Antti Klemola

Essays on irrational investors' behavioral biases and pricing efficiency

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Irrationaalisten sijoittajien käyttäytymisen vaikutus arvopapereiden hintoihin	

Tiivistelmä

Väitöskirjan viisi esseetä käsittelevät sijoittajien sentimentin sekä liiallisen itsevarmuuden vaikutusta arvopapereiden hintoihin. Tutkimuksissa analysoidaan amerikkalaisten piensijoittajien sentimentin muutosten tai Pohjoismaiden sähköpörssin markkinaosapuolien liiallisen itsevarmuuden potentiaalisia vaikutuksia arvopapereiden hintoihin.

Ensimmäisessä kolmessa esseessä analysoidaan irrationaalisten sijoittajien sentimenttimuutosten yhteyttä Yhdysvaltojen osakemarkkinoiden tuleviin tuottoihin, hyödyntämällä informaatiota Google-hakusanoista. Ensimmäinen esseen tulokset osoittavat, että kasvu positiivisessa (negatiivisessa) tiedonhaussa ennakoi positiivisia (negatiivisia) odotettuja tuottoja S&P 500 -indeksille. Toisessa ja kolmannessa esseessä havaitaan, että positiivinen (negatiivinen) odottamaton muutos amerikkalaisten piensijoittajien sentimentissä ei ennakoi pelkästään osakemarkkinatuottoja Yhdysvalloissa, vaan niillä on myös positiivinen (negatiivinen) yhteys tuleviin koko- ja arvopreemioihin Yhdysvaltojen osakemarkkinoilla.

Neljännessä ja viidennessä esseessä tutkitaan sijoittajien liiallisen itsevarmuuden potentiaalista vaikutusta Pohjoismaisen sähköpörssin hinnoitteluun. Neljännessä esseessä tulokset osoittavat, että sijoittajat ovat valmiita maksamaan ylihintaa tietynlaisista optioista. Viidennen esseen tulokset osoittavat lisäksi, että optioiden ylihinnoittelussa esiintyy myös kausivaihtelua. Tietynlaisten optioiden ylihinnoittelu sekä kausivaihtelu voivat viitata siihen, että sijoittajat ovat liian itsevarmoja heidän yksityisen informaationsa tarkkuudesta.

Asiasanat

Sijoittajasentimentti, Google-hakusanat, Osakemarkkinatuotto, Kokopreemio, Arvopreemio, Pohjoismaiset Sähkömarkkinat, Liiallinen itsevarmuus, Optioiden Hinnoittelu

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Abstract

This thesis analyzes the effect that investors' sentiment and overconfidence have on asset prices. Five interrelated essays examine the effect that the changes in U.S. small investor sentiment or the potential overconfidence of market participants in Nordic financial electricity market have on asset prices.

The three first essays analyze the effect of changes in irrational investors' sentiment on future U.S. equity market returns, both on the aggregate and cross-sectional level. The essays employ information from Google search volumes as a potential tool to gauge a new U.S. small investor sentiment. The first essay finds that increase in positive (negative) information retrieval in Google is associated with positive (negative) future returns on the S&P 500 index. The second and third essays find that positive (negative) unexpected changes in the new U.S. small investor sentiment predict not only positive (negative) future U.S. equity market returns, but also positive (negative) subsequent size and value premiums.

The fourth and fifth essays examine the effect of investors' potential overconfidence on option pricing in the Nordic financial electricity market. The fourth essay finds that the market participants are willing to overpay ex-ante for certain type of option contracts. The fifth essay also finds a seasonality effect in the ex-ante pricing of option con-tracts. Both, the investors' willingness to overpay and the seasonality in the ex-ante pricing of option contracts, might suggest that the irrational investors are overconfident about the precision of their private information.

Keywords

Investor Sentiment, Google Search Volumes, Stock Market Return, Size Premium, Value Premium, Nordic Financial Electricity Market, Overconfidence, Exante Option Pricing

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Helsinki, September 2019

Antti Klemola

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1 INTRODUCTION

One of the basic assumptions of traditional efficient market paradigm is that investors make rational and optimal decisions. By contrast, behavioral finance offers an alternative paradigm for the efficient market theory and argues that investors are prone to make irrational and suboptimal decisions that are affected by their basic human psychology and emotions. The literature offers several definitions for these less sophisticated investors: irrational investors, noise traders[6], retail investors, or small investors. There is a vast number of studies analyzing the impact of irrational investors' behavior on asset prices and pricing efficiency in the market. For example, irrational investors tend to trade in herds, either buying or selling, depending on the current state of their sentiment[7] (Nofsinger and Sias 1999; Barber, Odean and Zhu 2009). Change in the irrational investors' sentiment and its' effect on market liquidity can have an impact on asset prices and pricing efficiency if more rational investors are unable, due to limits to arbitrage[8], to counterbalance the change (Barberis and Thaler 2002).

As a warning example, Baker and Wurgler (2007) write that during the tech boom in the late 1990s many contrarian arbitrageurs misinterpreted the magnitude of the effect of the sentiment of irrational investors on asset prices and the length of time that effect was sustained. It was a misinterpretation that later forced some of those contrarian arbitrageurs into bankruptcy. Hence understanding the composition and predictability of irrational investor sentiment and its effect on asset prices is an important topic to study, which in turn makes the subject of irrational investors' sentiment an issue of practical significance.

The effect of irrational investors' sentiment on asset prices has already been extensively studied in the literature, and several studies (see, e.g., Fisher and Statman 2000; Lemmon and Portniaquina 2006) find an association between the sentiment of irrational investors and future equity market returns. As Baker and Wurgler (2007) state: "Now the question is no longer, as it was a few decades ago whether investor sentiment affects stocks prices, but rather how to measure investor sentiment and quantify its effects." In a recent study by Da, Engelberg, and Gao (2015), the authors raise some key concerns over why previously used and more traditional investor sentiment measurements might be insufficient, and a

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[6] Shleifer and Summers (1990) define noise traders as a not fully rational investors.
[7] Baker and Wurgler (2007) define investor sentiment as a belief about future cash flows and investment risk that is not justified by the facts available.
[8] Baker and Wurgler (2007) find that the effect of sentiment is especially strong on stocks that are more difficult to arbitrage; like small, young, unprofitable, volatile, non-dividend paying, and distressed stocks.

new internet search-based investor sentiment is needed. They argue that the internet search-based investor sentiment captures the sentiment of irrational investors in a timelier fashion.

The decision making of irrational investors is not only affected by the status of their current sentiment; the irrational investors also tend to be overconfident. Daniel and Titman (1999), and Gervais and Odean (2001) argue that irrational investors take too much credit for their success, leading them to become too overconfident about their skills. For example, irrational investors generally have long equity market positions and thus have benefited from the historical upward price trend, making them confident about their abilities (Gervais and Odean 2001). As a consequence, Daniel, Hirshleifer, and Subrahmanyam (1998) note that irrational investors place too much weight on the information they collect themselves, also known as private information, and overestimate the precision of that information. In contrast, Daniel et al. (1998) argue that irrational investors ignore, or at least underweight, the information that conflicts their views.

The well-documented overconfidence of irrational investors can also have a value decreasing effect on their wealth. Both Barber and Odean (2000) and Deaves, Lüders, and Luo (2009) report that overconfident investors tend to trade too aggressively, which according to Barber and Odean (2000) leads to decreasing long-run portfolio return performance. The authors find that high (low) turnover group has a net return of 11.4 (18.5) percentage points and Barber and Odean (2001) report that excessive trading reduces men's (women's) net returns by 2.65 (1.72) percentage points[9]. According to Baker and Nofsinger (2002), more overconfident investors increase their risk-taking and get surprised more often than they anticipate; because they are too certain and confident about their private information. Goetzmann and Kumar (2008) also report that overconfident investors tend to neglect to diversify their portfolios appropriately, which also has a wealth diminishing effect.

The impact of overconfidence of irrational investors on asset prices and pricing efficiency is not only limited to the equity market. The effect of irrational investors' overconfidence can also be found in the derivatives market. Feldman and Roy (2005), Chen and Sabherwal (2019) argue that the most overconfident investors prefer to operate in the option contract markets because they want to maximize the financial leverage when they make investment decisions based on their strong private information expectations. Both Feldman and Roy (2005) and Lakonishok, Lee, Pearson, and Poteshman (2006) list the call option buyers as the most

[9] Men are considered generally being the more overconfident gender (Barber and Odean 2001).

overconfident class of investors. The overconfident investors also prefer trading with option contracts, whose underlying assets are more speculative: like low-book-to-market stocks (Lakonishok et al. 2006). As a consequence, Bauer, Cosemans, and Eichholtz (2009) find that irrational investor[10] tends to perform poorly on average in the options market and prefer out-of-the-money options especially.

As Chen and Sabherwal (2019) write “The options market was supposed to create an efficient venue for investors to transfer risks so that risks are better allocated to meet investors’ different risk preferences and therefore enhance overall utility. However, the presence of overconfident investors may create additional risks not only in the equity market but also in the options market.” Hence, Chen and Sabherwal (2019) argue that some of the observed mispricings in the options market can be caused by the overconfident investors and it’s something that practitioners need to account for when operating in the derivatives market.

The current dissertation addresses the research path of Da, Engelberg, and Gao (2011) and Da et al. (2015) and empirically tests if a new small investor sentiment that is inferred from the popularities of specific Google search terms affects asset prices, both on the aggregate and cross-sectional levels. The first essay analyzes the effect of changes in irrational investors’ market attention and sentiment on future S&P 500 index returns. The study employs information inferred from the popularity of given Google search terms as a potential tool to gauge small investor sentiment and market attention. The study uses Google searches to measure investors’ attention (positive or negative) toward the U.S. equity market in general and its’ effect on future S&P 500 index returns. The choice of search terms ensures that they also represent the sentiment and beliefs of small and irrational investors. The choice of search terms was “bear market,” “bull market,” “market crash,” and “market rally.” The selection makes it possible to capture irrational investors’ information retrieval from the Internet that is related to their current beliefs about the U.S. equity market. The study finds that an increase in positive (negative) information retrieval in Google is associated with positive (negative) future returns on the S&P 500 index.

The second essay analyzes the effect of *unexpected* changes in a new U.S. small investors’ sentiment on future U.S. equity market returns and the subsequent size premium. I chose to use the search volumes of Google search terms such as “bull market,” and “bear market” to measure the sentiment. The selection of Google

[10] Chuang and Susmel (2011) argue that individual investors are more overconfident than institutional investors.

search terms is made so that they share similar terminology as used in the AAII (The American Association of Individual Investors) survey. The study's proposed small investor sentiment measurement should capture the attitude of small investors to the U.S. equity market in a timelier fashion. Also, the general effect of investor sentiment on cross-sectional asset prices should be stronger for stocks that are more difficult to value and arbitrage, like small-sized stocks, as suggested by Baker and Wurgler (2006). The study finds that an unexpected increase in optimism (pessimism) of U.S. small investors is associated positively (negatively) with the next week's equity market return and subsequent size premium.

The third essay further analyzes the effect of *unexpected* changes in the new U.S. small investors' sentiment on future U.S. equity market returns on the cross-sectional level. It analyzes the cross-sectional association between unexpected changes in the new U.S. small investor sentiment and future returns of stocks sorted by their book-to-market ratio; value premium. The study finds that an unexpected increase in optimism (pessimism) in the sentiment predicts positive (negative) subsequent value premium.

The dissertation also continues the research path of Feldman and Roy (2005), Lakonishok, Lee, Pearson, and Poteshman (2006), Bauer, Cosemans, and Eichholtz (2009), and Chen and Sabherwal (2019) by empirically testing the ex-ante pricing and historical performance of various option contracts that are traded in the Nordic financial electricity market. As Chen and Sabherwal (2019) state, part of the reported mispricing in the option market can be caused by the overconfident investors.

The fourth essay analyzes the ex-ante pricing of quarterly option contracts that are traded in the Nordic financial electricity market. The objective of the essay is to empirically analyze if quarterly option contracts are ex-ante mispriced, which could be potentially caused by overconfident investors who operate in the market. The analysis involves evaluating the performance of two covered option strategies on the Nordic financial electricity market; where one option strategy focuses on the ex-ante pricing of call options, and the other focuses on the ex-ante pricing of put options. The study finds that the covered option strategy that uses short call (long put) option positions have a lower (higher) performance measurements, accompanied by the negative (positive) average historical return. As Chen and Sabherwal (2019) suggest, the mispricings may be partly caused by the overconfident investors.

The fifth essay analyzes the seasonality in the ex-ante pricing of quarterly option contracts that are traded in the Nordic financial electricity market. The objective of the essay is to empirically analyze if seasonality exists in option pricing among the market participants. The analysis involves conducting dynamic delta option strategies for the short call and long put option positions. The dynamic delta option strategies uncover if a call or put options traded in the market are ex-ante over- or underpriced. The study finds some seasonality effect on the ex-ante pricing of quarterly option contracts. The call options are ex-ante over (under)-priced for the winter (summer) quarters and put options are ex-ante overpriced for the winter quarters. The results show that some seasonality exists in the pricing, and the effect is stronger for the winter quarters. Also, in this case, as Chen and Sabherwal (2019) suggest, the mispricing may be partly caused by overconfident investors who operate in the market.

As a whole, the purpose of this doctoral dissertation is to analyze further the irrational behavior of investors and its impact on asset prices. The dissertation focuses on two different forms of the irrational behavior of investors on two different financial markets and reports its findings in five individual essays. The three first essays analyze the effect that changes in the sentiment of U.S. small investors have on U.S. equity market returns. The study introduces a new U.S. small investor sentiment measurement and tests its effect on future U.S. equity market returns, on the aggregate and cross-sectional levels. The last two essays analyze the potential existence of investors' overconfidence in the Nordic financial electricity market by empirically analyzing the ex-ante pricing of call and put-option contracts using various option trading strategies.

This doctoral dissertation consists of the introduction chapter and five individual essays. The remainder of the introductory chapter is organized as follows: Section 2 describes the contribution of each essay and the dissertation as a whole. Section 3 provides a brief discussion of the theoretical fundamentals of this dissertation. Section 4 then briefly summarizes the five essays of this dissertation.

2 THE CONTRIBUTION OF THE DISSERTATION

The objective of the dissertation is to explore the effects of irrational investors' sentiment or overconfidence on asset prices. It makes two main contributions to the financial literature. The first is to investor sentiment literature, as the dissertation analyzes if changes in irrational investors' sentiment influence future U.S. equity market returns on both the aggregate and cross-sectional levels. The dissertation suggests a new measurement of U.S. small investor sentiment. The new small investor sentiment should capture the changes in U.S. small investor sentiment in a timelier fashion than the more traditional ones by utilizing the information retrieval by the small investors from their internet searches.

The second contribution of the dissertation is that it empirically analyzes the ex-ante pricing of derivative contracts traded in the Nordic financial electricity market. As the previous literature suggests, the existence of overconfident investors can lead to mispricing in option markets (see, e.g., Chen and Sabherwal 2019). This dissertation empirically analyzes if quarterly option contracts in the Nordic financial market are ex-ante mispriced, which could suggest that potentially some overconfident market participants exists. A more detailed discussion about the individual contribution of each essay is given below.

The first essay contributes simultaneously both to the investor sentiment and the market attention literature. In the former case, the essay complements traditional small investor sentiment studies; such as Solt and Statman (1988), Otoo (1999), and Fisher and Statman (2000). It also adds to a recent and specific strand of literature that utilizes information inferred from the popularity of Google search terms to test their association with future aggregate equity market returns (see, e.g., Da et al. 2011, Vozlyublennaia 2014 and Da et al. 2015). Da et al. (2011) use information on Google search volumes to measure investor attention to individual U.S. stocks and the association with future stock returns. The essay incorporated in the dissertation uses Google searches to measure investors' attention (positive or negative) directed at the aggregate U.S. equity market in general and the effect on future S&P 500 index returns.

The second essay contributes especially to the existing finance literature related to small investor sentiment and cross-sectional equity market returns (see, e.g., Baker and Wurgler 2006), by utilizing information from the new U.S. small investors sentiment measurement on the future size premium. It also complements the studies that examine the association between Google search popularities and future equity market returns (see, e.g., Da et al. 2011, Vozlyublennaia 2014, and Da et al. 2015). Da et al. (2015) develop a new *market-*

level investor sentiment that is based on the Google search volumes for search terms such as “recession,” “unemployment,” and “bankruptcy.” The study in this dissertation incorporates that idea of Da et al. (2015) and relates it specifically to small investor sentiment on the U.S. equity market.

The third essay further contributes to the existing finance literature related to small investor sentiment and cross-sectional equity market returns (see, e.g., Baker and Wurgler 2006), by utilizing the information from the new U.S. small investor sentiment measurement on the subsequent value premium. It also complements the studies that examine the association between Google search popularities and future equity market returns (see, e.g., Da et al. 2011, Vozlyublennaia 2014, and Da et al. 2015).

The joint findings from the three first essays, which document an association between investor sentiments inferred from Google search volumes and future returns of U.S. stock market, pave the way for future research that studies their usability as a base for profitable investment strategy.

The fourth essay contributes to and extends the strand of finance literature that analyzes the performance of option strategies on the equity market (see, e.g., Whaley 2002, Feldman and Roy 2005, Hill, Balasubramanian, Gregory and Tierens 2006, Kapadia and Szado 2007, Ungar and Moran 2009).

Some of the previous literature[11] on derivatives contracts traded in the electricity market focus more on their use as risk management tools. Some of the previous literature[12] focuses on empirically analyzing the ex-ante pricing of derivative contracts (futures and forward contracts) traded in the Nordic financial electricity market. The fourth essay of the dissertation focuses on analyzing the ex-ante pricing of quarterly option contracts traded in the Nordic financial electricity market.

The fifth essay contributes to the literature by empirically analyzing the seasonality in the pricing of quarterly option contracts. Only a few previous studies[13] examine the pricing of electricity option contracts in the Nordic markets, but they focus on the pricing from more a theoretical perspective and feature less empirical work. The empirical analysis of the ex-ante pricing of forward and futures contracts traded in the Nordic financial electricity market is a topic that has been covered

[11] See Shawky, Marathe and Barrett 2003; Fleten, Bråthen and Nissen-Meyer 2010; Frestad 2012
[12] See Kristiansen 2007; Botterud, Kristiansen, and Ilic 2010; Wimschulte 2010; Gjolberg and Brattested 2011; Lucia and Torró 2011; Weron and Zator 2014; Smith-Meyer and Gjolberg 2016
[13] See Benth and Schmeck 2014; Benth and Detering 2015; Schmeck 2016.

more extensively.[14] The fifth essay especially contributes to the literature by extending the empirical analysis from the forward and futures contract market into the option contract market in the Nordic financial electricity market. It also contributes to the literature by extending the theoretical analysis of pricing option contracts in the Nordic financial electricity market to make that analysis empirical and consider the seasonality effect.

The joint findings from the last two essays suggest that some mispricing and seasonality exists in the pricing of quarterly option contracts. Which could suggest that the market participants are overconfident about the precision of their private information, leading them to misprice the financial assets.

[14] See Kristiansen 2007; Botterud, Kristiansen, and Ilic 2010; Wimschulte 2010; Gjolberg and Brattested 2011; Lucia and Torró 2011; Weron and Zator 2014; Smith-Meyer and Gjolberg 2016.

3 THEORETICAL FUNDAMENTALS

This section provides a brief theoretical background to the dissertation. Section 3.1 addresses how the beliefs and overconfidence of irrational investors affect asset prices in general. There follows a more detailed discussion of the association between small investors' sentiment and their market attention and asset prices. Section 3.2 addresses the overconfidence of irrational investors and asset prices and is followed by a more detailed discussion of the ex-ante pricing of electricity derivatives.

3.1 Effect of irrational investors' beliefs and sentiment on asset prices

In past decades, the behavioral finance paradigm has challenged the key assumptions of the traditional finance framework, which includes a key assumption that investors base their decision-making on rationality. If some irrational decision-making were to exist in the market that affects asset prices, more rational investors were to intervene and balance the asset prices back to their fundamental level (Thaler 1999). However, the behavioral finance literature challenges this assumption by stating the following (see, e.g., Barberis and Thaler 2002):

i.) The biased beliefs and preferences of irrational investors can influence asset demand causing mispricing in financial assets.

ii.) Due to limits to arbitrage, more rational investors are unable to balance the mispricing caused by irrational investors.

Hence, the interaction of irrational beliefs and behavior of a specific subset of investor and simultaneous limit to arbitrage for more sophisticated investors can lead to an event where asset prices deviate from their more fundamental level.

In their seminal work, De Long, Shleifer, Summers, and Waldmann (1990) state that so-called noise traders[15] are prone to erroneous stochastic beliefs[16], or a sentiment in a more general context, that can cause asset prices to deviate from their fundamental value. However, the unpredictable nature of noise traders'

[15] Shleifer and Summers (1990) define noise traders as a not fully rational investors.
[16] Baker and Wurgler (2007) define the investor sentiment as a belief of about future cash flows and investment risks that is not justified by the facts in hand.

sentiment reduces the incentive for rational arbitrageurs to bet against them[17], hence allowing some mispricing to exist in the financial market.

In efficient market theory, arbitrage in financial markets is considered costless and riskless; however, in a more realistic context, arbitrage tends to be risky and costly, and accordingly arbitrageurs cannot fully offset the impact of irrational investors on asset prices, that is the behavior of irrational investors impacts on asset prices (Shleifer and Vishny 1997).

Generally, arbitrageurs face risk from three sources. The first source is a fundamental risk, where negative news related to the asset position the arbitrageurs hold can have a negative outcome. The second source of risk is a noise-trader risk, where the behavior of noise traders can worsen the mispricing. The third source of risk is time: If the arbitrageurs had unlimited time to wait for the mispricing to correct, they could more aggressively bet against irrational investors; however, in some cases, the arbitrageurs are working with other investors' money and might face a withdrawal/liquidate risk at the worst time, especially if the mispricing has moved against the arbitrageurs (Ilmanen 2011).

Where the limits to arbitrage are one of the two major pillars of behavioral finance literature, the second pillar of behavioral finance leans on basic human psychology (how the investors form their beliefs and preferences). It is beyond the scope of this dissertation to introduce and explain all of them in detail; hence, its focus is on the essential ones that help the reader to understand the dissertation better.

3.1.1 Investor sentiment and asset prices

As mentioned previously, the classical finance paradigm generally assumes that neither the behavior or sentiment of irrational investors affects asset prices. However, the seminal work of De Long et al. (1990) introduces a model where two types of investors exist in the market, irrational investors (or noise traders) and rational arbitrageurs. The rational arbitrageurs have rational expectations about asset prices, whereas the irrational investors' form expectations about asset prices that are subject to their stochastically changing sentiment[18], which is not supported by fundamentals. In some periods, irrational investors' expectations about the asset prices are more optimistic (pessimistic) than those of rational arbitrageurs. This difference in the expectations then creates trading in the

[17] Baker and Wurgler (2006) find that the effect of sentiment is especially strong on stock that are more difficult to arbitrage; like small, young, unprofitable, volatile, non-dividend paying and distressed stocks.
[18] According to Black (1986) investor sentiment can represent trading on noise rather than on news.

financial market. Baker and Wurgler (2006) argue that sentiment-based demand shock by irrational investors and simultaneous limits to arbitrage can cause mispricing among assets. When irrational investors experience a negative (positive) sentiment shock, they sell (buy) equities to (from) rational arbitrageurs. Therefore low (high) sentiment will generate downward (upward) price pressure in short-term. This liquidity shock can have a short-term effect on returns, as suggested by Campbell, Grossman, and Wang (1993).

What then is investor sentiment, how can it be measured, and does it affect asset prices? In the previous literature, investor sentiment is traditionally measured by three alternative methods. The first is a market-based investor sentiment measurement. These measurements include the likes of VIX[19], put-call ratio[20], a discount of closed-end funds[21] , and mutual fund data[22]. The second method is a survey-based investor sentiment measurement. These measurements include the likes of the *AAII* survey[23], consumer confidence surveys[24], and the *Investors Intelligence* survey[25]. The third method is a composite investor sentiment measurement[26]combining the information from some of the previously mentioned investor sentiment measurements into a single measurement.

Some previous studies find that survey-based investor sentiments are associated with future equity market returns. For example, Fisher and Statman (2000) find that a high (low) *level* of small investor sentiment (the AAII survey) during the present month is associated with negative (positive) returns for the S&P 500 index for the following month. Schmeling (2007) also finds in the more global context that the *level* of small investor sentiment (*Sentix*) is negatively associated with future equity market returns. Verma and Soydemir (2006) report that a one-standard-deviation *increase* in small investor sentiment (the AAII survey) in the U.S.A. has a positive effect on future equity market returns in the U.S.A. and the U.K. For the consumer confidence surveys, Charoenrook (2005), Lemmon and

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[19] Whaley 2000; Simon and Wiggins III 2001; Giot 2005.
[20] Simon and Wiggins III 2001; Wang et al. 2006.
[21] Lee et al. 1991; Chen et al. 1993; Swaminathan 1996; Neal and Wheatley 1998; Elton et al. 1998; Brown and Cliff 2005.
[22] Neal and Wheatley 1998; Brown et al. 2003; Brown and Cliff 2005; Frazzini and Lamont 2008; Beaumont et al. 2008; Feldman 2010; Ben-Rephael et al. 2012.
[23] De Bondt 1993; Fisher and Statman 2000; Brown and Cliff 2004; Verma and Soydemir 2006; Kurov 2008; Verma and Verma 2008; Verma and Soydemir 2009.
[24] Otoo 1999; Fisher and Statman 2003; Jansen and Nahuis 2003; Charoenrook 2005; Lemmon and Portniaguina 2006; Schmeling 2009; Zouaoui et al. 2011.
[25] Solt and Statman 1988; Clarke and Statman 1998; Fisher and Statman 2000.
[26] Baker and Wurgler 2006; Baker and Wurgler 2007; Baker et al. 2008; Ho and Hung 2009; Kurov 2010; Yu and Yuan 2011; Baker et al. 2012; Beer et al. 2012; Stambaugh et al. 2012; Huang, Jiang, Tu and Zhou 2015.

Portniaquina (2006) and Schmeling (2009) find a negative association between and future equity market returns and consumer confidence.

Some previous studies also document a link between market-based investor sentiment measurements and equity market returns. For example, Lee et al. (1991), Swaminathan (1996), and Neal and Wheatley (1998) find that discounting closed-end funds is associated with future equity market returns. Results from Neal and Wheatley (1998), Brown and Cliff (2005), Frazzini and Lamount (2008), Beaumont et al. (2008), Edelen et al. (2010), and Feldman (2010) suggest that investor sentiment inferred from mutual fund data is also associated with equity market returns.

Also, investor sentiment that is inferred from the derivative market has been reported to contain information that may help to predict future equity market movements; for example, Whaley (2000), Simon and Wiggins III (2001), and Giot (2005) document a negative relationship between VIX and stock market returns.

Baker and Wurgler (2006) show that investor sentiment does not just affect aggregate stock market returns. The authors document a relationship between investor sentiment and subsequent cross-sectional stock returns. They argue that the effect should be stronger for those stocks that are more prone to the behavior of irrational investors, and are also more difficult to value and arbitrage; like small or potentially financially distressed (high book-to-market ratio) stocks.

However, Da, Engelberg, and Gao (2015) raise some important reasons why market-based or survey-based investor sentiment measurements might be imprecise, and a new search-based investor sentiment measurement might be a good solution. First, the market-based sentiment might be the equilibrium outcome of many different economic forces and hence not purely reflect the current investor sentiment. Second, some survey-based sentiments are conducted on too low a frequency, such as every month. Third, respondents might not answer survey questions truthfully, especially if the incentive for telling the truth is low. Fourth, the search-based sentiment method reveals real attitudes rather than just inquiring about them, as is the case with survey-based sentiments, and can also be conducted in higher frequency.

Da et al. (2015) find that increased market-level investor sentiment (known as FEARS), constructed by aggregating the popularities of Google search term such as “recession,” “unemployment” and “bankruptcy,” predicts return reversals, increasing volatility and mutual fund flows from equity funds to bond funds. Also, several other studies[27] find that information inferred from the popularity of various Google search terms is linked to subsequent equity market returns.

3.1.2 Investor attention and asset prices

In an efficient market, the current asset price should be the present value of its future cash flows. The current asset price should also reflect all currently available information and react only if new information reaches the market. However, according to Hirshleifer (2001), investors have only limited attention, memory, and processing capacities, which forces the investors to focus on a specific subset of information. Barber and Odean (2008) find that the more limited attention mentioned tends to make individual investors (the irrational investors) more likely than institutional investors (the rational investors) to buy stocks that grab their attention, creating a demand shock for such stocks[28].

Huberman and Regev (2001) find that an article published in a Sunday edition of the *New York Times*, related to the development of a new cancer-battling drug caused a given company's stock price to increase substantially. An interesting fact is that the same information had already been released through various sources (including the Times itself). The authors argue that the public attention that the stock in question was given increased the value of stock substantially even without genuinely new information being released. Fang and Peress (2009) also find a link between media coverage and future stock returns. The authors find that stocks with higher media coverage earn lower risk-adjusted returns due to overpricing. The linkage is especially strong for those stocks more influenced by the behavior of irrational investors.

In recent years, information inferred from Google searches has been used to capture investors' levels of stock market attention. Vozlyublennaia (2014) states that high market attention, inferred from Google searches, for market indices (S&P 500, Dow, and Nasdaq) forecasts negative returns for the indices for the following two weeks. Furthermore, Chen (2017) finds that the popularity of Google searches market indices is associated with stock market returns in a more global context. Several studies[29] also report that a similar association is also evident between the

[27] Da et al. 2011; Joseph, Wintoki and Zhang 2011; Bank, Larch and Peter 2011; Takeda and Wakao 2014;Vozlyublennaia 2014; Tantaopas, Padungsaksawasdi and Treepongkaruna 2016; Chen 2017

[28] Gervais, Kaniel and Mingelgrin (2002) find and argue that stocks with extremely high trading volume capture the attention of investors, leading to subsequent positive excess return.

[29] Da et al. 2011; Joseph, Wintoki and Zhang 2011; Bank, Larch and Peter 2011; Takeda and Wakao 2014

popularity of Google searches and returns of individual stocks; hence, small investors' sentiment can be measured by incorporating their market attention as illustrated by the Internet searches they conduct as illustrated by Da et al. (2015).

3.2 Overconfidence

Daniel and Hirshleifer (2015) argue that overconfidence is another irrational behavior of investors, that also plays a key role in their financial decision-making. The authors define overconfidence as a tendency of investors having mistaken valuations and believing in them too strongly. The authors' accent that the effect of overconfidence on asset pricing is more substantial when the market is illiquid and short-selling is difficult and costly. When the short-selling is constrained, pessimist investors find it more difficult to trade based on their views than optimist investors do. Thus, the asset pricing reflects more the views of over-optimistic investors, resulting in equilibrium overpricing. (Miller 1977.) In line with the arguments of Miller (1977) and Daniel and Hirshleifer (2015), Hirshleifer (2001) argue that investors tend to misprice financial assets that have sparse information, and the mispricing becomes apparent only ex-post.

Daniel and Hirsleifer (2015) argue that in standard rational expectations framework, investors process information perfectly, and thus asset prices are always rationally discounted to their expected payoffs. In contrast, biased belief model assumes that investors make mistakes when they form expectations about asset payoffs. For example, overconfident investors tend to overestimate the precisions of positive private information that they perceive[30]. Thus, they pay too high price for the asset initially, which later in the future leads into return reversal. Daniel, Hirsleifer, and Subrahmanyam (2002) show that investors' overconfidence is associated with negative long-lag autocorrelations in returns.

3.2.1 Ex-ante pricing of electricity derivatives

In the literature on commodity forward contract ex-ante pricing, two primary types of models exist. The first is the so-called no-arbitrage or cost-of-carry model. In principle, it assumes that the forward contract can be synthesized by taking a physical position on the underlying asset and holding it until the expiration day.

[30] Chuang and Lee (2006) find that overconfident investors tend to overreact to private information and underreact to public information. Also, overconfident investors tend to underestimate the associated risk and trade more in riskier assets. Daniel, el al. (1998) show that if investors are overconfident, they overweight their own private information at the expense of ignoring publicly available information.

Since electricity is practically nonstorable, the literature on pricing electricity forward contracts mainly relates to the second model. The second model focuses more on the difference between the forward price and the expected future spot price. The difference between the forward price and the expected spot price is also known as the forward premium. The forward premium can be affected by hedging-pressure, for example, causing the forward premium to be positive or negative depending on which side the hedging-pressure is coming from (Longstaff and Wang 2004).

Fama and French (1987) represent the forward premium with the following two models:

$$(1) \qquad F(t,T) - S(t) = E_t[P(t,T)] + E_t[S(T) - S(t)]$$

where the difference between the current forward price and current spot price can be expressed as the sum of an expected premium and an expected change in the spot price. The expected premium can then be expressed as follows:

$$(2) \qquad E_t[P(t,T)] = F(t,T) - E_t[S(T)]$$

where the expected premium can be viewed as a biased estimate of the forward price for the future spot price.

Several studies have empirically investigated the existence of a forward premium in the Nordic financial electricity market. For example, Botterud, Kristiansen, and Ilic (2010), Gjolberg and Brattested (2011), Lucia and Torró (2011) find a positive and statistically significant forward premium. Also, Gjolberg and Brattested (2011) and Lucia and Torró (2011) find seasonal patterns in the forward premium. Whereas Weron and Zator (2014) find that the forward premium is also dependent on the holding period. However, in a recent study by Smith-Meyer and Gjolberg (2016), the authors find that since the year 2008, the forward premium has been diminishing.

In the equity market, one relatively popular option strategy that utilizes irrational investors' overconfidence bias is the so-called *covered call*-option strategy[31]. This strategy involves the rational investor writing a call option against a long position

[31] Feldmand and Roy (2005) and Lakonishok, Lee, Pearson and Poteshman (2006) list call option buyers as the most overconfident class of investors.

in an underlying asset already owned. By writing the call option, the option writer enables an irrational investor to buy a financial asset that they are overconfident.

For example, Whaley (2002) finds that a covered call-option strategy that writes a one-month at-the-money call option against a currently held long position on the S&P 500 index improves the risk-adjusted performance of the portfolio when compared to the situation where the investor holds only a long position on the S&P 500 index. Several other studies also document that the covered call-option strategy outperforms investing only in the index[32].

To empirically test if a specific option contract traded in the market is ex-ante under- or overvalued, Black and Scholes (1972) and Galai (1977) use the following model:

$$(3) \qquad (\Delta C - C_v \Delta V) - (C - C_v V) r \Delta t,$$

where ΔC is the change in option value; C_v is the delta value of the option contract; ΔV is the change in the value of the underlying asset. $C_v V$ gives the number of underlying assets to achieve a complete hedge; Δt is the time interval, and r is the interest rate. The option position is maintained throughout the life of the option. If a statistically significant positive profit can be made by buying (shorting) the option contract, the result suggests that the option contract in question is undervalued (overvalued).

The equation described above serves the purpose of maintaining the delta neutrality over time and for every single day. Every day the underlying asset V is bought or sold (depending on the change in C_v) so that the delta neutrality can be maintained, and the process continues until the option contract matures. On the maturity day, the positions are liquidated so that the dollar return can be calculated (see, e.g., Black and Scholes 1972; Galai 1977).

[32] Feldman and Roy 2005; Hill, Balasubramanian, Gregory and Tierens 2006; Kapadia and Szado 2007

4 SUMMARY OF THE ESSAYS

This dissertation consists of five individual essays that are briefly discussed in this section. Two of the essays are co-authored, and three are single-authored. All five essays are published in peer-reviewed journals.

Essay 1: "Changes in investors' market attention and near-term stock market returns" was published in 2016 in the Journal of Behavioral Finance, Volume 17 Issue 1.

Essay 2: "Small investors' internet sentiment and return predictability". Review of Behavioral Finance. Forthcoming.

Essay 3: "Internet search-based investor sentiment and value premium". Finance Research Letters. Forthcoming.

Essay 4: "Covered option strategies in the Nordic electricity markets" was published in 2015 in the Journal of Energy Markets, Volume 8 Number 3.

Essay 5: "Dynamic delta option strategies in Nordic electricity markets" was published in 2018 in the Journal of Energy Markets, Volume 11 Number 4.

4.1 Changes in investors' market attention and near-term stock market returns

This essay examines the association between changes in irrational investors' (i.e., small investors') market attention and sentiment and returns of the S&P 500 index. It measures small investors' market attention and sentiment as indicated by the popularity of the Google search terms "bear market," "market crash," "bull market," and "market rally." The Google search terms "bear market" and "market crash" ("bull market" and "market rally") proved more related to the negative (positive) sentiment. The purpose is to examine if changes in the small investors' sentiment, inferred from their information retrieval (market attention) from the Internet, is associated with S&P 500 index returns. I argue that public information retrieval by individuals is an element of stock price formation; that is irrational investors use Google to look for information to support their decision-making when trading. Hence the increase in positive (negative) information retrieval related to small investors' sentiment is associated with positive (negative) future returns of the S&P 500 index. The results indicate whether the behavior of irrational investors and especially their market attention and sentiment, have a statistically significant effect on asset prices or not.

The essay's hypotheses are mainly based on the earlier findings of Da et al. (2011). The authors find that increased investor attention, measured via Google search volumes for stock tickers of Russell 3000 companies, predicts higher returns of the given company for the following two weeks. Also, Da et al. (2011) find that increasing Google search volume for the stock tickers of IPO companies predict higher first-day IPO returns. The concern with the market attention measurement used by Da et al. (2011) is that it is one-way, that is, all attention is good. Whereas the essay referred to here extends the study of Da et al. (2011) more toward small investors' two-way sentiment on the overall equity market, that is it measures the positive and negative market attention and sentiment separately, as in Tetlock (2007).

The data used to measure the investor attention consist of the weekly search popularity of the Google search terms "bear market," "bull market," "market crash," and "market rally" in the United States. To analyze the effect of investor attention on stock market returns, this essay uses weekly returns and volumes of the S&P 500 index. The sample consists of 404 weekly observations, starting from January 2004 and ending on February 2011.

The authors use several statistical methods to empirically estimate the association between the popularity of given Google search terms and future returns of the S&P 500 index. First, the study employs a vector autoregression model to capture the interdependence between S&P 500 returns and lagged changes in the popularity of a given Google search term. Second, using the results from vector autoregression, the authors employ a Granger causality test, which indicates if the lagged changes in the popularity of a given Google search term contains some information that might predict the future S&P 500 returns. Third and finally, the study employs regression analysis to examine the statistical association between the variables of interest.

The study finds that an increase in the popularity of the Google search terms "bear market" and "market crash" ("market rally") predict negative (positive) returns for the S&P 500 index for the forthcoming week. Hence, it appears that overall, the behavior of irrational investors does affect asset prices.

4.2 Small investors' internet sentiment and return predictability

This essay examines the association between *unexpected* changes in U.S. small investor sentiment and future equity market returns and size premium in the U.S. The small investor sentiment in the essay is inferred from the popularity of the

Google search terms "bull market" and "bear market" or their spread. This new small investor sentiment is known as Small Investor Internet Sentiment (SIIS)[33]. The unexpected change in the SIIS is proxied as the first-order autoregressive model, where the residuals are considered to be the unexpected changes in the SIIS as in Peltomäki et al. (2017). The results will indicate whether the behavior and beliefs of irrational investors and especially their sentiment, have a statistically significant effect on asset prices.

Da, Engelberg, and Gao (2015) construct a market-wide investor sentiment that is inferred from the popularity of Google search terms such as "recession," "unemployment," and "bankruptcy." They argue that search-based investor sentiment has several advantages over the more traditional sentiment measures. First, market-based sentiment measures might be the equilibrium outcome of several different economic forces and therefore not entirely reflect true investor sentiment[34]. Second, survey-based sentiment measures can be conducted at too low a frequency. Third, the respondents in survey-based sentiment measures might not answer truthfully[35].

This essay contributes to the literature in several ways. First, it proposes a novel measurement of small investor sentiment. Second, it extends the study of Da et al. (2015) toward small investor sentiment on the equity market. Third, it examines if information inferred from the Google search volumes is related to the cross-sectional returns of companies sorted by their size, the size premium.

The study offers hypotheses based on the theory proposed by De Long et al. (1990) and the findings of Fisher and Statman (2000), Verma and Soydemir (2006), Baker and Wurgler (2006), Barber and Odean (2008), Yuan (2015). According to De Long et al. (1990), so-called noise traders or irrational traders can affect asset prices if more rational investors are unable to correct the asset prices due to limits to arbitrage. Barber and Odean (2008) find that irrational investors tend to be net buyers of attention-grabbing stocks; which makes the attention-grabbing stocks

[33] We argue that the SIIS captures the small investor sentiment since Google search volumes do not differentiate investors by the size of their portfolio. By numbers, there should be more small investors in the market than institutional investors.

[34] D'Avolio (2002) finds that shorting stocks can be too costly for investors. Shleifer and Vishny (1997), and Chevalier and Ellison (1999) argue that even more sophisticated investors might be reluctant to bet against the market due to reputations concerns. The Internet search-based investor sentiment is free from these constraints.

[35] Singer (2002) argues that people have little incentive to answer survey questions carefully or truthfully, especially if questions are sensitive. For example, Da et al. (2015) argue that possibility of job loss might be a sensitive topic for the respondent to answer in a survey, but it can show up search volumes such as "unemployment". Da et al. (2015) argue that answers from surveys cannot be externally and objectively verified, as can be done for the Internet search-based investor sentiment. Brown and Cliff (2004) report that the average number of respondents in AAII survey is only 137.

vulnerable to liquidity shock as described by Campbell, Grossman, and Wang (1993). Such liquidity shock, in turn, causes the price of attention-grabbing stocks to deviate from their fundamental value, that is, the rational investors are unable to balance the liquidity shock caused by irrational investors. Yuan (2015) finds that during market-wide attention events, investors increase the attention they pay to their portfolio and rebalance it, leading to increased trading. Yuan (2015) also finds that certain front-page news events increase selling orders from individual investors. Moreover, Kumar and Lee (2006) find that small investors tend to trade in concert.

The arguments of the study are as follows: First, past aggregate returns attract small investors' attention, as do terms such as *bear market* and *bull market* used in the financial media. Second, the small investors then use Google to look for information on such terminology or the news related to it, causing an unexpected change in search volumes. Third, the small investors then form their short-term equity market sentiment based on the information searched for, on which they then act, which leads to decisions on whether to sell or buy to rebalance their current portfolio. Finally, this then causes an irrational liquidity shock to the equity market, leading to negative or positive market movements. This effect should be stronger for small-sized companies since they tend to carry more noise-trading risk. The effect should also be stronger after extreme returns of large-sized companies, since those returns, and their corresponding terminology, are more likely to be reported in the financial media that catches the attention of small investors.

As suggested by Fisher and Statman (2000) and Verma and Soydemir (2006), the authors also expected that U.S. small investor sentiment affects future U.S. equity market returns. Moreover, as suggested by Baker and Wurgler (2006), the study also anticipated that the effect of sentiment is stronger for those stocks that are harder to arbitrage, like small-stocks.

The data used in this essay consist of a measure of the weekly search popularity of the Google search terms "bear market" and "bull market" in the United States. To analyze the effect of unexpected changes in the SIIS on equity market returns and size premium, this essay uses size portfolios of the bottom 30 % and top 30 % companies by market equity[36]. The sample consists of a total of 704 weekly observations, starting from January 2004 and ending on June 2017.

[36] Portfolio returns are downloaded from Kenneth R. French Data Library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The study measured the unexpected changes in the SIIS from the AR(1)-process, where the residual is considered the unexpected change in SIIS. To test for possible interdependence between equity market returns and the unexpected SIIS, the study employs a vector autoregressive model. To further analyze the association, a pairwise Granger causality test was conducted between the equity market returns and the unexpected SIIS. The authors also ran ordinary least square regressions, with several control variables as suggested by Da et al. (2015) to capture the effect that the unexpected changes in SIIS had on future equity market returns.

Results from Table 3 suggest that unexpected changes in the SIIS contain more information that helps to forecast future portfolios returns than unexpected changes in AAII[37] do. The UE[SIIS] generally needs a shorter lag structure to forecast the future portfolio returns and also has a higher statistical significance. The UE[SIIS_Bear] is also the only explanatory variable that helps to forecast the future size premium.

The empirical findings suggest that unexpected change in the SIIS when inferred from the search popularity of "bear market" is negatively associated with the next week's stock market returns. A one-standard-deviation unexpected increase in the search volumes of "bear market" is associated with a 17 (13) basis points lower return for small (large)-sized companies and 15 basis points lower size premium for the forthcoming week.

An unexpected change in the SIIS, when measured as the popularity difference between "bull market" and "bear market" (the spread), is positively associated with the next week's stock market returns. A one-standard-deviation unexpected increase in the spread is associated with a 13 (12) basis points higher stock market returns for small (large)-sized companies and eight basis points higher size premium for the forthcoming week.

As reported earlier, the findings suggest that the effects of unexpected changes in the SIIS are stronger for small-sized companies. As Baker and Wurgler (2006) report, stocks that are more difficult to arbitrage, like small-sized companies, are more affected by the sentiment and Lee, Shleifer and Thaler (1991) find that small stocks are disproportionally held by the small investors. The effects of unexpected changes in the SIIS are stronger when large-sized companies experience highly negative returns. Hence, it is possible to argue that overall, the behavior of irrational investors affects asset prices.

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[37] Also AAII-sentiment is measured every week.

4.3 Internet search-based investor sentiment and value premium

This essay examines the association between unexpected changes in U.S. small investor sentiment and future equity market returns in the U.S.A. The essay focuses particularly on the cross-sectional return difference between companies sorted by their book-to-market ratio[38]—the value premium. The essay also infers the small investor sentiment from the popularity of the Google search terms "bull market" and "bear market" or their spread. The popularity of searches is limited to cover only the United States and its finance-related searches. The unexpected change in sentiment is proxied as the first-order autoregressive model as in Peltomäki et al. (2017). The study hypothesizes that an unexpected change in the sentiment represents a shift in noise traders' sentiment that creates a liquidity shock in the market (see, e.g., Campbell et al. 1993). The effect should be stronger for those stocks that are more prone to the behavior of irrational investors and are also more difficult to value and arbitrage; like potentially financially distressed (high book-to-market ratio) stocks.

The theoretical background of this paper is based on two theories[39] of how the behavior of small investors can affect asset prices. The first theory is the association between small investor sentiment and asset returns. The second theory is the association between market attention of small investors, measured by Google searches, and asset returns. De Long et al. (1990) present a theory suggesting that the investor sentiment of so-called noise traders can affect asset prices if more rational investors are unable to balance the asset prices because of limits to arbitrage. Barber and Odean (2008) find that individual investors are net buyers of attention-grabbing stocks, causing the price of such stocks to deviate from their more fundamental value. That causes the attention-grabbing stocks to face a liquidity shock as described by Campbell et al. (1993). Campbell et al. (1993) argue that if irrational investors desire to trade for the stock for exogenous reasons, the more rational investors demand a higher expected return to accommodate the fluctuation in irrational investors' demand. According to Yuan (2015), small investors are not just net buyers but also net sellers, and small investors increase their attention and trading during market-wide events. Yuan (2015) finds that small investors can increase their selling during certain front-page news events.

We argue that: market-wide events capture small investors' attention. For example, terminology such as the bear market and the bull market can be used in financial media, and it captures small investors' attention. Then small investors

[38] Stocks with high (low) book-to-market ratio are considered as a value (growth) stocks.
[39] Discussed also in the previous paper.

use Google searches to look for information, causing an unexpected change in the search volumes. The small investors rebalance their sentiment and act accordingly in the market, causing a liquidity shock to the equity market. To accommodate the increased demand of small investors, rational investors demand a higher expected return. The effect of investor sentiment should be stronger for stocks that are also harder to value and arbitrage, like value stocks, as suggested by Baker and Wurgler (2006).

The data used in this essay consist of the weekly measure of the Google search volumes relating to the terms "bear market" and "bull market" in the United States. To analyze the effect of unexpected changes to the sentiment on value premium, the authors sorted companies into decile portfolios by their book-to-market ratios[40]. The sample consists of 704 weekly observations, from January 2004 to June 2017[41]. To test the effect of unexpected changes in the sentiment on the value premium, the authors use a predictive regression model with same set of control variables as Da et al. (2015): news-based measure of economic policy uncertainty (EPU)[42], the CBOE volatility index (VIX) and Aruoba-Diebold-Scotti (ADS)[43] business conditions index. As an additional control variable, the authors also use a news-based measure of US Equity Market Uncertainty Index (EMU), for textual analysis of U.S. equity market uncertainty.

The study's findings include that an unexpected increase in optimism (pessimism) in the sentiment predicts positive (negative) subsequent value premium. A one-standard-deviation unexpected increase in pessimism predicts six basis points lower value premium for the next week. An unexpected increase in the optimism of one standard deviation predicts a nine basis points higher value premium for the next week. An unexpected increase in the spread of one standard deviation predicts an 11 basis points higher value premium for the next week.

4.4 Covered option strategies in the Nordic electricity market

This essay examines the risk-adjusted performance of two option strategies on the Nordic financial electricity market. Amundsen and Bergman (2006) report that since liberalization the Nordic electricity market during the period of 1991 – 2000, the competition in the market has increased and profit margins have been

[40] Portfolio returns are downloaded from Kenneth R. French Data Library
[41] The base date for the Google search volume time series is January 2004.
[42] Baker, Bloom and Davis (2016).
[43] Aruoba, Diebold and Scotti (2009)

squeezed[44]. Fridolfsson and Tangerås (2009) find no evidence of systematic exploitation of system-level market power in the Nordic electricity market.

The analyzed option strategies are called covered call and protective put-option strategies. The covered call-option strategy consists of a long position on a quarterly forward contract and a simultaneous short position on a quarterly call-option contract, whose underlying asset is the quarterly forward contract itself. The protective put-option strategy consists of a long position on a quarterly forward contract and a simultaneous long position on a quarterly put-option contract, whose underlying asset is also the quarterly forward contract.

The purpose was to empirically analyze if the given option strategies produce positive or negative risk-adjusted returns. The results provide more information about the ex-ante pricing of quarterly option contracts that are traded in the Nordic financial electricity market. Furthermore, the results enhance the knowledge of the potential overconfidence bias among the market participants in the Nordic financial electricity market.

This essay contributes to the literature by extending the studies of Whaley (2002), Feldman and Roy (2005), Hill, Balasubramanian, Gregory, and Tierens (2006), Kapadia and Szado (2007), and Ungar and Moran (2009) from the equity market to the financial electricity market. Moreover, the study complemented previous studies[45] on the derivatives traded in the financial electricity market that focused more on their capabilities for risk-reduction, and less so on the return potential and its related overconfidence of market participants.

The data consist of daily settlement prices for financial forwards (quarterly contracts) and their corresponding option contracts in the Nordic financial electricity market. For option contracts, the study adopts different levels of moneyness. The moneyness levels range from 10 % out-of-the-money to 10 % in-the-money. The data period is from November 1999 to February 2012, with approximately 252 trading days per year. The authors chose quarterly contracts for their liquidity and seasonality and calculated the risk-adjusted performance of different strategies by way of annualized Sharpe ratios and Jensen's alphas. The study includes a review of how the different moneyness levels and holding periods

[44] According to Fingrid (2019), about 70 % of total spot electricity consumption in the Nordics is traded through an exchange, the annual value being in billions of euros. Whereas the value of financial derivatives market contracts traded is up to five to six times as large. Besides electricity buyers and sellers, also investment banks and risk management consulting companies operate in the financial derivatives market.

[45] See Shawky, Marathe and Barrett 2003; Fleten, Bråthen and Nissen-Meyer 2010; Frestad 2012

affect the performance, and what are the possible underlying reasons for the risk-adjusted-performance.

The results from the empirical part of the study suggest that the protective put strategy outperforms both the naked long forward strategy and covered call strategy [46]. However, the absolute performance of both strategies is also conditional on the moneyness levels and holding periods used[47]. The protective put strategy seems to generally perform better than the covered call strategy in rising and declining market environments[48].

The reported findings suggest that some mispricing exists in the Nordic financial electricity market, which might due to that, some of the market participants are too overconfident about their private information.

4.5 Dynamic delta option strategies in Nordic electricity markets

This essay examines the performance of two dynamic delta option strategies on the Nordic financial electricity market. The performances of dynamic delta option strategies are compared to the benchmark case of the so-called static futures strategy. The dynamic delta option strategy is constructed by writing (buying) quarterly call (put) option contracts and simultaneously also selling their underlying asset, a quarterly futures contract. The static futures portfolio is constructed by selling the quarterly futures contract alone[49]. The amount of quarterly futures contracts sold in portfolio one (the dynamic delta option strategy) is determined so that the risk level of portfolio one is equal to portfolio two (the static futures strategy). The risk level is measured with the Greek Delta.

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[46] Although Sharpe ratio is an adequate performance measurement when returns are normally distributed, Eling and Schuhmacher (2007) find that the ranking of hedge fund performances (with non-normal return distributions) stays virtually the same regardless what performance measurement is used. Also, Pedersen and Rudholm-Alfvin (2003) report a high rank correlation between different performance measurements.
[47] We follow the methodology of Lo (2002), equations 9 and 18, to calculate the standard errors for Sharpe ratios. We do not correct for autocorrelation since the first-order autocorrelation varies only between 0.04 and 0.07. We use bootstrapped standard errors to test statistical significance of Jensen's alphas.
[48] As Israelsen (2005) notes in his study, using the Sharpe ratio as a performance rank for equity funds with a negative excess returns can be cumbersome. By contrast, the author suggests an alternative performance ranking measurement; modified Sharpe ratio. The modified Sharpe ratio uses exponent in the denominator as an additional variable to control for the negative excess returns. Although, utilizing the modified Sharpe ratio does not alter the conclusions when one strategy has a positive and other strategy has negative Sharpe ratios.
[49] The set up reflects the dilemma that electricity sellers face.

Due to time-variation in the Greek Deltas of option contracts, portfolio one trades the futures contracts daily to maintain a fixed and comparable risk level[50].

The purpose is to empirically test whether price differences exist between the quarterly option and futures contracts. The existence of a price difference could suggest that some seasonality exists in the potential overconfidence of market participants. The price difference is defined as the inequality in euro terms between the dynamically managed delta option strategy and the corresponding static futures strategy. In theory, the monetary outcome of both strategies should be equal, as the risk levels related to future electricity prices are equal. If some price difference exists, it could indicate that the option contracts in question might be over- or underpriced.

The sample period is from 4/21/2005 to 12/9/2011. The underlying quarterly contracts cover the delivery period starting from the first quarter of 2006 and lasting to the first quarter of 2012, consisting of 25 quarters in total. The sample period contains quarters with different market states of electricity prices, both increasing and decreasing. Using three different levels of moneyness (5 % out-of-the-money, at-the-money, and 5 % in-the-money) produces close to 9000 daily observations for dynamic delta option strategies that use either call or put options. I test the existence of price difference first with univariate analysis by conducting a paired difference test between the static futures strategy and dynamic delta option strategies. In addition to the previously mentioned tests, I also employ multivariate analysis.

There is some seasonality in the ex-ante pricing of call and put options traded in the Nordic financial electricity market. This possibly reflects seasonally varying overconfidence bias among the market participants. For the dynamic delta option strategy that uses call options, the study finds that it performs better (worse) than static futures strategy during winter (summer) quarters. This suggests that call options are ex-ante over (under)-priced for the winter (summer) quarters. One possible explanation for the ex-ante overpricing is that due to highly volatile electricity prices during the winter quarters, the market participants might prefer buying call options in the hope of obtaining high returns; thus the market participants are ex-ante overpaying for those call options. This then further suggests that during the winter quarters, the market participants might be overconfident about their private information and want to capitalize it during highly volatile market environment. This then leads call options to be ex-ante overpriced during the winter quarters.

[50] I take into account the trading costs, but not the bid-ask spreads. This may have an effect on the implementation of the suggested strategy.

For the dynamic delta option strategy that uses put options, the study finds that it performs worse than the static futures strategy during the winter quarters. This suggests that put-option contracts are also ex-ante overpriced during the winter quarters. Hence, there is evidence of some seasonality in ex-ante put-option pricing in the Nordic financial electricity market during the winter quarters. The same argument as made for call options could also hold here. Due to highly volatile electricity prices during the winter quarters, the market participants overconfident about their private information and end up overpaying ex-ante.

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Appendix: Internet Search-Based Investor Sentiment and Value Premium

Table 1: Descriptive statistics

	ADS	EPU	EMU	VIX
Mean	-0.32	123.78	44.82	18.72
Median	-0.18	104.76	29.55	15.86
Std.Dev	0.78	71.61	55.72	9.15
Maximum	0.93	472.47	823.76	79.13
Minimum	-4.08	19.34	7.46	9.75
Skewness	-2.65	1.24	5.98	2.70
Kurtosis	10.96	4.60	65.01	12.93
Observations	704	704	704	704

This table shows the descriptive statistics for the control variables used in the study. ADS is the Aruoba, Diebold, and Scotti (2009) index. EPU is the Baker, Bloom, and Davis (2013) index. EMU is also developed by Baker, Bloom, and Davis (2013). VIX is the Chicago Board Options Exchange daily market volatility index.

Table 2: Correlation Matrix

	ADS	EPU	EMU	VIX
ADS	1.00			
EPU	-0.25	1.00		
	(-6.98)			
EMU	-0.28	0.44	1.00	
	(-7.84)	(12.90)		
VIX	-0.65	0.44	0.39	1.00
	(-22.41)	(13.10)	(11.27)	

This table shows correlation coefficient estimates for the control variables used in the study. ADS is the Aruoba, Diebold, and Scotti (2009) index. EPU is the Baker, Bloom, and Davis (2013) index. EMU is also developed by Baker, Bloom, and Davis (2013). VIX is the Chicago Board Options Exchange daily market volatility index. The data set consists of 704 weekly observations, from January 2004 to June 2017. T-statistics are reported in parentheses.

CHANGES IN INVESTORS' MARKET ATTENTION AND NEAR-TERM STOCK MARKET RETURNS

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1

CHANGES IN INVESTORS' MARKET ATTENTION AND NEAR-TERM STOCK MARKET RETURNS

Abstract

We use Google Search volume to track changes investors' positive and negative market attention. Our results support the hypothesis that this information reflects investors' optimistic and pessimistic anticipation and can be used to predict near-term future returns. We find that changes in negative search term volume of "market crash" and "bear market" and changes in positive search term volume "market rally" explain near-term stock returns. Changes in investors' attention are partly related to past stock market returns implying that investors are prone to pay attention to possible price reversals. These measures of market attention are potential gauges of investor sentiment.

JEL classification: G12, G14, G17

Keywords: Investor sentiment; Stock market; Returns; Google search volume; market attention

1. Introduction

Investors commonly apply two types of security analysis as a base of their investment decisions. The first type is a fundamental analysis, which has the goal of identifying under- and overpriced securities based on their fundamental information. The second one is a technical analysis, which aims to find predictability in stock prices using price and volume information. Technical analysis therefore builds its rationale on an observation that systematic human behavior can be observed in stock and volume patterns. However, less is recognized that the patterns of investor behavior may be observed even before the patterns are transmitted to the stock market. That is, when investors start directing their attention to the stock market. In this study, we consider public information retrieved by individuals as an essential element in stock price formation, which should be finally reflected in the stock prices.

Our purpose is to consider the Google Search Volume Index of negative and positive market-related search terms as measures of investors' market attention to gauge the stock market sentiment. We examine whether there is a relation between changes in investors' market attention and near-term returns and trading volumes of the S&P 500 index. The objective of this study is to examine predictability in stock prices by analyzing investors' information retrieval as an origin of stock price formation. We hypothesize that "bear market" and "market crash" ("bull market" and "market rally") searches relate to investor attention at bear market (bull market) and characterize the general stock market sentiment.

Our study contributes to studies on investor sentiment such as Solt and Statman [1988], Otoo [1999], and Fisher and Statman [2000], by employing the Google Search Volume Index as a potential tool to gauge investor sentiment. To the best of our knowledge, no previous studies have used the Google Search Volume Index as a measurement of investors' overall market attention and stock market predictor, even though information from Google is used to analyze individual stocks. Data provided by Google News service were previously used by Ozik and Sadka [2010] and the Google Search Volume Index is used to measure investors' attention to different stocks by Da et al. [2011].[1] Our study differs from that of Da et al. [2011] who measure investor attention to different stocks and is therefore more related to stocks' visibility like, for example, Gervais et al. [2001].[2]

Although the issue whether Google Search Volume can track investors' positive and negative market attention in order to gauge the stock market sentiment has not been examined previously, forecasting with Google search volume has received some recent attention in news media. For example, Mackintosh [2012] writes in the Financial Times that researchers at the Bank of Italy used information from Google search volumes to calculate Italy´s euro break-up premium. Furthermore, Ito and Odenheimer [2012] write in Bloomberg Businessweek that Israel´s central bank applies Google search volume as an economic indicator. This rising interest of practitioners covered in the media provides further motivation for our study.

We apply Ordinary Least Squares regression to examine the effects that the Google Search Volume Index possibly has on the near-term S&P 500 returns. We use the Granger Causality tests to analyze causal relations between the Google Search Volume Index and the returns and volumes of the S&P 500 index. We find that changes in the Google Search Volume Index for Google search terms “market crash,” “bear market” and “market rally” contain some information that helps in forecasting near-term S&P 500 returns. In contrast, we do not find that changes in the Google Search Volume Index for the Google search term “bull market” contains information that helps in forecasting near-term S&P 500 returns. We also find that past S&P 500 returns predict changes for the search terms “market crash” and “market rally”. This implies bi-directional causality between the measures of investor’s market attention and stock market returns.

The remainder of this study is organized as follows. Section 2 presents a literature review related to studies on investor sentiment and presents our hypotheses. Section 3 describes the data and methodology. The empirical results are discussed in Section 4 and Section 5 concludes.

2. Literature review and hypothesis development

2.1. Literature review on investor sentiment

Two main issues in academic literature on investor sentiment are often addressed. First, can investor sentiment forecast future market returns and second, can the investor sentiment be explained by market returns? In academic literature investor sentiment is broadly studied through time and the results are mixed. However, most studies suggest that investor sentiment contains some information that helps forecasting future stock market returns and that the investor sentiment also plays a role in asset pricing. In the whether past stock market returns are related to the investor sentiment, the literature is more consistent that past stock market returns are related to investor sentiment.

In the literature, investor sentiment is measured in various ways. One subclass of investor sentiment is small investor sentiment, for example, measured from *AAIS*'s (*American Association of Individual Investors*) surveys[3], consumer confidence surveys[4] or other different proxies for small investor sentiment[5]. Results from Fisher and Statman [2000], Fisher and Statman [2003], Charoenrook [2005], Kumar and Lee [2006], Lemmon and Portniaguina [2006], Verma and Soydemir [2006], Schmeling [2007], Schmeling [2009], Verma and Soydemir [2009], Zouaoui, Nouyrigat and Beer [2011] and Antoniou et al. [2011] suggest that small investor sentiment helps predict future stock market returns. By contrast, Otoo [1999], Jansen and Nahuis [2003], Brown and Cliff [2004] and Wang et al. [2006] find that the small investor sentiment helps only a little or not at all in predicting future stock market returns. Whether past or contemporaneous stock market returns have a relationship with small investor sentiment, the literature is more consistent. De Bondt [1993], Otoo [1999], Fisher and Statman [2000], Fisher and Statman [2003], Jansen and Nahuis [2003], Brown and Cliff [2004], Wang et al. [2006] and Verma and Verma [2008] document that small investor sentiment is related to past stock market returns.

Another investor sentiment subclass used in academic literature is the investor sentiment that represents the sentiment of more sophisticated investors (known as institutional investor sentiment), like the sentiment of newsletter writers measured by *Investors Intelligence* surveys[6], the sentiment of Wall Street strategists[7], futures market positions by large investors[8] or other proxies for institutional investor sentiment[9]. Results from Lee et al. [2002], Brown and Cliff [2005], Verma and Soydemir [2006] and

Schmeling [2007] suggest that the institutional investor sentiment helps to predict future stock market returns. By contrast, Solt and Statman [1988], Clarke and Statman [1998] and Brown and Cliff [2004] find that the institutional investor sentiment helps only a little or not at all in predicting future stock market returns. Wang [2001] and Wang [2003] report that institutional investor sentiment also helps to forecast future changes in futures markets and Kurov [2008] links institutional investor sentiment to trading activity of index futures traders. By contrast, Sanders et al. [2003] argue that institutional investor sentiment has only very marginal ability to forecast price changes in the futures market. In addition, Solt and Statman [1988], Clarke and Statman [1998], Fisher and Statman [2000], Sanders et al. [2003], Brown and Cliff [2004] and Verma and Verma [2008] document that institutional investor sentiment follows past and contemporaneous stock market and futures market returns.

One alternative method to measure investor sentiment is to derive it from market data. These methods, for example, are VIX[10], put-call ratio[11], discount of closed end funds[12] and mutual fund data[13]. Whaley [2000] documents a negative relationship between the VIX and stock market returns. The results from Simon and Wiggins III [2001] and Giot [2005] suggest that high and low levels of VIX have some ability to forecast future stock market and futures market returns. Han [2008] links investor sentiment to index volatility smile. Furthermore, Simon and Wiggins III [2001] find that the put-call ratio has some forecasting ability over subsequent futures market returns. By contrast, Wang et al. [2006] claim that the put-call ratio has no forecasting ability but is related to past stock market returns.

Lee et al. [1991] find a relationship between the discount of closed end funds and contemporaneous stock market returns. In addition, Swaminathan [1996] and

Neal and Wheatley [1998] find that the discount of closed end funds has some explanatory power for future stock market returns for small-cap stocks. By contrast, Chen et al. [1993], Elton et al. [1998], and Brown and Cliff [2005] criticize and challenge the findings of Lee et al. [1991].

Results from Neal and Wheatley [1998], Brown and Cliff [2005], Frazzini and Lamont [2008], Beaumont et al. [2008] and Feldman [2010] suggest that mutual fund data contain some information that helps forecast future stock market returns. In addition, Brown et al. [2003] and Ben-Rephael et al. [2012] find a relationship between mutual fund flows and contemporaneous stock market returns. In contrast, Edelen et al. [2010] document a relationship between the asset allocation of small investors and future stock market returns.

In recent years in academic literature, a new investor sentiment measurement has emerged, the composite investor sentiment, which is measured using principal component analysis[14]. Baker and Wurgler [2006], Baker and Wurgler [2007], Baker et al. [2008], Beer and Zouaoui [2011], Stambaugh et al. [2012] and Baker et al. [2012] find that the composite investor sentiment helps forecast future stock market returns. Yu and Yuan [2011] find that the composite investor sentiment is related to a market´s mean-variance tradeoff. Baker and Wurgler [2012] document that the composite investor sentiment does not only help predict future stock market returns, but also helps predict bond returns. In addition, results from Ho and Hung [2008] and Beer et al. [2012] suggest that the composite investor sentiment plays a role in asset pricing. Furthermore, Chau et al. [2011] and Liao et al. [2011] link the composite investor sentiment to trading activity. Results from Kurov [2010] suggest that changes in composite investor sentiment are related to monetary policy decisions.

Other investor sentiment proxies reported in academic literature are, for example, the share of equity issues in total new equity and debt issues (Baker and Wurgler [2000], NYSE seat prices Keim and Madhavan [2000], market liquidity Baker and Stein [2004], grey market prices Cornelli et al. [2006]). However, these studies are not discussed here any further.

Investor sentiment measures can also be based on media information. Tetlock [2007] finds that high media pessimism in *Wall Street Journal* columns forecasts negative future returns. However, Tetlock [2007] notes media pessimism is partly driven by past negative market returns.

As Google searches can be done by everyone and not just professionals, we conclude that our study and measure of investor attention considered as sentiment indicators would be most closely related to the studies by De Bondt [1993], Fisher and Statman [2000], Brown and Cliff [2004], Kumar and Lee [2006] Wang et al. [2006], and Verma and Soydemir [2009]. Our study is less related to investigating institutional investor sentiment (see, e.g., Schmeling, [2007]).

Our study, especially negative search terms we use, would also be closely related to the study by Tetlock [2007] on media pessimism but less related to sentiment measures related to concrete actions such as mutual fund flows (see, e.g., Beaumont et al. [2008]; Ben-Rephael et al. [2012]). On the other hand, our approach has technical similarities to bull and bear division of bull and bears as in *Investors Intelligence* surveys (see Fisher and Statman [2000]) since we use bullish and bearish search terms.

2.2 Hypotheses

We use four different Google web search terms to measure market attention and to track investor sentiment: “market crash”, “bear market”, “bull market”, and “market rally”. Many studies find the relationship between investor sentiment and future stock market returns is statistically significant (see, e.g., Fisher and Statman [2000]; Fisher and Statman [2003]; Brown and Cliff [2005]). We focus on changes in investors’ market attention and near-term stock market returns, assuming that the measured changes in investor attention are a timely proxy for changes in investor sentiment. Thus, the effect of measured changes in investors’ sentiment on stock market returns should be imminent.

The Google Search Volume Index measures how many searches have been done for the specific search terms entered on Google web search, relative to the total number of searches done for the specific search term on Google over time. Da et al. [2011] find Google search frequencies about stocks to be correlated with existing proxies of investor attention. We use negative and positive market-related search terms as measures of investors’ positive and negative stock market attention to gauge investors’ pessimism and optimism. As such, our approach to measure investor sentiment is similar to that of Investor Intelligence’s surveys (see Brown and Cliff [2004]) but, instead of carrying out of a survey, we focus on investors’ market attention. Following this analogy, when investors pay more attention to a certain market condition or state, for example, fear for the stock market crash, the Google Search Volume Index increases, reflecting pessimism and negative market sentiment and vice versa.

Our approach is similar to that of Joseph et al. [2011] who present evidence that higher online search intensity for a stock ticker forecasts higher future abnormal stock returns. However, the study does not similarly relate different search words to investor sentiment as we do. Following Tetlock [2007] who finds that media pessimism is related to future downward pressure on stock market prices, our hypotheses for the relationship of optimistic/pessimistic search and future stock returns are as follows:

H1a: Changes in search volume of "market crash" have a negative relationship to near-term stock returns.
H1b: Changes in search volume of "market rally" have a positive relationship to near-term stock returns.
H1c: Changes in search volume of "bear market" have a negative relationship to near-term stock returns.
H1d: Changes in search volume of "bull market" have a positive relationship to near-term stock returns.

If our measures of investors' market attention gauge investor sentiment, especially small investor sentiment, investors' market attention should be predictable because of the following evidence. De Bondt [1993], Fisher and Statman [2000], and Brown and Cliff [2004] present evidence that past stock market returns explain small investor sentiment. Wang et al. [2006] find that past returns and volatilities of the S&P 100 index Granger-cause small investor sentiment, but not vice versa. Tetlock [2007] notes that media pessimism is partly driven by past negative market returns. Consequently, we hypothesize the following relationships between stock returns and investor future market attention:

H2a: Stock returns have a negative relationship to near-term changes in search volume of “market crash.”

H2b: Stock returns have a positive relationship to near-term changes in search volume of “market rally.”

H2c: Stock returns have a negative relationship to near-term changes in search volume of “bear market.”

H2d: Stock returns have a positive relationship to near-term changes in search volume of “bull market.”

Some other aspects of investor behavior may also be relevant when forming expectations for our results. The expectations can be considered from the perspective of the ‘gambler’s fallacy’ versus the ‘hot hands’ effect. As explained by Rabin and Vayanos [2010], the former means that investors predict random sequences to exhibit excessive reversals; the latter means that investors predict random sequences to exhibit excessive persistence. If investors are prone to experience the gambler’s fallacy, they may perform negative (positive) searches after positive (negative) market returns. If they are prone to experience the hot hands fallacy, they may perform positive (negative) searches after positive (negative) returns and vice versa. Our hypotheses 2a-2d concur with the hot hands effect.

3. Data and methodology

Google Search Volume Index data used in this study are in relative mode. The Google Search Volume Index measures how many searches have been done for a specific search term on a Google web search on that specific week, relative to the total number of searches done for the same specific search term on Google web search over time. In the relative mode, the data are scaled by Google to the average traffic for the specific search term during the time period selected. When the Google Search Volume Index exceeds one, number of times the specific search term has been entered on a Google web search that week is above the historical average. Conversely, when the Google Search Volume Index is less than one, the number of times the specific search term has been entered on a Google web search that week is below the historical average. This study uses the period 1 January 2004 to 10 February 2011.

This study uses four different Google search terms to test possible relationships between of the Google Search Volume Index and logarithmic future near-term S&P 500 total return index returns. The four different Google search terms used in this study are: "bear market", "bull market", "market crash" and "market rally". Of these search terms, "bear market" and "market crash" represent negative market attention, and the search terms "bull market" and "market rally" represent positive market attention. Data for Google Search Volume Index are downloaded from Google[15]. Data for S&P 500 total return index returns are from Datastream. Data for AAII's (American Association of Individual Investors) individual investor sentiment (percentage of bullish investor minus percentage of bearish investors) is downloaded from AAII's homepage[16]. This study uses weekly first differences to calculate the changes in the Google Search Volume Index and AAII's individual investor sentiment. The Google Search Volume Index is updated every Sunday and AAII's individual investor sentiment is updated every Thursday. Returns for the S&P 500 total return index are calculated from Mondays' opening values. The logarithmic change of the volume of S&P 500 total return index is calculated from the week's daily average volume. Table 1 reports the descriptive statistics of the data.

(INSERT TABLE 1 HERE)

To test possible relationship between changes in the Google Search Volume Index and future S&P 500 returns, we use following Ordinary Least Squares (OLS) model:

$$(\Delta \mathrm{SP500}_t) = \beta_0 + \beta_1(\Delta \mathrm{Index}_{t-1}) + \beta_2(\Delta \mathrm{Volume}_{t-1}) + e_t \quad (1)$$

where $\Delta SP500_t$ defines the weekly logarithmic change for Monday opening of the S&P 500 index; $\Delta Index_{t-1}$ defines the weekly first difference for the Google Search Volume Index with a lag of one week; and $\Delta Volume_{t-1}$ defines the weekly logarithmic change for week's average daily volume of S&P 500 total return index with lag of one week.

In addition, to the regression model presented above, this study uses vector auto-regression analysis in order to analyze possible exogeneity of the Google Search Volume Index as a possible forecaster of future near-term S&P 500 returns. To analyze possible exogeneity of the Google Search Volume Index, this study uses following vector auto-regression (VAR) models with lags up to four weeks:

$$(\Delta \mathrm{SP500}_t) = \beta_0 + \sum_{s=1}^{4} \beta_s (\Delta \mathrm{SP500}_{t-s}) + \sum_{i=1}^{4} \beta_i (\Delta \mathrm{Index}_{t-i}) + \sum_{v=1}^{4} \beta_v (\Delta \mathrm{Volume}_{t-v}) + e_t \quad (2)$$

$$(\Delta \text{Index}_t) = \beta_0 + \sum_{s=1}^{4} \beta_s (\Delta \text{SP500}_{t-s}) + \sum_{i=1}^{4} \beta_i (\Delta \text{Index}_{t-i}) + \sum_{v=1}^{4} \beta_v (\Delta \text{Volume}_{t-v}) + e_t \quad (3)$$

where $\Delta SP500_{t-s}$ defines the weekly logarithmic change for Monday openings of the S&P 500 index with different weekly lags; $\Delta Index_{t-i}$ defines the weekly first difference for the Google Search Volume Index with different weekly lags; $\Delta Volume_{t-v}$ defines the weekly logarithmic change for a week's average daily volume of S&P 500 total return index with different weekly lags.

This study also uses the Granger causality test to further analyze the possible exogeneity of the Google Search Volume Index as a possible forecaster of future S&P 500 returns. The Granger causality test analyzes if past values of the Google Search Volume Index contain some information that helps forecast future S&P 500 returns.

Finally, this study carries out a series of robustness tests to further evaluate if the Google Search Volume Index helps forecast future S&P 500 returns. The robustness tests are carried out using three different estimation periods and adding changes of all Google search terms used in this study as explanatory variables into a single multiple OLS model. In addition, changes for the volume of the S&P 500 index and AAII's individual investor sentiment are added as control variables. The three different estimation periods used are 1 January 2004 to 10 February 2011, from 1 January 2004 to 30 December 2007 and from 1 March 2008 10 February 2011. The three different estimation periods were chosen so that they represent different kinds of stock market environment. For the Google search term "market rally" there are not enough searches during the estimation period 1 January 2004 to 30 December 2007. For this reason, the coefficient for Google search term “market rally” cannot be estimated. The estimated multiple OLS model is:

$$(\Delta SP500_t) = \beta_0 + \sum_{i=1}^{4} \beta_i (\Delta Index_{t-1,i}) + \beta_5 [\Delta(Bull - Bear_{t-1})] + \beta_6 (\Delta Volume_{t-1}) + e_t \tag{4}$$

where $\Delta SP500_t$ defines the logarithmic change for Monday openings of the S&P 500 index; $\Delta Index_{t-1,i}$ defines the weekly first difference for different Google Search Volume Indices with a lag of one week; $\Delta[Bull - Bear_{t-1}]$ defines the weekly first difference for AAII’s individual investor sentiment with a lag of one week; $\Delta Volume_{t-1}$ defines the weekly logarithmic change for a week’s average daily volume of S&P 500 with a lag of one week. The analysis of variance inflation factors (VIF) shows that multicollinearity is not present in the regression equations.

4. Empirical results

Table 2 reports regression results from equation (1) for each search term analyzed. The results are for hypotheses 1a-1d. The results support hypotheses 1a-1c, indicating that changes in the Google Search Volume Index for the search terms “market crash”, “market rally” and “bear market” have a statistically significant relationship with future near-term returns of the S&P 500 index. Estimated coefficients for the Google search terms “market crash” and “bear market” are negative whereas the estimated coefficient for the search term “market rally” is positive. However, the search term “bull market” does not have a statistically significant relationship with future near-term returns of the S&P 500 index. Furthermore, the control variable, change of week's average daily volume of the S&P 500 index, does not have a statistically significant relationship with the future near-term returns of the S&P 500 index in any of the four panels.

The adjusted R^2 values reported in Table 2 range from zero to 5.5%; the Google search terms "market rally" and "market crash" have the largest adjusted R^2 of 5.5 %. The Google search term "bear market" has an adjusted R^2 of 3.4 % and the Google search term "bull market" has an adjusted R^2 of zero. The results in Table 2 are consistent with results from earlier studies (see, e.g., Fisher and Statman [2000]; Lemmon and Portniaguina [2006]; Kumar and Lee [2006]; Schmeling [2009]), which report a relationship between investor sentiment and future stock market returns.

(INSERT TABLE 2 HERE)

Table 3 gives the vector auto-regression model estimates from equations (2) and (3) for each Google search term. The analysis results presented in Table 3 are for testing all the study's hypotheses. The results in Table 3 give more support to the findings in Table 2; there is a relationship between future near-term returns of the S&P 500 index and past first differences of the Google Search Volume Index for the search terms "market crash", "market rally" and "bear market". These findings further support hypotheses 1a-1c and are consistent with the Tetlock's [2007] evidence for media pessimism and stock returns.

The results in Table 3 also suggest that future first differences of Google Search Volume Index for search terms "market crash" and "market rally" are affected by past near-term returns of the S&P 500 index. These findings are consistent with results from earlier studies (see, e.g., De Bondt [1993]; Fisher and Statman [2000]; Brown and Cliff [2004]; Wang et al. [2006]), which report a relationship between past stock market returns and investor sentiment.

However, estimated coefficients for how past near-term returns of the S&P 500 index affect the Google Search Volume Index for search terms "market crash" and "market rally" are the reverse of those stated in hypotheses 2a and 2b, and also the results of Brown and Cliff [2004]. The results suggest that our measure of investor attention conveys some other information that predicts stock market returns, but the information does not fully reflect investor sentiment. Possibly these results may be related to the gambler's fallacy; investors find betting against the opposite direction of the recent market returns compelling and look information about the opposite direction. For example, after a string of negative market returns, investors want to bet that the market will rally and use positive search terms such as "market crash". Indeed, Rao and Diego [2009] present evidence that the gambler's fallacy rather than the hot hand fallacy exists during shorter intervals. Thus, this fallacy may explain our results because we use only lags of weekly S&P 500 returns, which is a relatively short time period.

For the Google search term "market crash", different lags of ΔINDEX have a negative estimated relationship with ΔSP500, which supports hypothesis 1a. For different lags of the ΔINDEX, the *t*-statistics range from -5.413 to -2.601; the ΔINDEX with a lag of one week has the largest estimated negative coefficient and *t*-statistic. In addition, different lags of the ΔSP500 have a positive relationship with the ΔINDEX, which is the reverse relationship to that stated in hypothesis 2a, thus does not support hypothesis 2a. For different lags of the ΔSP500, the *t*-statistics range from 0.494 to 2.976; the ΔSP500 with a lag of one week has the largest estimated positive coefficient and *t*-statistic.

For the Google search term “market rally”, different lags of the ΔINDEX have a positive relationship with ΔSP500, which supports hypothesis 1b. For different lags of ΔINDEX, the *t*-statistics range from 0.505 to 5.749; the ΔINDEX with a lag of one week has the largest positive coefficient and *t*-statistic. Different lags of the ΔSP500 have generally a negative relationship with the ΔINDEX, which is reverse of that stated in hypothesis 2b and thus does not support hypothesis 2b. For different lags of the ΔSP500, the *t*-statistics range from -3.396 to 1.538; the ΔSP500 with a lag of two weeks has the largest negative coefficient and *t*-statistic.

For the Google search term “bear market”, different lags of the ΔINDEX generally have a negative relationship with ΔSP500, which supports hypothesis 1c. For different lags of the ΔINDEX, the *t*-statastics range from -4.350 to 0.128; the ΔINDEX with a lag of one week has the largest negative coefficient and *t*-statistic. Different lags of ΔSP500 have a positive relationship with the ΔINDEX, which is the reverse of that stated in hypothesis 2c. However, the *t*-statistics for these coefficients are relatively small.

For the Google search term “bull market”, different lags of the ΔINDEX have a negative relationship with ΔSP500. However, the *t*-statistics for these coefficients are relatively small. Different lags of ΔSP500 generally have a positive relationship with the ΔINDEX in line with the results for the search term “market rally”. Nevertheless, the *t*-statistics for these coefficients are also relatively small.

(INSERT TABLE 3 HERE)

Table 4 reports the Granger causality results. The table is divided into four different panels, corresponding to the four different Google search terms used to construct the Google Search Volume Index. The results suggest that past first differences of the Google Search Volume Index for the Google search terms “market crash”, “market rally” and “bear market” contain some information that helps forecast future near-term returns of the S&P 500 total return index. These findings are statistically significant and hence support hypotheses 1a-1c. These findings are also consistent with the findings of earlier studies (see, e.g., Fisher and Statman [2000]; Lemmon and Portniaguina [2006]; Kumar and Lee [2006]; Schmeling [2009]), which report a relationship between investor sentiment and future stock market returns. Conversely, no statistically significant results support hypothesis 1d.

The results in Table 4 suggest that past near-term returns of the S&P 500 index contain some information that helps forecast future first differences in the Google Search Volume Index for the Google search terms “market crash” and “market rally”. These findings are statistically significant and hence support hypotheses 2a and 2b. These findings are also consistent with findings of earlier studies (see, e.g., De Bondt [1993]; Fisher and Statman [2000]; Brown and Cliff [2004]; Wang et al. [2006]), which report a relationship between past stock market returns and investor sentiment. Conversely, for the Google search terms “bear market” and “bull market”, the results in Table 4 are not statistically significant and hence do not support hypotheses 2c and 2d. In addition, the results in Table 4 suggest that past near-term changes of the S&P 500 index volume do not contain information that helps forecast future first differences of the Google Search Volume Index for all the Google search terms used in this study.

(INSERT TABLE 4 HERE)

Table 5 reports the robustness test results. The results in panels A, B and C, Table 5, suggest that first differences of the Google Search Volume Index for the Google search terms “market crash” and “market rally” are the only two that have statistically significant coefficients for forecasting future near-term returns of S&P 500 index; “market crash” has a negative coefficient and “market rally” has a positive coefficient. These findings further support hypotheses 1a and 1b, even with different estimation periods. These findings are consistent with findings from earlier studies (see, e.g., Fisher and Statman [2000]; Lemmon and Portniaguina [2006]; Kumar and Lee [2006]; Schmeling [2009]). The results in Table 5 for the Google search terms “bear market” and “bull market” do not support hypotheses 1c and 1d.

However, comparing the results among the three panels, it can be seen that the adjusted R-square has the highest value in panel C. This finding could indicate that the ability of the Google Search Volume Index to forecast future near-term returns of the S&P 500 index has improved in recent years. In addition, results from Table 5 suggest that the first differences of the more traditional investor sentiment measure, AAIS’s individual investor sentiment (measured as percentage of bullish investor minus percentage of bearish investors), do not have a statistically significant coefficient in any of the estimation periods.

In summary, the findings of this study suggest that changes in investors’ market attention constructed using the Google Search Volume Index for the Google search terms ”market crash” and ”market rally” contain some information that helps forecast future near-term stock market returns. Specifically, higher negative search term volumes are associated with lower future returns. As such, it may be considered that our results agree with the evidence of Tetlock [2007] for a negative relationship between media pessimism and future stock returns and a positive relation between individual stock search volumes and subsequent stock returns. The findings about the forecasting ability of the Google Search Volume Index for the Google search term “bear market” are mixed and not homogeneous. The search term “bull market” is not a good predictor of future stock market returns.

In line with De Bondt [1993], Otoo [1999], Fisher and Statman [2000], Jansen and Nahuis [2003], and Brown and Cliff [2004], whose results suggest that past returns have an effect on investor sentiment, we find that past returns explain our investors' market attention (changes in the Google Search Volume Index for the Google search terms “market crash,” and “market rally”) suggesting that ‘attention’ has similar characteristics to other measures of sentiment.

5. Conclusions

Measuring investor sentiment has been an interest of academic research (e.g., Solt and Statman [1988]; De Bondt [1993]; Lee et al. [1991]). In this study, we use Google Search volume to measure investors' market attention as sentiment information that can help to predict near-term stock market returns. Overall, we find that changes in the Google Search volume of some search words can predict future near-term stock market returns. Specifically, the search terms are “market crash”, “market rally” and “bear market”. As Google searches are related to attention and we did not find predictability using the term “bull market,” the results may be more related to negative attention bias (see, e.g., Smith et al. [2006]); the attention paid to negative information may just more effectively transmit into action. However, since a positive search term “market rally” had a positive effect, the evidence for negative attention is not conclusive. Our evidence on pessimistic search terms and future stock return is consistent with the evidence in Tetlock [2007] about media pessimism and future stock returns.

The relationship between the examined search terms and past near-term stock returns was different from that of the future stock returns. We find a positive relationship between the negative search term “market crash” and past stock returns. The relationship between the positive search term “market rally” and past stock returns is negative. An explanation for these results is that, because of the gambler’s fallacy, investors turn negative (positive) after good (poor) returns and search information accordingly.

Investors’ market attention is also affected by previous market returns, which suggests that our measure of investor attention is comparable to documented sentiment indicators (see Brown and Cliff [2004]). Information that tracks investor attention on the internet should be an important avenue for future academic research and in the industry to analyze stock markets.

Note

[1] Ozik and Sadka [2010] examine the effect of media coverage of hedge funds inferred from Google News on their performance.

[2] Zhang and Skiena [2010] use quantitative media data from blogs and newspapers to build profitable sentiment-based stock trading strategy. They find that portfolio that, on daily basis, goes long on positive sentiment stocks and goes short on negative sentiment stocks yields smooth positive daily returns. In addition, Klein et al. [2011] use automatic extraction of investor sentiment from blog texts to form a daily long-short portfolio that outperforms a simple buy-and-hold strategy. Both the portfolios of Zhang and Skiena [2010] and Klein et al. [2011] succeeded exceptionally well in 2008.

[3] De Bondt [1993]; Fisher and Statman [2000]; Brown and Cliff [2004]; Wang et al. [2006]; Verma and Soydemir [2006]; Kurov [2008]; Verma and Verma [2008]; Verma and Soydemir [2009].

[4] Otoo [1999]; Fisher and Statman [2003]; Jansen and Nahuis [2003]; Charoenrook [2005]; Lemmon and Portniaguina [2006]; Schmeling [2009]; Zouaoui et al. [2011]; Antoniou et al. [2011].

[5] Kumar and Lee [2006]; Schmeling [2007].

[6] Solt and Statman [1988]; Clarke and Statman [1998]; Fisher and Statman [2000]; Brown and Cliff [2004]; Kurov [2008]; Verma and Verma [2008].

[7] Fisher and Statman [2000].

[8] Wang [2001]; Wang [2003].

[9] Sanders et al. [2003].

[10] Whaley [2000]; Simon and Wiggins III [2001]; Giot [2005].

[11] Simon and Wiggins III [2001]; Wang et al. [2006].

[12] Lee et al. [1991]; Chen et al. [1993]; Swaminathan [1996]; Neal and Wheatley [1998]; Elton et al. [1998]; Brown and Cliff [2005].

[13] Neal and Wheatley [1998]; Brown et al. [2003]; Brown and Cliff [2005]; Frazzini and Lamont [2008]; Beaumont et al. [2008]; Feldman [2010]; Ben-Rephael et al. [2012].

[14] Baker and Wurgler [2006]; Baker and Wurgler [2007]; Baker et al. [2008]; Ho and Hung [2009]; Kurov [2010]; Beer and Zouaoui [2011]; Yu and Yuan [2011]; Chau et al. [2011]; Liao et al. [2011]; Baker and Wurgler [2012]; Baker et al. [2012]; Beer et al. [2012]; Stambaugh et al. [2012].

[15] http://www.google.com/trends

[16] http://www.aaii.com/sentimentsurvey

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Table 1. Descriptive statistics

Statistics	ΔMarket Crash	ΔMarket Rally	ΔBear Market	ΔBull Market	Δ[Bull− Bear]	ΔSP500	ΔSP500 Volume
Mean	-0.0019	0.0082	0.0076	0.0033	-0.0016	0.0001	0.0025
Median	0.0000	0.0000	0.0000	0.0000	-0.0066	0.0010	-0.0071
Maximum	3.6000	16.1000	3.5000	2.3800	0.5075	0.1086	0.9515
Minimum	-4.2000	-7.0000	-4.1000	-2.3800	-0.3656	-0.1844	-0.7624
Std. Dev.	0.4731	1.3109	0.5606	0.3123	0.1525	0.0266	0.1887
Skewness	0.2801	4.8443	0.4034	0.0245	0.1982	-0.8463	0.2954
Kurtosis	36.8943	72.0889	21.0422	25.9499	2.9543	10.3831	7.2785
Observations	404	404	404	404	404	404	404

Table 1 reports the descriptive statistics of weekly first differences for four different Google Search Volume Indices ("market crash", "market rally", "bear market" and "bull market") and AAII's individual investor sentiment (measured as percentage of bullish investors minus percentage of bearish investors). In addition, descriptive statistics of logarithmic changes for Monday opening of S&P 500 total return index and week's average daily volume of S&P 500 total return index are also reported. Symbol Δ denotes change. Estimation period is from 1 January 2004 to 10 February 2011.

Table 2. Regression estimates of the Ordinary Least Squares model

	Panel A: Market Crash		Panel B: Market Rally		Panel C: Bear Market		Panel D: Bull Market	
Variable	Coef.	*t-Stat.*	Coef.	*t-Stat.*	Coef	*t-Stat.*	Coef.	*t-Stat.*
C	0.000	*0.020*	0.000	*-0.003*	0.000	*0.054*	0.000	*0.040*
ΔIndex(-1)	-0.014***	*-4.559*	0.005***	*7.030*	-0.009**	*-2.269*	-0.005	*-1.047*
Δ Volume(-1)	-0.009	*-1.135*	-0.005	*-0.667*	-0.005	*-0.610*	-0.005	*-0.687*
Adjusted R^2	0.055		0.055		0.034		0.000	
F-statistic	12.792		12.788		8.135		0.999	
Prob(F-statistic)	0.000		0.000		0.000		0.369	
AIC	-4.465		-4.465		-4.443		-4.408	
SIC	-4.435		-4.435		-4.413		-4.378	
Durbin-Watson	2.084		1.904		2.150		2.094	

Table 2 reports Ordinary Least Squares model estimates. The model used is:

$$(\Delta SP500_t) = \beta_0 + \beta_1(\Delta Index_{t-1}) + \beta_2(\Delta Volume_{t-1}) + e_t$$

where $\Delta SP500_t$ defines the weekly logarithmic change for Monday opening of the S&P 500 total return index; $\Delta Index_{t-1}$ defines the weekly first difference for different Google Search Volume Indices ("market crash", "market rally", "bear market" and "bull market") with a lag of one week;$\Delta Volume_{t-1}$ defines the weekly logarithmic change for week's average daily volume of S&P 500 total return index with a lag of one week. This table also presents the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Durbin-Watson test. All standard errors are corrected for both heteroskedasticity and autocorrelation.
Each panel represents a different Google search term used to construct the Google Search Volume Index.
* refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level;
*** refers to statistical significance at the 0.01 level.

Table 3. Vector autoregression estimates

Panel A: Market Crash						
Variable	ΔSP500	*t-Stat.*	ΔINDEX	*t-Stat.*	ΔVOLUME	*t-Stat.*
ΔSP500(-1)	-0.064	*-1.269*	*2.642*	*2.976*	-1.158	*-3.833*
ΔSP500(-2)	0.058	*1.126*	*1.879*	*2.057*	-0.538	*-1.729*
ΔSP500(-3)	-0.039	*-0.759*	*0.453*	*0.494*	-0.509	*-1.633*
ΔSP500(-4)	0.042	*0.820*	*1.979*	*2.203*	-0.389	*-1.273*
ΔINDEX(-1)	-0.015	*-5.413*	*-0.230*	*-4.635*	0.163	*9.606*
ΔINDEX(-2)	-0.008	*-2.601*	*-0.103*	*-1.811*	0.069	*3.545*
ΔINDEX(-3)	-0.011	*-3.480*	*-0.001*	*-0.015*	0.043	*2.256*
ΔINDEX(-4)	-0.010	*-3.112*	*-0.213*	*-3.873*	0.000	*0.023*
ΔVOLUME(-1)	0.000	*0.036*	*0.078*	*0.547*	-0.437	*-8.962*
ΔVOLUME(-2)	0.006	*0.710*	*0.244*	*1.645*	-0.335	*-6.643*
ΔVOLUME(-3)	0.016	*1.883*	*0.247*	*1.671*	-0.332	*-6.582*
ΔVOLUME(-4)	0.010	*1.406*	*-0.003*	*-0.023*	-0.269	*-6.014*
C	0.000	*-0.127*	*-0.005*	*-0.216*	0.004	*0.533*
Adjusted R^2	0.095		0.110		0.340	
F-statistic	4.509		5.119		18.150	
AIC	-4.478		1.265		-0.890	
SIC	-4.348		1.395		-0.760	

Panel B: Market Rally						
Variable	ΔSP500	*t-Stat.*	ΔINDEX	*t-Stat.*	ΔVOLUME	*t-Stat.*
ΔSP500(-1)	0.060	*1.104*	-8.138	*-3.112*	-1.236	*-3.445*
ΔSP500(-2)	0.063	*1.124*	-9.133	*-3.396*	0.051	*0.140*
ΔSP500(-3)	-0.012	*-0.205*	-5.795	*-2.134*	-0.009	*-0.025*
ΔSP500(-4)	0.048	*0.868*	4.107	*1.538*	-0.157	*-0.428*
ΔINDEX(-1)	0.006	*5.749*	-0.207	*-3.893*	0.002	*0.222*
ΔINDEX(-2)	0.001	*0.505*	-0.193	*-3.487*	0.005	*0.694*
ΔINDEX(-3)	0.003	*2.587*	-0.125	*-2.270*	-0.003	*-0.443*
ΔINDEX(-4)	0.002	*1.862*	0.101	*1.887*	-0.002	*-0.338*
ΔVOLUME(-1)	-0.004	*-0.462*	0.739	*2.018*	-0.404	*-8.046*
ΔVOLUME(-2)	-0.009	*-1.177*	-0.155	*-0.403*	-0.292	*-5.548*
ΔVOLUME(-3)	0.004	*0.485*	0.214	*0.561*	-0.285	*-5.438*
ΔVOLUME(-4)	0.006	*0.768*	0.084	*0.232*	-0.247	*-4.973*
C	0.000	*-0.080*	0.011	*0.183*	0.003	*0.366*
Adjusted R^2	0.072		0.111		0.178	
F-statistic	3.617		5.156		8.186	
AIC	-4.453		3.304		-0.670	
SIC	-4.323		3.433		-0.540	

(continues)

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Table 3 (continues).

Panel C: Bear Market						
Variable	ΔSP500	*t-Stat.*	ΔINDEX	*t-Stat.*	ΔVOLUME	*t-Stat.*
ΔSP500(-1)	-0.077	*-1.465*	0.424	*0.387*	-0.704	*-2.200*
ΔSP500(-2)	0.050	*0.935*	0.033	*0.030*	0.053	*0.165*
ΔSP500(-3)	-0.087	*-1.639*	0.837	*0.754*	0.151	*0.465*
ΔSP500(-4)	-0.013	*-0.244*	1.371	*1.256*	-0.213	*-0.668*
ΔINDEX(-1)	-0.011	*-4.350*	-0.116	*-2.223*	0.099	*6.535*
ΔINDEX(-2)	0.000	*0.128*	-0.199	*-3.589*	0.042	*2.582*
ΔINDEX(-3)	-0.003	*-1.281*	-0.139	*-2.511*	0.060	*3.689*
ΔINDEX(-4)	-0.003	*-1.030*	-0.150	*-2.700*	0.034	*2.090*
ΔVOLUME(-1)	-0.006	*-0.691*	0.010	*0.058*	-0.448	*-9.055*
ΔVOLUME(-2)	-0.005	*-0.568*	0.242	*1.373*	-0.333	*-6.461*
ΔVOLUME(-3)	0.005	*0.576*	-0.021	*-0.117*	-0.326	*-6.331*
ΔVOLUME(-4)	0.005	*0.681*	0.092	*0.574*	-0.238	*-5.104*
C	0.000	*0.037*	0.009	*0.320*	0.003	*0.316*
Adjusted R^2	0.035		0.052		0.274	
F-statistic	2.222		2.807		13.521	
AIC	-4.413		1.669		-0.794	
SIC	-4.284		1.799		-0.664	

Panel D: Bull Market						
Variable	ΔSP500	*t-Stat.*	ΔINDEX	*t-Stat.*	ΔVOLUME	*t-Stat.*
ΔSP500(-1)	-0.046	*-0.889*	0.723	1.255	-0.915	*-2.875*
ΔSP500(-2)	0.046	*0.862*	-0.208	-0.355	-0.103	*-0.318*
ΔSP500(-3)	-0.081	*-1.529*	0.097	0.166	-0.008	*-0.026*
ΔSP500(-4)	-0.014	*-0.273*	0.676	1.160	-0.190	*-0.592*
ΔINDEX(-1)	-0.007	*-1.459*	-0.331	-6.497	0.153	*5.425*
ΔINDEX(-2)	-0.001	*-0.205*	-0.107	-1.934	0.112	*3.646*
ΔINDEX(-3)	-0.004	*-0.866*	-0.149	-2.665	0.064	*2.064*
ΔINDEX(-4)	-0.001	*-0.147*	-0.192	-3.635	-0.015	*-0.499*
ΔVOLUME(-1)	-0.005	*-0.592*	0.002	0.026	-0.450	*-9.032*
ΔVOLUME(-2)	-0.004	*-0.434*	0.104	1.093	-0.318	*-6.057*
ΔVOLUME(-3)	0.002	*0.288*	0.127	1.354	-0.288	*-5.548*
ΔVOLUME(-4)	0.008	*0.999*	0.031	0.364	-0.258	*-5.469*
C	0.000	*0.020*	0.005	0.335	0.002	*0.297*
Adjusted R^2	-0.007		0.116		0.247	
F-statistic	0.765		5.373		11.910	
AIC	-4.370		0.428		-0.628	
SIC	-4.241		0.558		-0.758	

Table 3 reports the vector auto-regression model estimates with lags up to four weeks. The models used are:

$$(\Delta SP500_t) = \beta_0 + \sum_{s=1}^{4} \beta_s (\Delta SP500_{t-s}) + \sum_{i=1}^{4} \beta_i (\Delta Index_{t-i}) + \sum_{v=1}^{4} \beta_v (\Delta Volume_{t-v}) + e_t$$

$$(\Delta Index_t) = \beta_0 + \sum_{s=1}^{4} \beta_s (\Delta SP500_{t-s}) + \sum_{i=1}^{4} \beta_i (\Delta Index_{t-i}) + \sum_{v=1}^{4} \beta_v (\Delta Volume_{t-v}) + e_t$$

where $\Delta SP500_{t-s}$ defines the weekly logarithmic change for the S&P 500 total return index with different weekly lags; $\Delta Index_{t-i}$ defines the weekly first difference for the different Google Search Volume Indices ("market crash", "market rally", "bear market" and "bull market") with different weekly lags; $\Delta Volume_{t-v}$ defines the weekly logarithmic change for a week's average daily volume of the S&P 500 total return index with different weekly lags. Each panel represents a different Google search term used to construct the Google Search Volume Index.

Table 4. Granger Causality

Panel A: Market Crash											
	Dependent variable: ΔSP500				Dependent variable: ΔINDEX				Dependent variable: ΔVOLUME		
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
ΔINDEX	47.28	4	0.000	ΔSP500	17.48	4	0.002	ΔSP500	21.26	4	0.000
ΔVOLUME	4.58	4	0.334	ΔVOLUME	4.64	4	0.327	ΔINDEX	96.68	4	0.000
ALL	49.78	8	0.000	ALL	20.58	8	0.008	ALL	113.65	8	0.000
Panel B: Market Rally											
	Dependent variable: ΔSP500				Dependent variable: ΔINDEX				Dependent variable: ΔVOLUME		
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
ΔINDEX	36.74	4	0.000	ΔSP500	27.99	4	0.000	ΔSP500	12.02	4	0.017
ΔVOLUME	3.10	4	0.541	ΔVOLUME	5.63	4	0.228	ΔINDEX	1.06	4	0.901
ALL	39.17	8	0.000	ALL	39.09	8	0.000	ALL	14.67	8	0.066

(contimues)

Table 4 (continues).

Panel C: Bear Market											
	Dependent variable: ΔSP500				Dependent variable: ΔINDEX				Dependent variable: ΔVOLUME		
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
ΔINDEX	20.261	4	0.000	ΔSP500	2.179	4	0.703	ΔSP500	5.346	4	0.254
ΔVOLUME	1.941	4	0.747	ΔVOLUME	2.829	4	0.587	ΔINDEX	52.261	4	0.000
ALL	22.600	8	0.004	ALL	5.030	8	0.754	ALL	67.670	8	0.000

Panel D: Bull Market											
	Dependent variable: ΔSP500				Dependent variable: ΔINDEX				Dependent variable: ΔVOLUME		
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
ΔINDEX	3.05	4	0.549	ΔSP500	2.89	4	0.576	ΔSP500	8.44	4	0.077
ΔVOLUME	1.91	4	0.753	ΔVOLUME	2.52	4	0.642	ΔINDEX	36.80	4	0.000
ALL	5.29	8	0.726	ALL	5.33	8	0.721	ALL	51.66	8	0.000

Table 4 reports the Granger causality test results. ΔSP500 defines the logarithmic change for Monday opening of the S&P 500 total return index; ΔIndex defines the first difference for different Google Search Volume Indices (“market crash”, “market rally”, “bear market” and “bull market”); ΔVolume defines the logarithmic change for a week’s average daily volume of the S&P 500 total return index. Each panel represents a different Google search term used to construct the Google Search Volume Index.

Table 5. Multiple Regression estimates of Ordinary Least Squares model

	Panel A: 1/1/2004 − 10/2/2011		Panel B: 1/1/2004 − 12/30/2007		Panel C: 1/3/2008 − 10/2/2011	
Variable	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.
C	0.000	0.010	0.001	1.374	-0.001	-0.463
ΔMarket Crash(-1)	-0.007**	-2.013	-0.008*	-1.752	-0.009*	-1.678
ΔMarket Rally(-1)	0.004***	4.782	N/A	N/A	0.004***	3.691
ΔBear Market(-1)	-0.006	-1.592	-0.004	-1.128	-0.008	-1.398
ΔBull Market(-1)	0.001	0.242	-0.001	-0.209	0.008	0.557
Δ[Bull – Bear](-1)	-0.001	-0.176	-0.005	-0.798	0.002	0.121
ΔVolume(-1)	-0.007	-0.853	0.004	0.683	-0.017	-1.402
Adjusted R^2	0.098		0.034		0.105	
F-statistic	7.257		2.201		4.255	
Prob(F-statistic)	0.000		0.044		0.000	
AIC	-4.500		-5.514		-3.956	
SIC	-4.420		-5.402		-3.822	
Durbin-Watson	1.967		2.123		1.965	
Number of observations	403		207		195	

Table 5 reports Ordinary Least Squares model results. The model used is:

$$(\Delta SP500_t) = \beta_0 + \sum_{i=1}^{4} \beta_i (\Delta Index_{t-1,i}) + \beta_5[\Delta(Bull - Bear_{t-1})] + \beta_6(\Delta Volume_{t-1}) + e_t$$

where $\Delta SP500_t$ defines the logarithmic change for Monday opening of the S&P 500 total return index; $\Delta Index_{t-1,i}$ defines the first difference for different Google Search Volume Indices ("market crash", "market rally", "bear market" and "bull market") with a lag of one week; $\Delta[Bull - Bear_{t-1}]$ defines first difference for AAII's individual investor sentiment (percentage of bullish investor minus percentage of bearish investors) with a lag of one week;$\Delta Volume_{t-1}$ defines the logarithmic change for week's average daily volume of S&P 500 total return index with a lag of one week. This table also presents the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Durbin-Watson test. All standard errors are corrected for both heteroskedasticity and autocorrelation.

The three different panels represent different estimation periods for the OLS model. For panel B, there were not enough searches made for the Google search term "market rally" during that estimation period.

* refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level;

*** refers to statistical significance at the 0.01 level.

1

Small Investors' Internet Sentiment and Return Predictability

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Abstract: Purpose

— The purpose of this paper is to propose a novel and new direct measurement of small investor sentiment in the equity market. The sentiment is based on the individual investors' internet search activity.

Design/methodology/approach

— The author measures unexpected changes in the small investor sentiment with AR (1) process, where the residuals capture the unexpected changes in small investor sentiment. The authors employ vector autoregressive, Granger causality and linear regression models to estimate the association between the unexpected changes in small investor sentiment and future equity market returns.

Findings

— An unexpected increase in the search popularity of the term bear market is negatively associated with the following week's returns. An unexpected increase in the spread (the difference in popularities between a bull market and a bear market) is positively associated with the following week's returns. We find that these effects are stronger for small-sized companies and especially after highly negative returns of large-sized companies.

Originality/value

– By author's knowledge, the paper is the first that measures the small investor sentiment that is based on the internet search activity for keywords used in the AAII's survey questions. The paper proposes an alternative small investor sentiment measure that captures the changes in small investor sentiment in more timely fashion than the AAII survey.

Keywords: Small Investor Sentiment, Internet Searches, Equity Market Returns, Return Predictability, G40

Type: Research paper

3

1. Introduction

Traditionally, investor sentiment is measured with two alternative approaches. The first is the survey-based investor sentiment approach, measured by surveying small investors or more sophisticated investors. These surveys include the likes of *Consumer Confidence*, *American Association of Individual Investor* (AAII) and *Investors Intelligence*. The second form is the market-data-based investor sentiment approach. These include the likes of VIX, the put-call ratio, a discount of closed-end funds, and mutual funds flows. Several previous studies find that investor sentiment is related to contemporaneous and future stock market returns[1].

In this paper, we propose a novel and more direct measurement of small investor sentiment in the equity market. We construct a weekly small investor sentiment measure based on the individual investors' internet search activity for the search terms as *bear market* and *bull market*. We argue that our Small Investors' Internet Sentiment (SIIS) measures the current market view of individual investors' in a more timely fashion than the AAII survey. As Baker and Wurgler (2007) state: "Now the question is no longer, as it was a few decades ago whether investor sentiment affects stocks prices, but rather how to measure investor sentiment and quantify its effects."

We find that unexpected change in our SIIS, when inferred from the search term *bear market*, is negatively associated with following week's returns. One-standard-deviation unexpected increase in the search volumes of *bear market* is associated with a 17 basis-points-lower return for small-sized companies and a 13 basis-points-lower return for large ones, and a 15 basis- points-lower size premium for the following week. When the SIIS is the difference between the popularities of

[1] (see, e.g., Lee et al., 1991; Brown and Cliff, 2005; Kumar and Lee, 2006; Lemmon and Portniaquina, 2006; Baker and Wurgler 2006; Baker, Wang and Wurgler, 2008; Baker, Wurgler and Yuan, 2012; Stambaugh, Yu and Yuan, 2012)

the terms *bull market* and *bear market* (henceforth known as the spread), the unexpected change in the SIIS is positively associated with the following week's returns. One-standard-deviation unexpected increase in the spread is associated with a 13 basis-points-higher equity market return for small-sized companies, and a 12 basis-points-higher equity market return for large ones, and an eight basis-points-higher size premium for the forthcoming week.[2]

We find that when large-sized companies are experiencing highly negative returns, the effect of unexpected change in the SIIS on the forthcoming returns of small-sized companies becomes stronger. That suggests that small investors form their short-term investor sentiment based more on the high negative returns of large-sized companies. In other words, the unexpected popularity of the search term *bear market* increases contemporaneously with the high negative returns of large-sized companies. This unexpected pessimistic growth in small investors' equity market views then reflects more on the forthcoming returns of small-sized companies, as suggested by the classic noise-trader model.

We also find that unexpected changes in the SIIS offer more information that helps predict the future market movements than do unexpected changes in the AAII survey. Investors need lags of two to four weeks of unexpected changes in the SIIS to help forecast the following week's market movements. Whereas investors need lags of four to six weeks of unexpected changes in the AAII survey to help forecast the following week's movements. These results suggest that our SIIS measures the changes in sentiment of small investors and their effect on returns in more timely fashion than the AAII survey can.

[2] We also document a statistically significant association between the unexpected changes in our SIIS and future cross-sectional return spread for companies sorted by profitability.

Why should one then measure or at least be interested in internet search-based investor sentiment instead of the more traditional forms? For example, Da, Engelberg, and Gao (2015) point out some important reasons why search-based sentiment might have an advantage over market-based and survey-based sentiments. First, the market-based sentiment might be the equilibrium outcome of many different economic forces and hence not purely reflect the current investor sentiment. Second, some survey-based sentiments are conducted on too low a frequency, such as on a monthly basis. Third, respondents might not answer survey questions truthfully, especially if the incentive for telling the truth is low. Finally, the search-based sentiment method also reveals real attitudes rather than just inquiring about them, as is the case with survey-based sentiments.

The purpose of this paper is to develop a novel and new alternative measure of small investor sentiment. By utilizing the data from Google search volumes, the aim is to capture the changing sentiment of small investors' and its effect on returns in more timely fashion than the more traditional AAII survey can. Earlier studies related to the ability of AAII survey to predict future market movements are divergent. Fisher and Statman (2000), Verma and Soydemir (2006) find the support that the AAII survey contains some information that helps to predict future market movements. Whereas, Brown and Cliff (2004) do not find support that the AAII survey contains information that helps to predict future returns. Hence the association between the small investor sentiment and future equity market returns is still questionable, and maybe an alternative measure of small investor sentiment could be needed.

We incorporate the idea of Da et al. (2015) to capture the changing sentiment of small investors' based on the popularity of Google search terms *bear market* and *bull market*. The choice of search words ensures they are as closely as possible related to the terminology used in the survey questions of the AAII. In the AAII survey, the investors are asked if their attitudes are bullish, neutral, or bearish about the market movements for the following six months. Where Da et al. (2015) use more macro-level condition terminology such as recession, unemployment, and bankruptcy, we use terminology more related to equity market condition. [3]

In recent years, a new line of academic research has emerged from utilizing data from Google searches volumes, known as the Google Search Volume Index (SVI). For example, Da, Engelberg, and Gao (2011) find a positive relationship between the SVI for stock tickers of Russell 3000 companies and their subsequent returns for the following two weeks. Da et al. (2011) also report that an increased SVI for the stock tickers of IPO companies predicts higher first-day IPO returns. Furthermore, Vozlyublennaia (2014) finds that the SVI is not only related to the performance of individual stocks but also to the performance of stock indices and commodities.

The previous studies that use the SVI consider themselves more market attention studies than investor sentiment studies. Da, Engelberg, and Gao (2015) construct a market-level sentiment (known as FEARS) by aggregating the SVIs of issues such as recession, unemployment, and bankruptcy. They find that an increase in this market-level sentiment predicts return reversals, increasing volatility, and mutual fund flows from equity funds to bond funds.

Our paper contributes to the existing literature in the following way. We propose a new and novel alternative measure of small investor sentiment in the equity market that captures the changes, and its effect on future equity market returns, in the small investor sentiment in more timely fashion than the AAII survey. In addition, we contribute to the existing literature by analyzing the effect that the investor sentiment inferred from Google search volumes has on future size premium.

[3] We find no statistically significant correlation between our sentiment measurements and average weekly Da et al. (2015) FEARS30 index.

2. Literature review and hypotheses development

The theoretical background of our study is based on the two theories of how the behavior of small investors can affect returns. The first theory is based on the sentiment of small investors and returns. The second theory is based on market attention, measured by Google searches, of small investors and returns.

De Long, Shleifer, Summers, and Waldmann (1990) present a theory suggesting that the investor sentiment of so-called *noise traders* can affect asset prices if more rational investors are unable to balance the asset prices owing to the limits of arbitrage. Barber and Odean (2008) find that individual investors are net buyers of attention-grabbing stocks, hence causing the price of such stocks to deviate from their more fundamental value. That causes the attention-grabbing stocks to face a liquidity shock as described by Campbell, Grossman, and Wang (1993). Yuan (2015) finds that the individual investors might not just be net buyers, but potentially also net sellers. Yuan (2015) argues that during market-wide attention events, investors increase the attention they pay to their portfolios and rebalance it, which then leads to increased trading. In fact, Yuan (2015) finds that certain front-page news events can increase the selling orders from individual investors. Kumar and Lee (2006) also find that small investors tend to trade in concert.

We argue that: First, past aggregate equity market returns grab small investors' attention. For example, terms such as *bear market* and *bull market* used in the financial media grab the attention of small investors. Second, the small investors then use Google to look for information on such terminology or the news related to it, causing an unexpected change in search volumes. Third, the small investors then form their short-term equity market sentiment based on the information searched for, on which they then act, which leads to decisions on whether to sell or buy to rebalance their current portfolio. Finally, this then causes an irrational liquidity shock to the equity market, leading to negative or positive equity market movements. This effect should be stronger for small-sized companies since they tend to carry more noise-trading risk. The effect should also be stronger after extreme returns of large-sized companies, since those returns, and their corresponding terminology, are more likely to be reported in the financial media that catches the attention of small investors.

2.1. Hypotheses

Based on the investor sentiment theory proposed by De Long et al. (1990) and the findings of Fisher and Statman (2000), Verma and Soydemir (2006), we form the following hypotheses:

H1: An unexpected change in the SIIS, measured as the popularity of the term *bear market*, has a negative relationship with the following week's equity market returns.

H2: An unexpected change in the SIIS, measured as the popularity of the term *bull market*, has a positive relationship with the following week's equity market returns.

H3: An unexpected change in the SIIS, measured as the popularity difference (the spread) between the terms *bull market* and *bear market*, has a positive relationship with the following week's equity market returns.

H4: The effect of an unexpected change in the SIIS is stronger for small-sized companies.

H5: The effect of an unexpected change in the SIIS is stronger after periods of highly negative or positive returns.

2.2. Small investor sentiment and aggregate equity market returns

Generally two types of investor sentiment surveys are referred to in research on small investor sentiment: The small investor sentiment survey conducted by the AAII and consumer confidence surveys. Fisher and Statman (2003) report that the AAII survey and consumer confidence surveys in the U.S.A move contemporaneously.

Fisher and Statman (2000) find that a high (low) *level* of small investor sentiment (the AAII survey) during the present month is associated with negative (positive) returns for the S&P 500 index for the following month. However, they find no statistically significant association between the present *level* of small investor sentiment and the returns of small-cap stocks for the following month. In addition, they do not find any statistically significant results that the *change* of small investor sentiment would forecast the following month's returns.

Consistent with the results of Fisher and Statman (2000), Schemling (2007) also finds in a more global context (Germany, Europe, the U.S.A., and Japan) that the *level* of individual investor sentiment (Sentix) is negatively associated with future stock market returns. Whereas, Verma and Soydemir (2006) come to a conclusion when they report that that a one-standard-deviation *increase* in small investor sentiment (the AAII survey) in the U.S.A. has a positive effect not only on the future U.S. returns but also on the future U.K returns. Contradicting the previously mentioned findings, Brown and Cliff (2004) find no or very weak evidence that either the level of or any change in small investor sentiment in the U.S.A. is associated with future returns.

An alternative proxy to measure small investor sentiment is consumer confidence. For example, Charoenrook (2005) finds that positive *changes* in consumer confidence predict negative excess stock market returns on one-month and one-year time horizons in the U.S.A. In addition, Lemmon and Portniaquina (2006) find a negative linkage between lagged consumer confidence and a small-stock premium with lags of 3, 6, and 12 months. They also find that lagged *excessive sentiment* (residuals when macroeconomic variables are regressed on consumer confidence) is negatively associated with a future small-stock premium.

In a more recent study, Schmeling (2009) also finds a negative association with consumer confidence and global stock market returns for the forecast horizons of 1, 6, 12, and 24 months. The same study also notes that consumer confidence correlates negatively with the size premium for the forecast horizons of one and six months. Zouaoui, Nouyrigat, and Beer (2011) in contrast find that consumer confidence in Europe and the United States positively affects the probability of stock market crises within a one-year period. Otoo (1999) and Jansen and Nahuis (2003) present contradictory results since they do not find any statistically significant association between the present consumer confidence and future returns in the U.S.A or Europe.

2.3 Investor sentiment and cross-section of equity returns

In their seminal work, Shleifer and Vishny (1997) underline that only in a textbook case the arbitrage does not require capital and is riskless. Whereas, in real-life the arbitrage does require some capital and is also risky, thus limiting the possibility for an arbitrage. Shleifer and Vishny (1997) argue that arbitrageurs especially tend to avoid investing in markets where the sentiment of noise trader can drive the asset prices away from their more fundamental value for a long time period. Shleifer and Vishny (1997) argue that the arbitrageurs are especially worried about their short-term performance in the eyes of outside investors and hence prefer arbitrage strategies with a shorter time period. That then makes the assets that are more affected by the movements in the sentiment of noise traders less appealing for the rational arbitrageurs. Reciprocally leading into larger cross-sectional mispricing in assets, especially where the noise traders more dominate the trading.

Whereas, Baker and Wurgler (2006) assume that investor sentiment can have a cross-sectional effect on equity returns due to two different reasons. The sentiment-based demand varies across the equities, or the limit to arbitrage varies across the equities. Although the authors note that these two reasons are closely correlated. Equities that are highly sensitive to speculative demand are whose valuation is highly subjective, are also usually the hardest ones to arbitrage. Baker and Wurgler (2006) find that the investor sentiment has a heterogenous effect on cross-sectional returns of equities: small, young, high volatility, unprofitable, non-dividend-paying, extreme growth, and distressed stocks are the most affected by the investor sentiment.

Lemmon and Portniaguina (2006) also document a cross-sectional linkage between the investor sentiment and returns of small stocks and stocks with low institutional ownership.

2.4. Google search volumes and equity market returns

Da et al. (2011) propose an alternative method to measure investor attention by using the Google Search Volume Index (SVI) for stock tickers of Russell 3000 stocks. They note two main arguments for using the SVI as a proxy of investor attention. First, the investors use Google to search for and gather information. Second, and more critically, Google searches constitute materialized investor attention; if you Google it, you are paying attention to it.

Da et al. (2011) find that an abnormal increase in the SVI for stock tickers predicts positive stock returns for Russell 3000 companies within the following two weeks. The abnormal increase in SVI is associated with 0.3 % characteristic-adjusted outperformance during the following two weeks. Moreover, as a robustness check, Da et al. (2011) also find that a higher SVI for the stock tickers is associated with higher first-day returns for IPO companies. The IPO companies with the highest abnormal SVI a week before the listing day outperform those with the lowest abnormal SVI by as much as by 6 % during the IPO listing day.

Joseph, Wintoki, and Zhang (2011) form quintile portfolios of S&P 500 companies based on their stock ticker SVI. They find that the quintile portfolio with the highest SVI has a statistically significant weekly risk-adjusted (by market, size, value, and momentum) alpha of 0.04 %. The same study reports that the zero-cost portfolio (the highest SVI minus the lowest SVI portfolio) also has a statistically significant positive risk-adjusted weekly alpha of 0.03 %.

Bank, Larch, and Peter (2011) extend the topic to the German stock market. They construct a double-sorted zero-cost portfolio that goes long on high SVI companies with high market value and short on low SVI companies with low market value for one month. They find that the alpha of such a portfolio is positive (0.77 % per month) and significant, even after controlling for market, size, value, and momentum factors. Moreover, Bank, Larch, and Peter (2011) find that a double-sorted zero-cost portfolio that goes long on high SVI companies with a low market-to-book ratio and short on low SVI companies with a high market-to-book ratio yields a monthly alpha of 1.9 %, even after controlling for the market, size, value, and momentum factors.

Takeda and Wakao (2014) extend the topic to the Japanese stock market. They also find that the quartile portfolio that holds stocks with the highest SVI yields a positive risk-adjusted alpha (by market, size, and value). However, the risk-adjusted alpha between the highest and the lowest SVI portfolios is not statistically significant as reported by Joseph, Wintoki, and Zhang (2011) and Bank, Larch and Peter (2011) for the U.S.A. and German stock markets.

Instead of the SVI for individual stocks, Vozlyublennaia (2014) focuses more on broader markets such as market indices, commodities, and bonds. The study reports that, generally, a high SVI for market indices (S&P 500, Dow and NASDAQ) forecasts negative market returns for the following one to two weeks; although return reversal will materialize within a month. In addition, Klemola et al. (2016), and Chen (2017) find an association between SVI and global stock market returns.

Tantaopas, Padungsaksawasdi, and Treepongkaruna (2016) test the linkage between the SVI and future stock market index movements in a more global respect. They find that the SVI affects the future market index movements in most stock markets analyzed within the following three weeks. Although, they conclude that the causality is more one-way, from returns to the SVI.

3. Data and methodology

The data used in this study are obtained from several sources. The data for annual Google search volumes are downloaded from Google Trends. The search terms used in this study are *bear market* and *bull market*. Furthermore, the popularity of searches is limited to cover only the United States and finance-related searches. The search volumes are scaled to range from 0 to 100, where zero represents a low relative popularity, and 100 represents a high relative popularity for the given search terms during the week in question. [4]

[4] In total, the data set consists of 704 weekly observations, from 1/4/2004 to 6/25/2017.

Data for different size portfolio returns are downloaded from the Kenneth R. French Data Library. The size portfolios are divided into the bottom 30 % and the top 30 % of companies by market equity.

For the set of control variables, we follow the Da et al. (2015) study. For volatility and the "fear gauge" control variable we use the Chicago Board Options Exchange volatility index (VIX). For the macroeconomic condition control variable, we use the ADS index developed by Aruoba, Diebold, and Scotti (2009). The ADS contains information on several seasonally-adjusted macroeconomic activities, including weekly initial jobless claims, monthly payroll employment, industrial production, and real gross domestic product. As a control variable for economic uncertainty, we use the US Economic Policy Uncertainty Index (EPU) as developed by Baker, Bloom, and Davis (2016). It is based on newspaper coverage frequency of policy-related economic news. As an additional control variable, we also use the US Equity Market Uncertainty Index (EMU). Instead of measuring the policy-related economic news, the US Equity Market Uncertainty Index measures news related to equity market. As an additional investor sentiment variable, this study uses the sentiment data of the American Individual Investors survey.

3.1. The construction of the SIIS

We use the relative search popularity of the Google search terms *bear market* and *bull market* to construct a measure of Small Investor Internet Sentiment or SIIS. In this study, we use three alternative methods to calculate the SIIS. In the first two methods the relative popularity rankings of the search terms bear market and bull market are used as standalone variables for the SIIS. It should measure how pessimistic (denoted by searches for bear market) or optimistic (denoted by searches for bull market) investors currently are. This approach should closely follow the method used in more traditional investor sentiment surveys, where investors are asked whether they are bullish, bearish, or neutral about future stock market movements. For example, Fisher and Statman (2000) use a percentage of bullish investors to reflect investor sentiment.

In the third method, we use the difference, or the spread, between the relative popularities of the search terms bull market and bear market, which should indicate if investors are currently more bullish or bearish. For example, Brown and Cliff (2004) and Verma and Soydemir (2006), Schmeling (2007), Verma and Verma (2008) use the difference in number between bullish and bearish investors as their investor sentiment.

We model the SIIS into two separate components; expected SIIS and unexpected SIIS. To capture the unexpected SIIS, we follow the method applied by Peltomäki, Graham, and Hasselgren (2017), who use the residuals from the AR (1) process to capture unexpected Google search volumes for a given search term at the certain time.

We model the AR (1) process as:

(1) $$\mathrm{SIIS}_{j,\mathrm{t}} = \mathrm{c}_j + \rho\mathrm{SIIS}_{j,\mathrm{t}-1} + \mathrm{u}_{j,\mathrm{t}} ,$$

where $\mathrm{SIIS}_{j,\mathrm{t}}$ is the Google Search Volume Index at time *t* for a given search term *j*. c_j is the constant for search term *j*, $SIIS_{j,t-1}$ is the lagged Google Search Volume Index for search term *j*. $u_{j,t}$ is the residual for the search term *j*.

We define the expected level SIIS as:

(2) $$\mathrm{E}\left[\mathrm{SIIS}_{j,\mathrm{t}}\right] = \mathrm{c}_i + \rho\mathrm{SIIS}_{j,\mathrm{t}-1},$$

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and we define unexpected SIIS as:

(3) $\mathrm{UE}[\mathrm{SIIS}_{j,t}] = u_{j,t}$

The descriptive data for the study are presented in Table 1. We argue that the UE[SIIS] captures a shock or an unexpected increase/decrease in the small investor sentiment. Hence it should have an effect on subsequent equity market returns caused by the portfolio rebalancing of small investors, reflecting possible liquidity shock as described by Campbell et al. (1993).

[Table 1 Descriptive Statistics]

To test the possible interdependence between equity market returns and the unexpected SIIS, we employ vector autoregressive models[5]. The estimated models are the following:

(4) $R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g \mathrm{UE}[\mathrm{SIIS}]_{j,t-g} + e_{i,t}$

(5) $\mathrm{UE}[\mathrm{SIIS}]_{j,t} = c_j + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{t=g}^{4} \gamma_g \mathrm{UE}[\mathrm{SIIS}]_{j,t-g} + e_{j,t}$,

where $R_{i,t}$ is the return of size portfolio *i* at time *t*. $\mathrm{UE}[\mathrm{SIIS}_{j,t}]$ is the unexpected Small Investors' Internet Sentiment at time t inferred from the search term *j*. The notation c_i represents the constant;

[5] We conducted several vector autoregressive models with different lag structures. Based on the Akaike Information Criterion, we consider the lag-structure with four lags to be the most robust one. These results are available upon a request.

$R_{i,t-s}$ are the lagged returns of a given size portfolio *i*. UE[$SIIS_{j,t-g}$] are the lagged UE[SIIS]s inferred from the given search term *j*. In addition to the vector autoregressive model, we also conduct pair-wise Granger causality tests to empirically analyze if the lagged UE[SIIS] or returns contain some information that helps to predict the future returns or the UE[SIIS]. In addition, we conduct pair-wise Granger causality tests between the equity market returns and unexpected components of AAII survey to test if our UE[SIIS] measure is able to forecast future equity market returns in more timely fashion than the existing alternatives.

If the lagged returns affect investor sentiment, as previous studies suggest[6], we account for that effect by including an interaction term between the lagged returns and the UE[SIIS]. Bearish (bull-ish) sentiment should have a stronger effect after highly negative (positive) equity market returns. For example, if the current week's returns are highly negative (positive) it should associate with the unexpected increase in popularity of the search term *bear market* (*bull market*). This increased bearish (bullish) small investor sentiment then leads to negative (positive) returns for the following week. In light of the findings of Vozlyublennaia (2014), we run the following regression model with a very similar set of control variables as that used by Da et al. (2015)[7].

$$(6) \qquad R_{i,t} = C_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t} \; ,$$

[6] (see, e.g., De Bondt , 1993; Brown and Cliff, 2004; Verma and Verma, 2008; Vozlyublennaia, 2014)
[7] For robustness, we also conducted a predictive regression with log-transformed Google search data. These results (and their interpretation) are closely similar as results with non-log-transformed Google search data later reported in this paper. These results are available upon request.

where $R_{i,t}$ is the return of size portfolio *i* at the time *t* and $R_{i,t-s}$ are its lagged returns. $UE[SIIS_{j,t-g}]$ denotes the lagged UE[SIIS]s inferred from the search term *j*. The coefficient λ measures the interaction between the lagged portfolio returns and the lagged UE[SIIS]. The set of control variables are the Aruoba-Diebold-Scotti (ADS) business conditions index, a news-based measure of the equity market uncertainty index (EMU), a news-based measure of economic uncertainty index (EPU) and the CBOE volatility index (VIX). The estimated coefficient λ measures how the contemporaneous returns affect the magnitude of UE[SIIS]. $D(R_{i,t-l})$ is a dummy variable for the 10 % decile of lowest or highest weekly returns.

4. Statistical causality between the unexpected changes in SIIS and equity market returns

Table 2 presents the estimates from a vector autoregressive model (see equations 4 and 5) for the UE[SIIS]s that are formed on the popularity of the bear market and bull market search terms and their spread in popularity (bull market minus bear market). For the UE[SIIS] inferred from the bear market popularity, we find that the one-week lagged unexpected SIIS is negatively associated with the following week's returns for portfolios of both sizes. The estimated coefficients vary from -0.03 to -0.02, the effect being stronger for the small-sized companies. This is further supported by the negative estimated coefficient for the low-minus-high (LMH) portfolio[8]. However, the initial negative shock of unexpected SIIS on the equity market returns is counterbalanced after four weeks. Vozlyublennaia (2014) also report a similar delayed counterbalancing effect between Google search volume index and the future aggregate equity market returns. This suggest that the effect of unexpected changes in our sentiment measurement is relatively short-term. Also Da et al.

[8] Formed by subtracting the returns of the top 30 % of companies by market equity from the returns of the bottom 30 % of companies by market equity.

(2015) document that the investor sentiment inferred from Google search popularities has only a short-term effect on future equity market returns.

When analyzing the effects that the past equity market returns have on the UE[SIIS] of bear market, we find no statistically significant evidence that the previous week's equity market returns are associated with the UE[SIIS]. Whereas, three-week lagged equity market return of small- and large-sized companies has a positive effect on the UE[SIIS]. This finding suggests that lagged positive (negative) returns increase (decrease) the unexpected component in the popularity of Google search term bear market. I.e. one could argue that our sentiment measure is an adaptive process.

[Table 2 VAR]

Table 2 also presents estimates from the vector autoregressive model for the UE[SIIS] formed on the basis of the popularity of the search term bull market. We do not find that the unexpected SIIS has any predictive power over future equity market returns for any of the size-portfolios. We do however find some weak evidence that past equity market returns, with lags of two to three weeks, negatively affect the unexpected popularity of the search term bull market. Also in this case, the results suggest that our sentiment measurement is an adaptive process. Lagged negative (positive) increase (decrease) the unexpected component in bull market popularity.

Table two also presents estimates from a vector autoregressive model for the UE[SIIS] that uses the difference between the popularity of the search terms bull market and bear market, also known as the spread. We find a positive and statistically significant estimated coefficient for the unexpected SIIS with a one-week lag when regressed on returns of the different-sized portfolios. The estimated coefficients vary from 0.02 to 0.01. In this case, the effect also seems to be stronger for the small-sized companies, as indicated by the statistically significant estimated positive coefficient for the LMH portfolio. These results indicate that an unexpected increase (decrease) in the spread forecasts positive (negative) equity market returns for the forthcoming week. In addition, as with the case of the bear market UE[SIIS], the spread UE[SIIIS] has a return reversal after four weeks.

When analyzing the effect of the past returns on the unexpected spread, we find that returns with one (two/three) weeks lag are positively (negatively) associated with the UE[SIIS] inferred from the spread. This implies that positive (negative) equity market returns in the preceding week lead into unexpected increase in optimism (pessimism) among the investors. Whereas, this effect is counter-balanced after two to three weeks.

To test the potential causality between the unexpected SIIS and the equity market returns, we employ a Granger causality test. Table 3 presents the results from pairwise Granger causality tests between the portfolio returns and the UE[SIIS] inferred from bear market, bull market, and the spread.

[Table 3 Pairwise Granger Causality tests]

The results reported in Table 3 suggest that both UE[SIIS] inferred from either bear market or from the spread have some predictive power over future equity market returns. The results are consistent whether we use the UE[SIIS] information from either the previous two or four weeks. The UE[SIIS] inferred from bear market also has predictive power for the LMH portfolio. The UE[SIIS] inferred from the popularity of bull market term does not contain any information that helps to predict future equity market movements.

These findings are consistent with the findings reported in some of the previous studies. For example, Da et al. (2015) select only those keywords in their sentiment that have negative loadings to equity market returns, and find a statistically significant association with the sentiment and future equity market returns. Tetlock (2007) finds that high level of media pessimism in Wall Street Journal is associated with negative future aggregate equity market returns. Whereas, Tetlock et al. (2008) find that stock prices of individual companies tend to react in negative wording in firm-specific news stories. Hence it is plausible to argue the bear market or negatively oriented news and information are more likely to capture the small investors' attention, which then reciprocally increases the popularity of Google search term bear market.

As a robustness check, the investor sentiments based on the percentage of bearish AAII survey respondents and the AAII's survey spread contain information that helps to predict the future equity market returns, but only with the lags of four weeks.[9] Neither of the AAII investor sentiment measurements contains information that helps to predict the size premium. Hence, the results suggest that the unexpected component of SIIS, which is based on the search popularity of the term

[9] The statistical significance is higher with lags up to six weeks. These results are available upon request.

bear market or the spread, do perform better compared to the more traditional AAII investor sentiment, especially, in the context of how many weekly lags have to be used for the forecasts. Also in the case of AAII sentiment measure, its' forecasting ability is more related to the pessimism of investors.

5. The effect of UE[SIIS] on portfolio returns is conditional on past returns.

We now focus on how the UE[SIIS] affects future equity market returns when conditional on past equity market returns. For example, it can be argued, that contemporaneous negative equity market returns increase the search popularity of the search term *bear market*, which then leads to an increase in the UE[SIIS] inferred from bear market. That then potentially leads to negative equity market returns for the forthcoming week, and thus, the effect of UE[SIIS] inferred from the popularity of bear market term on future equity market returns should be stronger after strongly negative equity market returns. To account for this effect, we include interaction coefficients between the lagged UE[SIIS] and the lagged returns. In addition, we use a model with a dummy variable for those weeks when the equity market returns appear in the lowest or the highest decile of returns.

Table 4 reports coefficient estimates when the UE[SIIS] is inferred from the search term bear market. In general, the results from Model l are consistent with the previously reported findings and suggest that the UE[SIIS] with a one-week lag is negatively and statistically significantly associated with the following week's equity market returns. The estimated coefficients for UE[SIIS] vary from -0.0260 to -0.015, being larger for small-sized companies; as is suggested by the LMH portfolio that has a negative and statistically significant coefficient. That indicates that a one-standard-deviation increase in the UE[SIIS] forecast leads to a 17 basis-points-lower equity market return for the forthcoming week for small companies and to a 13 basis-points-lower equity market return for large companies, and to a 15-basis-point lower size premium. As also suggested by the previous finding, the return reversal occurs after four weeks.

As previously argued, the popularity of the bear market search term should increase contemporaneously with negative equity market returns. For this reason, we focus on Model 2 to analyze the interaction term between the UE[SIIS] and negative equity market returns (the lowest decile of weekly returns). First, the estimated coefficient for UE[SIIS] itself remains negative and statistically significant for small-sized companies, but not for large-sized companies. Second, the interaction term is negative and statistically significant only for large-sized companies. That indicates that the previously identified negative association between the UE[SIIS] and the following week's equity market returns of large-sized companies is mainly driven by the interaction term of the lagged UE[SIIS] and the preceding week's low returns. The estimated interaction term for the large-sized companies is -0.051. That indicates that a one-standard-deviation increase in the UE[SIIS], contemporaneously with negative equity market returns, predicts 16-basis-point-lower equity market returns for the forthcoming week.

The estimated coefficient for UE[SIIS] on the returns of small-sized companies is -0.022 and statistically significant, whereas the estimated interaction term is not statistically significant. The small-sized companies are also more affected by the UE[SIIS] as a standalone variable, as suggested by the negative and statistically significant estimated coefficient for LMH portfolio. These results indicate that a one-standard-deviation increase in the UE[SIIS] is associated with 14 basis-points-lower returns for small-sized companies for the forthcoming week, and a 15 basis-points-lower size premium for the following week.

Together these findings suggest that the returns of small companies are more prone to the unexpected changes in the popularity of the bear market search term as a standalone variable than those of large firms, which are only affected by the unexpected changes in popularity of the search term *bear market* during periods of low equity market returns.

[Table 4 UE[*Bear market*] OLS]

Table 5 reports the result when the UE[SIIS] is formed on the popularity of the search term *bull market*. The results from Model 1 are consistent with the previously reported findings and suggest that the UE[SIIS] is not statistically significantly related to the following week's equity market returns on any of the size portfolios. When the UE[SIIS] is conditioned on the highest decile of returns (Model 2), we find no statistically significant relationship between the UE[SIIS] and forthcoming equity market returns. This finding further supports the previously reported findings, and also previously mentioned studies, that negatively oriented news and information are more likely to capture the small investors' attention and affect their sentiment. Causing a possible liquidity shock that affects future equity market returns.

[Table 5 UE[*Bull Market*] OLS]

Table 6 reports the result when the UE[SIIS] is formed on the spread, the difference between popularity of the search terms bull market and bear market. For Model 1, we find positive and statistically significant estimated coefficients for the UE[SIIS], with a one-week lag, for both size portfolios and for the LMH portfolio. A one-standard-deviation increase in the UE[SIIS] is associated with 13 basis-points-higher returns for small-sized companies and 11 basis-points-higher returns for large-sized companies for the forthcoming week[10]. The effect of UE[SIIS] on equity returns is larger for the small-sized companies, as suggested by the positive and statistically significant estimated UE[SIIS] coefficient for the LMH portfolio. A one-standard-deviation increase in the UE[SIIS] forecasts an eight basis-points-higher size premium for the following week. As in the case of the bear market UE[SIIS], we find a return reversal after four weeks.

When the UE[SIIS] is conditioned on the decile of the lowest returns (Model 2), we find a statistically significant positive interaction term between the UE[SIIS] and the returns for both portfolios. This finding indicates that the effect of UE[SIIS] on future returns is stronger by some magnitude after a week of negative returns, and the magnitude is greater for the large-sized companies. The interaction term indicates that a one-standard-deviation increase in UE[SIIS], contemporaneous with negative equity market returns, is associated with a 17 basis-points-higher return for large-sized companies and a nine basis-points-higher return for small-sized companies for the forthcoming week.

The estimated coefficients for the UE[SIIS] itself are positive and statistically significant for the small-sized companies, but not for the large-sized companies. That implies that a one-standard-deviation increase in the UE[SIIS] is associated with eight basis-points-higher returns for small-

[10] From the bear market perspective, one-standard-deviation decrease is associated with 13 to 11 basis-points-lower returns for the forthcoming week.

sized companies for the forthcoming week, and a ten basis-points-higher size premium for the following week.

This finding is similar that previously found for the UE[SIIS] that is inferred from the popularity of the search term *bear market*. The association between the UE[SIIS] and future equity market returns is stronger and more robust for the small-sized companies, whereas the effect of UE[SIIS] on large-sized companies is generally limited to those weeks that follow the weeks of negative returns.

[Table 6 UE[Spread] OLS]

As the previous findings suggest, the forthcoming returns of small-sized companies are more affected by the UE[SIIS] when the SIIS is inferred either from the term bear market or the spread. Moreover, the UE[SIIS] affects only the forthcoming returns of large-sized companies when conditional on past highly negative returns. One could argue that small investors form their short-term sentiment SIIS based more on the past returns of large-sized companies, which are also more likely to be reported in the financial media. This SIIS is then reflected on to the forthcoming returns of small-sized companies, as suggested by the traditional noise-trader model. We test this relation when we condition the UE[SIIS] on the past highly negative returns of large-sized companies (see Table 7).

Table 7 reports the result when the UE[SIIS] is conditional on the lowest decile of returns of the large-sized companies. The interaction term between the UE[SIIS] and the return of the small-sized companies is negative and statistically significant when the UE[SIIS] is inferred either from the bear market or the spread. These results imply that the UE[SIIS] has an even stronger effect on the forthcoming returns of small-sized companies when the large-sized companies have experienced relatively high negative returns.

Hence, it can be argued that the channel through which the UE[SIIS] affect future returns of small-sized companies is determined by the contemporaneous correlation of the returns of large-sized companies and the UE[SIIS]. In other words, the relatively high negative returns, the bear market scenario, of large-size companies is reported in the financial media and catches the attention of small investors. Then the small investors use Google to search for more detailed related information, and then base their short-term sentiment on the information they gather before subsequently rebalancing their portfolios.

[Table 7]

6. Conclusions

This paper develops a new and alternative method to measure small investor sentiment in the equity market. By utilizing the data of from Google search volumes, the aim is to capture the changing sentiment of small investors', and its effect on equity market returns, in more timely fashion than the more traditional AAII survey can. Study by Da et al. (2015) highlight several reasons why search-based investor sentiment might be a better alternative to measure the investor sentiment than more classical market-based or survey-based investor sentiment measures. We now extend the idea of Da et al. (2015) to encompass small investor sentiment in the equity market. Where Da et al. (2015) use search terms more closely related to macroeconomic conditions, such as “recession”, “unemployment” and “inflation rate”, whereas we focus more on the equity market condition. We chose a set of search words closely related to the terminology used in the AAII survey. The search terms in question are *bear market* and *bull market*. Based on the popularity of those search terms, we construct a novel and new small investor sentiment measure, Small Investor’s Internet Sentiment (SIIS).

We find that an unexpected change in levels of pessimism among small investors, measured as the popularity of the Google search term *bear market*, is negatively associated with the following week’s equity market returns. A one-standard-deviation unexpected increase in the search volumes of the term *bear market* is associated with a 17 basis-points-lower return for small-sized firms and a 13 basis-points-lower return for large firms, and a 15 basis-points-lower size premium for the forthcoming week.

When the SIIS is measured as the difference between the popularities of the bull market and bear market terms (the spread), the unexpected change is positively associated with the following week’s equity market returns. A one-standard-deviation unexpected increase in the spread is associated with a 13 basis-points-higher equity market return for small-sized companies and with a 12 basis-points-higher equity market return for their large counterparts, and an eight basis-points-higher size premium for the forthcoming week.

We argue that the effect of UE[SIIS] on the following week’s equity market returns is stronger by some magnitude when the financial media or other sources report news that captures small investors’ attention. Terminology such as bull market or bear market is more likely to be used during periods of high or low equity market returns, which is then reflected in the volume of Google searches made by the small investors. This then reflects more strongly on the future returns of small-sized companies that carry more so-called noise-trader risk.

We find that when the large-sized companies are experiencing low returns, the effect of unexpected changes in the SIIS, inferred from searches for bear market or the spread, on the forthcoming returns of small-sized companies is stronger. That suggests that the small investors form their short-term investor sentiment based more on the low returns of large-sized companies. In other words, the unexpected popularity of the search term *bear market* increases contemporaneously with the low returns of large-sized companies. This unexpected pessimistic increase in the small investors' equity market views is then reflected in the forthcoming returns of small-sized companies, as suggested by the classical noise-trader model.

The findings suggest that our SIIS measures the changes of small investor sentiment in a more timely fashion than the more traditional AAII survey, in that the unexpected changes in the SIIS are more associated with the forthcoming equity market returns in the short time horizon.

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Table 1. Descriptive statistics.

	N	Mean	Std.Dev	Min	Max
SIIS					
SIIS_Bear	704	40.04	23.06	0.00	100.00
E[SIIS_Bear]	704	40.00	12.44	18.46	72.37
UE[SIIS_Bear]	704	0.04	19.42	-58.34	73.57
SIIS_Bull	704	49.21	20.95	0.00	100.00
E[SIIS_Bull]	704	49.23	8.19	29.98	69.08
UE[SIIS_Bull]	704	-0.02	19.29	-59.30	56.91
SIIS_Spread	704	9.16	28.00	-92.00	89.00
E[SIIS_Spread]	704	9.22	11.90	-33.82	43.14
UE[SIIS_Spread]	704	-0.06	25.37	-97.30	81.38
AAII					
AAII_Bear	704	33.21	9.39	10.10	70.27
E[AAII_Bear]	704	33.18	6.65	16.81	59.43
UE[AAII_Bear]	704	0.03	6.64	-19.07	24.86
AAII_Bull	704	38.19	9.09	16.50	69.50
E[AAII_Bull]	704	38.22	6.30	23.18	59.91
UE[AAII_Bull]	704	-0.03	6.58	-17.86	26.90
AAII_Spread	704	4.98	16.72	-51.35	56.20
E[AAII_Spread]	704	5.04	11.34	-33.15	39.73
UE[AAII_Spread]	704	-0.06	12.33	-41.78	45.60
Portfolio Returns					
Low 30	704	0.163	3.07	-18.04	13.80
Med 40	704	0.193	2.89	-19.97	14.50
High 30	704	0.161	2.33	-21.94	10.87
LMH	704	0.002	1.41	-4.48	7.26
Control Variables					
VIX	704	18.73	9.14	9.75	79.13
ADS	704	-0.32	0.78	-4.08	0.93
EPU	704	123.78	71.61	19.34	472.47
EMU	704	44.82	55.72	7.46	823.76

This table reports the descriptive statistics for all the variables used in this study. SIIS_Bear, SIIS_Bull are Google search volumes for the bear market and bull market search terms. SIIS_Spread is the difference between search volumes for the bull market and bear market search terms. AAII is the survey of American Association of Individual Investors. AAII_Bear (AAII_Bull) is the percentage of respondents who are bearish (bullish) on their market view for the following six months. AAII_Spread is the difference between AAII_Bull and AAII_Bear. E[.] is the expected search volume for a given search term using the AR (1) process. UE[.] is the unexpected search volume for a given search term using the AR (1) process, i.e., the residual. Low 30, Med 40, and High 30 are portfolio returns for the bottom 30 %, middle 40 % and top 30 % of companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. VIX is the CBOE Volatility Index. ADS is the Aruoba-Diebold-Scotti Business Conditions Index. EPU is the news-based Economic Policy Uncertainty index. EMU is the news-based Equity Market Uncertainty index. The data are in weekly form from 4/1/204 to 6/25/2017.

Table 2. Vector Autoregressive estimates between the unexpected changes in bear market popularity and equity market returns.

Bear Market

	Low 30		High 30		LMH	
	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t
Intercept	-0.03	0.15	-0.08	0.18	0.03	-0.01
	(-0.04)	(1.32)	(-0.10)	(2.00)	(0.04)	(-0.11)
UE[$SIIS_{t-1}$]	-0.15	**-0.03**	-0.16	**-0.02**	-0.15	**-0.01**
	(-4.05)	(-4.24)	(-4.14)	(-3.33)	(-3.96)	(-3.75)
UE[$SIIS_{t-2}$]	0.08	0.00	0.08	0.00	0.08	-0.00
	(2.08)	(0.10)	(2.13)	(0.80)	(2.12)	(-1.51)
UE[$SIIS_{t-3}$]	0.22	0.01	0.23	0.01	0.21	-0.00
	(5.99)	(1.19)	(6.13)	(1.73)	(5.74)	(0.09)
UE[$SIIS_{t-4}$]	0.14	**0.02**	0.114	**0.01**	0.14	**0.01**
	(3.83)	(3.45)	(3.82)	(2.84)	(3.63)	(2.97)
R_{t-1}	-0.09	-0.01	-0.24	-0.08	0.25	-0.03
	(-0.40)	(-0.28)	(-0.79)	(-2.03)	(0.50)	(-0.66)
R_{t-2}	0.08	0.04	0.31	0.04	-0.38	0.03
	(0.36)	(1.00)	(1.02)	(1.16)	(-0.76)	(0.92)
R_{t-3}	**0.44**	-0.07	**0.66**	-0.08	0.32	0.01
	(1.89)	(-1.89)	(2.15)	(-2.23)	(0.64)	(0.27)
R_{t-4}	-0.09	0.03	-0.10	-0.01	-0.01	-0.02
	(-0.40)	(0.85)	(-0.32)	(-0.23)	(-0.19)	(-0.49)
Adj. R^2	0.070	0.034	0.073	0.033	0.067	0.019
F-Stat	7.60	4.08	7.89	3.99	7.25	2.71

Bull Market

	Low 30		High 30		LMH	
	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t
Intercept	-0.13	0.16	-0.16	0.18	-0.12	-0.01
	(-0.19)	(1.33)	(-0.22)	(2.02)	(-0.17)	(-0.11)
UE[$SIIS_{t-1}$]	-0.09	-0.00	-0.09	0.00	-0.09	-0.00
	(-2.29)	(-0.27)	(-2.28)	(0.22)	(-2.42)	(-1.23)
UE[$SIIS_{t-2}$]	0.11	-0.00	0.11	-0.00	0.12	-0.00
	(3.03)	(-0.43)	(2.92)	(-0.31)	(3.15)	(-0.63)
UE[$SIIS_{t-3}$]	0.12	0.00	0.12	0.00	0.12	-0.00
	(3.21)	(0.31)	(3.31)	(0.61)	(3.26)	(-0.30)
UE[$SIIS_{t-4}$]	0.13	-0.00	0.13	-0.00	0.13	0.00
	(3.60)	(-0.46)	(3.61)	(-0.61)	(3.53)	(0.15)
R_{t-1}	0.34	0.00	0.33	-0.06	0.59	-0.02
	(1.49)	(0.08)	(1.09)	(-1.65)	(1.17)	(-0.42)
R_{t-2}	**-0.42**	0.04	**-0.59**	0.04	-0.32	0.04
	(-1.83)	(0.93)	(-1.95)	(1.05)	(-0.63)	(0.92)
R_{t-3}	-0.14	-0.09	0.10	-0.10	**-0.98**	0.01
	(-0.60)	(-2.31)	(0.34)	(-2.62)	(-1.95)	(0.14)
R_{t-4}	0.31	0.01	0.38	-0.03	0.41	-0.02
	(1.36)	(0.39)	(1.25)	(-0.66)	(0.81)	(-0.62)
Adj. R^2	0.049	-0.001	0.049	0.008	0.048	-0.007
F-Stat	5.54	0.92	5.45	1.72	5.39	0.40

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Table 2. Continues

Spread

	Low 30		High 30		LMH	
	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t	UE [$SIIS_t$]	R_t
Intercept	-0.10	0.15	-0.09	0.18	-0.13	-0.01
	(-0.12)	(1.33)	(-0.10)	(2.02)	(-0.15)	(-0.10)
UE[$SIIS_{t-1}$]	-0.17	**0.02**	-0.17	**0.01**	-0.17	**0.00**
	(-4.60)	(3.16)	(-4.55)	(2.80)	(-4.53)	(2.09)
UE[$SIIS_{t-2}$]	0.13	-0.00	0.13	-0.00	0.13	0.00
	(3.60)	(-0.50)	(3.59)	(-1.00)	(3.58)	(0.67)
UE[$SIIS_{t-3}$]	0.29	-0.01	0.29	-0.01	0.28	-0.01
	(8.02)	(-1.14)	(8.06)	(-1.29)	(7.85)	(-0.51)
UE[$SIIS_{t-4}$]	0.18	**-0.02**	0.17	**-0.01**	0.18	**-0.00**
	(4.77)	(-3.23)	(4.66)	(-2.94)	(4.74)	(-2.21)
R_{t-1}	**0.55**	-0.00	**0.71**	-0.07	0.52	-0.02
	(1.90)	(-0.00)	(1.85)	(-1.76)	(0.82)	(-0.53)
R_{t-2}	-0.45	0.03	**-0.83**	0.03	0.12	0.03
	(-1.56)	(0.71)	(-2.16)	(0.87)	(0.20)	(0.83)
R_{t-3}	**-0.58**	-0.07	-0.55	-0.08	**-1.32**	0.01
	(-1.99)	(-1.86)	(-1.43)	(-2.22)	(-2.09)	(0.22)
R_{t-4}	0.31	0.03	0.39	-0.02	0.32	-0.01
	(1.08)	(1.33)	(1.01)	(-0.51)	(0.50)	(-0.33)
Adj. R^2	0.125	0.023	0.125	0.029	0.118	0.001
F-Stat	13.47	3.04	13.51	3.60	12.73	1.07

This table reports estimates from the following vector autoregressive models:

$$\mathrm{UE}[\mathrm{SIIS}_{j,\mathrm{t}}] = \mathrm{c}_j + \textstyle\sum_{s=1}^{4} \beta_s \mathrm{R}_{i,\mathrm{t}-1} + \sum_{t=g}^{4} \gamma_g \mathrm{UE}[\mathrm{SIIS}]_{j,\mathrm{t}-g} + \mathrm{e}_{j,\mathrm{t}}$$

$$\mathrm{R}_{i,\mathrm{t}} = \mathrm{c}_i + \textstyle\sum_{s=1}^{4} \beta_s \mathrm{R}_{i,\mathrm{t}-s} + \sum_{g=1}^{4} \gamma_g \mathrm{UE}[\mathrm{SIIS}]_{j,\mathrm{t}-g} + \mathrm{e}_{i,\mathrm{t}}$$

where $SIIS_{i,t}$ is the Google Search Volume Index at time *t* for the search term *bear market*, *bull market* and the difference (Spread) between the Google Search Volume Indices at time t for search terms *bull market* and *bear market*. $R_{i,t}$ is the return for given size portfolio at time *t*. UE[IS] is the unexpected SIIS using the AR (1) process, i.e., the residual. Low 30 is the portfolio consisting of the bottom 30 % companies by market equity. High 30 is the portfolio consisting of top 30 % companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. The data are in weekly form from 4/1/204 to 6/25/2017. *T*-stats are reported in parentheses.

Table 3. Pairwise Granger causality tests between unexpected SIIS, unexpected AAII and equity market returns.

	Panel A: Dependent Variable		
	Low 30	High 30	LMH
2 Weeks			
UE[SIIS_Bear]	**5.76*** **	**4.26*** **	**5.04*** **
UE[SIIS_Bull]	0.19	0.21	0.85
UE[SIIS_Spread]	**3.24** **	**3.42** **	1.07
UE[AAII_Bear]	0.22	0.09	0.28
UE[AAII_Bull]	0.14	0.20	0.45
UE[AAAII_Spread]	0.19	0.17	0.33
4 Weeks			
UE[SIIS_Bear]	**6.43*** **	**4.72*** **	**5.10*** **
UE[SIIS_Bull]	0.17	0.26	0.49
UE[SIIS_Spread]	**4.38*** **	**3.96*** **	1.84
UE[AAII_Bear]	**2.18* **	1.35	1.23
UE[AAII_Bull]	1.53	1.27	1.05
UE[AAII_Spread]	**2.11* **	1.50	1.24

This table report results from Granger Causality tests with lags of two and four weeks. Low 30 is the portfolio consisting of the bottom 30 % of companies by market equity. High 30 is the portfolio consisting of the top 30 % of companies by market equity. LMH is return difference between bottom 30 % and top 30 % companies. UE[SIIS] is the unexpected SIIS inferred from search terms bear market, bull market, and their spread (bull market minus bear market). UE[AAII] is the unexpected AAII, measured as a percentage of bearish or bullish respondents and their difference (the spread). The unexpected components are the residuals from the AR (1) process. *, **, *** refers to statistical significance at the 10 %, 5 % and 1 % level.

Table 4. Unexpected change in *bear market* popularity and future equity market returns.

	Low 30		High 30		LMH	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0.148	0.170	0.176*	0.197**	-0.006	-0.005
	(1.23)	(1.43)	(1.86)	(2.08)	(-0.11)	(-0.09)
$UE[SIIS_{t-1}]$	-0.026***	-0.022***	-0.015***	-0.007	-0.011***	-0.011***
	(-4.88)	(-3.54)	(-4.02)	(-1.56)	(-3.22)	(-3.59)
$UE[SIIS_{t-2}]$	0.001	0.002	0.004	0.006	-0.004	-0.003
	(0.17)	(0.36)	(0.82)	(1.23)	(-1.40)	(-0.88)
$UE[SIIS_{t-3}]$	0.008	0.012*	0.008*	0.007	0.000	0.001
	(1.24)	(1.66)	(1.75)	(1.43)	(-0.08)	(0.38)
$UE[SIIS_{t-4}]$	0.022***	0.019***	0.014***	0.009***	0.009***	0.009***
	(3.59)	(3.42)	(3.41)	(2.56)	(2.85)	(3.07)
R_{t-1}	0.045	0.051	-0.065	-0.065	-0.023	-0.028
	(0.73)	(0.77)	(-0.83)	(-0.87)	(-0.50)	(-0.59)
R_{t-2}	0.023	0.015	0.034	0.018	0.036	0.033
	(0.44)	(0.29)	(0.58)	(0.30)	(0.88)	(0.84)
R_{t-3}	-0.072*	-0.081**	-0.084*	-0.085*	0.011	0.016
	(-1.93)	(-2.14)	(-1.70)	(-1.85)	(0.21)	(0.30)
R_{t-4}	0.035	0.038	-0.005	-0.006	-0.017	-0.016
	(0.59)	(0.64)	(-0.10)	(-0.12)	(-0.38)	(-0.35)
$UE[SIIS_{t-1}]$		-0.028		-0.051**		0.006
$*D(R_{t-1})$		(-1.25)		(-2.56)		(0.57)
$UE[SIIS_{t-2}]$		-0.003		0.000		-0.012
$*D(R_{t-2})$		(-0.15)		(0.01)		(-1.22)
$UE[SIIS_{t-3}]$		-0.031		-0.002		-0.009
$*D(R_{t-3})$		(-1.54)		(-0.18)		(-1.20)
$UE[SIIS_{t-4}]$		0.021		0.021		-0.009
$*D(R_{t-4})$		(0.72)		(1.06)		(-0.92)
ADS_{t-1}	-2.432	-2.524	-2.235	-2.173	-0.305	-0.262
	(-1.18)	(-1.23)	(-1.12)	(-1.11)	(-0.62)	(-0.55)
EMU_{t-1}	0.063	0.075	0.008	0.018	0.060	0.058
	(0.58)	(0.69)	(0.10)	(0.23)	(1.18)	(1.12)
EPU_{t-1}	-0.126	-0.142	-0.126	-0.110	0.022	0.026
	(-0.51)	(-0.57)	(-0.74)	(-0.65)	(0.19)	(0.22)
VIX_{t-1}	1.976*	2.367**	0.483	0.922	0.024	-0.026
	(1.81)	(2.03)	(0.47)	(0.95)	(0.05)	(-0.06)
Adj R^2	0.040	0.044	0.037	0.056	0.016	0.017
F-Statistics	3.40	3.03	3.25	3.61	1.95	1.75
Obs	700	700	700	700	700	700

This table reports results from following model:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} v_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio *i* at time *t* and $R_{i,t-s}$ are its lagged returns. $UE[SIIS_{j,t-g}]$ are the lagged unexpected components of SIIS, inferred from search popularity of search term *bear market*. Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. D is a dummy variable for those weekly stock returns that belong to the lowest 10 % decile. Low 30, High 30 are portfolio returns for the bottom 30 % and top 30 % of companies by market equity. LMH is return difference between the bottom 30 % and top 30 % of companies. All standard errors are corrected for both heteroskedasticity and autocorrelation by the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

Table 5. Unexpected change in bull market popularity and future equity market returns.

	Low 30		High 30		LMH	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0.152	0.150	0.181*	0.176*	-0.006	-0.006
	(1.25)	(1.16)	(1.87)	(1.80)	(-0.11)	(-0.10)
UE[$SIIS_{t-1}$]	-0.002	-0.002	0.002	0.002	-0.003	-0.003
	(-0.28)	(-0.31)	(0.35)	(0.49)	(-1.15)	(-1.16)
UE[$SIIS_{t-2}$]	-0.003	-0.004	-0.001	-0.004	-0.002	-0.001
	(-0.55)	(-0.75)	(-0.32)	(-0.90)	(-0.57)	(-0.32)
UE[$SIIS_{t-3}$]	0.002	0.003	0.003	0.003	-0.001	-0.002
	(0.45)	(0.43)	(0.77)	(0.75)	(-0.41)	(-0.79)
UE[$SIIS_{t-4}$]	-0.002	-0.001	-0.003	-0.004	0.000	0.001
	(-0.34)	(-0.20)	(-0.55)	(-0.74)	(0.16)	(0.42)
R_{t-1}	0.049	0.048	-0.057	-0.054	-0.018	-0.016
	(0.78)	(0.75)	(-0.71)	(-0.66)	(-0.41)	(-0.35)
R_{t-2}	0.022	0.019	0.030	0.027	0.036	0.038
	(0.45)	(0.30)	(0.53)	(0.48)	(0.90)	(0.96)
R_{t-3}	-0.088**	-0.090**	-0.099**	-0.102**	0.008	0.003
	(-2.32)	(-2.18)	(-2.05)	(-2.05)	(0.15)	(0.05)
R_{t-4}	0.018	0.017	-0.022	-0.022	-0.022	-0.019
	(0.31)	(0.30)	(-0.41)	(-0.42)	(-0.48)	(-0.41)
UE[$SIIS_{t-1}$]		0.006		-0.007		0.004
*D(R_{t-1})		(0.31)		(-0.49)		(0.37)
UE[$SIIS_{t-2}$]		0.016		0.030		-0.010
*D(R_{t-2})		(0.54)		(1.35)		(-0.81)
UE[$SIIS_{t-3}$]		-0.005		-0.001		0.013
*D(R_{t-3})		(-0.16)		(-0.07)		(1.31)
UE[$SIIS_{t-4}$]		-0.010		0.012		-0.009
*D(R_{t-4})		(-0.36)		(0.50)		(-0.74)
ADS_{t-1}	-2.523	-2.493	-2.273	-2.270	-0.380	-0.396
	(-1.22)	(-1.19)	(-1.13)	(-1.12)	(-0.76)	(-0.78)
EMU_{t-1}	0.023	0.021	-0.021	-0.038	0.050	0.062
	(0.21)	(0.20)	(-0.25)	(-0.47)	(0.99)	(1.20)
EPU_{t-1}	-0.062	-0.056	-0.085	-0.055	0.041	0.026
	(-0.26)	(-0.23)	(-0.50)	(-0.31)	(0.36)	(0.24)
VIX_{t-1}	1.693	1.703	0.374	0.405	-0.104	-0.119
	(1.51)	(1.50)	(0.36)	(0.39)	(-0.24)	(-0.28)
Adj R^2	0.003	-0.002	0.012	0.011	-0.010	-0.011
F-Statistics	1.17	0.93	1.71	1.51	0.40	0.52
Obs	700	700	700	700	700	700

This table reports results from following model:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio *i* at time *t* and $R_{i,t-s}$ are its lagged returns. UE[$SIIS_{j,t-g}$] are the lagged unexpected components of SIIS, inferred from search popularity of search term bull market. Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. D is a dummy variable for those weekly stock returns that belong to the highest 10 % decile. Low 30 and High 30 are portfolio returns for the bottom 30 % and top 30 % of companies by market equity. LMH is return difference between the bottom 30 % and top 30 % of companies. All standard errors are corrected for both heteroskedasticity and autocorrelation by the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

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Table 6. Unexpected change in the spread and future equity market returns.

	Low 30		High 30		LMH	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0.151	0.146	0.179**	0.171*	-0.005	-0.005
	(1.25)	(1.20)	(1.89)	(1.80)	(-0.10)	(-0.10)
$UE[SIIS_{t-1}]$	0.015***	0.009**	0.010***	0.004	0.005*	0.005**
	(3.44)	(2.22)	(3.10)	(1.28)	(1.87)	(2.13)
$UE[SIIS_{t-2}]$	-0.003	-0.001	-0.004	-0.003	0.001	0.002
	(-0.59)	(-0.15)	(-1.11)	(-0.94)	(0.63)	(0.69)
$UE[SIIS_{t-3}]$	-0.005	-0.008	-0.005	-0.004	-0.001	-0.001
	(-1.10)	(-1.50)	(-1.20)	(-0.92)	(-0.57)	(-0.63)
$UE[SIIS_{t-4}]$	-0.015***	-0.011**	-0.011**	-0.006	-0.005**	-0.006**
	(-2.63)	(-2.30)	(-2.45)	(-1.61)	(-2.08)	(-2.47)
R_{t-1}	0.041	0.077	-0.062	-0.019	-0.024	-0.028
	(0.66)	(1.11)	(-0.78)	(-0.23)	(-0.54)	(-0.60)
R_{t-2}	0.015	0.007	0.023	0.020	0.033	0.031
	(0.29)	(0.14)	(0.42)	(0.38)	(0.83)	(0.76)
R_{t-3}	-0.070**	-0.061*	-0.084*	-0.063*	0.011	0.012
	(-1.99)	(-1.76)	(-1.80)	(-1.71)	(0.21)	(0.22)
R_{t-4}	0.029	0.029	-0.016	-0.022	-0.010	-0.008
	(0.50)	(0.55)	(-0.31)	(-0.46)	(-0.22)	(-0.18)
$UE[SIIS_{t-1}]$		0.031*		0.044***		-0.005
$*D(R_{t-1})$		(1.71)		(2.71)		(-0.60)
$UE[SIIS_{t-2}]$		-0.013		-0.009		-0.002
$*D(R_{t-2})$		(-0.61)		(-0.52)		(-0.27)
$UE[SIIS_{t-3}]$		0.025		-0.002		0.002
$*D(R_{t-3})$		(1.46)		(-0.15)		(0.22)
$UE[SIIS_{t-4}]$		-0.023		-0.023		0.006
$*D(R_{t-4})$		(-1.02)		(-1.53)		(0.73)
ADS_{t-1}	-2.640	-2.729	-2.307	-2.339	-0.445	-0.418
	(-1.31)	(-1.35)	(-1.17)	(-1.19)	(-0.92)	(-0.89)
EMU_{t-1}	0.037	0.067	-0.009	0.017	0.052	0.051
	(0.34)	(0.61)	(-0.11)	(0.21)	(1.04)	(1.02)
EPU_{t-1}	-0.057	-0.100	-0.088	-0.098	0.048	0.052
	(-0.24)	(-0.40)	(-0.52)	(-0.57)	(0.43)	(0.46)
VIX_{t-1}	1.545	2.172*	0.327	0.915	-0.173	-0.197
	(1.38)	(1.86)	(0.31)	(0.95)	(-0.40)	(-0.45)
Adj R^2	0.027	0.040	0.033	0.059	-0.002	-0.006
F-Statistics	2.62	2.84	2.99	3.76	0.88	0.74
Obs	700	700	700	700	700	700

This table reports results from following model:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{i,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio *i* at time *t* and $R_{i,t-s}$ are its lagged returns. $UE[SIIS_{j,t-g}]$ are the lagged unexpected components of SIIS, inferred from search popularity difference between the search terms bull market and bear market. Control variables are: ADS is a weekly change in Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of equity market uncertainty index, EPU is the weekly change in the news-based measure of economic uncertainty index and VIX is the weekly change CBOE volatility index. D is a dummy variable for those weekly stock returns that belong to the lowest 10 % decile. Low 30 and High 30 are portfolio returns for the bottom 30 % and top 30 % of companies by market equity. LMH is the return difference between the bottom 30 % and top 30 % of companies. All standard errors are corrected for both heteroskedasticity and autocorrelation using the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

Table 7. Interaction of returns of large-sized companies and unexpected changes in SIIS on future returns of small-sized companies.

	SIIS[*Bear market*]		SIIS[Spread]	
	Low 30	LMH	Low 30	LMH
Constant	0.159	-0.007	0.145	-0.006
	(1.30)	(-0.13)	(1.21)	(-0.12)
UE[$SIIS_{t-1}$]	-0.018***	-0.010***	0.008*	0.004*
	(-2.82)	(-3.14)	(1.79)	(1.81)
UE[$SIIS_{t-2}$]	0.002	-0.003	-0.001	0.002
	(0.37)	(-1.15)	(-0.26)	(0.88)
UE[$SIIS_{t-3}$]	0.006	0.000	-0.005	-0.001
	(0.96)	(-0.15)	(-0.92)	(-0.49)
UE[$SIIS_{t-4}$]	0.016***	0.007***	-0.009*	-0.004*
	(2.78)	(2.14)	(-1.85)	(-1.71)
R_{t-1}	0.046	-0.024	0.069	-0.024
	(0.71)	(-0.51)	(1.00)	(-0.53)
R_{t-2}	0.016	0.036	0.012	0.033
	(0.31)	(0.88)	(0.23)	(0.78)
R_{t-3}	-0.072*	0.012	-0.054	0.010
	(-1.93)	(0.22)	(-1.59)	(0.19)
R_{t-4}	0.038	-0.017	0.021	-0.010
	(0.64)	(-0.36)	(0.41)	(-0.22)
UE[$SIIS_{t-1}$]	-0.052**	-0.002	0.046***	0.001
*D(HR_{t-1})	(-2.10)	(-0.19)	(2.70)	(0.05)
UE[$SIIS_{t-2}$]	0.004	-0.003	-0.016	-0.005
*D(HR_{t-2})	(0.17)	(-0.33)	(-0.76)	(-0.54)
UE[$SIIS_{t-3}$]	-0.003	0.001	0.000	-0.001
*D(HR_{t-3})	(-0.14)	(0.11)	(0.01)	(-0.15)
UE[$SIIS_{t-4}$]	0.033	0.007	-0.033*	-0.009
*D(HR_{t-4})	(1.18)	(0.69)	(-1.65)	(-0.96)
ADS_{t-1}	-2.367	-0.302	-2.792	-0.541
	(-1.16)	(-0.62)	(-1.37)	(-1.09)
EMU_{t-1}	0.074	0.059	0.071	0.055
	(0.70)	(1.15)	(0.66)	(1.11)
EPU_{t-1}	-0.116	0.019	-0.080	0.038
	(-0.47)	(0.16)	(-0.32)	(0.33)
VIX_{t-1}	2.452**	0.056	2.019*	-0.159
	(2.19)	(0.13)	(1.77)	(-0.36)
Adj R^2	0.052	0.012	0.047	-0.004
F-Statistics	3.38	1.52	3.17	0.82
Obs	700	700	700	700

This table reports results from following models:

$$R_{i,t} = c_i + \sum_{s=1}^{4} \beta_s R_{i,t-s} + \sum_{g=1}^{4} \gamma_g UE[SIIS_{j,t-g}] + \sum_{l=1}^{4} \lambda_l UE[SIIS_{j,t-l}] * D(R_{hr,t-l}) + \sum_{h=1}^{4} \nu_h Control_{h,t-1} + e_{i,t}$$

where $R_{i,t}$ is the weekly return for size portfolio *i* at time *t* and $R_{i,t-s}$ are its lagged returns. UE[$SIIS_{j,t-g}$] are the lagged unexpected components of SIIS. Control variables are: ADS is a weekly change in the Aruoba-Diebold-Scotti business condition index, EMU is the weekly change in the news-based measure of the equity market uncertainty index, EPU is the weekly change in the news-based measure of an economic uncertainty index and VIX is the weekly change of the CBOE volatility index. HR is the return for size portfolio with the top 30 % of companies by market equity. D1 is a dummy variable for those weekly stock returns that belong to the lowest 10 % decile. Low 30 is portfolio return for the bottom 30 % of companies by market equity. LMH is the return difference between the bottom 30 % and top 30 % of companies. All standard errors are corrected for both heteroskedasticity and autocorrelation using the White diagonal method. * refers to statistical significance at the 0.1 level; ** refers to statistical significance at the 0.05 level; *** refers to statistical significance at the 0.01 level.

Internet Search-Based Investor Sentiment and Value Premium

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Abstract

We study how unexpected change in Internet search-based investor sentiment affects subsequent value premium in the U.S. stock market. For the investor sentiment, we use a sentiment that is based on individual investors' Internet search activity. We argue that stocks that are considered to be more sensitive to fluctuations in investor sentiment, like financially distressed (proxied by high book-to-market ratio) stocks, should also be more affected by unexpected changes in the sentiment. We find that an unexpected increase in optimism (pessimism) in the sentiment predicts positive (negative) subsequent value premium in the U.S stock market.

Keywords: Search-Based Investor Sentiment, Internet Searches, Cross-Sectional Stock Returns, Value Premium

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1. Introduction

In their seminal work, Baker and Wurgler (2006) show that the investor sentiment does not only affect the aggregate U.S. stock market returns, but they also document a relation between investor sentiment and cross-sectional U.S. stock returns. The authors argue that the effect of sentiment is stronger for stocks that are more difficult to arbitrage and value; for example small, growth, and distressed stocks. Both low (growth) and high (distress) book-to-market ratio stocks are reported to be the most sensitive to the fluctuations in investor sentiment, leading into a U-shaped sensitivity pattern, and the effect of investor sentiment being generally stronger for high book-to-market stocks[2]. The authors also note that the effect of investor sentiment on future stock returns is stronger during negative sentiment periods. On a more international level, Baker, Wurgler and Yuan (2012) and Corredor, Ferrer and Santamaria (2015) also document a closely similar association between investor sentiments and future returns of stocks sorted by their book-to-market ratios.

In academic literature, the investor sentiment is usually considered to be either surveys-based (like *American Association of Individual Investors* and *Consumer Confidence*) or market-based (like *VIX* and *put-call ratio)* or the combination of these two. However, Da, Engelberg and Gao (2015) highlight several important arguments why an investor sentiment inferred from Internet search volumes might have an advantage over the previously mentioned and more traditional investor sentiment measurements. First, the market-based sentiment might be the equilibrium outcome of many different economic forces and hence not purely reflect the current investor sentiment. Second, some survey-based sentiments are conducted on too low frequency. Third, the respondents

[2] However, they do not find a statistically significant association between lagged investor sentiment and value premium.

might not answer truthfully in the surveys. Whereas, the Internet search-based investor sentiment also reveals real attitudes rather than just conducting a Gallup poll about it.

In recent decade, a new line of research has emerged in the academic literature. These studies especially analyze the impact of Google search volumes on asset prices, where the Google search volumes can be seen as one form of investors' information retrieval and market attention. Da, Engelberg and Gao (2011) find that increase (decrease) in Google search volumes for the stock tickers of Russell 3000 companies predict positive (negative) subsequent returns for the stock in question. Da et al. (2011) also find that an increase in Google search volume for the stock tickers of IPO companies predicts a higher first-day IPO returns. Vozlyublennaia (2014) and Klemola, Nikkinen, and Peltomäki (2016) find that information inferred from Google search volumes can also help to predict future aggregate stock market returns.

Da et al. (2015) extend the previously mentioned Google studies more into investor sentiment literature by constructing a macro-based Internet search-based investor sentiment from Google search volumes. The authors construct the sentiment by aggregating the Google search volumes for such terminology as *recession*, *unemployment*, and *bankruptcy*[3]. Also, Klemola (2018) uses Google search volumes to construct an Internet search-based investor sentiment, but with terminology that is more specifically related to equity market conditions[4]and terminology used in *AAII*-survey. Both studies find that their investor sentiments are associated with future near-term aggregate stock market returns. Da et al. (2015) and Klemola (2018) also document a relation between their sentiments and subsequent returns of small-stocks. Klemola (2018) also finds a statistically significant association between the Internet search-based investor sentiment and size premium.

[3] This Internet search-based investor sentiment is known as FEARS.
[4] This Internet search-based investor sentiment is known as Small Investors' Internet Sentiment (SIIS).

The purpose of this paper is to further study the effect of Internet search-based investor sentiment on stock returns, by utilizing the same Internet search-based investor sentiment as in Klemola (2018), and study its effect on the subsequent value premium in the U.S. stock market. The findings can support the arguments of Da et al. (2015), that the usage of Internet search-based investor sentiment as an alternative investor sentiment measurement is a valid method. As Baker and Wurgler (2006) find, a good investor sentiment should not only effect stock returns on an aggregate level, but it also should have a cross-sectional stock return effect. Thus, this paper aims to strengthen the cross-sectional validation of Internet search-based investor sentiment as an alternative and more modern investor sentiment measurement.

The paper contributes to the literature in two separate ways. First, the paper contributes to the studies of Da et al. (2015) and Klemola (2018), by extending the literature of Internet search-based investor sentiment's effect on asset prices to cover also value premium. Second, the paper contributes to studies of Baker and Wurgler (2006), Baker et al. (2012) and Corredor et al. (2015) by studying the effect of investor sentiment on value premium, by utilizing an alternative and more modern investor sentiment measurement.

Consistent with our hypothesis, high book-to-market (a proxy for financial distress) stocks are the most affected by unexpected changes in the Internet search-based sentiment. We find that an unexpected increase in optimism (pessimism) in the sentiment predicts positive (negative) value premium for the next week in the U.S. stock market.

2. Data

The weekly data used in this study are obtained from multiple sources. The data for Google search volumes are downloaded from Google Trends. The search terms used in this study are *bear market* and *bull market*. Furthermore, the popularity of searches is limited to cover only the United States and its finance-related searches. The search volumes are scaled to range from 0 to 100 annually, where zero represents low relative popularity, and 100 represents high relative popularity for the given search terms during the week in question.

The data for the returns of 10 different portfolios sorted by their book-to-market ratios are obtained from Kenneth R. French Data Library[5]. The choice of control variables is closely similar to Da et al. (2015). For the macroeconomic condition control variable, we use the ADS index developed by Aruoba, Diebold, and Scotti (2009)[6]. The ADS contains information on several seasonally-adjusted macroeconomic activities, including weekly initial jobless claims, monthly payroll employment, industrial production, and real domestic product. As a control variable for economic uncertainty, we use the US Economic Policy Uncertainty Index (EPU) as developed by Baker, Bloom, and Davis (2016)[7]. It is based on newspaper coverage frequency of policy-related economic news. As a control variable for equity market uncertainty, we use the US Equity Market Uncertainty Index (EMU)[8]. Instead of measuring the policy-related economic news (EPU), the EMU measures news related to equity market conditions. We also include the Chicago Board Options Exchange volatility index (VIX)[9] as a control variable.

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[5] Downloaded from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[6] Downloaded from https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index
[7] Downloaded from http://www.policyuncertainty.com/
[8] Downloaded from http://www.policyuncertainty.com/
[9] Downloaded from Datastream

In total, the data set consists of 704 weekly observations, starting from the beginning of January 2004 and ending at the end of June 2017.

3. Hypotheses development

The methodology of our Internet search-based investor sentiment is based on the investor sentiment develop by Klemola (2018), who use the weekly popularity of Google search terms *bull market* and *bear market* or in their difference in popularity (known as a spread).

As Peltomäki et al. (2017) and Klemola (2018), we divide our sentiment into two components, expected and unexpected sentiment using AR(1)-process:

(1) $$\mathrm{Sentiment}_{j,t} = c_j + \rho \mathrm{Sentiment}_{j,t-1} + \varepsilon_{j,t}$$

(2) $$E\left[\mathrm{Sentiment}_{j,t}\right] = c_j + \rho \mathrm{Sentiment}_{j,t-1}$$

(3) $$UE\left[\mathrm{Sentiment}_{j,t}\right] = \varepsilon_{j,t}$$

where E[] is the expected sentiment, and UE[] is the unexpected sentiment.

We hypothesize that an unexpected change in the sentiment, UE[Sentiment], represents a shift in noise traders' beliefs that creates a liquidity shock in the stock market (see, e.g., Campbell et al. 1993). The effect should be stronger for those stocks that are more prone to the behavior of noise traders and are also more difficult to value and arbitrage; like potentially financially distressed (high book-to-market ratio) stocks.

We test the effect of unexpected changes in the sentiment to subsequent cross-sectional stocks returns with the following regression model:

(4) $$R_{i,t} = c_i + UE[Sentiment]_{j,t-1} + R_{i,t-1} + \sum_{h=1}^{4} \lambda_h Control_{h,t-1} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the return of portfolio i consisting of stocks that are sorted by their book-to-market ratios. $UE[Sentiment]_{j,t-1}$ is one week lagged unexpected change in the Internet search-based investor sentiment inferred from search term *j*.

4. Empirical Analysis

Table 1 presents results when the sentiment is inferred from the popularity of the *bear market*. We document linearly increasing negative relation between the unexpected changes in the sentiment and subsequent cross-sectional stock returns. One standard deviation unexpected increase in the popularity of *bear market* predicts nine basis points lower return for low book-to-market, and 12 basis points lower return for high book-to-market stocks for the next week. We also document a statistically significant negative cross-sectional return spread (value premium) between the high book-to-market and low book-to-market stocks. One standard deviation unexpected increase in the popularity of *bear market* predicts six basis points lower value premium for the next week.

Table 2 presents results when the sentiment is inferred from the popularity of the bull market. We do not document any statistically significant association between the individual portfolios sorted by their book-to-market ratio and unexpected changes in the sentiment. We do however, find that unexpected increase in the popularity of bull market predicts higher value premium for the next week. One standard deviation unexpected increase in the popularity of bull market predicts nine basis points higher value premium for the next week.

Table 1. An unexpected change in *Bear Market* popularity and future cross-sectional stock returns.

	1	2	3	4	5	6	7	8	9	10	10-1
C	-0.008	-0.079	-0.012	-0.137	0.055	-0.030	-0.114	0.374	0.264	0.273	0.303
	(-0.036)	(-0.385)	(-0.056)	(-0.577)	(0.205)	(-0.112)	(-0.423)	(0.988)	(0.726)	(0.572)	(0.890)
$UE[SIIS]_{t-1}$	**-0.010*****	**-0.012*****	**-0.014*****	**-0.015*****	**-0.016*****	**-0.017*****	**-0.016*****	**-0.018*****	**-0.020*****	**-0.018*****	**-0.008***
	(-2.585)	(-2.815)	(-3.429)	(-3.482)	(-3.231)	(-3.657)	(-3.172)	(-3.352)	(-3.461)	(-2.612)	(-1.737)
R_{t-1}	-0.062	**-0.094***	**-0.082***	-0.059	**-0.101***	**-0.092***	-0.072	-0.094	**-0.110****	-0.042	-0.039
	(-1.155)	(-1.951)	(-1.751)	(-1.122)	(-1.949)	(-1.803)	(-1.257)	(-1.409)	(-2.281)	(-0.758)	(-0.602)
ADS_{t-1}	0.362	**0.408***	**0.430****	**0.538****	0.413	**0.476****	**0.665****	0.387	0.245	0.353	-0.016
	(1.608)	(1.937)	(1.987)	(2.256)	(1.645)	(2.005)	(2.247)	(1.206)	(0.834)	(0.808)	(-0.046)
EMU_{t-1}	-0.003	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.005	-0.004	-0.001
	(-0.942)	(-0.751)	(-1.024)	(-0.831)	(-0.924)	(-0.806)	(-0.633)	(-0.801)	(-1.115)	(-0.805)	(-0.441)
EPU_{t-1}	0.000	0.001	0.000	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.001
	(0.295)	(0.523)	(0.326)	(0.325)	(0.225)	(0.437)	(0.626)	(0.083)	(0.841)	(0.348)	(0.293)
VIX_{t-1}	0.022	0.022	0.025	**0.030***	0.021	0.024	0.025	0.005	0.006	0.007	-0.017
	(1.431)	(1.503)	(1.555)	(1.795)	(1.190)	(1.349)	(1.346)	(0.223)	(0.264)	(0.238)	(-0.917)
R2	0.016	0.024	0.029	0.027	0.028	0.030	0.031	0.024	0.024	0.007	-0.000
F-stat	2.84	3.87	4.52	4.21	4.38	4.67	4.76	3.94	3.89	1.87	0.99
Obs	703	703	703	703	703	703	703	703	703	703	703

Notes: This table shows estimated coefficients for equation 4, where the sentiment is inferred from the popularity of Google search term *bear market*. Ten different stock portfolios are sorted by their book-to-market ratio from lowest (1) to highest (10). 10-1 is a long-short portfolio representing a value premium, formed by being long on top decile and short on low decile of stocks sorted by their book-to-market ratio. T-stats are reported in parentheses and *, **, *** refer to statistical significance at 0.1, 0.05, 0.01 level.

Table 2. An unexpected change in *Bull Market* popularity and future cross-sectional stock returns.

	1	2	3	4	5	6	7	8	9	10	10-1
C	-0.011	-0.076	-0.010	-0.127	0.066	-0.018	-0.103	0.403	0.282	0.326	0.359
	(-0.049)	(-0.372)	(-0.046)	(-0.544)	(0.250)	(-0.068)	(-0.394)	(1.075)	(0.785)	(0.689)	(1.047)
$UE[SIIS]_{t-1}$	0.000	0.002	0.001	0.003	0.004	0.004	0.003	0.006	0.004	0.013	**0.012****
	(0.056)	(0.429)	(0.320)	(0.620)	(0.664)	(0.693)	(0.595)	(0.959)	(0.615)	(1.498)	(2.421)
R_{t-1}	-0.056	**-0.085***	-0.075	-0.051	**-0.093***	**-0.084***	-0.065	-0.092	**-0.105****	-0.038	-0.039
	(-1.052)	(-1.771)	(-1.625)	(-0.967)	(-1.800)	(-1.680)	(-1.142)	(-1.357)	(-2.181)	(-0.700)	(-0.602)
ADS_{t-1}	0.341	**0.383***	**0.400***	**0.505****	0.378	**0.438***	**0.628****	0.343	0.200	0.308	-0.041
	(1.550)	(1.859)	(1.880)	(2.153)	(1.527)	(1.880)	(2.173)	(1.079)	(0.689)	(0.713)	(-0.121)
EMU_{t-1}	-0.003	-0.003	-0.003	-0.003	-0.004	-0.003	-0.003	-0.004	-0.005	-0.005	-0.002
	(-0.986)	(-0.805)	(-1.088)	(-0.903)	(-0.995)	(-0.878)	(-0.702)	(-0.867)	(-1.185)	(-0.877)	(-0.525)
EPU_{t-1}	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001
	(0.454)	(0.677)	(0.526)	(0.516)	(0.422)	(0.657)	(0.830)	(0.313)	(1.107)	(0.513)	(0.387)
VIX_{t-1}	0.021	0.021	0.023	**0.028***	0.019	0.021	0.022	0.002	0.003	0.002	-0.021
	(1.380)	(1.409)	(1.443)	(1.661)	(1.063)	(1.204)	(1.238)	(0.067)	(0.121)	(0.063)	(-1.110)
R2	0.008	0.014	0.015	0.014	0.015	0.015	0.019	0.014	0.011	0.004	0.005
F-stat	1.92	2.68	2.82	2.66	2.74	2.76	3.27	2.60	2.25	1.44	1.55
Obs	703	703	703	703	703	703	703	703	703	703	703

Notes: This table shows estimated coefficients for equation 4, where the sentiment is inferred from the popularity of Google search term *bull market*. Ten different stock portfolios are sorted by their book-to-market ratio from lowest (1) to highest (10). 10-1 is a long-short portfolio representing a value premium, formed by being long on top decile and short on low decile of stocks sorted by their book-to-market ratio. T-stats are reported in parentheses and *, **, *** refer to statistical significance at 0.1, 0.05, 0.01 level.

Table 3. An unexpected change in the spread and future cross-sectional stock returns.

	1	2	3	4	5	6	7	8	9	10	10-1
C	0.010	-0.056	0.015	-0.102	0.092	0.009	-0.077	0.423	0.314	0.332	0.344
	(0.044)	(-0.277)	(0.070)	(-0.431)	(0.341)	(0.035)	(-0.287)	(1.101)	(0.862)	(0.691)	(1.003)
$UE[SIIS]_{t-1}$	**0.006***	**0.007****	**0.008*****	**0.010*****	**0.011*****	**0.012*****	**0.011*****	**0.013*****	**0.014*****	**0.017*****	**0.011*****
	(1.871)	(2.255)	(2.775)	(3.004)	(2.745)	(3.040)	(2.658)	(2.776)	(3.033)	(3.036)	(3.086)
R_{t-1}	-0.056	**-0.086***	**-0.076***	-0.054	**-0.095***	**-0.084***	-0.066	-0.091	**-0.106****	-0.038	-0.036
	(-1.067)	(-1.817)	(-1.649)	(-1.012)	(-1.836)	(-1.690)	(-1.146)	(-1.349)	(-2.214)	(-0.693)	(-0.555)
ADS_{t-1}	0.353	**0.400***	**0.419***	**0.528****	0.404	**0.465****	**0.653****	0.376	0.233	0.354	-0.007
	(1.572)	(1.902)	(1.939)	(2.221)	(1.608)	(1.969)	(2.211)	(1.182)	(0.801)	(0.816)	(-0.020)
EMU_{t-1}	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.005	-0.004	-0.001
	(-0.978)	(-0.790)	(-1.075)	(-0.880)	(-0.974)	(-0.856)	(-0.681)	(-0.843)	(-1.163)	(-0.838)	(-0.457)
EPU_{t-1}	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.000	0.002	0.001	0.000
	(0.336)	(0.546)	(0.365)	(0.348)	(0.247)	(0.463)	(0.655)	(0.101)	(0.890)	(0.313)	(0.214)
VIX_{t-1}	0.021	0.021	0.024	**0.028***	0.019	0.022	0.023	0.003	0.004	0.004	-0.018
	(1.370)	(1.438)	(1.466)	(1.698)	(1.092)	(1.253)	(1.254)	(0.123)	(0.156)	(0.161)	(-0.972)
R2	0.012	0.021	0.024	0.024	0.025	0.027	0.028	0.023	0.021	0.011	0.008
F-stat	2.39	3.47	3.89	3.84	3.98	4.22	4.34	3.77	3.52	2.32	1.96
Obs	703	703	703	703	703	703	703	703	703	703	703

Notes: This table shows estimated coefficients for equation 4, where the sentiment is inferred from the spread between the popularities of Google search term *bear market* and *bull market*. Ten different stock portfolios are sorted by their book-to-market ratio from lowest (1) to highest (10). 10-1 is a long-short portfolio representing a value premium, formed by being long on top decile and short on low decile of stocks sorted by their book-to-market ratio. T-stats are reported in parentheses and *, **, *** refer to statistical significance at 0.1, 0.05, 0.01 level.

Table 3 presents results when sentiment is inferred from the difference in popularity of *bull market* and *bear market* (the spread). We document a linearly increasing positive association between the unexpected changes in the sentiment and subsequent cross-sectional stock returns. One standard deviation unexpected increase in the spread predicts six basis points higher return for low book-to-market stocks and 11 basis points higher return for high book-to-market stocks for the next week. We also document a statistically significant value premium between the high-book-to-market and low-book-to-market stocks. An unexpected increase in the spread predicts 11 basis points higher value premium for the next week.

4. Conclusions

We find a statistically significant relation between unexpected changes in the Internet search-based investor sentiment and subsequent value premium in the U.S. stock market. An unexpected increase in optimism (pessimism) in the sentiment predicts positive (negative) value premium for the next week. As Baker and Wurgler (2006) also observe, high book-to-market stocks (a proxy for potential financial distress) generally tend to be more strongly affected by the sentiment.

We also observe that when Google search term with a negative meaning, *bear market*, is used as a sentiment proxy; unexpected changes in the sentiment have a broader cross-sectional effect as we document a linearly increasing negative sensitivity between in the sentiment and future returns of stocks sorted by their book-to-market ratio. This result is consistent with the findings of Baker and Wurgler (2006) and Baker et al. (2012), who report that the sentiment has a stronger effect on future stock returns when the sentiment is on a negative side.

The previous result is also consistent with the findings of Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008) and García (2013). Tetlock (2007) finds that a high level of media pessimism in the Wall Street Journal predicts negative future market returns. García (2013) finds that the effect of news-based investor sentiment on future stock market returns is stronger during recessions than during expansions. Tetlock et al. (2008) find that individual stock prices tend to react in negative wording in firm-specific news stories.

The main contribution of the paper is that unexpected changes in the Internet search-based investor sentiment effects on the subsequent value premium in the U.S. stock market. Thus the sentiment has some cross-sectional effect on future stock returns. This finding further validates the use of the Internet search-based investor sentiment as an alternative and more modern investor sentiment measurement, as it has not the only effect on future aggregate stock markets returns (see, e.g. Da et al. 2015 and Klemola 2018), but it also has cross-sectional effect on future stock returns (see, e.g. Baker and Wurgler 2006). The main findings also contribute to studies of Baker and Wurgler (2006), Baker et al. (2012) and Corredor et al. (2015) by further documenting the effect of investor sentiment on value premium, by utilizing the Internet search-based investor sentiment instead.

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Covered option strategies in Nordic electricity markets

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ABSTRACT

We test the performance of popular option strategies in the Nordic power derivative market using twelve years of data. We find that protective put strategies outperform long forward and covered call strategies on a risk-adjusted basis, because the payoff function of the protective put seems a good fit to the market dynamics in both good and bad times. Detailed analysis reveals differences across moneyness levels and holding periods that can be further exploited. Different Delta levels of the analyzed strategies allow for flexible hedging solutions.

Keywords: Nord Pool; power derivatives; selective hedging; protective put; covered call; forward contract.

1 INTRODUCTION

Electricity companies are among the most active users of financial derivatives. This is mostly because highly volatile electricity prices require rigorous hedging, but also because increased competition within the industry forces companies to find new sources of profit, such as arbitrage and speculation. Consequently, the traditionally strict preference of hedging over trading is relaxed in the new business models, which try to optimally combine the two. Stulz (1996) refers to such flexible derivatives use

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as "selective hedging", arguing that it is value creating compared with full hedging, which does not allow one to take advantage of valuable investment opportunities in the market. Flexible use of derivatives is also in line with Ederington (1979), who argues that hedging should be implemented and assessed according to any other investment: that is, by the trade-off between risk and return. A typical example of selective hedging is an electricity company that uses forward and options contracts to take subjective market views within given risk management boundaries.

The increasingly important role of selective derivatives use in the electricity industry, reported, for example, by Sanda *et al* (2013), requires a new perspective of power derivatives as financial instruments. Specifically, the framework used to assess the performance of different power derivatives should comply with the electricity companies' growing interest in more investment-based hedging policies. However, the literature regarding the performance of power derivatives as investment products is scarce. Most empirical studies on power derivatives focus on their risk-reduction capabilities, in accordance with the traditional risk-minimization principle, while remaining silent about their return potential (for empirical studies on the hedging effectiveness of power derivatives, see, for example, Shawky *et al* (2003), Frestad (2012) and Fleten *et al* (2010)).

The aim of this paper is to provide an empirical assessment of the risk and return characteristics of power derivatives from an investment perspective. Specifically, we consider conservative but popular combinations of forwards and options that have been documented to deliver risk-adjusted excess returns in other financial markets. To our knowledge, this is the first study that focuses on the investment potential of power derivatives. The results can be easily applied to hedging, as we assume a forward contract as an underlying instrument. Choosing a forward position as a starting point allows conclusions to be drawn within the framework of selective hedging.

We focus on the Nordic power derivative market and consider the contracts traded in the Nasdaq OMX Commodities exchange, formerly known as Nord Pool ASA. Nasdaq OMX Commodities is the largest power derivative exchange in Scandinavia, with a 60% market share and an annual volume of 1028 TWh (€49 billion), three times the spot market. The Nordic spot market price is highly seasonal, which guides us to focus on forwards and options with quarterly expiration.

The results of the empirical analysis show large and somewhat systematic differences in the strategies based on various option types, holding periods and moneyness levels, which suggests that it is possible to achieve excess returns in the Nordic power derivative market with certain option strategies. Better reward-to-risk ratios are, however, only obtained with a careful selection of option characteristics and holding periods.

The paper is organized as follows. Section 2 briefly reviews the relevant work on hedging and derivative use. Section 3 describes the data and methodologies used in the empirical analysis, and the results are discussed in Section 4. Section 5 presents our conclusions.

2 PREVIOUS LITERATURE

Recent studies of risk management policies report a growing interest in selective hedging strategies (Stulz 2003, pp. 630–637). Selective hedging is a general term that refers to a company's decision to allow private information, perceived market mispricings and market timing to affect its use of derivatives. It can be viewed as a continuum of trading strategies from pure speculation to full hedging, although usually the selective hedging strategies are rather conservative. In practice, most companies appear to scale down their hedge ratio rather than holding fully covered positions.

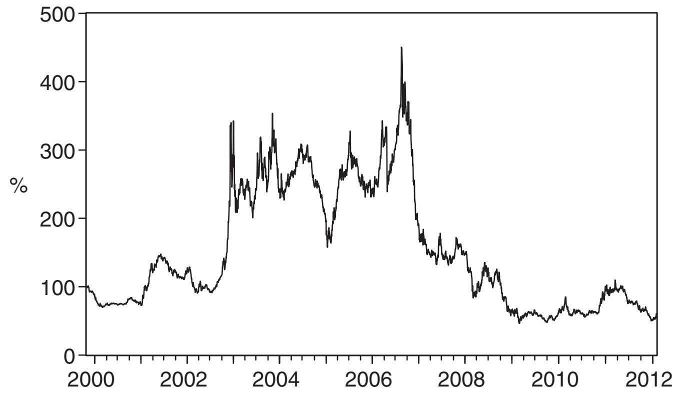
In terms of selective hedging instruments, Brown and Toft (2002) suggest that companies should use the combination of a forward contract and a plain vanilla option to achieve an optimal risk exposure. They argue that standard derivative products comply with most risk management policies, are flexible in terms of exposure adjustment and can be used to capture the convexity in returns.

While the optimal mixture of forward contracts and options depends on the risk appetite and risk profile of the company, there is evidence that some combinations have better properties than others from an investment perspective. For example, in equity markets Whaley (2002), Feldman and Roy (2005), Hill *et al* (2006) and Kapadia and Szado (2007) report high risk-adjusted returns from covered call strategies; these involve writing a call option against an investment in the underlying asset. A protective put strategy is a variant of the covered call strategy and involves buying both the underlying asset and a put option on the asset.

The covered call and protective put strategies are most often undertaken to enhance the return potential of a dedicated portfolio. That is, both strategies assume a long position in the underlying asset but have different return characteristics with respect to its future price development. First, both strategies provide at least some insurance against price declines in the underlying asset and so can be considered as hedging strategies. Second, the strategies have different sensitivities to positive market turns and so are "selective" in terms of upside return potential. For example, the covered call strategy pays off when the price of the underlying asset does not decrease too much or when the call option is overvalued. Equivalently, the protective put delivers high returns when the underlying asset increases sufficiently in price or when the put is undervalued. The relative performance of the strategies thus depends on the price development of the underlying asset and the relative valuation of the options.

The covered call and protective put are natural candidates for selective hedging strategies in electricity markets, because many trading companies in the industry have a future delivery commitment and want to hedge against spot price increases with a

FIGURE 1 The cumulative return index for quarterly forward contracts on Nordic electricity, 1999–2012.



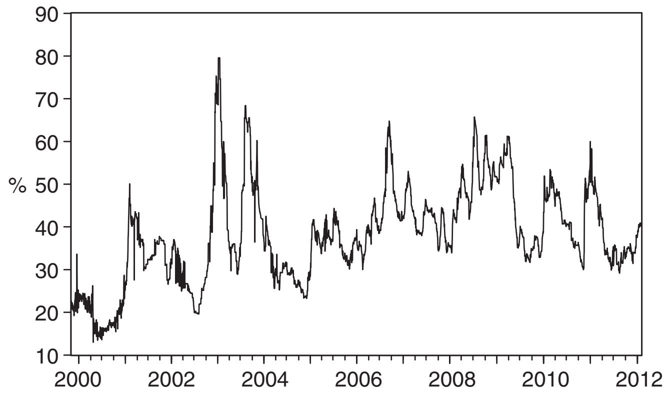
long forward contract position. While the forward position is considered mandatory from a risk management perspective, it can be adjusted with an option position in order to capture occasional jumps in the forward price (Bessembinder and Lemmon 2002; Longstaff and Wang 2004).

In the Nordic markets, Sanda *et al* (2013) report a normative use of forward contracts by Norwegian electricity companies. However, the results suggest that accompanying option positions are less common, likely because option strategies are considered to be expensive by the market participants (NordReg 2010). High option prices are argued to be caused by high volatility and, in particular, the occasional price spikes in the forward market. Krapels (2000) arrives at a similar conclusion with respect to the US power derivative market.

3 DATA AND METHODOLOGY

We compare the risk and return characteristics of covered call and protective put strategies in the Nordic electricity markets. Our data consists of daily settlement prices for financial forward and option contracts traded in the Nasdaq OMX Commodities Europe exchange. Following risk management practices in the Nordic electricity industry (Sanda *et al* 2013), we assume a long position in a quarterly forward contract. The forward position can be either held naked (the benchmark case) or combined with a position in a European-style call or put option with a matching maturity. The option contracts are settled on the forward price, which is based on the expected quarterly average price in the Nord Pool spot electricity market. We choose quarterly

FIGURE 2 The three-month option-implied volatility of electricity forward prices, 1999–2012.



contracts for their liquidity and correspondence to the seasonal effects in the Nordic spot price. The data spans from November 1999 to February 2012, with approximately 252 trading days per year.

The sample period can be divided into two subsamples with different market conditions. As can be seen from Figure 1 on the facing page, the returns for holding a front-quarter forward contract generally increase from 1999 to 2006 and decline from 2007 to 2012. The same general pattern holds for option-implied volatility in Figure 2, although upward deviations from the trend are frequent and large. All in all, the sample period includes various market conditions, which should increase the robustness of our analysis against sample-specific effects.

Regarding the examined option strategies, a covered call involves a long forward position and a short call option position (Figure 3 on the next page). The profit pattern of the portfolio is kinked downward, producing negative returns when the forward price drops below the strike price of the option. The covered call strategy is relevant for an investor who believes that the forward price will not rise much during the investment period and is therefore willing to sell the upside potential of the forward contract for the price of the call option. In this case, the return from writing the call option (the value premium effect) will enhance the investor's total holding-period return, compared with an uncovered forward position. The investor can choose how much upside potential they are willing to sell by selecting a suitable strike price for the call option. With higher strike prices, the investor holds more upside potential for themselves but receives a lower premium from the sale of the option.

FIGURE 3 The profit diagram for the covered call strategy.

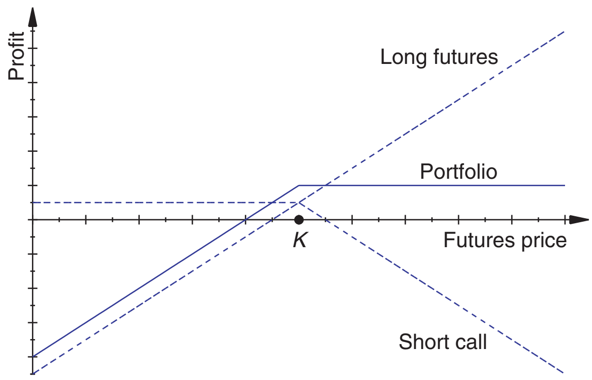
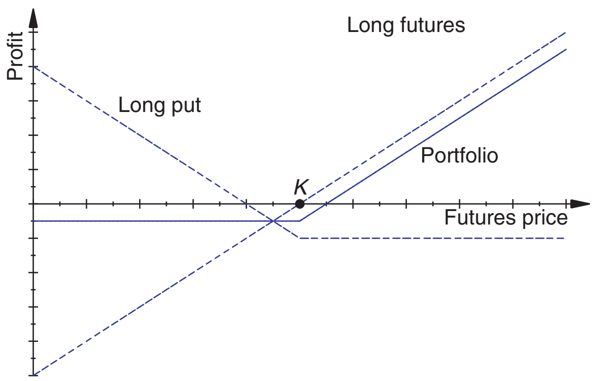


FIGURE 4 The profit diagram for the protective put strategy.



In the protective put strategy, the investor simultaneously purchases a forward contract and a put option. As can be seen from Figure 4, the profit–loss profile of the protective put strategy is kinked upward. For forward price levels lower than the strike price, the protective put strategy yields mildly negative returns. However, if the forward price exceeds the level of the strike plus the cost of the option, the strategy starts to deliver positive returns. Thus, the protective put strategy can be seen as a hedging maneuver against the downside risks of a naked forward position or a speculative trade that profits from potential underpricing of put options. Similarly to implementing the covered call strategy, the investor will choose the strike price of the option according to their risk aversion or perceived return potential. The put options with higher strike prices will cost more, but also provide more downside protection.

The strike prices for the options considered in the empirical analysis correspond approximately to 90%, 95%, 100%, 105% and 110% of the forward price on the day of the investment. For certain periods, however, options with suitable strike prices are not traded, and therefore the number of observations could vary across option moneyness levels. Different strike prices are considered in order to assess the performance of the strategies including in-, at- or out-of-the-money options. For example, the prices of deeply out-of-the-money options are low and typically much less sensitive to changes in the forward price, which would have an effect on the volatility of the strategy. Moreover, the rate of time decay in the option prices varies with moneyness levels and affects the returns for different holding periods differently.

In the empirical analysis, the strategies are implemented so that the forward and option positions are entered simultaneously 30, 60, 90 or 180 days before maturity, and then liquidated on the last trading day. The investment returns are calculated on a daily basis from the settlement prices. The capital required to buy an option, or the premium from selling one, is accumulated at an overnight deposit rate. We assume zero capital requirements on the forward positions.

4 PERFORMANCE OF THE OPTION STRATEGIES

In this section, we first analyze the statistical properties of the returns from different option strategies and compare them with the forward contract returns. We then examine the strategies' return–risk relationship with Sharpe ratios and Jensen's Alphas. The rest of the section is dedicated to finding the sources of the performance differentials.

4.1 Summary statistics

Table 1 on the next page presents descriptive statistics of the daily returns from the long forward position and different covered call strategies. It is divided into four panels corresponding to different holding periods. Table 2 on page 10 presents similar statistics for different protective put strategies.

The first row of Table 1 on the next page suggests that the long forward position performs better than the covered call strategies on the basis of average returns, with a few exceptions across moneyness levels. For the long forward position, all holding-period returns except for the one-month period are on average positive. The protective put strategies generally outperform the long forward position and the covered call strategies across holding periods and moneyness levels. The average returns on the forward position range from −8% to 6% in annualized terms, depending on the holding period, while the protective put strategies deliver up to 18% returns. The covered calls

TABLE 1 Descriptive statistics of covered call option strategies, 1999–2012. [Table continues on next page.]

(a) Six months

	Long forward	Covered call ITM 10%	ITM 5%	ATM	OTM 5%	OTM 10%
Mean*	4.58	2.55	−3.83	−2.76	2.11	14.29
Median*	0	0.14	1.05	3.12	5.93	7.87
SD*	37.91	16.66	19.84	21.21	21.59	21.05
Skewness	−0.08	−0.45	−0.4	−0.39	−0.35	−0.17
Kurtosis	8.81	20.59	15.67	13.45	12.6	9.98
Minimum	−15.65	−9.42	−10.63	−10.88	−10.91	−10.69
Maximum	23.03	9.68	10.92	11.12	11.58	9.12
Average Delta	1	0.35	0.42	0.48	0.52	0.57
No. of observations	5282	3299	5282	5282	4915	2552
No. of contracts	43	27	43	43	40	21

(b) Three months

	Long forward	Covered call ITM 10%	ITM 5%	ATM	OTM 5%	OTM 10%
Mean*	6.32	−5.89	−5.98	−5.46	−4.97	−0.35
Median*	0	0.14	1.62	1.92	4.28	7.25
SD*	41.22	18.48	19.99	23.19	25.39	27.31
Skewness	0.13	−0.94	−0.83	−0.55	−0.43	−0.42
Kurtosis	8.27	21.74	15.65	11.42	9.31	8.05
Minimum	−15.65	−10.82	−10.91	−10.97	−10.97	−10.97
Maximum	23.03	9.21	7.85	8.34	9.16	9.88
Average Delta	1	0.32	0.41	0.5	0.59	0.66
No. of observations	2619	2368	2496	2619	2619	2430
No. of contracts	42	38	40	42	42	39

have a relatively wide range (−14% to 14%) of average returns and usually perform approximately eight percentage points worse than a simple forward position.

The difference between average covered call and protective put returns is approximately 12% in annual terms, but the return differential narrows for longer holding periods. Overall, the returns across different strategies seem to trend downward, especially at shorter holding periods. For the protective put strategies, the intermediate holding periods seem to be the best performing. However, one month is clearly and

TABLE 1 Continued.

(c) Two months

	Long forward	Covered call ITM 10%	ITM 5%	ATM	OTM 5%	OTM 10%
Mean*	4.83	−1.22	−4.18	−4.71	−5.37	−3.64
Median*	0	0.33	2.44	3.36	3.91	6.05
SD*	41.53	16.19	19.43	22.51	25.34	28.43
Skewness	0.19	−1.72	−1.26	−0.97	−0.77	−0.6
Kurtosis	9.37	29.51	17.49	12.46	9.48	7.61
Minimum	−15.65	−10.63	−10.82	−10.91	−10.97	−11.18
Maximum	23.03	8.34	7.85	7.55	7.17	7.2
Average Delta	1	0.3	0.42	0.53	0.62	0.7
No. of observations	1805	1640	1805	1805	1805	1686
No. of contracts	43	39	43	43	43	40

(d) One month

	Long forward	Covered call ITM 10%	ITM 5%	ATM	OTM 5%	OTM 10%
Mean*	−8.09	−1.68	−7.83	−14.43	−12.52	−5.9
Median*	0	0.58	1.58	3.59	6.96	17.38
SD*	43.92	17.41	20.43	25.32	26.75	30.64
Skewness	0.33	−1.46	−1.31	−0.92	−0.78	−0.6
Kurtosis	11.76	30.64	22.34	13.9	7.93	6.23
Minimum	−15.65	−10.04	−11.17	−12.66	−10.82	−10.91
Maximum	23.03	7.28	8.37	9.34	6.87	7.05
Average Delta	1	0.26	0.38	0.53	0.65	0.76
No. of observations	923	727	880	923	882	858
No. of contracts	43	34	41	43	41	40

*The observations are annualized by multiplying by 252 ($\sqrt{252}$ for the standard deviation (SD)).

almost uniformly the worst performing choice for a holding period. This finding contradicts what has been found in equity markets. Hill *et al* (2006) and Kapadia and Szado (2007) report that a covered call strategy with a one-month holding period outperforms lengthier strategies.

The results across different moneyness levels are mixed and lack a clear trend. Some consistencies, however, can be found. First, the returns for the one-month holding period are dominated by the changing Delta of the option positions. The Delta, or

TABLE 2 Descriptive statistics of protective put option strategies, 1999–2012. [Table continues on next page.]

(a) Six months

	Long forward	Protective put ITM 10%	ITM 5%	ATM	OTM 5%	OTM 10%
Mean*	4.58	14.86	10.8	9.45	10.24	6.18
Median*	0	−0.01	−0.02	−0.03	−0.01	−4.6
SD*	37.91	27.12	25.26	25.9	27.46	29.27
Skewness	−0.08	0.68	0.29	0.24	0.18	0.59
Kurtosis	8.81	32.46	26.3	23.43	19.88	19.83
Minimum	−15.65	−14.73	−15.11	−15.42	−15.5	−14.31
Maximum	23.03	23.03	23.03	23.03	23.03	23.03
Average Delta	1	0.46	0.49	0.54	0.6	0.65
No. of observations	5282	2425	4915	5282	5282	3178
No. of contracts	43	20	40	43	43	26

(b) Three months

	Long forward	Protective put ITM 10%	ITM 5%	ATM	OTM 5%	OTM 10%
Mean*	6.32	6.54	14.59	14.72	16.95	18.21
Median*	0	−0.08	−0.17	−1.19	−1.09	−0.59
SD*	41.22	22.2	25.82	28.07	30.41	32.7
Skewness	0.13	−0.1	1.12	0.89	0.74	0.6
Kurtosis	8.27	18.04	31.71	23.92	18.97	15.26
Minimum	−15.65	−14.73	−15.24	−15.5	−15.59	−15.65
Maximum	23.03	9.94	23.03	23.03	23.03	23.03
Average Delta	1	0.37	0.43	0.52	0.61	0.7
No. of observations	2619	1991	2619	2619	2496	2432
No. of contracts	42	32	42	42	40	39

the sensitivity of the option component to changes in the forward price, converges rapidly toward −1 for the written in-the-money calls and the purchased puts at short maturities (the average Deltas of the strategies are presented in the eighth row). For this reason, the forward and option positions at these moneyness levels and maturities cancel each other out, and the returns converge toward zero. Second, the covered call strategies closest to the at-the-money level seem to perform the worst across holding periods. For the protective puts, the at-the-money choice performs relatively well

TABLE 2 Continued.

(c) Two months

	Long forward	Protective put				
		ITM 10%	**ITM 5%**	**ATM**	**OTM 5%**	**OTM 10%**
Mean*	4.83	12.97	14.96	12.72	12.09	11.8
Median*	0	−0.31	−1.61	−5.87	−8.31	−8.7
SD*	41.53	23.43	26.51	28.7	31.33	34.76
Skewness	0.19	2.47	1.55	1.22	0.95	0.73
Kurtosis	9.37	58.97	37.83	28.17	21.04	15.76
Minimum	−15.65	−14.31	−14.31	−14.31	−14.73	−15.24
Maximum	23.03	23.03	23.03	23.03	23.03	23.03
Average Delta	1	0.31	0.4	0.49	0.6	0.7
No. of observations	1805	1606	1762	1805	1805	1683
No. of contracts	43	38	42	43	43	40

(d) One month

	Long forward	Protective put				
		ITM 10%	**ITM 5%**	**ATM**	**OTM 5%**	**OTM 10%**
Mean*	−8.09	−0.75	4.86	9.28	8.29	5.03
Median*	0	−0.79	−4.99	−9.49	−11.05	−18.8
SD*	43.92	11.69	18.01	29.8	33.26	37.62
Skewness	0.33	0.94	0.33	1.89	1.43	1.12
Kurtosis	11.76	22.1	19.44	37.76	25.91	18.83
Minimum	−15.65	−5.57	−9.89	−14.3	−14.31	−14.31
Maximum	23.03	6.06	8.08	22.98	23	23.03
Average Delta	1	0.25	0.37	0.49	0.65	0.78
No. of observations	923	814	860	923	901 792	
No. of contracts	43	38	40	43	42	37

*The observations are annualized by multiplying by 252 ($\sqrt{252}$ for the standard deviation (SD)).

and is rather insensitive to different lengths of the holding period. Other choices for the level of put option moneyness seem to change in ranking with different holding periods.

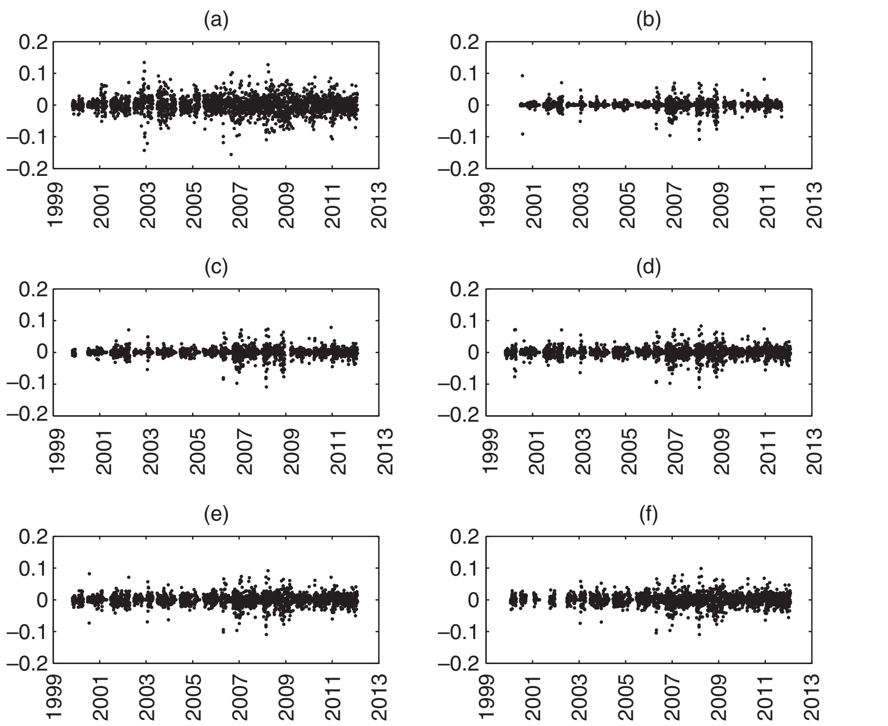
Inspection of the median returns in the second rows of Table 1 on page 8 and Table 2 on the facing page reveals several systematic patterns with respect to option type, moneyness and, in the case of protective puts, the holding periods. First, the covered call strategies have positive median returns, while the protective put strategies deliver negative median returns. This is in stark contrast with the findings from the average return analysis, and implies negative (positive) skewness of covered call (protective put) returns. Second, the median returns for the covered calls decrease monotonically with option moneyness, ranging from 0% to 17% for the one-month holding period and to 8% for the longer ones. Third, the median returns of the protective put strategies become almost uniformly worse for shorter holding periods and lower moneyness levels. For example, the median returns on the one-month put option strategies range from −19% to 0%, while being practically zero for the six-month holding period. The median returns on the forward position are zero across holding periods.

The gaps between average and median returns stem from the difference in the relative frequency of positive and negative returns, or skewness. The fourth rows of Table 1 on page 8 and Table 2 on page 10 show that all covered call strategies have negatively skewed returns, most probably because the written call option limits the upside potential of the strategy. In contrast, all protective put strategies and the long forward position have generally positively skewed returns. The skewnesses of the covered call strategies increase monotonically with option moneyness and the length of the holding period. The same pattern mostly holds for the protective put strategies and the long forward contract, which implies that the skewnesses of the strategies converge to zero as the holding period lengthens.

The annualized standard deviations, reported in the third rows of Table 1 on page 8 and Table 2 on page 10, clearly show an important benefit of the option-augmented strategies over a simple forward position. In particular, both the covered call and protective puts strategies deliver significantly less volatile returns than the forward contract. Overall, the covered call strategies also have lower standard deviations than the protective put counterparts. Once again, the changing Delta sensitivities play a part at the level of the one-month volatilities, making deeply in-the-money put strategies half as risky as the out-of-the-money alternatives. All volatilities, except for the in-the-money strategies, increase with decreasing holding period. This effect is most probably caused by the so-called Samuelson effect (Samuelson 1965), which refers to increasing volatility of the forward price as the contract approaches expiration. The Samuelson effect is particularly strong in a price discovery market, such as the electricity forward market.

The volatilities of the strategies are also clustered in time, as illustrated by Figure 5 on the facing page and Figure 6 on page 14. These figures plot the returns of the covered call (CC) and protective put (PP) strategies for the three-month holding period. The figures for other holding periods are available from the authors on request. Figure 6 shows that volatilities were especially high in, for example, 2003, when the forward price spiked frequently and caused large swings in the returns of the protective put strategies.

FIGURE 5 Covered call returns across different moneyness levels for the three-month holding period, 1999–2012.

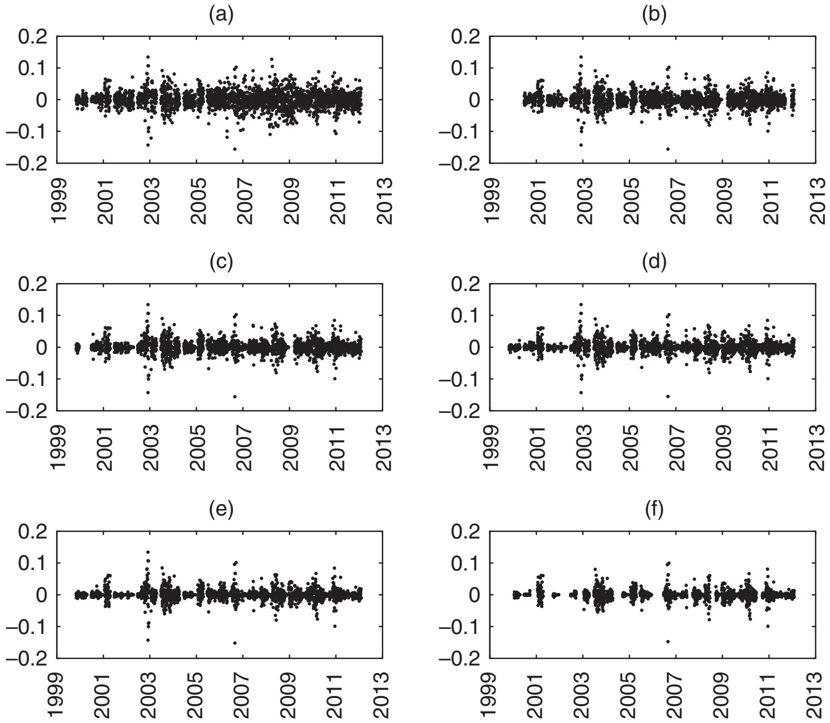


(a) Forward. (b) CC90. (c) CC95. (d) CC100. (e) CC105. (f) CC110.

The overall level of annualized standard deviation is 42% for the long forward position and ranged from 20% to 27% for the 5% in- and out-of-money covered call strategies. For comparison, Kapadia and Szado (2007) report numbers twice as small as those for similar strategies in the US equity market.

The lower standard deviations for the option strategies also imply that their returns are more clustered around the mean, which is confirmed by the kurtosis statistics in the fifth rows of Table 1 on page 8 and Table 2 on page 10. Kurtosis is directly related to the probability of large negative and positive returns, and, according to Tables 1 and 2, seems to vary with option moneyness, so that the kurtosis is highest for the strategies involving in-the-money options. The protective put strategies have on average higher kurtosis, which can also be observed from the number of extreme returns in Figure 6 on the next page. Overall, these results imply that both strategies exhibit occasional and relatively large jumps in returns, which, given the levels

FIGURE 6 Protective put returns across different moneyness levels for the three-month holding period, 1999–2012.

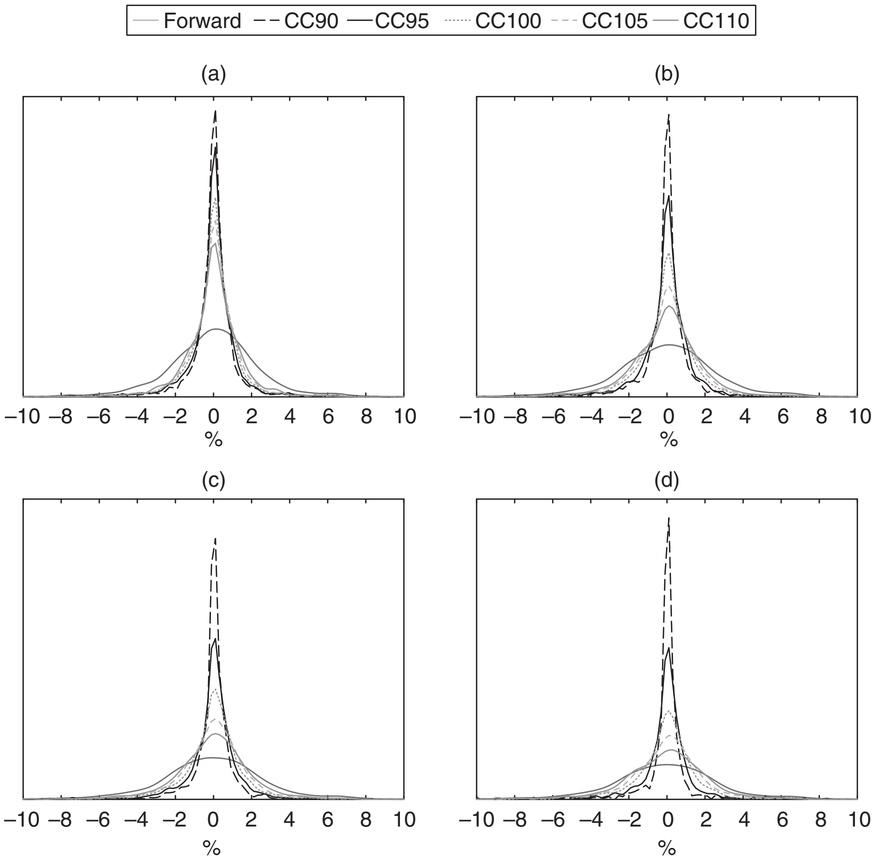


(a) Forward. (b) PP90. (c) PP95. (d) PP100. (e) PP105. (f) PP110.

of skewness, are more likely to be negative (positive) for the covered call (protective put) strategies. Whaley (2002) and Feldman and Roy (2005) also report high excess kurtosis and negative skewness for covered call strategies in the US equity markets.

The statistical descriptions of returns reported in the first five rows of Table 1 on page 8 and Table 2 on page 10 are also graphically illustrated in Figure 7 on the facing page and Figure 8 on page 16, which plot the kernel-estimated densities for the covered call and protective put strategies over the sample period. The figures show clearly that the return distributions become more peaked with decreasing holding periods. In addition, the kurtosis of the covered call strategies decreases (and for the protective put increases) with the option strike price, suggesting that short-term strategies implemented with in-the-money options exhibit relatively frequent jumps in the returns.

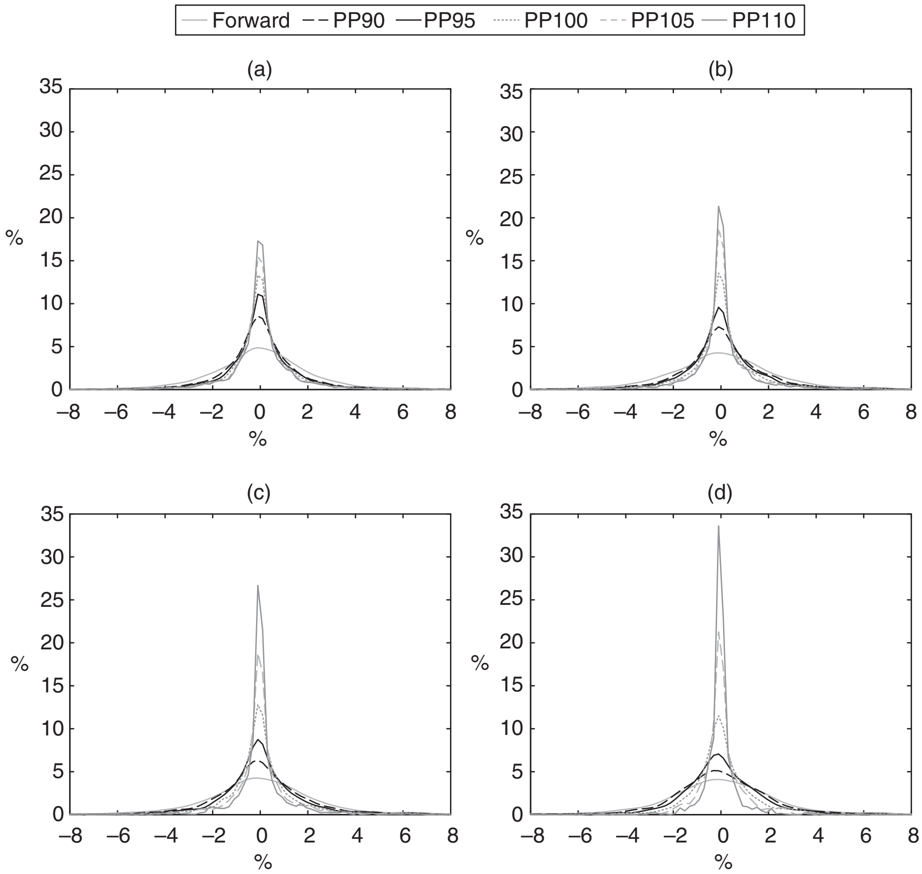
FIGURE 7 The distributions of covered call returns for different holding periods, 1999–2012.



(a) Six months. (b) Three months. (c) Two months. (d) One month.

Finally, the eighth rows of Table 1 on page 8 and Table 2 on page 10 report the average Deltas of the strategies. The numbers show that the option strategies involving in-the-money options have the lowest sensitivity to changes in the forward price. Intuitively, if the forward position is considered a full hedge, then the in-the-money strategies correspond to 25–49% hedges, depending on the length of the holding period. The at-the-money strategies have a stable 50% Delta across holding periods, while the out-of-money strategies provide a 52–78% hedge. These results imply that, by choosing a suitable moneyness level for each holding period, all economically sensible hedging outcomes can be achieved.

FIGURE 8 The distributions of protective put returns for different holding periods, 1999–2012.



(a) Six months. (b) Three months. (c) Two months. (d) One month.

4.2 Reward-to-risk measures

Next we compare different option strategies according to their reward-to-risk relationship. We first focus on part (a) of Table 3 on the facing page, where the Sharpe ratios for the strategies are presented. The Sharpe ratios are calculated by dividing the annualized average return by the corresponding annualized standard deviation (both values are available in Table 1 on page 8 and Table 2 on page 10). Intuitively, the Sharpe ratio measures the compensation in return for a unit of risk. The level of the risk-free rate is factored in at the return calculation phase.

TABLE 3 Annualized Sharpe ratios and Jensen's Alphas for option strategies with different holding periods (in months) and moneyness levels, 1999–2012.

(a) Sharpe (%)

Holding period (months)	Forward	Covered call					Protective put				
		10% ITM	**5% ITM**	**5% ATM**	**10% OTM**	**10% OTM**	**5% ITM**	**5% ITM**	**10% ATM**	**OTM**	**OTM**
6	12	15	−19	−13	10	68**	55*	43**	36*	37*	21
3	15	−32	−30	−24	−20	−1	29	57*	52*	56*	56*
2	12	−8	−22	−21	−21	−13	55	56	44	39	34
1	−18	−10	−38	−57	−47	−19	−6	27	31	25	13

(b) Alpha (%)

Holding period (months)	Forward	Covered call					Protective put				
		10% ITM	**5% ITM**	**ATM**	**5% OTM**	**10% OTM**	**10% ITM**	**5% ITM**	**ATM**	**5% OTM**	**10% OTM**
6		1	−6**	−5*	0	12**	12*	8**	7**	7**	3
3		−8*	−8*	−8*	−8*	−4	4	11**	11**	13**	14**
2		−2	−6	−7	−8	−6	11*	12**	10**	9*	8*
1		0	−5	−11	−9	−1	10	19	27*	28*	27

*Estimates are statistically significant at the 10% level. **Significance at the 5% level. Bootstrapped standard errors. The benchmark return in the Alpha calculations is the return on the long forward position.

Part (a) of Table 3 on the preceding page reveals that the Sharpe ratios are, overall, high for the protective put strategies and negative for the covered call strategies. The best-performing strategy, with a Sharpe ratio of over 50%, is the three-month protective put strategy that combines the 5% in-the-money option with the forward position. The uncovered forward position provides a 15% Sharpe ratio, except for the one-month holding period, when it becomes negative. The covered call strategies usually have deeply negative Sharpe ratios, but the ratios increase steadily with lengthening holding periods. All Sharpe ratios decline dramatically when moving from a two-month holding period to a one-month period.

With respect to option moneyness patterns in Sharpe ratios, the covered call strategies show a flat, declining or convex trend when moving from in-the-money strikes to out-of-money levels. The protective puts, in contrast, show increasing, flat or concave patterns with respect to option moneyness. However, statistical significance patterns of the Sharpe ratios show that the holding period and the option type are more important than the moneyness level in explaining the differences in performance.

For comparison, we also report Jensen's Alphas for the option strategies. Jensen's Alpha is used to determine the risk-adjusted excess return of the strategy over a benchmark rate, which here is naturally the return on the long forward position. The Beta parameter is estimated empirically from the returns. The Alpha values, shown in part (b) of Table 3 on the preceding page, confirm the performance differences between call- and put-based strategies. The put-based strategies perform well and deliver on average a 13% Alpha on an annual basis, compared with an average −5% Alpha for the covered call strategies. The performance gap between put and call strategies is widest in the short holding periods (which is statistically verified), but the abnormal returns converge universally toward zero with longer holding periods.

The results on performance measures imply large and somewhat systematic differences in the risk-adjusted returns between option types and holding periods (and moneyness levels to a certain extent), which suggests that it is possible to enhance derivative market returns with the examined option strategies. However, better reward-to-risk ratios are only obtained with a careful selection of option characteristics.

4.3 Probabilities of option profitability

The differences in the performance of the option strategies, as discussed above, may stem from biased expectations regarding the options expiring in-the-money. The price of a European option should reflect the probability-weighted present value of the profit at the expiry, and if the probabilities are systematically false, then the option is also mispriced. Therefore, by comparing the market-based probabilities of options ending

TABLE 4 The frequency (%) of options expiring in-the-money by holding period and moneyness, 1999–2012.

(a) Realized

Months	CC90	CC95	CC100	CC105	CC110	PP90	PP95	PP100	PP105	PP110
6	67	60	58	55	57	35	40	42	45	40
3	71	60	48	45	38	28	40	52	55	59
2	64	60	50	33	25	38	40	50	66	74
1	76	61	49	37	28	24	38	49	65	76

(b) Expected

Months	CC90	CC95	CC100	CC105	CC110	PP90	PP95	PP100	PP105	PP110
6	65	58	52	48	43	35	40	46	51	54
3	68	59	50	41	34	30	39	48	57	63
2	70	58	47	38	30	30	40	51	60	69
1	74	62	47	35	24	22	35	51	63	75

CC90 refers to a covered call strategy with an option strike price of 90% of the initial forward price. PP refers to a protective put strategy. A strike price below 100% is referred to as in-the-money for call options and out-of-money for puts. The expected values are based on option Delta sensitivities.

up in-the-money with the actual ex post probabilities, one is able to draw conclusions about the underlying causes of the excess returns.

Table 4 reports the actual and expected frequencies of option strategies expiring in-the-money. The expected values are based on the Delta sensitivities of the option strategies, which can be interpreted as market assumptions of the future moneyness. The Deltas should correspond to the actual outcomes in an efficient market. For example, an option with a 70% Delta is expected to expire in-the-money seven times out of ten.

The results in Table 4 show that the probability of an option strategy expiring in-the-money increases (decreases) with the strike prices for put (call) options, which can be considered as a basic requirement for fair option pricing. A more careful comparison of actual and expected outcomes reveals that the market-based expectations correspond well with the ex post frequencies, which implies that the options in the market are at least relatively efficiently priced. For example, the at-the-money option strategies having a 50% Delta do actually expire in-the-money every second time in the sample.

We also carry out a regression analysis, in which we regress the Delta levels on the ex post probabilities to statistically verify our interpretations. For brevity, we do not report the regression results in detail but note that the ex ante probabilities implied by the Delta levels are on average unbiased and efficient estimates of the

FIGURE 9 The difference between actual and expected probabilities of call options expiring in-the-money, 1999–2012.

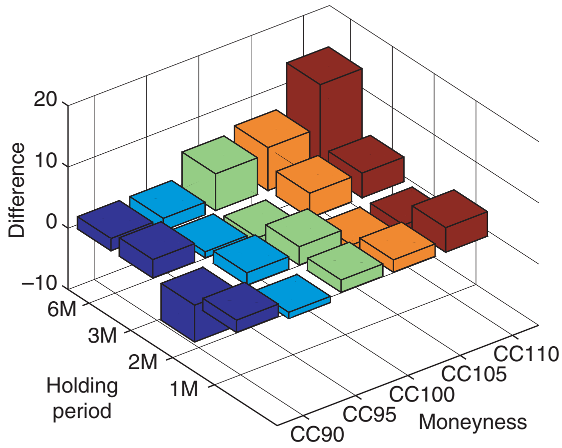
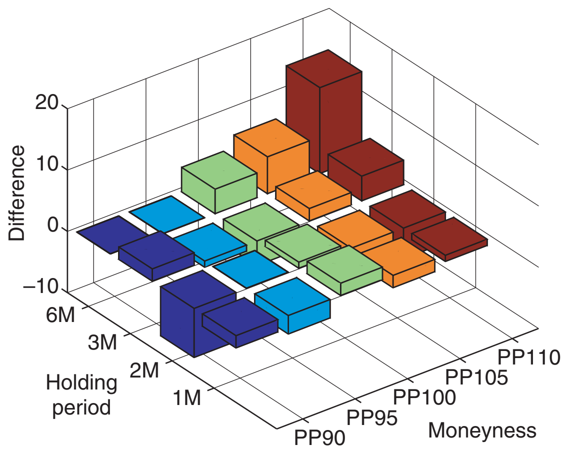
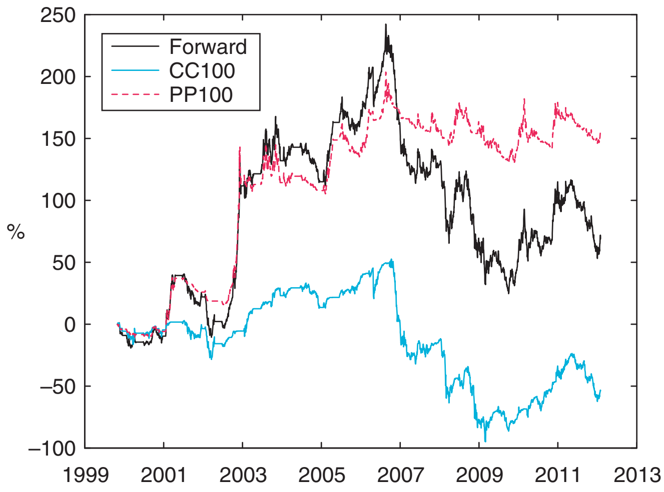


FIGURE 10 The difference between expected and actual probabilities of put options expiring in-the-money, 1999–2012.



probability that the option strategies end up in profit. However, as can be seen from Figure 9 and Figure 10, there are some systematic deviations that correlate with option moneyness and holding periods. In particular, the Delta levels of the call-based

FIGURE 11 The cumulative returns of quarterly forward contract and at-the-money covered call and protective put strategies, three-month holding period, 1999–2012.



strategies underestimate the true probabilities of option moneyness, especially at high strike prices and for long holding periods. The exact opposite holds for corresponding put options. These results suggest that both strategies are expected to pay relatively well when implemented with the highest strike price options for a six-month holding period.

4.4 Split-sample analysis

Because the covered call and the protective put strategies have different directional implications with respect to the price development of the underlying asset, it is important to check whether the performance of the two strategies is driven by up- or down-market periods. As an initial analysis, Figure 11 compares the cumulative returns from holding a forward contract with covered call and protective put strategies based on at-the-money options: the return index for the forward contract increases between 1999 and 2006 and then declines for most of the remaining sample period.

With regard to the option strategies, it can be clearly seen from the figure that the covered call strategy delivers relatively low returns in both up- and down-market conditions. Specifically, the covered call strategy delivers positive but relatively low returns until 2007 and also experiences large losses during the latter half of the sample period. This can be explained by the limited upside potential of the covered call

TABLE 5 Annualized Sharpe ratios (%) for option strategies with different holding periods, moneyness levels and subsamples: 1999–2006 and 2007–2012.

(a) 1999–2006

		Covered call			Protective put		
Months	**Forward**	**5% ITM**	**ATM**	**5% OTM**	**5% ITM**	**ATM**	**5% OTM**
6	48**	−13	−2	21**	69**	69**	70**
3	80**	7	7	11	112**	106**	107**
2	104**	65	64	56	112**	103**	101**
1	74	6	18	74	136*	88	114

(b) 2007–2012

		Covered call			Protective put		
Months	**Forward**	**5% ITM**	**ATM**	**5% OTM**	**5% ITM**	**ATM**	**5% OTM**
6	−29*	−25*	−22*	−1	0	−13	−11
3	−51*	−59**	−49*	−45*	−23	−21	−14
2	−77	−78	−82	−78	−21	−30	−38
1	−111	−78	−119	−120	−31	−44	−77

*Estimates are statistically significant at the 10% level. **Significance at the 5% level. Bootstrapped standard errors.

strategies, which curtailed the returns in 2003, and the inadequate protection against market crashes, which depressed returns in 2007.

In Figure 11 on the preceding page, the protective put strategy stands in sharp contrast to the covered call, performing relatively well in both rising and declining market environments. Over the twelve-year sample period, the protective put strategy delivers a cumulative return of 150%, which corresponds to an average 12% return on an annual basis. Unlike the covered call strategy, the protective put strategy benefited fully from the rising forward prices between 1999 and 2006 and provided important downside protection at the time of the market crash in 2007.

Regarding the realized return–risk ratios in the two subsamples, Table 5 presents the conditional Sharpe ratios for the different strategies. The results from the table give a strong indication that, in terms of reward for risk, the protective put strategies outperform the covered call strategies and the forward contract investment in both subsamples, irrespective of holding-period lengths or option moneyness levels. The average Sharpe ratio for the protective put strategies is as high as 100% in the first subsample, which means that every percentage point of risk that is taken is compensated by a 1 percentage point increase in the annualized return. For the same subsample, the average Sharpe ratio of the covered call strategies is only 26%, or one-quarter of the protective put. Consistently, in declining markets the average Sharpe ratio for the covered call strategies is approximately two and half times smaller than that for the protective put. The results of the split-sample analysis imply that period-specific effects are important but do not drive the relative performance gap of the option strategies. More detailed subsample statistics are available from the authors on request.

4.5 Return decompositions

In the previous sections, we have documented that the performance differences of the option strategies do not stem from period-specific market conditions or mis-estimated probabilities of the strategies expiring in-the-money. In order to understand the source of the relative performance gap between the strategies, we turn to the return decomposition approach by Hill *et al* (2006). Specifically, we decompose the holding-period returns of the option strategies into components attributable to option fair-value and volatility premiums. The fair value premium is the return component obtained if the option were to be valued at the realized volatility of the underlying asset rather than at the implied volatility. By using the realized rather than the implied volatility, one is able to isolate the investment effects of the higher moments of the underlying return distribution. The volatility premium, on the other hand, captures the option pricing effect of the spread of the implied volatility over realized volatility. It effectively measures the excess returns that can be earned by writing options on relatively high prices. The actual returns of the strategies can be calculated by summing the two return components.

Figure 12 on the next page presents the return effects of the fair value premium for different holding periods and moneyness levels. The two main observations from the figure are the relatively stable positive returns of the protective put strategies compared with the worsening negative performance of the covered call strategies over shorter holding periods. Given that the effect of volatility is controlled for, these results underline the unsuitability of the covered call strategy when the underlying asset price experiences large jumps (see the reported kurtosis statistic of the underlying asset in Table 1 on page 8). The adverse effects of the jumps are more pronounced in the short term, which can be seen in the extremely bad performance of the call-option-based strategies in the one-month holding period. The protective put strategies, on the other hand, fully capitalize on the positive price jumps and provide protection against the adverse effects of market crashes.

FIGURE 12 Average returns on fair-valued option strategies for different holding periods and moneyness levels, 1999–2012.

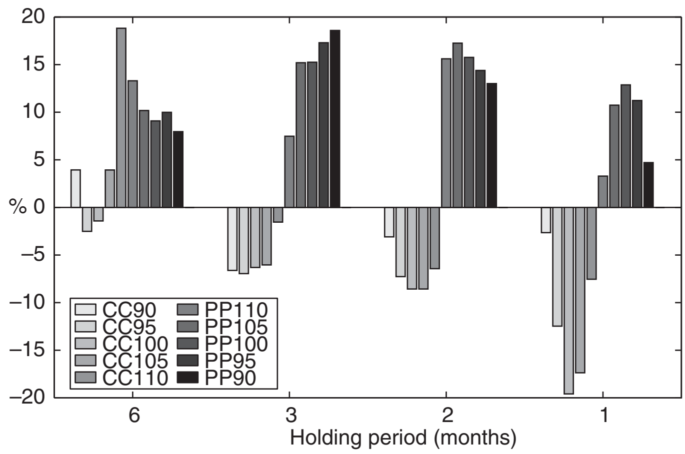
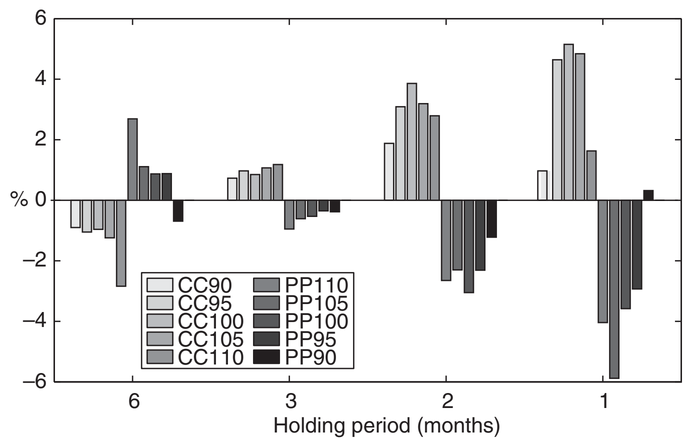


FIGURE 13 The average volatility premium on option strategies for different holding periods and moneyness levels, 1999–2012.



Moving from the effect of fair-value premiums to volatility premiums, Figure 13 shows a clear term structure of returns on excess volatility. Specifically, the covered call strategies, which are based on the writing options that are overpriced with respect to future volatility, show a strong, positive performance. The strong performance of the call-based strategies is manifested in the shorter holding periods, where it is enhanced by the increasing rate of decay in the time value of the written call option. The reverse pattern holds for the protective put strategies, which are based on long option positions. In general, the two return components seem to have an offsetting effect on the actual returns, but the return effects of the fair-premium investments have a much greater impact and thus drive the performance gap between the two strategies.

The results from the return decompositions are consistent with the view that the analyzed power options carry a price premium for the risk of price discontinuities. This affects the performance of short and long option positions oppositely. However, the dominance of the returns from the fair-value premiums over the returns from excess volatility suggests that the volatility premium in option prices has been too small to offset the adverse effects of jumps in the underlying asset price. This is especially apparent in the poor performance of the covered strategies based on written short-term call options, for which the adverse effects of price crashes are larger than the returns from selling slightly overpriced options.

5 CONCLUSIONS

This paper carried out an investment-based assessment of the risk and return characteristics of power derivatives. We considered different option strategies for the Nordic electricity market with twelve years of observations and conclude that it is possible to enhance investment returns with certain option strategies. Specifically, we found that the best-performing option strategy in the sample is the protective put strategy. This seems to perform well during rising and declining markets, and it is able to better capture the positive effects of the frequent price jumps in the underlying forward market. Compared with a covered call strategy, the protective put delivers on average 12 percentage points higher returns on an annual basis, and it has preferable skewness properties.

The performance of the strategies varied across option moneyness levels and holding periods, with the one-month holding period delivering generally poor performance and having the highest frequency of extreme returns. The option strategies based on at-the-money or mildly in-the-money put options seem to be the best choices from an investment perspective, because their returns are relatively high and stable across holding periods. Further, the Delta values of the best-performing strategies range from 25% to 75%, which implies that an economically sensible alternative to a traditional forward hedge can be achieved by moderately leveraging the protective put positions.

DECLARATION OF INTEREST

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Research Paper

Dynamic delta option strategies in Nordic electricity markets

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ABSTRACT

This paper examines how electricity options traded in the Nasdaq OMX Commodities Europe financial market are priced compared with their corresponding futures contracts. For this purpose, the dynamic delta portfolio is constructed using quarterly options and an underlying futures contract. Given that the risk level of such a portfolio is adjusted on a daily basis, in such a manner that it matches the corresponding static futures strategy, we can directly calculate the price difference between the dynamic delta option strategy and the static futures strategy. We find some seasonality in the price differences between the static and dynamic strategies. When using calls, we find a significant negative (positive) price difference during winter (summer) quarters. In contrast, for puts, we find a significant positive price difference during winter quarters, but not during summer quarters. We also find that the winter and summer quarters are associated with the reported price differences, which are not as universally related to the trends in electricity prices (ie, increasing or decreasing electricity prices).

Keywords: Nasdaq OMX Commodities Europe; futures; options; electricity; dynamic delta; option strategy.

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1 INTRODUCTION

In an electricity market where spot prices are generally highly volatile, employing well-functioning financial risk management practices can be an important competitive advantage for electricity companies or other practitioners. However, to achieve effective financial risk management, the instruments traded in a financial electricity market should be relatively fairly priced, and the risk sharing between market participants should be relatively equal. For example, Bessembinder and Lemmon (2002) state that the existence of forward premiums in an electricity market may imply that the

> power markets are not well integrated with the broader financial markets, that is, that outside speculators are not [a] significant presence in these markets. It will be [of] interest to see if mechanisms are developed to facilitate the sharing of power [price] risk with outside speculators, and if risk premium decline[s] as a consequence.

The purpose of this paper is to empirically test whether price differences exist between euro-nominated quarterly options and futures contracts that are traded in the Nasdaq OMX Commodities Europe financial market. In this study, the price difference is defined as the inequality in euro terms between the dynamically managed delta option strategy and the corresponding static futures strategy. In theory, the monetary outcome from both strategies should be equal, as the risk levels related to the future electricity prices are equal. However, nonzero and statistically significant price differences suggest that potential mispricing might exist that the investor, hedgers or speculators could exploit. For example, the hedger might choose the strategy that brings them the highest hedging price for the electricity.

The price difference is tested by constructing two separate portfolios and analyzing their performance. The first portfolio consists of only futures contracts, while the second portfolio consists of a joint position on futures and option contracts (call or put options). The risk level of the second portfolio is adjusted on a daily basis by trading the underlying asset of the option contracts: the futures contracts. The daily risk adjustment is done so that the risk level, measured using delta, of portfolio 2 equals that of portfolio 1 every day. This is known as the dynamic delta option strategy. In theory, the electricity price achieved with either one of the two portfolios should be the same, on average. Otherwise, the risk sharing of electricity price between market participants in the Nasdaq OMX Commodities Europe financial market, especially in the option contracts market, may not be fair enough.

In this paper, the static futures strategy is constructed by selling a futures contract, while the dynamic delta option strategy is constructed by writing (buying) a call (put) option contract and simultaneously selling a futures contract. In theory, if call (put) option contracts are overpriced (underpriced), the dynamic delta option strategy should outperform the static futures strategy. Instead, if call (put) options are underpriced (overpriced), the static futures strategy should outperform the dynamic delta option strategy.

While the existing research (see, for example, Bessembinder and Lemmon 2002; Longstaff and Wang 2004; Kristiansen 2007; Douglas and Popova 2008; Wimschulte 2010; Botterud *et al* 2010; Gjolberg and Brattested 2011; Lucia and Torró 2011; Frestad 2012; Bunn and Chen 2013; Weron and Zator 2014; Smith-Meyer and Gjolberg 2016) on financial electricity markets mainly focuses on futures/forward contract markets, this paper contributes to the literature by focusing on the price difference between futures and option contracts. For example, Botterud *et al* (2010), Gjolberg and Brattested (2011), Lucia and Torró (2011) and Weron and Zator (2014) analyze the price differences between forward/futures contracts and spot prices in the Nordic region. In addition, Kristiansen (2007), Wimschulte (2010) and Frestad (2012) analyze the price difference between forward/futures contracts with different maturities that are traded in the Nordic financial electricity market. However, to the best of the authors' knowledge, the price difference between futures and option contracts traded in the Nasdaq OMX Commodities Europe financial market has not been analyzed before.

From a practical point of view, it is important to analyze in more detail the pricing mechanism of option contracts that are traded in the Nasdaq OMX Commodities Europe financial market, since options could be practical hedging instruments for the electricity companies that operate in the Nordic region. For example, several previous studies have shown, using a simulation setup, that option contracts are useful hedging instruments (see, for example, Deng and Oren 2006; Oum *et al* 2006; Oum and Oren 2009, 2010; Pineda and Conejo 2012). However, Sanda *et al* (2013) report that Norwegian hydro-based electricity producers use option contracts as hedging instruments relatively rarely. Do practitioners feel that the option contracts traded in the Nasdaq OMX Commodities Europe financial market are perhaps too expensive to use? If, however, the option contracts are mispriced relative to the futures contracts, this offers practitioners an opportunity to boost their income level by exploiting the mispriced option contracts, ie, if call option contracts are overpriced relative to futures contracts, practitioners would financially benefit by writing call option contracts and selling futures contracts jointly, instead of just selling futures contracts. The findings of this study should aid and motivate practitioners to consider using option contracts on electricity price as a component of their risk management practice.

This topic is also of economic importance. For example, during February 2018, total trading in the Nasdaq OMX Commodities Europe financial market amounted to 86.7 TWh (4700 GWh) of electricity, or €2.4 billion (€122 million), on a monthly (daily) basis (Nasdaq Commodities Europe 2018a).

Results from the empirical part of our investigation suggest that some price differences exist between the dynamic delta option strategies vis-à-vis the static futures strategy. For the dynamic delta option strategy that uses call options, we find seasonal variation in the reported price differences (the static futures strategy minus the dynamic delta option strategy). We find the winter quarters (the first and fourth quarters of the year) are negatively associated with the reported price differences, whereas the summer quarters (the second and third quarters of the year) are positively associated with the reported price differences. Also, the price difference itself is statistically significant and negative (positive) for the winter (summer) quarters. This indicates that the dynamic delta option strategy that uses call options performs better (worse) during the winter (summer) quarters than the static futures strategy.

For the dynamic delta option strategy that uses put options, we find weaker seasonal variation in the reported price differences. We find the winter (summer) quarters are positively (negatively) associated with the reported price differences, but the price difference itself is only statistically significant and positive for the winter quarters. This indicates that the static futures strategy performs better than the dynamic delta option strategy that uses put options during the winter quarters only, with the average price difference being as high as 1.23 €/MWh in favor of the static futures strategy. For the summer quarters, we find no statistically significant price difference.

We find no evidence that the reported price differences are universally related to the trends in electricity prices (ie, increasing or decreasing electricity prices). We also find some cross-sectional variation in the reported price differences when analyzing the different moneyness levels employed in the dynamic delta option strategies that use call options. The reported price differences of such strategies seem to be driven by those strategies that utilize at-the-money and in-the-money moneyness call options.

These results suggest the call options traded on the Nasdaq OMX Europe Commodities financial market might be overpriced (underpriced) during winter (summer) quarters, and the put options might also be overpriced during winter quarters, especially for hedging purposes.

This paper is organized as follows. Section 2 briefly discusses earlier studies. Section 3 describes the data and methodology used in the present study. Section 4 presents the empirical results. Section 5 concludes, briefly discussing our main findings and their interconnection with previous studies.

2 PREVIOUS LITERATURE

2.1 Electricity forward/futures prices versus spot prices

The earliest, as well as the majority of previous, studies related to financial electricity markets generally focus on analyzing the price difference between forward/futures contract prices and spot prices. This price difference is also known as a forward premium, as described by Fama and French (1987). The forward premium can also be viewed as a risk premium paid to the seller of a forward/futures contract for exposing themselves to volatile spot prices.

Before the millennium, the behavior of electricity prices and the pricing of electricity derivatives were relatively uncovered topics. This was partly due to a lack of publicly available data and the problems this caused in performing reliable statistical tests. To improve the statistical power of small samples in highly volatile electricity markets, Bessembinder and Lemmon (2002) developed a theoretical cost-based equilibrium model to analyze the potential existence of forward premiums in US electricity markets. They found that, on average, one-month-ahead monthly forward contracts carry statistically significant positive forward premiums during times of high electricity demand (summer months). Moreover, the magnitude and statistical significance of the forward premiums diminish or become negative as demand for electricity decreases. However, when we compare our findings from the theoretical model, which is based on the cost expectation of future spot prices, with actual realized spot prices, the results become mixed. The statistical significance of positive forward premiums disappears, and the magnitude of negative forward premiums increases as does their corresponding statistical significance. Bessembinder and Lemmon (2002) argue that this difference is due to an unusual price spike in the summer of 2000 in the California Power Exchange (CalPX) market. Hence, Bessembinder and Lemmon (2002) motivate further research so that more conclusions may be reached.

Longstaff and Wang (2004) address the data problem raised by Bessembinder and Lemmon (2002) by using high-frequency day-ahead forward data from the PJM market. They find that the forward premium varies from negative to positive throughout the day, although the average hourly forward premium is not statistically significant. In line with the results of Bessembinder and Lemmon (2002), Longstaff and Wang (2004) find that the magnitude and statistical significance of positive forward premiums are highest during so-called peak periods. Douglas and Popova (2008) report similar results and find that the magnitude and sign of the forward premium vary within a day, although the daily mean and median stay close to zero. In addition, Hadsell and Shawky (2007) find that day-ahead forward premiums in the New York wholesale electricity market are dependent not only on the time of day but also on the day of the week and the calendar month. In a more recent study by Haugom and Ullrich (2012), however, no consistent evidence that the forward premium still exists on the PJM market for short-term forward contracts is found.

Botterud *et al* (2010) empirically analyze the potential existence of forward premiums for weekly futures contracts in the Nord Pool electricity market. They find that, on average, futures prices are higher than their corresponding spot prices, but they vary seasonally. Botterud *et al* (2010) also report that, generally, the forward premium increases monotonically with the holding period, as does the standard deviation of the forward premium. However, Botterud *et al* (2010) do not find any distinct seasonal pattern in forward premiums, as they are generally positive all around the year, although they do briefly turn negative during the snow-melting period.

Consistent with the findings of Botterud *et al* (2010), Gjolberg and Brattested (2011), Lucia and Torró (2011) and Haugom *et al* (2014) find evidence of positive forward premiums for short-term futures contracts traded in the Nord Pool electricity market. Lucia and Torró (2011) also find that the forward premiums for one-week futures contracts increase with the holding period. Lucia and Torró (2011) and Haugom *et al* (2014) also clearly demonstrate the seasonal pattern of forward premiums, showing that the magnitude of forward premiums is at its largest during winter periods. Gjolberg and Brattested (2011) find similar results for four- and six-week futures contracts in the Nord Pool.

Also, Weron and Zator (2014) empirically analyze forward premiums for one-week futures contracts for different holding periods. Their results suggest the forward premium can vary from negative to positive depending on the holding period. However, consistent with earlier studies, the forward premium is positive and increases for longer holding periods.

In a recent paper by Smith-Meyer and Gjolberg (2016), it is reported that after the year 2008 the forward premiums from short-term futures contracts appear to have diminished. Mork (2006) finds supporting evidence and argues that forward premiums diminished in the Nordic electricity market after the millennium.

Diko *et al* (2006) empirically analyze the potential existence of forward premiums in three major European electricity markets: German, Dutch and French. They find positive forward premiums for day-ahead forward contracts for all three markets. However, the positive forward premium is, in general, only statistically significant during peak hours. Ronn and Wimschulte (2009) find consistent and supporting results with regard to positive day-ahead forward premiums in the German and Austrian electricity markets. In addition, Bunn and Chen (2013) find day-ahead forward premiums to be positive (negative) during peak (off-peak) hours in the British electricity market; however, they find that month-ahead forward premiums have strong seasonality, being positive in winter and negative in summer for both peak and off-peak hours. Redl *et al* (2009) find the positive forward premiums for monthly delivery periods in the European Energy Exchange (EEX) and Nord Pool markets for month-ahead contracts.

Cartea and Villaplana (2008) find that the forward premium is conditional on the seasons in the PJM, English and Welsh, and Nord Pool markets. The forward premium is small, or even negative, during months of low demand volatility, and positive during months of high demand volatility.

Benth *et al* (2008) argue and find that the existence of forward premiums in the German electricity market is related to market participants' desire to hedge their positions. While producers are more willing to undertake long-term hedges, consumers prefer short-term hedges. This makes the forward premium time dependent and causes it to change sign. Huisman and Kilic (2012) show that forward premiums are related to the type of electricity supply (or storage possibilities of fuel) in the market. They find that time-varying risk premiums only exist in markets with nearly perfect fuel storability (fossils), that is, they do not exist in markets with imperfect fuel storability (hydro). In both markets, however, the futures prices contain information about future changes in spot prices.

Redl and Bunn (2013) exploit multifactor analysis to evaluate the components of forward premiums in the EEX market. They find that several components affect forward premiums in this market during the base load phase. These components are, for instance, daily variations on spot electricity and Brent prices, the realized ratio of generation and consumption, and the basis (the forward premium from the previous delivery month) and shift in supply/demand balance during the delivery month. During the peak load phase, gas forward premiums also affect electricity forward premiums. In fact, Redl *et al* (2009) find supporting results that year-ahead generation costs and spot market prices affect futures prices in the EEX and Nord Pool markets.

2.2 Short- versus long-term electricity forward prices

Kristiansen (2007) extends the literature related to forward premiums to the price difference between derivative contracts with different maturities, arguing that "in an efficient forward market the price of a seasonal forward contract should equal the time-weighted average of the underlying monthly forward contracts". By constructing synthetic seasonal forward contracts in the Nord Pool, and by using underlying monthly forward contracts for summer and winter in both 2003 and 2004, Kristiansen (2007) finds price differences, which are especially large in winter 2003. The same author also constructs synthetic yearly forward contracts from seasonal forward contracts for the respective year. In this case, Kristiansen (2007) again finds some price differences, but with a lower magnitude.

Wimschulte (2010) continues and extends the study of Kristiansen (2007) and analyzes price differences between short- and long-term derivative contracts in the Nord Pool market from 2003 to 2008. Wimschulte (2010) constructs synthetic monthly forward contracts from daily and weekly futures contracts. Although Wimschulte (2010) finds evidence of some price differences, the results are not statistically significant after transaction costs have been taken into account. Wimschulte's findings slightly contradict those of Kristiansen (2007). However, this demonstrates that pricing in the Nord Pool market might have become more accurate over time.

A study by Frestad (2012) is also closely related to price differences in the Nord Pool between derivative contracts with different maturities. Frestad finds that using delivery period mismatched hedging instruments with higher liquidity can overcome the loss of hedging effectiveness.

2.3 Options on electricity futures

At the moment, the empirical analysis related to the valuation of options on electricity futures contracts is a relatively uncovered topic. Where some studies discuss the electricity option contracts on spot electricity prices (see, for example, Deng and Oren 2006; Oum *et al* 2006; Oum and Oren 2009, 2010; Pineda and Conejo 2012; Boroumand *et al* 2015), only a few focus on option contracts on electricity futures/forward contracts. For example, Weron (2008) finds that by utilizing the market price of risk inferred from the more-liquid futures contracts, Asian-style options could efficiently be written on spot electricity prices. Also, those few studies that do focus on option contracts on electricity futures/forward contracts are mainly from a theoretical perspective.

Benth and Schmeck (2014a) go further and propose a model whereby they use different probability measures to price futures contracts in the electricity market, and different probability measures to price option contracts on those futures contracts. They find that if option contracts are priced with the probability measure derived from futures contract markets, it leads to mispricing. However, they did not suggest any specific probability measure for option contracts at present. In their study, Benth and Schmeck (2014b) prove the Black-76 pricing model can also be utilized when pricing electricity options on electricity futures contracts. In recent studies by Benth and Detering (2015) and Schmeck (2016), the authors propose alternative pricing methods for options contracts on futures/forwards in energy markets.

In a study by Zhang and Zhou (2004), the authors discuss and demonstrate the theoretical payoffs from different option strategies on electricity forwards in China. They conclude that forward options offer more potential payoff patterns for market participants, play an important role in risk reducing and strengthen the stability of the market. They suggest that option-type instruments will play an important role in future electricity markets.

2.4 Summary of earlier findings

Most of the previous studies related to financial electricity markets generally focus on the existence of forward premiums. Several studies find that forward premiums do exist in the financial electricity market in a global setup. Moreover, some of the studies report that the forward premium is conditional on the season, time of day or holding period. Some studies also report that price differences exist between short- and long-term forward contracts.

However, a new body of literature is emerging: the pricing of option contracts on electricity futures contracts. These studies focus on how to price option contracts on electricity futures from a more theoretical perspective.

3 DATA AND METHODOLOGY

The financial electricity market data used in this study was obtained from the Nord Pool and Nasdaq OMX Commodities Europe financial markets. The data set consists of 8997 daily closing prices for the quarterly call and put option contracts as well as closing prices for the corresponding futures contracts. The selection of call and put option contracts is made so that they represent 5% in-the-money (ITM), at-the-money (ATM) and 5% out-of-the-money (OTM) moneyness levels. The sample period is from April 21, 2005 to December 9, 2011. The underlying quarterly contracts cover the delivery period 2006 Q1–2012 Q1: twenty-five different quarters in total. The quarterly futures and option contracts are chosen for their liquidity and their ability to capture seasonal effects. In addition, the chosen period contains quarters with increasing and decreasing electricity prices. A more detailed description of option contract liquidity and volumes on the Nasdaq OMX commodities Europe financial market is provided by Nikkinen and Rothovius (2018).

Table 1 reports the descriptive statistics. The mean (median) futures price for the sample period is 46.26 (46.20) €/MWh, with a maximum (minimum) price of 84.73 (22.89) €/MWh. For the sample period, the average (median) value of all call options is 5.33 (4.16) €/MWh. For all of the put options, the corresponding value is 4.72 (3.34) €/MWh. For the sample period, the average (median) strike price for all call options is 45.68 (47.00) €/MWh, and for all put options it is 45.64 (47.00) €/MWh.

The formation of dynamic delta option strategies in this paper closely follows the methodology and model introduced by both Black and Scholes (1972) and Galai (1977). The purpose of this model is to identify if the option contract in question is overvalued or undervalued. If a significant positive profit can be made by buying (shorting) the option contract, the result suggests that the option contract is undervalued (overvalued). The model is expressed as follows:

$$(\Delta C - C_v \Delta V) - (C - C_v V) r \Delta t, \tag{3.1}$$

where ΔC is the change in option value, C_v is the delta value of the underlying asset, and ΔV is the change in value of the underlying asset. $C_v V$ gives the number

TABLE 1 Descriptive statistics of daily option and futures contract prices.

	Futures price	Call Price	Call Strike	Put Price	Put Strike
Mean	46.26	5.33	45.68	4.72	45.64
Median	46.20	4.16	47.00	3.34	47.00
Standard deviation	10.89	4.80	10.07	4.78	10.02
Minimum	22.89	0.01	29.00	0.01	29.00
Maximum	84.73	31.63	73.00	30.21	73.00
Skewness	0.55	1.55	0.42	1.91	0.42
Kurtosis	3.23	5.87	2.59	7.49	2.61
Number of observations	8997	8997	8997	8997	8997

The descriptive statistics for the option and futures contracts used in this study. "Futures" are quarterly futures contracts traded in the Nasdaq OMX Commodities Europe financial market. "Call" and "Put" are quarterly option contracts (with different levels of moneyness: 5% ITM, ATM and 5% OTM) that are traded in the same market. The underlying asset of quarterly option contracts is the previously mentioned quarterly futures contract. "Price" represents the daily closing prices for a given contract. "Strike" is the strike price of quarterly option contracts. We used daily data, measured in €/MWh, from April 21, 2005 to December 9, 2011.

of underlying assets needed to achieve a complete hedge, Δt is the time interval and r is the interest rate. The option position is maintained throughout the life of the option.

As can be seen from (3.1), the purpose of the equation is to maintain the delta neutrality over time and on every single day. The underlying asset V is bought or sold each day, depending on the change in C_v, so that the delta neutrality can be maintained. This process is repeated each day until the maturity day of the option contract. On the maturity day, the positions are liquidated so the dollar return can be calculated (see, for example, Black and Scholes 1972; Galai 1977).

In this paper, the dynamic delta option strategy is carried out by writing (buying) a call (put) option and simultaneously shorting an underlying quarterly futures contract. The positions are opened approximately six months before maturity, or the closest possible trading day. The delta value of the option contract at the time of opening the positions is used as a proxy for what percentage of the position is done with the option contract, and the remainder is done with the quarterly futures contract in such a way that their joint delta value equals the delta value of the futures contract. Due to the time-varying delta values of the option position, the underlying quarterly futures contracts are traded on a daily basis to keep the joint delta position fixed at the end of each trading day. The trading costs of 0.0045 €/MWh per traded quarterly futures contract are taken into account (Nasdaq Commodities Europe 2018b). The positions are held until maturity, when the position values from the two different strategies are compared (measured in €/MWh).

The dynamic delta option strategies with both call and put are constructed using a different level of moneyness from option contracts: 5% ITM, ATM and 5% OTM. In our empirical analysis, various market states of electricity price are considered. Hence, the results are reviewed separately for quarters with increasing or decreasing electricity price. Also, due to the strong seasonality of electricity prices, the empirical analysis takes winter and summer periods into account.

We follow the idea of Fama and French (1987) by first testing the price differences between the static futures strategy and the dynamic delta option strategies with the following paired difference test:

$$E[\text{Futures Price}_t - \text{Option Strategy Price}_t] = 0, \tag{3.2}$$

where Futures Price$_t$ is the hedging price achieved using the static futures strategy for a given time period t. Option Strategy Price$_t$ is the hedging price achieved using the dynamic delta option strategy for a given time period t.

Second, a nonzero "pricing error" for different dynamic delta option strategies is tested for seasonality (see Fama and French 1987) by applying the following model:

$$\text{Futures Price}_t - \text{Option Strategy Price}_t = \beta_0 + \beta_1 \text{Dummy}_{k,t} + e_t, \tag{3.3}$$

where Dummy$_{k,t}$ defines a set of dummy variables k ("Down", "Up", "Winter" and "Summer") for a given time period t. "Down" is a dummy variable for the quarters with decreasing electricity price. "Up" is a dummy variable for the quarters with increasing electricity price. "Winter" is a dummy variable for winter quarters (the first and fourth quarters of the year). "Summer" is a dummy variable for summer quarters (the second and third quarters of the year). Winter and summer dummies are used to capture seasonal effects.[1]

A similar test is also carried out using panel data, set up across different levels of moneyness, for dynamic delta option strategies with call and put options, separately.

4 RESULTS

4.1 Summary statistics for the strategies

Table 2 presents the summary statistics for the dynamic delta option strategies and the static futures strategy, which is viewed as a benchmark strategy.

On average, the electricity price achieved at maturity from the static futures strategy is 45.63 €/MWh. For a dynamic delta option strategy that uses call options, the

[1] Seasonality in electricity price can be observed, for example, when comparing the average price from the static futures strategy during the winter quarters (49.70 €/MWh) with the average price from the static futures strategy during the summer quarters (41.22 €/MWh). These results are not reported in this study but are available upon request.

TABLE 2 Summary statistics of dynamic delta option strategies and static futures strategy.

		(a) Call options			(b) Put options		
	Futures	**5% OTM**	**ATM**	**5% ITM**	**5% OTM**	**ATM**	**5% ITM**
Mean	45.63	45.80	45.60	45.67	44.92	44.92	45.05
Median	47.20	45.72	44.92	44.83	44.53	44.12	44.22
SD	10.02	9.81	9.89	9.91	10.45	10.69	10.83
Maximum	71.25	67.64	68.69	68.87	72.94	73.30	72.45
Minimum	30.73	29.65	29.66	29.93	30.74	30.91	30.96

The descriptive statistics for the dynamic delta option strategies and static futures strategy, measured in €/MWh. In panel (a), the dynamic delta option strategy uses call options, while in panel (b) it uses put options. SD stands for standard deviation. There are twenty-five quarters, and the estimation period is from Q1 2006 to Q1 2012, totaling seventy-five trajectories for the dynamic strategies with both call and put options.

comparable electricity prices achieved range from 45.60 €/MWh to 45.80 €/MWh, depending on the level of moneyness used. For a dynamic delta option strategy that uses put options, the average electricity prices achieved are slightly lower and range from 44.92 €/MWh to 45.05 €/MWh, depending on the level of moneyness used.

The electricity price achieved via the dynamic delta option strategy with call options equates to the electricity price achieved via the static futures strategy. Meanwhile, the electricity price achieved via the dynamic delta option strategy with put options is lower on average than that achieved via the static futures strategy or via the dynamic delta option strategy with call options.

The standard deviation of achieved electricity price is lowest for the dynamic delta option strategy that uses call options, while it is highest for the dynamic delta option strategy that uses put options. The dynamic delta option strategy that uses put options has the highest maximum and minimum achieved electricity prices, whereas the strategy that uses call options has the lowest maximum and minimum achieved electricity prices. The static futures strategy is between these two. Hence, from a naive perspective, the dynamic delta option strategy with call options can be considered a lower-risk strategy, while that with put options can be considered a higher-risk strategy.

4.2 Univariate analysis

To statistically test the price differential between the dynamic delta option strategies and the static futures strategy (see (3.2)), paired difference tests are carried out. Table 3 presents the results from these tests. The results indicate that there are no statistically significant price differences between the dynamic delta option strategy that uses call options and the static futures strategy when all quarters are considered.

TABLE 3 Paired difference test between dynamic delta option strategies and static futures strategy.

	Call options	Put options
All quarters ($N = 75$)		
Mean	−0.06	**0.66*****
Median	0.44	**0.41*****
Up ($N = 39$)		
Mean	0.14	**0.85*****
Median	0.52	**0.54*****
Down ($N = 36$)		
Mean	−0.27	0.47
Median	−0.11	0.28
Winter ($N = 39$)		
Mean	**–0.68****	**1.23*****
Median	**–0.58***	**1.48*****
Summer ($N = 36$)		
Mean	**0.62*****	0.05
Median	**0.71*****	0.04

The results from paired difference tests between the dynamic delta option strategies and static futures strategy of the following model:

$$E[\text{Futures Price}_t - \text{Option Strategy Price}_t] = 0.$$

The dynamic delta option strategy uses either call or put options. The estimation period is from Q1 2006 to Q1 2012. Both panels are divided into five different subsections representing different electricity price market environments, where N refers to the number of observations. "Up" are quarters with increasing electricity price. "Down" are quarters with decreasing electricity price. The winter period consists of Q1 and Q4, while the summer period consists of Q2 and Q3. The statistical significance of the mean difference is tested using a t test, and a Wilcoxon signed-rank test is used to test the median difference. The measurement is €/MWh. *, ** and *** represent statistical significance at the 0.1, 0.05 and 0.01 levels, respectively.

A similar conclusion can also be made when quarters with increasing or decreasing electricity price are being taken into account separately. However, statistically significant price differences are found when we focus on seasonality effects. The price difference is negative for winter quarters and positive for summer quarters. That indicates the dynamic delta option strategy that uses call options performs better (worse) than the static futures strategy during the winter (summer) quarters.

For the dynamic delta option strategy with put options, the reported price difference is positive and statistically significant when all quarters are considered. This indicates that the static futures strategy outperforms the dynamic delta option strategy with put options, on average. Also, when focusing on quarters with different electricity price changes, a positive and statistically significant price difference is found for quarters with increasing electricity price. In contrast, the price difference is not statistically significant for the quarters with decreasing electricity price.

TABLE 4 Multivariate analysis of the dynamic delta option strategies versus the static futures strategy.

(a) Call options

Intercept	Down	Winter	R^2	F-statistic
−0.06 (−0.30)			0.00	
0.14 (0.82)	−0.41 (−1.48)		0.00	0.79
0.62*** (2.80)		**−1.30***** (−3.61)	0.12	**5.00****
0.72*** (3.40)	−0.25 (−1.21)	**−1.27***** (−3.54)	0.11	**5.03****

(b) Put options

Intercept	Down	Winter	R^2	F-statistic
0.66*** (4.13)			0.00	
0.85*** (5.39)	−0.38 (−1.27)		0.00	**3.03***
0.05 (0.25)		**1.18***** (3.61)	0.12	**25.82*****
0.27 (1.24)	**−0.53**** (−2.03)	**1.24***** (4.00)	0.14	**9.45*****

Here we report the estimates from the following model:

$$(\text{Futures Price}_t - \text{Option Strategy Price}_t) = \beta_0 + \beta_1 \text{Dummy}_{k,t} + e_t,$$

where Futures Price$_t$ defines the hedging price achieved using the static futures strategy for a given time period t. Option Strategy Price$_t$ defines the hedging price achieved using the dynamic delta option strategy for a given time period t. Dummy$_{k,t}$ defines a set of dummy variables k ("Down" and "Winter") for a given time period t. "Down" is a dummy variable for quarters with decreasing electricity price. "Winter" is a dummy variable for winter futures contracts (the first and fourth quarter futures contracts). The number of observations is seventy-five in all regressions. "R^2" is the adjusted R-squared. "F-statistic" reports the F-statistic from the Wald test, which tests the null hypothesis that the estimated coefficients are jointly equal to zero. All standard errors are corrected for both heteroscedasticity and autocorrelation using the White diagonal method. *, ** and *** represent statistical significance at the 0.1, 0.05 and 0.01 levels, respectively.

In addition, seasonality effects are found for the dynamic delta option strategy with put options. As for the dynamic delta option strategy with call options, there is a statistically significant price difference for the dynamic delta option strategy with put options during the winter quarters. However, in contrast to the dynamic delta option strategy with call options, the price difference is now positive. This indicates that the static futures strategy outperforms the dynamic delta option strategy with put options during the winter quarters. For the summer quarters, no statistically significant price difference is found.

4.3 Multivariate analysis

Table 4 reports regression estimates from the model (see (3.3)) for the dynamic delta option strategy that uses call options. First, we find a statistically significant negative (positive) association between the winter (summer) quarters and the reported price differences.[2] Also, the results from the Wald test confirm that the null hypothesis about a zero price difference can be rejected at a 5% significance level for the winter and summer quarters separately.

All together, these results further support the earlier findings reported in Table 3, that is, the dynamic delta option strategy that uses call options outperforms (underperforms) the static futures strategy during the winter (summer) quarters. Moreover, some seasonality effects can be found in the reported price differences for the dynamic delta option strategies that use call options.

For the dynamic delta option strategy that uses put options, we find the reported price differences are positively (negatively) associated with the winter (summer) quarters with statistical significance.[3] However, the sign of the correlation is the opposite of that found for the dynamic delta option strategy that uses call options. We find when aggregating all the quarters that the reported price difference is positive and statistically significant. When focusing more on the seasonality of the reported price differences, we find the following. The results from the Wald test suggest that the expected price difference of zero for the summer quarters cannot be rejected. However, the results from the Wald test indicate that the this price difference can be rejected at a 1% significance level for the winter quarters. All together, these results further support the earlier findings reported in Table 3, that is, the dynamic delta option strategy that uses put options underperforms the static futures strategy during the winter quarters, but not during the summer quarters. Moreover, some seasonality effects can be found in the reported price differences for the dynamic delta option strategies that use put options.

We find there is no statistically significant support that quarters with increasing or decreasing electricity prices are generally associated with the reported price differences.

[2] The estimated coefficients using “Summer” and/or “Up” dummy variables are not reported in Table 4 but are available upon request.
[3] See previous footnote.

TABLE 5 Effects of moneyness on the dynamic delta option strategy with call options. [Table continues on next page.]

(a) 5% OTM

Intercept	Down	Winter	R^2	F-statistic
−0.17			0.00	
(−0.49)				
0.01	−0.38		0.01	0.54
(0.03)	(−0.79)			
0.30		−0.91	0.02	0.92
(0.73)		(−1.13)		
0.41	−0.28	−0.87	−0.02	1.04
(1.03)	(−0.60)	(−1.06)		

(b) ATM

Intercept	Down	Winter	R^2	F-statistic
0.03			0.00	
(0.10)				
0.12	−0.19		−0.04	0.01
(0.40)	(−0.34)			
0.72**		**−1.32****	0.11	1.47
(2.16)		(−2.50)		
0.73*	−0.03	**−1.31****	0.07	0.97
(1.98)	(−0.07)	(−2.52)		

4.4 Multivariate analysis and moneyness levels

Table 5 reports regression estimates that are also from the model (see (3.3)); however, it focuses more on the performance related to the different moneyness levels used in the dynamic delta option strategy with call options.

For the dynamic delta option strategy that uses call options, we find the winter (summer) quarters are negatively (positively) associated with the price differences, except for the OTM moneyness level.[4] Results from the Wald test suggest that the reported price difference for the winter quarters does not differ from zero with statistical significance. On the contrary, the results from the Wald test indicate that the reported price difference is positive and statistically significant for the summer quarters when the dynamic delta option strategy uses ATM and ITM moneyness levels for option contracts.

[4] The estimated coefficients using "Summer" and/or "Up" dummy variables are not reported in Table 5 but are available upon request.

TABLE 5 Continued.

(c) 5% ITM

Intercept	Down	Winter	R^2	F-statistic
−0.04 (−0.09)			0.00	
0.28 (0.96)	−0.65 (−1.07)		−0.01	0.33
0.84** (2.59)		**−1.68**** (−2.73)	0.15	1.87
1.03** (2.65)	−0.46 (−1.01)	**−1.62**** (−2.72)	0.13	1.86

Here we report the estimates from the following model:

$$(\text{Futures Price}_t - \text{Option Strategy Price}_t) = \beta_0 + \beta_1 \text{Dummy}_{k,t} + e_t,$$

where Futures Price$_t$ defines the hedging price achieved using the static futures strategy for a given time period t. Option Strategy Price$_t$ defines the hedging price achieved using the dynamic delta option strategy with call options for a given time period t. Dummy$_{k,t}$ defines a set of dummy variables k ("Down" and "Winter") for a given time period t. "Down" is a dummy variable for the market state of decreasing electricity price. "Winter" is a dummy variable for winter futures contracts (the first and fourth quarter futures contracts). The number of observations is twenty-five. "R^2" is the adjusted R-squared. "F-statistic" reports the F-statistic from the Wald test, which tests the null hypothesis that the estimated coefficients are jointly equal to zero. Each panel represents a different moneyness level used in the dynamic delta option strategy. All standard errors are corrected for both heteroscedasticity and autocorrelation using the Newey–West method. *, ** and *** represent statistical significance at the 0.1, 0.05 and 0.01 levels, respectively.

These results further suggest that there is a seasonality effect in the price differences. Further still, they seem to be mainly driven by the dynamic delta option strategies that use ATM and ITM moneyness levels during the summer quarters. This then implies that the static futures strategy performs better during the summer quarters than the dynamic delta option strategy that uses call options with ATM or ITM moneyness levels. That, in turn, suggests the call options (ATM and ITM) might be relatively underpriced during the summer quarters since we are writing call options.

Table 6 also reports regression estimates from the model (see (3.3)), focusing on the performance related to the different moneyness levels used in the dynamic delta option strategy with put options.

For the dynamic delta option strategy with put options, we find that, generally, the winter (summer) quarters are positively (negatively) associated with the price differences with statistical significance.[5] First, the reported price difference is positive and statistically significant when aggregating across all quarters. Second, the results from the Wald test suggest that the price difference is positive and statistically significant

[5] The estimated coefficients using "Summer" and/or "Up" dummy variables are not reported in Table 6 but are available upon request.

TABLE 6 Effects of moneyness on the dynamic delta option strategy with put options.

(a) 5% OTM

Intercept	Down	Winter	R^2	F-statistic
0.71** (2.41)			0.00	
0.75** (2.77)	−0.09 (−0.17)		−0.04	1.71
−0.01 (−0.02)		**1.38**** (2.67)	0.19	**9.41*****
0.10 (0.28)	−0.26 (−0.63)	**1.41***** (2.83)	0.16	**4.43****

(b) ATM

Intercept	Down	Winter	R^2	F-statistic
0.71** (2.45)			0.00	
0.86*** (2.83)	−0.31 (−0.55)		−0.03	1.22
0.19 (0.59)		0.99 (1.66)	0.07	**5.89****
0.37 (0.93)	−0.43 (−0.83)	**1.05*** (1.87)	0.05	2.25

(c) 5% ITM

Intercept	Down	Winter	R^2	F-statistic
0.58* (1.85)			0.00	
0.93*** (3.16)	−0.73 (−1.14)		0.00	0.11
−0.03 (−0.06)		**1.16*** (1.82)	0.06	**6.01****
0.34 (0.91)	−0.89 (−1.43)	**1.27**** (2.12)	0.09	1.32

See Table 5 note for details.

for winter quarters for all moneyness levels. However, the results from the Wald test suggest that the reported price differences are not statistically significantly different from zero for the summer quarters for all moneyness levels.

These results indicate the static future strategy performs better in all quarters, on average, than the dynamic delta option strategy that uses put options and is not so dependent on the moneyness levels used in the dynamic delta option strategy. The static futures strategy also outperforms the dynamic delta option strategy that uses put options during the winter quarters. This result is consistent across all moneyness levels. However, this is not the case for the summer quarters, where the price difference does not differ from zero with statistical significance. This result is also consistent across all moneyness levels.

Hence, these results support the previously reported findings of this study (see Tables 3 and 4) that the static futures strategy performs better during winter quarters than the dynamic delta option strategy with put options. However, the same cannot be said about the performance difference during summer quarters. In addition, there does not seem to be any cross-sectional variation depending on what level of moneyness is used in the dynamic delta option strategy with put options, which was the case for the dynamic delta option strategy with call options. These results may indicate that the put option contract is overpriced during the winter quarters. This overpricing could be due to two reasons. The first is the potentially high risk awareness of put option contract writers, since electricity prices are known to be highly volatile during the winter quarters in Nordic countries. To mitigate the risk of volatile electricity prices, put option contract writers want extra premiums. The second reason for this overpricing could be that there is a high demand for put option contracts for winter quarters, which then pushes the put option contract prices away from the equilibrium.

5 CONCLUSIONS

This paper examines how quarterly electricity option contracts traded in the Nasdaq OMX Commodities Europe financial market are priced compared with their corresponding futures contracts. The comparison is achieved by constructing two alternative strategies that share the same risk level (measured by delta). The first strategy is a dynamic delta option strategy. It combines a position on a short call (long put) option contract with a position on a short futures contract. The second strategy is a static futures strategy, where only a position on a short futures contract is held. The risk level of the dynamic delta option strategy is adjusted on a daily basis (due to the time-varying delta of the option contract) by trading the option contract's underlying asset, the futures contract. Hence, the risk level of the dynamic delta option strategy is able to be compared with the static futures strategy on a daily basis. Thus, we can directly calculate the price difference between the dynamic delta option strategy and the static futures strategy. In theory, both strategies should yield the same outcome (a zero price difference), since their risk levels are the same. If a nonzero pricing difference exists, it might offer an opportunity for practitioners to create a profitable trading strategy.

The results from the empirical part of our paper suggest that some price differences and seasonality do exist. For the dynamic delta option strategy with call options, the reported price difference is positive and statistically significant during the summer quarters (the second and third quarters of a given year). This result indicates that the static futures strategy performs better during the summer quarters than the dynamic delta option strategy with call options. In contrast, the reported price difference is negative and statistically significant during the winter quarters. This then implies that the dynamic delta option strategy that uses call options outperforms the static futures strategy during the winter quarters. These results, in turn, may imply the call options are relatively underpriced (overpriced) during the summer (winter) quarters, since in this scenario the dynamic delta option strategy writes call options. The possible reasons for this underpricing (overpricing) may come from two sources. The first is the low (high) risk awareness of call option contract writers during the summer (winter) quarters, especially since electricity prices are known to be highly volatile during winter quarters in the Nordic countries and less volatile during summer quarters. To mitigate the risk of volatile electricity prices, call option contract writers want extra premiums. The second source is the potentially high (low) demand for call option contracts in winter (summer) quarters, which then pushes the call option contract prices away from the equilibrium price.

For the dynamic delta option strategy with put options, statistically significant price differences and seasonality are found. First, the price difference is positive and statistically significant on average in all quarters. Also, the positive price difference is relatively large during the winter quarters. Second, the price difference is positive and statistically significant during the winter quarters. This indicates that the static futures strategy outperforms the dynamic delta option strategy with put options during the winter quarters. However, no statistically significant price difference is found during the summer quarters. These results might imply that put options are relatively overpriced during the winter quarters, since the dynamic delta option strategy is buying put options.

In addition, it seems that the seasonal variation is more influential for the dynamic delta option strategy that uses call options than it is for the dynamic delta option strategy that uses put options.

We find no statistically significant and universally consistent evidence that the electricity price trends (ie, quarters with increasing or decreasing electricity prices) are related to the reported price differences.

We also find some cross-sectional variation in the reported price differences when analyzing the level of moneyness used in the dynamic delta option strategies that use call options. The results seem to mainly be driven by the performance of the dynamic delta option strategy that uses call options with ATM and OTM moneyness levels. No similar conclusion can be made for the dynamic delta option strategy that uses put options.

The reported findings suggest that the producers and consumers who are net sellers of electricity and want to reduce electricity price risk during the winter quarters should utilize the dynamic delta option strategy with call options. For the summer quarters, however, they should utilize the static futures strategy.

The reported price differences between the static futures strategy and the dynamic delta option strategy in the Nasdaq OMX Europe commodities are partially consistent with the findings of Botterud *et al* (2010), Gjolberg and Brattested (2011), Lucia and Torró (2011) and Weron and Zator (2014), who report that price differences exist between forward/futures contracts and spot electricity prices in the Nordic region.

The reported price differences between the static futures strategy and the dynamic delta option strategy are also partially consistent with the findings of Kristiansen (2007), Wimschulte (2010) and Frestad (2012), who report that price differences exist between forward/futures contracts with different maturities in the Nordic financial electricity market.

Finally, the reported seasonal patterns in the price differences are consistent with the reported findings of Gjolberg and Brattested (2011) and Lucia and Torró (2011). The results of this paper could also potentially explain those reported by Sanda *et al* (2013), who document that Norwegian hydro-based electricity producers use option contracts as hedging instruments relatively rarely.

DECLARATION OF INTEREST

The author reports no conflicts of interest. The author alone is responsible for the content and writing of the paper.

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