The Impact of Social Mood on Financial Markets

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Abstract

This thesis presents three empirical papers that explore the extent of UK social mood on UK stock indexes. The first paper utilises mobile, broadband, landline and pay TV complaints as an extra factor in an augmented-CAPM setting. Using time series OLS, this study finds empirical evidence that people who complain about actual or perceived mobile or broadband service failure experience catharsis, as increased mobile and broadband complaints lead to increased excess returns for smaller indexes and reduced excess returns for larger indexes. By contrast, results show that people who complain about landline and pay TV experience frustration, as increased landline and broadband complaints lead to increased excess returns for larger indexes and lowered excess returns for smaller indexes.

In the second paper, wine, beer, spirits and cider receipts are used in Granger causality tests, VARs, and then impulse response tests. Using time series, this paper finds empirical evidence of mood enhancement through alcohol consumption – this is because an increase in wine, beer, spirits or cider consumption precedes a lowering of FTSE trading volume, which is consistent with the Mood Maintenance Hypothesis. Furthermore, an increase in beer consumption leads to an increase in smaller company index returns, which is consistent with the sentiment literature. Contrary to the existing literature, impulse response test results indicate that FTSE returns, or changes in trading volumes, have an insignificant impact on UK social mood measured by alcohol.

The final paper makes use of Google searches for music genre to develop a novel Music Search Index (Music Index). Using The Music Index level and its rate of

change on daily and monthly data, this paper finds evidence of mood affecting the FTSE through mood management. Mood management works by impacting peoples' search for music (cognitivism) in order to find music that will extend or modify their current mood (emotivism).

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Introduction

Traditional perspectives on Finance suggest that financial markets are efficient at pricing assets, so that assets prices reflect asset values. Efficient Market Hypotheses (EMH) is the bedrock of this view, whereby financial markets efficiently incorporate only new relevant information as it becomes available, and any mispricing is quickly removed by arbitrage (Fama, 1970). This traditional view may be accurate in the long-term, but it has been shown that financial markets are not completely rational as evidenced through several past market bubbles and many ‘anomalies’ that are at odds with EMH. Examples of bubbles include the South Sea bubble, Tulip Mania, Dot.com bubble (Abreu and Brunnermeier, 2003) and more recent crypto-currency bubble (Kyriazis, Papadamou and Corbet, 2020), which have attracted significant investor and regulator attention due to rapid growth of crypto-currency as an asset class (Giudici, Milne and Vinogradov, 2020). There are also some well-known ‘anomalies’ supporting the notion that financial markets are not completely led by rational behaviour – for example the January- effect (Haug and Hirschey, 2006), the Gone-Fishing effect (Hong and Yu, 2009), the School’s Out effect (Coakley, Kuo and Wood, 2012), and the Day-of-the-Week effect (Dubois and Louvet, 1996), inter alia.

The impact of non-rational effects on financial markets is endemic, which has been described as ‘animal spirits’ (Aggarwal, 2014) or ‘irrational exuberance’ (Shiller, 2015), has inspired a new stream of literature that focuses on non-fundamental factors that impact investor activity in financial markets. Non-fundamental factors that have been shown to influence financial markets include, but are not limited to, sports results (Edmans, García and Norli, 2007), weather (Hirshleifer and Shumway, 2003), geomagnetic activity (Robotti and Krivelyova, 2005), and Seasonal Adjustment Disorder (Rozeff and Kinney Jr, 1976; Kamstra, Kramer and Levi, 2003). The related literature shows evidence that financial markets are semi-efficient in incorporating fundamental information, but also provide ample evidence that non-fundamental factors are playing a significant role in pricing of assets in financial markets around the world.

Based on the relatively young field of Socionomics (Prechter and Parker, 2007; Prechter, 2016) within the field of Behavioural Finance, this thesis explores the extent to which in the United Kingdom (UK) social mood has an impact on activity in the London Stock Exchange (LSE). Social mood is a state of negative or positive affect that is present in a society (Prechter, 2016). The mood is consciously and subconsciously spread in society through ‘mood contagion’, which occurs not only through voice but also through non-verbal cues in body language during interactions (De Gelder, 2006). Social media and easy access to news greatly assists the mood contagion process, especially for people who follow influencers or news organisations. As people who participate in financial markets are part of society, some of this social mood is expected to be reflected in pricing or at least in some level of activity in the LSE. The impact of social mood on LSE participants is not uniform, as the existing literature suggests that retail or unsophisticated individual investors will be most likely affected by non-fundamental information or factors (Baker and Wurgler, 2007), whilst institutional investors are expected to be the least affected by non-fundamental information or factors. In the context of different sizes of LSE indexes, the larger FTSE 100 index is expected to be the least affected by non-fundamental information or factors, as it comprises of companies that are large, easy to buy-sell, consistent cashflows/profit, easy to value, and have assets to use as security (Baker and Wurgler, 2007). Conversely, the relatively smaller index of FTSE AIM is expected to be the most affected by non-fundamental information or factors, as the index contains companies that are mainly young corporations which are smaller, not easy to buy-sell, unpredictable cashflows/profit, difficult to value, and have fewer assets to use as security in case of refinancing.

This thesis investigates the research question ‘to what extent does UK social mood impact UK stock indexes?’. To do so, it adopts a top-down macro approach focusing on the possible proxies of UK social mood and the extent of mood’s impact on FTSE indexes. The top-down (macro) approach is used in this thesis is in line with a variety of research in the field (Hirshleifer and Shumway, 2003; Edmans, García and Norli, 2007) and it completements the approach by other papers which use the bottom-up (micro) approach whereby the studies focus on how individual investor biases affect investment decisions. Individual investor bias such as overconfidence (Daniel, Hirshleifer and Subrahmanyam, 1998), conservatism or representativeness (Barberis, Shleifer and Vishny, 1998), inter alia.

This research question is explored through different foci of investigation and indexes in the papers discussed in this thesis. The first paper uses Catharsis Hypothesis, mobile, broadband, landline and pay TV complaints in an Augmented CAPM framework. The second paper uses alcohol receipts in Granger causality tests, VARs and impulse response tests to illustrate mood-FTSE relationship. Finally, the third paper makes use of searches for music genres in Google to construct an original Music Index. The Music Index is a modified FEARS index that uses constant search terms rather than the dynamic-search terms used to construct the FEARS index.

This thesis contributes empirically to Socionomics (Prechter, 2016) through the findings stemming from three papers, each showing the relationship between social mood and FTSE indexes. The first paper shows evidence of how social mood has an impact on FTSE excess returns by using telecommunication (mobile, broadband, landline and pay TV) complaints as factors in augmented Capital Assets Pricing Model (CAPM) framework. The results indicate that digital (mobile and broadband) complaints are associated with (positive) catharsis-mood and increased excess returns of smaller indexes. Mobile and broadband coefficients are positive and statically significant when FTSE AIM 100, FTSE AIM All Share, FTSE Small and FTSE discretionary are regressed on mobile and broadband complaints. Conversely, mobile and broadband complaints coefficients are negative and statistically significant when FTSE Large excess returns are regressed on mobile and broadband complaints. Traditional (Landline and pay TV) complaints are shown to be associated with (negative) frustration-mood. This is observed when landline and pay TV complaints are positive and significant when FTSE Large excess returns are regressed on landline and pay TV complaints. The implication of these findings is that mobile, broadband, landline and pay TV complaints can be used as an extra factor in the augmented CAPM framework to show how catharsis-mood – or conversely also frustrating-mood – affects financial markets, by using the Catharsis Hypothesis from the field of Psychology.

The second paper shows evidence of how social mood has an impact on FTSE returns by utilising alcohol receipts in Granger causality tests, employing Vector Autoregressive Model (VAR), and impulse response tests. The results suggest that beer, wine, spirits and cider consumption has an impact on the reduction of FTSE 100 and FTSE 250 trading volume. Amongst the different types of alcohol, wine and beer had the biggest impact, when compared to spirits and cider. In terms of impact on returns, only beer had an impact on smaller index FTSE returns, as impulse response tests show that beer had an effect of increasing FTSE AIM 100 and FTSE AIM All Share returns. This finding is robust when market value or capitalization rate of change is used instead of index returns. The implication here is that drinking to enhance mood is more likely than drinking to cope, as increased alcohol consumption is associated with increased returns of smaller indexes. Also, there is reduction in trading volume, suggesting that the Mood Maintenance Hypothesis (MMH) is also more likely than the Affect Infusion Model (Lepori, 2015) in the UK.

The third paper shows evidence that social mood has an impact on FTSE returns and trading volume through the creation of the Music Index. The Music Index is bespoke for a particular FTSE index and works when daily and monthly data are used. The results show that contemporaneous and lagged Music Index level coefficients are significant as independent variables when dependent variables are FTSE returns and FTSE change in volume. When the Music Index rate of change is used as an independent variable, the results show the contemporaneous coefficient to be statistically significant. The Music Index for one index can also be used for other FTSE indexes, but the results are not consistent. The implication of this is that the Music Index captures peoples' application of mood management as their current mood affects selection of music (cognitivism), and listening to music has a mood extending or mood modification impact (emotivism).

The statistical methods and indicators (proxies for social mood) used in this thesis are motivated by existing literature in (Behavioural) Finance and Psychology. The first paper uses an augmented CAPM framework, which has been widely used in Finance since the mid-1960s to estimate the cost of capital and to evaluate firm, manager or portfolio performance (Fama and French, 2004). The indicator (proxy for social mood) used in the first paper is motivated by the Psychology literature, where it is linked to the notion of ‘catharsis’, a means to purge negative effect/emotion from oneself which has a long history from ancient Greece to more modern times (Verona and Sullivan, 2008; Bennett, 1997). The use of telecommunication complaints to capture catharsis and/or frustration of a large segment of the population during their ordinary activity benefits from its natural occurrence, which does not have the drawbacks of lab experiments or interviews, where participants’ answers may differ from their actions if no one is observing them.

In the second paper, the motivation to use VARs and impulse response tests is twofold, 1) there is widespread use of this statistical tool in the Finance literature such as in Vozlyublennaia (2014), and Beer, Herve and Zouaoui (2013); and 2) impulse response functions yield a visual time-show of how a one standard deviation shocks in independent variable(s) (Brooks, 2019). The use of alcohol as an indicator in the second paper is motivated by studies in the field of Psychology illustrating how alcohol can be used as a mood enhancer (in positive mood) or mood inhibitor (in negative mood) (Cyders and Smith, 2007; Cooper, 1994). In terms of sample size, using alcohol receipts incorporates peoples’ ordinary activity in a variety of settings and with different types of alcoholic drinks.

The third paper is inspired by the Financial and Economic Attitudes Revealed by Search (FEARS) index (Da, Engelberg and Gao, 2015) – this paper modifies this index by using a different country, period and search terms. The search terms used in the third paper are motivated by music, which has been used to change, or extend mood since Sumerian and Babylonian times (Murrock, 2005); more recently, music has been shown to help reduce anxiety for patients in intensive care (Chlan, 1998) – further use of music and benefits of Google searches are explained in section 2.2.

Overall, the broad contribution of this thesis is twofold: one is its empirical application of Socionomics to the UK context, and the more specific contribution is to the field of behavioural finance through the introduction of new proxies of social mood. While most research thus far has focused on investor sentiment, this thesis focuses on social mood. In particular, the three chapters also offer specific contributions: the first paper focuses on the catharsis-mood (and frustration-mood) relationship with FTSE returns when people are complaining about actual or perceived service failure. The second paper makes two further contributions by 1) adding alcohol as a new proxy to capture social mood and show that social mood is affecting financial markets, and 2) adding empirical evidence for the Mood-Maintenance Hypothesis (MMH) in the UK rather than Affect Infusion Model (AIM) (Lepori, 2015). The third paper makes three main contributions: first, the paper extends Socionomics Theory by exploring contemporary music genres that were not discussed in Prechter (1999); secondly, the paper constructs a new Music Index using freely and readily available music genre search information which does not suffer from some of the issues experienced with surveys; finally, it bridges two aspects of the literature by connecting Spotify/iTunes-music-mood papers with Google-search papers.

This thesis bridges the gap between the EMH and Socionomics by empirically illustrating that the FTSE indexes on the London Stock Exchange (LSE) do not behave fully rationally as three different indicators of social mood are significant when used in regressions as independent variables. The indicators used, which should not have explanatory power, are drawn from the field of Psychology (further discussed in sections 1.2, 2.2 and 3.2) and thus, this is not a data snooping exercise. The indicators are significant even when (fundamental) factors such as market risk premium, Gross Domestic Product (GDP) and Economic Policy Uncertainty (EPU) are used as 'control variables' when estimating these explanatory regressions in the first, second and third papers respectively. Interestingly, the estimated coefficients of 'control' variables and indicators are significant – this provides empirical evidence in the three papers that the LSE partly exhibits semi-strong efficiency as complaints, alcohol receipts and Music Index are all individually significant when FTSE returns or change in trading volume are employed as dependent variables. If FTSE indexes were a reflection of rational actors only, none of the indicators would be significant according to EMH; however, as the empirical results indicate, there is evidence of bounded-rationality or even behaviour in line with Socionomics theory.

This thesis contains three empirical chapters that examine the extent to which social mood affects FTSE indexes. This empirical work is presented in the next three chapters starting with a complaints chapter, followed by an alcohol chapter and then a Music Index chapter. The final chapter of the thesis presents concluding remarks, limitations of the thesis, and potential areas for further exploration.

Chapter 1: Catharsis Mood and the Stock Market

1.1. Introduction

Traditional perspectives suggest that financial markets are efficient and reflect relevant fundamental information only as any mispricing is corrected by arbitrage. This view is predicated on the notion that investors are rational and that there are negligible limits to arbitrage. Yet, long-term deviations from fundamentals, also known as financial market bubbles or fads, persist – for instance, the Tulip Mania in 17th century Holland, the Tronics Boom of early 1960s, and the Dot.com bubble in the late 1990s are well known examples. The latest manifestation of a financial bubble is the implosion of Crypto-currency in 2022, which lead to speculation about the possibility of similar future issues with speculative bubbles (Corbet, Lucey and Yarovaya, 2018; Kyriazis, Papadamou and Corbet, 2020). Evidence from non-traditional and non-rational behaviour in financial markets shows that individual as well as institutional investors are susceptible to mood or sentiment in financial decision-making (Baker and Wurgler, 2007). As such, far from being solely premised on logic and linear processes, financial markets can be affected by emotion-led decision making whereby the prevailing mood and contextual circumstances of the time can push asset prices away from fundamentals for sustained periods.

Even though the terms ‘mood’, ‘emotions’ and ‘sentiment’ are often used interchangeably, in this paper ‘sentiment’ denotes interpretations of data (cashflow and risk) by individual or institutional investors that are not logically justified by facts (Baker and Wurgler, 2007). Emotions are understood as a state of positive or negative affective state that is characterised by high arousal or valence (Scherer, 2005). By contrast, ‘mood’ – defined as a general feeling of positive or negative affect that individuals are experiencing. Mood does not require an external trigger and is longer in duration compared to emotions. Another important distinction is that mood has a lower level of arousal whilst emotions involve higher level of arousal/intensity that is more taxing on both the body and mind (Scherer, 2005; Scheff, 2015).

This paper investigates the extent to which UK social mood is reflected in FTSE returns. Past studies focus on investors and how investor sentiment affects stock market activities, while this paper examines how mood in the in the UK has an effect on the London Stock Exchange (LSE). The main assertion underpinning the research question is that retail and to a lesser extent institutional investors – are expected to be influenced by mood in society through ‘mood contagion’ as people experience behavioural mimicry and emotion empathy (Neumann and Strack, 2000; Nakahashi and Ohtsuki, 2015), which are further discussed in literature review below. There is an expectation that, due to social mood, a subset of FTSE returns, namely smaller and harder to value companies, will be more affected by non-fundamental factors than companies which are larger and easier to value.

The approach taken by studies exploring sentiment has taken two forms – top down or macro, and bottom up or micro. This paper uses the former approach to investigate the returns-complaints relationship on the LSE. Macro level studies such as research by Edmans, García and Norli (2007) and Hirshleifer and Shumway (2003), use sentiment at the aggregate level, and match this with company specific or index outcomes. On the other hand, micro level papers consider individual psychological influences on individual investors such as under- and overreaction (Hong and Stein, 1999), overconfidence (Daniel, Hirshleifer and Subrahmanyam, 1998), conservativeness and representativeness (Barberis, Shleifer and Vishny, 1998). These studies illustrate how biases affect individual decision making, and then financial market(s). By contrast, this paper uses the top-down approach that captures catharsis-mood in UK society and links it to the FTSE indexes via (retail) investor sentiment by using complaints as a proxy for social mood in Ordinary Least Square (OLS) regressions. In regressions, FTSE returns of different indexes are dependent variables, while complaints and market returns are independent variables in augmented CAPM framework.

This paper investigates the role of mood in financial decision-making by focussing on the concept of *catharsis*, implemented through complaints, as a way to manage and release negative mood that is induced by actual or perceived service failure. This paper focuses on social rather than individual mood as the former may potentially affect many people in any given location – for example a broadband problem usually affects a particular neighbourhood. One of the earliest records of the use of the term catharsis was in ancient Greece, where ‘katharsis’ was redeployed in plays to purge bad emotions. Later on, work by Sigmund Freud focused on ‘catharsis of aggression’ as the ability to make oneself feel better by targeting a wrongdoer through physical or verbal abreaction (Geen and Quanty, 1977). In this paper, catharsis is an act of making a complaint in order to remove negative mood that is experienced as a result of actual or perceived mobile, broadband, landline or pay TV service failure. Motivated by the catharsis hypothesis, this paper explores the link, if any, between catharsis (not) felt by digital (mobile phone and broadband) and by traditional (pay TV and landline users) service users, and small and medium company market indexes. The results of this research contribute to the Behavioural Finance literature by demonstrating the catharsis-mood impact on financial markets.

So far, there have been no studies linking society level complaints to smaller index returns. Drawing from the use of the term catharsis in the field of psychology, this study uses the concept of catharsis (through complaints) to link to peoples' state of mind with decision making and the Behavioural Finance literature. It investigates the relationship between catharsis-mood through service complaints and market indexes for small or larger cap companies. The results show significant relationship between mobile, broadband, pay TV and landline complaints, and returns on a range of FTSE indexes. This paper furthers understandings of how complaints in the UK are transmitted to relevant market index returns depending on company size, market capitalisation, age, ease of valuation and ease of trading. From the sentiment literature, FTSE 100 and FTSE Large (FTSE Staple to some extent) are the most liquid indexes and are the easiest (cheapest) to arbitrage, easier to value, large, older, profitable, large market capitalisation, and steady cashflows compared to the other indexes. Therefore, it could be expected for these indexes (FTSE 100 and FTSE Large) to be less susceptible to (retail) investor sentiment, and to be the 'destination of safety or quality' when investor sentiment is low. The latter is illustrated in Figure 1.1 below in the "sentiment see-saw" from Baker and Wurgler (2007). By contrast, one would expect the opposite for FTSE Small, AIM All Share and AIM 100 (FTSE Medium and FTSE Discretionary) as these involve companies that would be more prone to (retail) investor sentiment, and would expect a negative impact when investor sentiment is low.

[Insert Figure 1.1 around here]

The paper is structured as follows. The next section provides an overview of the role of mood in financial decision making, with a focus on catharsis and complaints. The third section discusses the data, and the methodology used to analyse data. The fourth section discusses the regression results using a dataset of variables over the October 2010 to June 2021 period. The final section provides concluding remarks and highlights the limitations of the paper.

1.2. Literature review

The influence of mood on financial decision-making has been shown to lead to short-term deviations from fundamentals in financial markets. This has been explored in research using specific mood stimulating proxies that affect society and (retail) investors, and become temporarily observed in financial markets. The relevant literature includes, but is not limited to, considerations of a range of different phenomena that are associated with an affective/mood impact on decision making – for example the weather influencing market returns in 26 different countries (Hirshleifer and Shumway, 2003), geomagnetic activity impacting financial markets in 9 countries (Robotti and Krivelyova, 2005), full moon lowering stock market returns in 48 countries (Yuan, Zheng and Zhu, 2006), and the end of popular TV series affecting returns of NASDAQ, S&P500, Russell 3000 and Russell 2000 indices (Lepori, 2015). The repercussions of sports results have also been shown to affect financial markets in 39 countries (Edmans, García and Norli, 2007). In the UK, the final scores of England men football team matches were shown to affect the next trading day FTSE returns (Ashton, Gerrard and Hudson, 2003). However, the impact of sporting results is not limited to the stock market, as Berument and Yucel, (2005) presented evidence of changes in the Turkish industrial production which are linked to one of the most popular Turkish football teams (i.e. Fenerbahçe). These papers show how short-term mood-induced price deviations in financial markets are not simply restricted to particular geographic regions but are in fact experienced in many financial markets around the world.

Mood is believed to be linked to financial market behaviour as investors are influenced by social mood in their decision-making processes (Prechter, 2016). The extent to which mood affects information processing and acquisition has been explored by Forgas (2017) and Clore et al. (1994), who concluded that being in a negative affective state promotes detail-oriented decision making, whilst positive affect promotes a less detailed, heuristics-based decision-making process. This argument is also supported by experimental evidence with over 500 participants in a study by Baillon et al. (2016) who found that negative to mild-negative mood (such as sadness) is good for decision making as it leads to ambiguity-neutral states, which maximises pay-off, compared to ambiguity seeking or ambiguity averse attitudes. Other studies have highlighted how shoppers who are in a positive mood tend to make quick decisions based on less information and ask fewer questions (Isen and Means, 1983; Furnham and Milner, 2013). However, Wright and Bower (1992) provide evidence that negative mood reduces objectivity and increases tendencies towards negative choices and opinions; they highlight how unsuspected negative mood bias could lead to suboptimal decisions – for example, negative interpretation of negative, positive, or neutral information may be observable through lower assets prices in financial markets.

The management of mood and emotions can be implemented in different ways, some of which may provide relief and act as a coping mechanism. Catharsis, as one of such mood management techniques or as a coping mechanism, is aimed at releasing a person from negative affective states (Schaar,1961). The so-called ‘catharsis hypothesis’ has been explored in the field of psychology, whereby some individuals feel relief when they let out pent up anger, aggression, or any negative feeling (Verona and Sullivan, 2008). In contemporary times, this process of emotional release has been channelled through various praxes, including complaints. Using a questionnaire to examine catharsis on 23 subjects, Bennett, (1997) found that customers who complained were more likely to re-use products/services, less likely to ask for refunds, and less likely to tell people than non-complainers. They also recognise that not everyone would experience catharsis after complaining, as the more probable beneficiaries of catharsis are likely to be individuals who are Type A, self-confident, and with less guilt-propensity. Existing literature suggests that some individuals might feel better and have lower heart rate post-catharsis than before, whilst other type of individuals would feel worse if they attempted to ‘vent’ (Verona and Sullivan, 2008). Earlier work by work Geen and Quanty (1977) found that catharsis helped to decrease physical arousal by lowering heart rate and blood pressure, but also concluded that catharsis is not felt when there is unequal power dynamics and inappropriate aggression, and when the aggressor is not comfortable being aggressive. Physical or verbal aggression – which can be channelled through complaints – was found to be cathartic and to lower both blood pressure and heart rate compared to doing nothing about a grievance or fantasising about aggression (Hokanson and Burgess, 1962). In terms of customer retention, a study by Ang and Buttle (2006) using 170 companies in Australia, found that a documented complaints-handling process is vital for customer retention, suggesting that complaints are invaluable instruments in understanding customer experience, and enhancing corporate decision-making processes.

Whilst there is no literature that explicitly links complaints to financial markets, there are studies linking mood and complaints. As mentioned before, research has shown how consumer experience is affected by the mood customers are in prior to and during consumption. Bujisic et al. (2019) found that customer mood had an impact on feedback given to restaurant, even after controlling for the quality of service. While good customer experience might mitigate against bad mood, bad mood has been found not only to reduce rating of consumption experience but also to shorten the length of online text review/feedback (Zhang et al., 2022). Despite the widespread perception that complaints are generally of a negative nature, Gruber, Szmigin and Voss (2009) considered complaints as a valuable tool to gain customer insights as repeat customers require less advertising than new customers – being taken seriously, friendliness and active listening were found to be pivotal aspects for customer satisfaction in terms of complaint resolution. As such, the nature and details around complaints can provide useful knowledge in understanding financial decision-making for both individuals and organisations. In addition to complaints being insightful, Cambra-Fierro, Melero and Sese (2015) found that customer profitability can be achieved by focusing on communication, compensation and timeliness of handling heterogenous customer needs; further, flexible complaint-handling allows bespoke solutions as a resolution to one customers' complaint might not be appropriate for another customer. Continuing with the theme of complaints being useful rather than intrinsically negative, some experimental evidence shows that increased customer loyalty, rebuying tendencies, and positive word of mouth are increasingly present after compensation and successful complaint resolution (Fu et al., 2015). Furthermore, Lee, Guchait and Madera (2020) concluded that customers tend to be happy post complaints, even when they behaved aggressively, if the complaints-handling staff are aware of their own emotion/mood state, and the staff were able to shift towards customer needs and adopt a customer-based perspective. Complaints can therefore be understood as an invaluable tool to gain some understanding of customer experience, and to improve quality of service or product(s).

A major weakness of using complaints data is that formal complaints do not capture all the customers who have suffered actual or perceived service failure. Baker and Wurgler (2007) argue that “there is no fundamental reason why one cannot find imperfect proxies that remain useful over time”. Using around 1,000 regional consumers spread in 749 houses in the United States, Bearden and Mason (1984) found that not all consumers show the same complaining tendencies – that younger, more educated, higher income and people with assertive personality have a higher tendency to complain. Companies also seem to lose dissatisfied customers who silently switch to other services providers/companies, and/or discuss their bad experience through word of mouth. Estimates about formal non-complaining customers vary from fifty percent (Gursoy, Ekiz and Chi, 2007) to ninety six percent (Stephens and Gwinner, 1998) – all this leads not only to lack of useful feedback about service or product quality, but also to loss of revenue and eventually reduction in profit and brand damage.

Unsatisfied customers or clients who do not complain are likely to experience negative affect, which may still impact profits as they share their experiences with family or friends through word-of-mouth (Chen and Yuan, 2020). Bennett (1997) found that only about 5% of dissatisfied customers complained, while the non-complainers relayed their bad experience to twice the number of people to whom they would relay their pleasurable experience. Additionally, Bennett (1997) found that about 15% of customers who had a problem with a company would complain about their experience to at least 20 people. According to Stephen and Galak (2012), word-of-mouth sharing in person or online is one of the most effective marketing tools, as identified by 61% of marketing executives (Stephen and Galak, 2012). Digital word-of-mouth can magnify specific service failures due to the popularity of social media in the UK, and around the world, which may affect brand/reputation and lead to loss of revenue and eventually profits. There are subtle differences in digitally shared word-of-mouth praxis, as Ransbotham, Lurie and Liu, (2019), and Melumad, Inman and Pham, (2019) found that mobile feedback was more emotional than computer feedback. Awareness of these differences may help organisations understand customer experience, and remedy possible negative customer impressions.

Mood is transmitted or shared from person to person through social, work, or other interactions as mood can be elicited by “facial, postural and behavioural expressions” (Neumann and Strack, 2000). It is generally accepted that most communication is not verbal, in fact, emotion-body-language (EBL) can be shared not only through sight when people are in close proximity to each other (De Gelder, 2006), but also in particular through consumption of social media or news (as the news reader or article/post-writer has their own affective state irrespective of the news or opinions being delivered or shared). In the psychology literature, this transmission of mood from person to person (there are animal studies as well) is referred to as mood contagion as the person receiving this mood (observer) is mostly not aware of what is happening (Neumann and Strack, 2000). The construct of boundaries such as work-life boundary is lowered in terms of separating or isolating mood from home to work or vice-versa (Song, Foo and Uy, 2008), even a simple retail excursion for necessities or discretionary product(s) or service(s) cannot be viewed in isolation as scent, music, lighting, colour of product and/or store temperature are all intentionally mood inducing to benefit a retailer, store or the service provider (Furnham and Milner, 2013). An example of this is the background music played whilst one is on hold to talk to customer service or reception.

Mood contagion could also be explained through behavioural mimicry, emotional empathy or cognitive empathy. Behavioural mimicry requires more time to understand what another person is experiencing and to then copy them; emotional empathy on the other hand happens when one person ‘absorbs’ someone else’s mood without thinking about it; and cognitive empathy is where the observer can deliberately decide to ‘absorb’, ignore or oppose someone else’s mood (Nakahashi and Ohtsuki, 2015). It is through cognitive empathy that someone is able to experience ‘schadenfreude’, by acknowledging someone else’s misfortune while experiencing the opposite affect/mood. Schadenfreude is a process of deriving pleasure when someone else experiences misfortune (Cambridge Dictionary, 2024). There is extensive literature on how mood is transferred to and from individuals, or between an individual and a group. For example, a leader’s mood can affect the mood of associates or collaborators, with research showing that leaders who are in positive mood induce positive mood in followers, which was associated with improved leaders’ rating for charisma, effectiveness and attraction (Bono and Ilies, 2006). Also, leaders who display positive mood were perceived to be more charismatic than leaders seen to be in a negative mood, even after controlling for the contents of their speech (Johnson, 2009). However, although the current literature has yet to provide direct evidence of social media leaders – known as ‘social media influencers’ - transmitting mood to their followers, some research implies that this automatically happens when they communicate with their followers, as influencers are considered to be opinion leaders with a significant following (De Veirman, Cauberghe and Hudders, 2017). In fact, social media influencer marketing is one of the fastest growing areas of marketing due to influencers' ability to engage and 'steer' their audience (Harrigan *et al.*, 2021), with the influencer global marketing size estimated to be around $16.4 billion in 2022, and expected to reach $84.89 billion by 2028 (Luo and Kim, 2023). This paper infers that social media platforms such as Twitter, Instagram, Tik Tok, Reddit (made famous by 'Wall Street bets'), and to a lesser extent Facebook, will accelerate mood contagion within a subset of society (followers) and eventually transmit it to the rest of society. This on aggregate would constitute social mood, as mentioned by Prechter (2016). In the financial literature, this 'common mood' is rationalised through terms like 'herding' and 'cascades' (Nofsinger and Sias, 1999; Prechter, 2001), 'co-movement' (Kumar and Lee, 2006; Liu *et al.*, 2015) or 'style investing' (Barberis and Shleifer, 2003). According to the financial literature, social mood would affect retail investors more than institutional ones but, as there is ample evidence of past bubbles, perhaps ESG (Environmental Social and Governance) investing is the latest manifestation of social mood.

The use of complaints data is relevant and appropriate in a study of how social mood affects financial decision making, as these data meet the three key mood-proxy characteristics set out by Edmans, García and Norli (2007). First, complaints capture the outcome of an event that impacts mood in a substantial way, such as not being able to access one's bank account and pay for necessities like food, rent or mortgage. Secondly, complaints capture the mood of a large proportion of people in the UK, and likely affect the mood of many (retail) investors. Finally, service failure by a company is normally experienced by many individuals in an area, or by many people who use the same service provider. This paper thus adds to the literature on non-logic linear decision making by investigating to what extent catharsis-mood in the UK affects LSE returns. When compared to surveys or interviews, complaints data have the added benefit of capturing peoples' actual activity, unlike surveys where respondents' answers might be different from their actions. Also, this paper does not use trading volume, discount/premium on ETFs, dividend paying stock premium, number of IPOs or returns on first day of trading to capture sentiment like in Baker and Wurgler, (2007) because whilst these provide reliable information about a financial market or index, this paper argues that all these data are outcomes of sentiment rather than the measure of it.

Data on complaints data capture the process of catharsis in its actual implementation or evolution through complaints. Mobile, broadband, pay TV and landline connectivity is crucial for a number of services such as calls, text messages, social media engagement, online shopping, access to TV programmes, web searches, and online entertainment. Figure 1.2 below shows that mobile phone usage in the UK has become ubiquitous with around 95% of the population using mobile phones. As such, mobile complaints capture a significant proportion of the population who make a complaint after experiencing or perceiving service failure. Figure 1.3 shows that this percentage is even higher at 97% when mobiles are compared to ownership of other electronic devices, with TV in second place at 88% (Statista, 2022). Figure 1.4 shows that Landline usage in the UK has been on a steady decline since 2007, with the exception of 2019 (the start of the Covid outbreak); 2020 data show about 32.1 million landlines still in use – this number is higher than the total population of smaller nations such as Eritrea, Latvia, or Jamaica.

[Insert Figures 1.2, 1.3 and 1.4 around here]

Figure 1.5 below shows that 75% of people in the UK go online to check their emails, 54% use the internet for online banking, and around 14% for remote work. At around 14 million users in 2021 and 2022, the UK has relatively modest number of pay TV subscribers compared to other nations in Western Europe. This number is projected to fall to 13 million by 2027 (see figure 1.6 below). Figure 1.7 shows widespread usage of broadband by UK adults as the percentage of users steadily increased from 52% in 2007 to 89% in 2021. Limitations or service failure on the usage of mobile phone, broadband and landline may affect retail investors' ability to trade, in addition to the change in the affective state caused by actual or perceived service failure by individuals. Lack of entertainment caused by Pay TV failure could cause negative affect/mood and change (retail) investors' affective state; previously, papers have demonstrated link between entertainment and the financial market by using data on comedy movie attendance (Lepori, 2015) and the end of popular TV series (Lepori, 2015).

[Insert Figures 1.5, 1.6 and 1.7 around here]

The importance of mobile, broadband and landline usage for basic needs cannot be underestimated, as seen in Figure 1.5. For instance, online, telephone or remote banking services have been growing as banks close branches in an apparent effort to save costs (Storey *et al.*, 1997). The education sector has made online resources increasingly more available due to the COVID-19 pandemic in order to enhance student accessibility, learning and experience. Primary and secondary schools, as well as Higher Education institutions, have online portals for homework and material repositories. An early example of this move to the digital access of education resources is the introduction of MOOCs (Massive Open Online Courses) in 2012 by Harvard, Yale and Stanford Universities, and the publication of the "Online Learning at Research-Intensive Universities" by LERU (League of European Research Universities) (Davies, 1998; Hunter, 2015). Some essential healthcare services are also provided remotely, from initial consultations with general practitioners, to booking appointments and follow ups (Murphy *et al.*, 2021; Ahmed and Teoh, 2020).

Although most of the aforementioned discussion has been from the customers' perspective, there has been a steady increase in remote working (commonly known as Working From Home or WFH) since 1998, from about 11% to 17.4% in 2020, as seen in Figure 1.8. As of 5th February 2023, the 2020 percentage of people working remotely in the UK more than doubled to 40% (see Figure 1.9). There is emerging evidence that working from home has benefited employers through increased productivity and more time spent on work tasks (Bloom *et al.*, 2015). From an employees' perspective, working from home can improve work commitment, organisational commitment, and work-related wellbeing (Felstead and Henseke, 2017). This implies that there is a large proportion of people in the UK who depend on their mobile, broadband and/or landline to earn a living. These services are an important part of life in the UK and any disruption, or perception of disruption, or poor/inadequate service related to these will impact people in a substantial way, irrespective of whether the problem is resolved on not.

[Insert Figures 1.8 and 1.9 around here]

1.3. Data and methodology

Monthly complaints data are collected from Ofcom, the UK's communications regulator, from October 2010 (the earliest collection point) to June 2021, at a monthly frequency (the highest frequency available). The data provided are the number of complains per 100,000 customers/connections for individuals or companies, and all available complaints for a particular month are added to generate monthly frequency time series. Mobile pay monthly complaints include BT Mobile, O2, iD Mobile, Sky Mobile, Talk Mobile, TalkTalk Group, Tesco Mobile, Three UK, Virgin Mobile, Vodafone, and EE (aggregate of T-Mobile, Orange & 4GEE). Fixed broadband complaints used incorporate BT, Sky, EE, Plusnet, Post Office, Shell Energy, TalkTalk Group, Virgin Media, and Vodafone. Landline complaints comprise BT, EE, Plusnet, Post Office HomePhone, Shell Energy, Sky, TalkTalk Group, Virgin Media, and Vodafone. Pay TV contain BT, Sky, TalkTalk Group, and Virgin Media. The FTSE data are collected using Eikon (formerly DataStream). Figure 1.10 shows that mobile complaints peaked between 2015 and 2016, and then went on a slight decline until 2021 despite the increasing number of mobile phone users. Figure 1.11 shows how broadband complaints peaked in 2011, then reached their lowest point in 2018, but have mainly remained steady despite increased numbers of broadband users. Figure 1.12 shows a peak in landline complaints in 2010-2011, which were steady from 2014 to 2021 despite a slight increase in users in 2019 and 2020. Figure 1.13 shows that pay TV complaints were highest in 2013 and troughed twice in 2021; however, pay TV complaints have been somewhat trending downwards since 2014. Mobile, broadband, landline and pay TV figures shows there is a difference in the volume of complaints. Landline and mobile complaints had the highest and lowest range respectively.

[Insert Figures 1.10, 1.11, 1.12 and 1.13 here]

This paper explores the potential links between stock returns and the malfunctioning of telecommunications and online networks through their impact on mood and, for some, the impact on the ability to trade. The basic assumption is that people live and work in a digital era where they increasingly rely on such networks, and expect them to function efficiently and smoothly. For much of the time, the latter is the case but, occasionally, there are outages, poor internet connections, or cases where devices or networks stop functioning. In these suboptimal circumstances, mood and emotions are impacted by the malfunctioning of networks, the process of making a complaint and by the swiftness, and effectiveness of the responses to complaints.

The regression methodology adopted in this paper is an augmented CAPM framework where it is postulated that excess returns on stock indexes (R_t) are explained by the market risk premium ($R_{Mt} - R_{rf}$) and by a vector of communication network complaints (X_t). The market risk premium is proxied by FTSE All Share index return (R_{Mt}) less UK government one month T-bill return (R_{rf}). All variables used in Augmented CAPM OLS estimations are FTSE returns and complaints rate of change. For robustness (shown in the appendix A1.2 – A1.12), the paper complements aforementioned index excess returns by using index returns and market capitalisation rate of change as a dependent variable to account for index rebalancing (Dimson and Marsh, 2001; Mase, 2007; Cai and Houge Todd, 2008). The aforementioned robustness estimations in appendix are a further simplification of CAPM and the derivation is shown in appendix A1.1; this simplification has the added benefit on not relying on risk-free rate, as most companies cannot borrow at this rate – further justification for using augmented CAPM are in the following paragraph. The paper uses FTSE All Share as a proxy for market return for the main estimations. This can be expressed formally as follows:

$$R_{it} - r_{it} = \alpha + \beta(R_{Mit} - r_{it}) + \delta' X_{it} + u_{it} \quad (1)$$

where R_{Mit} is proxied by the returns on the FTSE All Share index, r_{it} is the expected return of risk-free asset proxied by returns on UK one month T-bill, α is the y-intercept, β is the beta of an index, $R_t - r_{it}$ is excess return, i denotes the companies in the index, t is time, and u_{it} is an error term. The vector X_{it} includes broadband complaints, landline complaints, pay TV complaints and mobile complaints. This paper uses seasonally adjusted mobile, broadband, landline and pay TV complaints rates of change in the main regressions.

Even though CAPM is widely used in Finance, some of the assumptions of the model are difficult to implement in efficient financial markets; this includes, but it is not limited to, assumptions that investors are rational and risk averse, that all investors have homogeneous expectations about future returns and risks, financial markets are frictionless, that there is unrestricted borrowing at risk-free, and that investors have same investment horizon (Fama and French, 2004). Because of these assumptions, alternative augmentations are explored in the appendix (A1.2 – A1.12) in order to add validity to the findings in Table 1.5 and Table 1.6.

The impact of complaints operates via two distinct transmission mechanisms. On one hand, the immediate direct effect of telecommunication network malfunctioning may result in a series of negative moods and emotions that may trigger a reduction in an investor's holding of smaller/riskier stocks and increase holding of bigger/safer stocks, selling response leading to $\delta<0$ in equation (1), and buying response leading to δ>0 in equation (1). On the other hand, the provider's response to the malfunctioning of their network, including their handling of any complaint made, can also have a distinct impact in itself. In this case, the very act of making a complaint can be seen as a relief (cathartic) and this can exert a positive effect via catharsis leading to δ>0 in equation (1) for smaller/riskier indexes, and vice versa for larger/safer index.

Additionally, to ensure the regressions estimated using the augmented CAPM model are BLUE (Best Linear Unbiased Estimator), the Breusch-Godfrey test for autocorrelation is used on residuals after estimations, and also use White's test to examine heteroskedasticity (Brooks, 2019). As autocorrelation and heteroscedasticity in residuals is detected, 'Heteroskedasticity and Autocorrelation Consistent standard errors & covariance' OLS advocated by Newey-West is used in regressions. This OLS technique improves accuracy of inferences made about estimated augmented CAPM by taking into account autocorrelation and heteroskedasticity of residuals. On the data used, Table 1.1 and 1.2 shows summary descriptive statistics of independent variables. Tables, 1.3 and 1.4 show a summary descriptive statistics of dependent variables.

The explanatory variables used in regressions include mobile, broadband, landline and pay TV complaints that are not seasonally adjusted, and some that are adjusted for possible seasonality using Season-trend Decomposition (STL) (Eviews.com, 2023). STL technique for seasonal adjustment uses LOESS regressions and it has three main advantages: 1) STL works for time series data of any frequency; 2) it can be used on time series data of irregular patterns; and finally, 3) it can be used on time series with missing data values. 'MoveReg Weekly

Adjustment' or 'X-13 Force Annual Totals' were not used due to monthly frequency of the data, and the aforementioned advantages of STL.

Two opposing hypotheses are tested in this paper based on the complaints literature. On one hand, there are people who experience a positive catharsis after complaining, irrespective of the complaint resolution (Bennett, 1997; Verona and Sullivan, 2008). On the other, there are people who still experience a negative frustration after complaining. This estimation uses a sample period from October 2010 to June 2021, and assumes that catharsis or lack of catharsis will be dominant depending on the type (mobile, broadband, landline or pay TV) of complaints. The model has the advantage of capturing some parts of fundamental news as it uses market returns proxied by FTSE All Share index as an independent variable.

Two main hypotheses are tested in the empirical section:

1. The 'catharsis effect': complaints reflect catharsis that is experienced by people after complaining exert a positive impact on stock returns of small indexes.
2. The 'frustration effect': complaints reflecting frustration that is experienced by people after complaining exert a negative impact on stock returns of small indexes.

[Insert Tables 1.1, 1.2, 1.3, 1.4 around here]

1.4. Results

1.4.1. Mobile complaints

Table 1.5 presents the results of regressing excess FTSE index returns on the market return risk premium and on seasonally adjusted complaints rate of change (complaints hereafter). Using FTSE AIM 100, FTSE AIM All Share, FTSE Medium and FTSE Discretionary excess returns as dependent variables in OLS regressions, the coefficients on mobile phone complaints are all significantly positive at the 1% and 5% significance level. Conversely, when FTSE Large excess returns are regressed on mobile complaints, the coefficient is significantly negative at the 5% Level. The estimated coefficients imply that a 1% increase in mobile phone complaints leads to an increase of 0.0694%, 0.0632%, 0.0236% and 0.0261% in AIM 100, AIM All Share, Medium and FTSE Discretionary excess returns, respectively. Also, a 1% increase in mobile complaints leads to a decrease of 0.0107% in FTSE Large. However, the coefficient on Mobile phone complaints is not statistically significant for the FTSE 100 index as this can be seen as a large cap proxy for the market index. The interpretation is, that by complaining about actual or perceived mobile phone service failure, catharsis as explored by Schaar (1961) and Bennett (1997) is experienced. This increases the positive mood for people in general, but particularly for small (retail) investors. This leads them to buy small stocks, which is eventually is reflected in the price appreciation of the smaller company indexes like FTSE AIM 100 and FTSE AIM All Share. A similar effect is also observed for the FTSE Discretionary company index. The opposite is observed for FTSE Large, whereby an increase in positive mood leads investors to sell 'safer' as indicated by negative coefficient of mobile complaints, which is the opposite of 'flight-to safety/quality'.

[insert Table 1.5]

Baker and Wurgler, (2007) found that high investor sentiment is expected to induce (retail) investors to invest in smaller-harder-to-value companies/indexes that are riskier. This paper proposes that, through mobile phone complaints, the catharsis-mood/affect, influences (retail) investor decision making through mood contagion (Neumann and Strack, 2000; Nakahashi and Ohtsuki, 2015). This result is to be expected as large, easier to value, easy to arbitrage and large-capital companies that are in the FTSE 100 index are less prone to market sentiment than the smaller companies in the FTSE AIM. This is because FTSE 100 index companies normally have consistent cash-flows due to economies of scale, and to some extent, economies of scope in generating revenue, and (re)financing of their debts. It is also interesting to note that the mobile complaints coefficient is smallest when excess FTSE Large excess returns is the dependent variable, while mobile complaints coefficient is the largest when excess FTSE AIM 100 returns is the dependent variable, providing further evidence to the existing literature (Baker and Wurgler, 2007) with a view that investor sentiment affects smaller stocks and indexes to a greater extent than large stocks.

1.4.2. Broadband complaints

Using FTSE 250, FTSE Small and FTSE Medium excess returns as dependent variables in OLS regressions, Table 1.5 shows that the coefficient for contemporaneous broadband complaints is significantly positive at the 1% or 10% levels. Conversely, when FTSE Large and FTSE 100 excess returns are regressed on broadband complaints, the coefficients are significantly negative at the 1% level. The FTSE Large and FTSE 100 excess return regression also yields significantly negative coefficients that are smaller in magnitude compared to those from estimating FTSE 250, FTSE Small and FTSE Medium excess return regressions. This implies that a 1% increase in broadband complaints leads to change in excess returns of 0.0622%, 0.0451%, 0.0455%, -0.0279% and -0143% for the FTSE 250, FTSE Small, FTSE Medium, FTSE Large and FTSE 100 regression, respectively. The explanation here is that by complaining about actual or perceived broadband service failure, catharsis (Schaar, 1961; Bennett, 1997) is experienced, which increases (positive) mood in society, and for (retail) investors in particular. This is eventually reflected in price appreciation of the smaller and riskier indexes like FTSE 250, FTSE Small and FTSE Medium. By contrast, positive mood leads to negative coefficients for larger and less risky indexes such as FTSE Large and FTSE 100.

Like the case of mobile complaints, the coefficients Fixed Broadband complaints are significantly positive when ‘smaller’ index returns are used as dependent variables (FTSE 250, FTSE Small and Medium). Contrary to mobile complaints, broadband complaint coefficients are significantly negative for ‘larger’ indexes like FTSE Large and FTSE 100 index. As negative/(positive) coefficient indicates an inverse/(direct) relationship between broadband complaints and ‘large’/(‘small’), the inference here is that contemporaneous broadband complaints are consistent with catharsis (Bennett, 1997; Verona and Sullivan, 2008) and mood contagion that is spread from purging oneself from negative experiences of actual or perceived service failure (Neumann and Strack, 2000; Nakahashi and Ohtsuki, 2015). Like mobile complaints, this is reflected in broadband complaint coefficients that are significantly positive for smaller indexes (FTSE 250, Small and Medium), and broadband complaints that are significantly negative for ‘bigger’ FTSE Large and FTSE 100 indexes. These results are as expected and consistent with positive/high (retail) investor sentiment examined by Baker and Wurgler (2007), as higher contemporaneous broadband complaints are associated with increases in asset returns for ‘smaller’ indexes and decreased in asset returns for ‘bigger’ indexes.

1.4.3. Landline complaints

Using the FTSE 250, FTSE AIM 100, FTSE AIM All Share, FTSE Small, FTSE Medium and FTSE Discretionary excess returns as dependent variables in OLS regressions, Table 1.5 shows that the coefficient for contemporaneous Landline complaints is significantly negative at the 1%, 5% or 10% level. Conversely, when FTSE Large and FTSE 100 excess returns are regressed on landline complaints, the coefficient is significantly positive at the 1% Level. The FTSE Large and FTSE 100 excess return regression also yields significantly positive coefficient that are smaller in magnitude compared to those from estimating FTSE 250, FTSE AIM 100, FTSE AIM All Share, FTSE Small, FTSE Medium and FTSE Discretionary regressions. This implies that a 1% increase in landline complaints leads to change in excess returns of -0.0318%, -0.0425%, -0.0361%, -0.0198%, -0.0224%, -0.0210%, 0.0136% and 0.0069% for the FTSE 250, FTSE AIM 100, FTSE AIM All Share, FTSE Small, FTSE Medium, FTSE Discretionary, FTSE Large and FTSE 100 excess returns, respectively. The explanation here is that by complaining about actual or perceived landline service failure, catharsis (Schaar, 1961; Bennett, 1997) is not experienced, and this reduces (positive) mood in society, and for (retail) investors, in particular. This mood contagion is eventually reflected in price depreciation of smaller and riskier indexes like FTSE 250, FTSE AIM 100, FTSE AIM All Share, FTSE Small, FTSE Medium and FTSE Discretionary. Conversely, lack of catharsis is reflected in positive significant coefficient for larger and less risky index such as FTSE Large and FTSE 100.

In contrast to mobile and broadband complaints, the coefficients for landline complaints are negative when ‘smaller’ index returns are used as dependent variables (FTSE 250, FTSE AIM 100, FTSE AIM All Share, FTSE Small, FTSE Medium and FTSE Discretionary). Inversely to mobile and broadband complaints, landline coefficients are positive for FTSE Large and FTSE 100 indexes. As negative/(positive) coefficient indicates an inverse/(direct) relationship between landline complaints and ‘small’/ (‘large’); the inference here is that contemporaneous landline complaints are consistent with that fact that a proportion of the population does not experience catharsis but experience frustration (Hokanson and Burgess, 1962; Geen and Quanty, 1977) and negative mood contagion that is spread from negative experiences of actual or perceived landline service failure (Neumann and Strack, 2000; Nakahashi and Ohtsuki, 2015). Data on landline complaints does not capture catharsis but capture negative mood/affect of perceived or actual landline service failure. The findings here are consistent with those of Baker and Wurgler (2007) who found smaller and hard to value indexes are more prone to investor sentiment, and low investor sentiment is likely to lead to under-valuation of smaller companies/indexes – it is reasonable to argue that landline complaints capture part of this negative mood and this is eventually reflected in drop in ‘smaller’ FTSE index excess returns and the effect observed here is akin to flight to safety as FTSE Large and FTSE 100 has an increase in excess return.

1.4.4. Pay TV complaints

Using the FTSE Medium excess returns as dependent variable in OLS regressions, Table 1.5 shows that the coefficient for contemporaneous pay TV complaints is significantly negative at the 10% level. This implies that a 1% increase in pay TV complaints leads to change in excess returns of -0.0123% for the FTSE Medium regressions. The explanation here is that by complaining about actual or perceived pay TV service failure, catharsis (Schaar, 1961; Bennett,1997) is not experienced, and this reduces (positive) mood in society, and for (retail) investors, in particular.

This mood contagion is eventually reflected in a price drop of smaller and riskier index FTSE Medium.

Like in the case for landline complaints, the coefficients for pay TV complaints are negative when ‘smaller’ index excess returns are used as dependent variable (FTSE Medium). As a negative coefficient indicates an inverse relationship between pay TV complaints and ‘small’ index, the inference here is that contemporaneous pay TV complaints are consistent with the fact that a some people do not experience catharsis but experience frustration (Hokanson and Burgess, 1962; Geen and Quanty, 1977) and negative mood contagion that is spread from negative experiences of actual or perceived pay TV service failure (Neumann and Strack, 2000; Nakahashi and Ohtsuki, 2015). Pay TV complaints capture frustrations (negative mood/affect) of perceived or actual pay TV service failure. The findings here are consistent with Baker and Wurgler (2007) which found smaller and hard to value indexes are more prone to investor sentiment, and low investor sentiment is likely to lead to under-valuation of smaller companies/indexes that is eventually reflected in drop in ‘smaller’ FTSE index returns and flight to safety.

[insert Table 1.6 here]

Table 1.6 presents the results of regressing excess FTSE index returns on the market return risk premium (as proxied by FTSE All Share index return less UK government one month T-bill return), and on non-seasonally adjusted complaints rate of change. The results in Table 1.6 using non-seasonally adjusted complaints rate of change are similar to results in Table 1.5 using seasonally adjusted complaints rate of change, and therefore, similar inferences can be made. This shows the results in this paper are consistent even when seasonality of complaints is taken into account.

1.5. Robustness of the findings

The paper uses a variety of specifications to check robustness of the findings, all of which show that telecommunication complaints have some explanatory power. This involves using reduced form CAPM that does not utilise risk-free rate as most companies or investors cannot borrow unlimited amounts at risk-free rate. This leaves OLS regression that uses market return as an independent variable that accounts for systematic or macroeconomic factors, and individual index return as dependent variable, in these setting, excess returns are not used.

Another innovation for robustness involves regressing FTSE index market value/capitalisation rate of change on the market capitalisation rate of change (as proxied by FTSE All Share index), and on complaints. This ensures the results are not influenced by changes in way FTSE indexes are constructed, as FTSE indexes like other indexes are 'rebalanced' on a regular basis (Dimson and Marsh, 2001; Mase, 2007; Cai and Houge Todd, 2008).

Also, estimations involve using seasonally adjusted and non-seasonally adjusted complaints as independent variables in OLS when dependent variables are FTSE returns (Appendix A1.2 & A1.4) and then FTSE market value/capitalisation rate of change (Appendix A1.3 & A1.5). Further, even though the literature suggests that FTSE100 would be less susceptible to (retail) investor sentiment, the results in Appendix A1.6 and A1.7 show statistical significance at 1% level but the results could be argued to be economically not significant. These results confirm expected results as FTSE100 has companies which are bigger, safer and more liquid to trade and can be seen as 'destination of safety' even using market value/capitalisation. Finally, instead of using all complaints together in a regression, Appendices A1.8-A1.12 show estimated regressions using individual complaints on their own as independent variable/factor – this means that when mobile complaints is used as independent variable, no other complaints were used as an independent variable for that estimation. The regressions also use market value/capitalisation as dependent variable in addition to Price Index returns.

1.6. Conclusions

This is the first paper that explores to what extent catharsis mood in the UK affects FTSE returns. The paper uses digital (mobile and broadband) and traditional (landline and pay TV) complaints as an extra factor in an augmented CAPM framework. The results illustrate that digital complaints made by mobile and broadband users capture a 'catharsis effect' as mobile and broadband complaints lead to increase in smaller index excess returns (FTSE 250, AIM 100 AIM All Share, FTSE Small, FTSE Mid and FTSE Discretionary) and decrease in FTSE Large and FTSE 100 excess returns. The results are consistent with the view that a substantial proportion of mobile and broadband complaints represent some element of catharsis that is felt by or after complaining as a result of actual or perceived mobile or broadband service failure. In contrast, the results indicate majority of landline and pay TV complaints experience frustration as a result of actual or perceived service failure as landline and pay TV complaints lead to a decrease in smaller index excess returns and increase in larger (FTSE Large and FTSE 100) index excess returns. These findings are what is expected from catharsis literature as not everyone experiences catharsis through complaining. Indeed, research suggests that the most likely beneficiaries of catharsis are Type A personality, less guilt-propense and self-confident people. The findings are robust when returns are used instead of excess returns, market value/capitalisation is used in regressions and in alternative specifications such as using non-seasonally adjusted data, using complaints collectively and/or individually - mobile, broadband, landline and pay TV complaints are statistically significantly for various FTSE index excess returns when used as additional factors in augmented CAPM framework.

The implication of these findings is that the results provide empirical evidence to support the hypothesis that some people experience catharsis after complaining about mobile phone and broadband problems, and that this mood is spread through mood contagion – this is observed through significant and positive coefficients of mobile complaints when AIM 100, AIM All Share, FTSE Medium and FTSE Discretionary excess returns are regressed on mobile phone complaints. There is positive/(negative) coefficient for broadband complaints when ‘smaller indexes’/‘(larger indexes’) are regressed on broadband complaints rates of change. The results also support an alternative hypothesis that some people predominantly experience frustration and do not experience catharsis after complaining about landline and pay TV. This is observed through significantly positive coefficient for landline complaints when FTSE Large and FTSE 100 excess returns are regressed on landline complaints, the sigh of landline coefficient is negative when FTSE 250, AIM 100, AIM All Share, FTSE Small, FTSE Midium and FTSE Discretionary excess returns are regressed on landline complaints. Pay TV coefficient is negative when FTSE Medium excess returns is regressed on pay TV complaints.

These findings advance more broadly research in the Behavioural Finance literature by illustrating that smaller, not easy to value and harder to arbitrage indexes are more susceptible to social mood, which affects FTSE excess returns.

Complaints as proxy adds a continuous measure of social mood compared to sporting results, movie attendance, end of TV series, geomagnetic activity which are intermittent. It can also be argued that complaints data capture a larger proportion of the population that use mobile, landline, pay TV and broadband services compared to the previously considered users of Spotify or iTunes. Similarly, Kumar and Lee, (2006) found that retail or unsophisticated investors are more prone to asset mispricing as the significant coefficients on mobile complaints had bigger coefficients in the estimations compared to broadband, landline and pay TV complaints. Bigger coefficient of mobile complaints rates of change could be broadly consistent with findings of Melumad, Inman and Pham, (2019) who found people making mobile complaints tend to be more emotional than those making computer-based complaints.

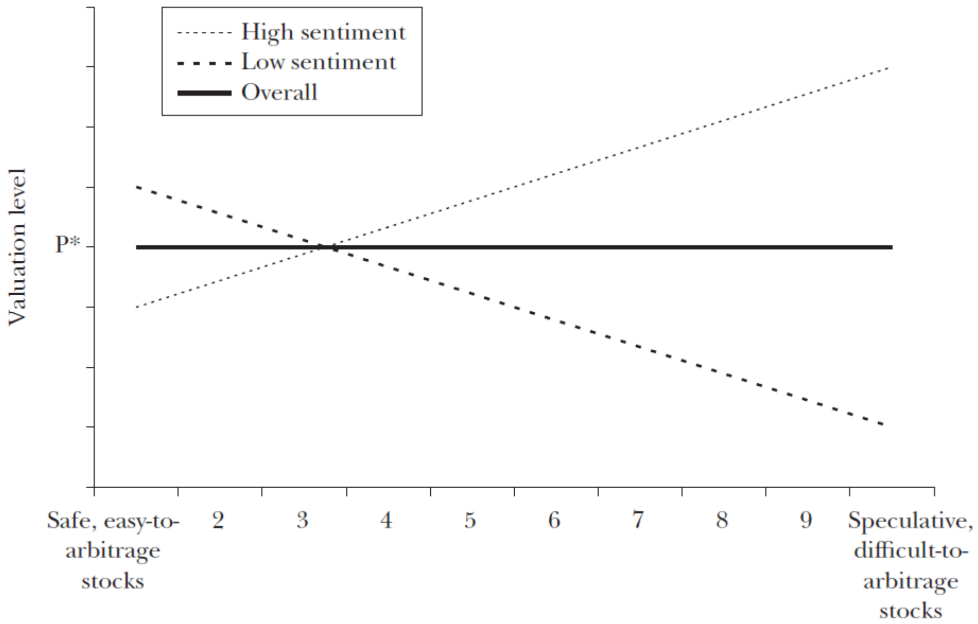
This paper has several limitations as it does not distinguish individual complaints from those from companies due to data unavailability. Further, the sample period is relatively short but this is due to data limitations which also did not permit this type of study for other sectors in the UK.

Areas for future exploration, when there is more data, inter alia could focus on exploring subperiods such as the sub-prime mortgage crisis, or when the crypo-currency bubble was bursting. Running the same regressions by including elements of the misery index such as inflation and employment could also yield compelling results. Further, a breakdown of complaints by age and location could inform an interesting area of future research.

Figure 1.1 Sentiment seesaw

This figure shows “sentiment seesaw” from Baker and Wurgler (2007)

Theoretical Effects of Investor Sentiment on Different Types of Stocks

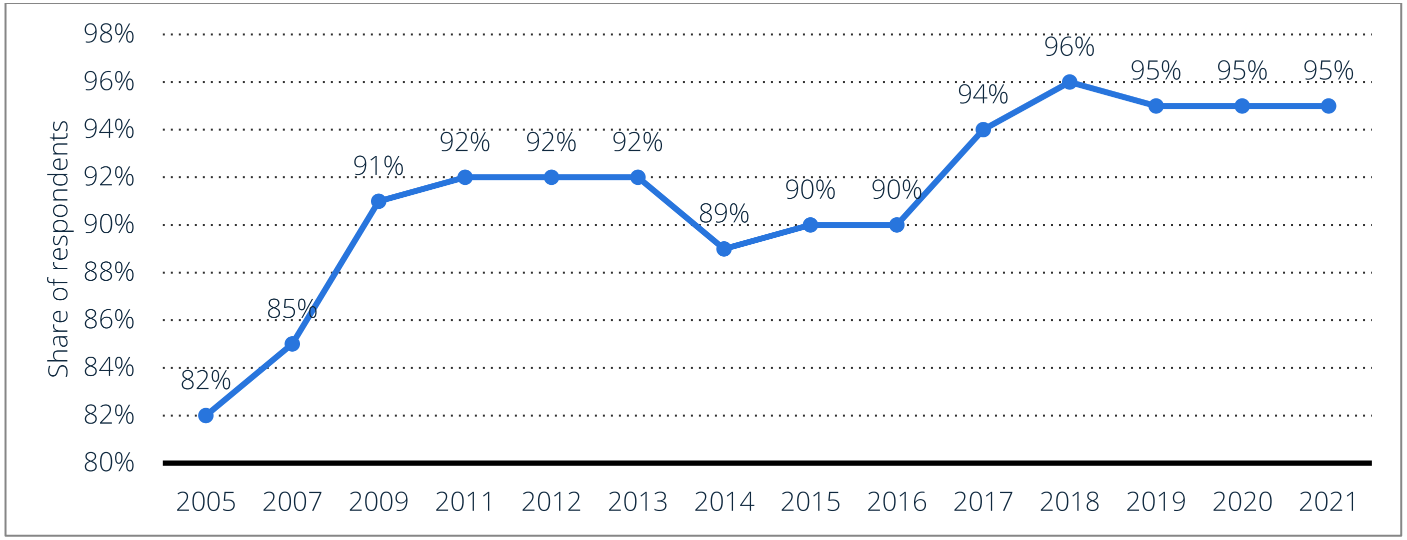


Note: Stocks that are speculative and difficult to value and arbitrage will have higher relative valuations when sentiment is high.

It can be observed that larger companies would have a higher valuation when investor sentiment is low as investors flock to safety or quality, and lower valuation when investor sentiment is high.

Figure 1.2 Mobile phone usage in the UK 2005-2021

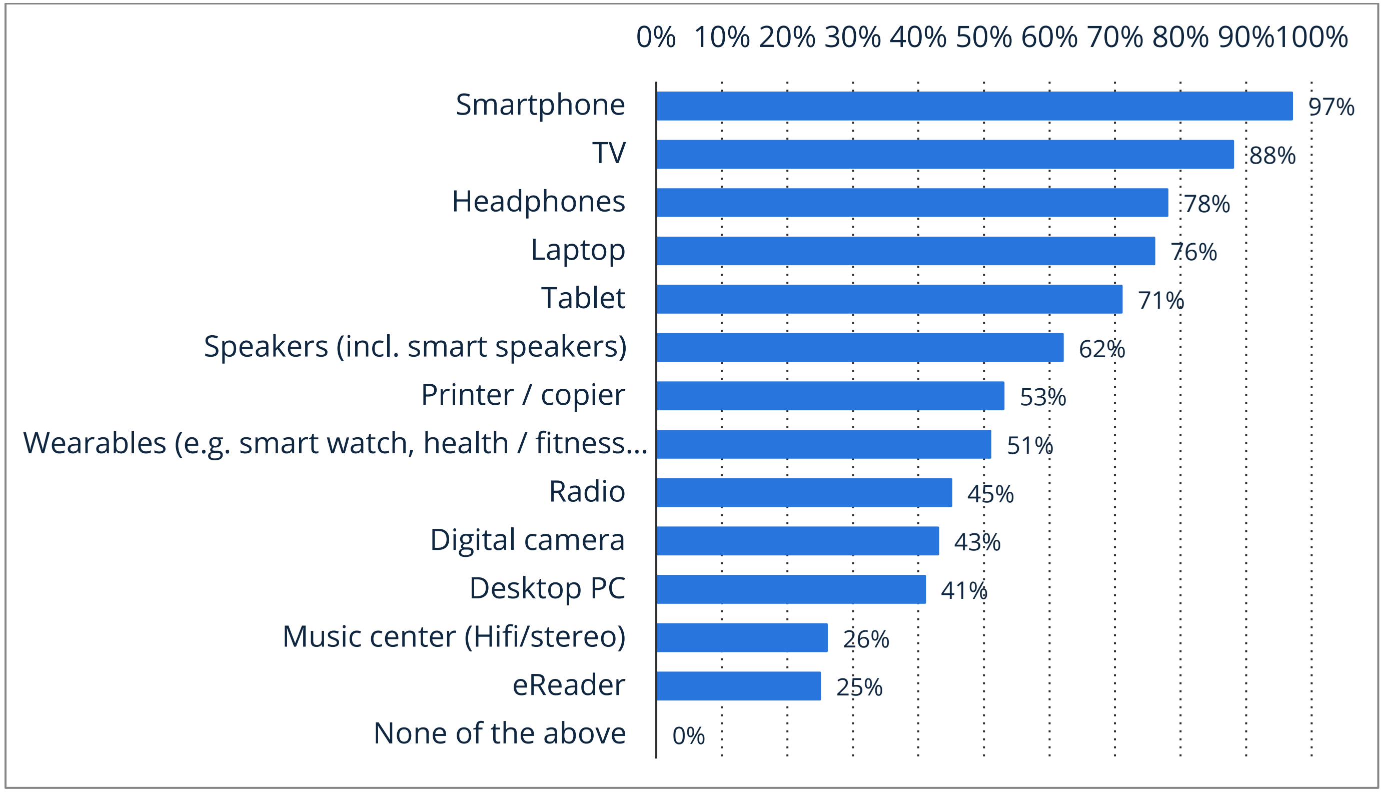
This figure illustrates the growth of mobile phone usage in the UK 2005-2021. The data are taken from Statista (2021) and the sample is based on 16 years and older; it is a sample of 2,792 respondents.



Percentage of mobile phone users started around 82% in 2005 but had climbed to the low 90s by 2009 where it remined until 2016. Thereafter it climbed again to remain at 95% or more from 2018 to 2021.

Figure 1.3 Consumer electronics ownership in the UK 2022

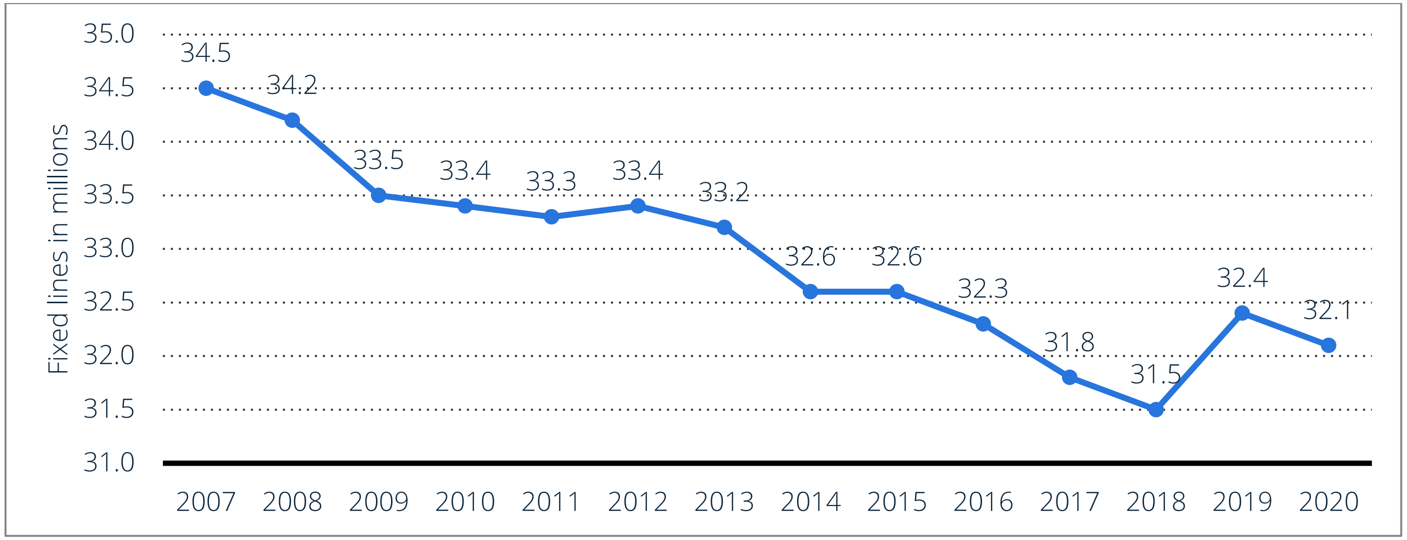
This figure shows electronic device ownership in the UK in 2022 from Statista (2022). Survey of 4,032 respondents between 18 and 64 years from 06/01/2022 to 14/12//2022



The survey shows 97% of the UK population has a smart phone, 76% own a laptop, 71% a tablet and 41% have their own desktop.

Figure 1.4 Landlines in the United Kingdom (UK) 2007-2020

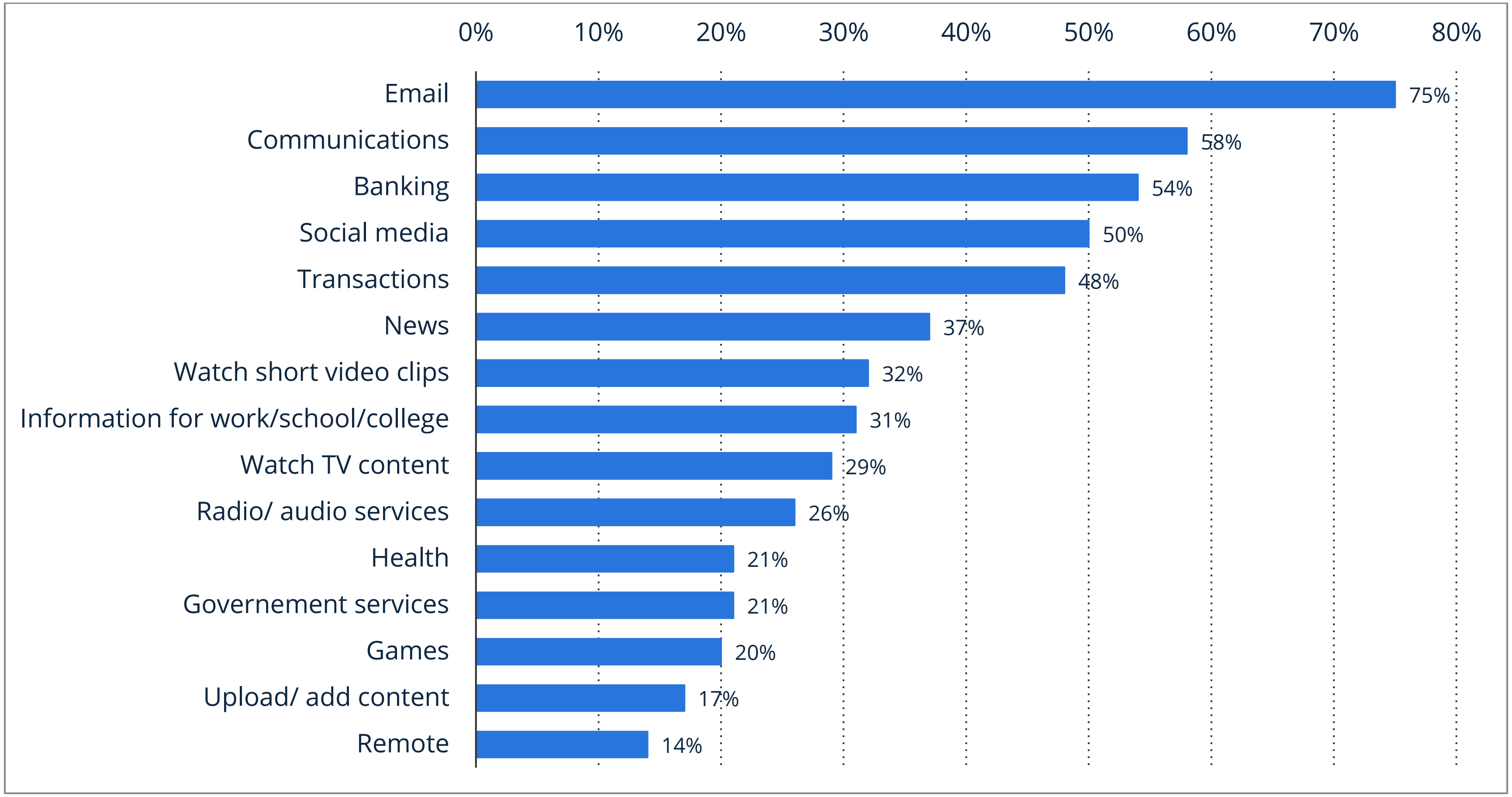
This figure illustrates land line usage in the UK in millions from 2007 to 2020. The data are from Statista (2021).



The number of fixed landlines has steadily decreased from peak of 34.5 million in 2007 to 31.5 million in 2018. This was followed by a relatively small increase in fixed landlines to 32.4 million and 32.1 million in 2019 and 2020 respectively.

Figure 1.5 Online activities carried out in the prior week in the UK 2020

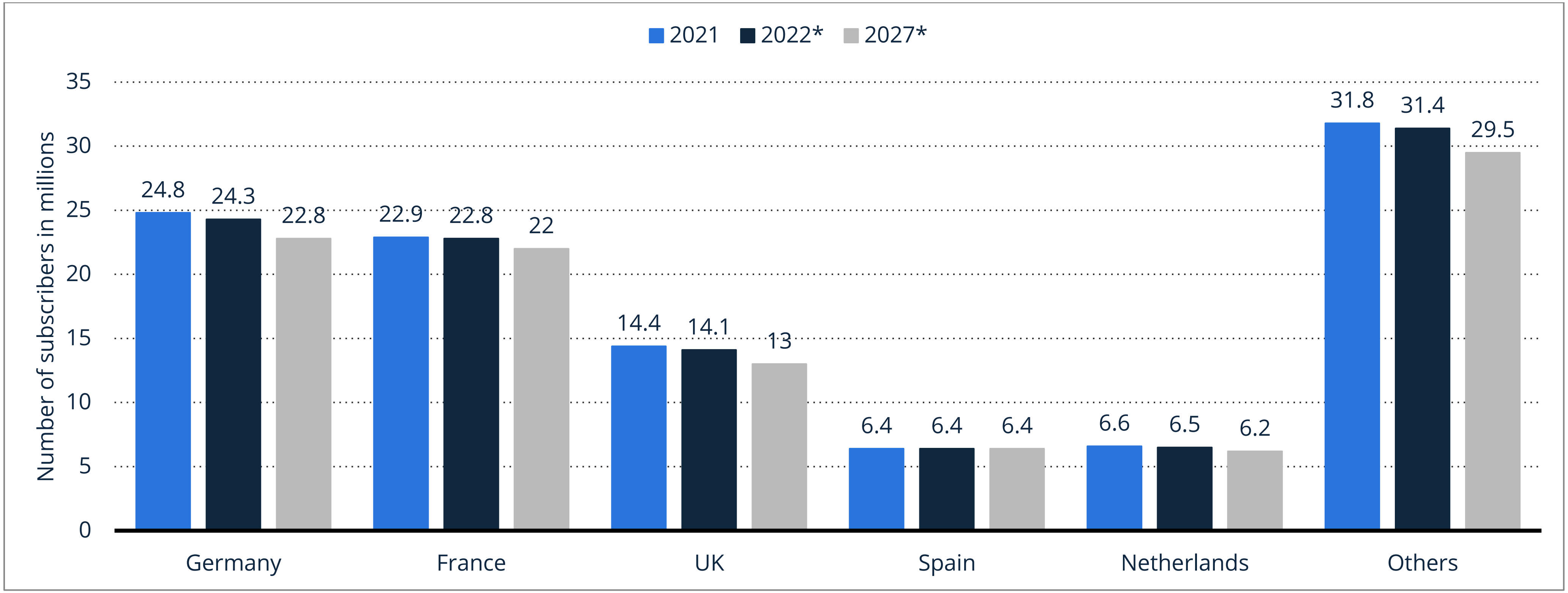
This figure illustrates online activities carried out by people in the UK by 3,422 respondents who were 16 years or older. This data were taken from Statista (2022).



This figure shows the prevalence of internet in daily life in the UK. 75% of respondents used internet for email, 58% for communication, 54% for banking, 31 for school or work information, and 21% to access government services and 21% for health.

Figure 1.6 Number of pay TV subscribers in selected countries in Western Europe from 2021 to 2027 in millions (Statista, 2022)

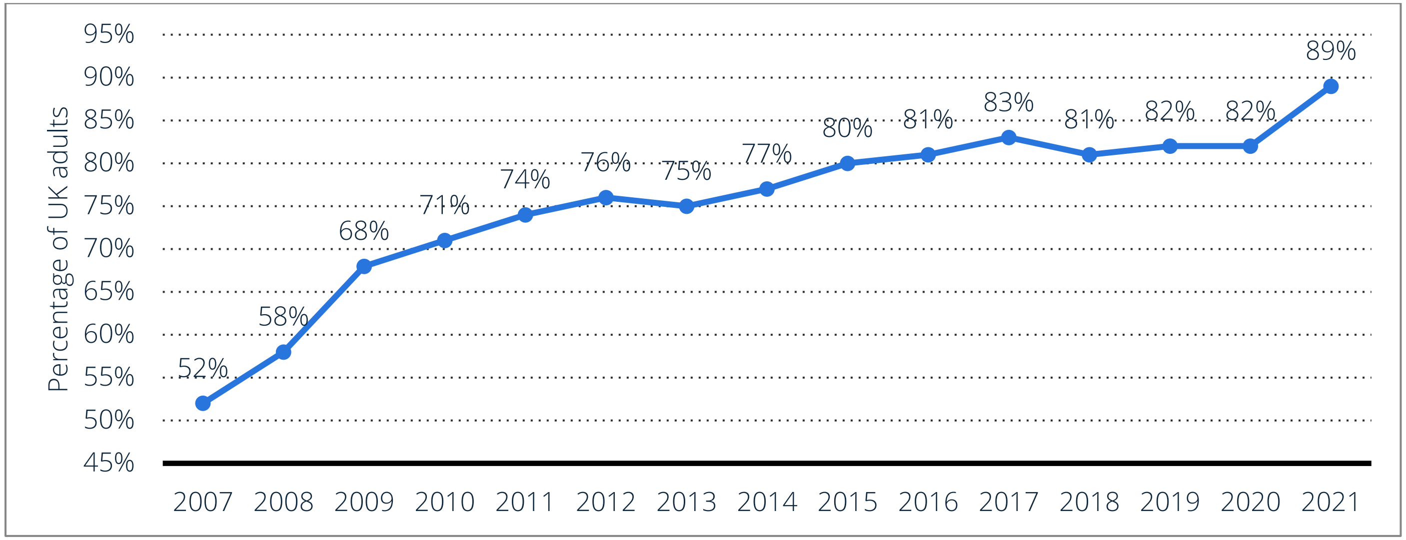
This figure illustrates number of paid TV subscribers in Western Europe 2021-2027



This figure shows a very slow decline of UK pay TV subscribers. UK is amongst nations with the highest number of subscribers in Western Europe.

Figure 1.7 Broadband penetration in the UK 2007-2021

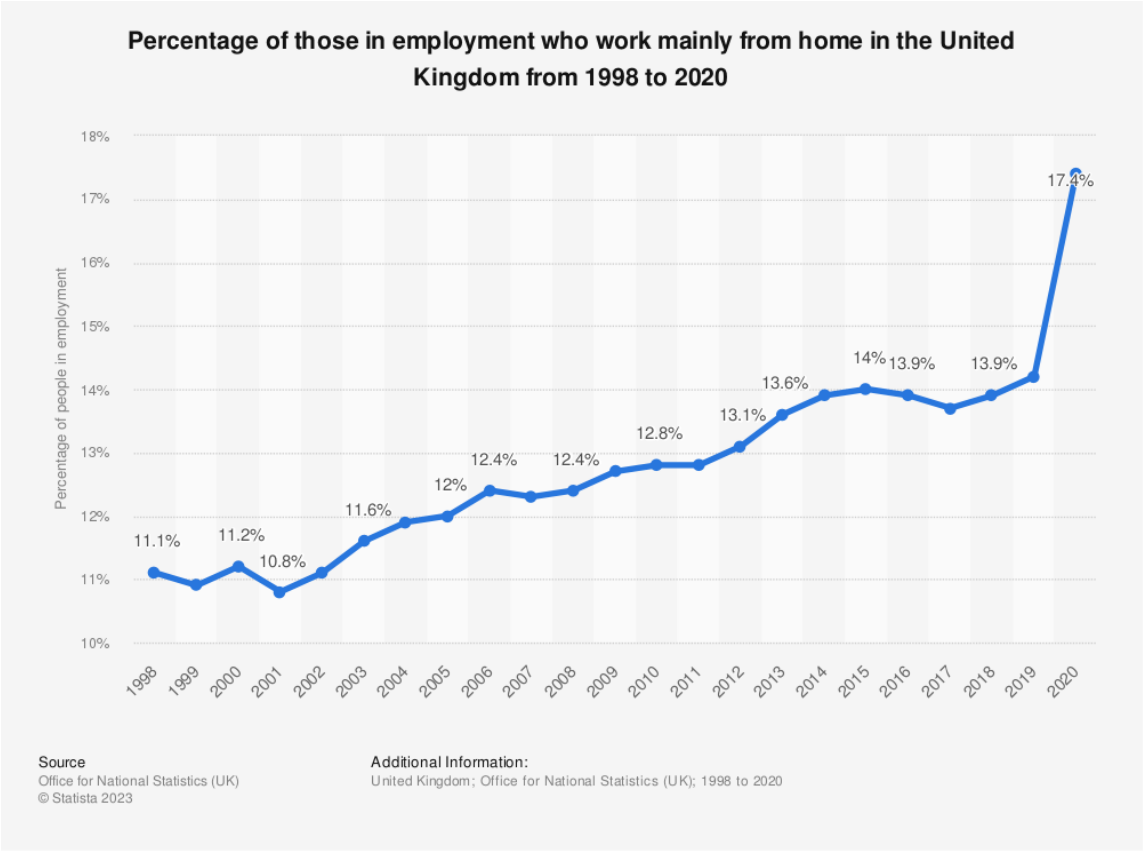
This figure illustrates percentage of UK adults using broadband from 2007 to 2021. The data are from Statista (2021).



Percentage of adults using broadband has steadily increased from a low of 52% in 2007, to high of 89% in 2021.

Figure 1.8 Percentage of employees who work from home in the UK 1998-2020

This figure illustrates percentage of those in employment who work mainly from home in the United Kingdom from 1998 to 2020 from Statista (2021).



This figure shows that has been a continual increase in percentage of people in the UK who work from home.

Figure 1.9 Recent trends in working from home

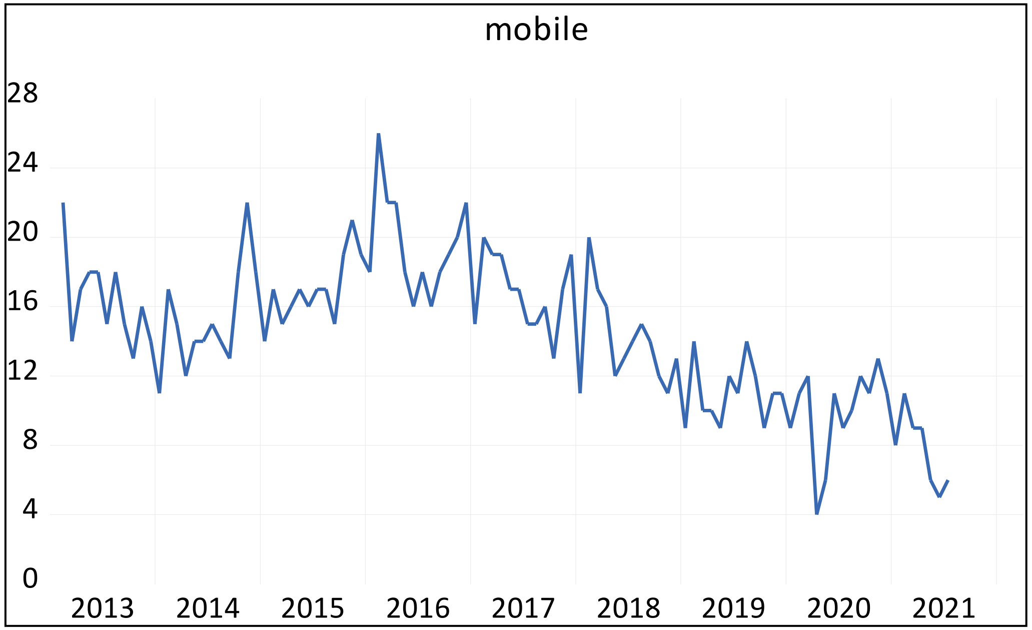
Proportion of working adults in Great Britain, March 2020 to February 2023 from ONS (2023).

Source: Office for National Statistics (ONS) – Opinions and Lifestyle Survey (OPN)

Figure above show around 40% of people are working from home in the UK since 2020.

Figure 1.10 UK mobile complaints from October 2010 to June 2021

This figure shows monthly mobile complaints in the UK from October 2010 to June 2021 constructed using data from Ofcom.

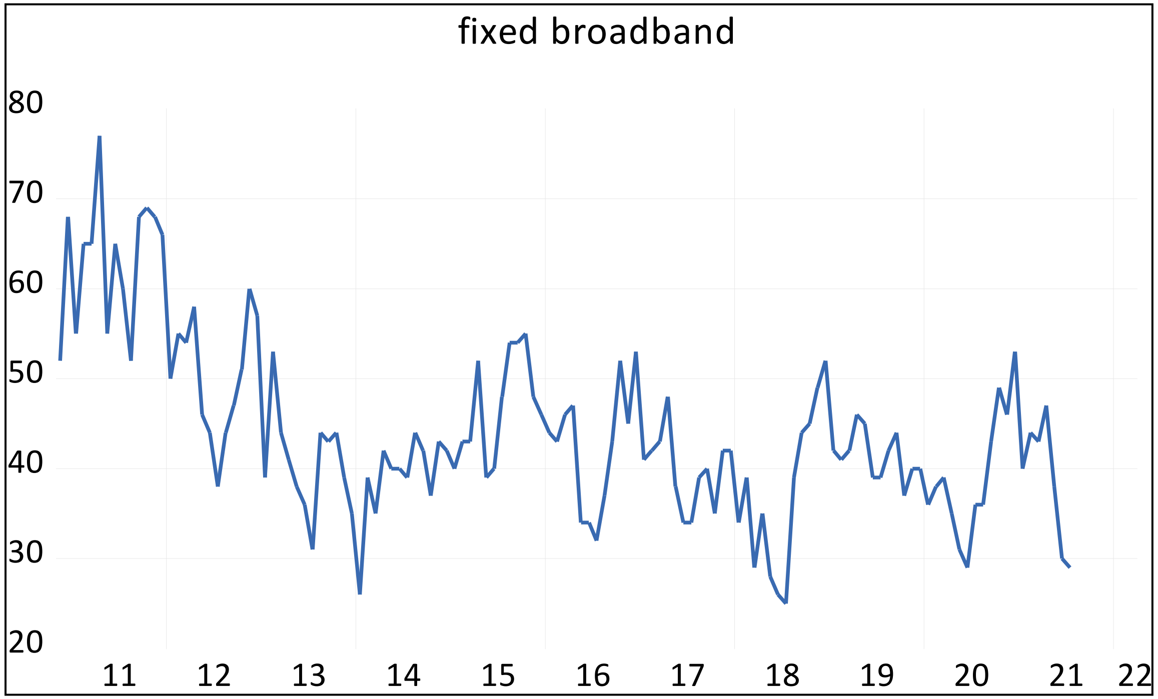


Mobile complaints peaked between 2015 and 2016, they have been on a slight decline until 2021.

The data provided are the number of complains per 100,000 customers/connection for individuals or companies. Individual service provider complaints for a particular month are added to generate overall monthly-frequency time series. Mobile pay monthly complaints include BT Mobile, O2, iD Mobile, Sky Mobile, Talk Mobile, TalkTalk Group, Tesco Mobile, Three UK, Virgin Mobile, Vodafone, and EE (aggregate of T-Mobile, Orange & 4GEE). This data is from The Office of Communication (Ofcom) which is the UK's government telecommunication, broadcasting and postal services regulator.

Figure 1.11 UK fixed broadband complaints from October 2010 to June 2021

This figure shows monthly fixed complaints in the UK from October 2010 to June 2021 constructed using data from Ofcom.

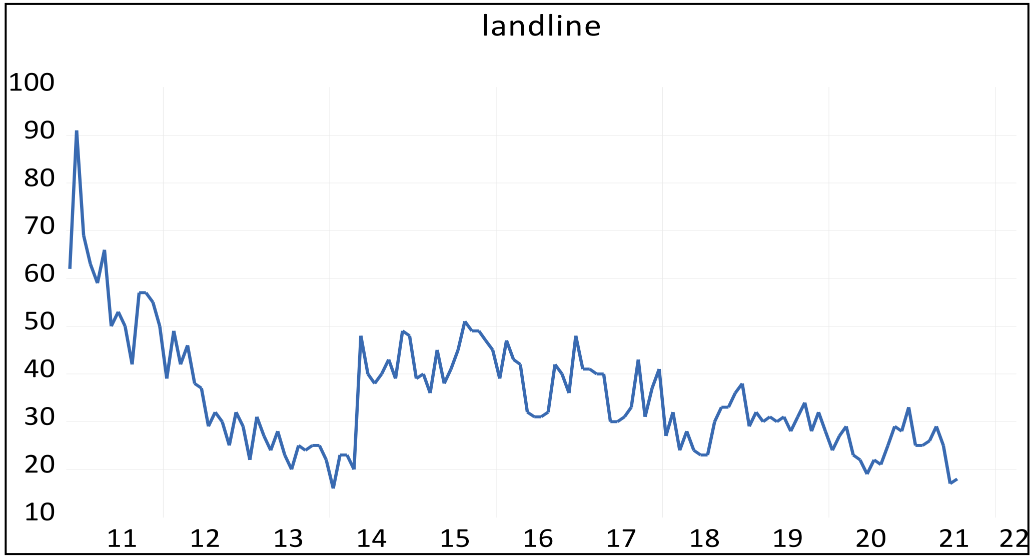


Broad band complaints peaked in 2011, and lowest in 2018 but have mainly remained steady despite increased numbers of broadband users.

The data provided are the number of complains per 100,000 customers/connection for individuals or companies. Individual service provider complaints for a particular month are added to generate overall monthly-frequency time series. Fixed broadband complaints used incorporate BT, Sky, EE, Plusnet, Post Office, Shell Energy, TalkTalk Group, Virgin Media, and Vodafone. This data is from The Office of Communication (Ofcom) which is the UK's government telecommunication, broadcasting and postal services regulator.

Figure 1.12 UK landline complaints from October 2010 to June 2021

This figure shows monthly landline complaints in the UK from October 2010 to June 2021 constructed using data from Ofcom.

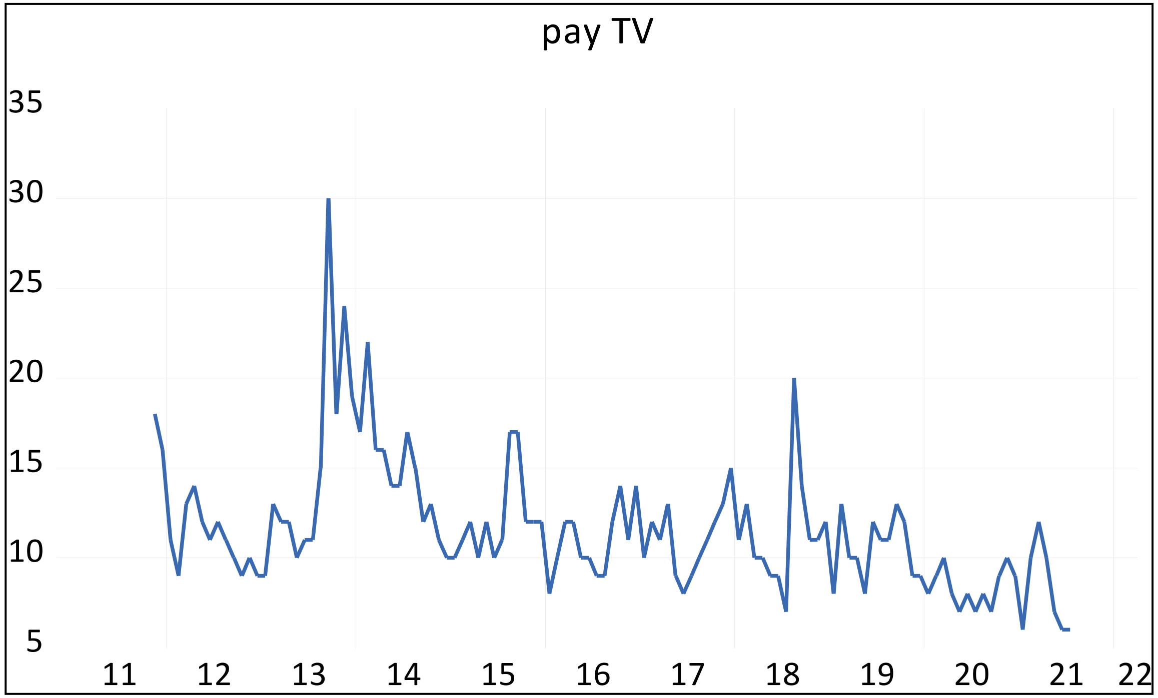


From a peak in 2010-2011, landline complaints have been steady from 2014 to 2021.

The data provided are the number of complains per 100,000 customers/connection for individuals or companies. Individual service provider complaints for a particular month are added to generate overall monthly-frequency time series. Landline complaints comprise BT, EE, Plusnet, Post Office HomePhone, Shell Energy, Sky, TalkTalk Group, Virgin Media, and Vodafone. This data is from The Office of Communication (Ofcom) which is the UK's government telecommunication, broadcasting and postal services regulator.

Figure 1.13 UK Pay TV complaints from October 2010 to June 2021

This figure shows monthly pay TV complaints in the UK from October 2010 to June 2021 constructed using data from Ofcom.



Pay TV complaints were highest in 2013, a troughed twice in 2021. Pay TV complaints have been slightly trending lower since 2014.

The data provided are the number of complains per 100,000 customers/connection for individuals or companies. Individual service provider complaints for a particular month are added to generate overall monthly-frequency time series. Pay TV complaints contain BT, Sky, TalkTalk Group, and Virgin Media. This data is from The Office of Communication (Ofcom) which is the UK's government telecommunication, broadcasting and postal services regulator.

Table 1.1 Descriptive statistics of mobile and fixed broadband complaints rate of change from October 2010 to June 2021

	RCMOBILE	RCMOBILE_SA	RCFIXEDBROADBAND	RCFIXEDBROADBAND_SA
Mean	1.5424	0.7326	0.7466	0.4081
Median	0.0000	-1.3771	0.0000	-1.0011
Maximum	83.3333	85.2796	56.0000	30.6165
Minimum	-66.6667	-65.1340	-31.5789	-23.0405
Standard. Deviation	24.1864	18.9902	15.8190	11.6022
Skewness	0.7562	0.8245	0.5720	0.4391
Observations	101	101	128	128

RCMOBILE is Mobile complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change, and RCFIXEDBROADBAND is Broadband complaints rate of change.

Table 1.2 Descriptive statistics of landline and pay TV complaints rate of change from October 2010 to June 2021

	RCLANDLINE	RCLANDLINE_SA	RCPAY_TV	RCPAY_TV_SA
Mean	0.7938	0.6735	2.1497	1.6450
Median	-2.1832	-2.0658	0.0000	-2.1092
Maximum	140.0000	175.3099	185.7143	144.1784
Minimum	-34.1463	-26.2765	-40.0000	-43.9027
Standard. Deviation	20.7016	20.4540	28.7770	24.5349
Skewness	2.5490	5.0203	2.7663	2.3332
Observations	128	128	116	116

RCPAY_TV is Pay TV complaints rate of change, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCLANDLINE is Landline complaints rate of change, and RCLANDLINE_SA is seasonally adjusted landline complaints rate of change.

Table 1.3 Descriptive statistics of FTSE index excess returns from October 2010 to June 2021

	EXCESS R250	EXCESS RAIM100	EXCESS RAIMALLSHARE	EXCESS RSMALL	EXCESS RMID	EXCESS RDISC
Mean	-0.0010	-0.0031	-0.0038	-0.0006	-0.0024	-0.0038
Median	0.0143	0.0116	0.0054	0.0127	0.0075	0.0069
Maximum	2.6550	2.6435	2.6484	2.6696	2.6348	2.6350
Minimum	-1.7594	-1.7937	-1.7819	-1.7471	-1.7796	-1.7988
Std. Dev.	0.4434	0.4455	0.4440	0.4444	0.4428	0.4427
Skewness	1.8271	1.7433	1.7817	1.8810	1.7881	1.7565
Observations	136	136	136	136	136	136

R250 is returns of FTSE 250 index, RAIM100 is returns of FTSE AIM100 index, RAIMALLSHARE is returns of FTSE AIM All Share index, RSMALL is returns of FTSE Small index, RMID is returns of FTSE Medium index, and RDISC is returns of FTSE Discretionary index.

Table 1.4 Descriptive statistics of FTSE index excess returns and risk-free returns from October 2010 to June 2021

	EXCESS RLARGE	EXCESS R100	Risk Free Return
Mean	-0.0051	-0.0045	0.7198
Median	0.0076	0.0090	-0.5051
Maximum	2.6274	2.6285	180.0000
Minimum	-1.7799	-1.7811	-266.6667
Std. Dev.	0.4429	0.4429	44.2010
Skewness	1.7593	1.7605	-1.6849
Observations	136	136	136

RLARGE is returns of FTSE Large index, R100 is returns of FTSE100 index, and risk-free return is the return on one month UK T-bill.

Table 1.5 FTSE excess returns and seasonally adjusted complaints rate of change from October 2010 to June 2021

Dep. Var:	EXCESS R250	EXCESS RAIM100	EXCESS RAIMALLSHARE	EXCESS RSMALL	EXCESS RMID	EXCESS RDISC	EXCESS RLARGE	EXCESS R100
C	0.0039***	0.0049	0.0037	0.0051***	0.0031*	0.0015	-0.0019**	-0.0009**
	(0.0018)	(0.0033)	(0.0030)	(0.0018)	(0.0016)	(0.0021)	(0.0008)	(0.0004)
RISKPREMIUM	0.9966***	0.9988***	0.9969***	1.0004***	0.9969***	0.9971***	1.0015***	1.0007***
	(0.0038)	(0.0068)	(0.0063)	(0.0038)	(0.0034)	(0.0044)	(0.0017)	(0.0009)
RCDPAY_TV_SA	-0.0044	-0.0053	0.0000	-0.0037	-0.0123*	-0.0106	0.0046	0.0011
	(0.0078)	(0.0138)	(0.0129)	(0.0077)	(0.0069)	(0.0090)	(0.0034)	(0.0018)
RCDMOBILE_SA	0.0103	0.0694***	0.0632***	0.0156	0.0236**	0.0261**	-0.0107**	-0.0029
	(0.0104)	(0.0185)	(0.0173)	(0.0103)	(0.0092)	(0.0121)	(0.0046)	(0.0024)
RCDLANDLINE_SA	-0.0318***	-0.0425**	-0.0361**	-0.0198*	-0.0224**	-0.0210*	0.0136***	0.0069***
	(0.0101)	(0.0180)	(0.0169)	(0.0101)	(0.0090)	(0.0118)	(0.0045)	(0.0023)
RCDFIXEDBROADBAND_SA	0.0622***	0.0463	0.0317	0.0451**	0.0455***	0.0265	-0.0279***	-0.0143***
	(0.0194)	(0.0345)	(0.0323)	(0.0193)	(0.0172)	(0.0225)	(0.0085)	(0.0045)
Observations:	101	101	101	101	101	101	101	101
R-squared:	0.9986	0.9957	0.9962	0.9987	0.9989	0.9982	0.9997	0.9999
F-statistic:	13931.0567	4405.3763	5013.6937	14254.2251	17777.2033	10337.3659	73059.8242	262904.7927
Prob(F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

This table presents OLS regression results of FTSE excess returns on seasonally adjusted mobile, broadband, landline, and Pay TV complaints rate of change.

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Seasonal adjustment done using STL method (explained in section 1.3).
EXCESSR100 is excess returns of FTSE100 index, EXCESSR250 is excess returns of FTSE 250 index, EXCESSRAIM100 is excess returns of FTSE AIM100 index, EXCESSRAIMALLSHARE is excess returns of FTSE AIM All Share index, EXCESSRSMALL is excess returns of FTSE Small index, EXCESSRMID is excess returns of FTSE Medium index, EXCESSRDISC is excess returns of FTSE Discretionary index, EXCESSRLARGE is excess returns of FTSE Large index, RISKPREMIUM is the market risk premium (returns of FTSE All Share index subtract returns on UK one month T-bill security). RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Table 1.6 FTSE excess returns and complaints rate of change from October 2010 to June 2021

Dep. Var:	EXCESS R250PI	EXCESS RAIM100PI	EXCESSRAIM ALLSHAREPI	EXCESS RSMALLPI	EXCESS RMIDPI	EXCESS RDISCPI	EXCESS RLARGEPI	EXCESS R100PI
C	0.0039**	0.0047	0.0035	0.0051***	0.0030*	0.0014	-0.0018**	-0.0009**
	(0.0019)	(0.0034)	(0.0031)	(0.0018)	(0.0017)	(0.0021)	(0.0008)	(0.0004)
RISKPREMIUM	0.9963***	0.9956***	0.9938***	0.9995***	0.9960***	0.9959***	1.0019***	1.0008***
	(0.0039)	(0.0070)	(0.0065)	(0.0038)	(0.0034)	(0.0045)	(0.0017)	(0.0009)
RCDPAY_TV	-0.0077	-0.0097	-0.0046	-0.0088	-0.0122*	-0.0080	0.0058*	0.0020
	(0.0073)	(0.0131)	(0.0122)	(0.0072)	(0.0065)	(0.0084)	(0.0032)	(0.0017)
RCDMOBILE	0.0047	0.0464***	0.0434***	0.0084	0.0188**	0.0203**	-0.0071*	-0.0013
	(0.0088)	(0.0158)	(0.0147)	(0.0086)	(0.0078)	(0.0101)	(0.0039)	(0.0020)
RCDLANDLINE	-0.0276**	-0.0339	-0.0264	-0.0136	-0.0199*	-0.0155	0.0113**	0.0058**
	(0.0114)	(0.0205)	(0.0191)	(0.0112)	(0.0101)	(0.0131)	(0.0051)	(0.0026)
RCDFIXEDBROADBAND	0.0430***	0.0324	0.0194	0.0345**	0.0298**	0.0142	-0.0186**	-0.0099***
	(0.0163)	(0.0291)	(0.0271)	(0.0159)	(0.0143)	(0.0186)	(0.0072)	(0.0038)
Observations:	101	101	101	101	101	101	101	101
R-squared:	0.9986	0.9954	0.9960	0.9986	0.9989	0.9981	0.9997	0.9999
F-statistic:	13200.1405	4117.5517	4730.1290	13837.4139	16968.4183	10076.3249	67979.0221	248810.6406
Prob(F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

This table presents OLS regression results of FTSE excess returns on seasonally adjusted mobile, broadband, landline, and Pay TV complaints rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

EXCESSR100 is excess returns of FTSE100 index, EXCESSR250 is excess returns of FTSE 250 index, EXCESSRAIM100 is excess returns of FTSE AIM100 index, EXCESSRAIMALLSHARE is excess returns of FTSE AIM All Share index, EXCESSRSMALL is excess returns of FTSE Small index, EXCESSRMID is excess returns of FTSE Medium index, EXCESSRDISC is excess returns of FTSE Discretionary index, EXCESSRLARGE is excess returns of FTSE Large index, RISKPREMIUM is the market risk premium (returns of FTSE All Share index subtract returns on UK one month T-bill security). RCPAY_TV is Pay TV complaints rate of change, RCMOBILE is Mobile complaints rate of change, RCLANDLINE is Landline complaints rate of change, RCFIXEDBROADBAND is Broadband complaints rate of change.

Table 1.7 List of abbreviations used in this paper

Symbol used	Definition
R100	Returns of FTSE100 index.
R250	Returns of FTSE 250 index.
RAIM100	Returns of FTSE AIM100 index.
RAIMALLSHARE	Returns of FTSE AIM All Share index.
RSMALL	Returns of FTSE Small index.
RMID	Returns of FTSE Medium index.
RDISC	Returns of FTSE Discretionary index.
RLARGE	Returns of FTSE Large index.
RALLSHARE	Returns of FTSE All Share index.
R100MV	Rate of change of FTSE100 market capitalisation.
R250MV	Rate of change of FTSE250 market capitalisation.
RAIM100MV	Rate of change of FTSE AIM100 market capitalisation.
RAIMALLSHAREMV	Rate of change of FTSE AIM All Share market capitalisation.
RSMALLMV	Rate of change of FTSE Small market capitalisation.
RMIDMV	Rate of change of FTSE Medium market capitalisation.
RDISCMV	Rate of change of FTSE Discretionary market capitalisation.
RLARGEMV	Rate of change of FTSE Large market capitalisation.
RALLSHAREMV	Rate of change of FTSE All Share index.
RCPAY_TV_SA	Seasonally adjusted Pay TV complaints rate of change.
RCMOBILE_SA	Seasonally adjusted mobile complaints rate of change.
RCLANDLINE_SA	Seasonally adjusted landline complaints rate of change.
RCFIXEDBROADBAND_SA	Seasonally adjusted broadband complaints rate of change.
RCPAY_TV	Pay TV complaints rate of change.
RCMOBILE	Mobile complaints rate of change.
RCLANDLINE	Landline complaints rate of change.
RCFIXEDBROADBAND	Broadband complaints rate of change.
R100	FTSE 100 is an equity index of one hundred corporations listed on the London Stock Exchange with the highest market valuation.
R250	FTSE 250 is an equity index of medium capitalised companies not in FTSE 100 index.
RAIM100	FTSE AIM 100 is an equity index of the largest hundred companies by full market capitalisation that are in the Alternative Investment Market index.

RAIMALLSHARE	FTSE AIM All ordinary shares is an equity index of companies that are listed in the Alternative Investment Market.
RSMALL	FTSE Small is an equity index of small market capitalisation corporations on the London Stock Exchange main market.
RMID	FTSE Medium is an equity index of medium market capitalisation corporations on the London Stock Exchange main market.
RDISC	FTSE Discretionary is an equity index of consumer discretionary corporations on the London Stock Exchange.
RLARGE	FTSE Large is an equity index of large market capitalisation corporations on the London Stock Exchange main market.
RALLSHARE	FTSE All-Share is an equity index that represents the performance of almost all companies in the London Stock Exchange. This index captures 98% of the UK's market capitalisation.
MV	Market Value or capitalisation is the number of shares issued multiplied by current market price per share.

Definition of FTSE indexes in this table is from LSGE via EIKON/Workspace.

Appendix

A1.1 The CAPM and extended model

The CAPM equation for companies in a market index is given as follows where i denotes an index

$R_i - r = \beta(R_M - r)$

where Ri is the return of an index

r is the return of UK risk-free asset proxied by returns on UK one month T-bill

β is the beta of an index i

R_M is the return of UK market proxied by returns on FTSE All Share index

$R_i - r$ is excess return of index i

$R_M - r$ is the UK market risk premium

For econometric analysis, the following augmented panel version of the CAPM is employed as in Chapter 1 (in Tables 1.5 and 1.6.)

$$R_{it} - r_{it} = \alpha + \beta(R_{Mit} - r_{it}) + \delta' X_{it} + u_{it} \qquad (1)$$

Where R_{Mit} is proxied by the returns on the FTSE All Share index, r_{it} is the expected return of risk-free asset proxied by returns on UK one month T-bill, α is the y-intercept, β is the beta of an index, $R_t - r_{it}$ is excess return, i denotes the companies in the index, t is time, and u_{it} is an error term. The vector X_{it} includes broadband complaints, landline complaints, pay TV complaints and mobile complaints.

For robustness, further augmenting CAPM is shown in appendix. The augmented CAPM model used in appendix has reduced form CAPM equation that uses market return but not risk-free asset. This simplification is done to overcome problems that are associated with some of the assumptions of CAPM mentioned in section 1.3. The

$$R_i - r = \beta R_M - \beta r$$

$$R_i = (1 - \beta)r + \beta R_M$$

Now replace $(1 - \beta)r$ with α

$$R_i = \alpha + \beta R_M$$

The simplified model used in appendix A1.2 to A1.12 (that uses returns and not excess returns) is formed by adding a vector of complaints, X_t that includes broadband complaints, landline complaints, pay TV complaints and mobile complaints.

$$R_{it} = \alpha + \beta R_{Mit} + \delta' X_{it} + u_{it}$$

Where R_{Mit} is proxied by the returns on the FTSE All Share index, α is the y-intercept, β is the beta of an index, R_{it} return of index, i denotes the companies in the index, t is time, and u_{it} is an error term. The vector X_{it} includes broadband complaints, landline complaints, pay TV complaints and mobile complaints.

A1.2 FTSE returns and seasonally adjusted complaints rate of change from October 2010 to June 2021

Dep. Var:	R250	RAIM100	RAIMALLSHARE	RSMALL	RMID	RDISC	RLARGE
C	0.3792**	0.4952	0.3905	0.5397***	0.2796*	0.1467	-0.1796**
	(0.1680)	(0.377)	(0.3478)	(0.1947)	(0.1575)	(0.2092)	(0.0827)
RALLSHARE	1.0167***	0.9705***	0.9019***	0.9008***	1.0898***	1.0051***	0.9809***
	(0.0763)	(0.0922)	(0.0913)	(0.0878)	(0.0532)	(0.0580)	(0.0324)
RCPAY_TV_SA	-0.0042	-0.0054	-0.0002	-0.0041	-0.0119**	-0.0105	0.0045*
	(0.0059)	(0.0109)	(0.0126)	(0.0078)	(0.0047)	(0.0064)	(0.0024)
RCMOBILE_SA	0.0109	0.0708***	0.0676***	0.019*	0.0214	0.0269**	-0.0105
	(0.014)	(0.0220)	(0.0242)	(0.0103)	(0.0163)	(0.0121)	(0.0072)
RCLANDLINE_SA	-0.0327***	-0.0428***	-0.0369***	-0.0198***	-0.0231***	-0.0218***	0.014***
	(0.0062)	(0.0091)	(0.0088)	(0.0047)	(0.0052)	(0.0051)	(0.0025)
RCFIXEDBROADBAND_SA	0.0613***	0.0473*	0.035	0.0488***	0.0418***	0.026	-0.027***
	(0.0155)	(0.0265)	(0.0264)	(0.0177)	(0.0151)	(0.0228)	(0.0069)
Observations:	101	101	101	101	101	101	101
R-squared:	0.8329	0.6342	0.6345	0.8107	0.8839	0.7842	0.957
F-statistic:	94.6819	32.9456	32.9803	81.3505	144.6306	69.0431	423.0527
Prob(F-stat):	0	0	0	0	0	0	0

This table presents OLS regression results of FTSE returns on seasonally adjusted mobile, broadband, landline, and Pay TV complaints rate of change. R100 is returns of FTSE100 index, R250 is returns of FTSE 250 index, RAIM100 is returns of FTSE AIM100 index, RAIMALLSHARE is returns of FTSE AIM All Share index, RSMALL is returns of FTSE Small index, RMID is returns of FTSE Medium index, RDISC is returns of FTSE Discretionary index, RLARGE is returns of FTSE Large index, RALLSHARE is returns of FTSE All Share index, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change, RCPAY_TV is Pay TV complaints rate of change, RCMOBILE is Mobile complaints rate of change, RCLANDLINE is Landline complaints rate of change, RCFIXEDBROADBAND is Broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.3 FTSE market value/capital returns and seasonally adjusted complaints rate of change from October 2010 to June 2021

Dep. Var:	R250MV	RAIM100MV	RAIMALLSHAREMV	RSMALLMV	RMIDMV	RDISCMV	RLARGEMV
C	0.2974	0.8417**	0.7233**	0.4803	0.2933	0.2913	-0.1745**
	(0.1882)	(0.3957)	(0.3591)	(0.3094)	(0.1793)	(0.2457)	(0.0816)
RALLSHAREMV	0.9854***	0.913***	0.8496***	0.8583***	1.053***	0.9333***	0.9987***
	(0.0786)	(0.0838)	(0.0853)	(0.1303)	(0.0671)	(0.0739)	(0.0405)
RCPAY_TV_SA	-0.004	-0.0132	-0.0081	-0.0056	-0.0071	-0.0217**	0.002
	(0.0064)	(0.0113)	(0.0129)	(0.0097)	(0.007)	(0.0093)	(0.0031)
RCMOBILE_SA	0.013	0.0611***	0.0558**	0.0297*	0.0197	0.0426**	-0.0134
	(0.0163)	(0.0230)	(0.0261)	(0.0161)	(0.0248)	(0.0180)	(0.0091)
RCLANDLINE_SA	-0.0336***	-0.0353***	-0.0365***	-0.0129	-0.0381***	-0.0259***	0.0176***
	(0.0061)	(0.0119)	(0.0091)	(0.009)	(0.0140)	(0.0070)	(0.0050)
RCFIXEDBROADBAND_SA	0.0617***	0.0335	0.0405	0.0246	0.0459**	0.0196	-0.0219**
	(0.0199)	(0.0366)	(0.0342)	(0.0301)	(0.0194)	(0.0265)	(0.0106)
Observations:	101	101	101	101	101	101	101
R-squared:	0.8168	0.576	0.5774	0.6427	0.7827	0.6822	0.947
F-statistic:	84.7339	25.809	25.9556	34.1785	68.4516	40.7865	339.3062
Prob(F-stat):	0	0	0	0	0	0	0

This table presents OLS regression results of FTSE market value/capital returns on seasonally adjusted mobile, broadband, landline, and Pay TV complaints rate of change. R100MV is rate of change of FTSE100 market capitalisation, R250MV is rate of change of FTSE250 market capitalisation, RAIM100MV is rate of change of FTSE AIM100 market capitalisation, RAIMALLSHAREMV is rate of change of FTSE AIM All Share market capitalisation, RSMALLMV is rate of change of FTSE Small market capitalisation, RMIDMV is rate of change of FTSE Medium market capitalisation, RDISCMV is rate of change of FTSE Discretionary market capitalisation, RLARGEMV is rate of change of FTSE Large market capitalisation, RALLSHAREMV is rate of change of FTSE All Share index, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.4 FTSE returns and complaints rate of change from October 2010 to June 2021

Dep. Var:	R250	RAIM100	RAIMALLSHARE	RSMALL	RMID	RDISC	RLARGE
C	0.3711**	0.4615	0.3592	0.5322***	0.2614	0.1235	-0.1727**
	(0.1700)	(0.385)	(0.3513)	(0.1925)	(0.1598)	(0.2104)	(0.0835)
RALLSHARE	1.0392***	1.0108***	0.9365***	0.9284***	1.1081***	1.017***	0.9686***
	(0.0881)	(0.0968)	(0.1031)	(0.0969)	(0.0606)	(0.0579)	(0.0385)
RCPAY_TV	-0.0075	-0.0094	-0.0045	-0.009	-0.0117**	-0.0078	0.0057**
	(0.0057)	(0.0118)	(0.0129)	(0.0075)	(0.0046)	(0.0059)	(0.0023)
RCMOBILE	0.0038	0.0461**	0.0447**	0.0099	0.0164	0.0199**	-0.0064
	(0.0104)	(0.0181)	(0.0190)	(0.01)	(0.0112)	(0.0090)	(0.0054)
RCLANDLINE	-0.0285***	-0.0351***	-0.0284***	-0.014***	-0.0207***	-0.0166***	0.0118***
	(0.0077)	(0.0106)	(0.0088)	(0.0047)	(0.0054)	(0.0055)	(0.0027)
RCFIXEDBROADBAND	0.0439***	0.0327	0.0179	0.0329**	0.0323***	0.0146	-0.0193***
	(0.0100)	(0.0208)	(0.0203)	(0.0132)	(0.0105)	(0.0196)	(0.0047)
Observations:	101	101	101	101	101	101	101
R-squared:	0.8244	0.6068	0.6064	0.8007	0.8801	0.7779	0.9542
F-statistic:	89.1819	29.3269	29.2691	76.3511	139.4157	66.5383	395.7621
Prob(F-stat):	0	0	0	0	0	0	0

This table presents OLS regression results of FTSE returns on mobile, broadband, landline, and Pay TV complaints rate of change. R100 is returns of FTSE100 index, R250 is returns of FTSE 250 index, RAIM100 is returns of FTSE AIM100 index, RAIMALLSHARE is returns of FTSE AIM All Share index, RSMALL is returns of FTSE Small index, RMID is returns of FTSE Medium index, RDISC is returns of FTSE Discretionary index, RLARGE is returns of FTSE Large index, RALLSHARE is returns of FTSE All Share index, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change, RCPAY_TV is Pay TV complaints rate of change, RCMOBILE is Mobile complaints rate of change, RCLANDLINE is Landline complaints rate of change, RCFIXEDBROADBAND is Broadband complaints rate of change.

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.5 FTSE market value/capital rate of change and complaints rate of change from October 2010 to June 2021

Dep. Var:	R250MV	RAIM100MV	RAIMALLSHAREMV	RSMALLMV	RMIDMV	RDISCMV	RLARGEMV
C	0.2927	0.8224**	0.705*	0.4962	0.2823	0.265	-0.1731**
	(0.1898)	(0.4020)	(0.3625)	(0.3094)	(0.1814)	(0.2475)	(0.0829)
RALLSHAREMV	1.007***	0.9443***	0.8815***	0.8826***	1.0646***	0.9448***	0.9903***
	(0.0924)	(0.0935)	(0.1057)	(0.1505)	(0.0822)	(0.0709)	(0.0500)
RCPAY_TV	-0.0079	-0.0123	-0.0086	-0.0096	-0.0111	-0.0164**	0.0043
	(0.006)	(0.0116)	(0.013)	(0.0079)	(0.0075)	(0.0079)	(0.0029)
RCMOBILE	0.0044	0.0337*	0.0303	0.0097	0.0129	0.0318**	-0.0072
	(0.0121)	(0.0171)	(0.0183)	(0.0134)	(0.0181)	(0.0149)	(0.007)
RCLANDLINE	-0.0317***	-0.0358***	-0.0356***	-0.0152*	-0.0347***	-0.0266***	0.0158***
	(0.0064)	(0.0119)	(0.0087)	(0.0087)	(0.0113)	(0.0075)	(0.0039)
RCFIXEDBROADBAND	0.0454***	0.0289	0.0293	0.0085	0.0416***	0.0182	-0.0132**
	(0.0129)	(0.0284)	(0.0246)	(0.0219)	(0.0138)	(0.0242)	(0.0066)
Observations:	101	101	101	101	101	101	101
R-squared:	0.8098	0.5526	0.5525	0.6323	0.7777	0.673	0.9434
F-statistic:	80.872	23.4703	23.4576	32.668	66.4721	39.1033	316.5997
Prob(F-stat):	0	0	0	0	0	0	0

This table presents OLS regression results of FTSE market value/capital returns on mobile, broadband, landline, and Pay TV complaints rate of change. R100MV is rate of change of FTSE100 market capitalisation, R250MV is rate of change of FTSE250 market capitalisation, RAIM100MV is rate of change of FTSE AIM100 market capitalisation, RAIMALLSHAREMV is rate of change of FTSE AIM All Share market capitalisation, RSMALLMV is rate of change of FTSE Small market capitalisation, RMIDMV is rate of change of FTSE Medium market capitalisation, RDISCMV is rate of change of FTSE Discretionary market capitalisation, RLARGEMV is rate of change of FTSE Large market capitalisation, RALLSHAREMV is rate of change of FTSE All Share index, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.6 FTSE 100 returns and complaints rate of change from October 2010 to June 2021

Dep. Var:	R100		Dep. Var:	R100
C	-0.0872**		C	-0.089**
	(0.0399)			(0.0397)
RALLSHARE	0.9952***		RALLSHARE	1.0011***
	(0.0219)			(0.0190)
RCPAY_TV	0.002		RCPAY_TV_SA	0.0011
	(0.0013)			(0.0014)
RCMOBILE	-0.0012		RCMOBILE_SA	-0.0031
	(0.0024)			(0.0031)
RCLANDLINE	0.006***		RCLANDLINE_SA	0.0071***
	(0.0016)			(0.0013)
RCFIXEDBROADBAND	-0.01***		RCFIXEDBROADBAND_SA	-0.0143***
	(0.0023)			(0.0035)
Observations:	101		Observations:	101
R-squared:	0.9876		R-squared:	0.9882
F-statistic:	1511.3216		F-statistic:	1597.7911
Prob(F-stat):	0		Prob(F-stat):	0

This table presents OLS regression results of FTSE returns on mobile, broadband, landline, and Pay TV complaints rate of change. R100 is returns of FTSE100 index, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change, RCPAY_TV is Pay TV complaints rate of change, RCMOBILE is Mobile complaints rate of change, RCLANDLINE is Landline complaints rate of change, RCFIXEDBROADBAND is Broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.7 FTSE 100 market value/capital rate of change and complaints rate of change from October 2010 to June 2021

Dep. Var:	R100MV		Dep. Var:	R100MV
C	-0.0657		C	-0.0659
	(0.0456)			(0.0456)
RALLSHAREMV	1.004***		RALLSHAREMV	1.0096***
	(0.0249)			(0.0209)
RCPAY_TV	0.0021		RCPAY_TV_SA	0.001
	(0.0014)			(0.0015)
RCMOBILE	-0.0014		RCMOBILE_SA	-0.0041
	(0.0028)			(0.0034)
RCLANDLINE	0.0067***		RCLANDLINE_SA	0.0071***
	(0.0015)			(0.0014)
RCFIXEDBROADBAND	-0.0094***		RCFIXEDBROADBAND_SA	-0.0135***
	(0.0031)			(0.0047)
Observations:	101		Observations:	101
R-squared:	0.9875		R-squared:	0.9881
F-statistic:	1501.6491		F-statistic:	1576.3808
Prob(F-stat):	0		Prob(F-stat):	0

This table presents OLS regression results of FTSE 100 market value/capital returns on mobile, broadband, landline, and Pay TV complaints rate of change. R100MV is rate of change of FTSE100 market capitalisation, RCPAY_TV_SA is seasonally adjusted Pay TV complaints rate of change, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change, RCPAY_TV is Pay TV complaints rate of change, RCMOBILE is Mobile complaints rate of change, RCLANDLINE is Landline complaints rate of change, RCFIXEDBROADBAND is Broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.8 FTSE returns and (seasonally adjusted) Mobile complaints rate of change from October 2010 to June 2021.

Dep. Var:	RAIM100	RAIMALLSHARE	RDISC		Dep. Var:	RAIM100	RAIMALLSHARE	RSMALL
C	0.4267*	0.3348*	0.1003		C	0.4491*	0.358*	0.5165***
	(0.3821)	(0.3449)	(0.2071)			(0.3805)	(0.3468)	(0.1902)
RALLSHARE	1.0127***	0.9401***	1.0196***		RALLSHARE	0.974***	0.9031***	0.9104***
	(0.1000)	(0.1073)	(0.0618)			(0.0906)	(0.0919)	(0.0920)
RCMOBILE	0.0367***	0.0367**	0.0139*		RCMOBILE_SA	0.0612***	0.0594**	0.0181*
	(0.0155)	(0.0157)	(0.0083)			(0.0225)	(0.0239)	(0.0101)
Observations:	101	101	101		Observations:	101	101	101
R-squared:	0.5932	0.5967	0.7725		R-squared:	0.612	0.6154	0.7956
F-statistic:	71.4513	72.5084	166.3819		F-statistic:	77.2794	78.404	190.7594
Prob(F-stat):	0	0	0		Prob(F-stat):	0	0	0

This table presents OLS regression results of FTSE returns on (seasonally adjusted) mobile complaints rate of change. RAIM100 is returns of FTSE AIM100 index, RAIMALLSHARE is returns of FTSE AIM All Share index, RSMALL is returns of FTSE Small index, RMID is returns of FTSE Medium index, RDISC is returns of FTSE Discretionary index, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change, RCMOBILE is Mobile complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.9 FTSE market value/capital rate of change and (lagged) seasonally adjusted Mobile complaints rate of change from October 2010 to June 2021.

Dep. Var:	RAIM100MV	RAIMALLSHAREMV	RSMALLMV	RDISCMV		Dep. Var:	RSMALLMV
C	0.7886**	0.6782*	0.4598*	0.2317		C	0.4829*
	(0.3926)	(0.351)	(0.2981)	(0.2385)			(0.2863)
RALLSHAREMV	0.913***	0.8512***	0.8623***	0.9321***		RALLSHAREMV	0.8783***
	(0.0816)	(0.0878)	(0.1313)	(0.0696)			(0.1527)
RCMOBILE_SA	0.0506**	0.0469*	0.0274*	0.0315*		RCMOBILE_SA(-1)	-0.0298***
	(0.0231)	(0.0253)	(0.0144)	(0.0177)			(0.0110)
Observations:	101	101	101	101		Observations:	101
R-squared:	0.5592	0.5586	0.6387	0.6625		R-squared:	0.6411
F-statistic:	62.1622	62.0089	86.6326	96.1825		F-statistic:	87.5381
Prob(F-stat):	0	0	0	0		Prob(F-stat):	0

This table presents OLS regression results of FTSE market value/capital returns on (lagged) seasonally adjusted mobile complaints rate of change. RAIM100MV is rate of change of FTSE AIM100 market capitalisation, RAIMALLSHAREMV is rate of change of FTSE AIM All Share market capitalisation, RSMALLMV is rate of change of FTSE Small market capitalisation, RMIDMV is rate of change of FTSE Medium market capitalisation, RDISCMV is rate of change of FTSE Discretionary market capitalisation, RCMOBILE_SA is seasonally adjusted mobile complaints rate of change Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.10 FTSE returns and (seasonally adjusted) broadband complaints rate of change from October 2010 to June 2021.

Dep. Var:	RMID	RLARGE		Dep. Var:	R250	RLARGE
C	0.23*	-0.1405**		C	0.3248**	-0.1421**
	(0.1373)	(0.0693)			(0.1453)	(0.0692)
RALLSHARE	1.0829***	0.9726***		RALLSHARE	1.0411***	0.9779***
	(0.0699)	(0.0368)			(0.0673)	(0.0351)
RCFIXEDBROADBAND	0.014*	-0.0066*		RCFIXEDBROADBAND_SA	0.0248*	-0.0122**
	(0.0084)	(0.0036)			(0.0139)	(0.0059)
Observations:	128	128		Observations:	128	128
R-squared:	0.8674	0.9576		R-squared:	0.8311	0.9583
F-statistic:	408.9115	1412.7251		F-statistic:	307.4413	1435.2984
Prob(F-stat):	0	0		Prob(F-stat):	0	0

This table presents OLS regression results of FTSE returns on (seasonally adjusted) broadband complaints rate of change. R250 is returns of FTSE 250 index, RMID is returns of FTSE Medium index, RLARGE is returns of FTSE Large index, RCFIXEDBROADBAND_SA is seasonally adjusted broadband complaints rate of change, RCFIXEDBROADBAND is Broadband complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.11 FTSE staple market value/capital rate of change and broadband complaints rate of change from October 2010 to June 2021.

Dep. Var:	RSTAPLEMV
C	0.3323
	(0.3215)
RALLSHAREMV	0.9979***
	(0.1831)
RCFIXEDBROADBAND	0.034*
	(0.0185)
Observations:	128
R-squared:	0.5478
F-statistic:	75.7077
Prob(F-stat):	0

This table presents OLS regression results of FTSE market value/capital returns on broadband complaints rate of change. RSTAPLEMV is rate of change of FTSE Staple market capitalisation, RCFIXEDBROADBAND is Broadband complaints rate of change.

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

A1.12 FTSE (market value/capital) rate of change seasonally adjusted landline complaints rate of change from October 2010 to June 2021.

Dep. Var:	RMIDMV
C	0.2498
	-0.1567
RALLSHAREMV	1.0506***
	(0.0805)
RCLANDLINE_SA	-0.0189**
	(0.0084)
Observations:	128
R-squared:	0.7739
F-statistic:	213.9239
Prob(F-stat):	0

This table presents OLS regression results of FTSE (market value/capital) returns on seasonally landline complaints rate of change. RMIDMV is rate of change of FTSE Medium market capitalisation, RCLANDLINE_SA is seasonally adjusted landline complaints rate of change. Seasonal adjustment done using STL method (explained in section 1.3).

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Chapter 2: Drinking to enhance mood or to cope: the alcohol-FTSE relationship.

2.1. Introduction

Neoclassical finance has long argued that financial markets are efficient in the long term, and that any mispricing of securities is arbitraged away. This is the main idea behind the Efficient Market Hypothesis (EMH) (Fama, 1970), whereby asset prices reflect value as all available information is included in the current asset price and new information is the only factor that changes future asset prices. However, there is growing acknowledgement that retail, and to some extent institutional investors, are not entirely rational as their current state of mind, or mood, has an impact in assessment and processing of information (Clore, Schwarz and Conway, 1994; Forgas, 2017), and subsequent pricing of assets. Additionally, research has shown how limits to arbitrage (Shleifer and Vishny, 1997, 2005) can foster environments where asset prices uncouple from fundamentals in the short or long term, resulting in overreaction, underreaction and financial bubbles (Nofsinger, 2012; Kyriazis, Papadamou and Corbet, 2020).

This paper explores to what extent social mood impacts FTSE indexes, and how FTSE indexes' returns affect social mood in the United Kingdom (UK). These research questions are based not only on many studies that have established how ex-ante mood affects information processing and later financial markets (Forgas, Bower and Krantz, 1984; Baillon, Koellinger and Treffers, 2016), but also how ex-post returns affect wellbeing (Deaton, 2012; Engelberg and Parsons, 2016). This paper furthers understanding of the mood-financial market relationship by focusing on the UK, as most studies are focused on the United States of America (US) and are mainly focused on investor sentiment.

Even though mood and sentiment are often used interchangeably, and are often also linked to emotions, there are some important nuances of meaning and usage. For this paper, mood is defined as a positive or negative affective state that does not require an external trigger, and is lower intensity compared to emotions (Scherer, 2005). On the other hand, sentiment refers to investors' positive or negative state of mind whereby their views of cashflow and information about an asset is not matching with facts available (Baker and Wurgler, 2007). Experienced both at the individual and collective level, mood does not require a specific trigger, can be transmitted orally, through facial expressions or body language (Scherer, 2005; Scheff, 2015). Emotions, in contrast, are understood as short term changes in affect that require specific trigger(s); emotions are shorter in duration compared to mood as changes in emotions tend to be taxing on the human body with noticeable changes in blood pressure, respiration and heart rate (Scherer, 2005; Scheff, 2015).

This paper uses bi-variate Vector Autoregressive Model (VAR) and then VAR with Gross Domestic Product (GDP) before performing impulse response tests to investigate the relationship between mood and financial markets. The VAR used in this paper is similar to the approach espoused by Beer, Herve and Zouaoui (2013) and Vozlyublennaia (2014), whereby the first stage involves no control variables, and then control variables are subsequently used. To capture aggregate social mood – that is social mood experienced at the collective level – this paper uses alcohol (i.e. wine, cider, beer and cocktails) as a proxy, since the Psychology literature has established that alcohol is used as a mood enhancer and/or for coping with negative moods such as despair. The paper uses correlation coefficients first, which is followed by Granger causality tests, VAR, and impulse response tests, to examine the bi-directional relationship, if any, between alcohol consumption and UK financial markets.

Results show that using alcohol as a proxy for social mood, mood in the UK society is reflected in London Stock Market (LSE) activity, but there is no statistically significant evidence of LSE activity affecting mood. It is to be expected for social mood to be affecting financial indexes based on investor sentiment, which is a subset of social mood. Surprisingly, results indicate that the UK Financial market does not affect mood in society, perhaps due to lack of attention by consumers and the public towards announcements by the Central Bank of inflation or interest rates (Lamla and Vinogradov, 2019), and/or low consumption of financial news, as indicated by low circulation figures of The Financial Times (109,640) when compared to more popular publications that are not finance-centred such as the Daily Mail (1.9 million), News Corp (934,570), Telegraph Media Group (188,370) (Press Gazette, 2023). Alcohol receipts is an imperfect measure, but it captures behaviour for a large proportion of the UK in their ordinary day-to-day activities. Based on this purpose, this paper embraces the view shared by Baker and Wurgler (2007), who stated that "there is no fundamental reason why one cannot find imperfect proxies that remain useful over time".

This paper therefore makes two main contributions: 1) adding alcohol as a new proxy to capture social mood in the field of Socionomics, and to examine to what extent social mood is affected by financial markets, and 2) adding further empirical evidence to competing positions of the Affect Infusion Model (AIM) and Mood Maintenance Hypothesis (MMH) when applied to UK alcohol consumptions and London Stock Exchange (LSE). Thus far, the Elliot wave has been used in Socionomics to infer social mood at a specific moment in time, together with other social changes in fashion, music, car design or popular movies (Prechter, 1999, 2016). At the time of writing, no paper has thus far used alcohol receipts to capture social mood – this paper does so by using quantifiable alcohol receipts data from the Office for National Statistics (ONS) to empirically examine the mood-financial market relationship.

The paper is structured as follows. The next section provides an overview of Socionomics hypothesis, mood contagion, and the mood-financial markets relationship. The third section discusses the data and econometric methods used on the data. The fourth section present and discusses the results. The final section provides concluding remarks, limitations and recommendations for areas of future exploration.

2.2. Literature review

The Socionomics hypothesis asserts that social mood is the main driver of financial markets, as investors are affected by mood in the society which they operate in (Prechter, 1999, 2016). This assertion is based on the idea that investors are not immune from societal mood, which is mostly transmitted automatically through mood contagion (Neumann and Strack, 2000). Even though some people experience cognitive empathy where they are able to observe and consciously decide to soak-up, ignore or oppose someone else’s mood, other people experience behavioural mimicry and emotional empathy whereby they copy what someone else is experiencing and absorb someone else’s mood without much discernment (Nakahashi and Ohtsuki, 2015). The mood contagion process does not have to happen through verbal communication, as emotional-body-language enables non-verbal communication to be shared through posture, facial expressions and body movements (De Gelder, 2006). Even though there is no specific literature exploring the impact of social media on users’ mood through mood contagion, this paper adopts the implied assumption that social media amplifies mood contagion in society, especially through mood shared or derived by social media ‘influencers’.

Most research thus far has focused on investor sentiment and not on social mood, across different contexts. For example, sport results (e.g. football, cricket and rugby) were found to affect stock returns in 39 countries (Edmans, García and Norli, 2007); the weather – and specifically cloud coverage – was shown to be lowering stock returns in 26 countries (Hirshleifer and Shumway, 2003); while attendance to comedy movies has been linked to the lowering of NYSE, AMEX and NASDAQ returns (Lepori, 2015). Robotti and Krivelyova (2005) found lowered returns in 9 countries following geomagnetic storms, with smaller stocks being more affected than larger stocks. Lepori (2015) found that the end of popular TV series with larger viewing figures lowered the risk appetite, which led to lower NASDAQ, S&P 500, Russel 2000 and Russell 3000 returns. Kim and Park (1994) found abnormally high returns before holidays in major US, UK and Japanese stock markets. Berument and Kiymaz (2001) found that even after controlling for news, the highest and lowest returns for S&P 500 were on Wednesday and Monday, respectively, whilst the highest and lowest volatility were on Friday and Wednesday, respectively. Yuan, Zheng and Zhu (2006) found that a full moon to be linked to lowered returns in 48 countries, even after controlling for news announcements. These papers use specific proxies to capture investor sentiment, which impact investor actions in financial markets as investors' level of optimism/pessimism affects perception, judgment and decision making.

There is also abundant evidence that financial markets affect societal wellbeing in different geographical contexts and lengths of times. In terms of locations, Deaton (2012), Cotti, Dunn and Tefft (2015), Frijters et al*.* (2015), and Cotti and Simon (2018) use survey data in the United States (US) and Australia to explore how a lower financial market return is associated with worsening emotional health and wellbeing – they (Deaton, 2012; Cotti, Dunn and Tefft, 2015; Frijters *et al.*, 2015; Cotti and Simon,

2018) employed surveys to capture participants' lived experiences, and were therefore dependent on participants' level of integrity and framing of questions. Engelberg and Parsons's (2016) research focused on corporations with headquarters in California and found increased hospital admissions for psychological conditions such as anxiety, panic disorder and depression, when stock returns were low (this study excludes non-admissions of patients who suffered psychologically but had not been admitted to hospital). Furthermore, these aforementioned studies all cover different time ranges: work by Deaton (2012) focused on the American context for a period of 1,000 days from 2008 to 2010, during the financial crisis; Cotti and Simon (2018) use a survey with 34,000 to 40,000 participants aged from 0-17 years from 2004 to 2012; Cotti, Dunn and Tefft (2015) use US state and federal level data from 1984 to 2010 in order observe worsening wellbeing during market downturns; Frijters et al. (2015) consider annual Australian data from 2001 to 2012 (around 53% of survey participants received dividend income or belonged in a household that has investments – meaning that they had a vested interest in Australia All Ordinaries Index). This paper focuses on the whole of the UK, not depending on framing of question(s) or responder integrity, and for a long period of 21 years and 8 months.

In this paper, social mood is captured by using a novel proxy of alcohol receipts. The choice of alcohol receipts as a proxy to capture social mood has been informed by papers in the field of Psychology that link alcohol consumption with mood coping or mood enhancement (Cooper, 1994). For instance, Desmet, Xue and Fokkinga (2019) found that positive mood increases impulsiveness, spontaneity, pleasurable experiences, optimism, and open mindedness – hence pleasure can be enhanced by drinking. Cyders and Smith,(2007) concluded that drinking with the purpose to enhance positive mood was more significant than drinking to cope, even after controlling for personal traits. Moderate alcohol consumption aimed at enhancing mood can be done in conjunction with other compounds or substances such as drugs (Webb *et al.*, 1996) and tobacco (Thrul *et al.*, 2019). Even sporting events, which are there to entertain, are seen to offer opportunities for 'extra' enjoyment thanks to the additional use of alcohol (Gornall, 2014; Gee, 2017). However, alcohol consumption can also have negative effects, as it can be used in harmful ways through self-medication and coping (Deaton and Case, 2021); it can cause disease, and even death (Holmes and Angus, 2021). National statistics confirm that alcohol is the leading cause of death in England for people aged 15 to 49 years, with around 21% of the adult population drinking at levels that are detrimental to their health (The Department of Health and Social Care, the Welsh Government, the Department of Health Northern Ireland, Public Health England, NHS England and NHS Improvement, 2021). Unsurprisingly, on the other side of the argument, there is evidence that moderate alcohol consumption has health benefits (Sayed and French, 2016), and can help with social bonding, which is one of the most important mitigation against mental and physical illness (Dunbar et al., 2017).

In considering alcohol receipts data, this paper focuses on the United Kingdom (UK) and uses country-specific data. The UK Office for National Statistics (ONS) publishes data that include the Alcohol Bulletin, which records the amount of alcohol receipts from Her Majesty's Revenue and Customs (HMRC). This data have four main advantages: 1) the inclusion of online and offline alcohol sales; 2) the capturing of peoples' actual activities in a variety of settings, from home consumption to restaurant and pubs; 3) the encompassing of a large proportion of the population, as the UK ranks in the top 15 European and Asian countries for alcohol consumption per capita (in figure 2.1), and 79% of people in the UK are reported to have drunk alcohol in the last 12 months (NHS, 2022); and 4) the inclusion of different types of alcohol consumed in the UK, including the top 3 types of beverage (see figures 2.2 and 2.3). The financial contribution of the alcohol industry to the UK economy is significant enough to be worth £46 billion, 2.5% of the GDP and 3.7% of all consumer spending (IAS, 2018), but it does not dominate the London Stock Market activity. However, the data fails to capture the experience in terms of mood enhancement or coping by the segment of the population who do not drink, as well as people with alcohol dependency issues. Further, there needs to be acknowledgment of different alcohol sales and licensing practices amongst the four nations, with England and Wales being more closely aligned compared to Scotland and Norther Ireland.

[Insert Figures 2.1, 2.2, 2.3 & 2.4 here]

2.3. Data and methodology

2.3.1. Data and correlation coefficient

Financial Times Stock Exchange (FTSE) data are downloaded from Eikon (formerly Datastream), and Alcohol receipts are downloaded from Office for National Statistics (ONS). This paper uses monthly data from April 1999 to December 2020 as this is the highest frequency and longest period available for monthly alcohol receipts at the time of writing. Alcohol receipts data include not only total alcohol receipts, but also its components (i.e. wine, spirits, cider, and beer). For robustness check after the main results, daily, weekly, and monthly UK Google searches for wine, beer, cocktail, and cider are downloaded from Google Trends to examine the relationship, if any, between interest in alcohol and FTSE indexes. There is a deliberate substitution of spirits with cocktails, as Google searches for spirits could have another meaning (e.g. ghosts) or be linked to other searches that are not related to alcohol. Another reason to use cocktail searches, is that spirits are used to make alcoholic cocktails. As Google trends has frequency-period constraints, this paper uses an algorithm developed by Chronopoulos, Papadimitriou and Vlastakis (2018) to construct wine, beer, cocktail and cider Search Volume Index (SVI) time series using data from Google Trends. Tables 2.1, 2.2 and 2.3 shows descriptive statistics of variables used in the main results of this paper.

The paper first uses correlation coefficients to investigate whether there are consistent significant relationships between alcohol receipts and FTSE price index (PI), market value (MV), trading volume (VO) and trading volume by value (VOV). Market value is used to complement price index as indexes are rebalanced on a regular basis (Dimson and Marsh, 2001; Cai and Houge Todd, 2008). After examining significant correlations, Granger causality tests are used to investigate Granger causal relationships between alcohol (wine, beer, spirits, cider and all alcohol) receipts and FTSE (FTSE 100, FTSE 250, FTSE AIM 100 and FTSE AIM All Share) indexes. Using Granger causality is a useful way to determine whether lagged variables of one time series can help predict another time series as it is a statistical tool used to detect correlation of one variable with past values of another variable (Brooks, 2019).

2.3.2. Vector Autoregressive Model (VAR), Granger causality tests and impulse response tests

Granger causality tests are useful statistical tools to examine statistical causality but do not give more information on the nature/sign of relationships or strength and duration of the relationship – this is where impulse response tests have value after estimating Vector Autoregressive Model (VAR). Bivariate Vector Autoregressive Model (VAR) is estimated on variables which have significant Granger causality results. In this paper, VARs are used like in Vozlyublennaia (2014) and Beer, Herve and Zouaoui (2013) due to several benefits which include, but are not limited to: 1) VAR allow checking of the bi-directional relationship amongst variables; 2) VAR allow closer inspection of the exact contribution of independent variables through variance decomposition; and, finally, 3) VAR allow impulse response functions (Brooks, 2019). FTSE returns and alcohol receipts rate of change are used in VARs, Granger causality and impulse response tests; level of alcohol receipts has not been used for VARs or the aforementioned tests.

2.3.3. Augmented Dickey-Fuller Stationarity tests

The variables used in VARs and impulse response tests are tested for stationarity (or unit root) using Augmented Dickey-Fuller (ADF) test (Brooks, 2019). The ADF test is used to test for stationarity as it can examine more complex patters of data (Moffatt, 2023 and Guo, 2023). From Table 2.4, stationarity is confirmed for all variables used in VARs and then impulse response tests at first difference. This is the case for all variables even at test critical values of 1% level.

2.3.4. Lag selection criteria, seasonal adjustments and order of variables

Unlike Vozlyublennaia (2014) and Beer, Herve and Zouaoui (2013) who impose lag length of 4 and 2 lags, respectively, the VARs lag length used in this paper is determined by Information Criteria for each pair - Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan–Quinn information criterion (HIC) are all used to consider the optimum lag length. For robustness, a variety of specifications are used: 1) Seasonal and Trend decomposition using Loess (STL) seasonally adjusted alcohol receipts are used as alcohol receipts show seasonal effects[1] ; 2) reversed order of variables in VARs from FTSE to receipt, and then from receipt to FTSE in order to explore if the results are different (most VARs remain the same whilst for others residuals suffer from autocorrelation and heteroscedasticity); 3) well-known seasonal dummies for the January effect; 4) higher frequency (daily, weekly and monthly) alcohol related (wine, beer, cocktail and cider) search terms to explore any differences from monthly alcohol receipts; and 5) raw data (no seasonal adjustment and no dummies), which allow capture of mood that causes seasonality and financial anomalies. Points 1) to 4) allow the capture of mood following 'traditional' finance methods by using dummies and removing seasonality, whilst specification 5) allows raw FTSE data to be examined with raw alcohol receipts data, without restrictions.

2.3.5. VARs model and hypothesis

The bivariate VAR model assumes there is a linear relationship between alcohol receipts (wine, beer, spirits and cider) and FTSE indexes. Drawing from Brooks (2019), if Y_{1t} and Y_{2t} represents FTSE returns (or trading volume rate of change), and alcohol receipts rate of change (alcohol here after), respectively, whose current

[1] There were four different VARs that are explored, these include raw VARs with no seasonal adjustments, raw VARs with dummies but no seasonal adjustments, seasonally adjusted VARs and seasonally adjusted VARs with dummies. Advantages of using STL over 'MoveReg Weekly Adjustment' and 'X-13 Force Annual Totals' are explained in section 1.3.

returns depend on previous K returns of both variables with error terms U_{1t} and U_{2t}, then the VAR used is shown below.

$$Y_{1t}=\beta_{10}+\beta_{11}Y_{1t-1}+\cdots+\beta_{1k}Y_{1t-k}+\alpha_{11}Y_{2t-1}+\cdots+\alpha_{1k}Y_{2t-k}+U_{1t}$$

$$Y_{2t}=\beta_{20}+\beta_{21}Y_{2t-1}+\cdots+\beta_{2k}Y_{2t-k}+\alpha_{21}Y_{1t-1}+\cdots+\alpha_{2k}Y_{1t-k}+U_{2t}$$

Hypothesis tested

Hypothesis 1 on Socionomics – social mood affects market returns

H_0: $\alpha =0$, α is not significantly different from zero, Y_{2t} coefficient does not explain Y_{1t}

H_1: $\alpha \neq 0$, α is significantly different from zero, Y_{2t} coefficient explains Y_{1t}

Hypothesis 2 on conventional finance – market returns affect social mood

H_0: $\alpha =0$, α is not significantly different from zero, Y_{1t} coefficient does not explain Y_{2t}

H_1: $\alpha \neq 0$, α is significantly different from zero, Y_{1t} coefficient explains Y_{2t})

Where:-

Y_{1t} is return of FTSE100, FTSE250, FTSEALLSHARE, FTSEAIM100 and FTSEAIM index, or market value rate of change, or trading volume rate of change

Y_{2t} is alcohol receipts rate of change

U_{1t} and U_{2t} is error term of a regression

[Insert Tables 2.1, 2.2, 2.3 & 2.4 here]

2.4. Results

2.4.1. Correlation between alcohol receipts and FTSE indexes

Table 2.5 shows the correlation coefficients between FTSE indexes and alcohol receipts ('alcohol' hereafter) with *p*-values. Table 2.5 results show that wine, spirits, beer, cider and all alcohol are positively significant with FTSE 100 and FTSE 250 price index and market value/capitalisation. The results also show that wine, spirits, beer, cider and all alcohol are negatively significant with FTSE 100 and FTSE 250 trading volume and trading volume by value. This means that all alcohol receipts have a direct relationship with bigger indexes' (FTSE 100 and FTSE 250) price index and market capitalisation, but alcohol receipts have an inverse relationship with FTSE 100 and FTSE 250 trading volume and trading volume by value.

For FTSE AIM 100 and FTSE AIM All Share, wine, spirits and beer follow the same trend as total alcohol receipts in terms of being positively correlated with FTSE AIM 100 and FTSE AIM All Share price index and market value/capitalisation. Conversely, cider receipts are negatively correlated with FTSE AIM 100 and FTSE AIM All Share price index and market value/capitalisation. This means that wine, spirits, beer and all alcohol have a direct relationship with FTSE AIM 100 and FTSE AIM All Share price index and market value. Conversely, cider has an inverse relationship with FTSE AIM 100 and FTSE AIM All Share price index and market value. The implication here is that drinking wine, spirits and beer to enhance mood is far more likely than drinking to cope (Cyders and Smith, 2007) as wine, spirits and beer are positively correlated with FTSE price index and market value/capitalisation. On the contrary, inference can be made that drinking cider to cope is more likely as cider is positively correlated to FTSE 100 and FTSE 250 price index and market value/capitalisation but negatively correlated to smaller FTSE AIM 100 and FTSE AIM All Share price index and market value/capitalisation. For cider, this is analogous to ‘flight to safety’ that is normally associated with low investor sentiment whilst wine, spirits and beer shows signs of high investor sentiment.

The above results are what is expected from investor sentiment literature in terms of company size and prevailing high/low sentiment according to the ‘sentiment see-saw' (Baker and Wurgler, 2007), and how cider has opposite relationships with large indexes (FTSE 100 and FTSE 250) and small index (FTSE AIM 100 and FTSE AIM All Share). The above results are also surprising as wine, spirits and beer all have the same directly proportional relationship with large indexes (FTSE 100 and FTSE 250) and small index (FTSE AIM 100 and FTSE AIM All Share). The results also indicate evidence that Mood Maintenance Hypothesis (Lepori, 2015) is more likely in the UK as wine, spirits and beer are negatively correlated with trading volume at the same time when they are positively correlated with price index and marker value/capitalisation. This contrast between wine and cider is could be due to the demographic differences in consumers of wine and cider, as highlighted in research by Touvier *et al.*, (2014) in France which concluded that wine consumption increases with age and income, and for staff at the executive level, whilst the core demographic of cider drinkers in the UK is men between the ages of 18 to 24 years (Mintel, 2021) and UK core consumers of beer are males between the age of 25 to 44 (Mintel 2022). This could indicate that cider captures the segment of a population whose habit of drinking to cope whilst drinking to enhance mood is reflected in habit of drinking beer and wine based on how all these are correlated with FTSE indexes’ price index, market value/capitalisation and trading volume. It should be noted that beer and wine are drunk by a larger proportion of the population as the most popular alcoholic drinks in the UK.

[Insert Table 2.5 here]

2.4.2. Statistical causality between alcohol receipts and FTSE indexes

2.4.2.1. Statistical causality between alcohol receipts and FTSE indexes (without GDP as a control variable)

To investigate causation, this paper uses Granger causality tests, and then VAR is used later to investigate the magnitude and sign of the relationship. Table 2.6 shows Granger causality test results between STL-seasonally adjusted alcohol rate of change and FTSE index returns (with January Effect dummy). Table 2.6 shows that most Granger tests results indicate that seasonally adjusted all alcohol, wine and beer Granger cause FTSE 100 and FTSE 250 trading volume and trading volume by value. Interestingly, seasonally adjusted all alcohol, wine and beer do not Granger cause FTSE 100, FTSE 250, FTSE AIM 100 and FTSE AIM All Share returns or market value/capitalisation rate of change. As drinking to enhance mood or cope is expected, a change in trading volume is expected, but the lack of significant Granger causality test for returns is surprising based on the sentiment literature. Another surprise is the lack of reverse causality, whereby neither FTSE index return, FTSE market value rate of change, nor FTSE trading volume Granger cause changes in alcohol.

Significant Granger causality relationships are used to construct VARs and run residual diagnostics. VARs, whose residuals have no autocorrelation and are homoscedastic, are used to run impulse response tests. Unlike Vozlyublennaia (2014) and Beer, Herve and Zouaoui (2013) who selected 4 lags and 2 lags in their VARs respectively, for succinctness, this paper's number of lags is guided by Information Criteria for each VAR. As VARs with many variables can be difficult to interpret, this paper uses impulse responses to show variable dynamics as suggested by Sims (1980). Impulse responses trace out a response of a dependent variable to a unit shock in the independent variable (Brooks, 2019).

[Insert Table 2.6 here]

For completeness, Table 2.7 shows significant Granger causality test results between alcohol and FTSE indexes with no seasonal adjustments or January dummy. Granger causality tests for non-seasonally adjusted and no dummy in Table 2.7 yield not only more significant Granger causality results, but also evidence of bi-directional Granger causal relationships between alcohol rate of change and FTSE returns. Similar to seasonally adjusted results in Table 2.6, Table 2.7 results show the majority of Granger tests indicating that all alcohol, wine and beer Granger cause FTSE 100 and FTSE 250 trading volume and trading volume by value. Unique results in Table 2.7 show spirits Granger cause FTSE 100 and FTSE 250 trading volume, beer Granger cause FTSE AIM 100 and FTSE AIM All Share returns and market value/capitalisation rate of change. Further, cider Granger cause FTSE 100 and FTSE 250 trading volume. The results also show FTSE 100 trading volume by value Granger cause beer, and FTSE 250 trading volume Grange cause beer and cider. This implies that there is empirical evidence of bidirectional relationship between alcohol and FTSE but mostly from alcohol to FTSE. Additionally, as literature suggests that smaller indexes are expected to be influenced more by mood compared to larger indexes (Baker and Wurgler, 2007), beer Granger cause FTSE AIM 100 and FTSE AIM All Share price index and market value/capitalisation is the only result found in this study that collaborates the aforementioned studies. Interestingly, no alcohol Granger cause

FTSE 100 or FTSE 250 returns or market capitalisation, this is what is expected from literature as FTSE 100 and FTSE 250 are the largest and second largest index in the London Stock Exchange, hence, less susceptible to non-fundamental factors.

[Insert Table 2.7 here]

2.4.2.2. Statistical causality between alcohol receipts and FTSE indexes (with GDP)

Table 2.8 shows the results of Granger causality tests of FTSE indexes and STL-seasonally adjusted alcohol. The tests also include GDP as a macroeconomic control variable to account for fundamentals that are expected to affect FTSE indexes. Surprisingly, by including GDP in VAR, Table 2.8 shows more significant Granger causality test results than Table 2.6, which does not include GDP. Furthermore, not only do all alcohol, wine and beer Granger cause FTSE 250 returns, FTSE 100 and FTSE 250 change in volume (and volume by value), but also Table 2.8 shows additional results that are not in Table 2.6 whereby wine Granger causes FTSE 100 returns, FTSE 250 market value rate of change, FTSE AIM 100 and FTSE AIM All Share returns and market value rate of change. These results are surprising because the inclusion of GDP into VARs is expected to reduce Granger causality of alcohol as GDP is a measure of economic activity that is supposed to affect pricing of assets in FTSE indexes while in this context alcohol captures mood. The common finding in Tables 2.6 and 2.8 is that FTSE activity does not Granger cause changes in alcohol consumption to cope or to enhance mood. As mentioned earlier, this result is surprising as Engelberg and Parsons (2016) and Deaton (2012) found that in the US stock market down turns affect people in a negative way.

[Insert Tables 2.9 and 2.9 here]

Table 2.9 shows results of Granger causality tests of FTSE indexes and alcohol. The tests also include GDP as a macroeconomic control variable to account for fundamentals that are expected to affect FTSE indexes. The results in Table 2.9 are similar to Table 2.7 as wine, beer, spirits, cider and all alcohol Granger cause FTSE 100 and FTSE 250 trading volume and trading volume by value. The main differences are that Table 2.9 (uses GDP in VAR) has more significant Granger causality tests compared to Table 2.7 (without GDP). Furthermore, in Table 2.9, cider Granger cause FTSE AIM All Share returns and market value rate of change, whilst this was not the case in Table 2.7. In terms of reverse causality, FTSE 100 and FTSE 250 returns and market value rate of change Granger cause wine and all alcohol. Inclusion of GDP into VARs has a surprising effect of increasing the number of significant Granger causality tests.

2.4.3. Sign and timing and of alcohol (Impulse response tests)

2.4.3.1. Response of FTSE trading volume to seasonally adjusted all alcohol, wine and beer (without GDP as a control variable)

Figure 2.4 shows the impulse response function of FTSE trading volume to one standard deviation shock in seasonally adjusted all alcohol, wine or beer. The figure shows that the response of FTSE trading volume and trading volume to one standard deviation in seasonally adjusted all alcohol is significantly negative first, and then it turns significantly positive before dissipating. This suggests that the impact of alcohol-mood is temporary, and the response turns to zero as the standard errors are also within zero. These results are replicated when FTSE 100 trading volume responds to one standard deviation shock in seasonally adjusted wine, FTSE 100 trading volume responds to one standard deviation shock in seasonally adjusted beer, and when FTSE 250 trading volume responds to one standard deviation shock in beer. Reduced trading volume with a high mood is what is expected from Mood Maintenance Hypothesis according to Lepori (2015). The inference here is that all alcohol, wine and beer is likely to be associated with mood enhancement as there is a significant decrease in trading volume for FTSE 100 and FTSE 250 indexes.

Beer and wine have the largest impact on lowering trading volumes and trading volume by value, whist cider and spirits have no impact. This suggests that social mood captured by wine and beer receipts is better reflected in the financial markets as wine is the UK's most favoured alcoholic drink, followed by beer (Well, 2021). This result supports the first hypothesis of Socionomics (Prechter, 1999, 2016) and Mood Maintenance Hypothesis (Lepori, 2015) - people in positive mood would engage in less activity in order to protect their positive mood. This result is also what is expected according Campbell, Grossman and Wang (1993) who found that stock returns have mostly an inverse relationship with trading volume; Tetlock (2007) also found that pessimism increased trading volume. Lower trading volume with increased social mood is contrary to Baker and Wurgler's (2007) findings suggesting that increased trading volume is a sign of high investor sentiment. This evidence is further corroborated by observing a significantly negative correlation between FTSE price index (or market values) and trading volume (or trading volume by value).

[Insert Figures 2.4 & 2.5 here]

2.4.3.2. Response of FTSE trading volume to all alcohol and wine (without GDP as a control variable)

Figure 2.5 shows impulse response function of FTSE trading volume to one standard deviation shock in all alcohol or wine. The figure shows that response of FTSE trading volume to one standard deviation in all alcohol is significantly negative first, and then it turns significantly positive before dissipating. This suggests that the impact of alcohol-mood is temporary, and the response turns to zero as the standard errors are also within zero. These results are replicated Table 2.5 when FTSE 100 trading volume and trading volume by value respond to one standard deviation shock in wine. Lepori (2015) asserts that reduced trading volume is normally associated with high mood according to Mood Maintenance Hypothesis. The implication here is that all alcohol and wine are likely to be associated with mood enhancement, as there is a significant decrease in trading volume for FTSE 100 and FTSE 250 indexes. These findings are not surprising as social mood captured by wine and beer is better reflected in the financial markets given that wine and beer are the top two alcoholic drinks in the UK (Well, 2021). These results also support the first hypothesis of Socionomics (Prechter, 1999, 2016) and the second of Mood Maintenance Hypothesis (Lepori, 2015).

2.4.3.3. Response of FTSE trading volume to spirits, cider and beer (without GDP as a control variable)

Figure 2.6 shows impulse response function of FTSE trading volume to one standard deviation shock in spirit, cider and beer. The results largely replicate Figure 2.4 and Figure 2.5 results, therefore the same inferences are made. It is quite apparent that the top two most popular alcoholic drinks have the largest effect in terms of impact responses, and the magnitude of beer induced impulse response is comparable to wine. Whilst all alcohol, spirits and cider have much smaller effect on FTSE 100 and FTSE 250 trading volume when observing impact response.

[Insert Figures 2.6 and 2.7 here]

2.4.3.4. Response of FTSE AIM 100 and FTSE AIM All Share to beer (without GDP as a control variable)

Figure 2.7 shows impulse response function of FTSE AIM 100 (and FTSE AIM All Share) to one standard deviation shock in beer. The figure shows that the response of FTSE AIM 100 and FTSE AIM All Share returns and market values rate of change to one standard deviation in beer is significantly positive first, and then it turns significantly negative before dissipating. This suggests that the impact of beer-mood is temporary, and the response turns to zero as the standard errors are also within zero. Increased price index and market value/capitalisation of FTSE AIM 100 and FTSE AIM All Share with a high mood is what is expected from Mood Maintenance Hypothesis, according to Lepori (2015). The inference here is that beer is likely to be associated with mood enhancement as there is a significant increase in smaller index of FTSE AIM 100 and FTSE AIM All Share indexes.

The results indicate that social mood as proxied by alcohol affects financial market returns, but there is no evidence of reverse causality using impulse response tests. This is what is expected in Socionomics (Prechter, 1999, 2016), but there is an additional contribution to Baker and Wurgler (2007) in terms of high sentiment increasing asset price of smaller indexes (FTSE AIM 100 and FTSE AIM ALL SHARE), and not asset prices in FTSE100 or FTSE250. According to Baker and Wurgler(2007), smaller indexes that contain new, harder to value and smaller companies will be more susceptible to investor sentiment, which in turn is influenced by social mood – this is indicated by the results in Figure 2.7.

2.4.3.5. Response of FTSE to alcohol (with GDP as control variable)

Figures 2.8, 2.9 and 2.10 show impulse response function of FTSE indexes to one standard deviation shock in all alcohol, wine, spirits, cider, and beer. The results largely replicate Figure 2.4, 2.5 and 2.6 results. Even with the addition of GDP in VARs, the same inferences are made about all alcohol, wine, beer, spirits and cider Granger causing a reduction in FTSE 100 and FTSE 250 trading volume. Going beyond trading volume and into FTSE returns and market value rate of change by comparing Figures 2.7 and 2.11, the addition of GDP into VARs reduces the number of significant impulse responses of smaller index from four to one. This is what is expected from a semi-efficient market (Fama, 1970) as GDP includes information about fundamentals that should be included in FTSE. To illustrate the aforementioned impact of GDP in the VARs system, Figure 2.11 includes impact response of FTSE indexes to one standard deviation of GDP. It can be suggested that GDP impacts FTSE returns and trading volume in opposite ways. In VARs with GDP, the January dummy for the January effect could not be used due to multicollinearity.

[Insert Figures 2.8, 2.9, 2.10 and 2.11 here]

2.5. Robustness of findings

2.5.1. Econometric specifications

The paper uses a variety of specifications to ensure robustness of the findings. First, the VARs lag length is determined by Information Criteria and residuals are tested for autocorrelation and heteroscedasticity. Secondly, VARS and subsequent impulse response tests are conducted with and without seasonal adjustments and the well-known January effect dummy or GDP.

2.5.2. FTSE and alcohol searches

Finally, this paper corroborates the notion that there is a well-known link between internet searchers and what people are thinking or feeling about or salient topics, and it does so by examining Google searches for alcohol related search terms (i.e. wine, beer, cocktail and cider) in the UK and the links (if any) to FTSE indexes. As Google searchers are available in a variety of frequencies, the paper uses algorithm developed by Chronopoulos, Papadimitriou and Vlastakis (2018) to construct daily, weekly and monthly alcohol (wine, beer, cocktail – instead of spirits – and cider) Search Volume Index (SVI). Google Trends is used as it is the largest search engine in the UK, capturing 87.7% of all internet searches (Statista, 2021); and SVI has been used in many spheres like Finance, Economics and Psychology, in order to capture salient social trends and issues. For instance, based on Google searches, Algan, Beasley, and Guyot (2014) and Algan *et al.*, (2016) used employment, financial security, family life and leisure related searches to ascertain societal wellbeing; and Ford (2020) found that internet searches can help reveal peoples' state of mind and intention to seek help or harm themselves. Furthermore, more broadly, internet searches have been known to help uncover some of the most important subjects or problems in the society (Scheitle, 2011; Mellon, 2014).

Tables A2.1, A2.2 and A2.3 in appendix show the correlation between alcohol search terms (i.e. wine, beer, cocktail and cider) and FTSE index with *p*-values using monthly, weekly and daily frequencies, respectively. Results in A2.1, A2.2 and A2.3 show significant correlation between FTSE (price index, market capitalisation and trading volume) and Google SVI for monthly, weekly and daily frequency. The results are similar to alcohol receipts in a sense that SVI is positively correlated to market value, and price index, but negatively correlated to trading volume or trading volume by value. Surprisingly, there is no significant Granger causality when alcohol receipts are substituted for alcohol searches. This means that there is compelling evidence of statistical correlation but not causation.

2.5.3. FTSE and tobacco

As there is well established evidence of alcohol being consumed in conjunction with smoking tobacco or e-cigarettes (Thrul et al., 2019), the approach applied to alcohol receipts is repeated here by using tobacco receipts that are obtained from the ONS. The receipts are made up of individual tobacco products – cigarettes, cigars, hand rolled tobacco (HRT), and other tobacco. Whilst all alcohol (wine, beer spirits, and cider) are all significant and positively correlated with FTSE 100 and FTSE 250 price index and market value (Table 2.5), Table A2.4 shows cigarettes, other tobacco and all tobacco are not significant, and cigars are negatively correlated with FTSE 100 and FTSE 250 price index and market value. Conversely, HRT is positively correlated with FTSE100 and FTSE 250 price index and market value. In terms of tobacco's correlation with trading volume, cigars are positively correlated to FTSE 100 and FTSE 250 trading volume whilst HRT is negatively correlated with trading volume. This implies that that HRT is similar to alcohol in terms of mood enhancement, and provides further evidence of Mood Maintenance Hypothesis whereby people in a positive mood reduce activity to protect their mood (Lepori, 2015). Surprisingly, cigars not only correlate negatively with price index and market value but are also positively correlated with FTSE 100 and FTSE 250 trading volume – this implies that cigars are the opposite of alcohol in terms of mood enhancement. In this context, there is evidence that cigars are used for coping rather than mood enhancement. In Table A2.5, cigarettes, cigars and all tobacco are not statistically significant and only HRT and other tobacco are positively correlated to FTSE AIM 100 and FTSE AIM All Share market value – similar inference can be made about mood enhancement, as mentioned above.

Tables A2.6 and A2.7 shows Granger causality tests for seasonally adjusted and non-seasonally adjusted tobacco receipts respectively. When tobacco Granger tests are compared to alcohol, fewer tobacco tests results are significant, and they are less than a third of the alcohol significant Granger causality tests. In terms of similarities, most of the causal relationship is from tobacco to FTSE where cigarettes, cigars and HRT are 'Granger causing' changes in FTSE 100 and FTSE 250 trading volume, and changes in smaller FTSE AIM 100 and FTSE AIM All Share market value.

Figures A2.8 and A2.9 show that the impact of tobacco is not strong, as the dashed lines showing standard errors are not away from zero. This means that even though tobacco is statistically significant, the economic significance is rather small compared to alcohol. The difference in results between alcohol and tobacco could be explained by the number of people who drink, which was 79% of the population as of 2021 (HealthSurveyEngland, 2021), and those who smoke – 6.4 million or 12.9% as of 2022 (ONS, 2023). This implies that the mood impact of alcohol was spread amongst a greater segment of the population than the mood impact of smoking, even though some people may do both.

2.6. Conclusion

This paper explores the extent to which social mood impacts on FTSE returns and trading volume by using alcohol receipts to capture social mood. The use of alcohol as a proxy is informed by literature from Psychology which links alcohol consumption to enhance mood or as a coping mechanism. The results indicate evidence of Socionomics Hypothesis whereby social mood in part explains FTSE returns for smaller indexes and change in trading volume for larger indexes. Through Granger causality tests, and then impulse response tests, the results show that FTSE 100 and FTSE 250 trading volume decreases when there are increases in beer, wine, spirits and cider. Further, an increase in market capitalisation and price index of smaller FTSE AIM and FTSE AIM All Share is observed when there are increases in beer consumption. The decrease in FTSE 100 and FTSE 250 trading volume is the same in magnitude when there is an increase in cider and spirits consumption, but small in effect when compared to the effect of beer and wine consumption. Further, there is no significant evidence that financial market activity affects social mood – this result is surprising, especially when pension income is linked to the financial market performance, but it could be due to the fact that pension funds allocate a bigger proportion of investment in bonds closer to retirement age.

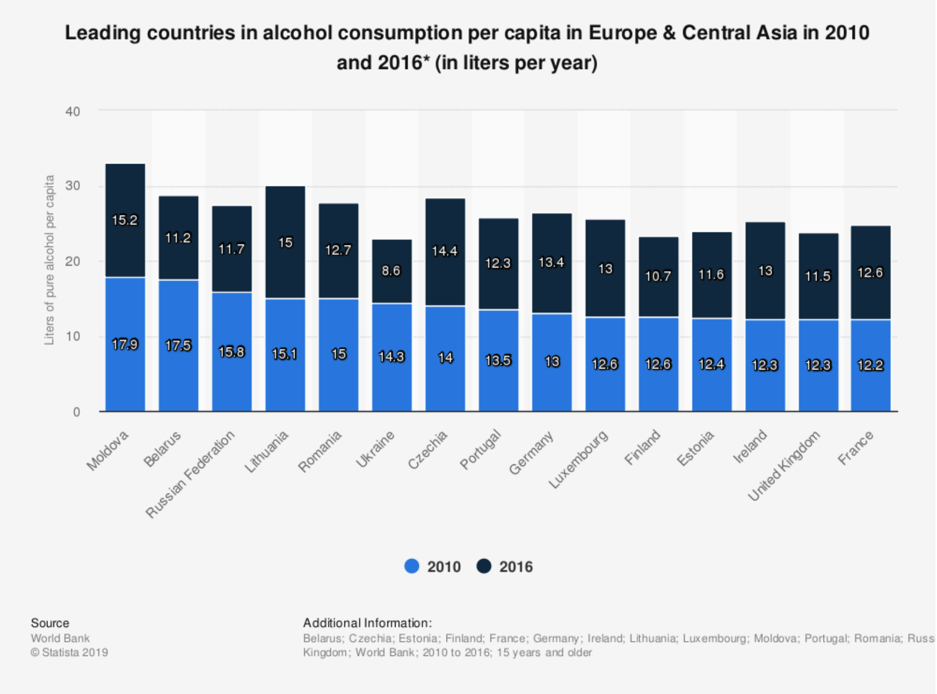
The implication is that alcohol consumption provides evidence of social mood as envisaged in Socionomics theories. The results indicate that alcoholic drink consumption (beer, wine, spirits and cider) in the UK is used to enhance mood rather than as a coping mechanism, as impulse response tests show increased smaller index returns and a reduction in larger index trading volume. The results also show evidence of alignment with Mood Maintenance Hypothesis, as alcohol (beer, wine, cider and all alcohol) is positively significant with price index and market capitalisation, but negatively significant with larger index trading volume and trading volume by value.

Limitations of the study include other factors that affect LSE activities such as other financial markets affecting FTSE (co-movement), and investment fads that were not taken into account. The paper uses UK wide data, however there are changing trends in alcohol related deaths amongst the nations, with England and Wales seeing an increase whilst in Scotland seeing a decrease. There are age and other demographic influences on alcohol consumption data that were not examined, and there was a drop in alcohol specific death rates by 22% for 30-34 and an increase in between 23-49% from 55- to 84-year-olds.

Areas for future research could consider the inclusion of variables that account for fundamental information such as default spread, term spread, Gilt rate, aggregate dividend yield, consumer confidence or FTSE VIX. Further, re-examining mood enhancing usage of alcohol during times of recession, high unemployment or high inflation.

Figure 2.1 Leading countries in alcohol consumption per capital in Europe and Asia in 2016 (Statista, 2016)

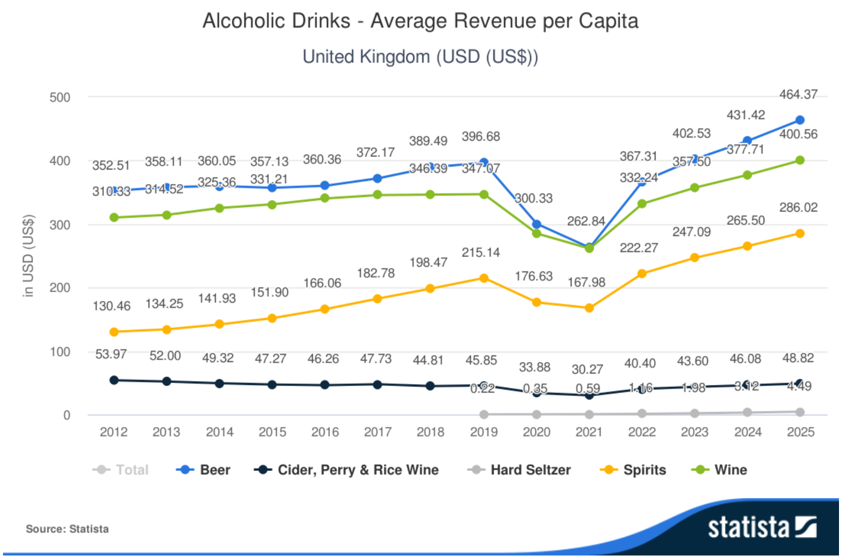
This figure illustrates leading countries in alcohol consumption per capital in Europe and Central Asia in 2016



This figure shows UK is amongst the leading countries in alcohol consumption per capita. Moldova, Lithuania and Czechia republic make up the top three countries.

Figure 2.2 UK alcoholic drinks average revenue per capital (Statista, 2020)

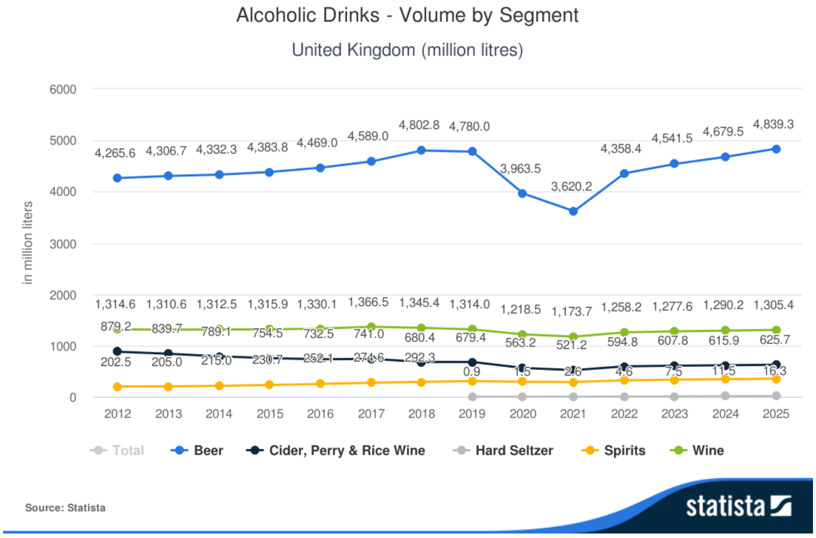
This figure illustrates UK alcoholic drinks average revenue per capital from 2012



This figure shows beer is the top revenue per capita generating alcoholic drink in the UK. Beer is followed by wine, spirits, cider/perry rice wine and hard seltzer.

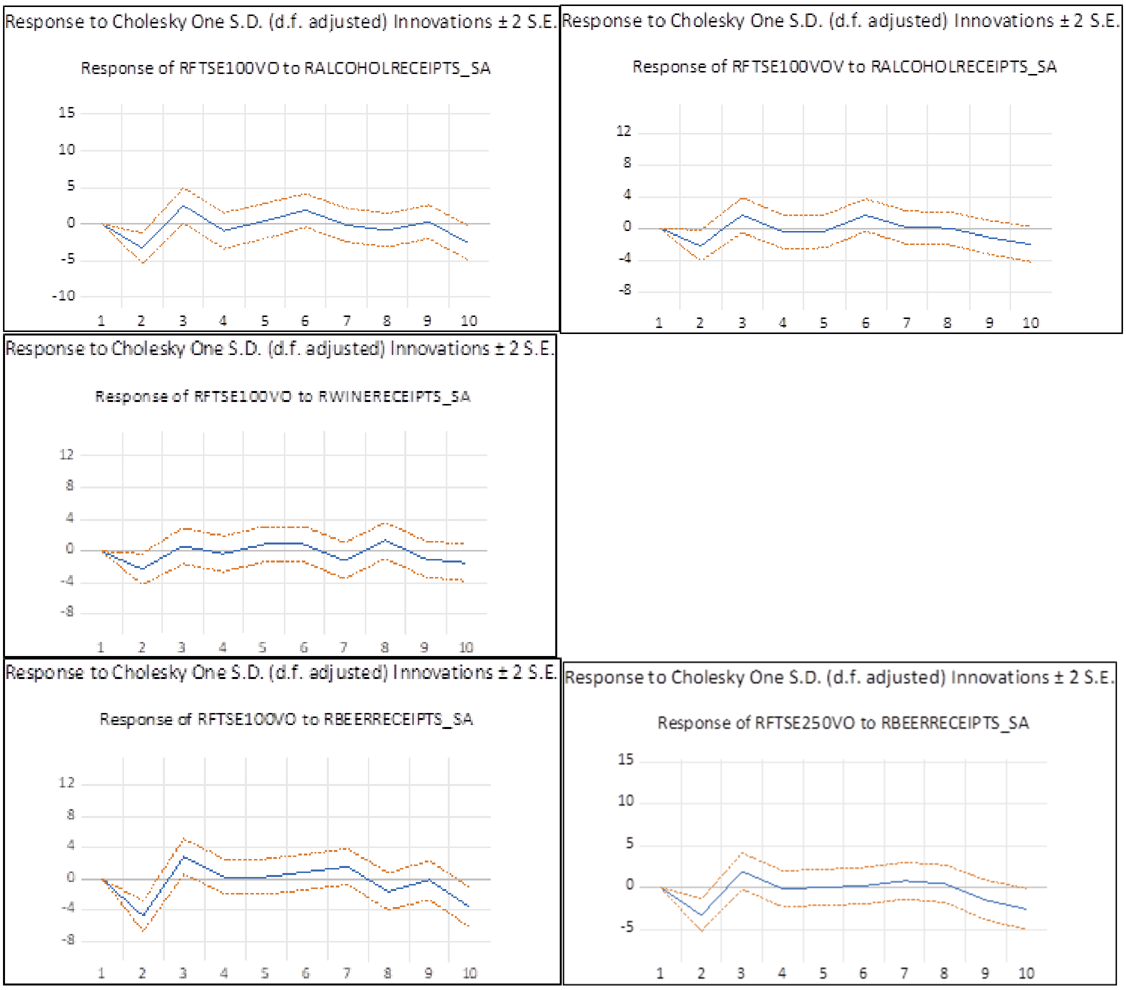
Figure 2.3 UK alcoholic drink volume (Statista, 2020)

This figure illustrates UK alcoholic drinks by volume from 2012



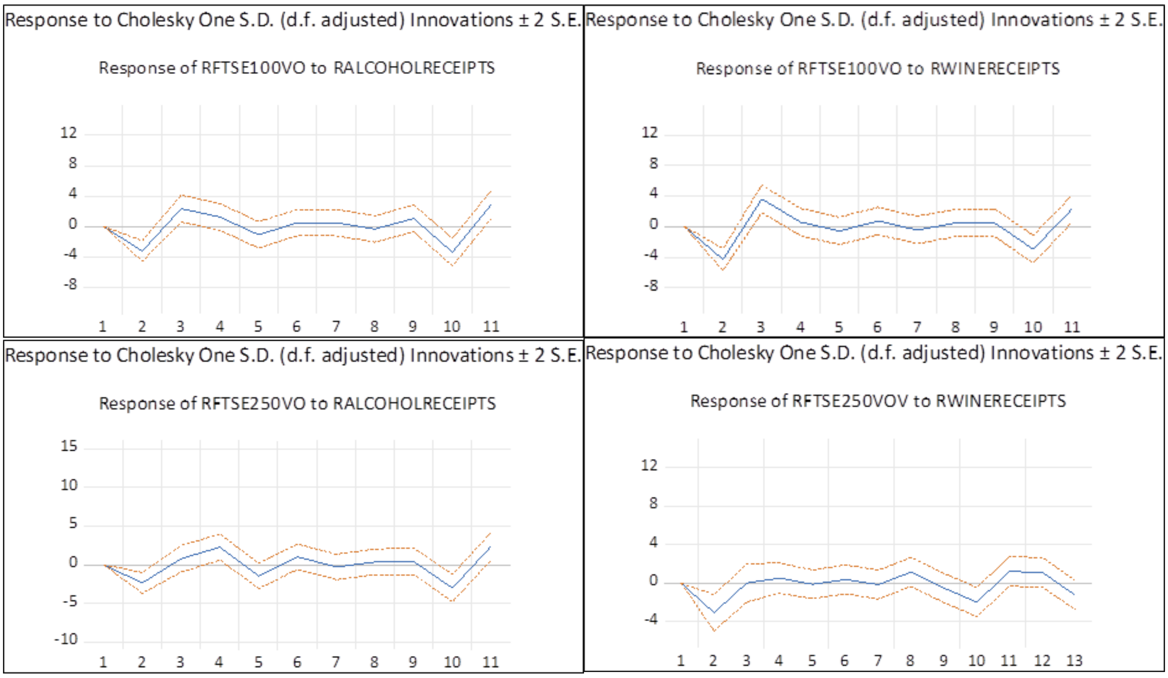
This figure shows beer is the top volume by segment alcoholic drink in the UK. Beer is followed by wine, spirits, cider/perry rice wine and hard seltzer.

Figure 2.4 FTSE-seasonally adjusted alcohol impulse response



Impulse response function for VARs of FTSE trading volume rate of change, wine, beer, and all alcohol. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.
RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RWINERECEIPTS_SA is seasonally adjusted wine receipts rate of change, RBEERRECEIPTS_SA is seasonally adjusted beer receipts rate of change, and RALCOHOLRECEIPTS_SA is seasonally adjusted all alcohol receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

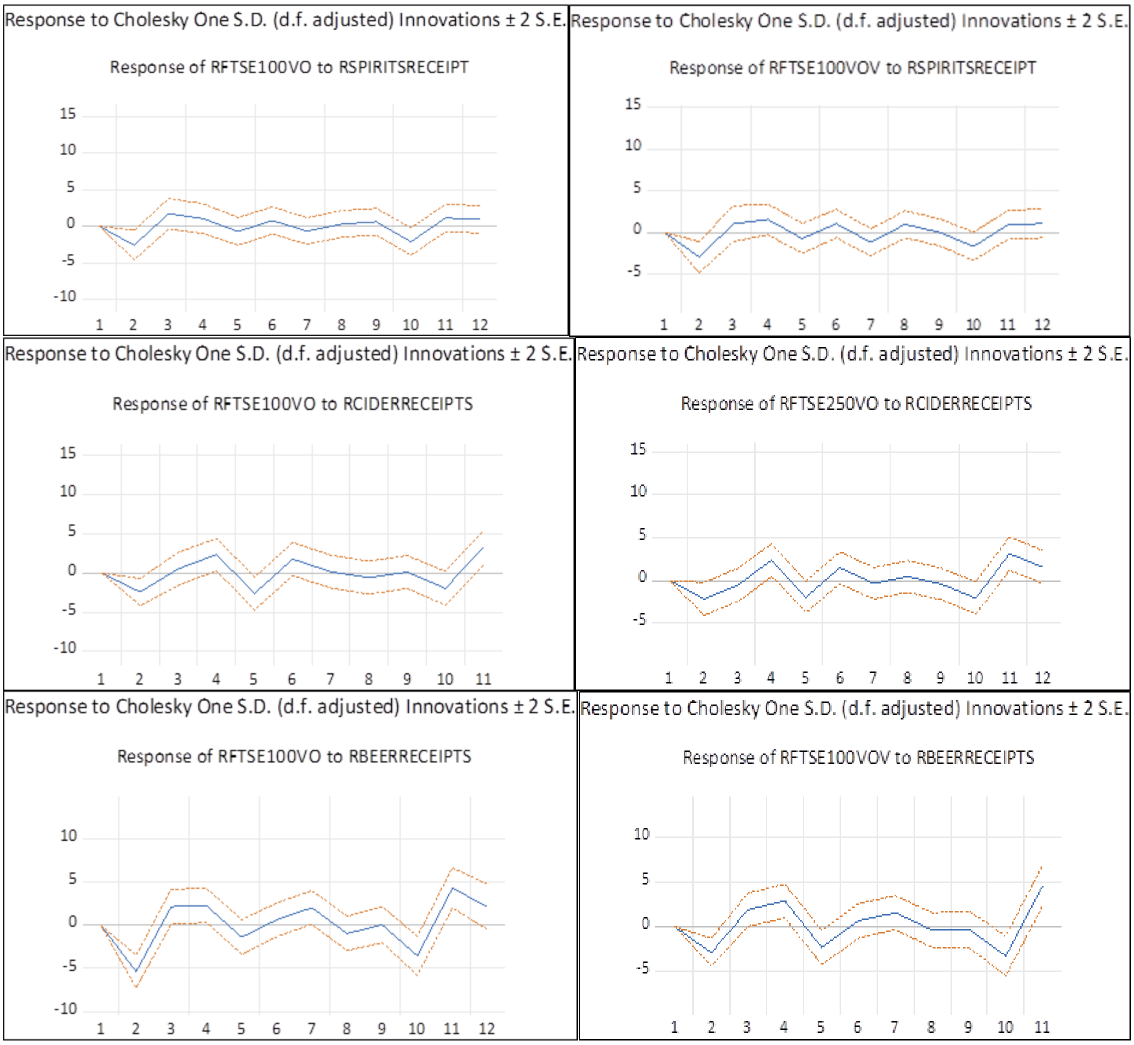
Figure 2.5 FTSE-alcohol impulse response (no dummies or seasonal adjustment)



Impulse response function for VARs of FTSE trading volume rate of change, wine, and all alcohol. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.

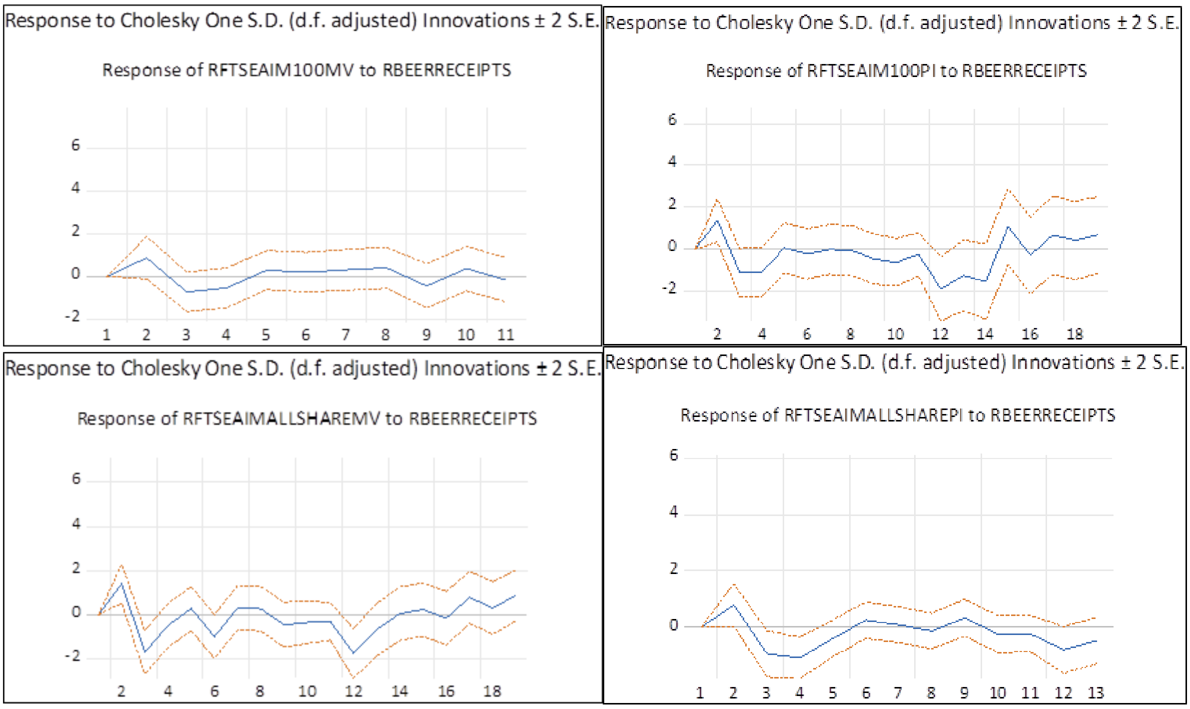
RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RWINERECEIPTS is wine receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change.

Figure 2.6 FTSE-alcohol impulse response (no dummies or seasonal adjustment)



Impulse response function for VARs of FTSE trading volume rate of change, spirits, beer, and cider. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.
RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RBEERRECEIPTS is beer receipts rate of change, RSPIRITSRECEIPTS is spirits receipts rate of change, and RCIDERRECEIPTS is cider receipts rate of change.

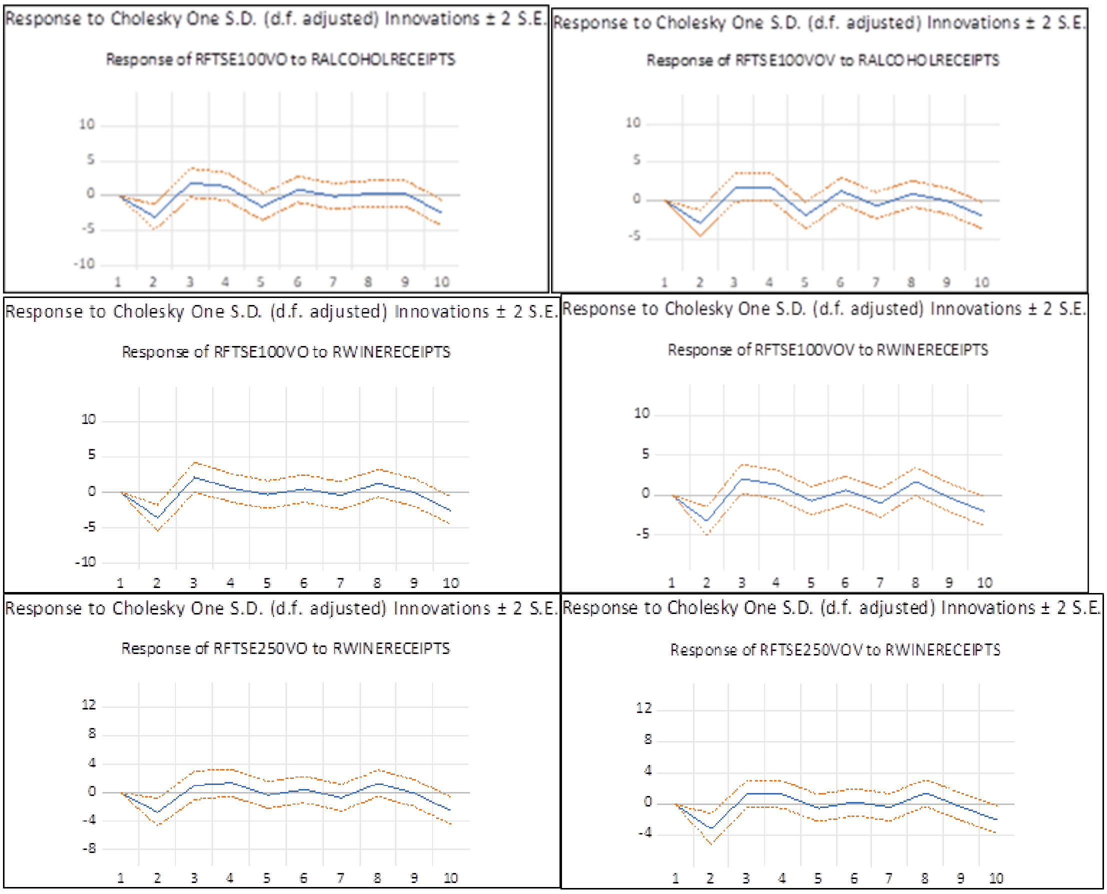
Figure 2.7 FTSE-beer impulse response (no dummies or seasonal adjustment)



Impulse response function for VARs of FTSE market value rate of change and beer. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.

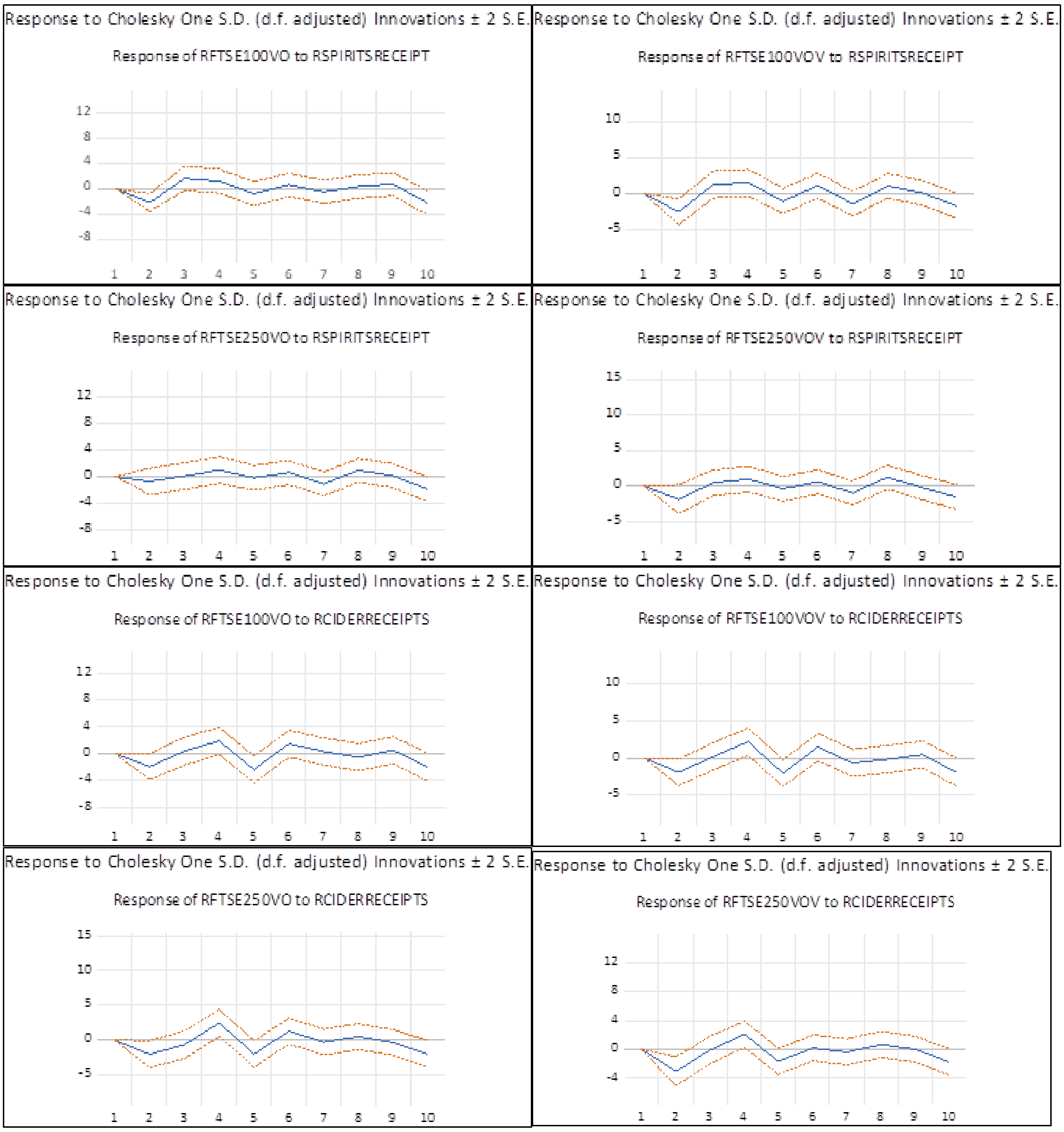
RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, and RBEERRECEIPTS is beer receipts rate of change.

Figure 2.8 FTSE-alcohol impulse response (with GDP, no January dummy, and no seasonal adjustment)



Impulse response function for VARs of FTSE trading volume rate of change, GDP, all alcohol, and wine. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.
RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RWINERECEIPTS is wine receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change

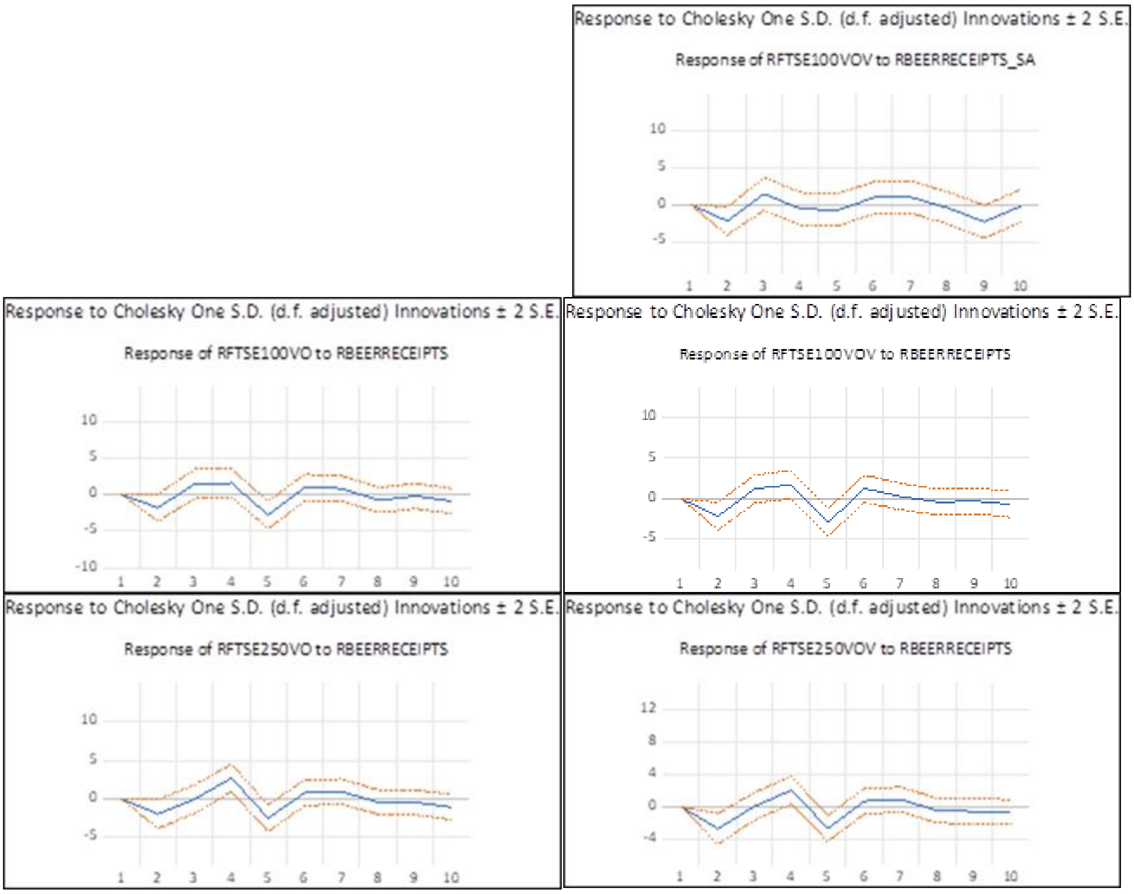
Figure 2.9 FTSE-alcohol impulse response (with GDP, no January dummy, and no seasonal adjustment)



Impulse response function for VARs of FTSE trading volume rate of change, GDP, spirits, and cider. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.

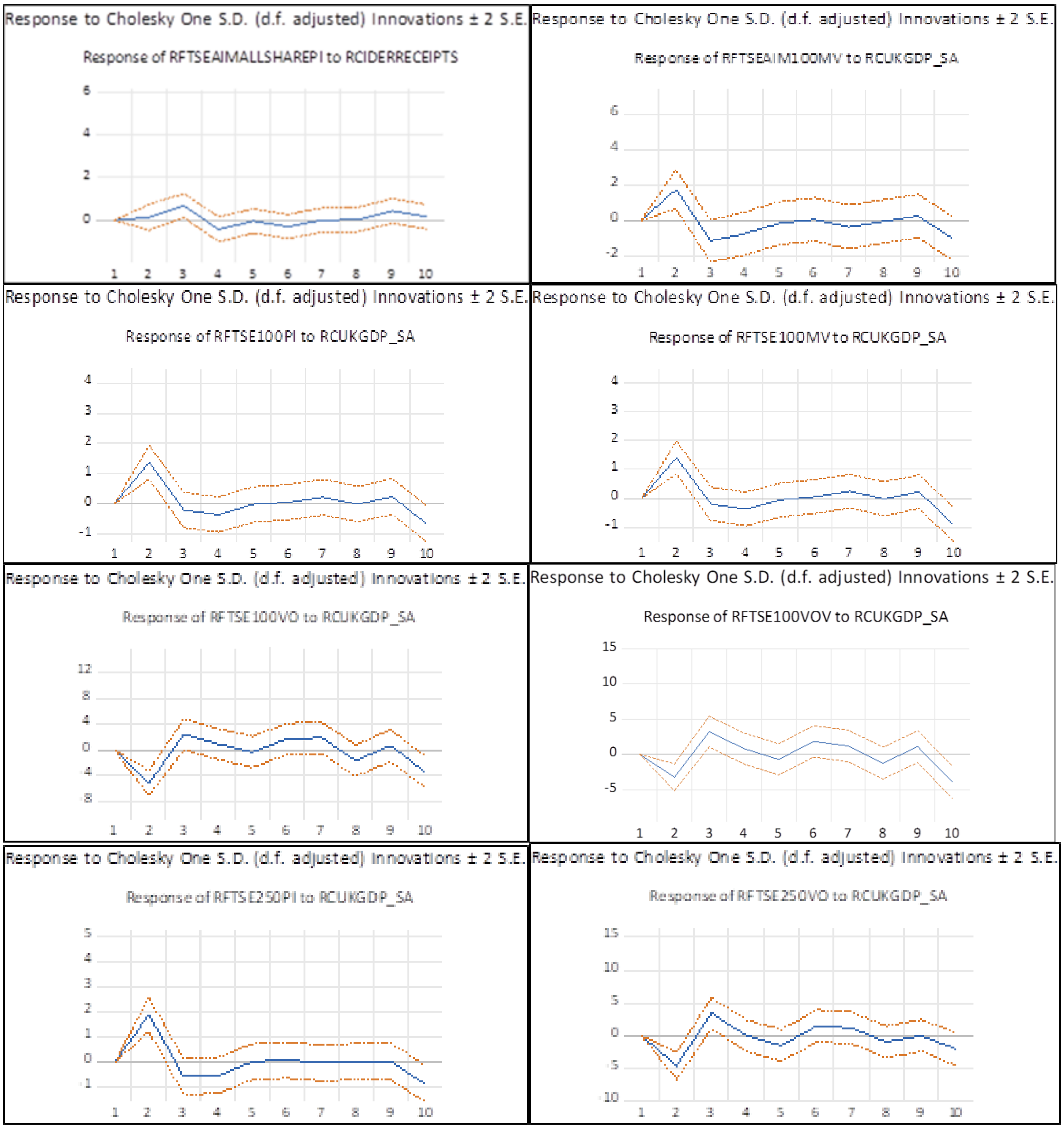
RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RSPIRITSRECEIPTS is spirits receipts rate of change, and RCIDERRECEIPTS is cider receipts rate of change.

Figure 2.10 FTSE-alcohol impulse response (with GDP)



Impulse response function for VARs of FTSE trading volume rate of change, GDP and beer. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020.
RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RBEERRECEIPTS_SA is seasonally adjusted beer receipts rate of change, and RBEERRECEIPTS is beer receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

Figure 2.11 FTSE impulse response to cider and GDP



Impulse response function for VARs of FTSE AIM All Share returns, GDP and cider. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for April 1999 to December 2020. RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE100MV is rate of change of FTSE100 market capitalisation, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RCIDERRECEIPTS is cider receipts rate of change, and RCUKGDP_SA is seasonally adjusted UK GDP rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

Table 2.1 Descriptive statistics of FTSE 100 and FTSE 250 index returns and trading volume rate of change April 1999 to December 2020

	RFTSE100PI	RFTSE100MV	RFTSE100VO	RFTSE100VOV	RFTSE250PI	RFTSE250MV	RFTSE250VO	RFTSE250VOV
Mean	0.315487	0.486346	0.540345	0.650922	0.640197	0.442056	0.80604	1.024936
Median	0.80343	0.855364	-0.694879	-0.485829	1.225888	0.991914	-0.956407	0.835022
Maximum	12.13744	16.27674	74.64004	66.03651	14.62756	16.3836	180.8679	190.2356
Minimum	-19.88981	-19.71286	-55.78325	-59.22707	-28.27946	-27.92927	-58.56619	-67.32097
Std. Dev.	4.286732	4.388438	22.11094	21.12591	5.084688	5.278001	24.65314	24.1348
Skewness	-0.680578	-0.498818	0.328993	0.32157	-1.04441	-1.059538	1.274778	1.372973
Kurtosis	4.875632	4.918266	3.544169	3.603483	7.306591	7.455676	10.7911	13.26277
Jarque-Bera	81.23244	70.70968	11.02711	11.76455	346.5122	368.1958	957.6218	1608.32
Probability	0	0	0.004032	0.002788	0	0	0	0
Sum	114.5219	176.5436	196.1451	236.2847	232.3916	160.4664	275.6657	350.5281
Sum Sq. Dev.	6652.139	6971.537	176979.5	161562	9359.165	10084.34	207252	198628.6
Observations	363	363	363	363	363	363	342	342

RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RFTSE100MV is rate of change of FTSE100 market capitalisation, and RFTSE250MV is rate of change of FTSE250 market capitalisation.

Table 2.2 Descriptive statistics of FTSE AIM index returns from April 1999 to December 2020

	RFTSEAIM100PI	RFTSEAIM100MV	RFTSEAIMALLSHAREPI	RFTSEAIMALLSHAREMV
Mean	0.108098	0.831221	0.062736	0.985447
Median	1.370185	1.97701	0.756315	1.504719
Maximum	18.04409	28.22064	28.5948	31.57835
Minimum	-34.7619	-34.04458	-31.53635	-45.4671
Std. Dev.	6.687029	7.430265	6.581639	8.0738
Skewness	-1.741285	-0.967899	-0.795313	-1.112326
Kurtosis	9.553246	7.479928	7.87118	9.2767
Jarque-Bera	435.9971	188.5518	331.5133	502.5885
Probability	0	0	0	0
Sum	20.53869	157.9321	19.00913	268.0417
Sum Sq. Dev.	8451.393	10434.47	13082.03	17665.47
Observations	190	190	303	272

RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, and RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation,

Table 2.3 Descriptive statistics of alcohol receipts rate of change April 1999 to December 2020

	RBEER	RBEER_SA	RCIDER	RCIDER_SA	RSPIRITS	RSPIRITS_SA	RWINE	RWINE_SA
Mean	-0.009323	-0.024953	0.080893	0.139845	0.305863	0.341987	0.406282	0.449901
Median	2.249061	-0.053379	0	0.171127	6.09607	1.005	3.046285	1.107387
Maximum	152.1378	138.78	69.0379	66.67318	73.84512	44.08037	47.84611	44.16882
Minimum	-157.9385	-176.0643	-84.72979	-54.44888	-113.3852	-110.5368	-64.75697	-53.2592
Std. Dev.	25.70299	18.26384	22.97366	16.61072	33.28138	19.54812	21.20386	11.81102
Skewness	-0.568486	-1.821341	-0.214267	0.127582	-1.002178	-2.685701	-0.590314	-1.055001
Kurtosis	12.42691	47.30834	4.318646	4.900541	4.076572	15.22702	3.123171	7.692847
Jarque-Bera	980.4823	21494.41	20.90683	39.98918	56.29392	1939.577	15.32345	287.9148
Probability	0	0	0.000029	0	0	0	0.00047	0
Sum	-2.433212	-6.512618	21.11298	36.49957	79.83018	89.2585	106.0397	117.4242
Sum Sq. Dev.	171767.4	86727.68	137225.1	71738.19	287989.2	99353.5	116897	36270.06
Observations	261	261	261	261	261	261	261	261

RWINE_SA is seasonally adjusted wine receipts rate of change, RBEER_SA is seasonally adjusted beer receipts rate of change, RSPIRITS_SA is seasonally adjusted spirits receipts rate of change, RCIDER_SA is seasonally adjusted cider receipts rate of change, RALCOHOLRECEIPTS_SA is seasonally adjusted all alcohol receipts rate of change, RWINE is wine receipts rate of change, RBEER is beer receipts rate of change, RSPIRITS is spirits receipts rate of change, RCIDER is cider receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change

Table 2.4 Augmented Dickey-Fuller test results

Null Hypothesis: Variable has a unit root				
Variable	Augmented Dickey-Fuller test statistic	Test critical values: 1% level	5% level	10% level
RFTSE100PI	-18.8428	-3.4482	-2.8693	-2.5710
RFTSE100VO	-6.1512	-3.4488	-2.8696	-2.5711
RFTSE100VOV	-5.3634	-3.4488	-2.8696	-2.5711
RFTSE250PI	-16.9385	-3.4482	-2.8693	-2.5710
RFTSE250VO	-7.1845	-3.4500	-2.8701	-2.5714
RFTSE250VOV	-5.9411	-3.4500	-2.8701	-2.5714
RFTSEAIM100PI	-9.8128	-3.4650	-2.8767	-2.5749
RFTSEAIMALLSHAREPI	-11.7700	-3.4518	-2.8709	-2.5718
RFTSEALLSHAREPI	-18.2864	-3.4482	-2.8693	-2.5710
RFTSE100MV	-18.9915	-3.4482	-2.8693	-2.5710
RFTSE250MV	-16.3466	-3.4482	-2.8693	-2.5710
RFTSEAIM100MV	-10.4642	-3.4650	-2.8767	-2.5749
RFTSEAIMALLSHAREMV	-12.7635	-3.4544	-2.8720	-2.5724
RFTSEALLSHAREMV	-18.2232	-3.4482	-2.8693	-2.5710
RWINE_SA	-13.1402	-3.4564	-2.8729	-2.5729
RBEER_SA	-10.6306	-3.4561	-2.8728	-2.5728
RSPIRITS_SA	-18.1188	-3.4564	-2.8729	-2.5729
RCIDER_SA	-10.5824	-3.4561	-2.8728	-2.5728
RALCOHOLRECEIPTS_SA	-14.0717	-3.4564	-2.8729	-2.5729
RWINE	-27.8433	-3.4564	-2.8729	-2.5729
RBEER	-9.6013	-3.4565	-2.8730	-2.5729
RSPIRITS	-15.7491	-3.4565	-2.8730	-2.5729
RCIDER	-19.0829	-3.4564	-2.8729	-2.5729
RALCOHOLRECEIPTS	-29.6798	-3.4564	-2.8729	-2.5729

RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSEALLSHAREPI is returns of FTSE all share index, RFTSE100MV is rate of change of FTSE100 market capitalisation, RFTSE250MV is rate of change of FTSE250 market capitalisation, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, and RFTSEALLSHAREMV is rate of change of FTSE all share market capitalisation.
RWINE_SA is seasonally adjusted wine receipts rate of change, RBEER_SA is seasonally adjusted beer receipts rate of change, RSPIRITS_SA is seasonally adjusted spirits receipts rate of change, RCIDER_SA is seasonally adjusted cider receipts rate of change, RALCOHOLRECEIPTS_SA is seasonally adjusted all alcohol receipts rate of change, RWINE is wine receipts rate of change, RBEER is beer receipts rate of change, RSPIRITS is spirits receipts rate of change, RCIDER is cider receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

Table 2.5 FTSE-alcohol receipts correlation coefficients with probability

	FTSE 100 MV	FTSE 100 PI	FTSE 100 VO	FTSE 100 VOV	FTSE 250 MV	FTSE 250 PI	FTSE 250 VO	FTSE 250 VOV	FTSE AIM 100 MV	FTSE AIM 100 PI	FTSE AIM ALL SHARE MV	FTSE AIM ALL SHARE PI
WINERECEIPTS	0.526	0.4663	-0.5208	-0.4417	0.5837	0.6761	-0.4542	-0.2765	0.5132	-0.0284	0.328	-0.0775
	0	0	0	0	0	0	0	0.0001	0	0.6998	0	0.2919
SPIRITSRECEIPT	0.35	0.3085	-0.297	-0.2674	0.4006	0.4637	-0.245	-0.146	0.4145	0.0429	0.2734	-0.0023
	0	0	0	0.0002	0	0	0.0007	0.0462	0	0.56	0.0002	0.9748
BEERRECEIPTS	0.1807	0.1541	-0.2393	-0.2217	0.1556	0.1797	-0.1802	-0.1472	0.1601	0.0266	0.0937	0.0124
	0.0134	0.0353	0.001	0.0023	0.0334	0.0138	0.0136	0.0444	0.0286	0.7175	0.2023	0.8663
CIDERRECEIPTS	0.1258	0.0489	-0.4786	-0.5046	0.0476	0.1613	-0.5024	-0.497	-0.0237	-0.4315	-0.1466	-0.4098
	0.0862	0.5063	0	0	0.5176	0.0274	0	0	0.7479	0	0.0453	0
ALCOHOLRECEIPTS	0.4264	0.3737	-0.4272	-0.3774	0.4637	0.5399	-0.3611	-0.23443	0.43999	0.0019	0.2786	-0.04173
	0	0	0	0	0	0	0	0.0012	0	0.9786	0.0001	0.5707

RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSE100MV is rate of change of FTSE100 market capitalisation, RFTSE250MV is rate of change of FTSE250 market capitalisation, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, and RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation.

Table 2.6 Statistically significant Granger causality tests (seasonally adjusted and January dummies)

Variables	Chi-squared	df	Prob	Number of lags for VARs
RALCOHOLRECEIPTS → RFTSE100VO	39.7151	15	0.0005	16
RALCOHOLRECEIPTS → RFTSE100VOV	27.5202	13	0.0106	14
RWINERECEIPTS → RFTSE100VO	23.8183	12	0.0215	13
RWINERECEIPTS → RFTSE100VOV	37.2086	13	0.0004	14
RWINERECEIPTS → RFTSE250PI	17.6363	11	0.0904	12
RWINERECEIPTS → RFTSE250VO	39.3078	15	0.0006	16
RWINERECEIPTS → RFTSE250VOV	35.7800	13	0.0006	14
RBEERRECEIPTS → RFTSE100VO	45.984	12	0	13
RBEERRECEIPTS → RFTSE100VOV	33.29393	12	0.0009	13
RBEERRECEIPTS → RFTSE250VO	42.0727	16	0.0004	17

RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RWINERECEIPTS is wine receipts rate of change, RBEERRECEIPTS is beer receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change,

Table 2.7 Statistically significant Granger causality tests (no seasonal adjustment and no dummies)

Variables	Chi-squared	df	Prob	Number of lags for VARs
RALCOHOLRECEIPTS → RFTSE100VO	71.1467	11	0	12
RALCOHOLRECEIPTS → RFTSE250VO	72.7359	11	0	12
RWINERECEIPTS → RFTSE100VO	73.9796	11	0	12
RWINERECEIPTS → RFTSE250VO	64.9463	13	0	14
RSPIRITRECEIPTS → RFTSE100VO	29.0934	12	0.0038	13
RSPIRITRECEIPTS → RFTSE100VOV	41.8883	13	0.0001	14
RSPIRITRECEIPTS → RFTSE250VO	30.6029	12	0.0023	13
RBEERRECEIPTS → RFTSE100VO	88.5776	12	0	13
RBEERRECEIPTS → RFTSE100VOV	98.7628	11	0	12
RBEERRECEIPTS → RFTSE250VO	90.7701	16	0	17
RFTSE250VO → RBEERRECEIPTS	32.016	16	0.01	17
RBEERRECEIPTS → RFTSE100VOV	60.2528	19	0	20
RFTSE100VOV → RBEERRECEIPTS	30.0941	19	0.0506	20
RBEERRECEIPTS → RFTSEAIM100MV	18.8303	11	0.0642	12
RBEERRECEIPTS → RFTSEAIM100PI	38.0544	19	0.0058	20
RBEERRECEIPTS → RFTSEAIMALLSHAREMV	59.3416	19	0	20
RBEERRECEIPTS → RFTSEAIMALLSHAREPI	26.7801	19	0.0133	20
RBEERRECEIPTS → RFTSEALLSHAREMV	50.3963	19	0.0002	20
RBEERRECEIPTS → RFTSEALLSHAREPI	22.3909	19	0.0334	20
RCIDERRECEIPTS → RFTSE100VO	52.6956	11	0	12
RCIDERRECEIPTS → RFTSE250VO	42.9745	12	0	13
RFTSE250VO → RCIDERRECEIPTS	19.9353	12	0.0683	13

RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSEALLSHAREPI is returns of FTSE all share index, RFTSE100MV is rate of change of FTSE100 market capitalisation, RFTSE250MV is rate of change of FTSE250 market capitalisation, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, and RFTSEALLSHAREMV is rate of change of FTSE all share market capitalisation.
RWINE_SA is seasonally adjusted wine receipts rate of change, RBEER_SA is seasonally adjusted beer receipts rate of change, RSPIRITS_SA is seasonally adjusted spirits receipts rate of change, RCIDER_SA is seasonally adjusted cider receipts rate of change, RALCOHOLRECEIPTS_SA is seasonally adjusted all alcohol receipts rate of change, RWINE is wine receipts rate of change, RBEER is beer receipts rate of change, RSPIRITS is spirits receipts rate of change, RCIDER is cider receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change.

Table 2.8 Statistically significant Granger causality tests (with GDP and seasonal adjustment and no dummies)

Variables	Chi-squared	df	Prob.	Number of lags for VARs
RWINERECEIPTS_SA→ RFTSE100PI	16.41136	10	0.0884	11
RWINERECEIPTS_SA→RFTSE100VO	19.87635	10	0.0304	11
RWINERECEIPTS_SA→RFTSE100VOV	19.66549	10	0.0326	11
RWINERECEIPTS_SA→RFTSE250VOV	19.55182	10	0.0338	11
RWINERECEIPTS_SA→ RFTSE250PI	18.48544	10	0.0473	11
RWINERECEIPTS_SA→RFTSE250MV	16.32192	10	0.0908	11
RWINERECEIPTS_SA→RFTSEAIM100PI	22.63167	10	0.0122	11
RWINERECEIPTS_SA→RFTSEAIM100MV	19.21345	10	0.0376	11
RWINERECEIPTS_SA→RFTSEAIMALLSHAREPI	16.78002	10	0.0794	11
RWINERECEIPTS_SA→RFTSEAIMALLSHAREMV	16.54089	10	0.0852	11
RBEERRECEIPTS_SA→RFTSE100VOV	22.59726	12	0.0313	13
RBEERRECEIPTS_SA→RFTSEAIMALLSHAREMV	18.64994	10	0.0449	11
RALCOHOLRECEIPTS_SA→RFTSE100VO	19.12841	12	0.0855	13
RALCOHOLRECEIPTS_SA→RFTSE100VOV	18.17296	12	0.1105	13
RALCOHOLRECEIPTS_SA→RFTSE250VOV	20.36126	12	0.0606	13

RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSEALLSHAREPI is returns of FTSE all share index, RFTSE100MV is rate of change of FTSE100 market capitalisation, RFTSE250MV is rate of change of FTSE250 market capitalisation, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, and RFTSEALLSHAREMV is rate of change of FTSE all share market capitalisation.
RWINE_SA is seasonally adjusted wine receipts rate of change, RBEER_SA is seasonally adjusted beer receipts rate of change, RSPIRITS_SA is seasonally adjusted spirits receipts rate of change, RCIDER_SA is seasonally adjusted cider receipts rate of change, RALCOHOLRECEIPTS_SA is seasonally adjusted all alcohol receipts rate of change, RWINE is wine receipts rate of change, RBEER is beer receipts rate of change, RSPIRITS is spirits receipts rate of change, RCIDER is cider receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

Table 2.9 Statistically significant Granger causality tests (with GDP and no seasonal adjustment and no dummies)

Variables	Chi-squared	df	Prob.	Number of lags for VARs
RFTSE100MV → RWINERECEIPTS	19.69032	12	0.0732	13
RWINERECEIPTS → RFTSE100VOV	57.88122	12	0	13
RWINERECEIPTS → RFTSE100VO	47.82209	12	0	13
RFTSE250PI → RWINERECEIPTS	26.46937	12	0.0092	13
RFTSE250MV → RWINERECEIPTS	25.19939	12	0.0139	13
RWINERECEIPTS → RFTSE250VO	43.28952	12	0	13
RWINERECEIPTS → RFTSE250VOV	47.02304	12	0	13
RBEERRECEIPTS→ RFTSE100VO	56.14349	12	0	13
RBEERRECEIPTS→ RFTSE100VOV	64.76436	12	0	13
RBEERRECEIPTS→RFTSE250VO	58.17725	12	0	13
RBEERRECEIPTS→RFTSE250VOV	61.14295	12	0	13
RSPIRITSRECEIPT→RFTSE100VO	43.95558	11	0	12
RSPIRITSRECEIPT→RFTSE100VOV	40.15357	12	0.0001	13
RSPIRITSRECEIPT→RFTSE250VO	25.73616	12	0.0117	13
RSPIRITSRECEIPT→RFTSE250VOV	27.23907	12	0.0071	13
RCIDERRECEIPTS→RFTSE100VO	38.58982	12	0.0001	13
RCIDERRECEIPTS→RFTSE100VOV	41.45394	12	0	13
RCIDERRECEIPTS→ RFTSE250VO	39.89755	12	0.0001	13
RCIDERRECEIPTS→ RFTSE250VOV	39.06446	12	0.0001	13
RCIDERRECEIPTS→RFTSEAIMALLSHAREPI	18.01351	11	0.0813	12
RCIDERRECEIPTS→RFTSEAIMALLSHAREMV	17.69882	11	0.0888	12
RFTSE250PI→RALCOHOLRECEIPTS	18.58917	12	0.0989	13
RALCOHOLRECEIPTS→RFTSE100VO	47.49612	12	0	13
RALCOHOLRECEIPTS→RFTSE100VOV	57.91573	12	0	13

RFTSE100PI is returns of FTSE100 index, RFTSE100VO is rate of change of FTSE100 trading volume, RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250PI is returns of FTSE 250 index, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE250VOV is rate of change of FTSE 250 trading volume by value, RFTSEAIM100PI is returns of FTSE AIM100 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM all share index, RFTSEALLSHAREPI is returns of FTSE all share index, RFTSE100MV is rate of change of FTSE100 market capitalisation, RFTSE250MV is rate of change of FTSE250 market capitalisation, RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, and RFTSEALLSHAREMV is rate of change of FTSE all share market capitalisation.
RWINE_SA is seasonally adjusted wine receipts rate of change, RBEER_SA is seasonally adjusted beer receipts rate of change, RSPIRITS_SA is seasonally adjusted spirits receipts rate of change, RCIDER_SA is seasonally adjusted cider receipts rate of change, RALCOHOLRECEIPTS_SA is seasonally adjusted all alcohol receipts rate of change, RWINE is wine receipts rate of change, RBEER is beer receipts rate of change, RSPIRITS

is spirits receipts rate of change, RCIDER is cider receipts rate of change, and RALCOHOLRECEIPTS is all alcohol receipts rate of change.

Table 2.10 Definition of abbreviated terms

Symbol used	Definition
RFTSE100PI	Returns of FTSE100 index.
RFTSE100VO	Rate of change of FTSE100 trading volume
RFTSE100VOV	Rate of change of FTSE100 trading volume by value
RFTSE250PI	Returns of FTSE 250 index.
RFTSE250VO	Rate of change of FTSE 250 trading volume
RFTSE250VOV	Rate of change of FTSE 250 trading volume by value
RFTSEAIM100PI	Returns of FTSE AIM100 index.
RFTSEAIMALLSHAREPI	Returns of FTSE AIM All Share index.
RFTSE100MV	Rate of change of FTSE100 market capitalisation.
RFTSE250MV	Rate of change of FTSE250 market capitalisation.
RFTSEAIM100MV	Rate of change of FTSE AIM100 market capitalisation.
RFTSEAIMALLSHAREMV	Rate of change of FTSE AIM All Share market capitalisation.
RWINE_SA	Seasonally adjusted wine receipts rate of change.
RBEER_SA	Seasonally adjusted beer receipts rate of change.
RSPIRITS_SA	Seasonally adjusted spirits receipts rate of change.
RCIDER_SA	Seasonally adjusted cider receipts rate of change.
RWINE	Wine receipts rate of change.
RBEER	Beer receipts rate of change.
RSPIRITS	Spirits receipts rate of change.
RCIDER	Cider receipts rate of change.
RCIGARETTESRECEIPTS_SA	Seasonally adjusted cigarette receipts rate of change.
RCIGARSRECEIPTS_SA	Seasonally adjusted cigar receipts rate of change.
RHRTRECEIPTS_SA	Seasonally adjusted hand rolled tobacco receipts rate of change.
RTOBACCORECEIPTS_SA	Seasonally adjusted tobacco receipts rate of change.
ROTHERRECEIPTS_SA	Seasonally adjusted other tobacco receipts rate of change.
RCIGARETTESRECEIPTS	Cigarette receipts rate of change.
RCIGARSRECEIPTS	Cigar receipts rate of change.
RHRTRECEIPTS	Hand rolled tobacco receipts rate of change.
RTOBACCORECEIPTS	Tobacco receipts rate of change.
ROTHERRECEIPTS	Other tobacco receipts rate of change.
FTSE100	FTSE 100 is an equity index of one hundred corporations listed on the London Stock Exchange with the highest market valuation.
FTSE250	FTSE 250 is an equity index of medium capitalised companies not in FTSE 100 index.
FTSEAIM100	FTSE AIM 100 is an equity index of the largest hundred companies by full market capitalisation that are in the Alternative Investment Market index.
FTSEAIMALLSHARE	FTSE AIM All ordinary shares is an equity index of companies that are listed in the Alternative Investment Market.

A2.1 Monthly FTSE-Google trends search correlation coefficients with probability

	FTSE 100 MV	FTSE 100 PI	FTSE 100 VO	FTSE 100 VOV	FTSE 250 MV	FTSE 250 PI	FTSE 250 VO	FTSE 250 VOV	FTSE AIM 100 MV	FTSE AIM 100 PI	FTSE AIM ALL SHARE MV	FTSE AIM ALL SHARE PI
WINE	0.5223 0.0000	0.4886 0.0000	-0.4269 0.0000	-0.3185 0.0000	0.6262 0.0000	0.6513 0.0000	-0.3066 0.0000	-0.1001 0.1662	0.5787 0.0000	0.2731 0.0001	0.4743 0.0000	0.2241 0.0017
BEER	0.6412 0.0000	0.5937 0.0000	-0.4368 0.0000	-0.3350 0.0000	0.7682 0.0000	0.8101 0.0000	-0.2886 0.0000	-0.0657 0.3642	0.7287 0.0000	0.3629 0.0000	0.5843 0.0000	0.2977 0.0000
COCKTAIL	0.6909 0.0000	0.6316 0.0000	-0.6571 0.0000	-0.5121 0.0000	0.7746 0.0000	0.8392 0.0000	-0.5444 0.0000	-0.2699 0.0001	0.6411 0.0000	0.1711 0.0173	0.4916 0.0000	0.1252 0.0827
CIDER	0.7337 0.0000	0.6829 0.0000	-0.5893 0.0000	-0.4435 0.0000	0.8040 0.0000	0.8695 0.0000	-0.4568 0.0000	-0.1809 0.0118	0.6908 0.0000	0.2376 0.0009	0.5372 0.0000	0.1704 0.0178

A2.2 Weekly FTSE-Google trends search correlation coefficients with probability

Probability	FTSE 100 MV	FTSE 100 PI	FTSE 100 VO	FTSE 100 VOV	FTSE 250 MV	FTSE 250 PI	FTSE 250 VO	FTSE 250 VOV	FTSE AIM 100 MV	FTSE AIM 100 PI	FTSE AIM ALL SHARE MV	FTSE AIM ALL SHARE PI
WINE	0.4630 0.0000	0.4346 0.0000	-0.2328 0.0000	-0.1656 0.0000	0.5661 0.0000	0.5890 0.0000	-0.1350 0.0001	0.0175 0.6137	0.5015 0.0000	0.2401 0.0000	0.4019 0.0000	0.1887 0.0000
BEER	0.6279 0.0000	0.5857 0.0000	-0.3579 0.0000	-0.2741 0.0000	0.7443 0.0000	0.7873 0.0000	-0.2338 0.0000	-0.0339 0.3281	0.6926 0.0000	0.3305 0.0000	0.5523 0.0000	0.2671 0.0000
COCKTAIL	0.6367 0.0000	0.5810 0.0000	-0.5050 0.0000	-0.3978 0.0000	0.7202 0.0000	0.7817 0.0000	-0.4113 0.0000	-0.1853 0.0000	0.5938 0.0000	0.1520 0.0000	0.4486 0.0000	0.1058 0.0022
CIDER	0.7016 0.0000	0.6544 0.0000	-0.5044 0.0000	-0.3878 0.0000	0.7800 0.0000	0.8441 0.0000	-0.3848 0.0000	-0.1460 0.0000	0.6623 0.0000	0.2217 0.0000	0.5102 0.0000	0.1526 0.0000

A2.3 Daily FTSE-Google trends search correlation coefficients with probability

Probability	FTSE 100 MV	FTSE 100 PI	FTSE 100 VO	FTSE 100 VOV	FTSE 250 MV	FTSE 250 PI	FTSE 250 VO	FTSE 250 VOV	FTSE AIM 100 MV	FTSE AIM 100 PI	FTSE AIM ALL SHARE MV	FTSE AIM ALL SHARE PI
WINE	0.4050 0.0000	0.3807 0.0000	-0.2541 0.0000	-0.1826 0.0000	0.4954 0.0000	0.5136 0.0000	-0.1634 0.0000	-0.0256 0.1044	0.4479 0.0000	0.2094 0.0000	0.3620 0.0000	0.1644 0.0000
BEER	0.5250 0.0000	0.4933 0.0000	-0.2605 0.0000	-0.1879 0.0000	0.6312 0.0000	0.6600 0.0000	-0.1403 0.0000	0.0173 0.2723	0.5904 0.0000	0.2983 0.0000	0.4709 0.0000	0.2410 0.0000
COCKTAIL	0.5351 0.0000	0.4918 0.0000	-0.4540 0.0000	-0.3529 0.0000	0.5985 0.0000	0.6460 0.0000	-0.3796 0.0000	-0.1878 0.0000	0.4797 0.0000	0.1111 0.0000	0.3617 0.0000	0.0735 0.0000
CIDER	0.6046 0.0000	0.5661 0.0000	-0.4119 0.0000	-0.3156 0.0000	0.6737 0.0000	0.7257 0.0000	-0.3058 0.0000	-0.1202 0.0000	0.5877 0.0000	0.2053 0.0000	0.4539 0.0000	0.1412 0.0000

A2.4 FTSE-tobacco receipts correlation coefficients with probability

Probability	FTSE 100 PI	FTSE 100 MV	FTSE 100 VO	FTSE 100 VOV	FTSE 250 PI	FTSE 250 MV	FTSE 250 VO	FTSE 250 VOV
CIGARETTESRECEIPTS	-0.0671	-0.0516	0.0363	-0.0013	-0.0484	-0.0579	0.0121	-0.0178
	0.3612	0.4835	0.6221	0.9864	0.5106	0.4315	0.8694	0.8090
CIGARSRECEIPTS	-0.1852	-0.1911	0.2621	0.1893	-0.1722	-0.1473	0.2517	0.1642
	0.0112	0.0088	0.0003	0.0094	0.0184	0.0442	0.0005	0.0248
HRTRECEIPTS	0.4105	0.4624	-0.4461	-0.3973	0.6347	0.5387	-0.3540	-0.2249
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0020
OTHERRECEIPTS	-0.1060	-0.0918	0.0567	-0.0419	0.0904	0.0385	0.1193	0.0217
	0.1487	0.2114	0.4409	0.5689	0.2183	0.6008	0.1038	0.7682
TOBACCORECEIPTS	0.0089	0.0318	-0.0421	-0.0685	0.0659	0.0407	-0.0474	-0.0532
	0.9041	0.6654	0.5670	0.3517	0.3702	0.5803	0.5192	0.4700

A2.5 FTSE-tobacco receipts correlation coefficients with probability

Probability	FTSE AIM 100 PI	FTSE AIM 100 MV	FTSE AIM ALL SHARE PI	FTSE AIM ALL SHARE MV
CIGARETTESRECEIPTS	-0.1078	-0.0828	-0.0975	-0.0989
	0.1421	0.2602	0.1843	0.1783
CIGARSRECEIPTS	0.0693	-0.0489	0.0738	-0.0304
	0.3458	0.5065	0.3154	0.6800
HRTRECEIPTS	0.0163	0.5399	-0.0410	0.3461
	0.8246	0.0000	0.5774	0.0000
OTHERRECEIPTS	0.0963	0.3106	0.0598	0.2145
	0.1899	0.0000	0.4159	0.0032
TOBACCORECEIPTS	-0.0920	0.0214	-0.0930	-0.0271
	0.2103	0.7714	0.2055	0.7131

A2.6 Statistically significant Granger causality tests (seasonally adjusted and December dummies)

Variables	Chi-squared	df	Prob	Number of lags for VARs
RCIGARETTESRECEIPTS_SA→ RFTSEAIMALLSHAREMV	23.03683	13	0.0412	14
RHRTRECEIPTS_SA→ RFTSE100VOV	26.17721	16	0.0516	17
RHRTRECEIPTS_SA→RFTSE250VO	31.58864	19	0.0348	20
RTOBACCORECEIPTS_SA→RFTSEAIMALLSHAREMV	34.09201	16	0.0053	17

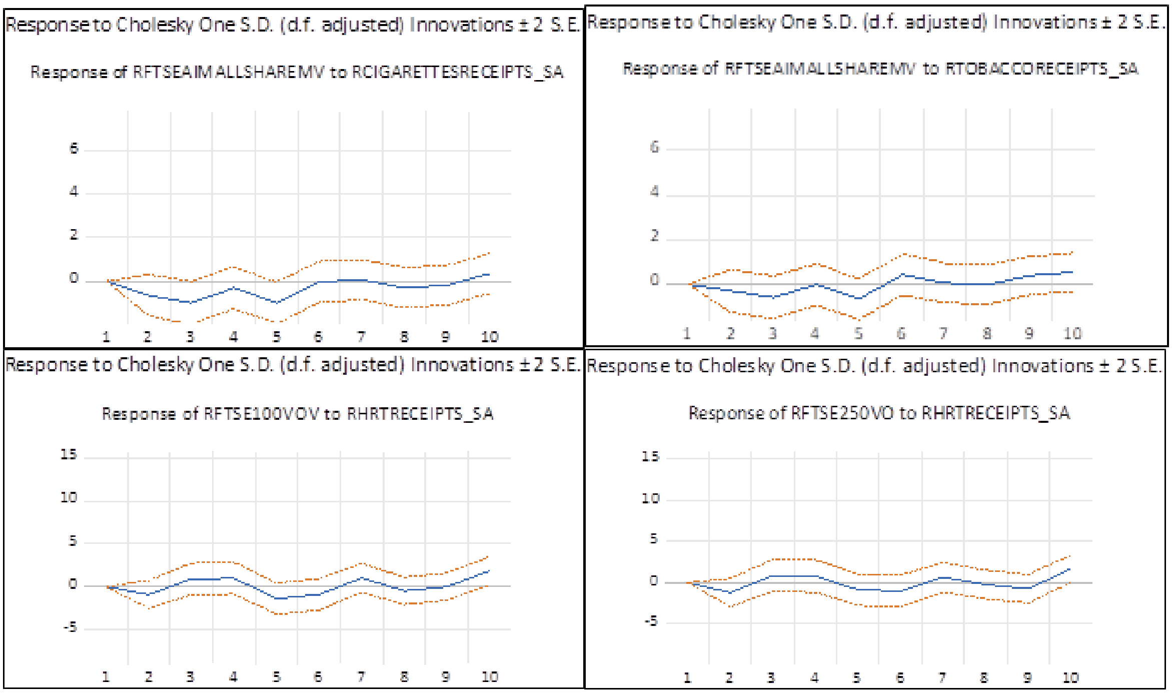
Tobacco receipts are seasonally adjusted using STL method.
RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, RCIGARETTESRECEIPTS_SA is seasonally adjusted cigarette receipts rate of change, RHRTRECEIPTS_SA is seasonally adjusted hand rolled tobacco receipts rate of change, and RTOBACCORECEIPTS_SA is seasonally adjusted tobacco receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

A2.7Statistically significant Granger causality tests (no seasonal adjustment and no dummies)

Variables	Chi-squared	df	Prob	Number of lags for VARs
RCIGARETTESRECEIPTS→RFTSEAIM100MV	20.96318	13	0.0737	14
RFTSEAIM100MV→RCIGARETTESRECEIPTS	25.65849	13	0.0189	14
RCIGARSRECEIPTS→RFTSE250VO	19.87339	12	0.0695	13
RCIGARSRECEIPTS→RFTSEAIM100MV	18.76972	11	0.0654	12
RHRTRECEIPTS→ RFTSEAIM100MV	20.80784	13	0.0768	14

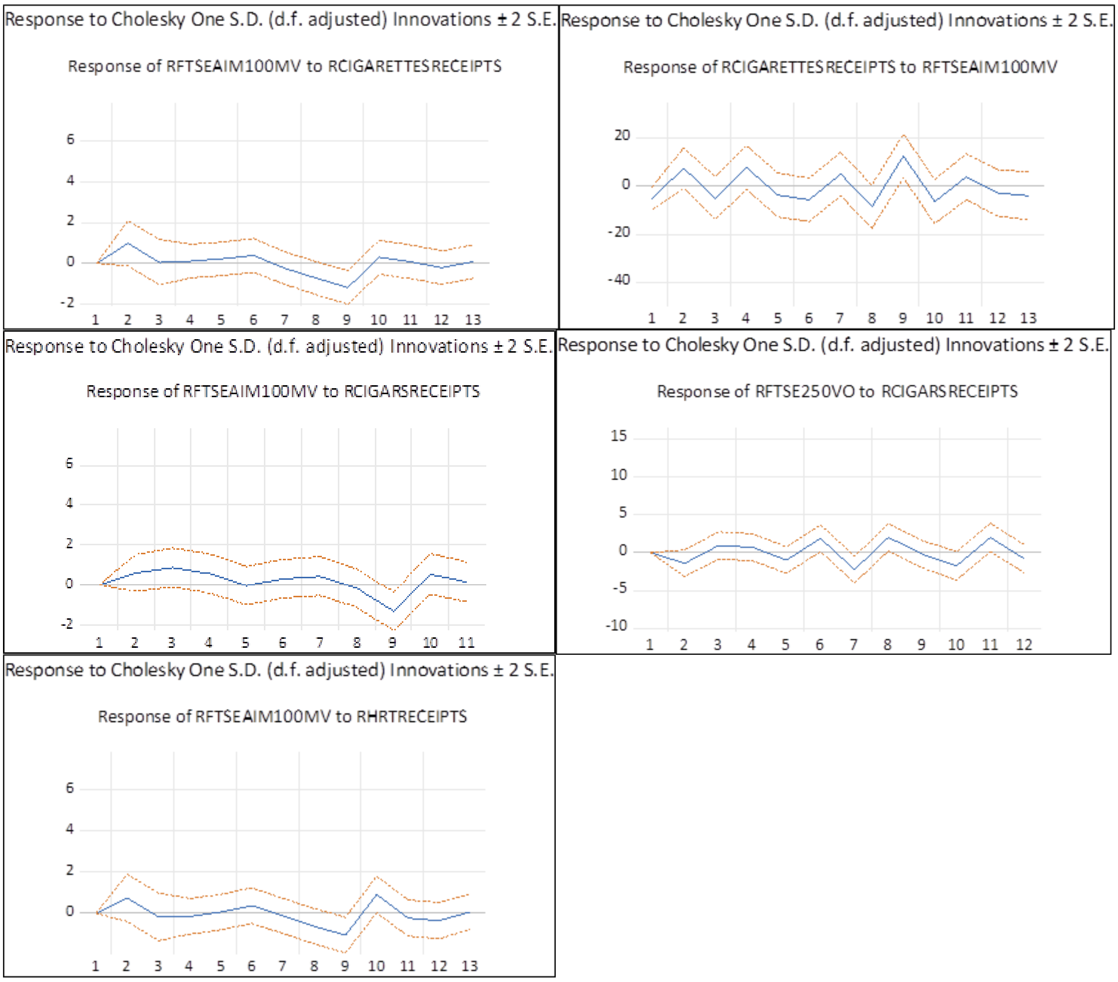
RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSE100MV is rate of change of FTSE100 market capitalisation, RCIGARETTESRECEIPTS is cigarette receipts rate of change, RCIGARSRECEIPTS is cigar receipts rate of change, and RHRTRECEIPTS is hand rolled tobacco receipts rate of change.

A2.8 FTSE-seasonally adjusted tobacco impulse response



Impulse response function for VARs of FTSE index and tobacco. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for January 1991 to December 2020. RFTSE100VOV is rate of change of FTSE100 trading volume by value, RFTSE250VO is rate of change of FTSE 250 trading volume, RFTSEAIMALLSHAREMV is rate of change of FTSE AIM all share market capitalisation, RCIGARETTESRECEIPTS_SA is seasonally adjusted cigarette receipts rate of change, RHRTRECEIPTS_SA is seasonally adjusted hand rolled tobacco receipts rate of change, and RTOBACCORECEIPTS_SA is seasonally adjusted tobacco receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

A2.9 FTSE-tobacco impulse response (no dummies or seasonal adjustment)



Impulse response function for VARs of FTSE index and tobacco. This figure plots impulse response to Cholesky one standard deviation innovations ±2 standard errors (dashed lines). The VAR lags differ and depend on Information Criteria. The data is obtained at monthly frequency for January 1991 to December 2020. RFTSEAIM100MV is rate of change of FTSE AIM100 market capitalisation, RFTSE250VO is rate of change of FTSE 250 trading volume, RCIGARETTESRECEIPTS is cigarette receipts rate of change, RCIGARSRECEIPTS is cigar receipts rate of change, and RHRTRECEIPTS is hand rolled tobacco receipts rate of change.

A2.10 Augmented Dickey-Fuller test results

Null Hypothesis: Variable has a unit root				
Variable	Augmented Dickey-Fuller test statistic	Test critical values: 1% level	5% level	10% level
RCIGARETTESRECEIPTS_SA	-12.7028	-3.4497	-2.8700	-2.5713
RCIGARSRECEIPTS_SA	-16.3807	-3.4489	-2.8696	-2.5711
RHRTRECEIPTS_SA	-15.5193	-3.4490	-2.8697	-2.5712
RTOBACCORECEIPTS_SA	-14.7924	-3.4489	-2.8696	-2.5711
ROTHERRECEIPTS_SA	-14.4606	-3.4489	-2.8696	-2.5711
RCIGARETTESRECEIPTS	-13.9436	-3.4497	-2.8700	-2.5713
RCIGARSRECEIPTS	-18.3489	-3.4489	-2.8696	-2.5711
RHRTRECEIPTS	-13.6332	-3.4490	-2.8697	-2.5712
RTOBACCORECEIPTS	-15.7524	-3.4489	-2.8696	-2.5711
ROTHERRECEIPTS	-13.2517	-3.4489	-2.8696	-2.5711
RCUKGDP_SA	-8.9186	-3.4488	-2.8696	-2.5711

RCIGARETTESRECEIPTS_SA is seasonally adjusted cigarette receipts rate of change, RCIGARSRECEIPTS_SA is seasonally adjusted cigar receipts rate of change, RHRTRECEIPTS_SA is seasonally adjusted hand rolled tobacco receipts rate of change, RTOBACCORECEIPTS_SA is seasonally adjusted tobacco receipts rate of change, ROTHERRECEIPTS_SA is seasonally adjusted other tobacco receipts rate of change, RCUKGDP_SA is seasonally adjusted UK GDP rate of change, RCIGARETTESRECEIPTS is cigarette receipts rate of change, RCIGARSRECEIPTS is cigar receipts rate of change, RHRTRECEIPTS is hand rolled tobacco receipts rate of change, RTOBACCORECEIPTS is tobacco receipts rate of change, and ROTHERRECEIPTS is other tobacco receipts rate of change. Seasonal adjustment is done using STL method, this is explained in section 2.3.4.

Chapter 3: Google music genre searches and the stock market.

3.1. Introduction

Traditional asset pricing models and Efficient Market Hypothesis (EMH) posits that financial markets efficiently price relevant information in a timely manner so that asset prices reflect the value of assets. If this were true, it is expected that mispricing of shares and other financial assets would be arbitraged away quickly in order to match price of an asset with corresponding value, and there would be absence of recurring calendar and other anomalies. However, there are limits to arbitrage such as implementation costs, information asymmetries, and liquidity risks, whereby an arbitrageur might be correct in the long-term but have difficulty taking advantage of a mispriced asset due to transaction fees, incomplete information or short-term liquidity constraints (Shleifer and Vishny, 1997, 2005). Also, research shows the persistent prevalence of calendar anomalies such as the January Effect (Haug and Hirschey, 2006), the Gone Fishing Effect (Hong and Yu, 2009), and the Schools Out Effect (Coakley, Kuo and Wood, 2012) which are at odds with EMH and are difficult to explain using rational-investor models only. These issues with EMH have therefore necessitated the use of models that recognise a less-rational decision-making process, including for example bounded rational investors, information asymmetry, momentum or sentiment/mood traders that operate in financial markets. For instance, Forgas, Bower and Krantz (1984) and Forgas (2017) illustrate that mood affects the way information is perceived and, eventually, the way decisions are made. This non-rational aspect of decision making is reflected in endemic asset price deviations from fundamentals whereby investors are influenced by “animal spirits” (Aggarwal, 2014) or “irrational exuberance”(Shiller, 2015). To address this complexity, this research investigates a particular source of decision making that is not captured by rational-investor models: social mood.

This paper focuses on the United Kingdom (UK) and explores to what extent social mood in the UK affects stock market returns and trading volume in the London Stock Exchange (LSE). The effect of UK social mood on UK financial markets has not been empirically explored as most studies focus on how investors’ state of mind affects stock market activities, without linking the investor sentiment to the social mood and financial markets. For instance, Schmeling (2009), Qiu and Welch (2004) and Statman and Fisher (2002) use consumer confidence reports as proxies for investor sentiment, while Baker and Wurgler (2007) and Neal and Wheatley (1998) consider proxy investor sentiment using number of Initial Public Offer (IPO), IPOs first day returns, trading volume, and close end funds discount. Research on passive investor attention captures investor sentiment in the market by applying content analysis through a comparison between the number of negative and positive/neutral words in newspapers articles (Tetlock, 2007; Tetlock, Saar-Tsechansky and Macskassy, 2008) or company annual reports[2] (Loughran and Mcdonald, 2011). The aforementioned literature uses US data based on information that takes time to collect, collate and analyse, which is therefore not up to date. Further, it could be argued that studies using newspaper articles, IPO first day return, number of IPOs, trading volume and discount on close-end funds use information that is an outcome of investor sentiment rather than a measure of it. To address this gap, this paper develops a music genre search index (Music Index hereafter) using Google searchers that are available at relatively short

[2] Annual reports are also referred to as Form 10-K in the United States of America.

notice and include a much higher number of users compared to surveys. This Music Index also benefits from the added advantage of using information that is collected directly from peoples' existing everyday activities and does not suffer the same issue whereby survey respondents could provide answers that do not actually mirror their actions.

There are two general approaches used in the literature to explore how investors are affected by non-fundamental factors when investing: the 'macro' or 'top-down' approach focuses on the general mood of investors and how this affects financial markets (Baker and Wurgler, 2007; Edmans, García and Norli, 2007), whilst the 'micro' or 'bottom-up' approach focuses on how financial markets are influenced by individual investor biases, such as overconfidence and self-attribution (Daniel, Hirshleifer and Subrahmanyam, 1998), conservative bias, and representative bias (Barberis, Shleifer and Vishny, 1998). This paper adopts the macro or top-down approach to explores to what extent the general mood in the United Kingdom (UK) is reflected in FTSE index returns and trading volume rate of change. In particular, this paper uses a novel approach of capturing mood-financial market relationship by analysing the link between music genre searches and FTSE returns and trading volume. More specifically, this paper develops the Music Index based on a modification of FEARS index developed by Da et al., (2015), utilising Google music genres searches in the UK. The Music Index is based on the assumption that the level of optimism or pessimism ('sentiment' hereafter) in retail and to some extent professional and institutional investors – is affected by social mood through mood contagion. In this paper, *social mood* can be understood as a positive or negative affective state that is consciously and subconsciously transmitted in a society (Prechter, 2001, 2016). Mood is shared from person to person or virtually through mood contagion (Neumann and

Strack, 2000). This paper poses that mood influences searches of music during peoples' day to day activities (cognitivism) as people try to change or enhance their current mood (emotivism), and therefore mood can also influence investment decisions through mood contagion. In this framework, (retail) investor, professional and institutional investor sentiment are considered as a subset of social mood since investors interact with society face-to-face or virtually.

The results show that the Music Index developed in this paper captures social mood impact on FTSE returns and trading volume. This Music Index is significant when used as independent variable in OLS regressions when FTSE returns, and FTSE trading volume rate of change are dependent variables. Specifically, when regressing FTSE 100 returns, FTSE 250 returns, FTSE AIM All Share returns, FTSE 100 and FTSE 250 trading volume on the Music Index, the Music Index is significant. This implies that the Music Index captures social mood for people in the UK through music genre searches, based on both emotivism and cognitivism (Kostopoulos and Meyer, 2018). The results show that the level of the Music Index follows an expected pattern of change in sign of coefficient from contemporaneous to lagged variable like in research findings reported by Da, Engelberg and Gao (2015); there is no change in sign of coefficients when the Music Index rate of change is used in regressions. These results are robust when using two different Music Index specifications, and when using daily and monthly frequency data.

This paper thus makes three main contributions. First, the paper extends *Socionomics Theory* by exploring contemporary music genres that were not discussed in Prechter (1999). Secondly, the paper contributes to the field of Behavioural Finance by constructing a Music Index which bridges research based on Google-search papers and Spotify/iTunes-music-mood papers. Finally, the article focuses empirically on the

UK, which has not been sufficiently researched across Google-search and music-mood studies.

The remainder of this paper is organised as follows: the next section will provide a literature review and present a hypothesis, focussing on previous papers on the Google searches and music. The third section discusses the data and methodology used to construct the Music Index. The following sections examine the results of OLS regressions and alternative specifications, before providing concluding remarks and the limitations of the paper.

3.2. Literature review and hypothesis

Investor decision making under the influence of mood with no specific cause has been studied in existing literature. For instance, Lucey and Dowling (2005), Baillon, Koellinger and Treffers (2016), Forgas (2017), Forgas, Bower and Krantz (1984) found that mood affects information collection and processing, while Lucey and Dowling, (2005) and Forgas, (2017) provide a comprehensive literature review of persistent links between mood and decision making. Forgas et al. (1984) and Baillon et al. (2016) conducted experiments with 24 and 500 participants respectively, finding that mild negative mood and sadness are good for optimum decision making. Further, specific mood proxies have been used in papers to explain short-term influences on investors and then stock market activities. For instance, Edmans, García and Norli (2007) use sports results in thirty-nine countries in Europe, America and Asia to explain a drop in returns. Hirshleifer and Shumway (2003) utilise weather information in twenty-six countries showing how cloud cover influenced lower stock market returns. Also, Dowling and Lucey (2008) employ weather information in thirty-seven countries to explain stock market return predictability and variance. Robotti and Krivelyova (2005) use geomagnetic storms to show how increased levels in these climate occurrences lowered returns in nine countries. Other types of information have also been used in relation to stock market returns – linked to entertainment and media – for example, Lepori (2015) links the end of popular TV series to NASDAQ, S&P500, RUSSEL 3000 and RUSSELL 2000 index returns due to viewers' attachment with characters. All these papers offer evidence of market irrationality, at least temporarily, based on specific and non-specific triggers of affect/mood that are not traditionally understood as rational or linked to financial decision-making. These aforementioned papers provide good illustrations of how financial markets are affected by non-fundamental factors. Contributing to this strand of the literature, this paper extends the understanding of the way mood is captured in society by adding a continuous Music Index based on music genre searches over time rather than one-off or infrequent events.

There has been increasing interest in the use of online word searches to investigate financial phenomena. For example, Google searches have been used over the past decade through Google's Search Volume Index (SVI hereafter) to link online searches for company name or stock-ticker with stock market activity in the context of investor attention or information demand/supply (Da, Engelberg and Gao, 2011; Joseph, K., Wintoki, B., and Zhang, Z., 2011; Vlastakis and Markellos, 2012; Ding and Hou, 2015). Further, other SVI papers use financial, economic or political word searches to link public interest with stock market activities (Mao, Counts and Bollen, 2011; Latoeiro, Ramos and Veiga, 2013; Preis, Moat and Eugene Stanley, 2013; Curme *et al.*, 2014; Vozlyublennaia, 2014; Da, Engelberg and Gao, 2015; Irresberger, Mühlnickel and Weiß, 2015; Algan *et al.*, 2016; Bukovina, 2016). All these papers focus on United States indexes (Dow Jones Industrial, NASDAQ and Russell 3000). Within the European context, Latoeiro, Ramos and Veiga (2013) use index, market and company name searches to find relationships with Euro Stoxx50 index returns and volatility in Eurozone, whilst Aouadi, Arouri and Teulon (2013) and Beer, Herve and Zouaoui (2013) use company name SVI to find relationship with CAC 40 index's returns, trading volume and volatility. Research conducted in the United Kingdom (UK) has not linked SVI with London Stock Market activities but rather focused on unemployment (McLaren and Shanbhogue, 2012). Choi and Varian (2012) use search terms relating to labour, housing and VAT to improve forecasting of UK unemployment and house prices. In addition to the widespread use in papers focusing on non-UK indexes, there is a strong case to use Google searches in this UK-focused paper as Google is an influential online search engine in the understanding of contemporary online search queries due to its reach and market share. Music searches is an interesting proxy to use as music creators have a particular emotion and/or message they are looking to express, convey or elicit, whilst music consumers have a certain mood or emotion that they are seeking to feel, extend or modify. The mood sought and presented through music is subjective and not rational as it depends on individual taste, personal circumstances, lyrics, pitch, rhythm, tempo, and harmony amongst other things. Music genre searches represent a large proportion of searches for the UK population as there is widespread use of the internet in the UK, and Google is the number one search engine in this country.

The link between the SVI and what people are thinking or feeling is well established. For example, Algan *et al.* (2019), predict peoples' wellbeing at federal and state level in the US using Google searches and Gallup surveys. Further, Google searches are shown to correlate with the Gallup-Healthways Wellbeing Index by Ford *et al.* (2018). In another study using 202 countries, Banerjee (2018) finds that Google searches correlate with the United Nations' World Happiness Index; and the same results are replicated by Brodeur *et al.* (2021) in many European countries using the General Health Questionnaire. Moreover, internet searches can be used to reveal salient topics or issues in society, as illustrated by Mellon (2014) using Gallup's Most Important Problem survey in the US, and by Scheitle (2011) using the general Gallup survey. As shown in the aforementioned papers, the SVI reveals not only the significance of some topics in linking social issues, but also people's mood, made explicit through the use of the Google search function.

The connection between music and financial markets that is espoused in this paper has been more recently explored using advancements in natural language processing and artificial intelligence. Edmans et al. (2022) and Fernandez-Perez, Garel and Indriawan (2020) develop music sentiment using Spotify and illustrate that an increase in music sentiment precedes an increase in mutual fund flows and a rise in stock market volatility. The aforementioned papers construct their index using affect and valence of each song. Affect gives information on the type of (positive or negative) mood in the song and valence is a classification of the strength of the positive or negative mood. Kaivanto and Zhang (2019) also used Spotify to show evidence of lowered returns in the months following high music sentiment. Music sentiment was significant in showing increased trading and flight to risk by about 79,000 German investors from a large brokerage using iTunes Germany music data (Kostopoulos and Meyer, 2018). The papers using Spotify's artificial intelligence to classify affect and valence[3] of songs have the advantage of being able to classify a large volume of songs using artificial intelligence software. On the other hand, the use of Spotify also presents

[3] Valence is the strength of the affect being experienced.

some challenges that limit the use of the tool, such as the skipping function being limited for non-premium users, the influence of record companies on Spotify song/playlist recommendations, and the classification of a song as having been listened to even if it is only played for 30 seconds.

The link between mood and music is well established – this can be seen in popular culture, movies, advertising, video games, children and adult television where music is used as a tool to prime audiences for a certain type of reaction or interaction, or to elicit a certain mood/state in customers. Mood Maintenance Hypothesis' view on music-mood connection is an amalgamation of two seemingly opposite perspectives of emotivism and cognitivism; according to Kostopoulos and Meyer (2018), emotivism ascribes to the idea that listening to music influence listeners mood, and this is separate from cognitivism whereby a persons' choice of music is influenced by their current mood. For example, there is empirical evidence illustrating how media consumption alters people's mood (Bruner, 1990; Westermann et al., 1996). Knobloch and Zillmann (2002) show how music can help individuals change an undesired mood or maintain their desired mood through selective media exposure. These papers focusing on 'mood management' provide evidence that a person's current mood affects which music or media content they choose to consume depending on their conscious or subconscious desired outcomes. Through experiments, Wegener and Petty (1994) demonstrated that when "happy", "sad" or "neutral" moods are induced through reading, film and thought, the participants' choice of music changed irrespective of the media used to induce the mood/state (Kostopoulos and Meyer, 2018). This paper agrees with the view that people who use mood management to choose what music they listen to will experience elements of cognitivism and emotivism.

The inclusion of music in various aspects of everyday life is not a modern phenomenon, as for instance, music was used by Sumerian, Babylonian, Chinese, Greek, Roman and Egyptian civilisations for healing (Murrock, 2005). Florence Nightingale also encouraged the use of music in the 19th century to improve wellbeing (Antrim, 1944) and, more recently, music has been used in a variety of settings to help reduce anxiety and promote relaxation of patients in receipt of ventilator assistance (Chlan, 1998). On the other end of the spectrum, music is also used to harm people (Johnson, 2009; Pieslak, 2009), for example through military interventions, a tool to spread violence or as a mechanism of crowd control. Music creators try to convey/induce a certain mood in the audience by a combination of lyrics, melody, harmony, rhythm, pitch, tempo and/or mode (Hevner, 1937; Ali and Peynircioğlu, 2006). Hevner (1937) work relates musical characteristics with the mood it is supposed to induce/convey (see table 3.1). There is no 'one size fits all' when it comes to people's affinity with certain type of music as taste, age, gender, culture, music training, mood and other individual factors play a role in individual choice of music (Stratton and Zalanowski, 1991). Also, people may be drawn to multiple and remarkably different styles of music at the same time, and music choices are also influenced by cultural and individual factors[4].In this paper, drawing on mood management *theory* (Chen, Zhou and Bryant, 2007), the focus is on the aggregate music genre searches of the UK as whole, as music genre searches are affected by the mood people are in (cognitivism) and also what mood they are (sub)consciously trying to experience after listening to music.

[4] This paper notes that two individuals may listen to the same music with opposite intended outcomes, one to extend current mood whilst the other to modify current mood. The aggregate level of this information is of interest to this paper, rather than individual responses.

[Insert Table 3.1 around here]

The hypothesis proposed in this paper is that people's online searches for music, which is indicative of social mood, will be reflected in the LSE. This is based on the understanding that mood contagion happens consciously and subconsciously through face-face and/or virtual social interaction, and that a proportion of the UK population can be expected to seek to extend or modify their current mood through online music searches. In the context of this paper, mood differs from emotions in two aspects: 1) mood is long in duration compared to emotions, and 2) unlike emotions, mood does not need a specific trigger (Scherer, 2005). Mood is transmitted consciously and subconsciously within a population through body language, facial expressions, voice, and other interactions (Chartrand and Bargh, 1999; Neumann and Strack, 2000). Music thus plays an important part in individual and social mood management through cognitivism and emotivism. Some of the digital music selection is likely to happen through a person's own playlist in their iTunes or Spotify accounts, but there is a proportion of the population that will search for a music genre they would like to listen to using Google. This provides data that is collected through ordinary day to day activities for a large section of the population.

Whilst past studies focused on political, corporate, economic, finance, financial-market, index and company search-terms, this paper uses music genre searches, motivated by the relatively new field of *Socionomics* (Prechter, 1999, 2016). *Socionomics Theory* postulates that social mood manifested through the popular music of the time, and other societal trends, drive financial markets and other human endeavours (see figure 3.1 for historic music trends). Figure 3.1 shows that popular music trends at a certain time had a relationship with Dow Jones Index – for example, more upbeat music such as happy rock-n-roll was en-vogue during the time of rising for the Dow Jones, which is contrasted by depressed and angry rock music in times of falling Dow Jones. Building on research done by Prechter (1999) in terms of the use of music in relation to social mood, in the period from 1950 to 1984, this study extends *Socionomics* theory and contributes more broadly to Behavioural Finance by 1) using new music genres that did not exist in the UK at that time, and 2) utilising a music genre SVI that was not available previously. This paper bridges the gap between one stream of literature that focuses on the financial market relationship with Google searches (which predominantly focus on searches of company names, stock ticker, financial, and economic search terms), and another stream of the literature that focuses on the relationship between financial markets and music, which thus far has predominantly used Spotify and iTunes.

[Insert Figure 3.1 around here]

Google has the largest market share of UK's non-mobile search queries (88.25%), followed by Bing (with only 8.43%). With regards to mobile searches, Google also has the largest market share at 95.46% (Statista, 2018). According to the Office for National Statistics (ONS, 2017), internet usage in the UK has increased year on year and has become more widespread, with 89% of all adults (99% between ages of 16 to 34) reported as having used the internet within a three-month timeframe. More recent figures show that Google continue to have a very dominant position in the space of UK search queries, with a market share of 94% for all device searches as seen in Figure 3.2 (Statista, 2023).This pervasive internet usage in society provides an opportunity to capture what is being searched by a large proportion of the UK population, and to investigate its link to the London Stock Exchange activities.

[Insert Figure 3.2 and 3.3 here]

Music media consumption takes a large proportion of peoples' days, even though there is no UK specific data on hours spent by consuming media, according to (Greenwald, 2000) an average American spends at least 3 ½ hours a day listening to music on the radio or via personal recordings. In the UK, the average internet user in 2017 registered a daily media consumption of 11.08 hours (WARC, 2017), while in 2018, 18% of internet users in the UK have at some point used a subscription-based audio services such as Spotify Premium or Apple Music (Ofcom, 2018). Currently, there are many sources of music – such as iTunes – where users can buy music; however, there are various free music listening/watching websites like YouTube, which has 1.9 billion monthly active users. In comparison, social networking sites such as Facebook, WhatsApp and Instagram have 2.23 billion, 1.5 billion and 1 billion monthly active users respectively (Buffer, 2018). In 2018, Ofcom reported that 35% of all media users in the UK turn to YouTube (which is part of Google) to find information; 76% of internet users watched videos online, and of these, 63% watched music videos (see figure 3.3). This high popularity of music and internet usage in the UK allows capture of large pool of participants who use the internet, and more specifically Google, to search for music depending on their current mood.

3.3. Data and methodology

Monthly data from June 2006 to May 2018 and daily stock market data from January 2005 to December 2019 were collected from Datastream (now known as Eikon). The music genre index developed in this paper – the Music Index – is inspired by

Prechter (1999), with the addition of additional contemporary music categories from Billboard (making a total of 18 music genres – more information on how the 18 genres of music were selected is in the following paragraph). The music genre SVI used are blues, classical music, grime, happy music, happy song, happy songs, hard rock, heavy metal, jazz, pop, rap, R & B, rock, reggae, rhythm and blues, sad song, sad songs and soul music. Google's SVI data has interval-frequency limitations: daily frequencies are only available for 90 days or less, weekly frequencies are available from a period of 90 days to 5 years, and monthly data is available for horizons over 5 years. This means the daily music SVI data is constructed using algorithm detailed in Chronopoulos, Papadimitriou and Vlastakis (2018). This service has three main advantages: 1) the music genre SVI is collected as a by-product of ordinary activity as opposed to surveys or experiments whereby participants' responses could differ from their ordinary actions; 2) music genre SVI data are normalised for a specified period with the highest number of searches for an interval given a score of 100 and the lowest zero; and 3) Google searches and music genre SVI is available much quicker when compared to surveys which may take longer to collate, process and distribute. SVI is normally available every week on Saturday for frequency that is lower than a week at the time of data collection.

This paper develops a music genre search index (the Music Index) using modification of the FEARS index which was made by Da, Engelberg and Gao, (2015). In order to objectively select search terms, the paper uses music categories that are identified in Prechter (1999) with the addition of contemporary genres of music that are included in the UK Billboard. The Music Index list omits music genres like "doo-wop" and "Rockability" genres which do not have enough Google searches for the periods under consideration; the paper also excludes the "punk rock" music category as it has no Google searches for long intervals. The finalised index in this article thus includes a final list of 18 genres that have enough Google searches (with no long intervals of zero searches) to construct a music genre SVI used to construct a novel music genre search index (the Music Index).

To build the Music Index, this paper follows steps similar to those taken by Da, Engelberg and Gao (2015) who constructed the FEARS index with some deviations from the aforementioned paper, and some modifications. First, Da, Engelberg and Gao (2015) used positive or negative economic words from a financial dictionary to decide which search terms to download from Google, and then proceeded to use only negative search terms. This paper uses all available music genre SVI from (Prechter, 1999) and UK Billboard, making no assumptions about the positive or negative connotation of a music genre and its impact on affect/mood state. Instead of winsorising and removing intra-day/week effects like Da, Engelberg and Gao (2015), this paper uses daily and monthly dummies to control for well known anomalies such as the “day of the week” and the “January effect” in FTSE data. Index specific dummies are used for each of the FTSE time series data which have outliers. Further, while Da, Engelberg and Gao (2015) used 30 financial or economic search terms with smallest *t*-statistic from regression of returns on adjusted SVI out of 118 search terms (which is about 25% of available search terms), this paper uses top/bottom 3 *t*-statistic of index returns on the music genre SVI rate of change, which accounts to 33.33% (6 out of 18) of music genre search terms. Da, Engelberg and Gao (2015) construct the FEARS index using a dynamic list of 30 Economic SVI by averaging dynamic 30 search terms using the most recent six months; on the other hand this paper adopts a static list for each financial index of music genre search-terms for index specific Music Index (Appendix A3.1 provides a sample of the static list containing the top and bottom 3 music genre searches *t*-statistic for FTSE 100 returns and trading volume rate of change). The study by Da, Engelberg and Gao (2015) uses ‘Aruoba-Diebold-Scotti Business Conditions Index’ (Aruoba, Diebold and Scotti, 2008) to capture actual business activities in the US. However, since there is no UK equivalent, this paper only utilizes news-based Economic Policy Uncertainty (EPU) (Baker, Bloom and Davis, 2016) in regression estimations as a control variable in order to capture UK news about fundamenatls that is expected to move financial markets. The choice of top (smallest) or bottom (largest) for each index (like FTSE100, and FTSEAIM) in this paper is from smallest to largest *t*-statistic, and both are used to create the Music Index. The Music Index construction shown below is akin to ‘Debt to Equity ratio’ and it has the benefit of including the smallest and the largest *t*-statistic rather than just focussing on only the smallest or largest. This study considers the level and then rate of change of two Music Index, using the specifications below:

Music Index uses top/bottom three t-statistics

(sum of bottom three music SVI) ***/*** (sum of top three music SVI)

Second specifiaction in the appendix that uses top/bottom one t-statistic

(bottom music SVI) / (top music SVI)

In line with in Da, Engelberg and Gao (2015), this study employs a linear form for regressions where the Music Index level or the Music Index rate of change is the independent variable, and FTSE index returns, or trading volume rate of change are dependent variables in OLS regressions. The dependent variables also include autoregressive lagged variables that are determined by information criteria minimisation, and an addition of Economic Policy Uncertainty (EPU). Dummies are used in regressions in order to account for not only index-specific outliers in the times series, but also to take into account commonly known effects such as ‘day of the week’ for daily data (Dubois and Louvet, 1996; Berument and Kiymaz, 2001) and January-effect for monthly data (Haug and Hirschey, 2006). Like in Da, Engelberg and Gao (2015), here ‘fundamentals’ control variable include Economic Policy Uncertaint (EPU) but not The Aruoba-Diebold-Scotti business conditions index which is available for the US but not the UK. To ensure estimated regressions are Best Linear Unbiased Estimator (BLUE), heteroscedasticity tests for residuals are conducted using Whites' heteroscedasticity test; any evidence of heteroscedasticity necessitates the use of Huber-White-Hinckley’s ‘heteroscedasticity consistent standard error’ regression in order to increase standard errors of the explanatory variables (Brooks, 2019) and make correct inferences from regression output. Autocorrelation is tested using Breusch-Godfrey method and regressions whose residuals have autocorrelation, Bartlett kernel Newey-West’s ‘Heteroskedasticity and Autocorrelation Consistent’ (HAC) regressions is used; Gauss-Newton’s ‘Generalised Least Squares’ (GLS) is used for daily data as autocorrelation is persistent in estimated regressions.

From the aforementioned investor sentiment literature, the impact of social mood is expected to temporarily impact (retail) investor sentiment; and reversal in the sign of the Music Index coefficients is expected to change in lagged Music Index coefficients after social mood changes and is reflected in financial markets. From the construction of the indexes, there is an expectation for the Music Index level and returns to be positive (higher) and then negative (lower); in other words, there is an expectation of positive contemporaneous coefficient on the Music Index when FTSE index returns is regressed on the Music Index. The positive contemporaneous coefficient is expected to turn negative when current social mood is wearing off when lagged Music Index is used. Tables 3.2 to 3.7 shows descriptive statistics of the daily and monthly variables used in this paper.

Null and alternative hypothesis:

> H_0: Music index=0; Music Index is not significantly different from zero. Music Index does not explain changes in LSE activity.
>
> H_1: SVI ≠ 0; Music Index is significantly different from zero. Music Index explain changes in LSE activity.

$R_t = \beta_0 + \beta_1 EPU + \beta_2 dummy_t + \beta_3 R_{t-i} + \beta_4 MusicIndex_{t-i} + e_t$

> where
>
> R_t is the FTSE return or trading volume rate of change of LSE at time t
>
> β_0 is the constant
>
> EPU is economic policy uncertainty
>
> $dummy_t$ is a dummy at time t, these are two FTSE index specific: the dummies like ‘January effect’ dummy takes the value of 1 for January and 0 for other months for monthly data, and ‘day of the week effect’ for daily return estimations where dummies take value of 1 for Wednesdays and Mondays and 0 for the rest of the days (for trading volume rate of change estimations,

daily dummies take value of 1 for Fridays and Wednesdays, and 0 for the rest of the days).

R_{t-i} are lagged terms at time t-i, where i can have values of 1, 2, 3… The lag length is determined using information criteria.

Music $Index_{t-i}$ is Music Index level or rate of change at time t-i for a particular index, where i can take the values of 1, 2, 3…

e_t is the error term

Null and alternative hypotheses:

H_0: $\beta_4=0$ or the Music Index is not significantly different from zero. This implies the Music Index does not explain changes in the FTSE.

H_1: $\beta_4 \neq 0$ or the Music Index is significantly different from zero. The Music Index can explain changes in the FTSE

[Insert Tables 3.2, 3.3, 3.4, 3.5, 3.6 and 3.7 around here]

3.4. Results

3.4.1. FTSE monthly returns and Music Index level

Table 3.8 presents the results of regressing FTSE 100 and 250 monthly returns on the Music Index level. Using FTSE100 and FTSE250 returns as dependent variables in OLS regressions, contemporaneous Music Index level coefficients are positively significance at 5% and 10% level. Lagged Index level are negatively significant at 5%

and 10% level. The estimated coefficients mean that an increase in the Music Index level of 1 leads the FTSE100 returns to an increase of 8.13% in the same month, and a decrease in the following month’s FTSE 100 return by 8.96%. Further, an increase in the Music Index level of 1 lead to the FTSE250 return increasing by 6.16% in same month, and to FTSE250 returns decreasing by 6.60% in the following month. The implication here is that the Music Index level captures mood in society using Google music genre searches as expected, whereby peoples’ choice of music is influenced by how they feel (cognitivism) and listening to music maintains or leads to a certain desired mood (emotivism) (Kostopoulos and Meyer, 2018). The sign of the coefficients is what is expected due to the way the Music Index level is constructed. This positive contemporaneous mood is then followed by reversion. The positive contemporaneous and subsequent negative coefficients of the Index is what is expected based on the construction of the Index, similar to findings from the study by Da, Engelberg and Gao (2015) in the context of the reversal of sign of coefficient.

Table 3.9 presents results of regressing FTSE AIM returns on the Index level. Using FTSE AIM monthly returns as independent variable in OLS regression, the coefficients on the Music Index level is positively significant at 10% level. Lagged coefficient of the Music Index level is not significant. This means an increase in the Index level of 1 lead to an increase in FTSE AIM returns of 9.43% in the same month. This implies that the Music Index captures mood management in its application, as mood affects choice of music according to cognitivism, and then there is a maintenance of current mood or change of mood as a result of listening to music in agreement with emotivism (Kostopoulos and Meyer, 2018). The results here are partly what is expected based from the construction of the Index and what was found by Da, Engelberg and Gao (2015) in terms of having a positive contemporaneous coefficient on the Index level; however, what is not expected is the lagged Index level not being significant.

[Insert Tables 3.8 and 3.9 around here]

3.4.2. FTSE daily returns and Music index level

Table 3.10 shows the results of regressing FTSE 100 daily returns on the Music Index Level. Using FTSE 100 daily returns as an independent variable in OLS regression, the coefficient of the Music Index level is positively significant at 5% level. This means that when the Music Index level increases by 1, FTSE 100 daily returns are expected to increase by 0.10%. This implies that the daily Index level captures the process of mood management in the UK like in the monthly Music Index, but here there is no reversal of sign of lagged coefficient, as the lagged Music Level coefficient is not significant. This is partially what is expected from the construction of the Index in terms of positive coefficient of the contemporaneous Music Level, but the coefficient of the lagged Music Index level was not expected to be insignificant.

Based on the construction of the FEARS Index (Da, Engelberg and Gao, 2015), the search-terms used were changed every 6 months, whilst the Music Index Level constituents remained the same throughout the periods under study. This could explain the difference in the sign of Music Level coefficients when monthly regressions results are compared to daily regression results in Tables 3.8, 3.9 and 3.10. Baker and Wurgler (2007) found that ‘smaller’ indexes were more susceptible to non-rational influences than larger indexes; and results in Table 3.8 and 3.9 party show this using monthly data when FTSE returns are regressed on the Music Index level. The FTSE AIM returns yield significantly positive coefficients that are larger in magnitude compared to those estimating FTSE 100 and FTSE 250 returns regressions.

3.4.3. FTSE monthly trading volume rate of change and Music Index level

Table 3.11 presents the results of regressing the FTSE monthly trading volume rate of change (trading volume hereafter) on the Music Index Level. Using FTSE 100 and FTSE 250 monthly trading volumes as dependent variables in OLS regressions, the coefficients on the contemporaneous Music Index level are positively significant at 1%, and the lagged Music Index level coefficients are negatively significant at 1% significance level. This means that an increase in the Music Index level of 1 leads FTSE 100 and FTSE 250 trading volumes in the same month to change by 42.70% and 30.50% respectively, which is followed by a decrease in the subsequent month trading volume by 50.02% (FTSE 100) and 43.79% (FTSE 250). This implies that the Music Index is able to capture positive mood using Google music genre searches – and is then followed by a reversion of trading volume in the following month. The findings here are consistent with Kostopoulos and Meyer (2018) who found that retail investors engaged with a positive mood purchase more securities, as reflected in a contemporaneous increase in trading volume followed by reversion. The reversion of sign of the Music Index level coefficient from positive to negative is what is expected due to the way the Index is constructed, and analogous to findings stemming from research by Da, Engelberg and Gao (2015).The positive contemporaneous and subsequent negative coefficients of Index is what is expected based on the construction of the Index. The Music level Index captures mood management as the Index level is significant.

[Insert Table 3.11 and 3.12 around here]

3.4.4. FTSE daily trading volume rate of change and Music Index level

Table 3.12 presents results of regressing FTSE 250 daily trading volume on the Index level. When using FTSE 250 as a dependent variable in OLS regression, the coefficient on contemporaneous Music Index is positive, and lagged is negative at 5% significance level. This means that an increase in the Music Index Level of 1 lead to the same day increase in trading volume of 0.37%, and a following day decrease in trading volume of 0.37%. Surprisingly, when the FTSE 100 trading volume is used as a dependent variable in OLS regression, the Music Index Level is not significant. This implies that mood management is reflected in the Music Index Level as peoples' music genre searches are significant – which is reflected in a change of FTSE 250 daily trading volume, but not in the FTSE 100 trading volume. The results indicate that the Music Index Level is able to capture the influence of social mood on FTSE 250 trading volume, but not FTSE 100. These daily results are what is expected from the sentiment literature (see Baker and Wurgler, 2007) suggesting that 'smaller' indexes like FTSE 250 are more prone to (retail) investor sentiment compared to larger indexes such as FTSE 100.

When comparing coefficients on monthly and daily regressions, coefficients on the Music Index level using monthly OLS regressions are significant when FTSE 100 and FTSE 250 trading volume are dependent variables. Conversely, the coefficient on the daily Music Index level is significant when the daily FTSE 250 trading volume is the dependent variable. These results are consistent with Da, Engelberg and

Gao’s study (2015) as there is a change in sign of coefficient for monthly data, and the Index coefficient is not significant when regressed on FTSE 100 trading volume.

3.4.5. FTSE monthly returns and Music Index rate of change

Table 3.13 presents the results of regressing FTSE monthly returns on the Index rate of change (the Music Index). Using FTSE 100 and FTSE 250 returns as dependent variables in OLS regression, the coefficients on contemporaneous Music Index are positively significant at 5% and 10% level. This means that for every 1% increase in Music Index, there is a 0.08% and 0.06% increase in FTSE 100 and FTSE 250 returns, respectively. This implies that the Music Index captures the application of mood management as peoples’ choice of music is influenced by their current mood in line with cognitivism; further, the post-music listening mood is shown to be influenced by the music choice, in agreement with emotivism. In terms of contemporaneous coefficients, this is what is expected from the construction of the Music Index and shows that the monthly Index is significant when FTSE 100 and FTSE 250 are regressed on Index. In this case, the results in Table 3.13 differ from Da, Engelberg and Gao, (2015) as Music Index lagged variables are not significant.

[Insert Table 3.13 and 3.14 around here]

3.4.6. FTSE daily return and Index Music rate of change

Table 3.14 presents the results of FTSE FTSE100 daily returns regressed on the Music Index. Using FTSE 100 daily returns as a dependent variable in OLS regressions, the coefficient on the Music Index is positively significant at 5% level. This means a 1% daily increase in the Music Index leads to a 0.0006% increase in

FTSE 100 returns. The implication is that even though the coefficient is statistically significant, it is economically insignificant as it is small. Surprisingly, the Music Index is significant when the FTSE 100 is a dependent variable, but not significant when the FTSE 250 is a dependent variable. This result is contrary to what is expected from Baker and Wurgler, (2007) who found that smaller indexes are more likely to be influenced by non-rational factors than larger index/companies.

3.4.7. FTSE monthly trading volume rate of change and Music Index rate of change

Table 3.15 presents the results of regressing the FTSE monthly trading volume rate of change on the Music Index. Using FTSE 100 and FTSE 250 trading volumes as dependent variables in OLS regressions, the coefficients on the contemporaneous Music Index are positive and statistically significant at 1% level. Coefficients on the lagged Music Index are positively significant at 5% and 10% significance level for FTSE 100 and FTSE 250 respectively. This means that for a 1% increase in the Music Index, there is a contemporaneous increase of 0.51% and 0.43% in the same month for the FTSE 100 and FTSE 250 trading volumes, respectively. Also, a 1% increase in the Music Index during the previous month leads to an increase of 0.47% (FTSE100) and 0.28% (FTSE 250) in the current month trading volume. The sign of coefficient on the contemporaneous Music Index is what is expected based on the construction of the Index, but the sign of coefficient on the lagged Music Index is not expected, as a change of sign from positive to negative is expected based on the construction of the FEARS index as indicated by Da, Engelberg and Gao (2015). The implication here is that the Music Index captures some element of societal mood, as positive mood is expected to increase trading volume, in agreement with Kostopoulos and Meyer (2018). Contrary to what is expected, a positive lagged coefficient suggests that the mood captured does not dissipate within two months in relation to the FTSE100 and FTSE 250 trading volumes, which is not what is expected based on research conducted by Da, Engelberg and Gao (2015).

[Insert Table 3.15 and 3.16 around here]

3.4.8. FTSE daily trading volume rate of change and Music Index rate of change

Table 3.16 presents the results of regressing the FTSE 100 and FTSE 250 daily trading volumes rate of change. Using FTSE 250 as a dependent variable in OLS regression, the coefficients on the Music Index are positively significant at 10% level. This means that a 1% increase in the Index leads to the same day increase of two basis points. This is what is expected from the Index construction, but there is no change in sign of coefficient for lagged Music Index variables. This implies that the daily Music Index captures contemporaneous mood, and there is evidence of implementation of mood management. The results here differ from research by Da, Engelberg and Gao (2015) as the coefficient of the lagged Music Index is not significant and positive. Conversely, using FTSE 100 as an independent variable in OLS regression, results in the coefficient on the lagged Music Index being negatively significant at 10% level. This means that an increase of 1% in daily Music Index leads to a reduction of 5 basis points in the FTSE 100 trading volume during the following days. This result is expected based on the way the Music Index was constructed, and shows partial similarity to Da, Engelberg and Gao's results (2015) in terms of change in sign of the coefficient of lagged variables.

3.5. Robustness of the findings

The results discussed in sections 3.4.1 to 3.4.8 are robust when there is a change of frequency of data; there are significant coefficients of the Music Index level and Music Index rate of change when daily and monthly frequency data are used. The aforementioned results are further complemented by three more specifications to ensure robustness of the findings. The first is to reduce the genre of music searches that are used to construct the Index from the top and bottom three, to construct an alternative monthly and daily Music Search Index which uses the top and bottom music genre searches. Descriptive statistics for this specification are in A3.2 to A3.5, and regression results are in A3.6 and A3.11. These results are the same as what is expected from the aforementioned results, but with fewer significant coefficients.

The second specification involves using the Music Index (using the top-bottom three and top-bottom one) for one financial index on other financial indexes. For example, regressing the FTSE 250 returns, FTSE AIM All Share returns, FTSE 100 and FTSE 250 trading volume rates of change on the Music Index constructed for the FTSE 100 returns (LFTSE100IINDEX3). These results are shown in Appendix A3.12 to A3.17 and replicate results in the aforementioned results sections, thus showing robustness and consistency. Interestingly, the inverse relationship between stock returns and trading volume rate of change is illustrated when Table 3.10 is compared to A3.16, and Table 3.14 is compared to A3.14.

The last specification entails using individual music genre searchers as regressors when FTSE AIM All Share returns, FTSE 100 returns, FTSE 250 returns and trading volumes are dependent variables[5].

3.6. Conclusion

This paper extends the field of Behavioural Finance by creating a new Music Genre Index based on the method that was used to create the FEARS Index. The results are obtained using daily and monthly OLS regressions whereby the Music Index level and the Music Index rate of change are used as dependent variables. This study assumes that social mood is transmitted consciously and/or subconsciously through mood contagion in UK society, and eventually to (retail) investors. This is reflected by the significant coefficients in the Music Index in OLS regressions.

The implications of the results are that this research finds evidence of social mood affecting FTSE returns and FTSE trading volume rate of change. The paper captures elements of mood management as searches of music genres are influenced by individual and social mood in line with cognitivism, and there is a change or extension in mood once music is listened to, as expected in emotivism. This paper further extends understandings of proxies of social mood as it challenges the notion that music searches are not supposed to have a relationship with stock market returns or trading volume based on rational-investor models. Furthermore, this paper extends field of Behavioural Finance by bridging the music-mood and the Google-search streams of research together through the development of a new

[5] These results are not in Appendix but can be shared show that individual music searchers are significant when used as independent variables and when used as dependent variables in the OLS regression.

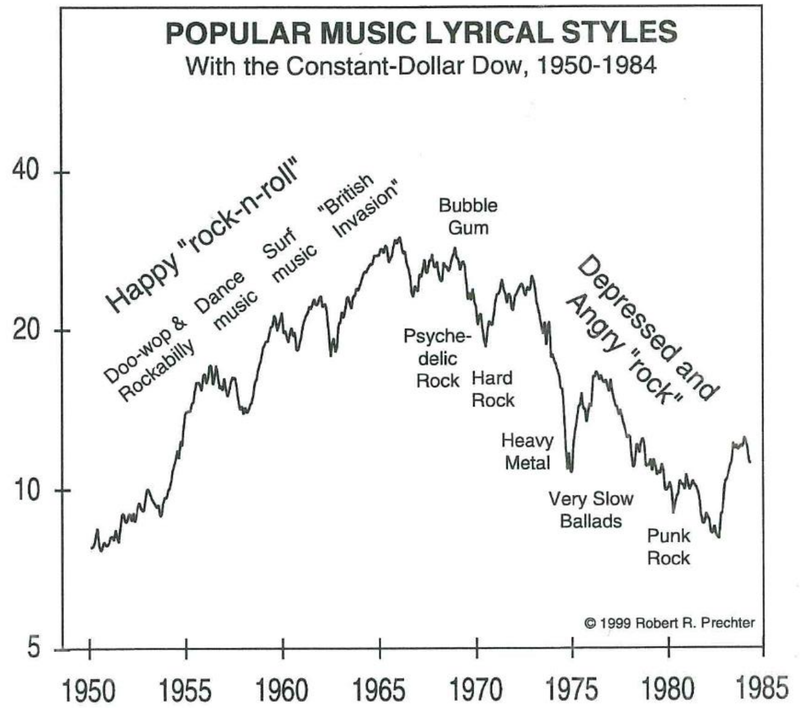
Music-search Index. This adds a new continuous way of using a proxy social mood that is easily available on a weekly basis and provides data that is less susceptible to lag times.

In terms of limitations, by focussing on the UK context, this paper does not consider the effect of social mood in other countries, which may impact stock returns and trading volume worldwide as LSE is a global financial market. There is also a large proportion of trade that is done through artificial intelligence or algorithmic trading which is not initially influence by mood; however, programming, training data set and trading parameters have been set under certain mood and bias of code-writers.

Further areas for future exploration could focus on adding music search proxies to improve daily and monthly forecast, or nowcast models. A “unified music-social mood model” which combines the individual music searches into one could also be another interesting area for future research development.

Figure 3.1 Popular music and Dow Jones Index

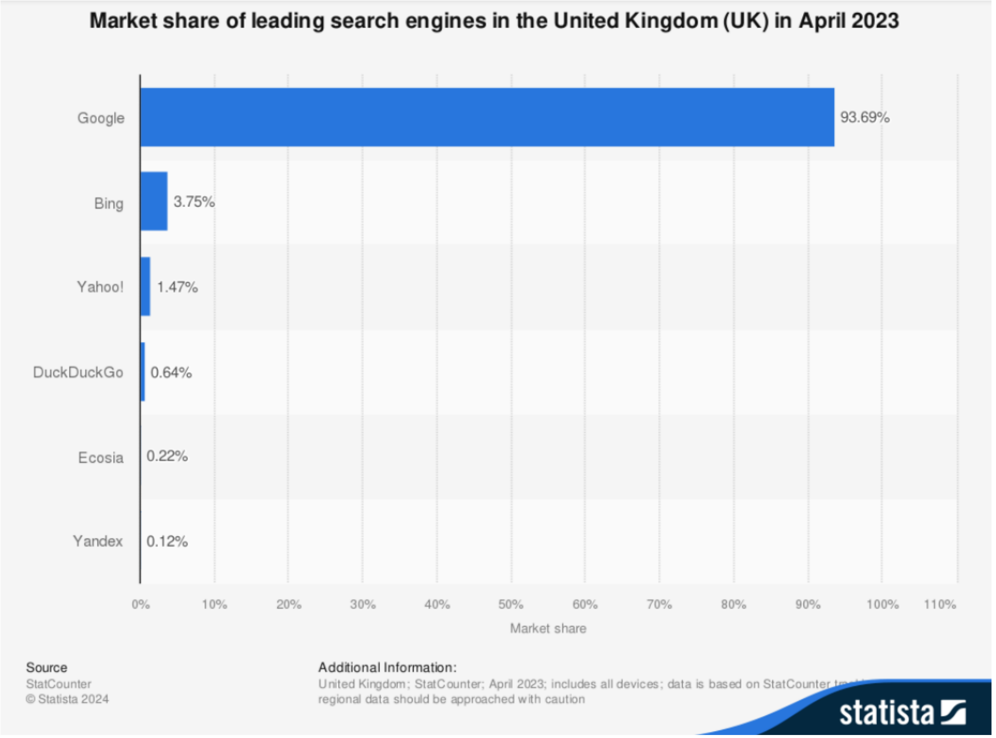
This figure illustrates popular music trends against constant-Dollar Dow from 1950 to 1984 (Prechter, 1999)



It can be observed that more upbeat happy rock-n-roll was popular during times when Dow Jones was in an upward trend and depressed and angry rock was popular when Dow Jones was in a downward trend.

Figure 3.2 UK search engine market share

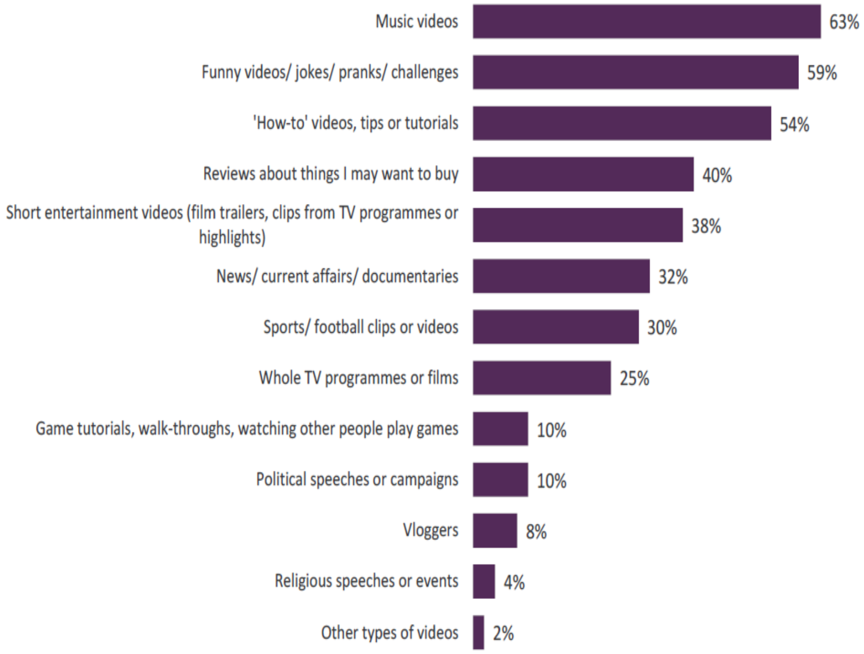
This figure illustrates the market share of search engines in the UK (Statista, 2023)



It can be observed that Google has the highest market share of all search engines in the UK and Bing is a distant second.

Figure 3.3 Content watched in UK using websites.

Type of content watched on video sharing websites (OFCOM, 2018)



Source: Ofcom Adults' Media Literacy Tracker 2017
IN19B. And what types of videos do you tend to watch on these sites or apps? (prompted responses, multi-coded)
Base: All aged 16+ who ever watch content on video sharing sites (1161 in 2017)

Music videos are the most popular content that is watched on video sharing websites at 63%, this is followed closely by funny videos and then 'how-to' videos.

Table 3.1 Relationship between music and mood

Music characteristics with mood from Hevner, (1937)

Musical element	**dignified/ solemn**	**sad/ heavy**	**dreamy/ sentimental**	**serene/ gentle**
Mode	major 4	minor 20	minor 12	major 3
Tempo	slow 14	slow 12	slow 16	slow 20
Pitch	low 10	low 19	high 6	high 8
Rhythm	firm 18	firm 3	flowing 9	flowing 2
Harmony	simple 3	complex 7	simple 4	simple 10
Melody	ascend 4	–	–	ascend 3
	graceful/ sparkling	**happy/ bright**	**exciting/ elated**	**vigorous/ majestic**
Mode	major 21	major 24	–	–
Tempo	fast 6	fast 20	fast 21	fast 6
Pitch	high 16	high 6	low 9	low 13
Rhythm	flowing 8	flowing 10	firm 2	firm 10
Harmony	simple 12	simple 16	complex 14	complex 8
Melody	descend 3	–	descend 7	descend 8

This table shows the music characteristics with the type of mood that is supposed to elicit.

Table 3.2 Descriptive stats for monthly dependent from June 2006 to May 2018

	RFTSE100PI	RFTSE250PI	RFTSEAIMPI	RCFTSE100VO	RCFTSE250VO
Mean	0.327467	0.704094	0.234972	1.990954	1.830291
Median	0.734179	0.801372	0.256912	-2.559108	-1.239735
Maximum	11.77247	15.36444	16.68509	76.41679	73.85775
Minimum	-21.60936	-22.9813	-30.04919	-41.09826	-50.91335
Std. Dev.	4.604841	4.880771	5.73924	24.57223	22.37827
Skewness	-0.937595	-0.778208	-1.098813	1.031934	0.884266
Kurtosis	5.792563	6.664001	7.985555	4.080581	4.31841
Jarque-Bera	66.94557	93.76339	175.6381	32.11096	28.78997
Probability	0	0	0	0	0.000001
Sum	46.50036	99.98142	33.36597	282.7154	259.9013
Sum Sq. Dev.	2989.843	3358.892	4644.381	85134.99	70610.98
Observations	142	142	142	142	142

RFTSE100PI is returns of FTSE100 index, RFTSE250PI is returns of FTSE 250 index, RFTSEAIMPI is returns of FTSE AIM100 index, RCFTSE100VO is rate of change of FTSE100 monthly trading volume, and RCFTSE250VO is rate of change of FTSE250 monthly trading volume.

Table 3.3 Descriptive stats for monthly music index level from June 2006 to May 2018

	LFTSE100INDEX3	LFTSE250INDEX3	LAIMINDEX3	LFTSE100VOINDEX3	LFTSE250VOINDEX3
Mean	0.816055	1.000421	1.05564	0.974224	1.051249
Median	0.809242	0.993711	1.049383	0.952512	1.015998
Maximum	1.188482	1.434524	1.478528	1.435583	1.583333
Minimum	0.625668	0.709544	0.798969	0.682243	0.722772
Std. Dev.	0.109559	0.144701	0.107045	0.146019	0.1862
Skewness	0.529041	0.476577	0.364476	0.541177	0.719233
Kurtosis	3.227076	2.955284	4.170698	2.878727	3.129134
Jarque-Bera	7.026601	5.46301	11.41143	7.117176	12.51516
Probability	0.029798	0.065121	0.003327	0.028479	0.001916
Sum	117.5119	144.0606	152.0122	140.2882	151.3799
Sum Sq. Dev.	1.716454	2.994207	1.638599	3.048985	4.95785
Observations	144	144	144	144	144

LFTSE100INDEX3 is FTSE100 Music Index level, LFTSE250INDEX3 is FTSE250 Music Index level, LAIMINDEX3 is FTSE AIM Music Index level, LFTSE100VOINDEX3 is FTSE100 trading volume Music level, and LFTSE250VOINDEX3 is FTSE250 trading volume level.

Table 3.4 Descriptive stats for monthly music rate of change from June 2006 to May 2018

	RCFTSE100INDEX3	RCFTSE250INDEX3	RCAIMINDEX3	RCFTSE100VOINDEX3	RCFTSE250VOINDEX3
Mean	0.388148	0.364956	0.539146	0.626049	0.963036
Median	-2.3965	-0.678791	-0.102916	1.247222	0.640301
Maximum	40.33484	42.54934	31.14587	47.12352	44.31354
Minimum	-29.16042	-27.48605	-26.55893	-29.24464	-34.04317
Std. Dev.	12.17834	11.62356	11.23124	11.36135	13.51287
Skewness	0.644889	0.533582	0.236469	0.153935	0.002912
Kurtosis	3.773022	3.969337	3.206446	4.318275	3.139618
Jarque-Bera	13.47234	12.38412	1.586643	10.91943	0.11635
Probability	0.001187	0.002046	0.45234	0.004255	0.943485
Sum	55.50514	52.18874	77.09783	89.52496	137.7142
Sum Sq. Dev.	21060.29	19185.22	17912	18329.41	25928.87
Observations	143	143	143	143	143

RCFTSE100INDEX3 is FTSE100 Music Index rate of change, RCFTSE250INDEX3 is FTSE250 Music Index rate of change, RCAIMINDEX3 is FTSE AIM Music Index rate of change, RCFTSE100VOINDEX3 is FTSE100 trading volume rate of change, and RCFTSE250VOINDEX3 is FTSE250 trading volume rate of change.

Table 3.5 Descriptive stats for daily dependent variables from 01 January 2005 to 31 December 2019

	RFTSE100PI	RFTSE250PI	RFTSEAIMALLSHAREPI	RCFTSE100TVOL	RCFTSE250TVOL
Mean	0.009882	0.025225	-0.006971	-0.341748	0.023925
Median	0.011699	0.045936	0.06648	-0.78043	-0.690777
Maximum	9.838771	8.370692	5.941042	323.6078	376.4724
Minimum	-10.87446	-9.353414	-10.50615	-100	-100
Std. Dev.	1.137569	1.112075	0.82775	30.6382	31.15027
Skewness	-0.203003	-0.47161	-1.983531	0.255727	0.696984
Kurtosis	14.34237	10.45751	19.76849	10.0859	13.83693
Jarque-Bera	21329.48	9356.138	49164.99	8081.764	19150.88
Probability	0	0	0	0	0
Sum	39.27038	100.2439	-27.70371	-1313.336	92.11087
Sum Sq. Dev.	5141.315	4913.453	2722.18	3606483	3734837
Observations	3974	3974	3974	3843	3850

RFTSE100PI is returns of FTSE100 index, RFTSE250PI is returns of FTSE 250 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM All Share index, RCFTSE100TVOL is rate of change of FTSE100 daily trading volume, and RCFTSE250TVOL is rate of change of FTSE250 daily trading volume.

Table 3.6 Descriptive stats for daily Music Index level from 01 January 2005 to 31 December 2019

	LFTSE100INDEX3	LFTSE250INDEX3	LAIMALLSHAREINDEX3	LFTSE100VOINDEX3	LFTSE250VOINDEX3
Mean	1.141743	0.892962	3.416647	1.543212	1.869701
Median	1.078947	0.853659	2.75	1.484848	1.833333
Maximum	4.714286	7.333333	54	4.580645	5.263158
Minimum	0.19	0.183099	0.19	0	0.448276
Std. Dev.	0.331009	0.263524	3.370363	0.410941	0.449066
Skewness	1.880978	5.032668	6.259127	1.099671	0.74615
Kurtosis	11.83536	98.09924	57.26209	5.912928	4.611076
Jarque-Bera	15269.41	1513908	512970.5	2205.943	798.5295
Probability	0	0	0	0	0
Sum	4537.286	3547.736	13564.09	6132.723	7430.19
Sum Sq. Dev.	435.3104	275.836	45085.25	670.9313	801.1955
Observations	3974	3973	3970	3974	3974

LFTSE100INDEX3 is FTSE100 Music Index level, LFTSE250INDEX3 is FTSE250 Music Index level, LAIMINDEX3 is FTSE AIM Music Index level, LAIMALLSHAREINDEX3 is FTSE AIM All Share Music Index level, LFTSE100VOINDEX3 is FTSE100 trading volume Music level, and LFTSE250VOINDEX3 is FTSE250 trading volume level.

Table 3.7 Descriptive stats for daily Music Index rate of change from 01 January 2005 to 31 December 2019

	RCFTSE100INDEX3	RCFTSE250INDEX3	RCAIMALLSHAREINDEX3	RCFTSE100VOINDEX3	RCFTSE250VOINDEX3
Mean	5.934192	5.71565	41.53008	3.285526	2.386664
Median	-0.159983	0	0	0.391134	0.026455
Maximum	395.5466	596.3462	3745.455	241.4141	208.1707
Minimum	-83.96875	-80.90035	-98.61516	-100	-73.10345
Std. Dev.	39.81933	39.45699	214.5322	27.6233	22.91343
Skewness	2.635938	3.450924	7.851935	1.571326	1.284644
Kurtosis	18.29837	34.11754	82.36639	9.887048	8.32763
Jarque-Bera	43333.32	168052.9	1081394	9482.035	5789.997
Probability	0	0	0	0	0
Sum	23570.61	22691.13	164666.8	13046.82	9479.829
Sum Sq. Dev.	6296334	6179153	1.82E+08	3029296	2084876
Observations	3972	3970	3965	3971	3972

RCFTSE100INDEX3 is FTSE100 Music Index rate of change, RCFTSE250INDEX3 is FTSE250 Music Index rate of change, RCAIMALLSHAREINDEX3 is FTSE AIM All Share Music rate of change, RCFTSE100VOINDEX3 is FTSE100 trading volume rate of change, and RCFTSE250VOINDEX3 is FTSE250 trading volume rate of change.

Table 3.8 FTSE monthly returns and Index 3 level from June 2006 to May 2018

Dep. Var:	RFTSE100PI		Dep. Var:	RFTSE250PI
C	0.9707		C	1.2695
	(2.9836)			(2.9145)
REPU	0.018		REPU	-0.0045
	(0.0119)			(0.0128)
DUMMYJANUARY	1.5638		DUMMYJANUARY	0.8848
	(1.2616)			(1.3956)
DUMMYFTSE100PI2008M10	-21.1313***		DUMMYFTSE250PI2008M10	-22.4694***
	(4.2199)			(4.5559)
LFTSE100INDEX3	8.1273**		LFTSE250INDEX3	6.1568*
	(3.8803)			(3.5482)
LFTSE100INDEX3(-1)	-8.955**		LFTSE250INDEX3(-1)	-6.6037*
	(3.9123)			(3.5249)
Observations:	142		Observations:	142
R-squared:	0.2185		R-squared:	0.2009
F-statistic:	7.6065		F-statistic:	6.8372
Prob(F-stat):	0		Prob(F-stat):	0

This table presents OLS regression results of FTSE returns on Index 3 level. Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE100PI is returns of FTSE100 index, RFTSE250PI is returns of FTSE 250 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is 'January effect' dummy for monthly estimations, DUMMYFTSE100PI2008M10 is FTSE100 index specific dummy, DUMMYFTSE250PI2008M10 is FTSE250 index specific dummy, LFTSE100INDEX3 is FTSE100 Music Index level, and LFTSE250INDEX3 is FTSE250 Music Index level.

Table 3.9 FTSE AIM monthly returns and Index 3 level from June 2006 to May 2018

Dep. Var:	RFTSEAIMPI
C	-6.3163
	(4.573)
REPU	-0.0038
	(0.0108)
DUMMYJANUARY	4.2042***
	(1.5281)
DUMMYFTSEAIMPI2008M10	-26.58***
	(1.7213)
RFTSEAIMPI(-1)	0.243**
	(0.1090)
LAIMINDEX3	9.4331*
	(5.6185)
LAIMINDEX3(-1)	-3.4723
	(5.0857)
Observations:	140
R-squared:	0.3359
F-statistic:	11.212
Prob(F-stat):	0

This table presents OLS regression results of FTSE AIM returns on Index 3 level. Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSEAIMPI is returns of FTSE AIM100 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSEAIMPI2008M10 is FTSE index specific dummy, and LAIMINDEX3 is FTSE AIM Music Index level.

Table 3.10 FTSE 100 daily returns and Index 3 level from 01 January 2005 to 31 December 2019

Dep. Var:	RFTSE100PI
C	-0.0841
	(0.1198)
REPU	0.0000
	(0.0000)
RFTSE100PI(-1)	-1.2436***
	(0.1417)
RFTSE100PI(-2)	-0.8786***
	(0.1781)
RFTSE100PI(-3)	-0.3225***
	(0.1066)
DUMMYDAYRETURN	-0.0100
	(0.0167)
DUMMYDAYVOLATILITY	0.0267
	(0.0166)
DUMMYRFTSE100PI	-1.1219***
	(0.1916)
LFTSE100INDEX3	0.1045**
	(0.0495)
LFTSE100INDEX3(-1)	0.0002
	(0.0518)
Observations:	3950
R-squared:	0.0263
F-statistic:	8.1770
Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE returns on Index 3 level. Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE100PI is returns of FTSE100 index, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSE100PI is FTSE100 index specific dummy for daily estimations, and LFTSE100INDEX3 is FTSE100 Music Index level.

Table 3.11 FTSE monthly trading volume rate of change and Index 3 level from June 2006 to May 2018

Dep. Var:	RCFTSE100VO		Dep. Var:	RCFTSE250VO
C	15.5548**		C	22.126*
	(6.7237)			(11.7188)
REPU	0.0573		REPU	0.0338
	(0.0347)			(0.0309)
DUMMYJANUARY	-31.2503***		DUMMYJANUARY	-25.5004***
	(7.1946)			(7.1049)
RCFTSE100VO(-1)	-0.9049***		DUMMYFTSE250VO2012M01	-20.0504
	(0.1396)			(17.8067)
RCFTSE100VO(-2)	-0.5555***		RCFTSE250VO(-1)	-0.8057***
	(0.1729)			(0.0721)
RCFTSE100VO(-3)	-0.1228		RCFTSE250VO(-2)	-0.6335***
	(0.1091)			(0.0903)
LFTSE100VOINDEX3	42.7012***		RCFTSE250VO(-3)	-0.3368***
	(13.0287)			(0.1097)
LFTSE100VOINDEX3(-1)	-50.0226***		LFTSE250VOINDEX3	30.4976***
	(12.8340)			(11.5420)
Observations:	136		LFTSE250VOINDEX3(-1)	-43.7905***
R-squared:	0.6333			(13.7493)
F-statistic:	17.6996		Observations:	136
Prob(F-stat):	0		R-squared:	0.6351
			F-statistic:	16.3355
			Prob(F-stat):	0

This table presents OLS regression results of FTSE trading volume on Index 3 level.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE100VO is rate of change of FTSE100 monthly trading volume, RCFTSE250VO is rate of change of FTSE250 monthly trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE250VO2012M01 is FTSE250 trading volume index specific dummy, and LFTSE100INDEX3 is FTSE100 Music Index level, and LFTSE250INDEX3 is FTSE250 Music Index level.

Table 3.12 FTSE 250 daily trading volume rate of change and Index 3 level from 01 January 2005 to 31 December 2019

Dep. Var:	RCFTSE250TVOL
C	-12.7241***
	(1.1789)
REPU	0.0002*
	(0.0001)
DUMMYDAYRETURN	7.7866***
	(2.4586)
DUMMYDAYVOLATILITY	24.0577***
	(2.3669)
DUMMYRFTSE250TVOL	0.3776
	(0.4043)
RCFTSE250TVOL(-1)	0.5845***
	(0.0306)
RCFTSE250TVOL(-2)	1.7503***
	(0.0236)
RCFTSE250TVOL(-3)	-1.0231***
	(0.0491)
RCFTSE250TVOL(-4)	-0.7748***
	(0.0221)
RCFTSE250TVOL(-5)	0.4547***
	(0.0241)
LFTSE250TVOINDEX3	0.366**
	(0.1533)
LFTSE250TVOINDEX3(-1)	-0.3704**
	(0.1527)
Observations:	3413
R-squared:	0.3645
F-statistic:	121.713
Prob(F-stat):	0

This table presents OLS regression results of FTSE trading volume rate of change on Index 3 level.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE250TVOL is rate of change of FTSE250 daily trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSE250TVOL is FTSE250 trading volume index specific dummy, and LFTSE250INDEX3 is FTSE250 Music Index level.

Table 3.13 FTSE monthly returns, and Index 3 rate of change from June 2006 to May 2018

Dep. Var:	RFTSE100PI		Dep. Var:	RFTSE250PI
C	0.1869		C	0.7629*
	(0.3834)			(0.4262)
REPU	0.0208		REPU	-0.0025
	(0.0123)			(0.0103)
DUMMYJANUARY	1.5980		DUMMYJANUARY	0.9383
	(1.2805)			(1.4183)
DUMMYFTSE100PI2008M10	-20.8579***		DUMMYFTSE250PI2008M10	-22.1885***
	(4.3524)			(1.1182)
RCFTSE100INDEX3	0.0791**		RCFTSE250INDEX3	0.0622*
	(0.0327)			(0.0340)
RCFTSE100INDEX3(-1)	0.0188		RCFTSE250INDEX3(-1)	0.0108
	(0.0363)			(0.0325)
RCFTSE100INDEX3(-2)	-0.0123		RCFTSE250INDEX3(-2)	-0.0457
	(0.0371)			(0.0406)
RCFTSE100INDEX3(-3)	0.0018		Observations:	140
	(0.0330)		R-squared:	0.2151
Observations:	139		F-statistic:	6.0745
R-squared:	0.2263		Prob(F-stat):	0.0000
F-statistic:	5.4751			
Prob(F-stat):	0.0000			

This table presents OLS regression results of FTSE returns on Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. RFTSE100PI is returns of FTSE100 index, RFTSE250PI is returns of FTSE 250 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE100PI2008M10 is FTSE100 index specific dummy, DUMMYFTSE250PI2008M10 is FTSE250 index specific dummy, RCFTSE100INDEX3 is FTSE100 Music Index rate of change, and RCFTSE250INDEX3 is FTSE250 Music Index rate of change.

Table 3.14 FTSE daily returns and Index 3 rate of change from 01 January 2005 to 31 December 2019

Dep. Var:	RFTSE100PI
C	0.0308
	(0.0587)
REPU	0.0000
	(0.0000)
DUMMYDAYRETURN	-0.0107
	(0.0168)
DUMMYDAYVOLATILITY	0.0272
	(0.0168)
DUMMYRFTSE100PI	-1.1165***
	(0.1905)
RFTSE100PI(-1)	-1.2472***
	(0.1398)
RFTSE100PI(-2)	-0.8919***
	(0.1754)
RFTSE100PI(-3)	-0.3333***
	(0.1059)
RCFTSE100INDEX3	0.0006**
	(0.0003)
RCFTSE100INDEX3(-1)	0.0001
	(0.0003)
Observations:	3949
R-squared:	0.0259
F-statistic:	8.0629
Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE returns on Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE100PI is returns of FTSE100 index, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, and RCFTSE100INDEX3 is FTSE100 Music Index rate of change.

Table 3.15 FTSE monthly trading volume rate of change, and Index 3 rate of change from June 2006 to May 2018

Dep. Var:	RCFTSE100VO		Dep. Var:	RCFTSE250VO
C	9.0139***		C	8.6181***
	(1.0983)			(2.6030)
REPU	0.0084		REPU	0.0222
	(0.0320)			(0.0229)
DUMMYJANUARY	-27.8208***		DUMMYJANUARY	-26.4823***
	(4.8605)			(5.9676)
RCFTSE100VO(-1)	-1.1875***		DUMMYFTSE250VO2012M01	-17.7010
	(0.1485)			(16.4631)
RCFTSE100VO(-2)	-0.7018***		RCFTSE250VO(-1)	-1.0001***
	(0.1877)			(0.0829)
RCFTSE100VO(-3)	-0.2045*		RCFTSE250VO(-2)	-0.7660***
	(0.1041)			(0.0899)
RCFTSE100VOINDEX3	0.5108***		RCFTSE250VO(-3)	-0.4705***
	(0.1316)			(0.1012)
RCFTSE100VOINDEX3(-1)	0.4728**		RCFTSE250VOINDEX3	0.4292***
	(0.1962)			(0.1329)
RCFTSE100VOINDEX3(-2)	-0.0466		RCFTSE250VOINDEX3(-1)	0.2805*
	(0.1998)			(0.1465)
RCFTSE100VOINDEX3(-3)	0.0029		RCFTSE250VOINDEX3(-2)	0.0212
	(0.1428)			(0.1344)
Observations:	136		RCFTSE250VOINDEX3(-3)	0.0931
R-squared:	0.6633			(0.1159)
F-statistic:	18.4918		Observations:	136
Prob(F-stat):	0.0000		R-squared:	0.6506
			F-statistic:	14.8990
			Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE trading volume rate of change on Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE100VO is rate of change of FTSE100 monthly trading volume, RCFTSE250VO is rate of change of FTSE250 monthly trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is 'January effect' dummy for monthly estimations, DUMMYFTSE250VO2012M01 is FTSE250 trading volume index specific dummy, RCFTSE100INDEX3 is FTSE100 Music Index rate of change, and RCFTSE250INDEX3 is FTSE250 Music Index rate of change.

Table 3.16 FTSE daily trading volume rate of change and Index 3 rate of change from 01 January 2005 to 31 December 2019

Dep. Var:	RCFTSE100 TVOL	Dep. Var:	RCFTSE250 TVOL
C	8.2478***	C	4.2091***
	(1.2060)		(1.0226)
REPU	0.0024	REPU	-0.0002
	(0.0027)		(0.0027)
DUMMYDAYRETURN	-18.5086***	DUMMYDAYRETURN	-16.4711***
	(1.2094)		(1.2792)
DUMMYDAYVOLATILITY	10.0237***	DUMMYDAYVOLATILITY	15.9981***
	(1.5436)		(1.2344)
DUMMYRFTSE100TVOL	121.6504***	DUMMYRFTSE250TVOL	85.4590***
	(18.1264)		(7.0860)
RCFTSE100TVOL(-1)	-0.6035***	RCFTSE250TVOL(-1)	-0.6938***
	(0.0459)		(0.0439)
RCFTSE100TVOL(-2)	-0.8269***	RCFTSE250TVOL(-2)	-0.5972***
	(0.0543)		(0.0535)
RCFTSE100TVOL(-3)	-0.5653***	RCFTSE250TVOL(-3)	-0.5951***
	(0.0527)		(0.0519)
RCFTSE100TVOL(-4)	-0.0461	RCFTSE250TVOL(-4)	0.1403***
	(0.0518)		(0.0528)
RCFTSE100TVOL(-5)	0.0413	RCFTSE250TVOL(-5)	0.1176***
	(0.0331)		(0.0343)
RCFTSE100TVOINDEX3	-0.0255	RCFTSE250TVOINDEX3	0.0245*
	(0.0197)		(0.0126)
RCFTSE100TVOINDEX3(-1)	-0.0465*	RCFTSE250TVOINDEX3(-1)	0.0036
	(0.0264)		(0.0126)
RCFTSE100TVOINDEX3(-2)	-0.0439	Observations:	3412
	(0.0293)	R-squared:	0.2761
RCFTSE100TVOINDEX3(-3)	-0.0342	F-statistic:	80.9203
	(0.0263)	Prob(F-stat):	0.0000
RCFTSE100TVOINDEX3(-4)	-0.0140		
	(0.0200)		
Observations:	3370		
R-squared:	0.2540		
F-statistic:	60.0480		
Prob(F-stat):	0.0000		

This table presents OLS regression results of FTSE trading volume rate of change on Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE100TVOL is rate of change of FTSE100 daily trading volume, RCFTSE250TVOL is rate of change of FTSE250 daily trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’

return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSE100TVOL is FTSE100 trading volume index specific dummy, RCFTSE100VOINDEX3 is FTSE100 trading volume rate of change, and RCFTSE250VOINDEX3 is FTSE250 trading volume rate of change.

Table 3.17 Definition of abbreviated terms

Symbol used	Definition
RFTSE100PI	Returns of FTSE100 index (Daily and monthly)
RCFTSE100VO	Rate of change of FTSE100 monthly trading volume (monthly)
RCFTSE100TVOL	Rate of change of FTSE100 daily trading volume (daily)
RFTSE250PI	Returns of FTSE 250 index (Daily and monthly)
RCFTSE250VO	Rate of change of FTSE250 monthly trading volume (monthly)
RCFTSE250TVOL	Rate of change of FTSE250 daily trading volume (daily)
RFTSEAIMPI	Returns of FTSE AIM100 index (monthly)
RFTSEAIMALLSHAREPI	Returns of FTSE AIM All Share index (daily)
LFTSE100INDEX3	FTSE100 Music Index level. (Daily and monthly)
LFTSE250INDEX3	FTSE250 Music Index level. (Daily and monthly)
LAIMINDEX3	FTSE AIM Music Index level. (monthly)
LAIMALLSHAREINDEX3	FTSE AIM All Share Music Index level. (Daily)
LFTSE100VOINDEX3	FTSE100 trading volume Music level. (Daily and monthly)
LFTSE250VOINDEX3	FTSE250 trading volume level. (Daily and monthly)
RCFTSE100INDEX3	FTSE100 Music Index rate of change. (Daily and monthly)
RCFTSE250INDEX3	FTSE250 Music Index rate of change (Daily and monthly).
RCAIMINDEX3	FTSE AIM Music Index rate of change. (monthly)
RCAIMALLSHAREINDEX3	FTSE AIM All Share Music rate of change. (Daily)
RCFTSE100VOINDEX3	FTSE100 trading volume rate of change. (Daily and monthly)
RCFTSE250VOINDEX3	FTSE250 trading volume rate of change. (Daily and monthly)
REPU	Economic Policy Uncertainty (EPU)
DUMMYJANUARY	‘January effect’ dummy for monthly estimations
DUMMYFTSE100PI2008M10	FTSE100 index specific dummy (for monthly estimations)
DUMMYFTSE250PI2008M10	FTSE250 index specific dummy (for monthly estimations)
DUMMYFTSEAIMPI2008M10	FTSE index specific dummy (for monthly estimations)
DUMMYRFTSEAIMALLSHAREPI	FTSE AIM All Share index specific dummy (for daily estimations)
DUMMYDAYRETURN	‘Day of the week’ return dummy (for daily estimations)
DUMMYDAYVOLATILITY	‘Day of the week’ volatility dummy (for daily estimations)
DUMMYRFTSE100PI	FTSE100 index specific dummy (for daily estimations)
DUMMYRFTSE250PI	FTSE250 index specific dummy (for daily estimations)
DUMMYFTSE250VO2012M01	FTSE250 trading volume index specific dummy (for monthly estimations)
DUMMYRFTSE100TVOL	FTSE100 trading volume index specific dummy (for daily estimations)
DUMMYRFTSE250TVOL	FTSE250 trading volume index specific dummy (for daily estimations)
FTSE100	FTSE 100 is an equity index of one hundred corporations listed on the London Stock Exchange with the highest market valuation.
FTSE250	FTSE 250 is an equity index of medium capitalised companies not in FTSE 100 index.
FTSE AIM	FTSE AIM is an equity index of the largest hundred companies by full market capitalisation that are in the Alternative Investment Market index.
FTSE AIM All shares	FTSE AIM All ordinary shares is an equity index of companies that are listed in the Alternative Investment Market.

Appendix

A3.1 Monthly and daily FTSE 100 returns and trading volume rate of change correlation with music genre search rate of change.

MONTHLY								
Music genre search rate of change	**RFTSE100PI**	**t-Statistic**	**Probability**		**Music genre search rate of change**	**RFTSE100VO**	**t-Statistic**	**Probability**
RMPOPUK	-0.1533	-1.8355	0.0686		RMCLASSICAL_MUSICUK	-0.2706	-3.3252	0.0011
RMHAPPY_MUSICUK	-0.0931	-1.1066	0.2704		RMBLUESUK	-0.1701	-2.0421	0.0430
RMREGGAEUK	-0.0280	-0.3312	0.7410		RMHAPPY_MUSICUK	-0.1470	-1.7582	0.0809
RMHAPPY_SONGSUK	0.1144	1.3628	0.1751		RMREGGAEUK	0.1520	1.8200	0.0709
RMHIP_HOPUK	0.1529	1.8306	0.0693		RMPOPUK	0.1593	1.9094	0.0583
RMSOUL_MUSICUK	0.1768	2.1253	0.0353		RMRHYTHM_AND_BLUESUK	0.2530	3.0937	0.0024
Daily								
Music genre search rate of change	**RFTSE100PI**	**t-Statistic**	**Probability**		**Music genre search rate of change**	**RFTSE100TVOL**	**t-Statistic**	**Probability**
RMGRIME	-0.0150	-0.5676	0.5704		RMHARDROCK	-0.0798	-3.0274	0.0025
RMJAZZ	-0.0102	-0.3841	0.7010		RMPOP	-0.0464	-1.7556	0.0794
RMSOULMUSIC	-0.0093	-0.3518	0.7251		RMCLASSICALMUSIC	-0.0455	-1.7206	0.0855
RMRNB	0.0363	1.3738	0.1697		RMHAPPYMUSIC	0.0400	1.5126	0.1306
RMHEAVYMETAL	0.0494	1.8696	0.0617		RMJAZZ	0.0699	2.6498	0.0081
RMPOP	0.0743	2.8151	0.0049		RMRAP	0.0706	2.6765	0.0075

This table presents Monthly and daily FTSE 100 returns and trading volume rate of change correlation with music genre search rate of change with p value and t statistics. These individual music genre search SVI is used to construct the Music Index.

A3.2 Descriptive stats for monthly dependent from June 2006 to May 2018

	LFTSE100INDEX	LFTSE250INDEX	LAIMINDEX	LFTSE100VOINDEX	LFTSE250VOINDEX
Mean	0.713605	0.713605	0.933909	0.734356	0.734356
Median	0.64359	0.64359	0.937645	0.720115	0.720115
Maximum	1.352113	1.352113	1.416667	1.703704	1.703704
Minimum	0.411111	0.411111	0.581633	0.322034	0.322034
Std. Dev.	0.210083	0.210083	0.185777	0.306257	0.306257
Skewness	0.828203	0.828203	0.183883	0.479738	0.479738
Kurtosis	3.155166	3.155166	2.154904	2.35343	2.35343
Jarque-Bera	16.60653	16.60653	5.096634	8.031892	8.031892
Probability	0.000248	0.000248	0.078213	0.018026	0.018026
Sum	102.7591	102.7591	134.4829	105.7473	105.7473
Sum Sq. Dev.	6.311277	6.311277	4.935369	13.41249	13.41249
Observations	144	144	144	144	144

LFTSE100INDEX is alternative FTSE100 Music Index level, LFTSE250INDEX is alternative FTSE250 Music Index level, LAIMINDEX is alternative FTSE AIM Music Index level, LFTSE100VOINDEX is alternative FTSE100 trading volume Music level, and LFTSE250VOINDEX is alternative FTSE250 trading volume level.

A3.3 Descriptive stats for monthly dependent from June 2006 to May 2018

	RCFTSE100INDEX	RCFTSE250INDEX	RCAIMINDEX	RCFTSE100VOINDEX	RCFTSE250VOINDEX
Mean	1.140036	1.140036	0.225272	1.120155	1.120155
Median	1.190476	1.190476	-1.492537	0	0
Maximum	63.81868	63.81868	37.54386	77.99564	77.99564
Minimum	-38.03201	-38.03201	-23.89918	-47.17391	-47.17391
Std. Dev.	19.13894	19.13894	10.14725	19.36543	19.36543
Skewness	0.559207	0.559207	0.657139	0.633838	0.633838
Kurtosis	3.629448	3.629448	3.917565	4.423392	4.423392
Jarque-Bera	9.813701	9.813701	15.30847	21.64691	21.64691
Probability	0.007396	0.007396	0.000474	0.00002	0.00002
Sum	163.0252	163.0252	32.2139	160.1821	160.1821
Sum Sq. Dev.	52014.45	52014.45	14621.26	53252.82	53252.82
Observations	143	143	143	143	143

RCFTSE100INDEX is alternative FTSE100 Music Index rate of change, RCFTSE250INDEX is alternative FTSE250 Music Index rate of change, RCAIMINDEX is alternative FTSE AIM Music Index rate of change, RCFTSE100VOINDEX is alternative FTSE100 trading volume rate of change, and RCFTSE250VOINDEX is alternative FTSE250 trading volume rate of change.

A3.4 Descriptive stats for daily Music Index level from 01 January 2005 to 31 December 2019

	LFTSE100INDEX	LFTSE250INDEX	LAIMALLSHAREINDEX	LFTSE100VOINDEX	LFTSE250VOINDEX
Mean	7.035941	2.356085	7.035941	2.451747	2.451747
Median	6.5	2.125	6.5	2.25	2.25
Maximum	50	16.66667	50	22	22
Minimum	0.19	0.186813	0.19	0.214286	0.214286
Std. Dev.	3.54414	1.3927	3.54414	1.25208	1.25208
Skewness	1.860113	1.909468	1.860113	2.597187	2.597187
Kurtosis	10.24635	10.17335	10.24635	23.48014	23.48014
Jarque-Bera	10936.64	10373.98	10936.64	73435.7	73435.7
Probability	0	0	0	0	0
Sum	27834.18	8882.442	27834.18	9679.499	9679.499
Sum Sq. Dev.	49678.47	7310.402	49678.47	6187.728	6187.728
Observations	3956	3770	3956	3948	3948

LFTSE100INDEX is alternative FTSE100 Music Index level, LFTSE250INDEX is alternative FTSE250 Music Index level, LAIMALLSHAREINDEX is alternative FTSE AIM All Share Music Index level, LFTSE100VOINDEX is alternative FTSE100 trading volume Music level, and LFTSE250VOINDEX is alternative FTSE250 trading volume level.

A3.5 Descriptive stats for daily Music Index rate of change from 01 January 2005 to 31 December 2019

	RCFTSE100INDEX	RCFTSE250INDEX	RCAIMALLSHAREINDEX	RCFTSE100VOINDEX	RCFTSE250VOINDEX
Mean	10.1582	14.87346	10.1582	15.49975	15.49975
Median	0	0	0	0	0
Maximum	2882.456	680	2882.456	907.5	907.5
Minimum	-97.46667	-81.95489	-97.46667	-95.1049	-95.1049
Std. Dev.	68.33245	65.2916	68.33245	74.80048	74.80048
Skewness	19.97781	2.108804	19.97781	3.91044	3.91044
Kurtosis	802.589	11.55563	802.589	30.7522	30.7522
Jarque-Bera	1.05E+08	13667	1.05E+08	135960.5	135960.5
Probability	0	0	0	0	0
Sum	39992.83	53618.83	39992.83	60836.53	60836.53
Sum Sq. Dev.	18378458	15363825	18378458	21955218	21955218
Observations	3937	3605	3937	3925	3925

RCFTSE100INDEX is alternative FTSE100 Music Index rate of change, RCFTSE250INDEX is alternative FTSE250 Music Index rate of change, RCAIMALLSHAREINDEX is alternative FTSE AIM All Share Music rate of change, RCFTSE100VOINDEX is alternative FTSE100 trading volume rate of change, and RCFTSE250VOINDEX is alternative FTSE250 trading volume rate of change.

A3.6 FTSE monthly returns and Index 1 level from June 2006 to May 2018

Dep. Var:	RFTSE100PI		Dep. Var:	RFTSE250PI		Dep. Var:	RFTSEAIMPI
C	0.1339		C	0.926		C	0.8441
	(1.3582)			(1.4507)			(2.0452)
REPU	0.0181		REPU	-0.0062		REPU	-0.0057
	(0.012)			(0.0129)			(0.0111)
DUMMYJANUARY	0.9886		DUMMYJANUARY	1.0915		DUMMYJANUARY	3.0345**
	(1.2916)			(1.3795)			(1.6992)
DUMMYFTSE100PI2008M10	-21.8131***		DUMMYFTSE250PI2008M10	-22.8304***		DUMMYFTSEAIMPI2008M10	-26.7718***
	(4.2337)			(4.5221)			(0.9743)
LFTSE100INDEX	5.0334**		LFTSE250INDEX	4.3529		RFTSEAIMPI(-1)	0.2764***
	(2.499)			(2.6692)			(0.0849)
LFTSE100INDEX(-1)	-4.7235*		LFTSE250INDEX(-1)	-4.4981*		LFTSEAIMINDEX	12.8584*
	(2.4676)			(2.6357)			(6.7433)
Observations:	142		Observations:	142		LFTSEAIMINDEX(-1)	-13.6491**
R-squared:	0.2091		R-squared:	0.1968			(6.1137)
F-statistic:	7.1901		F-statistic:	6.6653		Observations:	140
Prob(F-stat):	0		Prob(F-stat):	0		R-squared:	0.3457
						F-statistic:	11.714
						Prob(F-stat):	0

This table presents OLS regression results of FTSE returns on Index 1 level.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE100PI is returns of FTSE100 index, RFTSE250PI is returns of FTSE 250 index, RFTSEAIMPI is returns of FTSE AIM100 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE100PI2008M10 is FTSE100 index specific dummy, DUMMYFTSE250PI2008M10 is FTSE250 index specific dummy, DUMMYFTSEAIMPI2008M10 is FTSE index specific dummy, LFTSE100INDEX is alternative FTSE100 Music Index level, LFTSE250INDEX is alternative FTSE250 Music Index level, and LAIMINDEX is alternative FTSE AIM Music Index level

A3.7 FTSE monthly trading volume rate of change and Index 1 level from 01 January 2005 to 31 December 2019

Dep. Var:	RCFTSE100VO		Dep. Var:	RCFTSE250VO
C	11.5545***		C	13.7067**
	(3.3356)			(6.3719)
REPU	0.0526		REPU	0.0294
	(0.0339)			(0.0313)
DUMMYJANUARY	-33.5319***		DUMMYJANUARY	-26.9484***
	(8.1391)			(6.4889)
RCFTSE100VO(-1)	-0.9083***		DUMMYFTSE250VO2012M01	-24.0961
	(0.0739)			(15.7469)
RCFTSE100VO(-2)	-0.7641***		RCFTSE250VO(-1)	-0.8539***
	(0.0968)			(0.0671)
RCFTSE100VO(-3)	-0.4109***		RCFTSE250VO(-2)	-0.6734***
	(0.0982)			(0.0961)
LFTSE100VOINDEX	23.7918***		RCFTSE250VO(-3)	-0.422***
	(7.9994)			(0.1076)
LFTSE100VOINDEX(-1)	-25.9703***		LFTSE250VOINDEX	19.5841***
	(8.6165)			(6.5492)
Observations:	136		LFTSE250VOINDEX(-1)	-26.2691***
R-squared:	0.6381			(9.3620)
F-statistic:	18.0691		Observations:	136
Prob(F-stat):	0		R-squared:	0.6167
			F-statistic:	15.1018
			Prob(F-stat):	0

This table presents OLS regression results of FTSE trading volume on Index 1 level.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE100VO is rate of change of FTSE100 monthly trading volume, RCFTSE250VO is rate of change of FTSE250 monthly trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE250VO2012M01 is FTSE250 trading volume index specific dummy, LFTSE100VOINDEX is alternative FTSE100 trading volume Music level, and LFTSE250VOINDEX is alternative FTSE250 trading volume level.

A3.8 FTSE monthly returns and Index 1 rate of change from June 2006 to May 2018

Dep. Var:	RFTSE100 PI		Dep. Var:	RFTSE250 PI		Dep. Var:	RFTSEAIM PI
C	0.2576		C	0.7343		C	0.0598
	(0.3765)			(0.4187)			(0.5003)
REPU	0.0203*		REPU	-0.0054		REPU	-0.0062
	(0.0120)			(0.0105)			(0.0102)
DUMMYJANUARY	0.8615		DUMMYJANUARY	1.0205		DUMMYJANUARY	3.1572*
	(1.2909)			(1.2598)			(1.7915)
DUMMYFTSE100PI2008M10	-20.0706***		DUMMYFTSE250PI2008M10	-22.4572**		DUMMYFTSEAIMPI2008M10	-27.2049***
	(4.2629)			(0.8817)			(1.0557)
RCFTSE100INDEX	0.0447**		RCFTSE250INDEX	0.0410**		RFTSEAIMPI(-1)	0.2659***
	(0.0208)			(0.0196)			(0.0933)
RCFTSE100INDEX(-1)	0.0046		RCFTSE250INDEX(-1)	0.0188		RCFTSEAIMINDEX	0.1192**
	(0.0223)			(0.0208)			(0.0578)
RCFTSE100INDEX(-2)	-0.0353*		Observations:	141		RCAIMINDEX(-1)	0.0224
	(0.0204)		R-squared:	0.1985			(0.0394)
Observations:	140		F-statistic:	6.6884		RCAIMINDEX(-2)	0.0257
R-squared:	0.2377		Prob(F-stat):	0.0000			(0.0403)
F-statistic:	6.9115					Observations:	139
Prob(F-stat):	0.0000					R-squared:	0.3430
						F-statistic:	9.7689
						Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE returns on Index 1 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

RFTSE100PI is returns of FTSE100 index, RFTSE250PI is returns of FTSE 250 index, RFTSEAIMPI is returns of FTSE AIM100 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is 'January effect' dummy for monthly estimations, DUMMYFTSE100PI2008M10 is FTSE100 index specific dummy, DUMMYFTSE250PI2008M10 is FTSE250 index specific dummy, DUMMYFTSEAIMPI2008M10 is FTSE index specific dummy, RCFTSE100INDEX is alternative FTSE100 Music Index rate of change, RCFTSE250INDEX is alternative FTSE250 Music Index rate of change, and RCAIMINDEX is alternative FTSE AIM Music Index rate of change.

A3.9 FTSE daily trading volume rate of change and returns on Index 1 rate of change from 01 January 2005 to 31 December 2019

Dep. Var:	RFTSEAIMALLSHAREPI
C	0.0122
	(0.0202)
REPU	-0.0000
	(0.0001)
DUMMYDAYRETURN	-0.1144***
	(0.0236)
DUMMYDAYVOLATILITY	0.1310***
	(0.0233)
DUMMYRFTSEAIMALLSHAREPI	-2.5784***
	(0.1114)
RFTSEAIMALLSHAREPI(-1)	0.0692
	(0.0404)
RCAIMALLSHAREINDEX	0.0004
	(0.0002)
RCAIMALLSHAREINDEX(-1)	0.0003*
	(0.0002)
Observations:	3899
R-squared:	0.1940
F-statistic:	93.5532
Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE trading volume rate of change and returns on Index 1 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSEAIMALLSHAREPI is returns of FTSE AIM All Share index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSEAIMALLSHAREPI is FTSE AIM All Share index specific dummy for daily estimations, and RCAIMALLSHAREINDEX is alternative FTSE AIM All Share Music rate of change.

A3.10 FTSE monthly trading volume rate of change and Index 1 rate of change from June 2006 to May 2018

Dep. Var:	RCFTSE100VO		Dep. Var:	RCFTSE250VO
C	9.4672***		C	8.6266***
	(1.2642)			(2.5807)
REPU	-0.0348		REPU	0.0288
	(0.0351)			(0.0309)
DUMMYJANUARY	-29.7624***		DUMMYJANUARY	-26.0630***
	(4.7975)			(6.6957)
RFTSE100VO(-1)	-1.1585***		DUMMYFTSE250VO2012M01	-19.7321
	(0.1406)			(17.1399)
RFTSE100VO(-2)	-0.7259***		RFTSE250VO(-1)	-0.8781***
	(0.1846)			(0.0888)
RFTSE100VO(-3)	-0.2490**		RFTSE250VO(-2)	-0.7301***
	(0.1006)*			(0.0986)
RCFTSE100VOINDEX	0.2726***		RFTSE250VO(-3)	-0.4983***
	(0.0817)			(0.1081)
RCFTSE100VOINDEX(-1)	0.1769**		RCFTSE250VOINDEX	0.2074***
	(0.0831)			(0.0738)
Observations:	136		RCFTSE250VOINDEX(-1)	0.0708
R-squared:	0.6344			(0.1005)
F-statistic:	19.5600		RCFTSE250VOINDEX(-2)	0.0820
Prob(F-stat):	0.0000			(0.1065)
			RCFTSE250VOINDEX(-3)	0.0648
				(0.0967)
			Observations:	136
			R-squared:	0.6120
			F-statistic:	12.6191
			Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE trading volume rate of change on Index 1 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE100VO is rate of change of FTSE100 monthly trading volume, RCFTSE250VO is rate of change of FTSE250 monthly trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE250VO2012M01 is FTSE250 trading volume index specific dummy, and RCFTSE100INDEX is alternative FTSE100 Music Index rate of change.

A3.11 FTSE daily trading volume rate of change and returns on Index 1 rate of change from 01 January 2005 to 31 December 2019

Dep. Var:	RCFTSE250TVOL
C	-12.5902***
	(1.1687)
REPU	0.0004**
	(0.0002)
DUMMYDAYRETURN	7.2794***
	(2.4346)
DUMMYDAYVOLATILITY	24.2184***
	(2.3464)
DUMMYRFTSE250TVOL	-0.0294
	(0.4641)
RCFTSE250TVOL(-1)	0.5832***
	(0.0314)
RCFTSE250TVOL(-2)	1.7526***
	(0.0237)
RCFTSE250TVOL(-3)	-1.0273***
	(0.0498)
RCFTSE250TVOL(-4)	-0.7772***
	(0.0222)
RCFTSE250TVOL(-5)	0.4601***
	(0.0242)
RCFTSE250TVOINDEX	0.0010*
	(0.0006)
RCFTSE250TVOINDEX(-1)	-0.0014**
	(0.0006)
Observations:	3373
R-squared:	0.3699
F-statistic:	123.1586
Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE trading volume rate of change and returns on Index 1 rate of change.

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RCFTSE250TVOL is rate of change of FTSE250 daily trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSE250TVOL is FTSE250 trading volume index specific dummy, and RCFTSE250TVOINDEX is alternative FTSE250 trading volume rate of change.

A3.12 FTSE 250 monthly returns and FTSE 100 Music Index from June 2006 to May 2018

Dep. Var:	RFTSE250PI
C	1.9206
	(3.0635)
REPU	-0.0063
	(0.0101)
DUMMYJANUARY	1.5751
	(1.2098)
DUMMYFTSE250PI2008M10	-22.1768***
	(0.8477)
LFTSE100INDEX3	7.6509*
	(4.2174)
LFTSE100INDEX3(-1)	-5.9328
	(5.0119)
LFTSE100INDEX3(-2)	-3.1195
	(5.0955)
Observations:	141
R-squared:	0.2025
F-statistic:	5.6717
Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE 250 returns on FTSE 100 Index 3 level.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE250PI is returns of FTSE 250 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE250PI2008M10 is FTSE250 index specific dummy, and LFTSE100INDEX3 is FTSE100 Music Index level.

A3.13 FTSE monthly returns and FTSE 100 Music Index from June 2006 to May 2018

Dep. Var:	RFTSE250PI		Dep. Var:	RFTSEAIMPI
C	0.6900*		C	-0.0948
	(0.4053)			(0.4943)
REPU	-0.0051		REPU	-0.0083
	(0.0130)			(0.0113)
DUMMYJANUARY	1.6030		DUMMYJANUARY	4.9372***
	(1.3657)			(1.2180)
DUMMYFTSE250PI2008M10	-22.2820***		DUMMYFTSEAIMPI2008M10	-26.5055***
	(4.6429)			(1.6928)
RCFTSE100INDEX3	0.0674*		RFTSEAIMPI(-1)	0.2474**
	(0.0345)			(0.1085)*
RCFTSE100INDEX3(-1)	0.0225		RCFTSE100INDEX3	0.0661*
	(0.0371)			(0.0377)
RCFTSE100INDEX3(-2)	-0.0056		RCFTSE100INDEX3(-1)	0.0450
	(0.0351)			(0.0399)
Observations:	140		RCFTSE100INDEX3(-2)	0.0001
R-squared:	0.2030			(0.0430)
F-statistic:	5.6452			
Prob(F-stat):	0.0000		Observations:	139
			R-squared:	0.3319
			F-statistic:	9.2981
			Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE returns on FTSE 100 Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE250PI is returns of FTSE 250 index, RFTSEAIMPI is returns of FTSE AIM100 index, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE250PI2008M10 is FTSE250 index specific dummy, DUMMYFTSEAIMPI2008M10 is FTSE index specific dummy, and RCFTSE100INDEX3 is FTSE100 Music Index rate of change.

A3.14 FTSE monthly trading volume and FTSE 100 Music Index from June 2006 to May 2018

Dep. Var:	RCFTSE100VO		Dep. Var:	RCFTSE250VO
C	10.6313***		C	9.9427***
	(1.3817)			(2.8123)
REPU	0.0138		REPU	0.0250
	(0.0358)			(0.0303)
DUMMYJANUARY	-32.4823***		DUMMYJANUARY	-28.8751***
	(6.3722)			(5.6075)
RCFTSE100VO(-1)	-1.1461***		DUMMYFTSE250VO2012M01	-12.5831
	(0.1539)			(11.2390)
RCFTSE100VO(-2)	-0.7465***		RCFTSE250VO(-1)	-0.9505***
	(0.2048)			(0.0396)
RCFTSE100VO(-3)	-0.2520**		RCFTSE250VO(-2)	-0.8369***
	(0.1224)			(0.0558)
RCFTSE100INDEX3	-0.1455		RCFTSE250VO(-3)	-0.6202***
	(0.1580)			(0.0795)
RCFTSE100INDEX3(-1)	-0.4174*		RCFTSE100INDEX3	0.1552*
	(0.2256)			(0.0831)
RCFTSE100INDEX3(-2)	-0.3341**		RCFTSE100INDEX3(-1)	0.0508
	(0.1479)			(0.0852)
Observations:	136		RCFTSE100INDEX3(-2)	-0.0350
R-squared:	0.6197			(0.0886)
F-statistic:	15.2909			
Prob(F-stat):	0.0000		Observations:	136
			R-squared:	0.6350
			F-statistic:	15.0340
			Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE 100 and FTSE 250 trading volume rate of change on FTSE 100 Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

RCFTSE100VO is rate of change of FTSE100 monthly trading volume, RCFTSE250VO is rate of change of FTSE250 monthly trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYJANUARY is ‘January effect’ dummy for monthly estimations, DUMMYFTSE250VO2012M01 is FTSE250 trading volume index specific dummy, and RCFTSE100INDEX3 is FTSE100 Music Index rate of change

A3.15 FTSE 250 daily returns and FTSE 100 Music Index from 01 January 2005 to 31 December 2019

Dep. Var:	RFTSE250PI
C	-0.0421
	(0.1040)
REPU	-0.0000
	(0.0000)
DUMMYDAYRETURN	-0.0908***
	(0.0366)
DUMMYDAYVOLATILITY	0.1021***
	(0.0363)
DUMMYRFTSE250PI	-1.4164
	(1.2892)
RFTSE250PI(-1)	0.0806***
	(0.0280)
RFTSE250PI(-2)	-0.0050
	(0.0326)
RFTSE250PI(-3)	-0.0236
	(0.0293)
LFTSE100INDEX3	0.0680
	(0.0622)
LFTSE100INDEX3(-1)	-0.0482
	(0.0584)
LFTSE100INDEX3(-2)	0.1143**
	(0.0570)
LFTSE100INDEX3(-3)	0.0057
	(0.0603)
LFTSE100INDEX3(-4)	-0.0789
	(0.0571)

Observations:	3947
R-squared:	0.0214
F-statistic:	7.1675
Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE 250 returns on FTSE 100 Index 3 level.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE250PI is returns of FTSE 250 index, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSE250PI is FTSE250 index specific dummy, and LFTSE100INDEX3 is FTSE100 Music Index level.

A3.16 FTSE daily trading volume and FTSE 100 Music Index from 01 January 2005 to 31 December 2019

Dep. Var:	RCFTSE100TVOL		Dep. Var:	RCFTSE250TVOL
C	16.5061***		C	15.7684***
	(4.2529)			(4.6453)
REPU	0.0015		REPU	0.0010
	(0.0028)			(0.0024)
DUMMYDAYRETURN	-17.9927***		DUMMYDAYRETURN	-17.4825***
	(1.2205)			(1.2853)
DUMMYDAYVOLATILITY	11.1441***		DUMMYDAYVOLATILITY	16.8642***
	(1.4870)			(1.2823)
DUMMYRFTSE100TVOL	132.2330***		DUMMYRFTSE250TVOL	67.0213***
	(18.4211)			(6.5068)
RCFTSE100TVOL(-1)	-0.6261***		RCFTSE250TVOL(-1)	-0.7272***
	(0.0458)			(0.0440)
RCFTSE100TVOL(-2)	-0.7960***		RCFTSE250TVOL(-2)	-0.6525***
	(0.0539)			(0.0559)
RCFTSE100TVOL(-3)	-0.5693***		RCFTSE250TVOL(-3)	-0.6874***
	(0.0523)			(0.0530)
RCFTSE100TVOL(-4)	-0.0209		RCFTSE250TVOL(-4)	0.1133**
	(0.0517)			(0.0549)
RCFTSE100TVOL(-5)	0.0578*		RCFTSE250TVOL(-5)	0.0444
	(0.0331)			(0.0357)
LFTSE100INDEX3	-4.4021***		LFTSE100INDEX3	-4.0705***
	(1.4165)			(1.4652)
LFTSE100INDEX3(-1)	-0.4997		LFTSE100INDEX3(-1)	-2.2086*
	(1.2404)			(1.1580)
LFTSE100INDEX3(-2)	-2.0863		LFTSE100INDEX3(-2)	-0.8848
	(1.3120)			(1.1255)

LFTSE100INDEX3(-3)	-2.6541**		LFTSE100INDEX3(-3)	-4.1421***
	(1.2439)			(1.1502)
LFTSE100INDEX3(-4)	1.3395		LFTSE100INDEX3(-4)	1.5603
	(1.4522)			(1.5075)
Observations:	3373		Observations:	3410
R-squared:	0.2568		R-squared:	0.2901
F-statistic:	60.9670		F-statistic:	72.9030
Prob(F-stat):	0.0000		Prob(F-stat):	0.0000

This table presents OLS regression results of FTSE 100 and FTSE 250 trading volume rate of change on FTSE 100 Index 3 level.

Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

RCFTSE100TVOL is rate of change of FTSE100 daily trading volume, RCFTSE250TVOL is rate of change of FTSE250 daily trading volume, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is 'Day of the week' return dummy, DUMMYDAYVOLATILITY is 'Day of the week' volatility dummy, DUMMYRFTSE100TVOL is FTSE100 trading volume index specific dummy, and DUMMYRFTSE250TVOL is FTSE250 trading volume index specific dummy, LFTSE100INDEX3 is FTSE100 Music Index level,

A3.17 FTSE daily returns and FTSE 100 Music Index from 01 January 2005 to 31 December 2019

Dep. Var:	RFTSE250PI		Dep. Var:	RFTSE AIM ALL SHAREPI
C	0.0175		C	0.0025
	(0.0264)			(0.0213)
REPU	-0.0000		REPU	-0.0000
	(0.0000)			(0.0001)
DUMMYDAYRETURN	-0.0914**		DUMMYDAYRETURN	-0.1160***
	(0.0365)			(0.0235)
DUMMYDAYVOLATILITY	0.1018***		DUMMYDAYVOLATILITY	0.1318***
	(0.0363)			(0.0232)
DUMMYRFTSE250PI	-1.4106		DUMMYRFTSEAIMALLSHAREPI	-2.5808***
	(1.2888)			(0.1113)
RFTSE250PI(-1)	0.0807***		RFTSEAIMALLSHAREPI(-1)	0.0689*
	(0.0280)			(0.0407)
RFTSE250PI(-2)	-0.0046		RCFTSE100INDEX3	0.0003
	(0.0328)			(0.0003)
RFTSE250PI(-3)	-0.0231		RCFTSE100INDEX3(-1)	0.0006
	(0.0294)			(0.0004)
RCFTSE100INDEX3	0.0005		RCFTSE100INDEX3(-2)	0.0009**
	(0.0005)			(0.0004)
RCFTSE100INDEX3(-1)	-0.0000		RCFTSE100INDEX3(-3)	0.0008**
	(0.0005)			(0.0004)
RCFTSE100INDEX3(-2)	0.0009*		RCFTSE100INDEX3(-4)	0.0002
	(0.0005)			(0.0003)
RCFTSE100INDEX3(-3)	0.0005		Observations:	3945
	(0.0005)		R-squared:	0.1934
			F-statistic:	72.4910

RCFTSE100INDEX3(-4)	-0.0001		Prob(F-stat):	0.0000
	(0.0005)			
Observations:	3945			
R-squared:	0.0209			
F-statistic:	6.9808			
Prob(F-stat):	0.0000			

This table presents OLS regression results of FTSE 250 and FTSE AIM on FTSE 100 Index 3 rate of change.
Standard errors are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
RFTSE250PI is returns of FTSE 250 index, RFTSEAIMALLSHAREPI is returns of FTSE AIM All Share index, REPU is Economic Policy Uncertainty (EPU), DUMMYDAYRETURN is ‘Day of the week’ return dummy, DUMMYDAYVOLATILITY is ‘Day of the week’ volatility dummy, DUMMYRFTSE250PI is FTSE250 index specific dummy, DUMMYRFTSEAIMALLSHAREPI is FTSE AIM All Share index specific dummy and RCFTSE100INDEX3 is FTSE100 Music Index rate of change.

A3.18 Definition of abbreviated terms used in appendix

Symbol used	Definition
LFTSE100INDEX	Alternative FTSE100 Music Index level. (Daily and monthly)
LFTSE250INDEX	Alternative FTSE250 Music Index level. (Daily and monthly)
LAIMINDEX	Alternative FTSE AIM Music Index level. (monthly)
LAIMALLSHAREINDEX	Alternative FTSE AIM All Share Music Index level. (Daily)
LFTSE100VOINDEX	Alternative FTSE100 trading volume Music level. (Daily and monthly)
LFTSE250VOINDEX	Alternative FTSE250 trading volume level. (Daily and monthly)
RCFTSE100INDEX	Alternative FTSE100 Music Index rate of change. (Daily and monthly)
RCFTSE250INDEX	Alternative FTSE250 Music Index rate of change (Daily and monthly).
RCAIMINDEX	Alternative FTSE AIM Music Index rate of change. (monthly)
RCAIMALLSHAREINDEX	Alternative FTSE AIM All Share Music rate of change. (Daily)
RCFTSE100VOINDEX	Alternative FTSE100 trading volume rate of change. (Daily and monthly)
RCFTSE250VOINDEX	Alternative FTSE250 trading volume rate of change. (Daily and monthly)

Concluding remarks

Contributing to Socionomics in the field of Behavioural Finance, this thesis explores the extent to which social mood affects FTSE indexes in the UK. Empirical results indicate evidence of social mood affecting FTSE returns and trading volume. The first paper results show that some people experience catharsis-mood when complaining about actual or perceived mobile or broadband service failure, and this is reflected by an increase in returns of smaller indexes and a decrease in larger index returns. Conversely, other people experience frustration-mood when they complain about actual or perceived landline or pay TV failure, which is reflected by increased returns of larger index returns and decreased smaller index returns, with the latter akin to flight to safety/quality. The second paper outcomes illustrate mood enhancement whereby increased wine, beer, cider and spirits consumption lead to lowered trading volume of larger indexes (FTSE 100 and FTSE 250). Further, alcohol enhanced mood by beer consumption lead to increased smaller index returns (FTSE AIM 100 and FTSE AIM All Share), but this is not the case for larger index returns (FTSE 100 and FTSE 250). The third paper develops a novel Music Index using music genre searches in Google. Based on the method used to construct the Music Index, the Index level and rate of change lead to an increase in same day and month FTSE returns and trading volume. The level of the Music Index has reversion of sign of significant coefficient of lagged Music index, but the Music Index does not have significant coefficients of lagged Music Index rate of change.

The main implication is that there is evidence to support Socionomics theory (Prechter, 1999, 2016) by using three different proxies and diverse econometric methods. The first paper uses mobile, broadband, landline and pay TV complaints in an augmented CAPM framework to illustrate how Catharsis Hypothesis (Verona and Sullivan, 2008), which has been widely explored in Psychology, is applied in the UK. If FTSE was only affected by new fundamental information, as proposed by Fama (1970), complaints should not be significant in the augmented CAPM. The results also confirm earlier findings by Baker and Wurgler (2007) posing that smaller, younger, and harder to value companies are more affected by non-fundamental factors compared to larger, older and easier to value corporations.

The second paper results imply that in the UK the mood enhancement effects of wine, beer, spirits and cider consumption are more significant than the effects of drinking to cope for FTSE indexes. Even though applied to a different context, the findings of the second paper are aligned to the results presented by Cyders and Smith (2007) who reported that drinking to enhance mood was more prevalent than to cope. However, the results are opposite to what was reported by Deaton and Case (2021), who found that drinking to cope was more dominant in the US for the middle class. The results also illustrate how the most popular alcoholic drinks in the UK (i.e. wine and beer) have larger impulse responses when compared to spirits and cider. Further, as alcohol manufacturers do not dominate the FTSE index, increased alcohol consumption should not be affecting FTSE index using fully rational investor models.

The results of the third paper highlight that mood management through selective media exposure is prevalent in the UK. This is based on findings from Psychology suggesting that peoples' choice of the media they consume (Knobloch and Zillmann, 2002) is largely determined by the mood they are currently in (cognitivism), and what they want their mood to be after the consumption of the chosen media (emotivism) (Kostopoulos and Meyer, 2018). These results show that the UK population searches for music in Google can be used to construct a new Music Index, which is significant when used as independent variable. The Music Index bridges two streams of literature: one that focuses on the music-mood relationship (Kostopoulos and Meyer, 2018; Fernandez-Perez, Garel and Indriawan, 2020; Edmans *et al.*, 2022) with another stream of literature focussing on salient topics (Scheitle, 2011; Mellon, 2014; Ford, 2020), information demand/supply (Vlastakis and Markellos, 2012; Chronopoulos, Papadimitriou and Vlastakis, 2018), and investor attention (Aouadi, Arouri and Teulon, 2013; Ding and Hou, 2015). These results add more evidence to support the notion that financial markets are, in part, influenced by non-rational factors – ‘animal spirits’ (Aggarwal, 2014) or ‘irrational exuberance’ (Shiller, 2015).

This thesis has several limitations in terms of the data included in each study. The data used in the first and second paper have a limitation in the length of the period under exploration. The first paper also does not include catharsis or frustration of people who have suffered actual service failure but did not complain or had other avenues to release their frustrations. The second paper does not include data on people who do not drink, and also people who have alcohol dependency. The latter has a devastating effect as alcohol is the leading cause of death, ill-health and disability among people aged 15 to 49 years in England, and alcohol misuse is known to be causing a public health problem in the UK (the Department of Health and Social Care, the Welsh Government, the Department of Health Northern Ireland, Public Health England, NHS England and NHS Improvement, 2021b). The third paper does not take into account people who have pre-prepared playlists for the different mood management needs they may want at specific times.

There is also an inherent limitation to this study due to advancements in artificial intelligence, machine learning and cloud storage. These advancements offer the promise of more market efficiency through less mood-induced information collection and processing, quicker processing of information, and faster execution of trades (Barbopoulos et al., 2021). Furthermore, this thesis does not take into account the effects of ‘dark trading’ which might be conducted based on private information that is not publicly available (Barbopoulos, Putniņš and Rzayev, 2023). It is also difficult to take into account the effect of shocks such as OPEC oil production announcements, natural disasters and geopolitical tensions. The latter can cause significant friction in trading even though the events are far away from the UK (Smith, 2023) – for example, the current crisis in Gaza (Gulf of Eden), and China's August 2022 military exercises around the East China Sea, the Philippine Sea, and the South China Sea.

Further areas of exploration for future research could include the use of complaints from companies in other sectors. Also, depending on data availability, exploring sub-periods such as during the Sub-prime mortgage crisis could yield interesting results. If and when the UK FTSE VIX becomes available again, re-estimating the impact of UK social mood on VIX, or vice versa, would be fascinating. It would also be interesting to explore if legal stimulants like caffein also have an impact on financial markets.

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