

Anxiety, Expectations Stabilization and Intertemporal Markets: Theory, Evidence and Policy*

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Abstract

In this paper, we develop a simple model that captures the link between anxiety, strategic uncertainty driven by multiple narratives and investment in risky assets and allows a role for policy measures to stabilise expectations. We construct a new empirical measure of anxiety via a machine learning algorithm that applies sentiment analysis on news articles published online by Daily Mail, Reuters and Press Association. We examine the plausibility of our anxiety measure and use it to carry out empirical tests of how anxiety shocks impact on stock market outcomes and, in the process, verify a key prediction of the theoretical model. We discuss the policy implications our analysis focusing on the role of "lighthouse" policies in stabilising expectations.

Keyword: anxiety, expectations, policy

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1 Introduction

It is certain that a very large part of what we experience in life depends not on the actual circumstances of the moment so much as on the anticipation of future events.

William Stanley Jevons. The Theory of Political Economy

Since the 2008 global financial crisis, automation and the rise of the gig economy, a revival of populism and nationalism, Brexit and now of course the COVID-19 pandemic have led to a perception the future is increasingly uncertain and expectations are de-anchored, resulting a shift towards increased anxiety.

Anxiety aversion refers to a negative emotion regarding the anticipation of a future event: it constitutes a psychological payoff experienced by a decision-maker today in response to perceived future risk (Caplin and Leahy, 2001). Anxiety aversion implies that a higher perceived future risk will trigger a higher negative psychological payoff today. When anxiety rises, economic actors put more weight on (expected) negative outcomes, overreacting to negative news and discounting positive ones.

In this paper, we develop a simple model that captures the link between anxiety, strategic uncertainty driven by multiple narratives and investment in risky assets and allows a role for policy measures to stabilise expectations. We construct a new empirical measure of anxiety via a machine learning algorithm that applies sentiment analysis on news articles published online by Daily Mail, Reuters and Press Association. We examine the plausibility of our anxiety measure and use it to carry out empirical tests of how anxiety shocks impact on stock market outcomes and in the process verify a key prediction of the theoretical model. We discuss the policy implications our analysis focusing on the role of "lighthouse" policies in stabilising expectations.

Rousseau's parable of the stag-hare hunting game (Rousseau, 1964) is useful here. Rousseau uses the game to contrast the gains of hunting hare, where the risk of non-cooperation is small or non-existent (in our case, investing in a riskless low return storage technology like a savings deposit) and the individual reward and social benefit equally small, against the gains of hunting the stag (in our case, investing in the risky asset whose returns depend on average level of investment), where maximum coordination is required and the risk of non-cooperation is greater but both the individual reward and social benefit (if successful) are much greater. The point is that hunting the hare is risk dominant as success in this activity does not depend on what other agents do even though coordinating to hunt the stag is Pareto dominant.

In our model, anxiety is a psychological payoff experienced by the decision-maker today

in response to a perception of future risk. Anxiety aversion is modelled as a psychological payoff which is decreasing in the perceived variance in the lottery over future consumption will matter more to the decision maker. A key, potentially testable implication of the way we model anxiety is that a higher degree of impatience is associated with a higher degree of anxiety aversion because the psychological payoff associated with anxiety aversion is experienced today. Risk aversion, on the other hand, captures the impact of current risk on current payoffs. So, a variation in the discount factor should have no effect on risk aversion but will change the degree of anxiety aversion.

We show that increased anxiety (modelled as exogenous increase in the anxiety aversion parameter) implies that the range of economic fundamentals for which there is positive investment in the risky asset occurs shrinks because the range of economic fundamentals for which investment in the risky asset is risk-dominant decreases. Assuming a fixed probability distribution over economic fundamentals, our result has the empirical implication that the equilibrium variance in the asset price must decrease.

We measure anxiety through a machine learning algorithm that applies sentiment analysis on news articles published online by Daily Mail, Reuters and Press Association. First, we label a training set of articles with different values of anxiety from “no anxiety” to “high anxiety”. Then, we apply these labels to the whole archive of articles on the website dailymail.com. These labels are then re-scaled on a score between zero and one. The detailed methodology is described in the appendix.

To assess the plausibility of our anxiety score, we compare it with the rise of a general feeling of anxiety at the onset of the Covid-19 pandemic, unrelated to specific economic perspectives. Our theoretical analysis predicts that an increased level of anxiety reduces investment in risky assets and the volatility of asset prices. We test this prediction by estimating the impact of anxiety on stock market volatility, using daily differences between maximum and minimum prices of FTSE250 from 2019. We show that both series show counter-cyclical movements: The spikes of anxiety mimic the drop in stock market volatility: the counter-cyclical link between the two series is confirmed by their negative correlation.

Next, we apply a Vector Autoregression (VAR) model which exploits the joint dynamics of anxiety and stock market volatility as a direct test of the impact of anxiety on stock market outcomes. The causal impact is extracted by leveraging the key characteristics of anxiety, namely, its forward-looking generation. We demonstrate the short and cumulative impact of anxiety on stock market volatility. We find that a positive anxiety shock impacts negatively on stock market volatility. This effect is statistically significant with a 2-days lag, it remains significant for the subsequent two days and then becomes insignificant. The cumulative impact is negative and significant (the size is a cumulative drop of 3 log points in stock market volatility for an increase of one standard deviation in anxiety).

Our analysis suggests policy actions – rather than simple announcements – can act as a focal point in effect, as a lighthouse. Traditionally, such effects are thought to be the result of economic actors complying with certain regulations even though they are not directly affected. In our understanding, lighthouse policies can have the additional effect of guiding the economy through times of high economic anxiety by stabilising expectations and creating a degree of common knowledge about the future mitigating strategic uncertainty today, enabling welfare enhancing productive investments. By stabilising expectations and creating a common, credible narrative, lighthouse policies can help address economic anxiety.

The rest of the paper is structured as follows. The next provides a literature review; the following section develops the simple theoretical model. Section 4 is devoted to the empirical analysis. Section 5 concludes with a discussion of policy. The appendix sets out the methodology used in the empirical section in detail.

2 Literature review

Anxiety is not a typical concept used in economic analysis. In Psychology, it refers to an “an emotion characterized by an unpleasant state of inner turmoil”, according to the corresponding Wikipedia entry, with the aim to “preserve life” (Sylvers et al., 2011). In other words, it can be related to what in Behavioural Economics is referred to as loss aversion, a state of mind or heuristic that aims at avoiding low-probability but extremely negative economic outcomes that would cause bankruptcy or even death. In contrast to loss aversion, however, anxiety can undergo significant variations over short period of time, often leading to medical conditions, known as “generalised anxiety disorder” (for a recent empirical analysis of this phenomenon in the United Kingdom, see Slee et al., 2020). Linking such psychological variability to the standard decision-making-under-constraints framework that economics uses is not straightforward. In the following we provide an overview of the various approaches that have been undertaken in the economics literature to account for such conditions.

In contrast to anxiety, uncertainty is a more familiar concept to economists and one that has attracted increasing interest, in particular since the global financial crisis in 2008-09. While not identical, both concepts are closely related, as we will see. Uncertainty feeds into anxiety, certain forms of it being a necessary condition for people feeling anxious.

Three different forms of uncertainty can be distinguished: aleatoric uncertainty or risk, parametric uncertainty and epistemic uncertainty. The first form, risk, is obviously a notion well anchored in modern economic analysis. In standard (dynamic) macro-economic models, such uncertainty is integrated through a stationary process of one or more random variables (typically asset returns) over which households can form stable

beliefs through rational expectations. In more sophisticated theories, some heterogeneity can exist among households when parametric uncertainty leads to heterogeneous beliefs regarding the characteristics of the random processes. The last form, epistemic uncertainty or disagreement over the underlying economic model, however, has only recently found some echo among economists. It is this form, that most directly underpins anxiety.

In addition to focusing on aleatoric uncertainty, traditional dynamic business cycle models also assumed ergodicity, i.e. the possibility to deduct the properties of a random variable by looking at its evolution over time. This allowed for a neat separation between long-term trends and short-term fluctuations by separating macro-economic variables into a non-ergodic (trend) part and an ergodic one (deviations from the trend). Most importantly, it provided a simple way of discarding the Knightian idea of radical uncertainty, when individuals are not in a position to formulate (stable) expectations (Knight, 1921; Kay and King, 2020).

This assumption of ergodicity was questioned early on when (some) economists pointed out that in the case of irreversible investment, such separation does not hold (Pindyck, 1991). In these situations, the variance and the mean of an economic variable are closely related, although the sign of the relationship is open to empirical validation (Ramey and Ramey, 1995; Bloom, 2014). In the presence of (convex) adjustment costs, for instance when hiring a worker involves fixed search costs, the choice to undertake an investment or to hire a worker resembles that of a real option that rewards waiting with the investment for periods of less uncertainty (McDonald and Siegel, 1986; Ernst and Viegelahn, 2014). However, as highlighted by Bloom (2014), in situations when losses are bounded but gains appear limitless even though uncertain, growth options arise, which would spur investment rather than reduce it. Which way uncertainty affects growth, hence, is an empirical question.

Rather than as a result of randomness, uncertainty can also arise when there are strategic complementarities. In such a situation, expectations can be formed rationally and individually but the outcomes are being determined by actions undertaken by other economic agents. The most basic example of such situation is a coordination game where gains are highest when both agents coordinate their actions (Cooper, etc.). In macro-economic models, such situations arise, for instance, when increasing returns to scale arise at the macro-economic level, a deviation from the traditional concavity assumption in production functions that led to a large literature analysing expectations-driven sunspots (Azariadis and Guesnerie, 1986; Cass and Shell, 1983; Farmer, 1993). In such models, external signals can be used to coordinate the strategic choices of individual actors, although it remains unclear what determines which signal is being used. Sometimes, it is assumed that policy makers, such as central bankers, provide such a “natural” focal point in the language of Schelling (1960). Such “global games” where players receive public information have become an area of intensive research, in particular related to exchange

rate fluctuations (see [Morris and Shin, 1998, 2002](#)).

At the macro-economic level, irreversible investment and strategic complementarities are closely linked: When investment is irreversible, for instance because no second-hand market for capital goods exist, the rate of returns can be significantly altered in the case of strategically complementary inputs of other agents ([Bertola and Caballero, 1994](#)). Similarly, strategic complementarities in investment can be thought to arise when an alternative usage of the investment good is not possible. Search externalities provide a particularly striking illustration: Entering a market to search for trading opportunities is associated with a fixed and irreversible entry cost (“shoe-leather” cost) that can be recuperated the more potential trading partners in a market exist. If investment were reversible, the number of trading partners would not matter as opportunity costs of leaving the market were essentially zero. Conversely, the fact that trading externalities exist does mean that trading partners are not indifferent about leaving the market once they entered it ([Diamond, 1982](#)).

Understanding the coordination of individual actions beyond simple game-like situations has triggered interest among economists about the existence and role of “narratives” ([Akerlof and Snow, 2016](#); [Shiller, 2017, 2019](#); [CurzonPrice et al., 2020](#)). In contrast to simple signals, narratives are complex, multi-dimensional stories that specific actors convey to influence people’s opinions and expectations. Sociologists and historians have long speculated about the importance of such narratives to shape the direction of research, investments, and consumption ([Beckert, 2016](#); [Radkau, 2017](#)). In particular among scholars analysing the role of central banks, communication and the different narratives that central bankers try to convey has increasingly been seen as an essential tool of monetary policy making ([Haldane and McMahon, 2018](#); [Holmes, 2013, 2019](#); [Stankova, 2019](#)). Nevertheless, whether one considers simple signals or complex narratives, they would only act as signalling device to the extent they have sufficient legitimacy or carry enough conviction, such as in the case of an (independent) central bank.

This is why the latest development in this area has looked at the role of competing narratives. In a simple, bi-narrative model, [De Grauwe \(2011\)](#) shows that agents continuously switch between bouts of optimism and pessimism, thereby leading to expectation-driven, animal-spirit-like cycles unrelated to fundamentals. While agents’ expectations are coordinated on expectations equilibria, small shifts or (random) behavioural mistakes lead to the breakdown to expectations coordination and a switch to the opposite equilibrium. In the long-run, not all coordination equilibria have the same likelihood to be visited as the stochastically evolutionary stable strategy (SESS) will eventually dominate in such a setting, as shown by [Young \(1998\)](#). Characteristics of the environment such as the distribution of actions or the number of assets ([Desgranges and Ghosal, 2020](#)), the network structure of interactions ([Ernst, 2001](#)), the predisposition that influences individuals’ “anticipatory utility” ([Eliaz and Spiegler, 2020](#)) as well as the type and structure of

communication (Candia et al., 2020) will shape the relative size of each narrative's basin of attraction and hence whether it is an SESS or not. Again, only empirical analysis can determine, which of the various narratives have the stronger conviction power at any given point in time.

Empirically characterizing the impact of narratives, communication and uncertainty has not been easy and to date there is no clear consensus as to the preferred approach to take. Initial attempts focused primarily on readily available measures of the variation in stock price returns (such as the VIX) or sectoral profitability (Ghosal and Loungani, 2000). With the availability of digital archives of newspaper articles, more or less sophisticated forms of natural language processing have been used to identify bouts of policy uncertainty (Baker et al., 2016) or the focus of monetary policy communication (Ernst et al., 2018). The resulting anxiety among households their social and economic conditions has been captured through pre-classified news articles in the ILO's Social Unrest indicator (ILO, 2015). Finally, specific survey evidence, for instance provided by the Manpower Hiring Index, has been used to characterise the implied uncertainty for firms to find the right skills on labour market, the so-called hiring uncertainty index (Ernst and Viegelahn, 2014). Similarly, Makridis (2019) leverages individual-level Gallup data to construct a business cycle sentiment indicator.

Each one of these empirical measures of uncertainty needs to be analysed in its specific context to understand the impact on (macro-)economic outcomes. In particular, the specific transmission mechanism through which uncertainty is believed to impact the economy is important. Both Lagerborg et al. (2020) and Makridis (2019) consider the impact of sentiment shocks on the economy through household consumption. In their approach, higher uncertainty leads to less household consumption over a protracted period of time, substantially lowering economic activity. In contrast, Bloom (2009) considers the impact of uncertainty on investment decisions, similarly concluding that it leads to a reduction in investment, production and employment. Yet another approach considers deviations from rational expectations through the formation of subjective beliefs and Bayesian learning, demonstrating the large quantitative impact of bouts of pessimism on unemployment (Bhandari et al., 2019). Common to all these papers is the exogenous nature of the sentiment shock, whether in the form of negative news (see also Song and Tang, 2018), higher (policy) uncertainty or unexplained shifts in beliefs.

None of these approaches considers that sentiment shifts might arise endogenously out of the individual predisposition to different psychological states, such as anxiety. As Andy Haldane pointed out, however, such endogenous, ratcheting-up effects in peoples' mood are likely at work and might explain why mood swings persist long after any negative news have been reversed (Haldane, 2020). Media coverage and the strategic interaction between journalists and their readership might be one possibility that explains such an endogenous interaction between news and mood (Ghosh et al., 2020). Alternatively, mood swings can

arise from comparing oneself with others, an effect famously dubbed the “Tunnel effect” by [Hirschman and Rothschild \(1973\)](#). In the following, we want to explore the evolution of such mood swings by building an indicator of economic anxiety that will help trace the collective predisposition towards shifts in sentiments.

3 Anxiety, Consensus and Aggregate Welfare: A Simple Model

In our setting, anxiety takes the form of an anticipatory component in a model where, at an initial point in time, each individual must decide how to allocate savings between a riskless storage technology and risky asset whose expected returns depend on the aggregate investment to finance future consumption. Anxiety is decreasing in the variance, but increasing in the mean, of future consumption. In the model, multiple, Pareto ranked equilibria exist. An equilibrium selection argument is developed to deal with issues of equilibrium selection in the presence of multiple narratives and strategic uncertainty. The role of policy is examined. In the model multiple, Pareto ranked equilibria exist. An equilibrium selection argument is developed to deal with issues of equilibrium selection in the presence of multiple narratives and strategic uncertainty. The role of policy is examined.

3.1 Model setup

There is a continuum of identical agents $i \in [0, 1]$. We consider two time periods $t = 1, 2$ and a single good in each period denoted by $x_t, t = 1, 2$. Individuals are endowed with one unit of the good at $t = 1$ and have zero endowments at $t = 2$. All consumption occurs in $t = 2$. Individuals have linear utility over consumption in period 2, $u(x_{2,i}) = x_{2,i}$. Each individual owns a storage technology where one unit of input invested at $t = 1$ yields one unit of output at $t = 2$.

In addition, there is a price-taking firm in which each individual $i \in [0, 1]$ is an equal shareholder. At $t = 1$, the firm mobilizes investment in the risky asset by issuing a contingent claim over its output at $t = 2$. The returns to the risky asset depend on aggregate amount investment in it and an underlying state of the world (interpreted as representing economic fundamentals). Let $\theta \in [0, 1]$ denote the economic fundamentals.

Let $s_i \in [0, 1]$ denote the investment made by individual i in the risky asset; $s_i = 0$ denotes the choice whereby individual i invests entirely in the storage technology while $s_i = 1$ denotes the choice whereby individual i invests entirely in the risky technology. Let \bar{s} denote the average investment in the risky technology. Let s denote the

average investment in the risky asset associated with $s^*(\theta) = \{s_i^*, i \in [0, 1]\}$, an assignment of strategies.

The production technology of the risky asset is as follows: one unit input at $t = 1$ yields either $R_H > 1$ units of output with probability θs or $R_L < 1$ units of output with probability $1 - \theta s$ at $t = 2$. The underlying stochastic production technology of the risky asset has constant returns to scale where the probability distribution over returns depends both on economic fundamentals as well as the average level of investment. In what follows, for ease of exposition, we set $R_L = 0$.

The firm mobilizes investment in the risky asset by issuing a contingent claim on the return of the risky asset in period $t = 1$. When the individual invests s_i in the firm, the individual obtains a contingent claim of $p_H s_i$ when the state of the world is H and of $p_L s_i$ when the state of the world is L on the future output of the firm. The price of the consumption good in period $t = 1$ is the numeraire so that p_H (respectively, p_L) is the relative price of the consumption good at $t = 2$ in state H (respectively, state L). The expected price of the contingent claim at $t = 1$ is $p = \theta s p_H + (1 - \theta s) p_L$. As each agent derives positive marginal utility from consumption at $t = 2$, by no arbitrage, both $p_H \geq 0$ and $p_L \geq 0$ with at least two inequalities holding as a strict inequality. As $R_L = 0$, without loss of generality we set $p_L = 0$.

The firm takes s, p_H (and hence, p) as given. Let y denote the amount of the investment demanded by the firm. The expected profit of the firm is $\pi(s, \theta) = \theta s (R_H - p_H) y = (\theta s R_H - p) y$ where the expected output at $t = 2$ is $\theta s R_H y$ and expected input cost is py .

Hence, at $t = 1$, given s_i, s, θ, p_H , the lottery over future consumption at $t = 2$ is denoted by $l(s_i, s, \theta) = \{1 - s_i + p_H s_i, \theta s; 1 - s_i, 1 - \theta s\}$. By computation, the corresponding average level of future consumption is $\mu(l(s_i, s, \theta)) = 1 - s_i + \theta s R_H s_i$ and the variance of future consumption is $\sigma^2(l(s_i, s, \theta)) = \frac{\theta s (1 - \theta s) p_H^2 s_i^2}{2}$. Note that the average level of future consumption is when the individual invests only in the storage technology is $\mu(l(0, s, \theta)) = 1$ and the variance of future consumption is $\sigma^2(l(0, s, \theta)) = 0$.

Following [Caplin and Leahy \(2001\)](#), we assume that at $t = 1$, individuals obtain an anticipatory utility that depends on the lottery over future consumption as follows: $a(l(s_i, s, \theta)) = -\tilde{\gamma} \sigma^2(l(s_i, s, \theta))$, where $\tilde{\gamma} > 0$ is a strictly positive preference parameter reflecting anxiety aversion so that a lottery over consumption at $t = 2$ with a higher variance will induce a higher level of anxiety at $t = 1$ than another such lottery with a lower variance. Investing in the storage technology implies that mean consumption tomorrow is one with zero variance. Investing a positive amount in the risky asset extra variance in consumption tomorrow while increasing its mean level.

Given s, θ, p_H, p_L , each individual solves the following maximization problem:

$$\max_{s_i \in [0,1]} \tilde{v}(s_i, s, \theta) = -\tilde{\gamma} \frac{\theta s(1-\theta s)p_H^2 s_i^2}{2} + \delta[1 - s_i + \theta s p_H s_i + \pi] \quad (1)$$

where $0 < \delta \leq 1$ is a discount factor the discount factor. The individual is anxiety averse so that a higher level of anxiety corresponds to lower discounted expected utility. Note that we can re-write the expected utility function as follows:

$$\tilde{v}(s_i, s, \theta) = \delta \left(-\frac{\tilde{\gamma} \theta s(1-\theta s)p_H^2 s_i^2}{2} + [1 - s_i + \theta s p_H s_i + \pi] \right) \quad (2)$$

As long as $0 < \delta \leq 1$, the above expected utility function represents the same preferences as

$$\begin{aligned} v(s_i, s, \theta) &= -\frac{\tilde{\gamma} \theta s(1-\theta s)p_H^2 s_i^2}{\delta} + [1 - s_i + \theta s p_H s_i + \pi \delta] \\ &= -\gamma \frac{\theta s(1-\theta s)p_H^2 s_i^2}{2} + [1 - s_i + \theta s p_H s_i + \pi \delta] \end{aligned} \quad (3)$$

where $\gamma = \frac{\tilde{\gamma}}{\delta}$. It follows that more impatient the decision-maker is (the lower the value of δ) the higher the degree of anxiety aversion. That the degree of anxiety aversion varies with the changing values of δ is key to differentiating anxiety aversion from risk aversion over lotteries over consumption at $t = 2$ and generating potentially different testable implications: if the individual is risk averse over consumption at $t = 2$ (equivalently, has strictly concave preferences over consumption at $t = 2$), then the degree of risk-aversion will be unaffected by varying the discount factor as long as $0 < \delta \leq 1$. Equivalently, the degree of risk aversion can be modified without affecting the discount factor and the degree of anxiety aversion by adapting methods described in Hansen e. al. (2016). For ease of exposition, in what follows, we will work with the expected utility function $v(s_i, s, \theta)$.

In our model an agent's payoffs depend on both the average level of investment and prices. We require that in equilibrium, given prices and the level of average investment, each agent must act optimally, and prices must clear markets.

Definition 1 For each $\theta \in [0, 1]$, a Nash-Walras equilibrium is a triple $(s^*(\theta), p_H^*(\theta), y^*(\theta))$ where $s^*(\theta)$ is an assignment of investment strategies, $p_H^*(\theta)$ is an asset price and $y^*(\theta)$ a level of investment demanded by the form such that given $s^*(\theta)$ (the level of aggregate investment corresponding to $s^*(\theta)$):

- (i) $s_i^*(\theta) \in \operatorname{argmax}_{s_i \in [0,1]} v((s_i, s^*(\theta), \theta)$, for all $i \in [0, 1]$,
- (ii) given $p_H^*(\theta), s^*(\theta), y^*(\theta) \in \operatorname{argmax}_{y \geq 0} \pi(s^*(\theta), \theta)$
- (iii) $p^*(\theta) = \theta p_H^*(\theta)$,

$$(iv) \ y^*(\theta) = s^*(\theta)$$

3.2 Results

The following proposition characterizes the set of Nash-Walras equilibria:

Proposition 3.1. *There exists a threshold value $0 < \hat{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} < 1$, such that (i) for each $\theta < \hat{\theta}$, $s^*(\theta) = 0$, $p^*(\theta) = 0$, $y^*(\theta) = s^*(\theta) = 0$ is the only Nash-Walras equilibrium, and (ii) when $\theta > \hat{\theta}$, both $(s^*(\theta) = 0, p_H^*(\theta) = R_H, p^*(\theta) = 0, y^*(\theta) = s^*(\theta) = 0)$ and $(s^*(\theta) = 1, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = s^*(\theta) = 1)$ are Nash-Walras equilibria and the latter equilibrium Pareto dominates the former.*

Proof. Given that $R_L = 0$, it must be the case that $p_L = 0$ so that the price of a share is $p = \theta s p_H$. Given constant returns to scale, in equilibrium, the firm must make zero profits. Hence, $p_H^*(\theta) = R_H$ and $\theta s^*(\theta) R_H = p^*(\theta)$ in equilibrium. At $t = 1$, given s_i, s, θ , $p_H^*(\theta) = R_H$ in equilibrium the lottery over future consumption at $t = 2$ is denoted by $l(s_i, s, \theta) = \{1 - s_i + R_H s_i, \theta s; 1 - s_i, 1 - \theta s\}$. By computation, the corresponding average level of future consumption is $\mu(l(s_i, s, \theta)) = 1 - s_i + \theta s R_H s_i$ and the variance of future consumption is $\sigma^2(l(s_i, s, \theta)) = \frac{\theta s(1 - \theta s) R_H^2 s_i^2}{2}$. Note that the average level of future consumption is when the individual invests only in the storage technology is $\mu(l(0, s, \theta)) = 1$ and the variance of future consumption is $\sigma^2(l(0, s, \theta)) = 0$.

By computation, for a given s and θ , setting $s_i = 0$ implies a payoff of

$$v(0, s, \theta) = 1, \forall s \in [0, 1] \quad (4)$$

In equilibrium, setting $s_i = 1$ implies a payoff of

$$v(1, s, \theta) = \theta s R_H - \gamma \frac{\theta s(1 - \theta s) R_H^2}{2}. \quad (5)$$

Let $b_i(s, \theta)$ denote the best-response by player i . It follows that:

$$b_i(s, \theta) = \begin{cases} 1, & \text{if } (\theta s R_H - 1) - \gamma \frac{\theta s(1 - \theta s) R_H^2}{2} \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

It follows that if $s = 0$, the best response is to set $s_i = 0$ for all $i \in [0, 1]$. Hence, for each θ , the investment strategy profile $(s_i^*(\theta) = 0 : i \in [0, 1])$ is an equilibrium. Next, by computation, note that when $s = 1$:

$$v(1, 1, \theta) = (\theta R_H - 1) - \gamma \frac{\theta(1 - \theta) R_H^2}{2} \quad (7)$$

Observe that

$$\lim_{\theta \rightarrow 0} v(1, 1, \theta) = 0 < 1 = v(0, s, \theta), \quad (8)$$

while

$$\lim_{\theta \rightarrow 1} v(1, 1, \theta) = R_H > 1 = v(0, s, \theta), \forall s \in [0, 1] \quad (9)$$

Hence, there exists value $0 < \hat{\theta} < 1$ such that whenever $\theta > \hat{\theta}$, the investment strategy profile $(s_i^*(\theta) = 1 : i \in [0, 1])$ is also an equilibrium.

By computation, the roots of the equation $v(1, 1, \theta) - 1 = 0$ are $\frac{\gamma R_H - 2 \pm \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H}$. Of the two roots, only $\frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} > 0$ and when $\delta R_H > 1$, $\frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} < 1$. By computation, note that $\frac{\partial v(1, 1, \theta)}{\partial \theta} > 0 \iff \delta R_H > \frac{\sigma R_H^2}{2}(1 - 2\theta) \iff \theta > \frac{\gamma R_H - 2}{2\gamma R_H}$. Moreover, by computation, it must be the case that $\hat{\theta} > \frac{\gamma R_H - 2}{\gamma R_H}$ as $v(1, 1, \frac{\gamma R_H - 2}{\gamma R_H}) < 0$. Hence, $\hat{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H}$. Finally, note that when $\theta > \hat{\theta}$, $v(1, 1, \theta) > v(0, 0, \theta)$, $\forall s \in [0, 1]$. Hence the Nash-Walras equilibrium $(s^*(\theta) = 1, p_H^* = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = s^*(\theta) = 1)$ Pareto dominates the Nash-Walras equilibrium $(s^*(\theta) = 0, p_H^* = R_H, p^*(\theta) = 0, y^*(\theta) = s^*(\theta) = 0)$. \square

The key implication of Proposition 3.1 is that the when (a) economic fundamentals are low, $0 \leq \theta < \hat{\theta}$, there is no investment in the risky asset, (b) when economic fundamentals are high, $\hat{\theta} < \theta < 1$, then there are multiple Nash Walras equilibria, one where there is no aggregate investment in the risky asset which is Pareto dominated by the one where all endowments in period 1 are invested in the risky asset.

Intuitively, when economic fundamentals are low, $0 \leq \theta < \hat{\theta}$, the return from investing in the risky asset, even when all other individuals choose to do so, cannot compensate for the negative impact of the resulting level of anxiety. Hence, it is a dominant action for individuals to invest in the storage technology.

When economic fundamentals are high, $\hat{\theta} < \theta < 1$, there is no dominant action. If all individuals expect all other individuals to invest in the storage technology, then investing in the storage technology is a best response: hence, the expectation that no individual invests in the risky asset becomes self-fulfilling. On the other hand, the return from investing in the risky asset, even when all other individuals choose to do so, more than compensates for the negative impact of the resulting level of anxiety; hence, the expectation that every individual invests in the risky asset becomes self-fulfilling. So when fundamentals are good, when individuals coordinate on the Pareto dominated equilibrium, there is coordination failure and aggregate welfare is reduced.

Given the existence of multiple Pareto dominated Nash Walras equilibria, which one do agents coordinate on? In the context of two player coordination games, Harsanyi and Selten (1988)'s answer was that the risk-dominant equilibrium, which has a higher degree of immunity to strategic uncertainty when there is a lack of an economy-wide consensus about what each agent believes other agents are going to do, will prevail. In what follows, we adapt the concept of stochastic stability (developed by Young (1988) to

our setting, to develop an equilibrium selection argument that selects the risk-dominant equilibrium and examine how the risk-dominant equilibrium depends on the underlying value of fundamentals.

One way to gain intuition about the equilibrium selection argument we deploy is by relating it to equilibrium coordination in stag-hare hunting game (Rousseau, 1964). Rousseau uses the game to contrast the gains of hunting hare, where the risk of non-cooperation is small or non-existent (in our case, investing in the storage technology) and the individual reward and social benefit equally small, against the gains of hunting the stag (in our case investing in the risky asset), where maximum coordination on is required and the risk of non-cooperation is greater but both the individual reward and social benefit (if successful) is much greater. The point is that hunting the hare is risk dominant as success in this activity does not depend on what other agents even though coordinating to hunt the stag is Pareto dominant.

To motivate why strategic uncertainty may raise, it is useful to consider a setting where are multiple narratives. A narrative map associates economic fundamental to potentially different perceived average level of investment in the risky asset across individual agents. Formally, a narrative map $\sigma : [0, 1] \rightarrow [0, 1]$ specifies the proportion of agents $\sigma(\theta) \in [0, 1]$ who associate an average level of investment 1 in the risky asset when economic fundamentals take on the value of θ ; the corresponding fraction of agents who disagree and associate an average investment level of 0 in the risky asset when economic fundamentals are θ is given $1 - \sigma(\theta)$. Whenever $0 < \sigma(\theta) < 1$, the narrative map allows for multiple narratives: there are two null sets of agents who disagree with each other about the what the average level of investment in the risky asset is going to be when economic fundamentals are θ .

Suppose an agent believes that whenever any other agent chooses to play a specific action, she ends up choosing some other action with probability $q, 0 < q < 1$. In the presence of multiple narratives, this introduces strategic uncertainty as agents who associate an average level of investment 1 when economic fundamentals take on the value of θ will choose to invest in the risky asset with probability $1 - q$ and invest in the storage technology with probability q and vice versa, agents who associate an average investment level of 0 when economic fundamentals are θ will invest in the storage technology with probability $1 - q$ and in the risky asset with probability q . So, by Proposition 3.1, when $< \hat{\theta}$, there is only one possible outcome namely that all individuals will invest in the storage technology. In this case, there is, endogenously, no strategic uncertainty. When $> \hat{\theta}$, unless $\sigma(\theta) = 1$ or $\sigma(\theta) = 0$, multiple narratives will result in strategic uncertainty.

We will adapt the notion of a stochastically stable equilibrium (Young, 1998) to select between the two equilibria. Let G be an arbitrary finite normal form game with a set of N players, an action set A^i for each player $i = 1, \dots, N$ and a payoff $u^i : \prod_{(i=1)}^N A^i \rightarrow \mathfrak{R}$. Suppose each player believes that whenever any other player chooses to play a specific

action, with probability $q, 0 < q < 1$, she ends up choosing some other action in A^i (with probability $1 - q$ he plays the chosen action). Let $G(q)$ denote the perturbed game. For each action profile, let each player pick a best response to that action state in $G(q)$ i.e. taking into account the possibility that other individuals will make a mistake with probability q . This defines a function σ from the set of action profiles to itself. If there are many best responses, then there will be many such functions σ . When q is small enough, let the set of σ 's that remain best responses for all smaller q be denoted by $S(G)$. Any $\sigma \in S(G)$, together with q , defines a Markov process over the set of action profiles that is both irreducible and aperiodic and therefore has a unique steady-state distribution. A stochastically stable action profile is one which has positive probability under the limit of the steady state distribution of the preceding Markov process as q goes to zero for any selection $\sigma \in S(G)$. If an action profile is both a Nash equilibrium of G and is stochastically stable, then it is said to be a stochastically stable equilibrium of G .

To be able to use the concept of stochastically stable equilibria in our setting we proceed as follows. First, we reformulate the Nash Walras equilibrium as a Nash equilibrium. As the firm has constant returns to scale technology it must make zero profits in equilibrium so that $p_H^* = R_H$ and $\pi^* = 0$. Hence, a payoff equivalent reformulation of the model is a non-cooperative game where each individual can invest in either the storage technology or the risky asset and the returns of the risky asset depend on θ and s in a manner already described and $p_H = R_H$ and $\pi = 0$ throughout. In this formulation, the role of the firm is eliminated and there is no market where contingent claims on the risky asset are traded and instead of a Nash-Walras equilibrium, we have a Nash equilibrium. Formally:

Definition 2 For each $\theta \in [0, 1]$, a Nash equilibrium is $s^*(\theta)$ an assignment of investment strategies, such that given $s^*(\theta), s_i^*(\theta) \in \operatorname{argmax}_{s_i \in [0, 1]} v((s_i, s^*(\theta)), \theta)$, for all $i \in [0, 1]$.

It follows directly from Proposition 3.1, that there exists a threshold value $0 < \hat{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} < 1$, such that (i) for each $\theta < \hat{\theta}$, $s^*(\theta) = 0$, the only Nash equilibrium, and (ii) when $\theta > \hat{\theta}$, both $(s^*(\theta) = 0)$ and $(s^*(\theta) = 1)$ are both Nash-Walras equilibria and the latter equilibrium Pareto dominates the former. Second, it will be useful to define $\bar{s}(\theta)$ as a solution to the equation $v(1, s, \theta) - 1 = 0$. The following result provides characterization of $\bar{s}(\theta)$:

Lemma There is a unique solution define $\sigma(\theta)$ to the equation $v(1, s, \theta) = 1$ given by

$$\bar{s}(\theta) = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} \quad (10)$$

Proof. The equation $v(1, s, \theta) = 1$ can be written as $(\theta s R_H - 1) - \gamma \frac{\theta s(1 - \theta s) R_H^2}{2} = 0$. Let $x = \theta s$, $0 \leq x \leq 1$. Substituting x in the preceding equation, we obtain $\delta(x R_H - 1) -$

$\gamma \frac{x(1-x)R_H^2}{2} = 0$. By computation, the roots of the equation are $\frac{\gamma R_H - 2 \pm \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H}$. Of the two roots, only $\frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} > 0$ and when $R_H > 1$, $\frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} < 1$. By computation, note that $(xR_H - 1) - \gamma \frac{x(1-x)R_H^2}{2} > 0 \iff \frac{\gamma R_H^2}{2}(1 - 2x) \iff x > \frac{\gamma R_H - 2}{2\gamma R_H}$. Moreover, by computation, it must be the case that $\frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} > \frac{\gamma R_H - 2\delta}{\gamma R_H}$. Hence, $x = \theta s = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H}$ or equivalently, $\bar{s}(\theta) = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H \theta}$. \square

Third, for a fixed value of $\theta \in [0, 1]$, consider a sequence of finite grids contained in $[0, 1]$ whose limit is $[0, 1]$. Denote such a sequence of finite grids by $\hat{N}_j, j \geq 1$. Let $N_j = \#\hat{N}_j$. We call a sequence of finite grids admissible if (i) there exists a $\tilde{N}_j, 0 < \tilde{N}_j < N_j$ such that $\frac{\tilde{N}_j}{N_j} = \bar{s}(\theta)$, (ii) the payoff to agent i is $v(s_i, s, \theta)$ where $s_i \in \{0, 1\}$. We are now able to state the following definition:

Definition 3 A Nash equilibrium $s^*(\theta)$ (equivalently, a Nash Walras equilibrium $(s^*(\theta), p_H^*(\theta), p^*(\theta), y^*(\theta))$) to be stochastically stable if it is the limit of the sequence of stochastically stable equilibria of all admissible sequences of finite grids converging to $[0, 1]$. The following proposition characterizes which equilibrium will be selected:

Proposition 3.2. *If $\theta > \tilde{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2\delta - \gamma R_H)^2 + 8\gamma}}{\gamma R_H}$, then $(s_i(\theta) = 1)$ (respectively, $(s^*(\theta) = 1, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = 1)$ is the only stochastically stable Nash (respectively, Nash Walras) equilibrium; if $\theta < \tilde{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2\delta - \gamma R_H)^2 + 8\gamma}}{\gamma R_H}$, then $(s_i(\theta) = 0)$ (respectively, $(s^*(\theta) = 1, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = 0)$ is the only stochastically stable Nash (respectively, Nash Walras) equilibrium.*

Proof. Fix j and consider \hat{N}_j . For q small enough, if at least \tilde{N}_j individuals invest in the risky asset, then the best response of other individuals must be to invest in the risky asset as well. Similarly, if at most $\tilde{N}_j - 1$ invest in the risky asset, then the best response of each other individual must be to continue to invest in the storage technology. In action profiles where exactly $\tilde{N}_j - 1$ invest in the risky asset, choosing either of the two options, invest in the risky asset or invest in the storage technology, are both possible best responses for an individual investing in the storage technology. It follows that that best responses differ only in action profiles where the number of individuals choosing to invest in the risky asset is exactly $\tilde{N}_j - 1$. Now, consider the associated Markov process for small q . There are two recurrent communication classes (for the definition of the terms "recurrent communication classes", "resistance" and "minimum stochastic potential", see Young, 1993), one where all individuals invest in the risky asset (labelled **a**) and one in which all individuals invest in the storage technology (labelled **b**). By Theorem 4 in Young (1993), only action profiles in a recurrent communication class with least resistance will have positive probability weight in the limit of the steady state distribution of the Markov process as q goes to zero. Consider the action profile **b**. Then, (i) there is a best response selection such that

given $N_j - \tilde{N}_j + 2$ errors, the best response of each individual is to be in **a** and (ii) there is a best response selection such that given $N_j - \tilde{N}_j + 1$ errors, the best response of each individual is to be in **a**. Therefore, the minimum resistance of leaving the action profile **b**, depending on the selection made, is either $N_j - \tilde{N}_j + 1$ or $N_j - \tilde{N}_j + 2$. It follows that the minimum resistance of a tree oriented from the action profile **b** to the action profile **a**, depending on the best response selection made, is either $N_j - \tilde{N}_j + 1$ or $N_j - \tilde{N}_j + 2$. Next, consider the action profile **a**. Then, there is both a best response selection such that given $\tilde{N}_j - 1$ errors, the best response of each individual is to be in **b**, and a best response selection such that given $\tilde{N}_j - 2$ errors, the best response of each individual is to be in **b**. Therefore, the minimum resistance of leaving the action profile **a**, depending on the best response selection is either $\tilde{N}_j - 1$ or $\tilde{N}_j - 2$. It follows that the minimum resistance of a tree oriented from the action profile **a** to the action profile **b**, depending on the best response selection made, is also either $\tilde{N}_j - 1$ or $\tilde{N}_j - 2$.

The action profile **b** is the unique stochastically stable equilibrium if and only if both $N_j - \tilde{N}_j + 1 < \tilde{N}_j - 1$ and $N_j - \tilde{N}_j + 2 < \tilde{N}_j - 2$ or equivalently, both $\tilde{N}_j > \frac{N_j+2}{2}$ and $\tilde{N}_j > \frac{N_j+4}{2}$. As $\frac{N_j+2}{2} < \frac{N_j+4}{2}$ if $\tilde{N}_j - 1 > \frac{N_j}{2}$, the action profile **a** is the unique stochastically stable equilibrium. Rewriting these inequalities, it follows that action profile **a** is the unique stochastically stable equilibrium if and only if $\frac{\tilde{N}_j-2}{N_j} > \frac{1}{2}$. Given θ , for any admissible sequence of finite grids, $\lim_{j \rightarrow \infty} \frac{\tilde{N}_j-2}{N_j} = s(\theta)$ so that when $s(\theta) > \frac{1}{2}$, the unique stochastically stable equilibrium is one where all individuals invest in the storage technology or conversely, when $s(\theta) < \frac{1}{2}$, the unique stochastically stable equilibrium is one where all individuals invest in the risky asset. Finally, by computation, note that $\bar{s}(\theta) < \frac{1}{2}$ (respectively, $\bar{s}(\theta) > \frac{1}{2}$) if and only if $\theta > \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{\gamma R_H}$ (respectively, $\theta < \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{\gamma R_H}$). \square

Heuristically, note that for a given value of θ when $\bar{s}(\theta) < \frac{1}{2}$ (when $\theta > \tilde{\theta}$) the Nash (respectively, Nash-Walras) equilibrium where $(s_i^*(\theta) = 1)$ (respectively, $(s^*(\theta) = 1, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = 1)$) is risk dominant; conversely when $\bar{s}(\theta) > \frac{1}{2}$ (when $\theta < \tilde{\theta}$) the Nash (respectively, Nash-Walras) equilibrium where $(s_i^*(\theta) = 0)$ (respectively, $(s^*(\theta) = 1, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = 0)$) is risk dominant.

Hence, in the presence of multiple narratives and the resulting strategic uncertainty, using stochastic stability as an equilibrium selection argument, we select the equilibrium that is risk dominant.

3.3 Comparative Statics and Policy Implications

We are now able to examine comparative statics of the Nash-Walras equilibrium and derive predictions which can be taken to the data.

So far, we have taken θ , the value of economic fundamentals, to be a constant. It will be convenient, at this point, to assume that there is a continuous CDF $F(\theta)$ (with $f(\theta)$) which determines the distribution of θ in $[0,1]$. Given our equilibrium selection argument in 3.2, the distribution over θ induces a distribution over asset prices $p(\theta)$. A straightforward calculation shows that, in equilibrium, the mean asset price is $E(p(\theta)) = R_H \int_{\tilde{\theta}}^1 \theta dF(\theta)$ and the variance of asset prices is $V(p(\theta)) = \int_{\tilde{\theta}}^1 (\theta R_H - Ep(\theta))^2 dF(\theta)$. The following proposition characterizes the link between the value of the anxiety parameter and the equilibrium variance of asset prices $V(p(\theta))$:

Proposition 3.3. *An increase in the value of the anxiety parameter, γ , reduces the value of the equilibrium variance prices $V(p(\theta))$ of the asset price $p(\theta)$.*

Proof. The proof is in two steps. First, we show that $\tilde{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{\gamma R_H}$ is increasing for all $\gamma > 0$. By computation:

$$\frac{d\tilde{\theta}}{d\gamma} = \frac{2 + \{\gamma[(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}}(2 - \gamma R_H)^2 R_H + 4\} - [(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}}}{R_H \gamma^2} \quad (11)$$

By computation:

$$\{\gamma[(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}}(2 - \gamma R_H)^2 R_H + 4\} - [(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}} \geq 0 \quad (12)$$

if and only if $\gamma \geq \frac{R_H - 2}{2}$. When $0 \leq \gamma < \frac{R_H - 2}{2}$, note that $\{\gamma[(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}}(2 - \gamma R_H)^2 R_H + 4\} - [(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}} \geq -2$. Hence, it follows that $2 + \{\gamma[(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}}(2 - \gamma R_H)^2 R_H + 4\} - [(2 - \gamma R_H)^2 + 8\gamma]^{\frac{1}{2}} > 0$ for all $\gamma > 0$. Second, we show that $V(p(\theta)) = \int_{\tilde{\theta}}^1 (\theta R_H - Ep(\theta))^2 dF(\theta)$ is decreasing in $\tilde{\theta}$. Indeed, by computation,

$$V(p(\theta)) = (Ep(\theta))^2 + R_H^2 \int_{\tilde{\theta}}^1 \theta^2 dF(\theta) + 2R_H Ep(\theta) \int_{\tilde{\theta}}^1 \theta dF(\theta) \quad (13)$$

Note that $Ep(\theta)$, $\int_{\tilde{\theta}}^1 \theta^2 dF(\theta)$, $\int_{\tilde{\theta}}^1 \theta dF(\theta)$ are all decreasing in $\tilde{\theta}$; hence by the product rule, $Ep(\theta) \int_{\tilde{\theta}}^1 \theta dF(\theta)$ is also decreasing in $\tilde{\theta}$. It follows that an increase in the value of the anxiety parameter, γ , reduces the value of the equilibrium variance prices $V(p(\theta))$ of the asset price $p(\theta)$. \square

Proposition 3.3 establishes the key empirical prediction of the model, that the variance of the price of the risky asset is negatively correlated with the level of anxiety. The intuition is simple. Each agent reacts to an increased degree to anxiety by reducing their exposure to the risky asset so that its variance is reduced. In the process, however, opportunities for socially valuable investment is lost. Later in the paper, we will provide empirical evidence consistent with this empirical prediction.

What are the policy implications of our analysis? By Proposition 3.2, note that $\frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{2\gamma R_H} = \hat{\theta} < \tilde{\theta} = \frac{\gamma R_H - 2 + \sqrt{(2 - \gamma R_H)^2 + 8\gamma}}{\gamma R_H}$. Hence, when $\theta \in (\hat{\theta}, \tilde{\theta})$, both

$(s^*(\theta) = 0, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = s^*(\theta) = 0)$ and $(s^*(\theta) = 1, p_H^*(\theta) = R_H, p^*(\theta) = \theta R_H, y^*(\theta) = s^*(\theta) = 1)$ are Nash-Walras equilibria with the latter equilibrium Pareto dominant but crucially, risk dominated by the former equilibrium. In this case, in the presence of multiple narratives, the Pareto dominated equilibrium is the one all agents will coordinate on to mitigate the anxiety resulting from extra variance in asset returns due to strategic uncertainty.

Hence, when $\theta \in (\hat{\theta}, \tilde{\theta})$, there is a role for policy to enable agents to coordinate on the Pareto dominant equilibrium when it is not risk dominant. In the paper we call such a lighthouse policy one that resolves an underlying coordination problem in the presence of strategic uncertainty. Such a lighthouse policy can be consistent with a balanced budget. Essentially, the policy maker can impose a Pigouvian tax $t(\theta) = \bar{s}(\theta) + \epsilon > 0$ for small but positive $\epsilon > 0$, on every unit invested in the storage technology and use it finance investment in the risky technology. What such a policy does is to ensure that there is floor in the investment in the risky technology. With such a policy in place, it follows that investing in the risky asset becomes a dominant action for each individual. In this way, the underlying coordination problem is solved.

Note that with such a policy in place, no actual taxation will need to be levied on the investment in the storage technology as in no individual will invest in the storage technology. It is the fact that such a policy intervention is common knowledge which ensures that the underlying coordination problem is solved. We call such policies lighthouse policies and they are discussed in greater detail later on in the paper.

4 Empirical analysis

4.1 Scoring the anxiety

In order to measure the level of anxiety, we first start from its definition. From the Cambridge Dictionary anxiety refers to "an uncomfortable feeling of nervousness or worry about something that is happening or might happen in the future".

With this definition in mind, we extract economic anxiety from the news published online by Daily Mail, Reuters and Press Association. The methodology we used is explained in two different sections: in this section we illustrate the scoring criteria; in the Appendix A we explain the sentiment analysis using a machine learning approach to extend the scores of a training set of articles to the whole population of articles we deploy in the empirical analysis.

We associate each article to a perceived level of anxiety based on the content of the article. We focus on economic anxiety, related to macroeconomic facts (unemployment,

Table 1: Examples of article labelling.

	Article
High anxiety	Could we see a repeat of the roaring twenties or the Wall Street Crash? Experts believe the 2020s could see a rise in prosperity much like in the 1920s - but also warn that recession "looks inevitable"
Medium anxiety	Tesco chairman launches blistering attack on business rates and calls for major overhaul of tax system to help struggling High Street stores survive
Low anxiety	Dollar dips as investors prepare for volatile markets, Fed meeting

inflation, GDP, government policy.

We distinguish between four levels of anxiety. Given the impossibility of collecting a population average of the emotions, the distinction between the four levels is necessarily subjective because it seeks to capture the emotions of the "average" person who is reading the article. We proceed as follows. We label an article *high anxiety* when it deals with an "extraordinary" fact, e.g. "the largest crisis" or "the highest unemployment rate". Next, we label *medium anxiety* an article which refers to a bad situation which is however known and already tackled by the key agents (firms, workers, government) or when the negative connotation of the topic is limited to a specific sector and points to a structural weakness. For instance, the article deals with bail-out interventions in a period of high insolvency or with private considerations on the tax system. Then, we label an article *low anxiety* when the fact reported is of limited impact or when the negative connotation of the topic is just sketched. Usually the article content deals with small changes in unemployment rate or with reference to vague pessimistic outlook. Finally, in order to train the machine learning algorithm, we also use the label *no anxiety*, which either indicates no reference to bad events or presents a mix of positive and negative outlook.

We construct a distribution of anxiety scores between 0 to 1. We assume that the anxiety we detect from the newspaper articles corresponds to the average anxiety within each tercile of the distribution. Our assumption is that the anxiety score assigned to a newspaper article is a proxy for the anxiety experienced by the median reader.

On a scale of individual anxiety σ between zero and one, logically no anxiety has a $\sigma = 0$. Low anxiety corresponds to the average level within zero and the first tercile of the anxiety burden, which means $\sigma = 0.17$. Medium anxiety corresponds to $\sigma = 0.50$. High

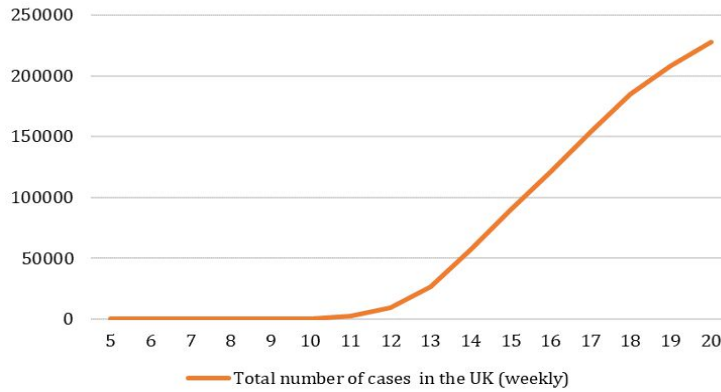


Figure 1: Comparison between general personal anxiety (ONS) and economic anxiety.

anxiety corresponds to $\sigma = 0.83$. Then, we build an index of daily anxiety by using the weighted average number of articles corresponding to each anxiety level. The index σ_d for day d goes from 0.17 to 0.83 with a continuous of values in between, depending on the number of articles for each anxiety level. Formally, it corresponds to

$$\sigma_d = \frac{0.17N_{dL} + 0.50N_{dM} + 0.83N_{dH}}{Nd} \quad (14)$$

where N_{dL} is the number of articles in day d labelled with low anxiety, N_{dM} is the number of articles labelled with medium anxiety and N_{dH} is the number of articles labelled with high anxiety.

4.2 Descriptive statistics

In this section, we begin by presenting a visualization and the descriptive statistics of the anxiety index.

First, we provide evidence for the plausibility of our anxiety score. The spread of the pandemic due to the virus COVID-19 provides an ideal ground to test whether and to what extent our score for economic anxiety mimics the feeling of general anxiety. Figure 1 plots the total number of cases in the week (data is publicly available on the COVID webpage of the UK Government) starting from the 30th of January 2020. The trend takes off around the 10th week, i.e. the 1st of March, which is the date after which the expression "stay at home" started to appear in the titles of our population of articles. Although a proper lockdown was not yet implemented back then, it is reasonable to expect that people had started to be worried about their personal health, their social life and, most importantly for us, their economic conditions.

The Office of National Statistics (ONS) of the UK measures an overall sentiment of anxiety, not related in particular to the economic perspectives. The survey asks "Overall,

Table 2: Example of article labelling.

	Observations	Mean	SD	Min	Max
Macroeconomic anxiety	255	0.41	0.04	0.28	0.50
Stock market volatility	255	5.04	0.46	3.75	7.02

how anxious did you feel yesterday?” and answers are given on a scale of 0 to 10, where 0 is ”not at all anxious” and 10 is ”completely anxious”. The data is available from the 13th week of 2020. It is a useful indicator because it embeds also the concept of economic anxiety, depending on whether the respondent is more anxious about her health, her economic situation and her social life. Figure 2 plots the mean of the ONS responses on a weekly basis together with the weekly mean of economic anxiety (smoothed with an HP filter). Economic anxiety indicator shows anxiety starts increasing rapidly in February, peaking mid-March. Economic anxiety maintains peak longer and reduces more slowly than the self-reported subjective anxiety recorded in the ONS Well-being and Quality of Life Survey. This signifies greater amplification coming from news generated anxiety than self-reported anxiety.

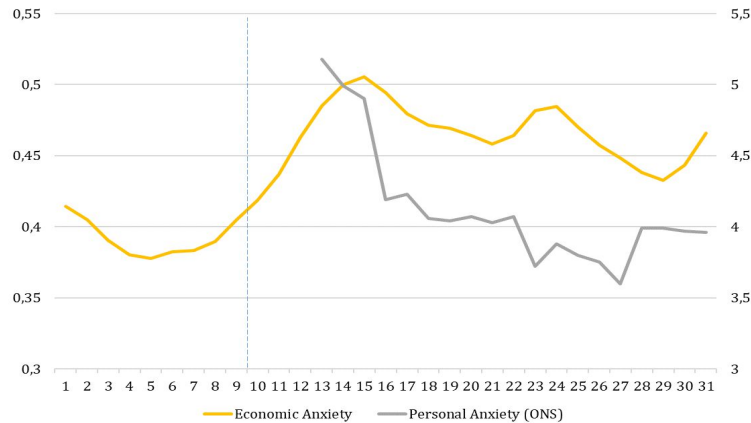


Figure 2: Comparison between general personal anxiety (ONS) and economic anxiety.

In the econometric analysis, we will estimate the shock of anxiety on the volatility of the stock market in 2019. To this purpose, we use data from investing.com and compute the (log) difference in the max-min daily price of FTSE 250. After excluding the weekends and holidays to match the two series, we end up with 255 observations.

Average anxiety is 0.41, with a relatively small standard deviation of 0.04. The mean points to a slight prevalence of low anxiety sentiment. Anxiety fluctuates substantially across time, which reflects a change of newspaper sentiment in a relatively short time. The same is true for the volatility of the stock market. Figure 3 plots the two series for 2019,

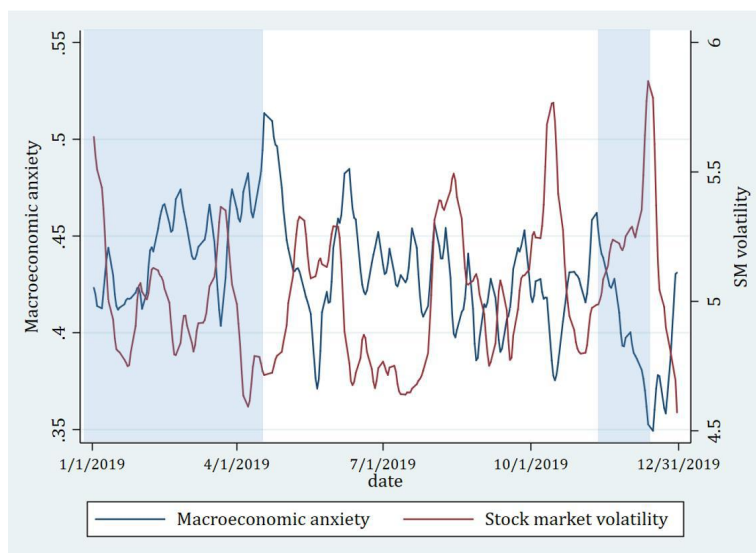


Figure 3: Economic anxiety and stock market (FTSE250) volatility.

the base year for our econometric analysis. We smoothed both series using an HP filter. A first interesting pattern is a counter movement of anxiety and stock market volatility. The up spikes of anxiety mimic the drops in stock market volatility. This counter-cyclicality is confirmed by the negative correlation between the two series ($\rho = -0.50$). Despite the intense fluctuation, there are stable trends which corresponds either to periods of political instability or to clearer expectations concerning the Brexit and political scenarios in the UK. For instance, the shaded area (1st of January – 18th of April) at the beginning of 2019 corresponds to a period of Brexit impasse, namely, when premier Teresa May was not able to pass an agreement with the EU while the negotiation deadline of the 29th of March was approaching. After the last attempt to pass her proposal on a deal, Theresa May asked the EU Parliament to extend the Brexit and the 11th of April the EU leaders agreed to postpone it to the 31st of October. Conversely, the shaded area in the second half of 2019 (8th of November – 16th of December) follows a period of remarkable political instability in the UK, namely, when the premier Boris Jonson expressed himself in favour of a hard Brexit against a large majority of the Parliament. Failing to go for new elections, the UK government was forced to negotiate a Brexit deal and the Parliament agreed on holding Early Parliamentary General Elections the 12th of December 2020.

Stock market volatility fluctuates in a way similar to economic anxiety (the coefficient of variations are 0.10 and 0.09 respectively). We observe two important positive spikes at the end of the series: one on the 11th of October and another on the 13th of December, the day of the general elections.

4.3 Estimation

Our purpose is to measure the dynamic properties of anxiety on the stock market (henceforth, SM) volatility. Therefore, in our econometric analysis we will use unfiltered daily data. Both series are statistically stationary, according to the Dickey-Fuller test (see Table B1 in the Appendix B). This allows us to estimate the relationship between the two variables in a vector autoregressive (VAR) setting. We start with the following model

$$y_t = c_0 + \sum_{i=1}^d A_i y_{t-i} + u_t \quad (15)$$

where y_t represents the vector of the two endogenous variables log of volatility and anxiety, A_i are $n \times n$ coefficients capturing their interlinkage and u_t is an n -dimensional vector of white noise errors. As deterministic term, we allow for a $n \times 1$ vector of constants c_0 .

In order to estimate causal dynamic effects, we need to impose a set of restrictions on our coefficients. In this context, the conceptualization of anxiety, especially its forward looking generation, is of great usefulness, because it provides the ground for our identification strategy. Hence, we test two specifications: one with short-run/contemporaneous restrictions and another one with long-run restrictions.

In the short-run specification, we select a Cholesky identification imposing a lower-triangular matrix A and an identity matrix B of the error terms. This is equivalent to assume zero contemporaneous impact of SM volatility on economic anxiety. The impulse response functions of this identification strategy are reported in Figure 4. Positive economic anxiety shocks impact negatively on SM volatility, statistically significant with a 2-days lag. This negative impact remains significant for the subsequent two days and then become insignificant. The cumulative impact is negative and significant.

As a robustness check, we allow for the opposite restriction, namely, that is economic anxiety to have no contemporaneous impact on SM volatility. This identification strategy delivers very similar results (see Figure B1 in the Appendix B).

Both strategies illustrated above do not allow both series to contemporaneously affect each other. Therefore, we use a third identification strategy and impose the long-run restrictions. Given the forward-looking generation of anxiety and the stationarity of the two series, we impose a restriction on the impact that SM volatility has on economic anxiety on the long-run, while we leave both series to be interlinked contemporaneously and economic anxiety to impact on the SM volatility in the long-run. In other words, if anxiety corresponds to the bad feeling on future outcome, we assume that it is unlikely that old information on stock market volatility can impact in a significant manner on economic anxiety today. If it were the case, it would mean that a person expects the future to change even further, which would likely imply a non-stationary stock market volatility.

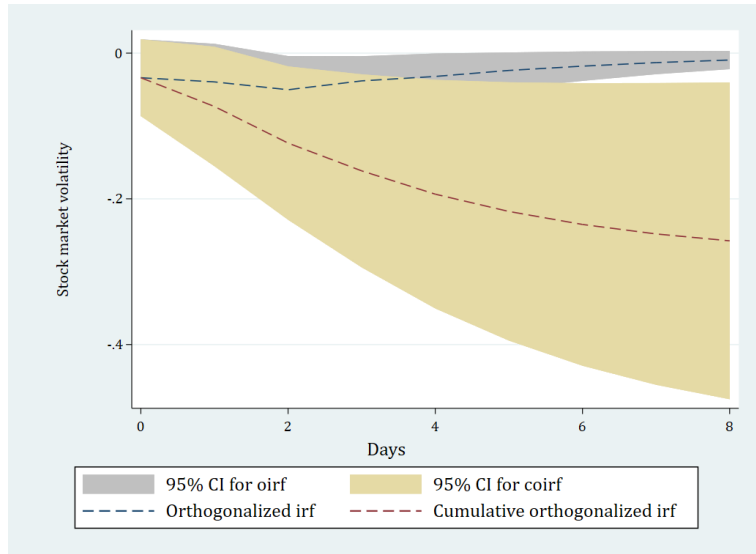


Figure 4: Impulse response of stock market volatility from a shock of economic anxiety (short-run restrictions).

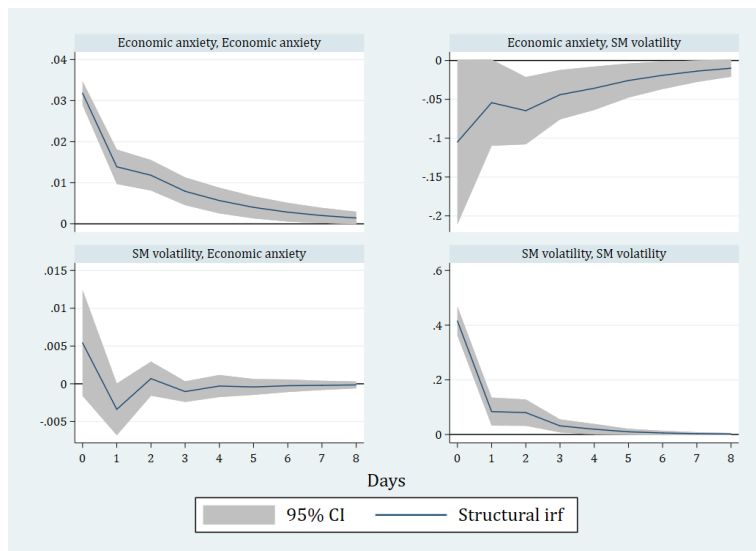


Figure 5: Impulse responses of stock market volatility from a shock of economic anxiety (long-run restrictions).

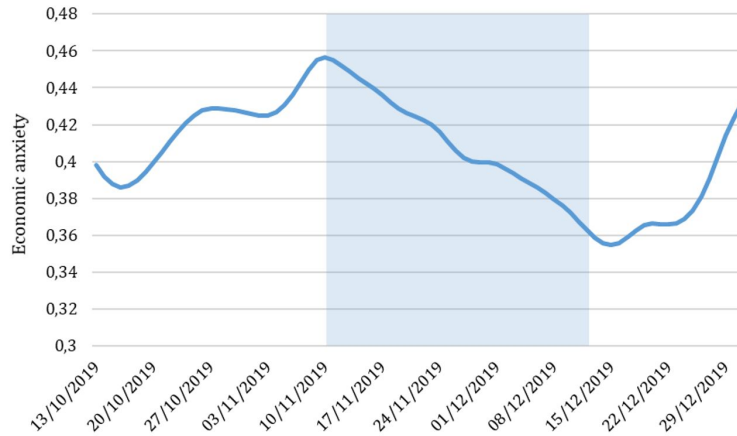


Figure 6: Economic anxiety across UK General Elections of December 2019.

Figure shows the impulse responses of this identification strategy. Shocks of both series have no contemporaneous impact on each other. Shocks on economic anxiety, similarly to the short-run specification, shows a negative and significant impact on SM volatility which starts already from day one and lasts for nearly a week before turning insignificant. Conversely, shocks from SM volatility have no impact in the short-run and, as imposed by the identification strategy, no impact also in the long-run.

5 The role of policy

In this section we apply our analysis to Brexit and the 2019 UK General Election. This episode can be viewed as quasi-natural experiments with before and after the ‘shocks’ and multiple equilibria thus allowing us to analyse the dynamic interactions of economic anxiety and policy.

5.1 Brexit and Competing Narratives

With UK voters’ (IE $[0,1]$) anticipatory preferences at one initial point in time ($t = 1$) - and subsequent point in time ($t = 2$) - with competing narratives regarding the best possible equilibrium, dependent on whether economic agents choose to invest in remain or leave (storage technology v risky asset). In this example, the referendum triggers a multiplicity of policy options (from continued full access to the EU single market to no deal), with policy-makers facing a time limited choice for selecting a new equilibrium. The multiple failures of the Government to persuade parliament to vote in favour of any of its options resulted first in the proroguing of parliament and then the 2019 general election. It was assumed that the outcome of the general election would decisively bring domestic Brexit negotiations on the UK’s preferred type of relationship with the EU to a close.

As shown in Figure 6 peak economic anxiety occurs mid-November, one month before the UK General Election. This is intuitive, as an anticipatory emotion anxiety will peak before any actual event/decision, and be amplified by competing narratives (firstly, continuing policy decisions such as failing to reach consensus in the House of Commons and the proroguing of Parliament). Following peak anxiety it gradually reduces to previous levels. This may seem counter-intuitive as anxiety is steadily falling during the election campaign. However, it is also purdah, when there is a halt to policy announcements and a switch to political campaigning. Anxiety then drops in the run up to the election and stabilises from two weeks before the election before increasing until the end of the year.

The fact that our anxiety indicators shows a steady decline in anxiety during the election campaign is consistent with parametric anxiety as earlier defined (households can form stable beliefs through rational expectations). This is because anxiety is anchored within ‘a range of indeterminacy’: the general election outcome is bounded within a limited number of possible outcomes – Conservative majority; Labour majority; minority government; coalition government; hung parliament and re-election. This reduces anxieties for households, investors and consumers. Then following the outcome of the election anxiety reduces further, and stabilises around the outcome (established new equilibrium). Once the Conservative government was elected many believed this would be the end of the Brexit debate, as they had been elected on a ‘Get Brexit done’ mandate. Though general elections are just that – not a referendum - and should be contested on multiple policies.

5.1.1 Focal Points and Brexit

[Schelling \(1960\)](#) explains the focal point’s role in co-ordinating economic activity. However, what happens when the previous focal point changes? [Dow \(2015\)](#) asserts that “expectations are socially constructed, communicated and believed”. Focal points are not absolutes but also social constructs. Focal points can be explicitly communicated or can be social norms. However, for a new focal point to work a degree of common knowledge must be established and agreed.

Economic models rely on the assumption of “knowing others will do the same” ([Basu 2015](#)) demonstrating a need for common knowledge ([Schelling, 1960](#)). Keynes’ beauty contest is the clearest example of the importance of common knowledge. In order to judge the winner of a beauty contest there must be, some degree, of consensus as to what constitutes beauty. If indeed ‘beauty is in the eye of the beholder’ then every individual member of the beauty contest judging panel will have their own preferences and no overall consensus as to the outcome of the beauty contest can be agreed upon. However, social norms, convention and rules change over time. Thereby endogenously shaping our common conceptions of beauty, and the rules of the game. In the absence of a fixed focal point partial consensus ([Desgranges and Ghosal, 2020](#)) comes into play and may still allow a

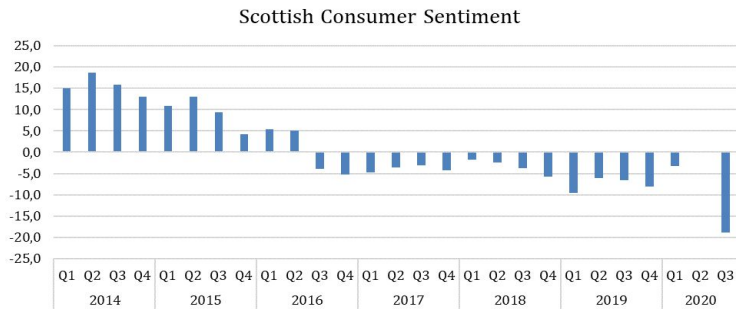


Figure 7: Source: Scottish Government 2020.

degree of strategic co-operation and stabilisation.

Galbraith defined the concept of conventional wisdom: “people approve most of what they understand . . . acceptable ideas have great stability” (Galbraith, 1998, p7-8). Obliquely Galbraith also discussed the difficulty in establishing new “conventional wisdom” reliant as it is on vested interests and past experiences.

The Brexit negotiations were domestically fraught within the UK due to a lack of clarity and agreement over such ‘acceptable ideas’, the UK’s strategy and even its objectives. Contrasted with an EU27 seemingly agreed on a mutual position. With a thin 52% v 48% majority that approval was never consolidated through establishing the required policy focal point to guide the path forward through the Brexit negotiations.

5.1.2 Economic Instability and Anxiety

Although on the surface the period post referendum ($t=2$) shows strong economic fundamentals (lowest unemployment rate in 40 years) there are signals of remaining anxiety and instability in investment and consumption data. An illustration of this is Scottish Consumer Sentiment indicator which shows strong co-relation to the Brexit referendum result. Turning from positive to negative after the Brexit shock. This negative sentiment intensified in the run up to the first date that the UK was due to officially leave the EU March 2019.

Since the 2016 referendum the UK’s decision to leave the EU has had continuing impact investment expectations and consumer confidence. This may be attributed to anxiety, as we have defined it as an anticipatory preference, demonstrating a strategic ‘wait and see’ consensus view among investors and consumers (congruent with our storage asset investment strategy).

Our model of anxiety considers the temporal nature of news sentiment. A shorter horizon (for example if the prevailing narrative was that Brexit negotiations were going to be concluded quickly, or if a coronavirus lockdown would be short – is one factor which

may minimise ‘wait and see’ investment effects). [Faccini and Palombo \(2019\)](#) argue that “the expected duration of the negotiations is key for the propagation of the news, and that its effects are larger, the sooner uncertainty is expected to resolve. The policy implication is that to keep postponing the Brexit deadline generates a succession of cliff edges in the negotiations that, by setting up expectations of a quick resolution of uncertainty, maximizes its damage”. Our analysis supports this. The Brexit timeline is a factor and heightened anxiety can be seen in the run up to the Brexit “cliff edges” – the initial date for leaving the EU, subsequent extensions, and the election date. We see this in our economic anxiety indicator (Figure 6) and in the Scottish Consumer Sentiment data (Figure 7).

Time is one factor, as we have shown with the Brexit timeline – but so also is the nature of the Brexit policy agreement (hard/soft/no deal). Thus we argue that the role of policy is fundamental in stabilising sentiment and expectations. We must consider the dynamic interaction of the policy time horizon and policy detail. However, anxiety is also a function of the level of perceived risk based on sentiment, beliefs and competing narratives to heuristically make sense of the level of risk.

Distinct from uncertainty, anxiety can turn into fear of future and endogenously lead to endogenous amplification of anticipation effects. Anxiety deters investment today in long term productive investment, not only resulting in a misallocation of resources today but a reduction in resources tomorrow. Thus anxiety is different from uncertainty because of its dual aversive and anticipatory future looking nature. It is the anticipatory and aversive nature of anxiety, which skews the distribution to endogenously amplify perceived risk and aversion (irrationally). This allows our model to operate outwith the rational expectations framework.

We propose policy communication as a stabilization tool which can re-anchor economic and societal expectations, not through policy announcements alone but policy forward guidance and policy implementation. The policy response to the coronavirus pandemic in the UK provides us with examples.

5.2 Discussion: Lighthouse Policies and Economic Anxiety

Lighthouse policies can be thought of as policies with the potential to guide the economy through times of economic anxiety.

Actual light houses are public goods – non-rivalous and non-excludable (Tucker 2020). The coronacrisis has created the largest increase in government and central bank spending since the second world war. Many are calling for a ‘New Deal’ type of recovery as implemented by President Roosevelt in the 1930s. The assumption is that this necessitates a return of ‘big state’. However, our conception of lighthouse policies does not automatically mean public spending. At the heyday of the European sovereign debt crisis in 2012, for

instance, ECB President Mario Draghi, announced to undertake “whatever it takes” to save the euro. Without spending a single euro by intervening in the market, this simple – and credible – announcement created a floor against the speculation regarding the sovereign debt of individual member countries. Our model aims to reduce anxiety to encourage strategic complementarities in investment (Rousseau’s stag and hare), hence guiding all sectors of our economy and society to support greater investment in productive welfare enhancing activities. This facilitates opportunities for a raft of complementary public, private, education and civil society solutions. such a combination of lighthouse policies; guiding the direction of policy consensus, development and implementation.

Thus, the concept of narrative as policy has the potential to play an important role in our understanding of the dynamics of anxiety. We see narratives as complex, multi-dimensional stories that specific actors convey to influence people’s opinions and expectations. However, their signalling and coordination capacity hinges on their legitimacy and credibility, such as in the case of an (independent) central bank. Sometimes, it is assumed that policy makers, such as central bankers and government, provide such a “natural” focal point in co-ordinating economic activity, in the language of [Schelling \(1960\)](#). However, because of their complexity, competing narratives might arise and gather partial consensus, albeit to varying degrees ([Desgranges and Ghosal, 2020](#)). While still allowing some degree of strategic co-operation and stabilization, no single focal point exists, and anxiety remains unresolved.

In such a situation, policy actions – rather than simple announcements – can play the tipping point. Such an effect has long been considered as the lighthouse effect of policy making. Traditionally, such effects are thought to be the result of economic actors complying with certain regulations even though they are not directly affected. In our understanding, lighthouse policies can have the additional effect of guiding the economy through times of high economic anxiety by stabilising expectations and creating a degree of common knowledge and strategic certainty, which enables and encourages investment in future welfare enhancing productive investments today.

By stabilizing expectations and creating a common, credible narrative, lighthouse policies can help address economic anxiety. One example in this regard is to create a lower floor on expected returns through policy announcements. Similarly, when the coronavirus pandemic struck markets responded by flocking to safe havens/assets and a run towards gold and government bonds. The scale of the coronavirus shock resulted in central banks increasing the supply of government bonds to match the demand for safe assets and investments to prevent a sudden rise in spreads for assets considered to be high-risk. Even when bond yields turned negative investors were still choosing ‘safe’ government bonds at a negative rate of return because the alternatives – provided even greater risk of loss). Distinct from myopia (preference for payoff now regardless of the variance of future uncertainty) anxiety (fear of future uncertainty) was greater than loss today (the

guaranteed minor loss on government bonds), leading to a massive drop on stock market that could be reverted through a broad-based provision of liquidity across different asset classes.

In times of crises then the role of policy needs to be to create a credible floor to risky assets. If expectations are not anchored competing narratives and sentiment will create instability, perhaps radical uncertainty. The ultimate goal of lighthouse policies is to provide a floor supporting a range of indeterminacy within which a degree of strategic co-ordination can happen. Most importantly through the combination of lighthouse policy communication, forward guidance and implementation (of floors) it provides a (simple) viable and actionable way to implement strategic coordination at an aggregate macroeconomic level.

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Appendix

A. Technical Appendix of the Machine Learning methodology

The construction of the dataset can be broken down into 3 key steps:

1. Data Acquisition (Data Warehousing)
2. Data Set Generation (Search, Dataset generation)
3. Machine Learning (ML) Model as a Service (MaaS) / Anxiety Classification

A1. Data Acquisition (Data Warehousing)

The Data Warehouse is a pool of source articles/documents harvested using proprietary software methods. In the context of this project it contains news articles from the Daily Mail, however it does not have the support for articles/documents/reports in formats such as DOC (word), PDF and other news sources for further possible enhancement/research. Articles are harvested from the various sources either using published API's or text scraping / formats such as DOC/PDF are additionally processed with Apache Tika. The resulting raw data is cleaned, structured and stored in Elastic Search (nonSQL) document store for later retrieval.

A2. Data Set Generation (Search, Dataset generation)

The research team is able to query the data warehouse through the project specific portal <https://anxietydata.com/> to generate research datasets. The researcher provides search terms and/or date ranges along with a label to name their dataset. The results are stored as a labelled dataset in a graph database. During the dataset generation each article is extracted from the data warehouse, processed with Natural Language Processing (NLP) to extract additional metadata and classified with machine learning for anxiety. All this data is stored to allow for near real-time retrieval/querying to support simple through to deep complex extractions. Researchers use the Neo4J Query language to extract directly from the Graph Database to downloadable files for additional analysis.

A3. Machine Learning Model as a Service (MaaS) / Anxiety Classification

The classification approach builds upon the method proposed by Joulin et al (2016) of the Facebook AI Research team, a technique that is particularly efficient for text

Original Text

Chef Lee Holmes has shared her top tips for keeping your kitchen clean and coronavirus-free, after virologists warned that COVID-19 can 'live on any surface

Analysis Result

chef lee holmes have share her top tip for keep your kitchen clean and coronavirus - free , after virologist warn that covid-19 can ' live on any surface

Figure 8: Example of lemmatization.

classification on very large datasets. Two classification models are generated to classify the news articles within a dataset: the class of anxiety (Macroeconomic; None) and the level of anxiety (High; Medium; Low; None).

The creation of the classifier has involved:

1. **Generation of a training dataset of class and levels of anxiety.** Initially a set of articles are extracted from the data warehouse without any classification (cold start problem).
2. **Machine Learning Models building and training.** Once the articles are labelled, the labels, the unique article ID's (UID) and the full text of each article are extracted from the data warehouse using the UID as a reference. Article texts are pre-processed, cleaned and formatted into a unified format. Additionally every word is reduced to its lemma using lemmatization provided by the NLP library spaCy. This set of articles is separated into two parts for each classifier: a Training Set (approximately 75% of the articles) and a Validation Set (approximately 25% of the articles). The training data is presented to fastText for supervised classifier generation. The validation set is used to assess the level of performance of the trained classifier (model generated). The resulting models are then embedded within a microservice which provides the anxiety scoring to the dataset generator.
3. **Deployment of the Model for augmenting the dataset.** Once the model has been built, it is deployed as part of a highly scalable microservice (written in Golang) to servers and accessed using a RESTful call mechanism, potentially available for other research studies. The classifiers are invoked during the dataset generation resulting classification stored within the graph database for later query by the researchers.

All the technology blocks are built upon proprietary data acquisition/intelligence platforms provided by East Village Software Consultants Ltd . Due to the proprietary software in use source code will not be published. The authors are willing to provide their training set of articles to the purpose of replicating the scoring methodology.

Appendix B

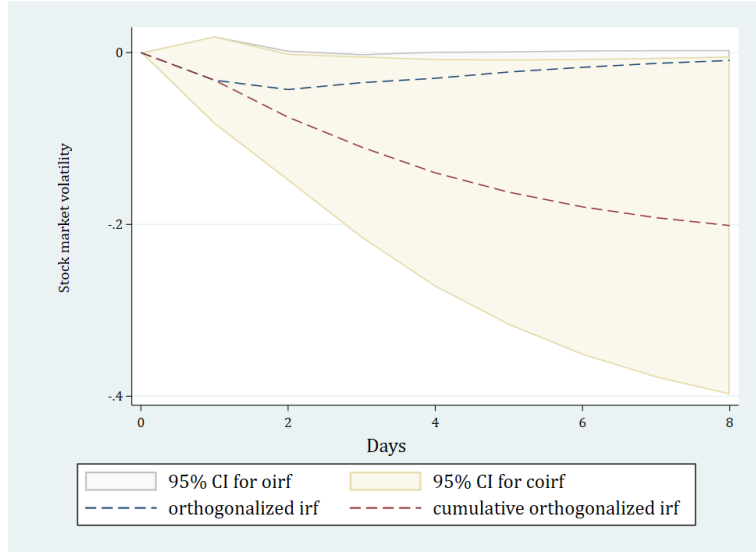


Figure B1: Robustness check. Impulse response of stock market volatility from a shock of economic anxiety (short-run restrictions inverted).

Table B1: Augmented Dickey-Fuller test on economic anxiety and stock market volatility.

$Y_t :$				
	$\Delta Anxiety_t$	(SE)	$\Delta SMvolatility_t$	(SE)
Y_{t-1}	-0.32	(0.07)	-0.59	(0.08)
ΔY_{t-1}	-0.31	(0.07)	-0.17	(0.08)
ΔY_{t-2}	-0.16	(0.06)	0.00	(0.06)
$Z(t)$ test	-4.94		-7.13	

Critical values: 1% = -3.460; 5% = -2.880; 10% = -2.570. MacKinnon approximate p-value for $Z(t) = 0.000$.