Is There a Bubble in the Sky?

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Abstract

Cloud computing allows the delivery of computing services in an on-demand fashion over Internet, taking the form of software or storage. The growing use of Cloud computing in our daily lives bears striking resemblance to the spread of Internet before the Internet bubble, which leads to an itching question: is there (going to be) a Cloud bubble?

Using the similarities between Internet stocks during the Internet bubble and current Cloud stocks, the established causes behind the Internet bubble are applied to the firms in the ISE Cloud Computing Index.

In addition to two conventional measures of market sentiment: P/E and M/B ratios, I also examine first-day returns and Google SVI in search of retail investor hype, and price targets for analyst hype. Following the literature, short-sales constraints are also analysed for the sample of Cloud firms to shed light on the possibility of a new bubble, a Cloud bubble.

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Lastly, and most importantly, I would like to thank each reader for taking the time and interest to view my work. Regardless of the purpose behind reading this paper, I would love nothing more than for the reader to enjoy this story of the Cloud as much as I enjoyed telling it.

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1. Introduction

When you use instant messaging or play games on Facebook you are in the Cloud. When you stream videos from YouTube you are in the Cloud. When you collaborate with colleagues on a project on Google Docs, you are in the Cloud. Even when you upload a file to any online storage, you are in the Cloud. It is clear that Cloud services are everywhere, even extending beyond our personal lives – with more than 500 million active users of Facebook[1], 2 billion views on YouTube per day (Kincaid, 2010) – to businesses. Savvas (2011) asserts that 80% of businesses use Cloud services at least in some of their IT systems. According to some, the firms providing these services represent a mere tip of the iceberg of rapidly growing numbers of Cloud firms to come.

1.1. The Cloud

So what is the Cloud? Cloud services or Cloud computing refers to delivery of data or software via a computer network, most commonly over Internet. A useful analogy to the role played by the Cloud is to think of how utility providers replaced the need for water pumps and power generators. Similar to how water and power are now delivered on demand by utility providers, Cloud service providers seek to rid the need to install software or store data on a physical hard drive by delivering services over Internet. Examples of such computing needs include word processing, video streaming and data storage. Such tasks are done through services provided by Cloud firms that allow any computer connected to Internet to have access to the same software and files. By doing this, Cloud firms, as providers of these computational resources, are quickly growing towards becoming necessities.

1.2. Selecting Cloud Firms

One of the first obstacles of this study is to define what a Cloud firm is. Beyond the fact

[1] http://www.facebook.com/press/info.php?statistics

that it is a firm that provides Cloud computing services, even the definition of what constitutes a Cloud service is ambiguous. Take Facebook as an example. It does not provide use of installed software over Internet yet it clearly provides alternatives to some software that would require installation, with the most prominent example being games. Additionally, it provides an online space for its users to share and store their photos, but the limitation of only being able to store pictures makes its status of being a Cloud firm debatable. In relation to this issue, a report[2] by Morgan Stanley, *Internet Trend,* suggests that Facebook has so many connections to other Cloud services that it could be described as a Cloud firm itself. These services include, as mentioned: photo sharing capabilities, instant messaging, games, and links to YouTube. However, Facebook's main service is to provide social networking, not Cloud services. Even among industry participants there is no consensus on which firms are indeed Cloud firms. Arguing against the claim by Savvas (2011) that more than 80% of businesses utilise the Cloud, a survey by the prominent security software firm, Symantec, suggests that less than 20% of firms have completed integration with the Cloud[3], indicating that the difficulty in defining Cloud firms is not one that is exclusive to this study. So, what *does* define a Cloud firm? Is there an objective way to select a sample of Cloud firms for the purposes of this study? Luckily, there is.

A set of firms is selected through comprehensive criteria (discussed in the data section) by the International Securities Exchange (ISE) in order to represent trends in the Cloud computing industry. The ISE Cloud Computing Index (ticker: CPQ) developed by the ISE, provides an ideal sample of Cloud firms. This set of 39 firms is referred to as 'Cloud Firms' in this thesis. Cloud Firms are selected by the ISE to allow investors to "quickly take

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[2] Source: http://www.morganstanley.com/institutional/techresearch/pdfs/Internet_Trends_041210.pdf

[3] Source:
http://www.symantec.com/en/uk/about/news/release/article.jsp?prid=20111004_02&om_ext_cid=biz_socmed_twitter_facebook_marketwire_linkedin_2011Sep_worldwide_stateofCloudsurvey

advantage of both event-driven news and long term economic trends as the market for Cloud computing technology continues to evolve"[4]. This purpose aligns well with the goals of my study, and provides me with an objective benchmark to answer the fundamental question: is there (going to be) a Cloud bubble?

Encouragingly, there are consistencies between the selection of Cloud Firms and stocks industry participants refer to as Cloud firms. For example, a market research report[5] by Renub Research, reviews providers of the Cloud: Amazon (AMZN), Salesforce.com (CRM), IBM (IBM), Oracle (ORCL) and Microsoft (MSFT). All these firms are also included in the ISE Cloud Computing Index (see Table 1). Additionally, a CNNMoney article (Lev-Ram, 2011) discusses the possibility of a Cloud bubble (as a note of interest, the writer believes it is too early to tell). Out of the 6 Cloud firms discussed, 5 are included in the Cloud Computing Index – Oracle, SAP (SAP), IBM, RightNow Technologies (RNOW), SuccessFactors (SFSF) – with the exception (DemandTec, DMAN), having been acquired by IBM. Moreover, the top companies mentioned in the media in relation to the term "cloud computing" according to Factiva also support the ISE's choice in the Cloud Index constituents. The 10 companies with the most frequent mentions of the term "cloud computing" are all in the Cloud Index as at 25/06/2012: Microsoft, IBM, HP (HPQ), Google (GOOG), Apple (AAPL), SAP, Amazon.com, Salesforce.com, Cisco (CSCO) and Oracle.

The next subsection establishes the connection between the Internet bubble and Cloud Firms, and why this connection is used to investigate the research topic of this paper. The subsequent subsection provides perspective on how fast the Cloud is growing. The final

[4] ISE Cloud Computing Index Methodology Guide available at: www.ise.com

[5] *Cloud Computing – SaaS, PaaS, IaaS Market, Mobile Cloud Computing, M&A, Investments, and Future Forecast, Worldwide* available at: http://www.reportlinker.com/p0293136-summary/Cloud-Computing-SaaS-PaaS-IaaS-Market-Mobile-Cloud-Computing-M-A-Investments-and-Future-Forecast-Worldwide.html

subsection of Section 1 describes the approach in connecting these stylised facts to investigate the possibility of a Cloud bubble.

1.3. Why the Internet Bubble?

With Cloud computing seeming to become omnipresent, a question may arise at this point on whether this situation is similar to the situation before the Internet bubble. Indeed, the motivation behind this study arises from that very bubble of the late 1990's. In the two year period from 1998 to 2000, the Internet bubble had a substantial impact on many investors with the Internet sector earning over 1,000% returns on its public equity. During the Internet bubble, many firms were able to sell their ideas to investors on the back of the dot-com concept. It is now widely accepted that the Internet bubble was driven by hype among retail investors, who saw how widespread Internet was becoming. The results of Cooper, Dimitrov, and Rau (2001) provide a good example of the hype behind the dot-com concept. The authors find that the dot-com effect produced permanent positive cumulative abnormal returns from simply announcing a name change (i.e. adding ".com" to names) to reflect the dot-com concept. For example, simple name changes led to an average of 53% excess return over the five-day period surrounding the name change announcement. As further support for the hype-driven bubble, in their examination of carve-outs, Lamont and Thaler (2003) find evidence to support hyped behaviour of investors purchasing technology stocks, even when those stocks could have been effectively acquired for less by purchasing stocks of their parent firms. The Cloud provides an interesting case in terms of potential creation of another bubble as it is clear to even retail investors that the Cloud is becoming widespread. In addition to hype as a potential driver in causing a new bubble, The Economist article suggests higher recent activity in the IPO market for Internet firms, with many providing Cloud services ("Welcome to IPOville," 2011).

The resemblance to the Internet bubble provides a starting point to look for signs of a new bubble. The literature on what caused the creation and burst of the Internet bubble is now relatively well-established and the similarities between Internet stocks behind the Internet bubble and Cloud stocks are striking. These similarities include the fact that both groups of firms consists of technology companies. The strong growth of Internet firms and the pervasiveness of Internet during the Internet bubble period are also similar to the current growth in Cloud services and Cloud firms.

The connection between the Internet bubble and the Cloud is not unique to this study. In a Business Insider article, Rosoff (2011) summarises the findings of an analysis done by UBS Investment Research, named *Are We in a Cloud Computing Bubble?* In this analysis, the top 40 most expensive technology stocks (presumably Cloud stocks) – based on forward P/E ratios, enterprise value to sales ratios and minimum market capitalisation of $500 million – are compared to the top 40 most expensive Internet stock during the peak of the dot-com bubble. They find more reasonable ratios for the Cloud firms than for Internet firms during the dot-com bubble. However, compared to the Internet bubble where growth seemed apparent for the whole sector, the growth in the Cloud industry is seen among only a few top performers, who seem to be bullish despite a down market in the technology industry. If this is true, this proposition has an interesting implication for investors in the Cloud. If growth is concentrated in the top few firms in the Cloud, a burst-like effect of a bubble will occur if those few firms cannot sustain their growth to meet expectations. This notion is supported by recent key acquisitions in the industry such as Oracle's acquisition of RightNow Technologies, SAP's acquisition of SuccessFactors and IBM's acquisition of DemandTec. These purchases could be viewed as the major players buying out smaller players who focus on the Cloud to sustain and meet growth expectations, or as a signal that the market is maturing. Either way, the concentration of growth among fewer companies suggests investors need to keep their eyes open for a potential bubble, which only amplifies the importance of the research question of this paper.

The motivation for this paper and its connection to the Internet bubble is best illustrated by a comparison between the two sets of trends shown in Figure 1 and 2. The former is constructed from equally weighted returns of Cloud Firms against the equally weighted S&P 500 and NASDAQ 100. In addition to these two benchmarks, the NASDAQ Computer Index (ticker: IXCO), which is classified by the Industry Classification Benchmark[6] to consist of technology stocks, is also added to represent the returns in the technology industry. Figure 2, a replica of Figure 1 in Ofek and Richardson (2003), on the other hand, depicts a comparison between Internet firms to benchmark indices during the Internet bubble period.

The Cloud trend in Figure 1 from late-2008 to 2011 is remarkably similar to the initial stages of the Internet bubble shown in Figure 2 from late-1998 to mid-1999, which provides support for applying suggested drivers of the Internet bubble to the Cloud. Furthermore, not only do the returns of Cloud Firms experience a series of positive shocks relative to the two benchmark indices, Cloud Firms from late-2008 onwards seem to be consistently earning considerably more positive returns over and above the technology industry which is represented by the NASDAQ Computer Index. This is surprising considering the close integration the Cloud industry has with the rest of the computing and technology industry. However, the observation may be easier to swallow if forecasts such as IDC's – that 46% of the incremental IT spending growth in 2015 will be due to public IT Cloud services growth[7] – are to be believed.

[6] The NASDAQ Computer Index includes securities of NASDAQ-listed companies classified according to the Industry Classification Benchmark (ICB) as Technology excluding Telecommunications Equipment.

[7] The report can be obtained from: http://www.idc.com/getdoc.jsp?containerId=228485 and its press release can be found at: http://www.idc.com/getdoc.jsp?containerId=prUS22897311

While the representative Cloud Firms have been rising above other representative benchmarks in recent periods, it would be rash to assume that the Cloud would continually follow the pattern of the Internet bubble. A bubble occurs when the financial value of firms diverge above the economic value (Mills, 2002), but if the economic value rises along with the prices, the trend observed in Figure 1 would point towards genuine (possibly sustainable) growth in the industry.

In addition to the bubble-like shape of the Cloud returns, the number of searches on Google, depicted as a graph over time in Figure 3, is also a good indication of investor interest. Da, Engelberg, and Gao (2011) believe that the Google SVI (search volume index) represents retail investor attention (this is followed in further detail in later sections). The upper part of the graph shows the number of searches of the term "cloud computing" on Google over time, scaled by the time-series average value from beginning of 2004 to 14 June 2012. The lower panel shows the number of times "cloud computing" was mentioned on Google News (not scaled)[8]. According to both measures, the interest for Cloud computing builds up during 2007, and the SVI measure suggests a clear increase in retail interest for information on Cloud computing.

1.4. The Growing Cloud

Pervasive use and rapid growth of Cloud computing in a manner similar to Internet before the Internet bubble gives rise to the suspicion of another bubble, and the similarity also justifies my approach to follow the Internet bubble literature. Before this study delves into the evidence of a Cloud bubble, however, further supporting evidence for the significance and potential of the Cloud is established to provide a clearer picture of where Cloud computing currently stands and how widespread it has become.

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[8] Data on news reference volume from Google Trends is limited to the graph plotted in Figure 3. Detailed spreadsheet output on news volume is not available.

Evidence on the resemblance between the Internet bubble and the Cloud industry's rapid growth can be found in many financial forecast reports. In his summary of the *IDC Cloud Services Forecast*, Gens (2010) outlines that spending on worldwide Cloud services will grow to $55.5 billion by 2013 compared to $16.5 billion observed in 2009, and will constitute around 12% of the total IT spending in 2014 from 4% observed in 2009[9]. Such growth resembles the growth of Internet services during the Internet bubble, where the number of users using Internet services grew from 70 million in December 1997 to 248 million by March 2000 (Internet World Stats[10]). Furthermore, Cloud services are heavily web dependent. Internet can therefore be thought of as a stepping stone on which Cloud computing bases its rapid growth. Gobry (2011)'s Business Insider article claims that the Internet sector accounted for 20% of economic growth over the past 5 years, suggesting that the stepping stone is growing taller, further fuelling momentum behind the growth of the Cloud.

The reach of Cloud computing extends beyond several boundaries. First, it extends beyond the boundaries of a desktop computer. While Cloud computing is indeed computing by nature, this does not mean that it is only accessible through a traditional desktop computer. Being relatively new technology, most Cloud services extend to laptops, netbooks, tablet computers and smartphones. With the recent trend in such mobile devices becoming more common, it is not difficult to see the potential growth of Cloud services that is yet to be observed. Second, despite the leading companies providing Cloud services being U.S. firms, hype about Cloud computing extends to Eastern countries as well. Third, participation in the competition of providing the Cloud reaches beyond corporate level to government level. Prominent examples of the last two points mentioned are China and Korea. Baidu is a well-

[9] Report available at: http://www.idc.com/getdoc.jsp?containerId=prUS22393210. If expired, summary can be found at http://blogs.idc.com/ie/?p=922

[10] Source: http://www.Internetworldstats.com/emarketing.htm

known Cloud service in China offering on-demand searches, maps, anti-virus service, and a desktop system which allows users to access files on online. In many ways it is the Chinese equivalent of Google (although Google is offered in China, it ranks second after Baidu as a search engine), and recognising the importance of these Cloud services, the Chinese government is working with the firm to protect its users from hackers (Tang & Lee, 2011). In Korea, a more direct approach is used to compete in the growing industry. The Korean government is supporting Samsung and LG to develop its own Cloud OS (operating system) to compete in the field of ever growing Clouds (Gabriel, 2011). Kim Jae-Hong, the deputy minister of the Ministry of Knowledge Economy in Korea, mentions their goals quite explicitly: “We will forge ahead in developing a new kind of operating system, which is being seen as a next generation product, in order to build the kind of advantage we do not enjoy in the market for smartphones and tablet PCs, which is dominated by Google and Apple”. The active participation in the Cloud industry by the governments is a good illustration of how big Cloud computing has already become. It also implies that Cloud computing is more than a short-term fashionable hype.

1.5. The Approach

For the majority of this study, various aspects of Cloud Firms are compared against two sets of size-matched non-Cloud firms. One consists of firms from the technology industry (referred to as ‘Tech Firms’ for the remainder of this paper) and the other consists of simple size-matched firms regardless of industry (‘Non-tech Firms’). The rationale behind having two sets of matched samples is to distinguish the characteristics of being a Cloud firm from those of being a technology firm. For example, if Cloud Firms had significantly higher first-day returns, it may be driven by retail investor hype about Cloud stocks, but it may just as likely be driven by hype about technology stocks in general. By adding the sample of technology firms, trends in the general technology industry and trends unique to the Cloud industry can be observed separately.

1.5.1. Investor Sentiment

As discussed, a bubble occurs when financial value of firms diverges above economic value. In order for this to happen, optimistic investors are necessary to drive up prices (i.e. investor sentiment must be high). Accordingly, establishing investor hype is the first step in testing the possibility of a Cloud bubble. As preliminary insight into market (investor) sentiment for Cloud Firms, price-to-earnings and market-to-book ratios are examined. In addition to these preliminary measures, several other analyses are conducted to test for hype.

Ofek and Richardson (2003) look at first-day returns after IPOs as a way to measure a shift in investor clientele towards Internet firms. That is, a shift in the preferences of optimistic (and likely retail) investors, who drive up prices. Their rationale can be summarised to three points. First, the first day after an IPO is the first chance for the public (largely retail investors) to buy shares in a company (Ljungqvist, Nanda, & Singh, 2002). Second, it leads to significant increases in volume, representing new entries to the market as reported in Bradley, Jordan, and Ritter (2003). Lastly, the first day after an IPO is associated with large price responses according to Loughran and Ritter (2001). Following their reasoning, first-day returns of Cloud Firms and non-Cloud firms are compared to test for hype about the Cloud.

Da et al. (2011) report a creative way to measure retail investor attention (and thus, hype) more directly. Google SVI refers to the search volume index, representing aggregate search frequencies on Google. Some Internet users use search engines to gather financial information, and as the leading search engine with around 84% global market share[11], search

[11] Source: Net Market Share (http://marketshare.hitslink.com/search-engine-market-share.aspx?qprid=4) as at February 2012.

frequency data on Google provides a rich source of data in terms of what the authors argue to be a direct measure of investor attention. They argue that the searches for stocks on Google are likely to be retail investors as opposed to more sophisticated institutional investors who are likely to use more comprehensive financial information services (e.g. Reuters or Bloomberg). Using a sample of Russell 3000 stocks from 2004 to 2008, they present evidence to support a strong relationship between SVI changes and trading by retail investors. Specifically, they find that on average, 1% increase in the level of SVI leads to 0.62% increase in individual (retail) orders[12] for shares and 0.7% increase in individual turnover. Both relationships are found to be statistically significant at the 1% level (standard errors of 0.015 for both relationships). Furthermore, the authors find increasing SVI level during an IPO contributes to a large first-day return which fits well with our first-day return analysis. Accordingly, SVI is utilised in a comparison between Cloud and non-Cloud firms as a measure of retail investor hype.

Extending tests for hype beyond retail investors, analyst expectations are also examined as a measure of sentiment. It is possible that analysts are able to observe factors (e.g. true growth prospects) not observed by retail investors. In the Internet bubble literature, the rise in the bubble was not only attributed to retail investors, but also to institutional investors (Brunnermeier & Nagel, 2004; Greenwood & Nagel, 2009; Hong, Scheinkman, & Xiong, 2008). Unlike investor sentiment, optimism among analysts can be observed directly from various forecasts they issue, which the market reacts to. In particular, Asquith, Mikhail, and Au (2005) find, using analyst reports during 1997 to 1999, that the market reacts strongly to price targets and earnings forecasts. Market reaction, measured by the five-day market adjusted cumulative abnormal returns centred on the release date of reports, is regressed with changes in price targets. The coefficient is 0.3191, which is highly significant (t-statistic of

[12] Obtained from SEC Rule 11Ac1-5 (Dash-5) reports.

9.34). For earnings forecasts, the authors report a coefficient of 0.0545 (t-statistic of 2.81). Since price and earnings forecasts represent analysts' expectations, and because the market strongly reacts to their expectations, examination of these measures provides a valid method of determining whether analyst hype contributes to a bubble.

1.5.2. Short-Sales Constraints

Arguably the most documented cause behind the Internet bubble is short-sales constraints (Bris, Goetzmann, & Zhu, 2007; Chang, Cheng, & Yu, 2007; Haruvy & Noussair, 2006; Hong, Scheinkman, & Xiong, 2006; Hong & Stein, 2003; Ofek & Richardson, 2003). Based on the assumption of differences of investor opinion (Hong & Stein, 2007), the role of short-sales constraints in causing bubbles can be explained by the views of pessimistic investors not being reflected in prices as a result of being restricted in selling stocks short. This limits downward pressure on prices, leaving prices to reflect the views of more optimistic investors. Following this explanation, differences of opinion and short-sales constraint measures are explored for Cloud Firms. Specifically, the measures of short-sales constraints are percentage of shares outstanding available for short-selling, percentage of shares outstanding actually sold short, utilisation of the available lendable shares and cost of short-selling (rebate rates). If the Cloud industry is a mirror image of the Internet bubble, differences of opinion and constraints on short-selling on Cloud stocks are expected to be more severe relative to non-Cloud stocks.

1.5.3. Summary of the Approach

In sum, this study provides evidence on the likelihood of a Cloud bubble by following selective causes behind the Internet bubble suggested in the literature. The evidence is likely to point towards one of two possible explanations for the bubble-like phenomenon in Figure 1. The considerably more positive returns of Cloud Firms is due to either: 1) a combination of heterogeneous expectation among investors (Hong & Stein, 2007), high investor sentiment

(Baker & Wurgler, 2006) and short-sales restrictions (Ofek & Richardson, 2003), or 2) the market consistently being positively surprised, reflecting genuine growth in the industry.

The remainder of the study is organised as follows. Section 2 reviews the literature on the Internet bubble, summarising the theoretical framework and empirical evidence. Section 3 describes the data, and discusses Cloud Firms and its matched peers. Section 4 explains the research and presents the results, and Section 5 concludes.

2. Literature Review

Anecdotal evidence on the similarities to the Internet bubble such as rapid growth of the Cloud industry, pervasiveness of Cloud services and potential hype among retail investors on Cloud stocks provide the motivation to analyse the key causes behind the Internet bubble, suggested in the literature. Accordingly, this section reviews these causes and their applications to examine the likelihood of a Cloud bubble.

2.1. Suggested Internet Bubble Causes Applied to Cloud Firms

2.1.1. Differences of Opinion

The implications of differences of opinion on cross-sectional asset pricing have been well-documented in the literature (Chen, Hong, & Stein, 2002; Diamond & Verrecchia, 1987; Jarrow, 1980; Mayshar, 1982; Miller, 1977; Morris, 1996). Differences of opinion in pricing stocks are a necessary condition for impediments to arbitrage to inflate stock prices. Continuing the price-optimism model of Miller (1977), the key common notion in Chen et al. (2002) and Morris (1996) is that, if short-sales constraints are binding, optimistic investors hold their stock because they value it the highest. However, because the best estimate of the true value is the average valuation of all investors, they suffer eventual losses as prices correct. A supplementary notion in this model is that wider divergence of opinion leads to higher prices away from its fundamentals.

Divergence of opinion as a driver behind low returns is not unique to opinions of retail investors. Diether, Malloy, and Scherbina (2002) show that higher dispersion in analysts' earnings forecasts, which proxies for differences of opinion among analysts, also leads to lower future returns. Using analyst forecast data from 1983 to 2000 to look at dispersion, they find stocks with higher analyst dispersion suffer lower returns. In addition to their main finding, they put forward an interesting argument and evidence regarding impediments to arbitrage. The authors claim that it is analysts' incentive structure that creates an upward bias, deterring them from issuing pessimistic earnings forecasts below a certain threshold. This, just like short-sales constraints, prevents revelation of negative or pessimistic opinion into the market, leaving prices to be determined by more optimistic valuations. In testing their hypothesis, they suggest that analyst optimism is related to uncertainty, which is best illustrated by a truncated normal distribution consisting of analysts' forecasts. Since the lower side is truncated, representing analysts' unwillingness to issue a pessimistic forecast below a certain point, the mean for earnings forecasts lies above the true mean. Disagreement among analysts widens the range of values, stretching the distribution and moving the mean of forecasts up (towards the right), away from the true mean. As evidence, they find a strong positive association between optimism of analyst forecasts – proxied by forecast error – and uncertainty – proxied by dispersion of earnings forecasts – with a t-statistic of -33.42.

In light of these arguments for divergence of opinion as a necessary condition for a bubble, I compare bid-ask spread and forecast errors between Cloud Firms and matched peers.

2.1.2. Excess Volatility

Excess volatility is generally defined as the volatility in prices that is not justified by the underlying fundamentals. According to Black (1986), noise trading and excess volatility arises from investors who trade for no apparent reason, or from investors who trade on what they believe to be new information when it is not. Furthermore, there is considerable support for the view of volatility being driven by trading, including French and Roll (1986), Barclay, Litzenberger, and Warner (1990) and Barclay and Warner (1993).

This view is consistent with retail investor hype driving up prices. That is, hyped investors may trade excessively on what they believe to be new information (i.e. growth prospects of the Cloud) when it is not. Extending the view of excess volatility as being induced by noise trading (Black, 1986) to the Internet bubble literature, Ofek and Richardson (2002) also present excess volatility for Internet firms relative to their matched firms. Using Internet and non-Internet stocks over the period from 1998 to 2000, they find that the average (median) daily volatility across the Internet stocks to be 7.4% (7.3%) relative to the mean (median) of non-Internet stocks of 3.5% (3%). In a similar fashion, excess volatility is examined for Cloud stocks as evidence of trading hype relative to non-Cloud peers. If investors are hyped about Cloud stocks and trade them excessively, higher excess volatility should be observed for Cloud Firms relative to its peers.

2.1.3. Short-Sales Constraints

To reiterate, the role short-sales constraints played in creating the Internet bubble is supported and well-documented by many (Bris et al., 2007; Chang et al., 2007; Haruvy & Noussair, 2006; Hong et al., 2006; Hong & Stein, 2003; Ofek & Richardson, 2003). However, the view that short-sales constraint was a cause behind the Internet bubble is not unanimous. Battalio and Schultz (2006) argue, using intraday option data, that investors could have shorted stock synthetically by purchasing put options and writing call options. They also argue that even stocks that were hard to borrow for short-selling could have been shorted synthetically, reasoning that patient investors could have taken considerable synthetic short positions before the burst of the bubble. As to why this was not exploited to mitigate the effect of the Internet bubble, Brunnermeier and Nagel (2004) offer an explanation. They find that institutions (with abilities to create synthetic short positions and arguably more sophistication to time the expiration of options) did not exert downward pressure on prices. Instead, they invested heavily into Internet stocks, magnifying the emergence of the bubble. This is also supported by Greenwood and Nagel (2009), in finding that younger fund managers invested heavily into technology stocks during the period.

As supporting evidence to how short-sales constraints and divergence of opinion may lead to high prices, Chen et al. (2002) associate low breadth of ownership of mutual funds (i.e. when few funds have long positions), a proxy for divergence of opinion, to low returns. Based on existing short-sales constraints, they assert (and confirm) that when breadth is low (i.e. fewer funds hold a particular stock), more mutual funds are kept out of the market. Therefore, they cannot reflect pessimistic views in prices by selling (as they do not own the stock) or short-selling (due to existing short-sales constraints). Using data on mutual fund holdings, they find that stocks in the lowest decile of change in breadth in the prior quarter underperformed the top decile by 4.95% during the year after the formation of the deciles after controlling for size, book-to-market and momentum effects. Though this provides additional support for the role short-sales constraints plays in increasing prices, I do not examine the change in breadth in this thesis because of the lack of access to data on mutual fund holdings from the Mutual Fund Common Stock Holding/Transactions database of CDA/Spectrum.

To conclude this section, short-sales constraints provide a channel that is likely to affect the emergence of a Cloud bubble. In addition to the conventional arguments of pessimistic investors being kept out due to low levels of lendable shares or high costs of short-selling, evidence on constraints on mutual funds to arbitrage presented by Chen et al. (2002) provides a rationale for investigating short-sales constraints as potential cause of a bubble.

2.1.4. Retail and Institutional Investors

Given that retail investors tend to be the more trend-driven investors (Barber & Odean, 2008), Ofek and Richardson (2003) suggest that the emergence of the Internet bubble was partly due to dominance of retail investors in the Internet IPO market. They also suggest that high retail holdings (therefore low institutional holdings) on these Internet stocks limited the supply of loanable shares, which imposed further restrictions on short-selling. As additional support for retail investors' suboptimal trading, Odean (1999), and Barber and Odean (2000, 2001, 2002) consistently find that self-directed retail traders lower their expected returns through excessive trading, largely driven by overconfidence. This is also supported by Hvidkjaer (2008) who finds that stocks favoured by small trades – a proxy for retail investor trading – underperform stocks that are out of favour by small trades. Additionally, it is documented that individual investors are more likely to buy stocks that attract attention (Barber & Odean, 2008). That is, they are more likely to buy stocks that are in the news, experience high abnormal trading or extreme one-day returns. In the bubble setting, this is consistent with the story of individual traders being hyped, herding towards stocks that grab their attention, driving up prices.

Opposing the view that the lack of institutional holdings contributes to bubbles, Brunnermeier and Nagel (2004) show that hedge funds were of no aid in keeping prices down during the time of the dot-com bubble. Rather, they invested heavily into it, capturing the upturn of the bubble while avoiding much of the downturn by selling the stocks before the burst. In particular, Greenwood and Nagel (2009) find that younger fund managers tend to show trend-chasing behaviour, investing heavily in technology stocks by increasing their holdings during the upturn and decreasing their holdings during the downturn. As a result, the actions of younger fund managers amplified the bubble.

Similar to short-sales constraints, observing institutional holdings can be done with relative ease and is done in Section 3.

2.1.5. IPO Underpricing

The use of SVI and analyst forecasts as measures of hype was discussed in Section 1. The extensive literature on IPO underpricing as a measure of investor sentiment, however, warrants a more comprehensive review. As discussed, short-sales constraints seem to play an important role in keeping pessimistic investors out, but in order to explain bubble, hype among optimistic investors is just as important. Since retail investors are more susceptible to buying hyped (attention-grabbing) stocks (Barber & Odean, 2008) and buying stocks on optimistic beliefs (Barber & Odean, 2000, 2001; Shiller & Pound, 1989), examining the activities of retail investors is a logical place to search for hype.

Baker and Wurgler (2006) report on high investor sentiment being associated with relatively low subsequent returns for small, young, volatile, unprofitable, growth stocks. They also use average first-day returns on IPOs as one of their proxies for investor sentiment. The authors argue that IPOs on these types of stocks tend to be ones that are harder to value, and are therefore more likely to be affected by sentiment. In other words, these characteristics allow optimists and speculators to defend and justify a wide range of valuations, creating noise-trader risk which causes arbitragers (who wish to avoid this risk) to keep out of the market. Since the characteristics of Cloud Firms (as technology firms) tend to be similar to the stocks these authors find to be more affected by sentiment, using IPO underpricing as they did provides a good basis to test investor hype.

Overall, examining the returns from the first day after IPOs provides a method of observing retail investor sentiment due to relatively more dramatic price changes during these events. If there is indeed greater hype for Cloud stocks, greater first-day returns should be observed for the Cloud group relative to non-Cloud peers.

2.2. Suggested Internet Bubble Causes *Not* Applied to Cloud Firms

This short subsection presents a brief overview of ‘Internet bubble methods’ not applied to Cloud Firms, and the reasons as to why I decided not to use these methods.

2.2.1. Name Change Announcements

- Examples: Cooper et al. (2001) and Cooper et al. (2005)
- Finding in Internet bubble literature
    - Changing company names to include “.com” or “.net” resulted in excess stock returns
- Reason for not applying
    - Cloud-equivalent name changes are not as clear as simply adding the term phrase “.com” or “.net” in the name

2.2.2. Financial Advisors

- Examples: Hong et al. (2008), and Greenwood and Nagel (2009)
- Findings in Internet bubble literature
    - Based on heterogeneity of advisors (‘tech-savvy’ and ‘old foggy’ advisors in Hong et al.; age of mutual fund managers in Greenwood and Nagel).
    - Upward bias in forecasts by tech-savvy advisors to signal that they are not old fogies (Hong et al.).
    - Young fund managers exhibit trend-chasing behaviour, investing heavily in technology stocks.
- Reasons for not applying
    - Theoretical studies that are difficult to test empirically (e.g. distinguishing tech-savvy and old fogies).
    - Age data on mutual fund managers is not available.

2.2.3. Block Trading

- Example: Ofek and Richardson (2003)
- Finding in Internet bubble literature

- Block trading can represent institutional trades (and therefore identify trades by retail investors the complement).

- Reason for not applying
  - Order splitting strategies become popular after decimalisation of 2001 and small trades are therefore less likely to be only retail trades.

2.2.4. The Media

- Examples: Bhattacharya, Galpin, Ray, and Yu (2009); Ofek and Richardson (2003)
- Finding in Internet bubble literature
  - Using Internet IPOs, they find positive news tend to be released more at times of rise in prices.
- Reason for not applying
  - Small explanatory power: the media effect can only explain 2.9% of the 1,646% difference in returns between Internet stocks and non-Internet stocks.

3. Data

3.1. Sample Selection

3.1.1. Cloud Index

The ISE Cloud Computing Index provides a sample of objectively selected Cloud stocks. Components are added and removed based on the requirements set out in the ISE Cloud Computing Index Methodology Guide[13], meaning firms may not apply to be included in the index nor can they be nominated by others[14].

While the full details of the requirements for being included in the index are available in the methodology guide, the requirements that constitute being "actively involved" in the Cloud industry can be summarised into three main points. First, firms must be engaged in a

[13] Available at: www.ise.com

[14] Any changes to the index, both in terms of its components and returns, are publicly available on ISE's website

business activity supporting or utilising the Cloud computing space to be eligible as a component security. Second, firms must not be listed in a country restricting foreign capital investments nor can it be a closed-end fund, exchange-traded fund, holding company, investment vehicle or REIT. The second condition that the components need to qualify therefore is that they must be considered to be investible. Finally, all qualifying firms must have a minimum market capitalisation of $100 million.

The selected components for the index are then grouped into three segments. 1) Pure-play Cloud computing companies that provide direct service for the Cloud or deliver goods and services that utilise Cloud computing technology, 2) Non-pure-play Cloud computing companies that focus outside the Cloud computing space but provide goods and services in support of the Cloud computing space, and 3) Technology conglomerate Cloud computing companies that are large broad-based companies that indirectly utilise or support the use of Cloud computing technology. All components within a segment are weighed equally.

The weight allocation of the index to each of the three segments according to the methodology guide is:

i. $W_{TC} = 10\%$

ii. $W_{NPP} = \frac{\sum CAP_{NPPi}}{\sum(CAP_{PPi}+CAP_{NPPi}+CAP_{TCi})}$

iii. $W_{PP} = 100\% - (W_{NPP} + W_{TC})$

where:

W_{TC} = Aggregate weight of technology conglomerates

CAP_{TCi} = Market capitalisation of each technology conglomerate

W_{NPP} = Aggregate weight of non pure play components

$\mathrm{CAP_{NPPi}}$ = Market capitalisation of each non pure play component i

$\mathrm{W_{PP}}$ = Aggregate weight of non pure play components

$\mathrm{CAP_{PPi}}$ = Market capitalisation of each pure play component i

As an example of the weights on Cloud Firms according to the weight allocation method of the index, Table 2 shows the weights and provides insight into the approximate weightings of the three segments. Following the rebalance at 21/03/2011, the total weighting of pure-play, non-pure-play and technology conglomerates equalled 78.95%, 11.05% and 10%, respectively.

This study makes no distinction between pure-play Cloud Firms and non-pure-play Cloud Firms. The distinction is not made mainly due to the small size in the number of samples. Furthermore, both pure-play and non-pure-play firms meet the requirement of being "actively engaged in a business activity supporting or utilising the Cloud computing space", meaning any difference should still be observable for Cloud Firms when compared to non-Cloud peers if there is indeed a Cloud effect. On the other hand, the technology conglomerates of the Cloud Index are excluded for some analyses conducted. The reasoning specific to each analysis will be clearly expressed where the conglomerates are excluded.

3.1.2. Size-Matched Samples

The data on market capitalisation for the size matching process was obtained using CRSP. Non-tech Firms are selected from the best size-matching NYSE, AMEX or NASDAQ Composite components[15]. Ideally, Non-tech Firms should also be matched in terms of B/M ratio (in addition to size). However, matching Non-tech Firms on B/M ratio often resulted in the match to be a technology firm. If this was not the case, it resulted in a considerable

[15] Detailed discussion of the issues in selecting Tech and Non-tech Firms is presented in Appendix A.

sacrifice in the proximity in size between the Cloud Firm and the match. Accordingly, I did not match non-Cloud firms on B/M ratios, but only on size.

Tech Firms are selected from a pool of stocks consisting of the components of the NASDAQ Computer and Dow Jones Internet Index (ticker: DJINET). While the closest size-matching firms were selected for Tech and Non-tech Firms, a firm was only eligible to be selected as a matched peer if the difference of the market capitalisations between the Cloud Firm and its match was less than 10% of the market capitalisation of the Cloud Firm. In other words, the maximum difference in market capitalisation of matched peers is 10% of the size of its corresponding Cloud Firm. For all size matching procedures, efforts have been made to have at least one uniquely size-matched firm for each available Cloud Firm. If two or more Cloud Firms conflicted with each other by having the same size-matched non-Cloud firm, the closest Cloud Firm by size to the non-Cloud firm was matched, and the conflicting Cloud Firm was matched with the next best size-matching non-Cloud firm. Further details and reasoning behind the selection procedure is presented in Appendix A.

Out of the 39 Cloud Firms, the four technology conglomerates (Apple, HP, IBM and Microsoft) were excluded from the size matching process. There is difficulty in finding peers due to their sheer size, especially when finding peers within the technology industry. More importantly, their status as Cloud Firms is less convincing due their wide range of operations, relative to the activity of smaller pure-play or non-pure-play Cloud Firms. This issue is also recognised by the ISE, who limit the total weighting of the Cloud Index delegated to the four conglomerates to 10%. Accordingly, the four technology conglomerates are not matched based on size.

Table 3, Panel A summarises the results of the size matching process. It reports the number of Tech and Non-tech Firms matched to the sample of Cloud Firms. Of the 35 remaining Cloud Firms after the exclusion of the conglomerates, all the firms found matches within the technology indices with the exception of Google (due to the same problem as the conglomerates), resulting in a total of 34 successful size-matched Tech Firms. All 35 Cloud Firms found matching Non-tech Firms from the components of the three major U.S. indices. Panel A also reports an overview of how close Cloud Firms were matched on size. The mean absolute size difference was much closer than the formal criterion of 10% for both sets of matches. However, as expected, due to a greater number of stocks that are included in the NYSE, AMEX and NASDAQ indices combined, Non-tech Firms resulted in closer size matches with the average absolute difference of 0.65% relative to 2.75% for Tech Firms. Overall, both samples provide good matches on size for Cloud Firms.

3.2. What is in the Price?

The detailed sample statistics presented in Panel B of Table 3 present mean, median, standard deviation, low and high values over the period from 31/07/2007 to 30/03/2012 for the three sample groups. These values are computed by first calculating cross-sectional monthly mean values of all the firms in each of the three groups. For example, the mean price of Cloud Firms is obtained by calculating the average of all Cloud Firms for each month. These cross-sectional values are then averaged across the sample period to obtain the value presented (i.e. time-series mean, median, standard deviation, low and high values). Several interesting observations can be made. First, using the price-scaled bid-ask spread as proxy for dispersion of opinions, there seems to be little or no difference between Cloud Firms and its peers. Second, firms in the technology industry seem to be traded more. Turnover, defined as daily volume over shares outstanding, is significantly lower for Non-tech Firms relative to the other two groups (t-statistics of 8.51 and 10.27 when the mean is compared to the means of Cloud and Tech Firms, respectively). Surprisingly, Tech Firms also have significantly higher turnover than Cloud Firms (t-statistic of 2.06). Considering studies that view turnover as an indicator of investor sentiment (Baker & Wurgler, 2006), the results suggest investors are relatively hyped about technology stocks in general, but not particularly for Cloud stocks.

The daily standard deviation of returns for Cloud Firms reported in Table 3 was on average, 2.88%. The mean daily standard deviation was the lowest of the three groups and its median was lower than the matched Tech Firms, which offers little to suggest that there is hype for Cloud stocks.

3.3. Institutional Holdings and Free Float

Table 4 provides a cross-sectional[16] comparison of institutional holdings and float shares between the three sample groups as at 31/05/2012, collected from Yahoo! Finance. All variables are scaled by the total shares outstanding for easy comparison between the three groups. Float, representing the percentage of total shares outstanding that are publicly owned and available for trading, potentially impose restrictions on short-selling by limiting the number of shares that are tradable and available for lending. The proportion of float shares available for Cloud and Non-tech Firms seem to be significantly smaller (t-statistics of -2.59 and -2.21, respectively) than the sample Tech Firms. However, the mean proportion of float shares available for Cloud Firms is not significantly different to the mean for Non-tech Firms, offering little to suggest that Cloud Firms are uniquely constrained to short-sell. With data on shares held by institutions, this table also serves as a preliminary insight to the discussed implications of institutional holdings on Cloud stocks. Institutional holdings are higher for Cloud and Tech Firms (5% level of significance), which goes against the notion that Cloud stocks may be more difficult to short-sell. As a reminder, the view that low institutional holdings contributing to bubbles is not unanimous. Some claim that at least some causes behind the Internet bubble are attributed to institutions investing heavily in Internet stocks

[16] It should be cautioned that since the data used in Table 4 provides a cross-sectional outlook as at the end of May, some results observed may be event driven. Time-series data on institutional holdings was not available.

during the period. Therefore, I remain open in interpreting the higher institutional holdings of Cloud and Tech Firms.

4. Formal Tests

4.1. M/B and P/E Ratios

4.1.1. Method and Data

To form a preliminary view on market sentiment, market-to-book and price-to-earnings ratios of Cloud Firms are investigated. I use quarterly book values and earnings data from Compustat and present the mean quarterly values of Cloud Firms in Panel A (M/B ratio) and Panel B (P/E ratio) in Figure 4.

4.1.2. Results

The two graphs provide two main insights. First, the means of both ratios are very high, peaking above 8 and 250 for M/B and P/E, respectively. These ratios are suggestive of hype. Second, patterns in neither of the two ratios offer an explanation to the rise in Cloud stock prices of late-2008 to 2011, shown in Figure 1. In each panel, even the later peaks in 2011 do not seem to be as high as the peaks before 2008. In other words, there seems to be no increase in investor sentiment to explain the rising Cloud returns in the period from 2008 to 2011. In sum, examining M/B and P/E ratio leaves two contrasting interpretations on investor hype. Noting this inconsistency, I reserve making inference on these results and move onto subsequent tests to investigate the likelihood of a Cloud bubble.

4.2. IPO Underpricing

As discussed, IPO underpricing has been used as a proxy for investor sentiment. I therefore compare the magnitude of underpricing of Cloud Firms, with that of Tech Firms and Non-tech Firms. If there is indeed hype for Cloud stocks among investors, underpricing should be more severe for Cloud Firms relative to the two matched groups.

4.2.1. Method

IPO underpricing in this analysis is defined as the abnormal first-day returns. The abnormal first-day return for the IPO of a given firm in each sample group (Cloud, Tech or Non-tech) is measured using the following definition:

$$Raw\ first\ day\ returns_i = \frac{Stock\ price\ at\ first\ day\ close_i}{Offer\ price_i} - 1$$

$$Abnormal\ first\ day\ returns_{i,t} = Raw\ first\ day\ returns_i - Normal\ first\ day\ returns_t$$

$$Normal\ first\ day\ return_t = Average\ of\ \sum_{j=1}^{n} Raw\ first\ day\ returns_{j,t}$$

Where *i* is an individual firm within a sample group with its IPO issued in the year *t*, and *j* denotes a firm with an IPO issued during the same year as the sample firm, *i*. For a sample firm with an IPO issued in year *t*, the normal first-day returns is the mean of the raw first-day returns of all IPOs during the same year. Calculating the abnormal first-day returns of each firm by subtracting the normal first-day return (computed as above) for the same year aims to mitigate the effect of IPO cycles.

There are two separate sets of normal first-day returns. The first, labelled the 'Aggregate IPO Benchmark' (and presented in Table 5) is the mean of first-day returns for all IPOs[17] issued each year during the sample period. This data is publicly available from the website (http://bear.cba.ufl.edu/ritter) updated by Jay R. Ritter. In addition to using the average of all IPO first-day returns as the benchmark to compute the abnormal first-day returns for Cloud

[17] Restricted to offer prices of at least \$5, excluding ADRs, unit offers, closed-ended funds, REITs, partnerships, small best efforts offers, banks and S&Ls, and stocks not listed on CRSP.

Firms, a test for higher investor sentiment for Cloud stocks above that of technology stocks is conducted. For this, a benchmark for the normal first-day returns specific to the technology industry is required. This benchmark (named 'Tech IPO Benchmark' and also presented in Table 5) was produced using the SDC database.

For the construction of the Tech IPO Benchmark, the Advanced SIC Keyword Lookup function on SDC Platinum is utilised. This functionality produces objectively and logically selected SIC codes related to computing. For example, the term "computing" is typed into the search, which produces SIC codes related to the computing industry, even without the term included the description, such as the SIC code *7372: Prepackaged Software*. Using all SIC codes produced from the search, data on every available IPO from 1985 to 2012 is obtained to be used as the Tech IPO Benchmark[18].

As an example to illustrate the method described, Table 6 shows the IPO of Google in 2004, with a raw first-day return of 18.04%. The average first-day return in the technology industry in 2004 was 11.59% (Tech IPO Benchmark), and against this benchmark Google has an abnormal first-day return of 6.44%. Similarly, the average first-day return for all IPOs (Aggregate IPO Benchmark) in 2004 was 12.2%, and against this benchmark Google has an abnormal return of 5.8%.

4.2.2. Sample

In this analysis, I exclude the four technology conglomerates from the Cloud Index. The IPO for these firms occurred too far in the past to provide any useful insights. Three out of the four technology conglomerates' IPOs were issued before the 1990's, with the IPO of the

[18] As a robustness test, an additional version of the Tech IPO Benchmark was constructed using common SIC codes among 5 or more Cloud and Tech Firms. The aim of this was to pick up relevant SIC codes that the Advanced SIC Keyword Lookup missed. All tests conducted using this version of the Benchmark yield similar results as the main tests and are not reported.

other, IBM, extending as far back as 1916.

The data on offer price and price on first-day close to calculate raw first-day returns was obtained from SDC, or if missing, hand-collected from the Investor Relation section of each firm's website. Unfortunately, because of missing IPO data on SDC, four Cloud Firms – CA Inc (CA), SAP AG, J2 Global Communication Inc (JCOM), and Wipro Ltd (WIT) – were excluded from this analysis. Accordingly, the matched Tech and Non-tech Firms to the four Cloud Firms were also excluded. From the original 39 Cloud Firms, 4 technology conglomerates and 4 firms missing IPO data were excluded, leaving 31 Cloud Firms to be compared with the matched 31 Non-tech Firms. For comparison with Tech Firms, an additional firm, Google, was excluded due to the lack of firms in the technology industry that match it on size (discussed previously in Section 3), leaving 30 Cloud Firms to be compared with 30 Tech Firms.

4.2.3. Results

Table 6 presents the results of the first-day returns analysis for Cloud Firms. Simple t-tests are conducted to test whether the mean of first-day returns of the sample firms are different to the benchmark (or normal) returns. In addition, sign tests are conducted using the number of positive and negative abnormal returns. The results of both statistical tests are consistent and are presented in Table 7. Moreover, Table 7 also presents the results of an identical analysis conducted for Tech Firms. The mean and median abnormal returns of Cloud Firms (Table 6) are presented again in Table 7 for easy comparison with the mean and median for Tech Firms.

Presented in *Column 1* of Table 7, the average first-day return of Tech Firms is found to be higher than the average return on all IPO issues, but the difference is only marginally significant (10% level). Interestingly, the results for Cloud Firms are similar to Tech Firms.

The mean first-day return of 54.11% shown in Table 6 is not significantly higher than that of the average return for IPOs of technology firms (see *Column 2*, Table 7). The average first-day returns of Cloud and Tech Firms are significantly higher than the average of all IPOs in the same period (*Column 1 and 3*).

The results collectively indicate that underpricing is more severe in the technology industry in general (including Cloud Firms) relative to the average underpricing of all IPO issues. From the results of this particular analysis there seems to be no indications of hype that uniquely applies to the Cloud group[19].

4.3. Search Volume Index

According to Da et al. (2011), Google SVI provides a useful way to look at retail investor sentiment. They find that the level of SVI is positively related to market capitalisation, abnormal turnover, analyst coverage and frequency of news. In light of their finding that the price pressure related to SVI does not persist beyond two weeks, high levels of SVI, *per se*, would not indicate the existence of a bubble. However, SVI levels do provide a useful way of looking into retail investor sentiment. Furthermore, because the sample groups are size-matched, group averages of SVI should indicate relative retail interest for each of the three groups of sample firms (Cloud, Tech and Non-tech).

4.3.1. Method

Following Da et al. (2011), I use ticker symbols for the SVI searches. Also to note, every SVI value computed is relative to one common reference ticker: Microsoft[20]. For example, a

[19] Though these results suggest that there was no greater retail investor hype about these firms during their IPO periods, the power of explanation is limited if retail hype increased in late-2008 as the returns in Figure 1 suggests. This is due to most of the IPOs of Cloud Firms being issued before 2008.

[20] It is to be noted that any other stock and ticker that met the same ideal conditions could potentially be used as the reference ticker but the results of the analysis would not be any different.

search for the SVI level of EMC Corp. (EMC) would be obtained by typing “EMC, MSFT” on Google Trends which would output a value of SVI for EMC relative to that of Microsoft.[21] There is a potential bias caused by firms that went public after 2004 that likely have observations missing for the dates before their issue. To control for possible bias caused by these, the SVI analysis is also conducted using a sample excluding firms with IPO dates later than 2004. The results were very similar to those obtained using the full sample and are not reported.

Various efforts have been made to exclude searches that are not likely to be searches intended for financial information on the sample firms. Firms with SVI values of more than 2 were investigated. Since Microsoft is a well-known firm which attracts considerable amount of attention by the media, firms with search frequencies of twice the value for Microsoft could potentially be searches for other information than the stock at hand. These identified firms are then filtered using numerous methods. First, they are checked for high SVI concentration in one particular region. While there is a general trend for searches to be higher in the U.S. compared to other regions, noticeably higher concentration of searches in other regions often meant they were searches for other information. For example, the SVI value for “PAA”, the ticker for Plains All American Pipeline, was heavily driven by searches in India seeking information on an Indian movie, *Paa*. Other searches with concentrated searches in one particular region were checked in a similar fashion. Second, tickers that have generic meanings such as “CA”, “PAY” or “JAZZ” were also identified. Lastly, high SVIs that resulted from the ticker having the identical name as the company name (e.g. IBM, SAP or CA) were also identified. Searches identified using the above methods were excluded from

[21] Microsoft is used as the reference ticker for two reasons. First, there is SVI data on Microsoft for the full sample period of 2004 to 2011. Second, its SVI value is not too small (close to 0) that Google Trends fails to output a numerical value.

the analysis[22].

4.3.2. Data

As with the first-day returns analysis, the four technology conglomerates are excluded in the examination of SVI. The factors driving the search volume for the technology conglomerates are more likely to be due to services they provide other than Cloud services, compared to smaller firms that are more focused on providing Cloud services. Furthermore, these larger firms are more likely to engage in marketing activities that create noise in search frequencies.

All SVI data is limited to weekly intervals and stretches back to 2004. Since the sample period is identical, this allows for direct comparison of SVI values between the sample firms.

4.3.3. Results

Figure 5 shows the level of SVI for each group in a time-series setting from 2004 to 2011. The mean of SVI levels shown for Cloud Firms is clearly higher than those of its matched peer groups. Note that the level of SVI for Cloud Firms appears to be relatively constant, suggesting little bias caused by firms with IPO dates later than 2004. Considering Cloud computing is a relatively recent trend, a pattern more or less similar to that observed in Figure 2 is expected if the level of SVI is an indication of hype about Cloud stocks. At the very least, an increasing trend of some sort should be observed post-2007, but it is not. Secondly, the relatively constant levels among all three groups over the years seem to suggest that Cloud Firms are simply more well-known firms that are consistently searched more frequently. There is no indication of time-varying retail investor hype.

[22] Although these searches could have been identified as 'noisy' tickers as done by Da et al. (2011) to create two sets of results (one with and one without 'noisy' tickers) this approach was not adopted. The main reason for this was that these tickers had extreme SVI values (mean of 54.8 and largest of 209.4) which rendered the majority of SVI (largely with values of less than 1, especially in the Tech and Non-tech group) values obsolete in comparing the sample groups.

To verify the validity of the results, other measures of retail investor attention are also examined. Panel A and B of Figure 6 respectively present turnover and analyst coverage for the three groups in a similar fashion as the SVI levels. Though there is positive correlation between SVI and turnover for Cloud, Tech and Non-tech Firms of 0.3117, 0.3691 and 0.1434 (untabulated), respectively, there is no noticeably higher turnover for Cloud Firms. Also, there is no indication of periods of sharply increased turnover for Cloud Firms suggestive of retail investor hype. An analogous observation can be made from Panel B of Figure 6. Analyst coverage, measured by the time-series average number of analysts following for stocks in each group, shows that the number of analysts following is higher for Cloud and Tech Firms relative to Non-tech. However, again, there is no evidence that seems to suggest higher analyst coverage specific to the Cloud in any specific period. Finally, the frequency of 'news' for the three groups is also briefly examined. From Factiva, I collect the number of news articles that mention the firms in each group. Consistent with the measure of turnover and analyst coverage, Cloud and Tech Firms are mentioned more frequently over the sample period (from January 2004 to March 2012) with 647,586 and 696,803 related news articles, respectively, compared to 449,657 articles for the matched Non-tech Firms. The three measures collectively and consistently suggest higher news-worthiness for technology firms (i.e. Cloud Firms and Tech Firms) but provide no explanation for the strong increase in prices for Cloud Firms during the period from 2008 to 2011.

4.4. Price Targets

Asquith et al. (2005) scale price targets and earnings forecasts by their previous values to examine the effect of changes in price targets and earnings forecasts on market reaction. Based on their finding of significant impact to stock returns, I examine the two measures as proxies for analyst hype that could possibly explain the high Cloud returns. As an additional measure, sales forecasts are also examined. Unlike the authors who scale price targets and earnings forecasts by their previous values, I scale these measures by their actual values known at the time of each forecast (price target, earnings forecasts and sales forecasts). This is done to eliminate any changes in forecasts that result from changes in actual values. By eliminating changes in price targets (and forecasts) that are due to changes in actual prices (earnings and sales) it allows the optimism embedded in analyst forecasts to be observed. For example, as the price of a Cloud Firm is increasing, analysts are likely to incorporate this into their price targets by increasing them accordingly. Scaling by actual values isolates changes in forecasts over time that are due to changes in analysts' views on future prospects from changes that are due to changes in actual prices. For price targets, this is possible because price targets are issued within short intervals by different analysts, often no more than a few days apart from each other. Furthermore, because stock prices are updated daily, it provides timely updates to scale each price target by. Though not updated as frequently as price targets or stock prices, the same scaling can be applied to earnings and sales forecasts. Data on price targets, earnings (sales) forecasts and actual earnings (sales) are available from I/B/E/S, while stock prices are collected from CRSP.

Figure 7, Panel A shows the change in unadjusted price targets of Cloud Firms during the same period as the returns comparison shown in Figure 1. The increase during the period from late-2008 to 2011 in price targets simply reflects prices (see Figure 1). It illustrates changes in price targets that incorporate changes in actual prices. Indeed, once the price targets are scaled to eliminate changes in actual prices in Panel B, analysts' expectation on growth over time displays a more flat trend. It appears that analysts expect, on average, Cloud Firms to grow approximately 20% in a year, with no noticeable increase in this ratio to match the increases in Cloud Firms' returns during late-2008 to 2011. In other words, throughout the whole sample period, growth expectations for Cloud Firms are fairly constant. A similar story is told by four-quarters-ahead forecasts on earnings and sales in Panel C. Analysts' expectations on the growth of earnings and sales in a year fluctuate largely below 20% over the period from 2007 to 2011, with no considerable increases that help to explain the observed increases in the Cloud returns in the period from late-2008 to 2011.

In sum, no measure of analyst forecasts investigated suggests that optimistic expectations of analysts are behind the strong uptrend in the returns of Cloud Firms in the period from 2008 to 2011.

4.5. Summary on Hype

The compilation of evidence so far has been consistent: first-day returns, search volume index, and analyst price targets and forecasts do not show indications of incremental hype for Cloud Firms above Tech Firms that explains the period of increased Cloud stock prices in the period from late-2008 to 2011. With little evidence to suggest that there is hype for Cloud stocks in particular, I move on to look at the possibility of short-sales constraints in causing a bubble. Tests consistently show that investor sentiment is higher for technology stocks (represented by Cloud and Tech Firms) than non-tech stocks (represented by Non-tech Firms). Even if there is no greater hype about Cloud Firms that is distinguished from hype for technology stocks in general, the possibility of tighter short-sales constraints for Cloud Firms may still explain the increased prices and possibly give rise to a bubble.

4.6. Short-Sales Constraints

4.6.1. Method and Data

In investigating direct short-sales restrictions in this analysis, four measures are examined. 1) *DEMAND*: percentage of shares outstanding that are actually shorted, 2) *SUPPLY*: percentage of shares outstanding that is available for short-selling, 3) *FEE*: rebate rate on short-sales shown on a scale from 0 to 5 (0 being easy to short-sell and 5 being impossible to short-sell) and 4) *UTILISATION:* the percentage of shares available for short-selling actually sold short. The sample period for comparing the three measures of the sample groups is from 03/07/2006 to 31/12/2009.

4.6.2. Results

Figure 8 illustrates the three measures of short-sales constraints over the sample period for the three groups of firms. As tests for significance, monthly cross-sectional t-tests are conducted to test for differences in the means of short-sales constraint measures of sample groups. In terms of lending fees in Panel A, it appears Cloud Firms are harder to sell short during 2007 to 2008, but the difference is not significant at any point during the sample period. From all monthly t-tests conducted, t-statistic of the difference in means of Cloud and Tech (Non-tech) Firms never exceeded 0.96 (1.14). In Panel B, for the majority of the sample period, shares of Non-tech Firms are less available for short-selling, showing no evidence of incremental difficulty in short-selling Cloud stocks. This is the same with the actual percentage of share outstanding being sold short (Panel C), where greater proportions of Cloud Firms are being sold short relative to Non-tech Firms. Despite the average percentage of Non-tech Firms being sold short increasing above the percentage of Cloud Firms after early-2009, at no point in the sample period is the difference in means statistically significant. The point in time with the highest t-statistic in any of the measures is the difference between the means of *DEMAND* (Panel C) of Tech and Non-tech Firms at the date 06/08/2007 with a value of 1.25. Finally, a similar finding is obtained for *UTILISATION* in Panel D. A greater percentage of shares available for short-selling are actually sold short for Cloud Firms in the early half of the sample period. In the second half, differences are minimal, with t-statistics not exceeding 0.35 at any point in time.

None of the four direct measures of short-sales constraints shows more severe constraints on short-selling Cloud Firms that would indicate the potential in a bubble.

4.7. The Bubble Story

Summing up the results so far, multiple possible explanations behind the excess returns seen by Cloud Firms have been explored with no satisfactory answer to why the Cloud seems to be doing so well, even in relation to other technology and computing firms. The results from the search for hype and binding short-sales constraints strongly suggest that the high Cloud returns are not due to a bubble. Instead, it seems more likely that Cloud Firms consistently outperformed expectations in the period from 2008 to 2011, driving up prices. This hypothesis is further examined in the next subsection.

4.8. Surprised?

The results in the previous sections consistently show that the high prices for the Cloud are due to neither greater hype nor more binding short-sales constraints. Hence, a rapid burst-like effect of a bubble is unlikely to occur for the Cloud, and if a burst is unlikely to happen, the logically deducted explanation is that the market is consistently and positively surprised by the performance of Cloud providers.

4.8.1. Method

It is well-established that positive surprises to analyst forecasts lead to positive stock returns. I use this connection to directly test my final explanation for the excess returns of Cloud Firms. I look at surprises to analyst forecasts on two performance measures: earnings and sales. A surprise on either earnings or sales is defined as *the actual value minus the forecasted value scaled by the forecasted value*. For example, actual earnings for the first quarter of 2007 is subtracted by the earnings forecast made for that quarter four quarters ago (i.e. the first quarter of 2006), which is then scaled by the forecasted value. Effectively, it outputs the forecast error as a percentage of the forecast itself. The quarterly forecast error for each group is obtained by calculating the cross-sectional mean of forecast errors for all firms in each group.

4.8.2. Data

Forecasts and actual values on earnings and sales for the sample groups are obtained from I/B/E/S for the period of 31/01/2005 to 31/01/2012.

4.8.3. Results

Panel A, B and C of Figure 9 graph the level of surprise on earnings and sales for Non-tech, Tech and Cloud Firms, respectively for each quarter. As seen in Panel A, surprises to forecasts on sales for Non-tech Firms are minimal, hovering around zero over the sample period. In contrast, the earnings surprise depicts the positive bias in earnings forecast suggested in the literature. The effect of this positive bias is seen even more clearly as surprises are accumulated over time (Panel A, Figure 10). Cumulative surprise levels to earnings are shown to be incrementally more negative, showing consistent positive bias in earnings forecasts by analysts (see Diether et al. (2002), for example). Similar results can be observed for Tech Firms in Panel B in Figure 9 and 10. Intriguingly, earnings and sales surprises on Cloud Firms, as shown in Panel C in Figure 9, are positive for large portions of the sample period and do not seem to show consistent positive bias in earnings forecasts. This supports the explanation that the market was consistently and positively surprised by the performance of these firms. Support for this explanation is painted even more clearly in Panel C of Figure 10, showing the cumulative surprises over time for the two types of forecasts on Cloud Firms. The power of this graph in explaining the Cloud returns is considerable for two reasons. Firstly, unlike most of the results from previous analyses conducted, surprises to fundamentals provide an explanation that uniquely applies to Cloud Firms much like the high returns that was exclusively experienced by the group. Secondly, a pattern of negative surprises that starts in 2008 and one of positive surprises that starts in 2009 align with their respective decreases and increases in returns of Cloud Firms displayed in Figure 1.

As proposed at the start of this subsection, the results indeed indicate that the high returns experienced by the sample of Cloud Firms seem to be driven by the market being consistently positively surprised by the performance of these firms.

5. Conclusion

In the period from late-2008 to 2011, Cloud Firms showed stock returns that diverged above benchmark indices, including the NASDAQ Computer Index. In providing an explanation to this phenomenon, two main drivers suggested in the Internet bubble literature were examined: hype among retail investors and analysts, and binding short-sales constraints. Consistently, the measures of hype (first-day returns, SVI, and analyst price targets and forecasts) examined in this study provide little to no evidence of hype that is applicable to Cloud Firms. Furthermore, Cloud stocks do not seem to be more difficult to short-sell relative to matched Tech or Non-tech Firms. Unlike the explored drivers of a bubble, positive surprises to forecasts on earnings and sales exclusive to Cloud Firms coincide with the high returns. The answer to the main question in this thesis – is there (going to be) a Cloud bubble? – is addressed by explaining why high returns are observed for Cloud Firms in the period from late-2008 to 2011: Cloud Firms consistently outperformed expectations, leading to a strong increase in prices. This suggests that the Cloud trend is unlikely to be (or to lead to) a bubble.

Appendix A: Selecting Tech Firms and Non-tech Firms

Tech Firms

The aim in selecting Tech Firms was to find a group of firms that are as close to the Cloud computing industry as possible. By design, the infrastructure of Cloud computing requires Internet as its pathway to deliver computing services. Naturally, this close tie between Internet and Cloud computing means Internet firms serve as very closely matched samples to Cloud Firms, even within the tech industry. A sample set similar to the 400 companies in "pure Internet-related sectors" examined by Ofek and Richardson (2003) would have been ideal, but many firms in the list were either merged or acquired, and an updated version since year 2000 was unobtainable. As an alternative, the index used in Figure 1 is used to select the size-matched sample firms for Cloud Firms within the tech industry, the NASDAQ Computer Index, in conjunction with another, the Dow Jones Internet Index. The Computer Index serves as a solid set of 404 potential firms to be matched with Cloud Firm, while the Internet Index has a smaller number of securities totalling 41. As the two Cloud computing related indices within the tech industry, out of the total components of 445 potential candidates, one unique Tech Firm was matched for each of the firms in the Cloud Index according size. Since firms from the Internet Index deal with the common infrastructure with Cloud Firms (namely, Internet), matches from the Dow Jones Internet Index were given priority over the NASDAQ Computer Index, but due to the sheer number of components in the Computer Index, 30 out of 34 Tech Firms were from the Computer Index while only 4 out of 34 Tech Firms matched were from the Internet Index. Matched samples were only drawn from the Computer Index when the closest unique matching sample from the Internet Index exceeded difference in size with a Cloud Firm by more than 10%.

Non-tech Firms

The sample of size-matched Non-tech Firms to the Cloud stocks are selected from a pool of stocks listed on the three major U.S. stock exchanges – NYSE, AMEX and NASDAQ – and aim to incorporate a large number of firms as potential samples in order to obtain closest matches on size, to each Cloud Firm. The considerably larger sample of firms listed on the three exchanges included firms that were large enough to match one additional Cloud Firm – Google – compared to the industry match, resulting in a total of 35 size-matched Non-tech Firms. It should be noted that, while this set of matched samples is labelled 'non-tech', it may include some firms within the technology industry as a result of being the best fit in terms of market capitalisation with the matching Cloud Firms. Ideally, technology firms should be excluded from the non-tech match in order to best observe the difference between the matched Tech Firms and Non-tech Firms, however, the technology firms in all the indices used span across many 'non-tech' classifications of SIC codes such as *Pharmaceutical Preparations (2834), Telephone & Telegraph Apparatus (3661), Television Broadcasting Stations (4833)*, and even *Services – Racing, Including Track Operations (7948)*, which causes difficulty in identifying and excluding technology firms in the non-tech size matching process. However, if the matched Non-tech Firm to a given Cloud Firm is the same firm as the matched Tech Firm, the next best size-matching firm replaces the sample as the matching Non-tech Firm in order to ensure that the Tech and Non-tech Firm matched to a Cloud Firm are not one and the same.

Financial firms were excluded from potential matches as Non-tech Firms. Financial firms were used as matching Tech Firms to each Cloud Firm because they were rightfully a Computer firm or an Internet firm as they met the criteria of the respective indices. On the other hand, for the selection Non-tech Firms, where the firms did not meet any specific criterion other than being listed on one of the three exchanges, financial firms were excluded.

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Figure 1

Returns on Equally Weighted Cloud Index, S&P 500, NASDAQ 100 and NASDAQ Computer Index

Comparison of index levels of equally weighted Cloud Index, the S&P 500 Index, the NASDAQ 100, and the NASDAQ Computer Index. The sample period is from 31/12/2007 to 30/03/2012. All four indices are standardised to 100 on 31/12/2007.

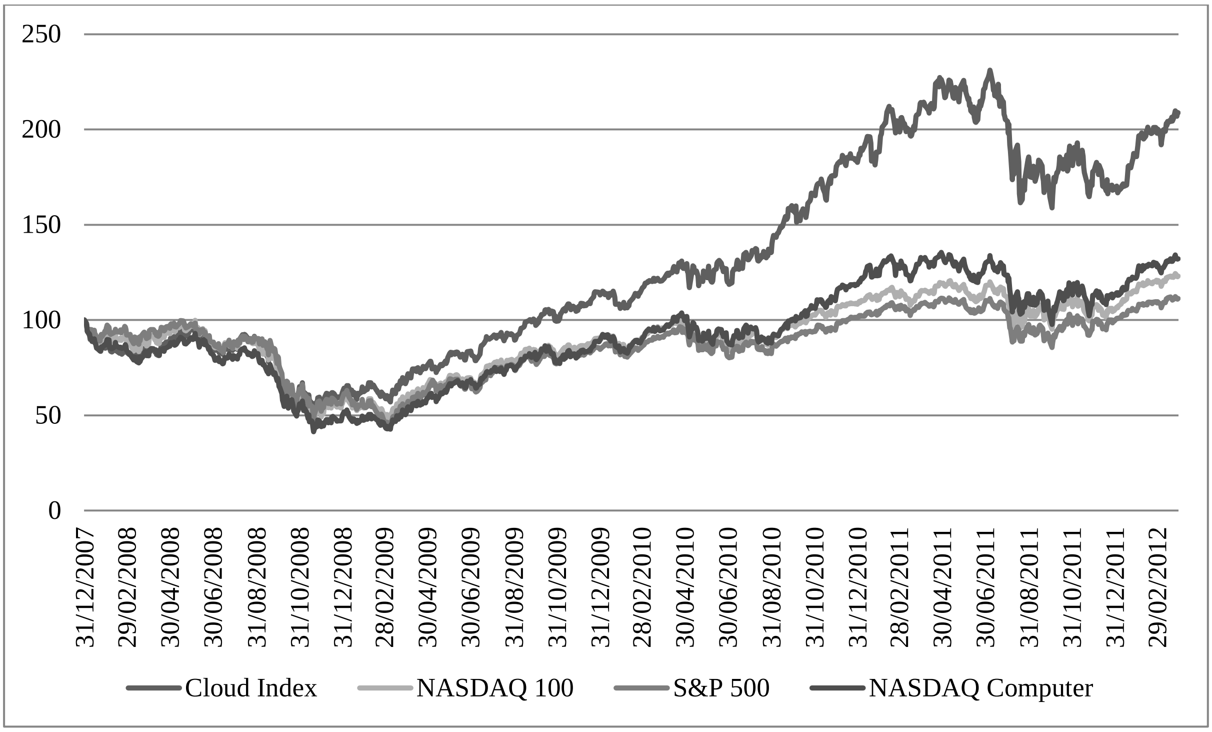


Figure 2
Returns on Equally Weighted Internet Index, S&P 500 and NASDAQ Composite Index

Comparison of index levels of equally weighted Internet Index, the S&P 500 and the NASDAQ Composite Index is charted for the period from 31/12/1997 to 31/12/2000. All index values are scaled to 100 on 31/12/1997. Reproduced from Ofek and Richardson (2003).

Figure 3
Illustration of Google Search Frequencies for the Term "Cloud Computing"

The upper panel labelled 'Search Volume index' plots the weekly aggregate search frequency (SVI) for the term "cloud computing" on Google from January 2004 to June 2012. The SVI is scaled by the average value of the time period mentioned. The lower panel labelled 'News reference volume', or the lower trend line, simply graphs the number of times the term has appeared on Google News stories for illustrative purposes. It is not scaled.

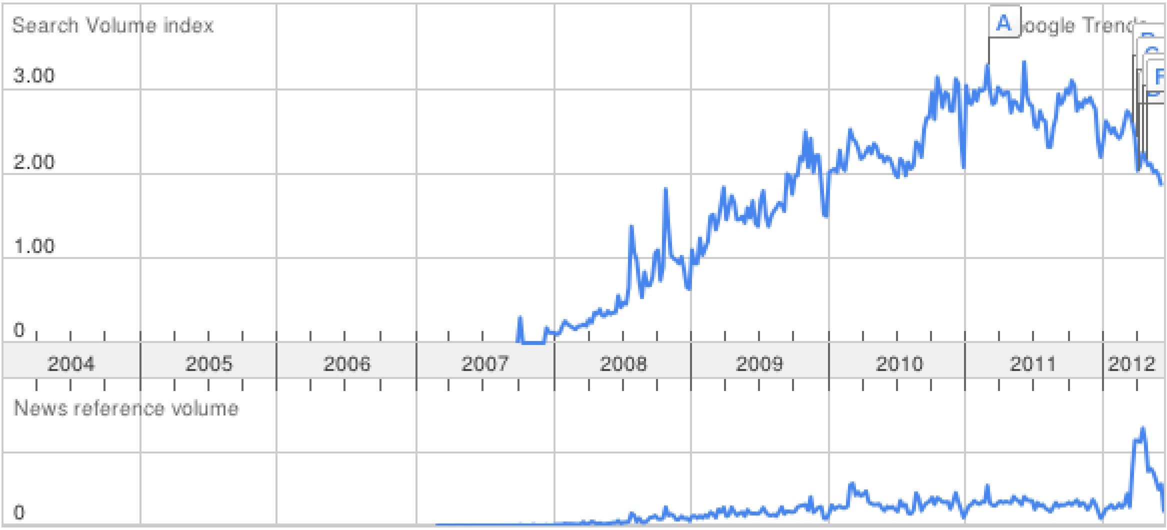
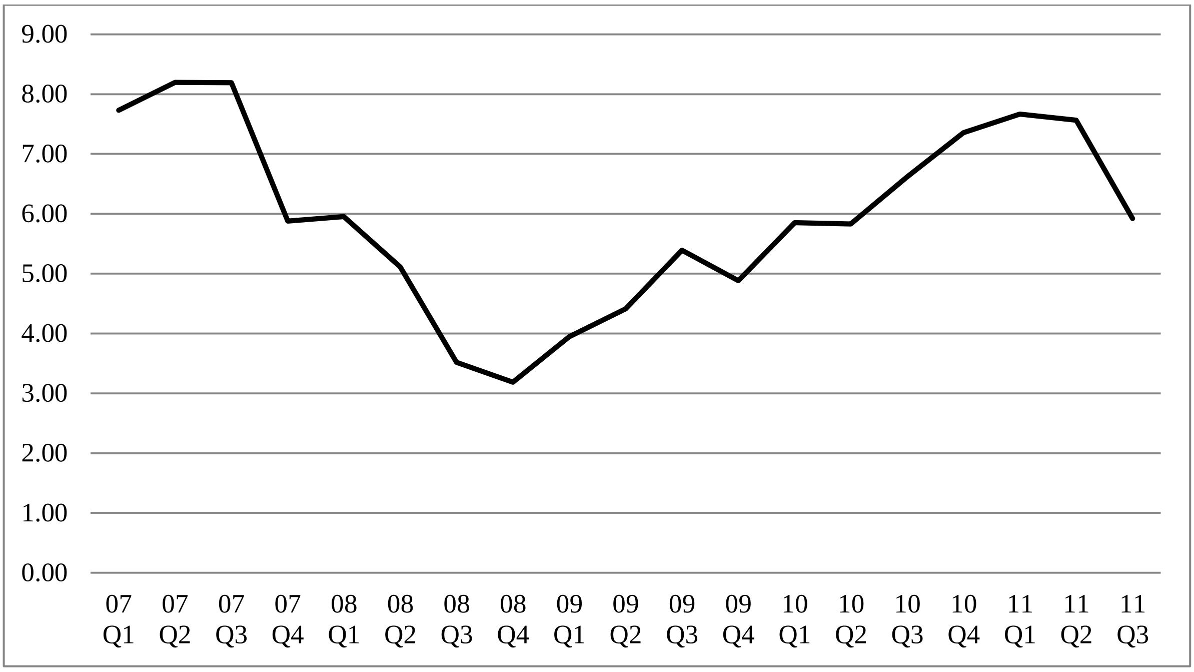


Figure 4
Market-to-Book and Price-to-Earnings Ratio of Cloud Firms

Market-to-book and price-to-earnings ratios of Cloud Firms calculated from quarterly book values and earnings data. Book values and earnings are obtained from Compustat. Data on prices is obtained from CRSP. Sample period is from 2007 to 2011.

Panel A: Market-to-book



Panel B: Price-to-earnings

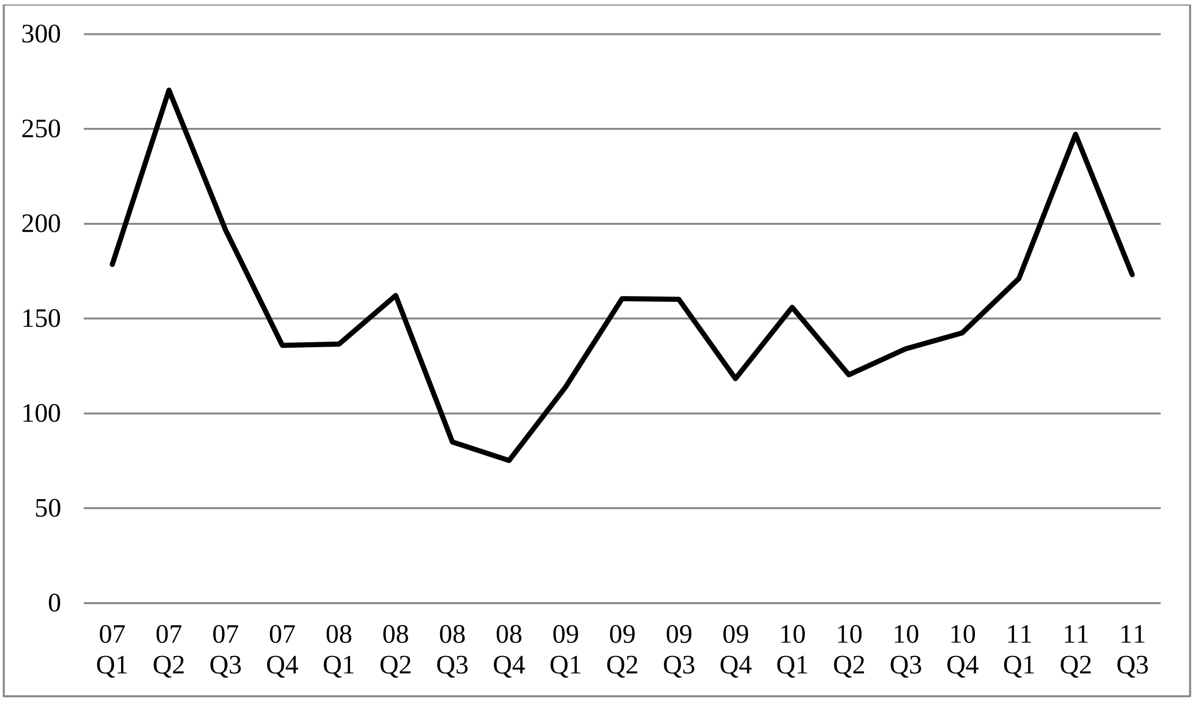


Figure 5
Levels of SVI for Cloud, Tech and Non-tech Firms

Graph illustrating the level of SVI (search volume index) for each sample group from January 2004 to March 2012. Each line shows the mean of SVI value of all firms within a group. SVI is the weekly frequency of searches for the sample firms scaled by the times-series average value over the sample period. Every SVI value is scaled relative to the SVI of Microsoft.

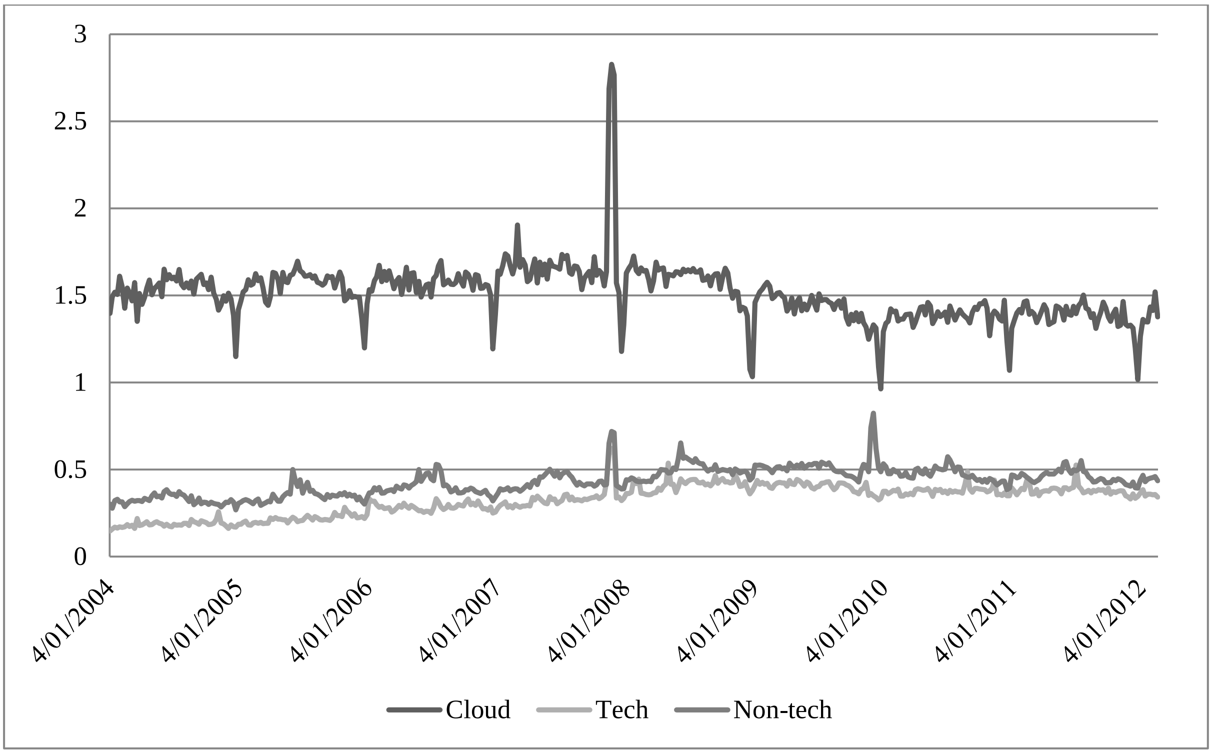
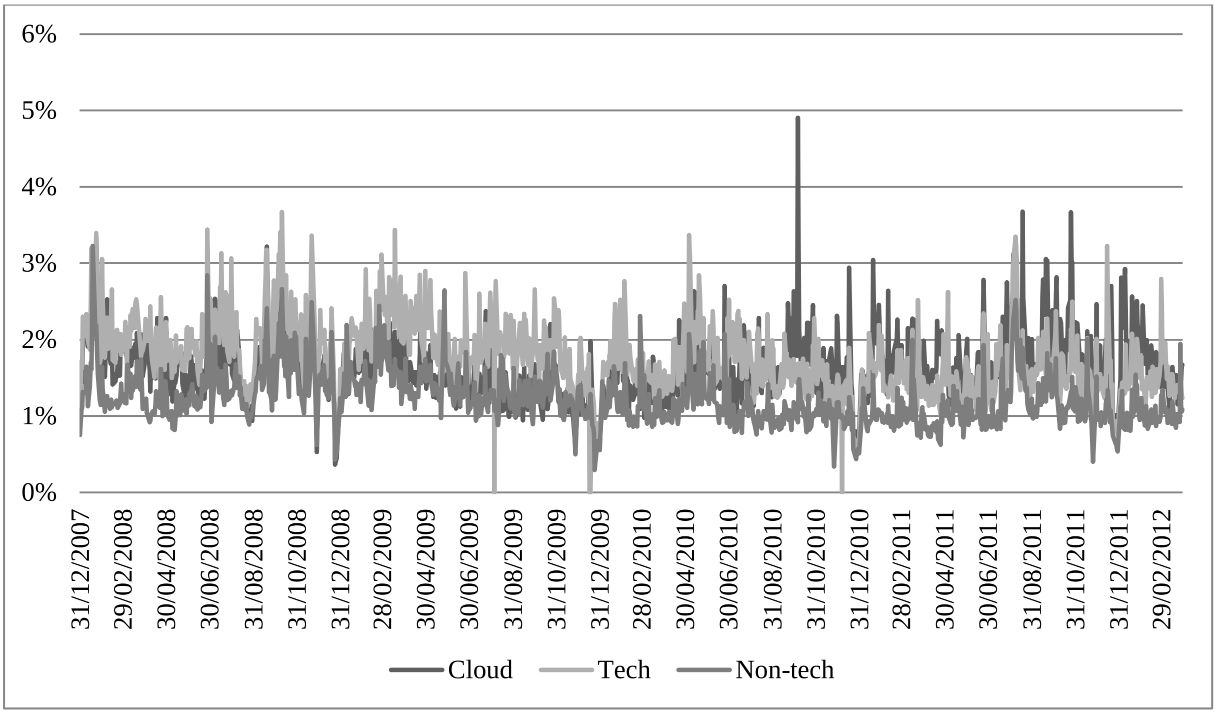


Figure 6
Times-series Turnover and Analyst Coverage for Cloud, Tech and Non-tech Firms

Turnover value for the sample firms shown for the period from 31/12/2007 to 30/03/2012, and is computed as daily volume over shares outstanding (Panel A). Number of analysts following for the sample firms in the period from 31/01/2004 to 31/01/2012 is shown in Panel B.

Panel A: Turnover



Panel B: Analyst coverage

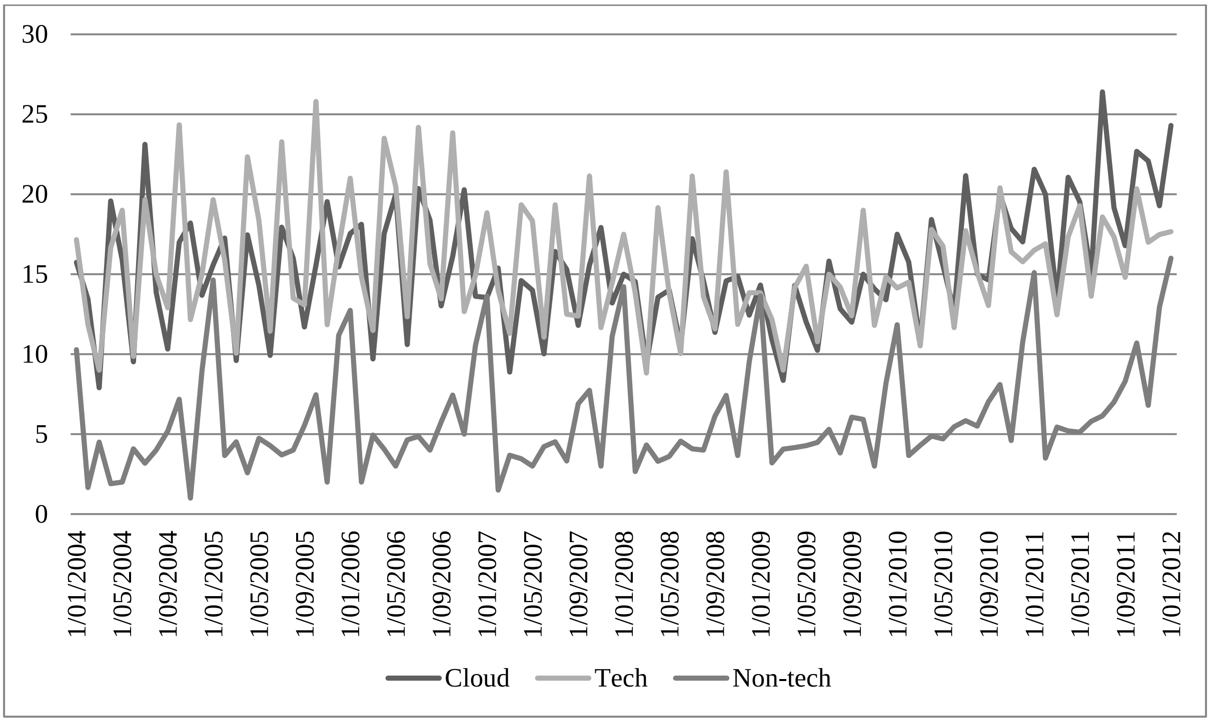
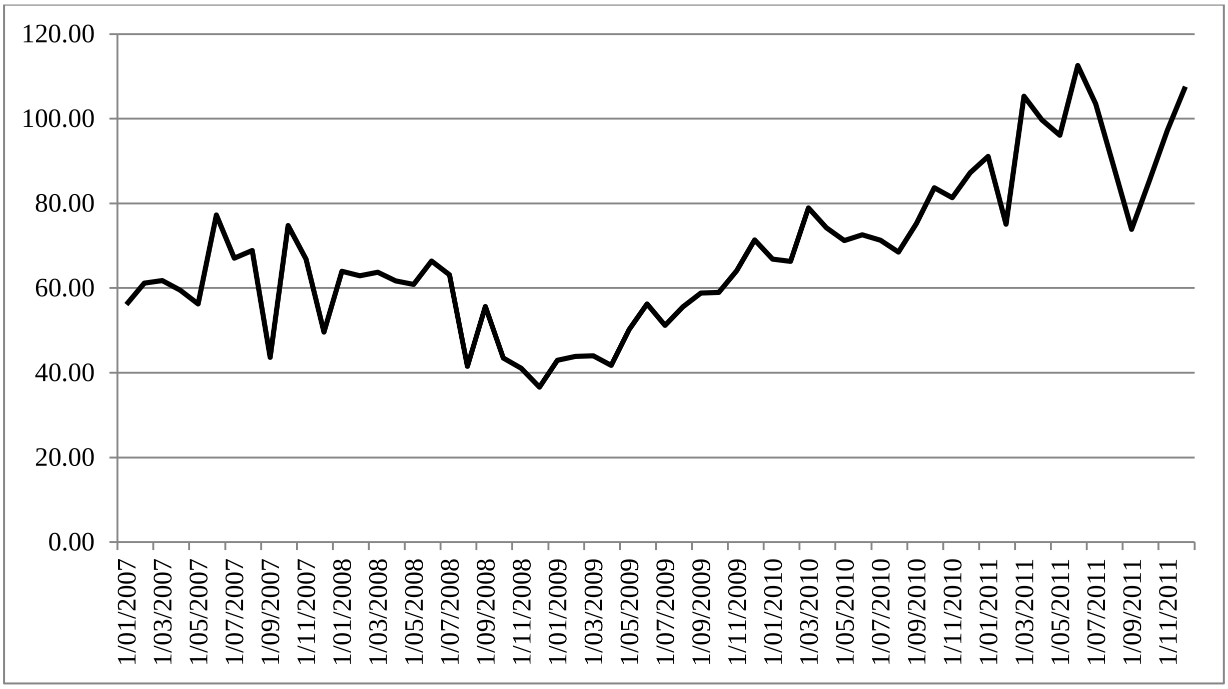


Figure 7
Price Targets and Analyst Forecasts on Cloud Firms

Time-series data on raw one-year price targets on Cloud Firms (Panel A), one-year price targets on Cloud Firms scaled by actual prices (Panel B) and four-quarters-ahead earnings and sales forecasts scaled by their actual values (Panel C). Sample period for price targets is from 2007 to 2011. Sample period for earnings and sales forecasts is from 2007 to 2011.

Panel A: Unadjusted one-year price target



Panel B: One-year price target over actual price

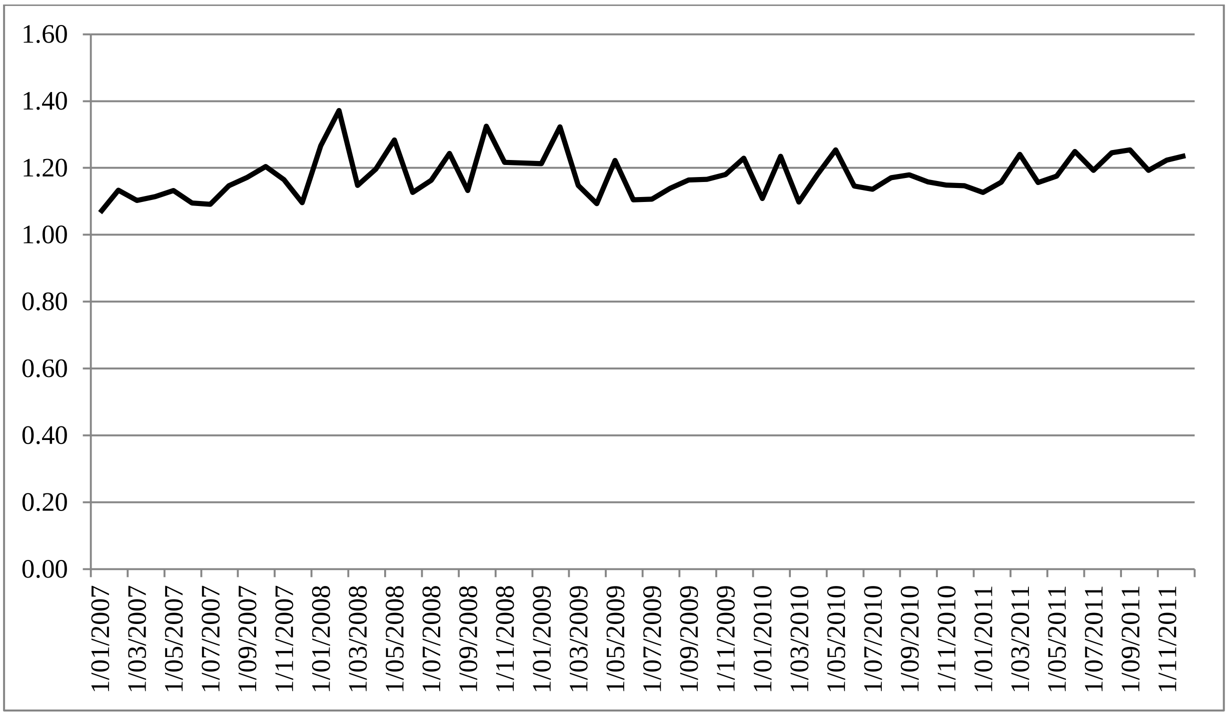


Figure 7 (continued)

Panel C: Forecasts on four-quarters-ahead earnings and sales scaled by actual values

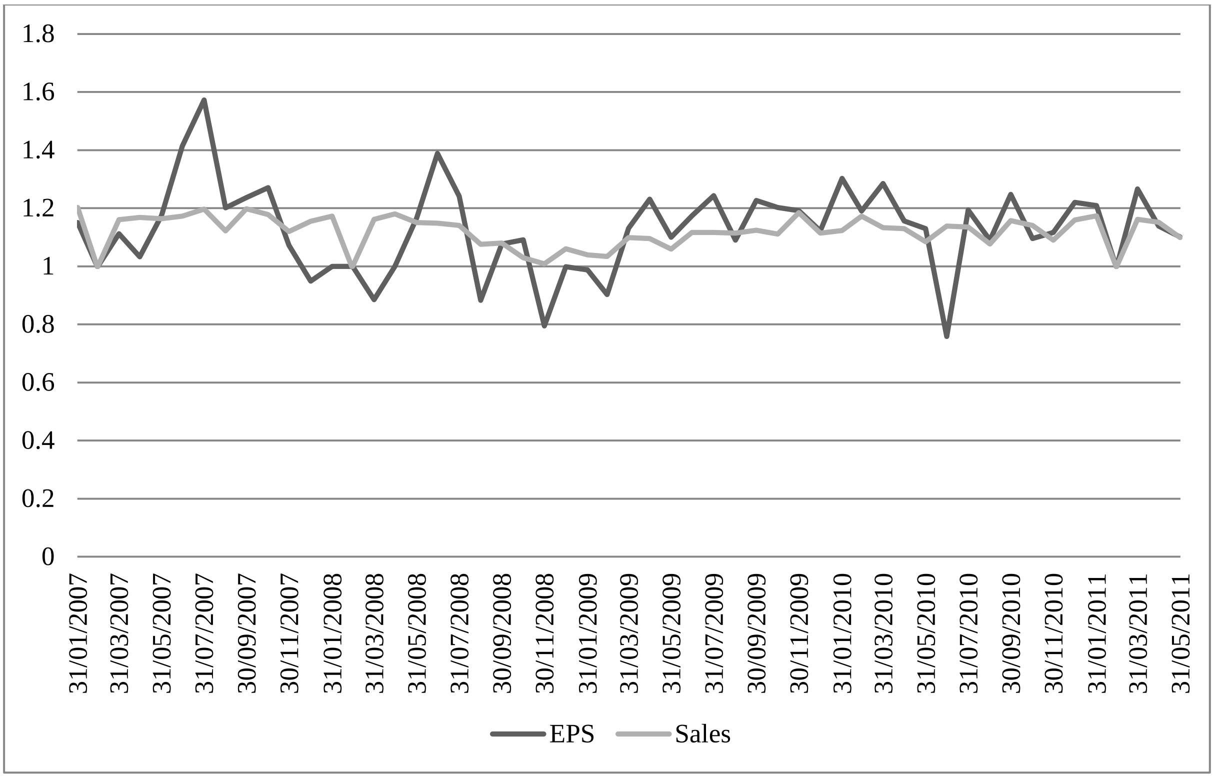
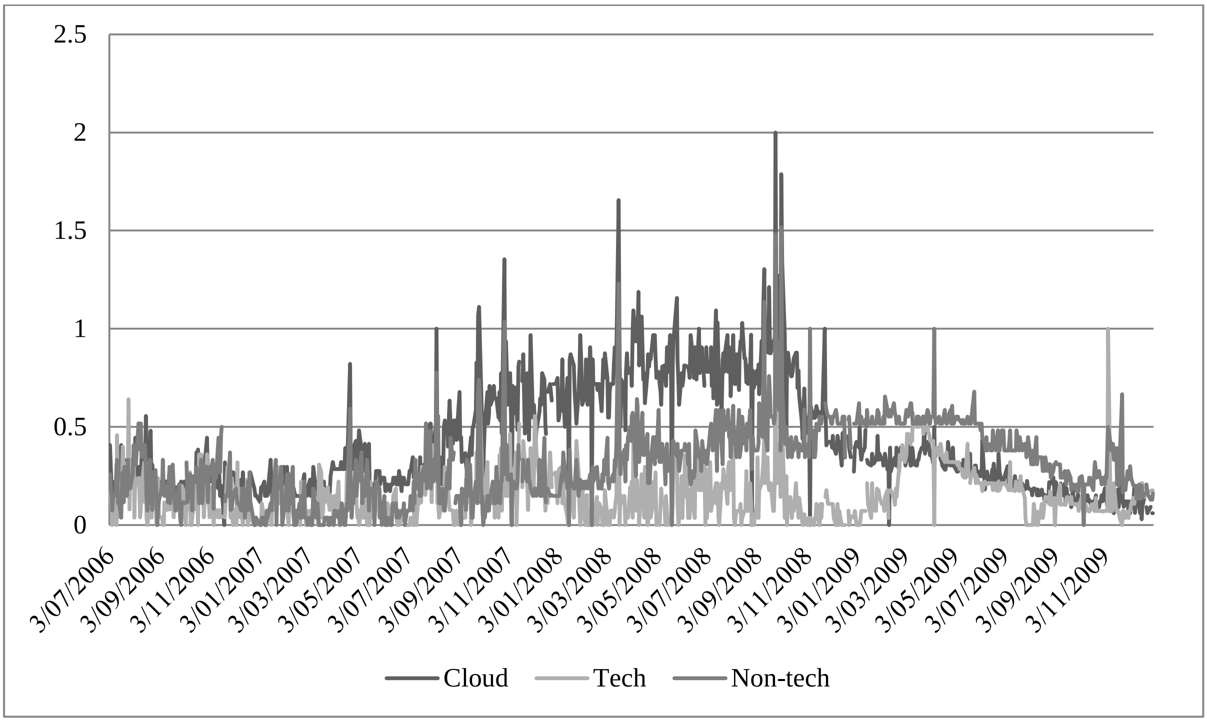


Figure 8
Measures of Short-Sales Constraints of Cloud, Tech and Non-tech Firms

Short-selling constraints for the sample groups as measured by lending fees (Panel A), the percentage of shares outstanding available for short-selling (Panel B), the percentage of shares outstanding actually sold short (Panel C) and utilisation (Panel D). Utilisation is calculated by dividing the percentage of shares actually sold short by the percentage of shares available for short-selling. The sample period is from 03/07/2006 to 31/12/2009.

Panel A: *FEE*



Panel B: *SUPPLY*

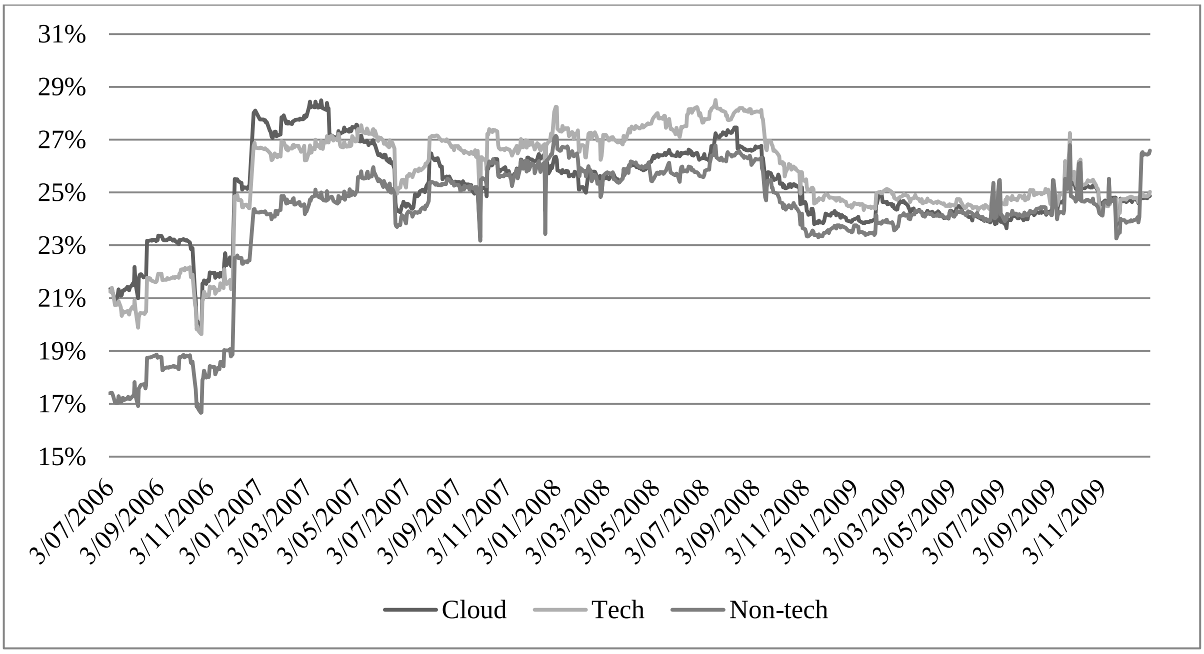
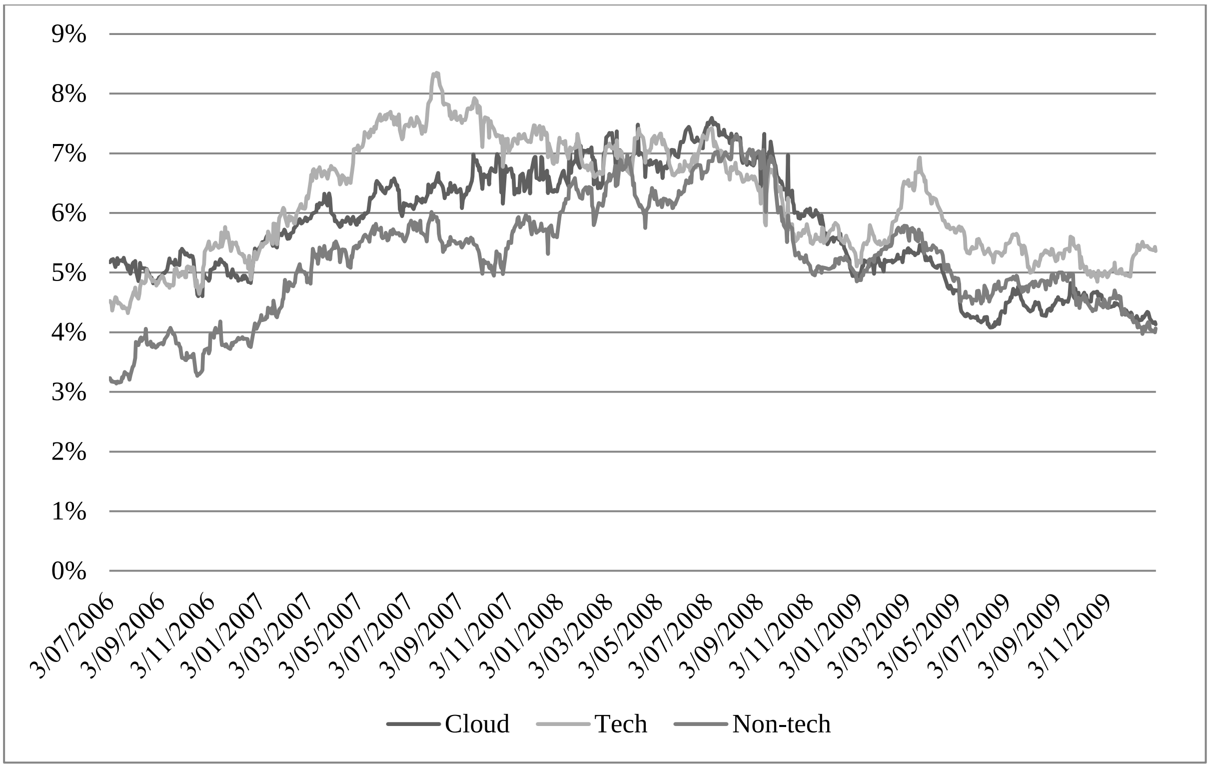


Figure 8 (continued)

Panel C: *DEMAND*



Panel D: *UTILISATION*

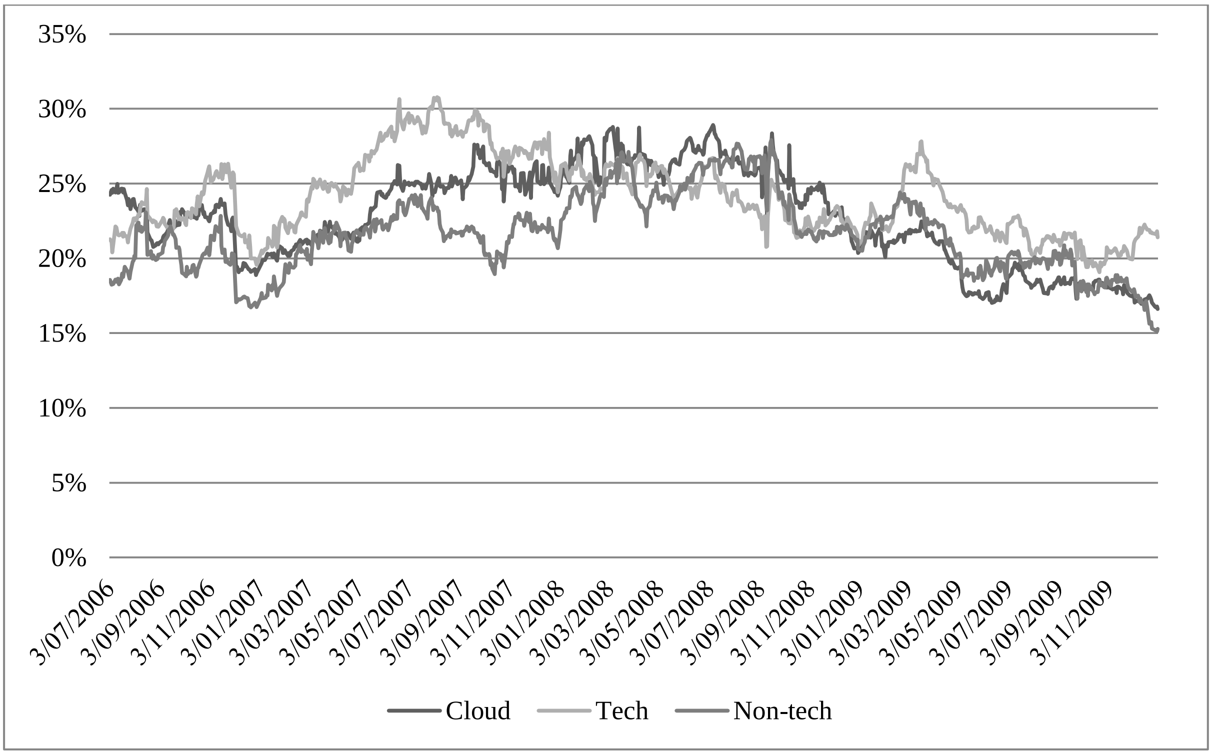
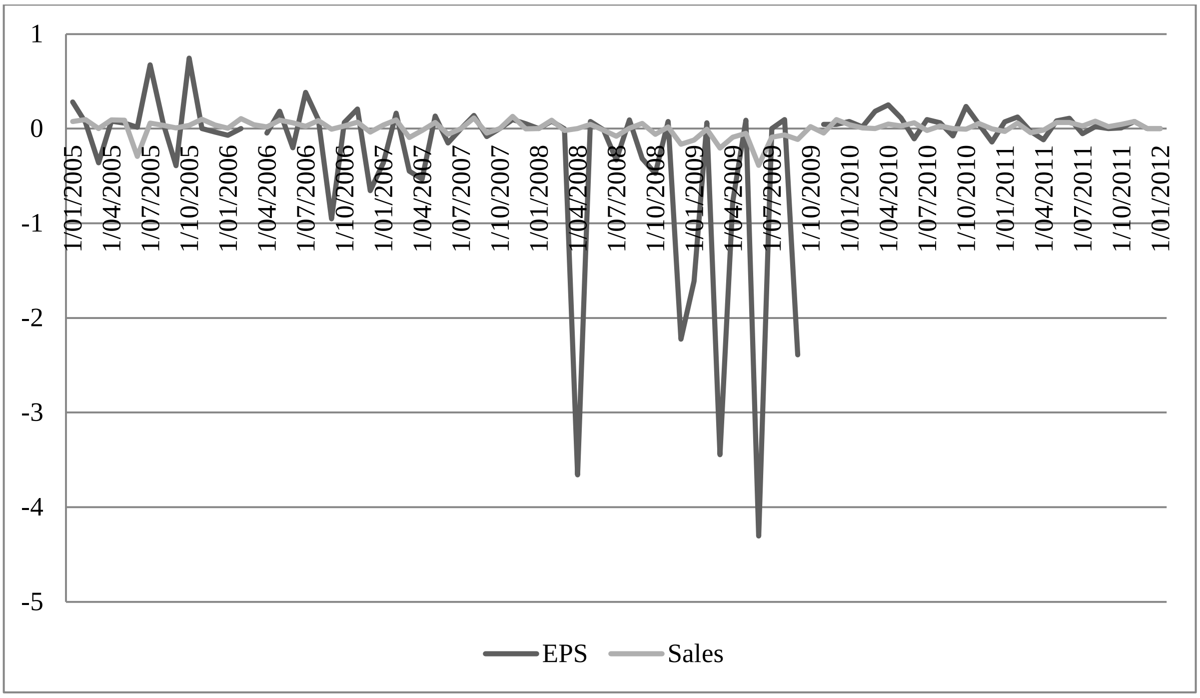


Figure 9
Level of Surprise to Earnings and Sales Forecasts for Cloud, Tech and Non-tech Firms

Monthly levels of surprise to forecasts on earnings or sales for Non-tech (Panel A), Tech (Panel B) and Cloud Firms (Panel C). Each monthly value of surprise on both earnings and sales is calculated by: *(actual value – forecasted value) / forecasted value*. Forecasted values are consensus analyst forecasts and the sample period is from 31/01/2005 to 31/01/2012.

Panel A: Non-tech Firms



Panel B: Tech Firms

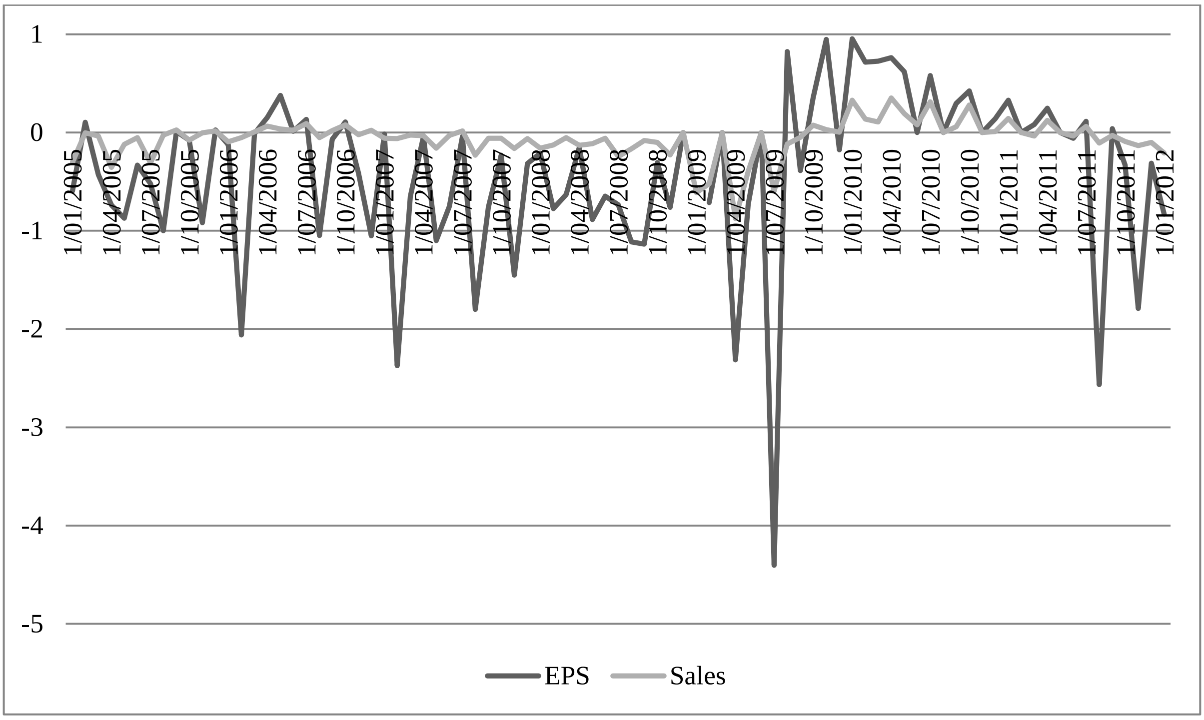


Figure 9 (continued)

Panel C: Cloud Firms

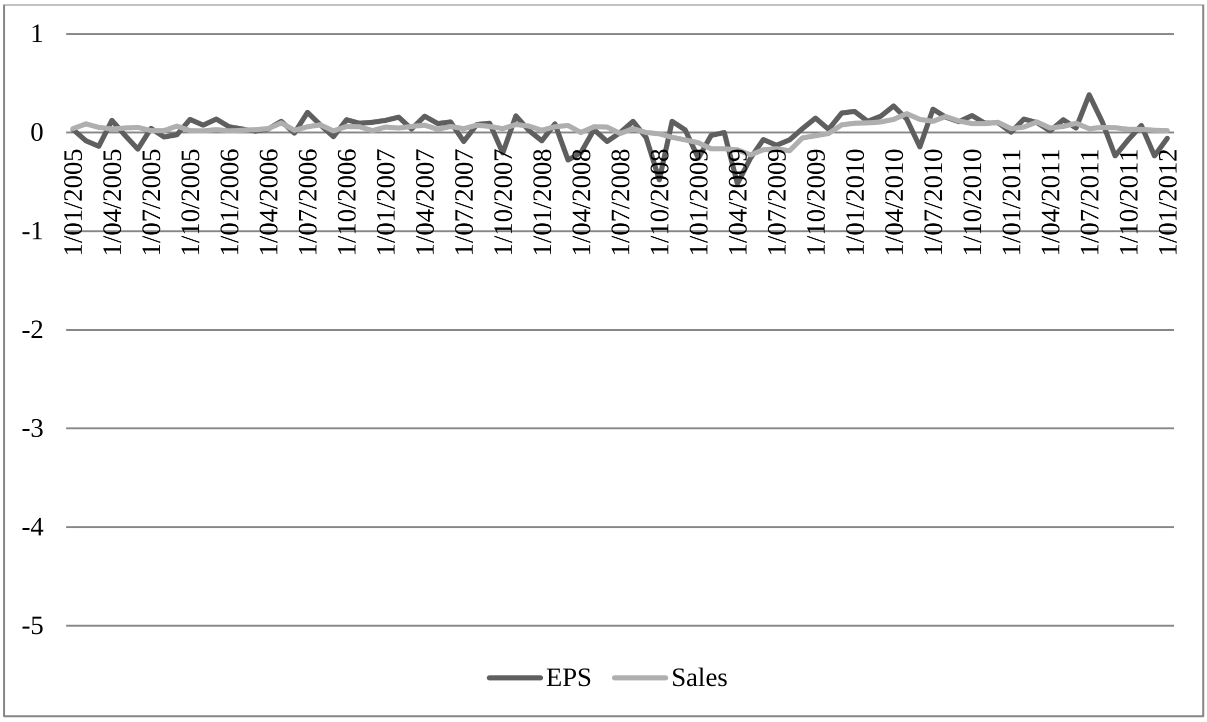
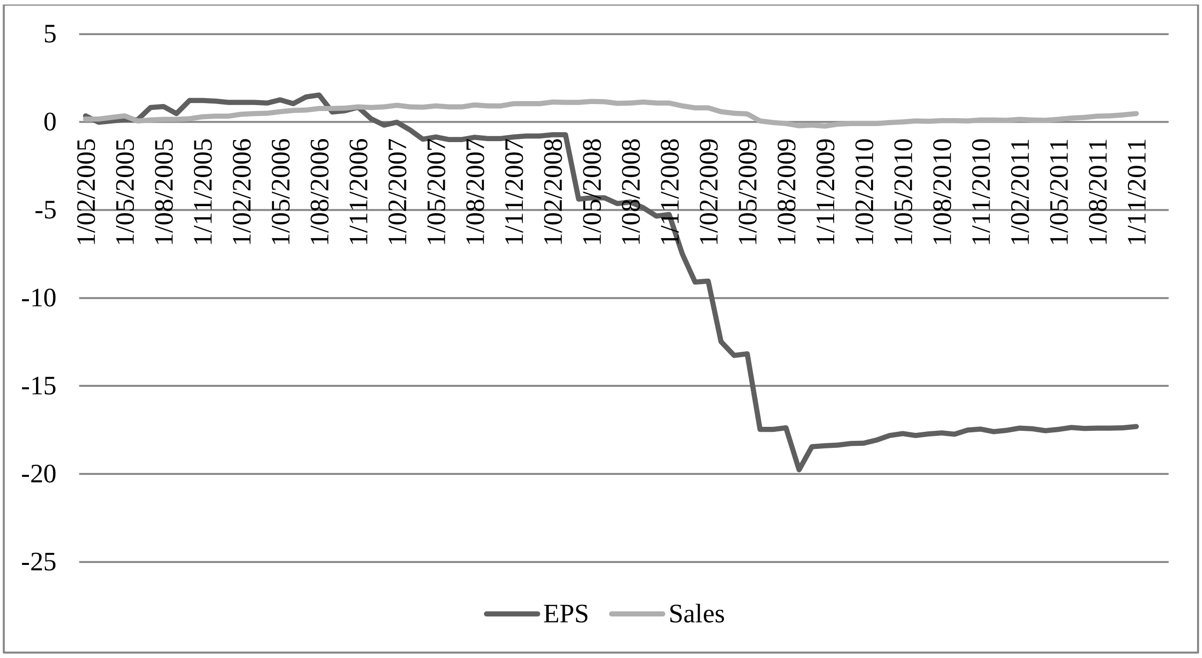


Figure 10
Cumulative Surprise to Earnings and Sales Forecasts

Cumulative surprises to forecasts, either on earnings or sales, for the sample groups. Each monthly value of surprise on both earnings and sales is calculated by: *(actual value – forecasted value) / forecasted value*. Forecasted values are consensus analyst forecasts. Sample period is from 31/01/2005 to 31/01/2012.

Panel A: Non-tech Firms



Panel B: Tech Firms

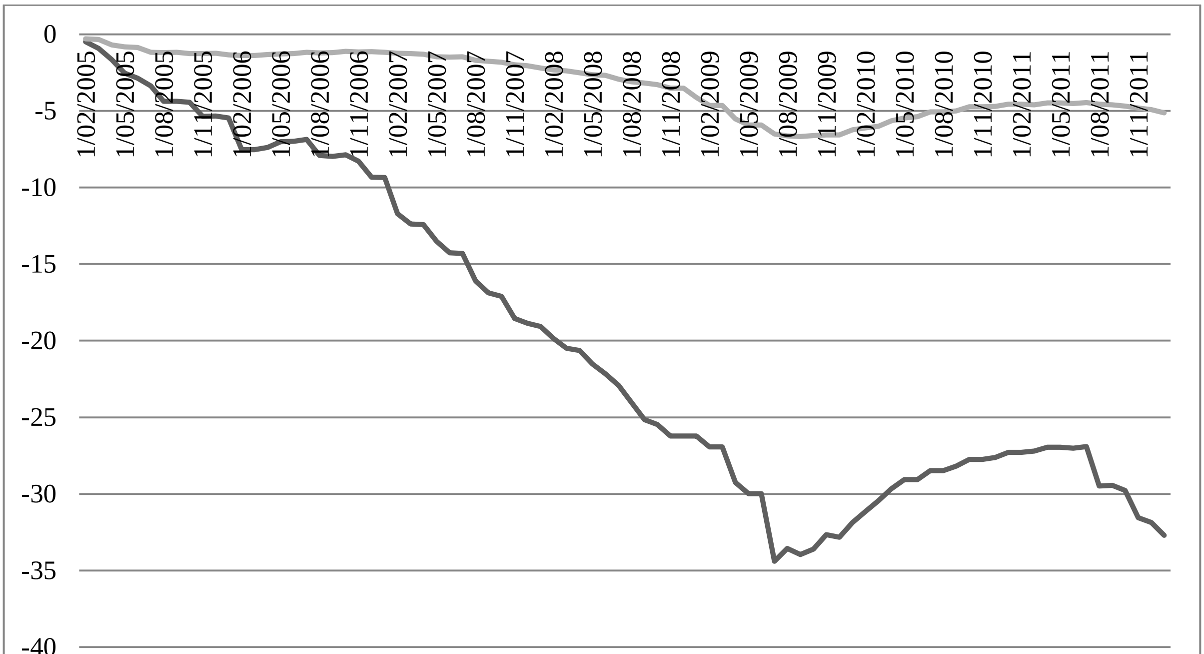


Figure 10 (continued)

Panel C: Cloud Firms

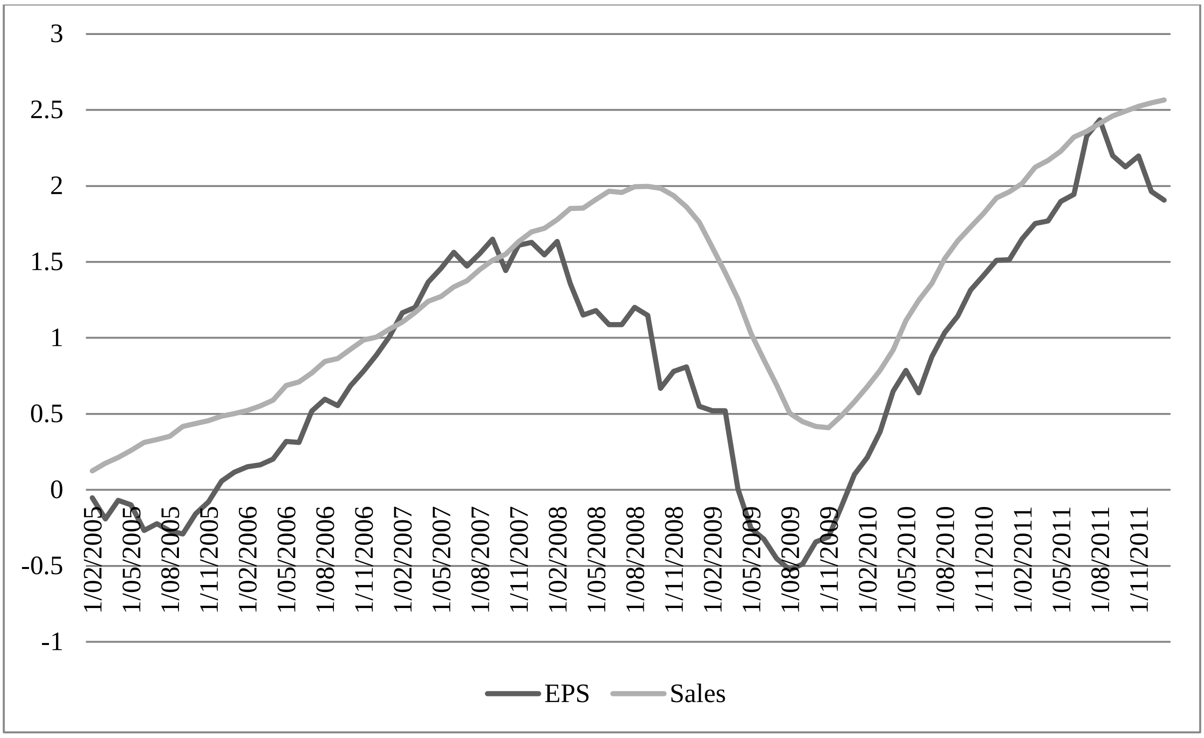


Table 1
Components of the Cloud Index

Name, ticker symbol, number of assigned shares, price and weights of the ISE Cloud Computing Index components as at 17/03/2012.

Name	Ticker	Assigned shares	Price	Weight
Apple Inc.	AAPL	96,408,748	585.6	3.28%
Adobe Systems Inc	ADBE	475,114,707	33.82	0.93%
Akamai Technologies Inc	AKAM	1,779,912,350	37.36	3.86%
Amazon.com Inc	AMZN	260,121,885	185.1	2.80%
Acme Packet Inc	APKT	1,452,453,786	27.55	2.32%
Aruba Networks Inc	ARUN	2,388,740,599	23.62	3.28%
BMC Software Inc	BMC	383,925,545	38.6	0.86%
CA Inc	CA	622,242,709	27.23	0.98%
Check Point Software (US)	CHKP	243,639,656	61.74	0.87%
Salesforce.com	CRM	405,322,307	151.4	3.56%
Cisco Systems Inc	CSCO	2,659,498,273	20.03	3.09%
EMC Corp	EMC	2,132,115,813	28.89	3.58%
Equinix Inc	EQIX	481,828,302	141.8	3.97%
F5 Networks Inc	FFIV	437,609,616	131.9	3.35%
Financial Engines Inc	FNGN	612,234,209	22.11	0.79%
Google Inc	GOOG	80,028,254	625	2.91%
Hewlett-Packard Co	HPQ	1,360,158,113	24.49	1.93%
IBM Corp	IBM	195,047,345	206	2.33%
Informatica Corp	INFA	1,128,344,436	51.63	3.38%
Intuit Inc	INTU	250,088,538	60.14	0.87%
Iron Mountain Inc	IRM	445,261,243	29.19	0.76%
J2 Global Inc	JCOM	491,413,368	30.13	0.86%
Juniper Networks Inc	JNPR	2,523,182,281	21.43	3.14%
Microsoft Corp	MSFT	1,476,591,881	32.6	2.80%
Netsuite Inc	N	1,051,986,746	48.18	2.94%
NetFlix Inc	NFLX	708,299,159	110	4.52%
NetApp Inc	NTAP	1,321,003,088	43.39	3.33%
Netscout Systems Inc	NTCT	751,818,081	20.24	0.88%
Opnet Technologies Inc	OPNT	338,384,973	29.81	0.59%
Oracle Corp	ORCL	3,362,171,109	29.74	5.81%
Open Text Corp	OTEX	917,604,667	59.28	3.16%
Polycom Inc	PLCM	789,230,829	18.65	0.86%
Rackspace Hosting Inc	RAX	1,140,648,055	56.42	3.74%
Red Hat Inc	RHT	1,010,288,277	50.64	2.97%
SAP AG ADR	SAP	854,224,692	72	3.57%
Teradata Corp	TDC	951,512,742	68.24	3.77%
TIBCO Software Inc	TIBX	1,852,133,065	30.52	3.28%
Vmware Inc	VMW	520,702,348	107.1	3.24%
Wipro Corporation Ltd	WIT	1,273,634,455	10.95	0.81%

Note that the components are subject to change. Updated components can be obtained at:
http://www.ise.com/webform/options_product_indexDetails.aspx?categoryID=96&symbol=CPQ

Table 2
Components of the Cloud Index in Segments

Modified version of Appendix A of the ISE Cloud Index Methodology Guide with the Cloud Firms sorted into their respective segments. The weightings are as at 21/03/2011. Aggregate percentage of 99.94% (and not 100%) is due to a rounding difference.

Pure-play firms (total 78.89%)		**Non-pure-play firms (total 11.05%)**		**Technology conglomerates (total 10%)**	
Company Name	Weight	Company Name	Weight	Company Name	Weight
GOOGLE INC-CL A	3.43%	WIPRO LTD-ADR	0.85%	APPLE INC	2.50%
ORACLE CORP	3.43%	ADOBE SYSTEMS INC	0.85%	MICROSOFT CORP	2.50%
CISCO SYSTEMS INC	3.43%	CA INC	0.85%	IBM CORP	2.50%
AMAZON.COM INC	3.43%	CHECK POINT SOFTWARE TECH	0.85%	HEWLETT-PACKARD CO	2.50%
SAP AG-SPONSORED ADR	3.43%	BMC SOFTWARE INC	0.85%		
EMC CORP/MASS	3.43%	IRON MOUNTAIN INC	0.85%		
VMWARE INC-CLASS A	3.43%	POLYCOM INC	0.85%		
NETAPP INC	3.43%	SUCCESSFACTORS INC	0.85%		
JUNIPER NETWORKS INC	3.43%	SAVVIS INC	0.85%		
SALESFORCE.COM INC	3.43%	J2 GLOBAL COMM INC	0.85%		
F5 NETWORKS INC	3.43%	FINANCIAL ENGINES INC	0.85%		
NETFLIX INC	3.43%	NETSCOUT SYSTEMS INC	0.85%		
AKAMAI TECHNOLOGIES INC	3.43%	OPNET TECHNOLOGIES INC	0.85%		
TERADATA CORP	3.43%				
INFORMATICA CORP	3.43%				
RACKSPACE HOSTING INC	3.43%				
EQUINIX INC	3.43%				
TIBCO SOFTWARE INC	3.43%				
OPEN TEXT CORP	3.43%				
ARUBA NETWORKS INC	3.43%				
BLACKBOARD INC	3.43%				
TERREMARK WORLDWIDE INC	3.43%				
RIGHTNOW TECHNOLOGIES INC	3.43%				

Table 3
Sample Description

Descriptive statistics on an initial sample of 39 Cloud Firms before size matching. Panel A shows details of the size matching according to the market capitalisation of the firms as at 30/12/2011. The statistics in Panel B are all computed using data from 31/12/2007 to 30/03/2012. Using daily data, a monthly value for each variable for each firm was obtained. For each month a cross-sectional mean is obtained for each group using the monthly values for each firm. The data presented in Panel B presents the time-series means, medians, standard deviation, low and high values constructed using the montly cross-sectional mean values.

Panel A: Number of matched firms and size difference in sample matching

	Number of firms matched	Mean absolute size difference with Cloud Firms
Number of Cloud Firms with available data	35	-
Size match within technology industry (Tech Firms)	34	2.75%
Size match regardless of industry (Non-tech Firms)	35	0.65%

Table 3 (continued)

Panel B: Detailed sample statistics

Variable	Group	Mean	Median	STD	Low	High
Stock price	Cloud	57.36	56.39	16.05	29.62	85.73
	Tech	34.56	35.44	6.07	22.06	43.60
	Non-tech	39.69	39.42	8.98	23.09	55.48
Bid ask spread/mid price	Cloud	0.0358	0.0308	0.0142	0.0213	0.0941
	Tech	0.0368	0.0320	0.0156	0.0196	0.0946
	Non-tech	0.0350	0.0310	0.0162	0.0187	0.0960
Bid ask spread $	Cloud	1.6766	1.6570	0.4521	0.9793	3.1182
	Tech	1.1860	1.0254	0.4067	0.6919	2.5267
	Non-tech	1.2269	1.1538	0.3767	0.7115	2.5702
Volume	Cloud	8,572,351	8,139,678	1,711,647	5,757,095	14,352,275
	Tech	17,365,700	17,497,435	8,035,736	6,838,098	38,689,796
	Non-tech	3,951,835	3,689,011	754,197	2,855,143	6,266,344
Turnover	Cloud	0.0166	0.0162	0.0029	0.0095	0.0223
	Tech	**0.0178	**0.0172	0.0031	0.0114	0.0247
	Non-tech	***0.0123	***0.0118	0.0022	0.0087	0.0180
Daily standard deviation of return	Cloud	0.0288	0.0272	0.0077	0.0138	0.0478
	Tech	0.0297	0.0280	0.0086	0.0165	0.0565
	Non-tech	0.0292	0.0250	0.0126	0.0130	0.0801

** Significantly higher than Cloud Firms at the 5% level

*** Significantly lower than Cloud and Tech Firms at the 1% level

Table 4
Free Float Shares and Shares Held by Insiders and Institutions

Free float shares, shares held by insiders and institutions are for the three sample groups. Data is collected from Yahoo! Finance and is as at 31/05/2012. All variables are scaled by the total shares outstanding.

Variable	Group	Mean	Median	STD	Low	High
Float	Cloud	84.59%	92.97%	20.60%	18.45%	99.81%
	Tech	**94.30%	**97.13%	7.90%	69.14%	103.37%
	Non-tech	88.32%	92.39%	13.56%	59.30%	103.56%
% Held by Insiders	Cloud	9.82%	5.04%	12.98%	0.00%	59.60%
	Tech	**4.91%	**1.49%	7.07%	0.04%	31.01%
	Non-tech	**4.96%	**0.83%	7.77%	0.02%	28.52%
% Held by Institutions	Cloud	83.99%	87.55%	19.19%	23.00%	116.20%
	Tech	81.22%	84.60%	19.06%	2.60%	105.30%
	Non-tech	**73.42%	**78.80%	27.24%	1.10%	108.40%

**Significantly different to the Cloud group at the 5% level.

Table 5
Mean Equally Weighted Benchmark First-Day Returns

Table showing a summary of equal-weighted mean IPO first-day returns from 1985 to 2012 used as the normal first-day returns. The left panel shows the mean first-day returns for each year of all firms searched using the Advance SIC Keyword Lookup on the SDC database as a representation of the average IPO underpricing in the technology industry. The right panel shows the mean first-day returns for each year of all firms that issued IPOs, obtained from Jay Ritter's webpage (http://bear.cba.ufl.edu/ritter).

Tech IPO Benchmark			Aggregate IPO Benchmark		
Year	Return	IPO count	Year	Return	IPO count
1985	-21.2%	8	1985	6.3%	183
1986	159.5%	152	1986	6.1%	396
1987	27.8%	122	1987	5.7%	284
1988	41.4%	50	1988	5.7%	102
1989	33.6%	52	1989	8.2%	113
1990	13.6%	49	1990	10.8%	110
1991	19.0%	104	1991	11.9%	287
1992	13.4%	130	1992	10.3%	412
1993	18.2%	160	1993	12.7%	509
1994	7.9%	138	1994	9.8%	404
1995	36.3%	232	1995	21.2%	457
1996	15.7%	320	1996	17.2%	675
1997	11.3%	193	1997	14.1%	473
1998	42.5%	133	1998	21.7%	284
1999	84.9%	286	1999	70.9%	477
2000	61.4%	242	2000	56.4%	380
2001	17.8%	34	2001	14.2%	79
2002	6.2%	25	2002	9.1%	66
2003	18.4%	24	2003	12.1%	62
2004	11.6%	76	2004	12.2%	175
2005	7.5%	65	2005	10.2%	160
2006	12.8%	75	2006	12.1%	157
2007	16.6%	84	2007	13.9%	160
2008	-7.9%	8	2008	6.4%	21
2009	29.2%	21	2009	9.8%	41
2010	10.2%	52	2010	9.1%	94
2011	27.5%	48	2011	13.3%	81
2012	32.7%	18			
Mean	**26.7%**			**15.2%**	
Median	**18.0%**			**11.9%**	
Total number of IPOs		2901			6642

Table 6
Abnormal IPO First-Day Returns of Cloud Firms

Issue date, name, raw returns and two sets of abnormal returns shown for Cloud Firms computed from two benchmarks. Technology IPOs refers to the mean first-day returns for each year of all firms searched on SDC database. All IPOs refers the mean first-day returns for each year of all firms that issued IPOs during the year.

			Technology IPOs		All IPOs	
Issue Date	Issuer	Raw returns	Benchmark	Abnormal return	Benchmark	Abnormal return
18/08/04	Google Inc	18.04%	11.59%	6.44%	12.2%	5.8%
16/02/90	Cisco Systems Inc	23.61%	13.60%	10.01%	10.8%	12.8%
15/05/97	Amazon.com Inc	30.56%	11.25%	19.30%	14.1%	16.5%
04/04/86	EMC Corp	-10.61%	159.47%	-170.08%	6.1%	-16.7%
13/08/07	VMware Inc	75.86%	16.57%	59.29%	13.9%	62.0%
21/11/95	Network Appliance Inc	51.85%	36.30%	15.56%	21.2%	30.7%
24/06/99	Juniper Networks Inc	190.82%	84.90%	105.92%	70.9%	119.9%
22/06/04	SalesForce.com Inc	56.36%	11.59%	44.77%	12.2%	44.2%
04/06/99	F5 Networks Inc	55.00%	84.90%	-29.90%	70.9%	-15.9%
22/05/02	Netflix Inc	11.67%	6.15%	5.51%	9.1%	2.6%
28/10/99	Akamai Technologies Inc	458.42%	84.90%	373.52%	70.9%	387.5%
11/08/87	Teradata Corp	20.00%	27.79%	-7.79%	5.7%	14.3%
28/04/99	Informatica Corp	83.63%	84.90%	-1.28%	70.9%	12.7%
07/08/08	Rackspace Hosting Inc	-19.92%	-7.89%	-12.03%	6.4%	-26.3%
26/03/07	Aruba Networks Inc	28.64%	16.57%	12.07%	13.9%	14.7%
23/01/96	Open Text Corp	46.67%	15.73%	30.94%	17.2%	29.5%
17/06/04	Blackboard Inc	42.93%	11.59%	31.34%	12.2%	30.7%
12/10/06	Acme Packet Inc	67.47%	12.75%	54.72%	12.1%	55.4%
05/08/04	RightNow Technologies Inc	0.00%	11.59%	-11.59%	12.2%	-12.2%
13/08/86	Adobe Systems Inc	22.73%	159.47%	-136.74%	6.1%	16.6%
27/06/96	CheckPoint Software Tech	75.00%	15.73%	59.27%	17.2%	57.8%
12/08/88	BMC Software Inc	-4.11%	41.44%	-45.55%	5.7%	-9.8%
29/07/97	Iron Mountain Inc	30.89%	11.25%	19.63%	14.1%	16.8%
29/04/96	Polycom Inc	-1.33%	15.73%	-17.06%	17.2%	-18.5%
19/11/07	SuccessFactors Inc	32.50%	16.57%	15.93%	13.9%	18.6%
12/03/93	Intuit Inc	58.75%	18.23%	40.52%	12.7%	46.1%
15/03/10	Financial Engines Inc	43.75%	10.20%	33.55%	9.1%	34.7%
12/08/99	NetScout Systems Inc	25.00%	84.90%	-59.90%	70.9%	-45.9%
10/08/00	Equinix Inc	9.42%	61.37%	-51.95%	56.4%	-47.0%
01/08/00	OPNET Technologies Inc	42.31%	61.37%	-19.06%	56.4%	-14.1%
13/07/99	TIBCO Software Inc	115.87%	84.90%	30.96%	70.9%	45.0%
	Mean first-day returns	**54.25%**		**13.11%**		**28.01%**
	Median first-day returns	**32.50%**		**12.07%**		**16.46%**

Table 7
Abnormal IPO First-Day Returns of Cloud and Tech Firms

Table presenting the mean and median abnormal IPO first-day returns of the sample groups where the normal returns used as benchmarks are either the mean of all IPOs or all IPOs of technology firms, for each year matching each Cloud or Tech Firm's year of issue. Results of t-tests and sign tests are also presented. Data on all IPOs is available from Jay Ritter's webpage (http://bear.cba.ufl.edu/ritter) and data on technology IPOs was collected from the SDC database.

	Tech Firms	Cloud Firms	
	Against all IPOS	Against Tech IPOs	Against all IPOs
	Column 1	*Column 2*	*Column 3*
Mean abnormal return	31.86%	13.11%	28.01%
Median abnormal return	9.28%	12.07%	16.46%
Number of positive abnormal returns	19	19	22
Number of negative abnormal returns	8	12	9
Sign test p-value	*0.0522	0.2810	**0.02945
t-statistics	*1.66	0.76	**1.75

**, * denote significant values to the 5% and 10% level, respectively (one-tailed tests).