante preguntarse si un estudio público de factores afectivos constituye un esfuerzo constructivo para mejorar el sistema financiero. El capítulo concluye con que, en efecto, el dinero y el crecimiento económico son los indicadores más convenientes para medir directamente el bienestar. El bienestar individual, sin embargo, es un constructo afectivo que se puede medir. Esto sugiere que el futuro de la economía residirá en medir el bienestar directamente, reemplazando así medidas importantes como los retornos monetarios o el crecimiento del PIB. De hecho, esta tesis supone la infancia de este movimiento y determina la facilidad y el grado de satisfacción que supondría mover la economía en esa dirección. Por ahora los resultados son más que prometedores.

Appendix B

Spanish translation of Conclusion Chapter to opt to the International Doctorate

Conclusión

1. Resumen y comentarios finales

Esta tesis presenta tres capítulos sobre la relación entre el afecto y los mercados financieros, la toma de decisiones financiera y la política financiera corporativa. Se incide en la crítica de las finanzas conductuales que señala que no existe una teoría comprensiva sobre ellas y que, sin embargo, no son más que una colección de efectos psicológicos sobre los precios. Esto es aplicable especialmente al “sentimiento inversor”, la teoría que establece que los participantes del mercado no se comportan de manera racional, y pueden hacer subir los precios hasta niveles injustificados basados en información fáctica. Normalmente, una política de precios injustificados no dura mucho porque los participantes del mercado pueden ver los beneficios resultantes y hacer que los precios bajen de nuevo a niveles sostenibles (proceso denominado arbitraje). La segunda teoría de las finanzas conductuales: el “arbitraje limitado” expone que los arbitrajistas algunas veces no corrigen los precios, dejando que se mantengan unos precios incorrectos, que incrementen y lleguen a ser insostenibles. Las burbujas económicas se producen cuando los precios están sometidos a niveles elevados del sentimiento inversor y no se controlan por los arbitrajistas. En estos tres capítulos, esta tesis especifica las limitaciones del sentimiento inversor como teoría, proporciona un marco específico para la definición y medida del sentimiento inversor basado en el afecto, el impulsor primario del comportamiento y prueba si el ya mencionado estudio resulta sostenible empíricamente.

Que el sentimiento inversor sea un término complejo no resulta sorprendente, puesto que se refería originariamente a las habladurías que los profesionales escuchaban en el salón de transacciones. Hoy por hoy, en la era del comercio electrónico, estos salones están desapareciendo pero los intercambios todavía muestran más conmoción cuando los comerciantes están agitados que en un día en el que no pase nada. Los investigadores de las finanzas conductuales han dado muchas explicaciones y definiciones para los procesos que ocurren en tales circunstancias. Una definición común del sentimiento inversor es la diferencia entre los precios observados y los predichos por un modelo financiero racional. Esta definición asume que “algo” está ocurriendo que hace que los precios se desvíen de sus valores racionales, pero no abunda en el tipo de proceso o en cómo medirlo. Esta es la definición más usada en las finanzas estándar, pero considera la causa del sentimiento inversor exógena a la formación del precio y, por tanto, no define claramente en qué consiste el sentimiento inversor. Esto hace que los estudios basados en esta definición sean limpios empíricamente y fáciles de llevar a la práctica pero se evita el tema de cuáles son los mecanismos inductores que actúan cuando se produce una burbuja económica.

Una definición posterior está basada en la psicología. Reconoce los muchos avances en las finanzas conductuales relacionados con la heurística y las tendecias cognitivas que explican las reacciones exageradas de los inversores y los precios irracionales. Aunque esta definición no es incorrecta, no resulta práctica porque existen más de cien heurísticas y tendencias documentadas, y a pesar de que son responsables de la subida de los precios, solo se pueden medir en contextos experimentales o a posteriori con los datos de los inversores. Por lo tanto, los métodos basados en tendencias cognitivas resultan bastante restrictivos en términos de identificación, medición y predicción de las burbujas. Otras causas del sentimiento inversor basadas en la psicología han sido examinadas y añadidas a la lista de tendencias cognitivas. Estas incluyen tanto causas corporales como ambientales: hormonas, el clima, ciclos lunares, comportamiento de la piel y acontecimientos deportivos mundiales. La colección actual de causas del sentimiento inversor conforma una lista increíblemente larga de explicaciones, lo que sugiere que la crítica hecha a las finanzas conductuales: que sirve “para todo”, no está ausente de justificación.

Los estudios aquí mostrados pretenden encontrar una alternativa innovadora al concepto de “para todo” de las finanzas conductuales. Proponen que todas las explicaciones psicológicas existentes se vean reflejadas y se puedan medir en procesos afectivos. Para probar esta propuesta, acumulan evidencias sobre la naturaleza de las medidas afectivas en los mercados financieros y sus participantes. El primer capítulo examina la relación entre el afecto y el corte transversal del retorno accionario. El segundo capítulo examina la relación entre el afecto y las decisiones de mercado de los pequeños inversores. El tercer y último capítulo examina la relación entre el afecto y la política financiera corporativa en confrontación con las burbujas económicas. Cada capítulo sirve tanto para respaldar el uso de tales medidas en la economía al examinar cómo se comportan en diferentes contextos, como para construir un marco teórico aún inexistente sobre el papel que juega el afecto en la economía. En este sentido, esta tesis es una aportación creativa y novedosa a la investigación financiera: la disciplina acaba de empezar a arañar ligeramente la superficie del papel del afecto en la economía y el número existente de estudios económicos que se refieren explícitamente al afecto se pueden contar con los dedos de una mano. El trabajo de esta tesis ayuda a la economía a dar un paso adelante en la dirección en que deberían ir todas las demás ciencias sociales: superando modelos raciones de comportamiento obsoletos y estudiando temas con una comprensión descriptiva renovada del comportamiento. En particular, la investigación ha hecho uso de resultados descriptivos neurocientíficos para producir la teoría que respalda con creces la inclusión del afecto en el estudio de temas financieros.

Motivada por el problema práctico que resulta del fallo de las finanzas conductuales de reparar la casi perenne repetición de las burbujas económicas en todo el mundo, esta tesis se ha centrado en el hecho de que la teoría sobre el sentimiento inversor es demasiado general, está mal definida y, por tanto, mal cuantificada. Estas características significan que los profesionales y reguladores no han sido capaces de usar los estudios para encontrar una solución real al problema de las burbujas. Desde un estudio multidisciplinar que comprende la neurociencia y la psicometría, esta tesis propone reestructurar el sentimiento inversor en el marco de otras disciplinas afectivas, como, por ejemplo, el marketing , que poseen las herramientas necesarias para tratar y analizar las emociones. Este trabajo pretende, por lo tanto, llevar a las finanzas conductuales en la dirección del afecto, el sistema cerebral primario para reaccionar frente a un estímulo. Proporciona el trabajo preliminar para establecer una definición específica sobre el sentimiento inversor basado en el afecto así como un sistema de medidas fiable y estructurado para cuantificar y estudiar tales efectos afectivos.

El debate comienza con el desarrollo de una teoría que declare que todas las causas documentadas del sentimiento inversor constituyen diferentes partes móviles del mismo sistema que impulsa al comportamiento. Estas partes están relacionadas en serie, como en una cadena. Las medidas de cada impulsor afectivo estarán, por tanto, relacionadas con los precios: el medio ambiente, incluyendo el tiempo y los ciclos lunares, influye en la fisiología, lo que influye en el afecto, lo que determina la incidencia de sesgos cognitivos, lo que concluye en una decisión y, finalmente, causa un resultado. Por tanto, la pregunta no reside en si el sentimiento inversor existe (resulta bastante intuitivo que sí existe). La pregunta es cómo definirlo. Sin embargo, definir el sentimiento inversor como la cadena de procesos desde el estímulo hasta el resultado de mercado es aún demasiado amplio como para ser de utilidad: proporciona una estructura a las causas documentadas sobre los comportamientos anómalos de los precios, pero aún es demasiado un tipo de definición “para todo”. Además, también es redundante: los precios que cambien debido al tiempo también lo harán debido a cambios fisiológicos causados por el tiempo, así como el afecto resultante, y los sesgos cognitivos usados por los inversores al tomar una decisión. Para que los inversores y responsables políticos hagan uso de las finanzas conductuales, el sentimiento inversor tiene que estar definido específicamente de tal manera que respete nuestra manera de entender la cadena de causas del sentimiento inversor, pero que sea lo suficientemente preciso como para que no pueda surgir ninguna confusión al usar el término. Esta tesis ha mantenido que el afecto es el vínculo más poderoso en el que basar la definición del sentimiento inversor, así como el más práctico con objetivos metodológicos y de medición.

El primer capítulo de esta tesis desarrolla este tema. Condensa las muchas medidas y causas del sentimiento inversor en seis categorías: medio ambiente, fisiología, afecto, sesgos cognitivos, decisiones y resultados. El capítulo se concentra en el afecto como la categoría más flexible, práctica e informativa de la que se puede desarrollar un marco de medidas específico. Varias razones respaldan esta elección: el afecto se puede dividir en un número extenso de estados de ánimo individuales, emociones, actitudes o sentimientos; también se puede medir de numerosas formas (como sondeos, software de reconocimiento facial, análisis semántico de mensajes de internet); es intuitivo; se puede relacionar con procesos cerebrales específicos y constituye un enfoque ya usado y probado en disciplinas que focalizan en el afecto, como el marketing y la psicología. Para probar si el afecto resulta efectivo para caracterizar el sentimiento inversor y si conforma unos cimientos teóricos robustos, el capítulo examina la relación entre el afecto y el corte transversal del retorno accionario. Los descubrimientos muestran que ciertos factores afectivos producen los patrones y relaciones que la teoría actual del sentimiento inversor predice (como la actitud del riesgo, por ejemplo). Sin embargo, estos hallazgos también muestran que otros factores afectivos (como la percepción de riesgo) presentan patrones diferentes. Los hallazgos exponen que el sentimiento inversor no está compuesto de un solo factor afectivo sino que, sin embargo, está constituido por varios factores y, a su vez, cada uno de ellos ejerce su propio efecto en los precios y su propia descripción del sentimiento inversor específico que motiva los efectos en los precios.

El capítulo dos proporciona evidencia adicional para sustentar lo argumentado. Así como el capítulo uno examina la relación entre el afecto y el corte transversal del retorno accionario, el capítulo dos se centra en la relación entre el afecto y la adquisición de acciones ordinarias y las decisiones de venta de los inversores minoristas. Los hallazgos muestran que ciertos factores afectivos (como la actitud del riesgo) están relacionados con las compras, mientras que otros (como la percepción de riesgo) están relacionados con las ventas. También se muestra cómo las interacciones entre factores afectivos tienen un impacto en la toma de decisiones financieras. Esto es importante porque respalda los hallazgos del primer capítulo: el sentimiento inversor definido como afecto no es un constructo homogéneo y unitario. En realidad, es más un constructo complejo y heterogéneo que ejerce efectos diversos sobre las decisiones y los precios. Esto significa que el sentimiento inversor no es útil solo para predecir la oscilación de los precios, sino también para gestionar las emociones de los participantes del mercado y, consecuentemente, sus decisiones. Este estudio muestra que con los datos afectivos adecuados las empresas puede cuantificar la probabilidad de que sus inversores compren o vendan. Además, también podrían promulgar estrategias de relaciones de inversores que se centren específicamente en los factores afectivos que incrementarían la posibilidad de compra, posesión o venta de acciones por parte de un inversor. Otra institución que puede salir beneficiada con este enfoque son los bancos centrales. Los bancos centrales están en constante comunicación con el público y, especialmente, con los inversores con la intención de influir en su afecto: su confianza en el sistema financiero, su certidumbre en la economía y su optimismo en el crecimiento. Este capítulo identifica con éxito dos, de los potencialmente muchos factores afectivos que los bancos centrales pueden usar en sus estrategias de relaciones públicas que influirían en la compraventa. Estas perspectivas fascinantes se discuten un poco más en la sección de más abajo sobre investigación futura.

El tercer capítulo es una prueba directa de la efectividad del uso de datos afectivos para dirigir las interacciones con el mercado bursátil. Se examina la relación calidad precio de empresas de inversión públicas condicionadas a niveles de sentimiento inversor. Se muestra cómo la cotización de las acciones de empresas con un alto nivel de clientes satisfechos se corrigen menos que la de las empresas con un bajo nivel de clientes satisfechos cuando el sentimiento inversor es demasiado elevado (la señal de un próximo hundimiento del mercado bursátil). Esto significa que las empresas que atienden a las necesidades afectivas de sus accionistas están protegidas frente a las caídas bursátiles. Este hallazgo es importante puesto que confirma que los factores afectivos son una parte fundamental del ciclo económico de una burbuja y su estallido y que los factores afectivos pueden resultar útiles para identificar y gestionar el comienzo y la consecuencia de las burbujas. De hecho, los hallazgos muestran el poder que tienen las medidas no financieras y poco tradicionales para influenciar en los resultados financieros. Empresas que reconocen la utilidad de medir los factores afectivos, en este caso la *satisfacción del cliente*, se benefician de este tipo de información adicional. Este hallazgo debería hacernos reflexionar porque la medición actual financiera y los sistemas de comunicación de datos no consideran que los datos afectivos sean relevantes y, por esto, no informan sobre ellos. Como muestra el capítulo 3, en concordancia con los hallazgos de los dos capítulos anteriores, la información afectiva es útil para todos los participantes del mercado y es muy probable que ayudara a que los mercados fueran más efectivos.

Los tres capítulos de esta tesis muestran que el afecto es un tipo de información increíblemente útil y claramente relevante para todos los participantes del mercado. Los arbitrajistas pueden mejorar su habilidad de corrección de los precios trabajando con factores afectivos específicos. Además, los problemas de comunicación potenciales que se puedan dar entre arbitrajistas al usar el término “sentimiento inversor” podrán referirse, sin embargo, a causas de sentimiento, en particular a factores afectivos específicos, lo que les permitiría sincronizar sus esfuerzos en el caso de que se den grandes burbujas económicas. Al usar el método afectivo aquí descrito, las empresas pueden estimar específicamente cómo reaccionará la cotización de sus acciones al cambiar uno de los factores afectivos, en vez de tener que confiar en lo que es, por contra, una vaga noción del sentimiento inversor. La medición de la información afectiva también puede permitir a los bancos centrales analizar las reacciones a sus políticas de relaciones públicas con respecto a la manera en que el afecto de mercado cambia y su posterior efecto en los mercados. Cada grupo de participantes de mercado, inversores, corporaciones y reguladores, podría dirigir mejor su participación en el sistema financiero si tuviera acceso a información afectiva. De hecho, esta afirmación cierra el círculo de nuestro estudio: si los participantes del mercado tienen la oportunidad de acceder a una información mejor, pueden tomar mejores decisiones y es posible esperar que los mercados se vuelvan más eficaces, lo que reduciría la incidencia y gravedad de las burbujas económicas.

La conclusión final es que si se dan burbujas económicas se debe también a que el mecanismo financiero contemporáneo, una maquinaria económica impresionante, puede contener una pieza conductual que si se cambiara o recondujera, se podría mejorar el alto grado de eficacia que ya existe. La investigación presentada en esta tesis presenta evidencias que sugieren la relación de esto último con el papel atribuido a la información financiera, su medida, su diseminación y su importancia en el proceso de formación de los precios. Hace falta mucha más investigación para demostrar sin dejar lugar a dudas que esto es así y las consideraciones que habría que tener en cuenta en investigaciones futuras son extensas y motivadoras. Antes de pasar a la prospectiva investigadora, revisamos las limitaciones de la investigación presentada en esta tesis.

2. Limitaciones de esta investigación

Este trabajo pretende arrojar luz sobre una ambiciosa e importante parte del área de las finanzas conductuales que no se ha estudiado y resulta bastante polémica usando una perspectiva fresca y novedosa. Aún así, esta investigación hace frente a numerosas e importantes limitaciones que derivan en su mayoría del hecho de que este estudio se encuentra en su estado preliminar y aún le queda mucha andadura por delante. Estas limitaciones incluyen métodos de muestreo, la elección de los marcos sobre los que establecer un modelo teórico, un alcance limitado en términos del ámbito de la investigación y la confianza en lo que aún son suposiciones neurocientíficas sin demostrar.

La primera limitación a la que se enfrenta este estudio está relacionada con los métodos de muestreo y de recolección de datos. Esto se debe a la naturaleza de la investigación conductual en economía: al hecho de que la economía no pueda ser estudiada en un ambiente experimental controlado y que la información afectiva es difícil de medir. El estudio llevado a cabo en los capítulos 1 y 2 se benefició de que el muestreo incluía la sustancia más importante de la crisis económica de las *subprime.* Algunas de las situaciones incluidas en el muestreo son el colapso de *Lehman Brothers*, la nacionalización de *Northern Rock*, y la entrada en vigor de la ley de estímulo económico. Sin embargo, la información se recolectó mensualmente desde abril del 2008 hasta abril del 2009, por lo que constituye menos que una muestra ideal del período anterior a la crisis así como de su lenta formación, que empezó en febrero de 2007 con el primer comunicado de prensa sobre una *subprime* de *Freddie Mac*. Además, en estos capítulos tampoco se incluye información sobre el momento posterior a la crisis.

Lo que quiere decir que en los capítulos 1 y 2 hay dos características poco adecuadas en la muestra estudiada. Por una parte, podemos perder de vista una visión general porque carecemos de las variaciones de los factores afectivos anteriores y posteriores a la crisis y es necesario interpretar correctamente el afecto agente durante el período de la crisis propiamente dicho. Por otra parte, y especialmente relacionado con el capítulo 1, el tamaño del muestreo resultante de la recolección de datos durante 13 meses, restringe extremadamente los métodos analíticos a nuestro alcance. Aunque se ha hecho mucho esfuerzo para obtener el máximo partido de la información disponible y se realizaron modificaciones cuantitativas para compensar el tamaño de las muestras, haber tenido una serie de datos más completa hubiera sido mucho más reconfortante. El motivo por el que no se pudo recoger una serie de datos ideal se debe a la complejidad subyacente a tal recolección: conseguir registros comerciales y encuestar a sus propietarios requiere un alto nivel de compromiso y cooperación entre una universidad y una organización privada como un banco o un corredor de bolsa. Puede ser difícil que tal relación se materialice, especialmente dados los elevados costes monetarios y no monetarios que conlleva. Una última puntualización sobre las limitaciones de la muestra, sin embargo, es que ésta es relativa: no existen ningunos otros datos de este tipo por lo que, a pesar de sus limitaciones, son pioneros en el campo de la economía.

Las limitaciones que hemos comentado ejercen una repercusión directa en la elección de los métodos analíticos empleados. La fortaleza de un modelo de regresión se asocia generalmente con el número de observaciones que precisa. Con una gran cantidad de información, la selección del modelo que se puede usar en el análisis es dificultosa por el gran número de opciones disponible; lo ideal es que se estudien modelos múltiples usando una gran cantidad de datos y que las conclusiones se obtengan de las distintas perspectivas que nos ofrezcan. En el caso particular de esta tesis, el plan inicial consistía en utilizar modelos de datos de panel, pues los datos eran longitudinales. Sin embargo en la práctica el panel carecía de suficientes períodos de tiempo para que resultara apropiado y acabó estando desequilibrado ya que los índices de respuesta de los encuestados resultaron impredecibles: algunos encuestados respondían en múltiples ocasiones en un mes, otros lo hacían intermitentemente y otros solo una vez. Lo que significó que las metodologías analíticas se tuvieron que adaptar a este contexto. Para favorecer el principio de parsimonia, un estudio se basó en un modelo sencillo de series temporales (capítulo 1), apropiado para muestras de pequeño tamaño, y otro en un análisis transversal (capítulo 2). Así, se evitaron las complicaciones de adaptar un modelo de datos de panel a los datos esperando que se recogiera más información en el futuro con el propósito de llevar a cabo modelos más avanzados.

El ámbito de esta tesis es relativamente limitado como evidencia el hecho de que solo se han examinado cuatro factores afectivos: actitud de riesgo, percepción del riesgo, actitud hacia el mercado bursátil y satisfacción del cliente. Esto se debe a los problemas de muestreo anteriormente expuestos. A no ser que los datos ya existan, como en el caso de satisfacción del cliente, estudiar más factores afectivos requiere añadir más artículos al sondeo. Este número influye en el índice de respuesta porque es menos probable que los encuestados completen el estudio si les lleva demasiado tiempo. Como las encuestas utilizadas en este estudio se mandan mensualmente a los encuestados, responder se vuelve cada vez más pesado y con cada interacción posterior, la posibilidad de que el encuestado siga participando disminuye. Lo que significó que este proyecto tenía que encontrar el punto medio entre el número de factores que tenían que ser estudiados y la viabilidad de la recolección de datos. Adoptando una postura moderada, este proyecto se centró en un número pequeño de factores afectivos validados sacrificando, así, la oportunidad de medir otras alternativas más creativas. En última instancia, como este es primer estudio que se realiza de tal naturaleza, investigaciones futuras ofrecerán más oportunidades para dirigir el margen de acción de este enfoque hacia el sentimiento inversor, y en particular creando una taxonomía, como se expone más abajo en la sección tercera.

La limitación final que se analiza aquí es que se confíe en las suposiciones neurocientíficas específicas: concretamente en que los factores afectivos se obtengan por las mismas raíces somáticas. Esto quiere decir que si medimos un factor afectivo con una encuesta, estamos abogando por un proceso neurológico específico a ese factor afectivo. La cuestión es que ningún estudio neurocientífico ha demostrado en realidad que la actitud de riesgo o la satisfacción del cliente sean factores afectivos que surgen de sus propios procesos fisiológicos. Si un estudio así existiera, completaría la información de la metodología de medición del sentimiento de esta tesis. Sin embargo, la suposición de que el factor afectivo está causado por su propio proceso fisiológico no resulta del todo inverosímil. Se ha demostrado con el miedo, otro factor afectivo, a pesar de que no se estudie aquí. Además, los investigadores de marketing obtienen en escasas ocasiones la corroboración neurocientífica de los factores afectivos que documentan y, aún así, siguen progresando en sus investigaciones.

Muchas de las desventajas del estudio llevado a cabo en esta tesis se deben a problemas de tipo práctico que no se podían resolver en el marco temporal del proyecto de investigación. Sin embargo, representan un trampolín favorable para numerosa investigación futura en esta materia. Esto se discute más abajo.

3. Consideraciones para futuras investigaciones

Por un lado, puede parecer improbable llegar a la conclusión de que los sentimientos puedan jugar un papel tan importante en las instituciones económicas y financieras, que están dirigidas por expertos altamente cualificados. Por otra parte, la comprensión cada vez más exhaustiva de la naturaleza humana que ha ido teniendo lugar poco a poco nos indica que, independientemente de la educación o formación a la que se ha sometido un individuo, su mecanismo de toma de decisiones todavía se basa fundamentalmente en procesos afectivos. Las consiguientes implicaciones son trascendentales: el libre albedrío de los individuos es más limitado de lo que se pensaba anteriormente. Cuando hablamos de los descubrimientos "de gran impacto" sobre el afecto y su repercusión en la economía, hablamos eufemísticamente. Corriendo el riesgo de sonar futurista, o quizás conductista, se está convirtiendo en un hecho científico el que las preferencias humanas se pueden influenciar, las conductas programar y las decisiones persuadir. Los investigadores de marketing han hecho de estos temas su especialidad y la gran revolución de datos ha atraído primero su atención: saben que si lo conocen todo sobre ti, no pueden solo predecir lo que harás, también pueden moverte a que lo hagas.

En el mundo actual en el que vivimos los individuos proporcionan de forma voluntaria información a empresas como Facebook y están siendo constantemente monitorizados por Microsoft y Google, que a su vez le proporcionan esa información a los diferentes gobiernos. De cierta manera ya vivimos en una versión burda de *Un mundo feliz* – pero parece extraño que toda la información pueda ser usada para vender más o para espiar al ciudadano, cuando una aplicación útil de tal información sería informar a los mercados de que una gran burbuja económica, como un tsunami después de un terremoto, está en proceso de formación. Los mercados que fueran conscientes de un terremoto intangible, afectivo podrían detenerlo o mitigar el posterior tsunami de una burbuja, especialmente dado el amplio abanico de problemas que puede causar una gran caída del mercado. De este estudio se desprende que el tema es digno de más atención investigadora, y habría que establecer más detalladamente cómo los procesos afectivos influyen en los mercados y cómo construir un marco de medidas afectivas. Para hacernos una idea de cuánto queda por hacer en esta investigación, consideremos lo siguiente: en esta tesis se han examinado cuatro factores afectivos mientras que los investigadores de marketing y psicología examinan cientos de ellos al cabo de un año.

Por lo tanto, para los investigadores del campo de la economía, hay un amplio espacio para desarrollar una taxonomía de factores afectivos. En marketing se han publicado volúmenes completos de factores afectivos que describen su proceso de investigación y su relevancia con respecto a varios problemas y cuestiones de marketing . Establecer una taxonomía permitiría no solo la identificación de los factores afectivos que juegan un papel importante en las diferentes partes del sistema financiero, sino también la identificación de cómo interaccionan entre ellos. El propósito último al desarrollar esta taxonomía consistiría en determinar si realmente hace falta que los factores afectivos se midan y se mande información sobre ellos a los mercados. De resolverse que hay que actuar así, esta medida contribuiría con la primera mejora revolucionaria a las normas de información financieras desde la Gran Depresión. Las medidas afectivas complementarían la información actual sobre contabilidad y economía con las medidas de la propensión del mercado a interpretar esta información. En última instancia, resulta verosímil que un sistema público, estandarizado, consistente, fiable y válido para medir procesos afectivos relevantes mejoraría el actual impresionante mecanismo que constituye el sistema financiero global. Asimismo, los investigadores de contabilidad también pueden beneficiarse de esta tesis para aumentar sus campos de investigación con relación a la medición y divulgación de información afectiva.

La redacción del catálogo de factores afectivos es, sin duda, una perspectiva de investigación muy interesante en economía y contabilidad pero también es importante otro aspecto de la investigación sobre el afecto para la economía y otras disciplinas análogas: la heterogeneidad latente de los agentes del mercado. Los mercados financieros se resienten por el gregarismo de sus participantes, pero subsumirlos a todos ellos como miembros de una manada oculta el hecho de que mucha de esa gente muestra características individuales intangibles relevantes a su comportamiento financiero. Si tuviéramos que medir el afecto para informar a los mercados, sería interesante conocer si, por ejemplo, existe heterogeneidad entre el afecto de cada categoría de los participantes del mercado. Es posible que los arbitrajistas, inversores minoristas y directores de políticas financieras corporativas seleccionen ellos mismos dentro de sus posiciones debido a sus compensaciones afectivas. En su defecto, a lo mejor confrontar ciertas decisiones como arbitrajista o director de política financiera corporativa esculpe el perfil afectivo de esa persona en cuestión. No hace falta decir que a pesar de la dirección de la causalidad ya mencionada, las dinámicas de sus perfiles afectivos también serían de alto valor informativo en el caso de que sus decisiones difieran.

Solamente analizando temas relacionados con la dinámica latente y heterogeneidad de los participantes de mercado, las perspectivas de investigación al alcance son bastante extensas. Esto aportaría información a los investigadores interesados en analizar inversores y si sus hallazgos pueden hacerse extensibles entre los demás participantes de mercado o no. Este estudio también proporcionaría más información al tema más extenso del comportamiento en la toma decisiones referente a la relación entre incentivos y procesos afectivos. Otras preguntas de investigación originales también pueden estar relacionadas con la disyuntiva de si los perfiles afectivos de los participantes del mercado cambian según el mercado en el que están participando, y si sus perfiles cambian o no si trabajan en múltiples mercados. Existen muchos factores afectivos y saber cuáles son relevantes y en qué casos nos pueden ayudar, perfecciona nuestra comprensión de la relación entre las decisiones específicas y el afecto específico. Las decisiones de compraventa de distintos productos pueden depender de varios factores afectivos que dependen de la decisión y del mercado en cuestión.

También hay mucho campo para investigar las metodologías de medidas y análisis. Aunque este estudio haya hecho uso de técnicas frecuentemente utilizadas en marketing , ahora existen algunos estudios interesantes que han recibido escasa atención hasta ahora. El afecto es difícil de medir pero hay muchas metodologías de medición novedosas que ofrecen diferentes soluciones para capturar la variación en el afecto de los participantes del mercado. Además de encuestas, análisis textual, reconocimiento facial y monitorización del corazón basado en cámaras, todas ellas tecnologías que existen y cuyos desarrolladores están buscando aplicaciones prácticas y de investigación para utilizarlas. Si osáramos imaginarnos, la estación comercial del futuro puede que incluya todos esos artilugios, sometiendo al comerciante a un escrutinio intenso para obtener información sobre él mismo, el resto del mercado e incluso los reguladores. Cuando se menciona a los reguladores es cuando volvemos a los problemas que plantea la tecnología, la privacidad y los límites de la introspección gubernamental, especialmente en lo que respecta al espacio afectivo (un espacio tan personal como pueda ser concebido). Por esto, la investigación futura también nos brindará la oportunidad de desarrollar preguntas de carácter ético y quizás también legal. De hecho, la cuestión es que la sociedad en general se está moviendo en la dirección de este *Mundo feliz,* y que la economía no será una excepción.

Ahora mismo estamos siendo testigos de algunas discusiones “extrañas” en la esfera pública que reflejan los tipos de temas que se estudian en esta sección. La perspectiva de que la gente sea monitorizada incansablemente y de que sus datos sean medidos constantemente, sin duda, molesta. Sin embargo no es necesario asumir que estos datos serán utilizados de forma maliciosa, pueden ser usados en nuestro beneficio. Tomemos el ejemplo de la discusión de un panel europeo sobre la medida del crecimiento económico y sus limitaciones: algunos economistas han sugerido que las medidas afectivas totales habrían sido una alternativa a las medidas actuales del PIB sobre las que se basan muchos análisis del bienestar económico. Puede parecer que estos economistas estén locos o que sean innovadores simplemente incluso por debatir este tema seriamente - debido a nuestra tendencia cultural a minimizar la importancia de las emociones - pero existe un ejemplo tangible: el caso del Reino de Bután, un país en el cual las encuestas sobre la felicidad de sus súbditos se consideran una medida seria de progreso. Un posible resultado de seguir estudiando el afecto en el campo de la economía es que se le considere una medida económica seria y que, de repente, vivamos en un mundo en el que la felicidad de la humanidad sea la medida que todos persigamos.