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Temperature Shocks and Price Stability

Evidence From Four Decades of Temperature Stresses on the UK Economy

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Abstract

This thesis investigates the interplay between temperatures and prices in an advanced economy context. To this end, I estimate the impulse response to a 1 °C temperature anomaly on the UK economy. By combining high-frequency geospatial temperature data with sub-national population estimates, I construct a quarterly population-weighted temperature series spanning from 1975 to 2021. Making use of the fact that macroeconomic data for the UK is available at high frequencies and with a broad coverage across sectors and price groups, I uncover the dynamic response of both aggregate price indices as well as the major underlying channels of impact. I find that unexpected temperature stresses place upward pressure on key components of the consumer price index, particularly energy and food prices. As to the quantity-response, my findings suggest that the effect on prices on the UK economy act primarily through supply-side channels, which is consistent with the effects documented in the broader climate-economy literature.

Keywords: Climate Change, Price Stability, Local Projections, United Kingdom

JEL Codes: C32, E32, E58, Q54

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1 Introduction

Climate change will push the weather experienced by economic agents outside the bounds of historic norms, making previously uncommon weather events more prevalent (IPCC 2021, pg. 27). The escalating scale and frequency of such events is becoming a growing concern for central banks around the world. For example, weather shocks can give rise to adverse supply-side shocks that propagate through sectors exposed to weather, potentially yielding uncomfortable trade-offs for monetary policy (Cœuré, 2018). Coupled with the transition risks associated with the implementation of green policies, physical risks from climate change serve as a justification of climate commitments made by central banks. As of March 2021 the Bank of England officially holds an environmental mandate (Bank of England, 2021). The European Central Bank has taken similar steps to integrate climate change into its monetary policy operations (European Central Bank, 2022), following the motivation recently set out by its governor Christine Lagarde: *"If we do not account for the impact of climate change on our economy, we risk missing a crucial part in our work to keep prices stable"*[1].

This thesis investigates the effect on price stability when economic agents are exposed to temperatures that fall outside the bounds of recent experience. To this end, I study the effects of temperature stresses on the UK economy over the past four decades. The analysis builds on a large climate-economy literature that studies the effect of weather shocks on economies, political systems and the risk of conflict (see, for example, Dell, *et al.* (2014) for a review). While this literature has documented persistent negative effects on economic output and productivity from weather-related shocks, fewer attempts have been made to understand the potential implications for price stability (NGFS, 2020).

Data on both temperatures and macroeconomic indicators for the UK is available at high frequencies going back several decades, allowing me to study the propagation of temperature shocks at a generous level of granularity compared to previous studies. By pairing high-frequency geospatial temperature estimates with sub-national population data, I construct a population-weighted temperature series ranging from Q1 1975 to Q4 2021. I define a temperature shock as the deviation from a rolling five-year mean temperature, thus producing a temperature shock series that captures the exogenous and, by design, unexpected movement in temperatures. Following these steps, I extract the impulse responses to a 1 °C deviation from the average temperature that prevailed in the same quarter over the past five years. I estimate the dynamic price responses using local projections à la Jordà (2005) which, unlike a traditional VAR framework, allows me to generate robust empirical estimates without relying on assumptions about the underlying data generating process.

My findings suggest that temperature shocks places non-negligible pressure on prices in

[1] See Lagarde (2022)

the UK economy. Producer prices respond quicker than consumer prices, indicating that producers pass on some of the weather-related costs to consumers. The impact is more notable for energy and food prices compared to the core components of CPI. Consistent with previous findings, temperature shocks depress aggregate output, industrial production, and consumption expenditures. Most of the estimated responses of prices, output and consumption persists over a 2 to 3-year time horizon. Together, these empirical patterns suggest that extreme temperature stresses may have an adverse and persistent impact on price stability and the business cycle, potentially limiting the ability of monetary policymakers to *"see through"* relative price adjustments stemming from abnormal temperature realisations. A set of robustness checks indicate that these results hold up along a number of dimensions, including the shock identification, the model specification and the sample period.

This thesis makes several contributions to the existing literature. Instead of focusing on balance sheet disruptions of banks, output losses or productivity, areas which have already been subject to much research, it addresses the direct transmissions of abnormal weather events on prices, where research efforts are only recent, and the literature therefore remains scant. Because this narrow literature has been focused largely on cross-country comparisons of macroeconomic aggregates, my paper, which studies the propagation of temperature stresses within a single economy, is one of the first to break down the aggregate indices into subcomponents and thereby attempt to detangle the channels though which a temperature shock transmits onto the economy.

I have not come across previous literature that quantifies the effect of weather shocks on the economy, including prices, at the same level of granularity as I have in this paper. To the best of my knowledge, my paper is the first to leverage the official decomposition of price indices published by the UK's Office for National Statistics. It is also one of the first studies to estimate the effect on both consumer and producer prices, as well as the sectoral decomposition of aggregate output, adding to the findings for the United States recently presented by Natoli (2022). Finally, by estimating temperature anomaly in relation to a rolling five-year average temperature as opposed to a long-term average temperature, I aim to capture the economy's response to extreme and, crucially, unexpected weather events. With this, I lay forward a straightforward computation of temperature shocks, one which can easily be applied to study the effect across different contexts. In defining a temperature shock, I consider the theoretical notion that economic agents adapt to long-term changes in climate based on some distribution of realized weather events, reconciling the empirical estimates with the notion of climate adaption and Bayesian experience-based learning (Moore, 2017; Deryugina, 2013).

The remainder of the thesis will be structured as follows. Section 2 provides an overview of the related literature. Section 3 discusses the relevance of empirical estimates derived from historic weather fluctuations and reviews the main channels of transmission. Section 4 presents the data and introduces the temperature series. Section 5 stipulates the empirical strategy, whereas section 7 presents the results and subjects the estimated responses to a series of robustness exercises. The final section discusses the results and formulates the main conclusions.

2 Related Literature

The purpose of this first section is to highlight some of the related literature, focusing in on the empirical estimates in the existing literature on prices and extreme weather events. Studying the effects of weather on society has proven to be essential in understanding historic economic development and is becoming increasingly important in managing climate change. This thesis contributes to the broad literature utilizing time-series data on weather fluctuations to study the effects of climate on society (Dell *et al.*, 2012; Carleton and Hsiang, 2016), and more specifically to the literature focusing on the financial and macroeconomic effects repercussion of extreme weather events, appealing to the discussion of physical climate risks to price and financial stability.

Much remains to be uncovered regarding the macroeconomic and financial stability effects of climate change. The Central Banks and Supervisors' Network for Greening the Financial System (NGFS) recently published a comprehensive overview of the current research gap, emphasizing the need to identify the short- and long-term transmission of climate risks on financial stability and monetary policy. Part of the research agenda moving forward involves establishing the potential transmission of physical risks to aggregate price dynamics, a primary concern for monetary policy (NGFS, 2020). Despite of this, only a small number of recent papers have begun exploring the potential price effects of temperatures (notably Ciccarelli and Marotta, 2021; Mukherjee and Ouattara, 2021; Faccia *et al.*, 2021; Natoli, 2022; Kabundi *et al.*, 2022; Acevedo *et al.*, 2020). A handful of studies have also investigated the impact of natural disasters on prices (Heinen *et al.*, 2019; Cavallo and Rigobon, 2014). Both these strands have thus far identified both deflationary and inflationary price pressures stemming from weather shocks, suggesting that weather shocks disseminate though both demand and supply side channels (refer to section 3.2 below for a discussion).

A common finding in this literature is that the impact seems to be highly contingent on country-specific characteristics. Seminal work has consistently found developing countries to be more vulnerable to extreme temperatures than developed countries (Dell *et al.*, 2012, 2009; Nordhaus, 2006; Burke *et al.*, 2015). Recent cross-country evaluations confirm that this pattern holds true for price stability as well, with developing countries typically experiencing more persistent inflationary pressures following temperature shocks (Mukherjee and Ouattara, 2021; Faccia *et al.*, 2021).

A notable and non-linear relationship between extreme temperatures and prices has also been recorded in advanced economy contexts. Ciccarelli and Marotta (2021) present evidence that physical risks, as measured by the incidence of extreme weather events, is associated with deflationary pressures on prices working though demand-side channels in a sample of OECD countries. In Ciccarelli, Kuik, and Martínez Hernández (2023) above-average temperatures in the summer and autumn months are found to have an inflationary effect on prices in France, Spain, Germany and Italy, mainly acting through food, energy and service-sector prices. The impact differs significantly between the four countries, with Spain and Italy experiencing greater effects on prices compared tothan France and Germany. By contrast, Natoli (2022) finds that extreme temperatures have an overall deflationary effect on the US economy. Several country-specific characteristics could act as means for this observed impact heterogeneity. Kabundi, Mlachila, and Yao (2022) find that the impact of temperature shocks on inflation depend on the intensity of the shock, country level income and monetary policy regime.

It is thus clear that the small existing literature has focused largely on cross-country settings, which stands in contrast to the single-country context of this thesis. The cross-country literature has focused on aggregated and broad divisions of aggregate price indices, which are readily available and comparable across countries. It is also important to recognise that this empirical literature has addressed different dimensions of climate change. Future climate change is expected to lead to both to *global warming*, an increase in average global temperatures (IPCC, 2021, pg. 14), as well as the emphvariability on climate, rendering more extreme and previously unprecedented weather events (IPCC, 2021, pg. 27). Figure 15 (Appendix A) illustrate this pattern, showing the projected change in the climate distribution for the United Kingdom under two seperate RCP scenarios. Because the aforementioned studies adopt varying measures of climate shocks, some have focused on the effect global warming by looking at increasingly hot temperatures (Ciccarelli *et al.*, 2023), whereas others have focused on the incidence of extreme weather events (Heinen *et al.*, 2019).

This thesis, alongside the studies mentioned above, aligns with the broader climate-economy literature. Hence, the fundamental approach involves extrapolating insights from ex-post empirical observations of *past* weather events to project the potential impacts of *future* climate changes. In the subsequent section, I will delve deeper into this discussion, exploring the potential usefulness of empirical estimates derived from historic weather variations in forecasting the impact of future climate change.

3 Theoretical Motivation

The purpose of this section is twofold. Firstly, I will discuss the relevance of empirical estimated derived from historic weather fluctuations when assessing the physical risks associated with future climate change (section 3.1). Secondly, I highlight the possible transmissions through which extreme weather events can affect price stability (section 3.2). To shed light on the underlying dynamics, I review current empirical evidence and relate the findings to a simple New Keynesian framework.

3.1 What do Past Weather Realizations Teach us About Future Climate Change?

Because future climate change is both unrealised and unprecedented, accurately estimating the effect on economic activity across time poses specific challenges. The core of the empirical problem lies in the fact that economic agents may hold some capacity to adapt to persistent changes in temperatures, which plausibly alters the historically observed relationship between climate variables and economic activity (Acevedo *et al.*, 2020; Dell *et al.*, 2014; Carleton and Hsiang, 2016). The purpose of this sub-section is to discuss the conditions under which empirical estimates derived from historic time-series weather variations provide useful forecasts for future climate change.

The role of climate adaption. Adaption to climate change can be decomposed into an extensive and an intensive margin. At the *extensive margin*, households and firms adopt to long-run changes in climate though long-run adaption behaviour (investing in new air conditioning) whereas the *intensive margin* involves short-run responses (more frequent use of air conditioning). Empirical estimates of economic damage functions based on past climate realizations generally suffer from the exclusion of extensive margin adaption response (Auffhammer, 2018). This has served as a motivation for a growing stance of non-parametric macroeconomic models, building on the idea of long-run climate adaption alters past relationships between climate and economic outcomes. Unlike the empirical approach, non-parametrical estimates can control for long-run climate adaption mechanisms, such as migration, trade and innovation (Cruz and Rossi-Hansberg, 2023) or local capital investments (Krusell and Smith, 2022). .

Economists consider such long-term investments in climate adaption to be a *private good*, whereby households and firms invest in adaption based on their own intrinsic preferences (Mendelsohn, 2000). A branch of models has therefore focused on assumptions regarding the behaviour of individuals to understand as a means of explaining adaption. Climate adaption has been put forward as an application of the idea of experience-based Bayesian learning (Kelly *et al.*, 2005; Deryugina, 2013; Moore, 2017). Economic agents hold believes about the climate based on some distribution of past weather realisations. From this perspective, the rate at which long-term adaption occurs hinges on how efficiently agents learn about the changing climate.

The role of expectations. It follows from the above discussion that extensive-margin adaption behaviour arises from agents' individual *expectations* about the weather (Moore, 2017). Hsiang (2016) provide a framework to illustrate this mechanism in the context of empirical estimations. Begin by denoting the current climate that prevails in a location as C. This can be thought of as a set of possible weather realizations for a specific location. The effect of the climate C on the outcome of interest Y (such as output) relies on two factors: [1] actual weather realizations c observed by economic agents and [2] what actions agents take based on their believes about the structure of C. It follows intuitively that both weather-realizations and climate-beliefs are functions of the current climate C. Denoting the vector of possible actions resulting from these believes as b, then $Y(C)$ is expressed as:

$$Y(C) = Y[c(C), b(C)]$$

Supposing that b has a length of N possible actions and there are K possible weather realizations c to the current climate C. The derivatives $\frac{dc}{dC}$ and $\frac{db}{dC}$ are thus the $K \times K$ and $J \times J$ Jacobian vectors of partial derivatives. The marginal effect of the climate C on outcome Y will therefore be given by the following first-order condition[2]:

$$\nabla_c Y(C) \cdot \frac{\Delta c}{\Delta C} + \nabla_b Y(C) \cdot \frac{\Delta b}{\Delta C} = \sum_{k=1}^{K} \frac{\partial Y(C)}{\partial c_k} \times \frac{\Delta c_k}{\Delta C} + \sum_{k=1}^{K} \frac{\partial Y(C)}{\partial b_k} \times \frac{\Delta b_k}{\Delta C}$$

Any one change in the climate C gives rise to a direct effect and a belief effect. By studying time series variations in weather abnormalities, the econometrician can feasibly estimate the direct effect of historic climate. However, the actions that economic agents take, based on their beliefs or expectations on the climate, may alter the direct impact of the weather realizations $\frac{\partial Y}{\partial c_k}$. In this framework, climate adoption refers to the interaction between beliefs and direct weather realizations $\frac{\partial^2 Y}{\partial c_k \partial b_n}$. This rationale gives rise to the expectations channel of weather events of climate variations.

Climate change will push the experienced weather realizations c outside the bounds of historic norms. Because of this, agents are likely to change their beliefs on the climate C, incurring investments in climate adaptation, which in turn can affect historically observed economic outcomes. Because expectations are both difficult to observe and potentially endogenous to other economic variables, the recent literature, including the emerging empirical literature on the price effects of past weather realizations, has largely focused on the direct impact channel $\frac{\partial Y}{\partial c_k}$. From this perspective, it is concerning that the sizable empirical weather-climate literature

[2]See Appendix B.1 for further details. Hsiang (2016) defines the gradient vectors as $\nabla_c Y = [\frac{\partial Y}{\partial c_1}, \ldots, \frac{\partial Y}{\partial c_k}]$ and $\nabla_b Y = [\frac{\partial Y}{\partial b_1}, \ldots, \frac{\partial Y}{\partial b_n}]$.

omits the impact of expectations when studying the economic effects of time series weather variations (Lemoine, 2017).

Recent studies have tried to incorporate the idea of Bayesian experience-based learning into empirical estimates, conceptualising temperature anomalies as the deviations from the expectation on the local weather pattern. Choi, Gao, and Jiang (2020) define a temperature anomaly as the deviation from the rolling average 10-year temperature for each month of year, allowing them to better account for predictability and seasonality. Natoli (2022) recently proposed a similar approach to investigate the price-effect of unexpected weather shocks. In this context, studying deviations from expected weather helps reconcile the definition of a temperature shock with the conventional understanding of a shock in the empirical macroeconomic literature. Specifically, a shock is traditionally defined as an *unexpected* movement in economic variables (Ramey, 2016).

This thesis adopts a similar approach in order to produce estimates consistent with the idea of experience-based learning and long-run adoption (please refer to section 4.3 for details on the shock construction). Whilst the discussion so far has centred around the overall significance of employing historical weather time series to comprehend the economics of climate change, I will now specifically delve into the price impact.

3.2 Transmissions Channels

The goal of this sub-section is to make explicit the mechanisms through which a temperature shock transmits into the economy and, specifically, prices. The broader climate-economy literature has documented both demand and supply-side channels of impact, particularly in weather-exposed sectors. This section discusses these findings through the lens of standard economic theory. To do this, I base my discussion around the Basic New Keynesian model set out in Galí (2008, Ch. 3).

3.2.1 Supply-Side Channels

Adverse supply shocks. How does such adverse supply shocks transmit to aggregate prices? The feed-though mechanisms are well documented in workhorse economic models. For the sake of understanding the mechanisms at play and state a hypothesis regarding the potential price impacts of abnormal temperatures, it will be helpful to briefly review some of these fundamentals. Begin by considering the proposition that abnormal weather transmit though supply side channels. As noted further down in the section, there is some empirical evidence to support this view, particularly in weather exposed sectors like food and energy sectors. Furthermore, in the context of the policy discourse, central banks are particularly concerned about the prospect of adverse supply shocks in relation to increasingly extreme climate events.

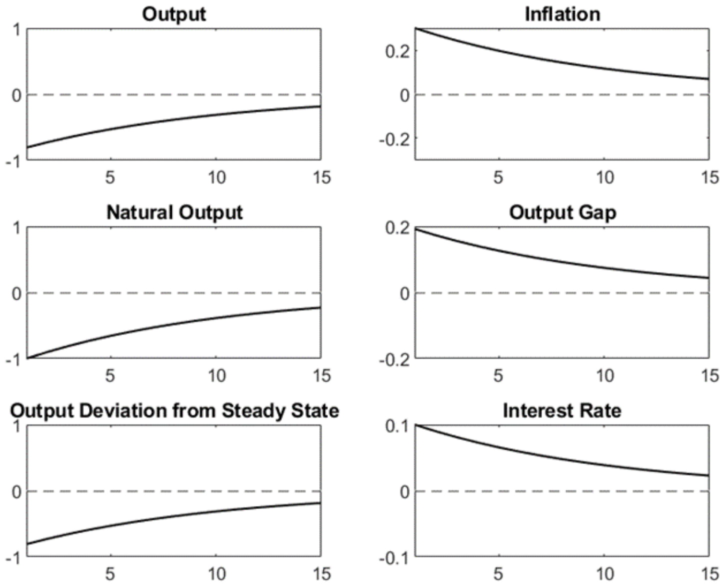
Whilst demand side shocks tend to pull inflation, output and growth in the same directions, adverse supply shocks generate a difficult trade-off between stabilising output fluctuations and inflation (Cœuré, 2018).

Economists think of supply-shocks as changes in relative prices, or, more accurately, shifts in the short-run Phillips curve. Seminal work by Reis and Watson (2010) has shown that the classic Phillips correlation, the correlation between inflation and economic activity, largely diminishes when controlling for the relative price of food and energy, and becomes entirely insignificant when controlling for more sophisticated indices of relative prices. In the broader macroeconomic literature, it is generally accepted that adjustments in relative goods prices constitute the majority of shifts in inflation, while pure inflation makes up a significantly smaller proportion of aggregate price movements (Reis and Watson, 2010). Whilst the potential prevalence of major supply shocks has been demonstrated though historic experiences - the class-room example being the famous oil supply shocks of the 1970s - classic real business cycle theory stipulates that the price level is determined strictly by money supply, whilst relative price adjustments are determined solely though real factors. Following this rationale, an increase in the (nominal) price of one good will be accompanied by a drop in the price of another, a proposition that rests fully on the assumption that price setting is perfectly flexible. Subsequent seminal work has abstracted from the idea of perfectly flexible nominal prices, primarily turning to the idea that firms face menu costs associated with price adjustment (the idea that prices are sticky, at least in the short run, remains the dominating view) (Galí, 2008; Ball and Mankiw, 1995).

Because price adjustment is inherently costly, firms update prices only if the shock is large enough to warrant the costs (Ball and Mankiw, 1995; Midrigan, 2011). Nominal rigidities give rise to an aggregate price inertia that in turn provide a mechanism though which changes in monetary policy has real effects on the economy. This forms a fundamental building block of traditional New-Keynesian analysis, where the presence of menu costs is the micro foundation underpinning the assumptions made on price setting behaviour in markets. To this end, New Keynesian models commonly draw from the classic works on staggered contracting and the implied forward looking price setting behaviour of firms, building on (Taylor, 1980; Calvo, 1983) and others. The individual firm's pricing equation relates the optimal pricing to a discounted flow of current and future marginal costs. Aggregating across firms yields the New Keynesian Phillips curve, formed from firm's expectation about future inflation and real marginal costs (Carlsson and Skans, 2012; Christiano *et al.*, 2005).

To illustrate the trade-off that arises from adverse supply disruptions, it is useful to think stylistically about a weather shock as a negative technology shock affecting all firms in an economy at the same time. Figure 1 illustrates this by simulating the effect of a negative technology shock in the three-equation (log-linearized) New Keynesian model set out in (Galí, 2008, chapter 3)[3]. Firms are assumed to have identical production technologies (but produce a differentiated set of goods). Prices are sticky à la Calvo and monetary policy is determined though a classic Taylor Rule. It follows naturally that monetary policy is non-neutral in the short term[4].

Figure 1: Effects of a Negative Technology Shock in the Basic New Keynesian Model



Note: The simulation shows how of the three-equation log-linearized version of the baseline New Keynesian framework presented in (Galí, 2008) responds to a negative technology shock. Natural output refers to the level of real GDP that would prevail in the economy without nominal rigidities or frictions. The output gap is defined as the difference between real output and natural output. The interest rate is determined though a simple Taylor rule.

A negative technology shock leads to an increase in both inflation and the output gap, while depressing real output in the long run. Firms anticipate higher marginal costs, which are, in part, passed on to prices (New Keynesian Phillips curve). As only a set share of firms can update prices every period, this process is subject to some inertia (the Calvo assumption on price stickiness). Following a classic Taylor rule, the central bank responds to the increase in inflation by hiking the real interest rate (thus depressing money supply). In reality, output and unemployment levels play well into monetary policy decision, giving rise to the trade-off referred to above.

The baseline models provide a highly stylized prediction of how prices might respond to adverse supply-side shocks stemming from extreme weather. If such events disrupt economic activity, one would anticipate that quantities and prices will move in different directions. The

[3]Please refer to Appendix B.2 for further details on the calibration. All parameter values are taken from chapter 3 of Galí (2008).

[4]Non neutrality implies that the equilibrium path of real variables cannot be determined independently of monetary policy

observation of these effects hinges on two fundamental questions: Firstly, can we establish a connection between extreme weather events and shifts in relative prices? Secondly, if such adjustments in relative prices occur in response to extreme weather, do they have the potential to notably impact the aggregate price index? This thesis addresses both questions by examining both aggregate producer and consumer prices, along with a decomposition of these factors. Empirical evidence of adverse supply disruptions from extreme weather events has also been documented in the weather-economy literature. Below, I provide a few brief examples.

Agricultural Production. In terms of supply-side channels of impact, such as output or productivity losses, the literature has primarily focused on weather-exposed sectors like agriculture and energy (Carleton and Hsiang, 2016). Early studies examining the economic consequences of weather effects focused in on agricultural production as the main outcome of interest (Auffhammer and Schlenker, 2014). Adverse effects of abnormal temperatures on agricultural production have been documented across both emerging and developed market economies [5] Moreover, a significant adaptation gap has been observed within the agricultural sector, contrasting with the longer-term historical patterns of farming innovation and adaptability (Carleton and Hsiang, 2016). While the link between food inflation and weather-induced yield losses has received less attention, natural hazards such as hurricanes have been found to exert significant effects on food inflation in both emerging market and developed market contexts (Parker *et al.*, 2021).

Energy Supply. Both energy and labour markets have also been put forward as potentially important supply-side channels of impact (Carleton and Hsiang, 2016). For example, thermodynamic models suggest that both electricity generation and transmissions is depressed at high temperatures (Jaglom *et al.*, 2014) . Whilst isolating the supply-side empirically is difficult, studies have for example shown that droughts shift energy production from hydropower to more energy-intensive sectors (Muñoz and Sailor, 1998; Eyer and Wichman, 2018).

Labour Markets. Weather shocks can also give rise to potentially significant labour market disruptions, particularly in weather-exposed service sector industries, such as tourism and hospitality (Heal and Park, 2015). Extreme heat has a thoroughly documented and significant effects on human health and may thus impact hours worked as well as productivity levels. For example, heat stresses have been found to reduce work intensity and cognitive performance (Zivin *et al.*, 2015). The relationship between productivity has been recorded at the firm-level in developing economies (Somanathan *et al.*, 2021; Colmer, 2021). Whilst studies on firm-level productivity have been scarcer in advanced economy contexts, case studies have recorded productivity losses from temperature shocks in specific context, such as automobile-assembly

[5] Auffhammer and Schlenker (2014) provide a broad overview of this literature. In an early study, Lobell and Field (2007) report significant losses on global yield crops form temperature increases. Moore and Lobell (2015) record a similar relationship for European crop yields, Welch *et al.* (2010) studies rice and crop yields in Asia, whereas Schlenker and Roberts (2009) studies the effect of weather of US crops.

(Seppanen *et al.*, 2006).

3.2.2 Demand-Side Channels

While the discussion so far has laid out a simple rationale for the adverse supply-side narrative often surfacing in the broader policy discourse, temperature stresses may also transmit through demand-side channels of impact. The direction of this impact is ambiguous. For example, the literature on weather and energy demand has recorded a highly U-shaped relationship between demand and temperatures, whereby demand falls with a mildening of exceptionally cool temperatures, only to rise when temperatures exceed a certain threshold (Auffhammer and Mansur, 2014)[6]. The context, timing, and direction of a temperature shock clearly matter for identification. For example, an exceptionally mild winter may set temperature records, whilst still weighing down on energy prices. The below passages provide a few examples of possible demand-side responses to temperature shocks.

New Keynesian Supply Shocks. Building on the simple rationale laid out above, the supply and demand-side channels of impact may interact in complex ways to form inflationary pressures. Because high temperatures can weigh down on both supply (for example, by weighing down on labour or food supply) and depress demand in complimentary sectors (reducing consumer spending), such shocks may elicit the defining characteristics of a New Keynesian demand shock (Guerrieri *et al.*, 2022). This refers to a situation where shocks to aggregate demand can originate from sectoral supply shocks that spread to complementary sectors through Keynesian supply mechanisms (Cesa-Bianchi and Ferrero, 2021). Recent working papers, such as Natoli (2022) and Faccia, Parker and Stracca (2021) indeed allude to New Keynesian supply shocks to explain observed dynamics between temperatures and prices

Energy Demand. The literature has documented a highly nonlinear relationship between energy demand and temperatures. Households and firms consume significant amounts of energy to maintain a comfortable indoor environment, and adverse temperatures raise demand for heating and cooling. Intensive-margin adaptive responses to extreme temperatures, particularly the use of air conditioning, can lead to noticeable hikes in short-run energy demand (Deschênes and Greenstone 2011). The prognosis for future energy demand is more difficult to estimate, however, due to long-run extensive margin adaptive responses (Auffhammer and Mansur 2014).

Behavioural Responses. A bulk of literature also documents notable behavioural effects from hot temperatures. For example, the time allocated for leisure has been found to decrease in high temperatures (Graff Zivin and Neidell, 2014). Consumer spending may suffer as a result, weighing down on retail sales (Starr-McCluer, 2000). The concept of climate beliefs (described

[6] In the methodology used by the Eurostat Statistics in the computations of heating and cooling degree days, this threshold is often set at 18 °C

in section 3.1) finds applications when studying the financial-market effects of climate change. If temperature has a significant effect on the preferences of investors, financial market actors could attempt to hedge against the augmented sense of climate risk by investing in a different type of assets. Indeed, Choi, Gao and Jiang (2020) have linked exceptionally warm temperatures to shifts in investment from brown to green assets.

4 Constructing the Temperature Series

The main objective of this section is to describe the construction of the temperature shock series, which will be used to estimate impulse response functions later in the thesis. The weather-economy literature discussed in the previous section lacks a coordinated, uniform definition of a temperature shock. Instead, shock construction varies depending on the data and the research question at hand. When defining the shock series, my aim is to isolate the unexpected component of historic weather fluctuations rather than long-term temperature anomalies, which has been the focus of much of the literature up to this point (Lemoine, 2017). The upcoming section (4.1) will proceed to briefly discuss the choice of context and present the inherent limitations following this choice. The subsequent sub-section (4.2) presents the Had-UK geospatial model used for the temperature estimates. The final section (4.3) formally introduces my proposed definition of a temperature shock and further builds upon the previous background section to outline the underlying rationale.

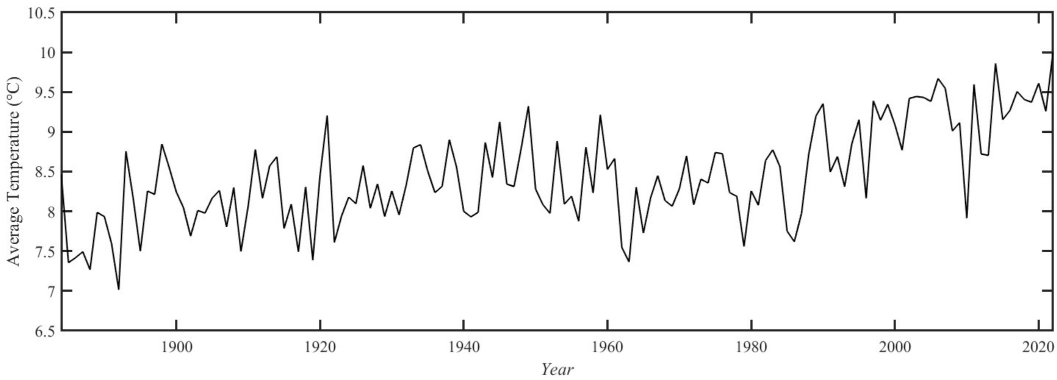
4.1 Context of Study

The identification strategy employed in this thesis relies on leveraging exogenous variations in climatic conditions to evaluate the causal impact of temperature stresses on prices in the United Kingdom. Consequently, two fundamental choices have shaped the context of this empirical case study. The first choice involves a sole focus on the United Kingdom, while the second choice centres on evaluating the impact of temperatures specifically, rather than considering other climate variables, such as precipitation or snowfall.

The advantage of studying price dynamics in a single country rather than a cross-country setup was discussed in Section 2. Whilst climate change is a global concern, the extent to which this change in climatic conditions will be felt is largely heterogenous across countries. Furthermore, because both demand-side and supply-side channels may interact in complex ways to form both deflationary and inflationary price pressures, the fallout of temperature abnormalities may be contingent on the specific structure of the economy. The UK exhibits a number of traits that that are relevant in this context. It forms its own monetary unit headed by the Bank of England (BoE), which adapts an inflation targeting regime. Independent monetary policy regimes may be more robust to sudden temperature persistent temperature shocks due to continuous inflation targeting. Moreover, both data on macroeconomic outcome variables and temperature observations is available at high frequencies spanning long time periods, allowing me to uncover some of the channels through which a temperature shock may impact prices. This is particularly true for CPI components, which are published monthly by the Office of National Statistics (ONS).

Average temperatures in the UK have risen notably over the past decades. Figure 2 shows how annual temperatures in the UK have evolved over the 20th century. To the best of my knowledge, this is the first paper to empirically investigate the short-and medium run price dynamics as a result of temperature shocks on the UK economy.

Figure 2: Average Annual Temperature for the United Kingdom, 1885 – 2022



Note: The figure displays how average annual temperatures evolved between 1885 and 2022 in the United Kingdom. Data source: HadUK Gridded Climate Observations (McCarthy *et al.*, 2022).

The second limitation of this study is to focus strictly on the effects of abnormal temperatures as the main climate variable. The effects from increasingly extreme temperatures have been a focus in the wider discussion surrounding climate change and is discussed extensively in the IPCC reports. The focus on temperatures as the outcome of interest is also supported by the fact that high temperatures are intimately associated with other climate events. For example, a prolonged period of exceptionally hot temperatures may cause droughts and wildfires, and be associated with low precipitation. Furthermore, temperatures materialising within a specific spatial unit can be measured accurately and at high frequency, often spanning several decades and sometimes even centuries. Evaluating the potential impact of alternative climate indicators, such as precipitation or windstorms, is thus left for the future literature.

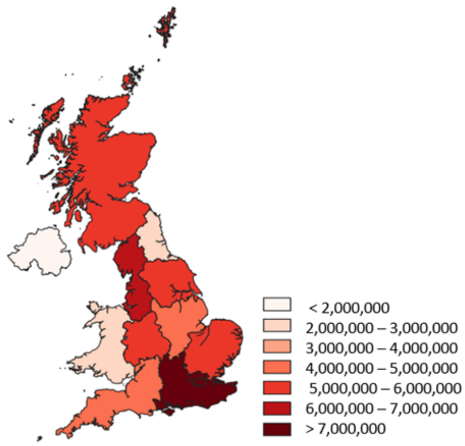
4.2 Data Construction

The first step of the data construction process consists in extracting regional temperature estimates for the UK. All temperature input data comes from HadUK geospatial grid of near-surface climate observations, produced by the Met Office Hadley Centre for Climate and Science and Services (McCarthy *et al.*, 2022). High-frequency climate observations are interpolated to provide and consistent coverage over the United Kingdom at a 1x1 kilometre grid, allowing me to compute reliable estimates at the sub-national level. The observational data underpinning the is mostly collected from the Met Office's own Integrated Data Archive System of weather station, combined with archived station data dating back to 1836.

In the wider weather-economy literature, economists have often turned to similar interpolated geospatial models to produce reliable climate estimates. There are several advantages to such models when construction estimates for economic analysis compared to alternative methods, such as relying on raw station-level observations. Because the HadUK produces a balanced panel of complete coverage over time, issues like missing or patchy station data are mitigated. Entry or exit of weather stations in the time series can cause irregularities in the data, so called *exit-bias*. It furthermore helps the economist circumvent obvious obstacles related to the so-called *heat island bias*, whereby urban areas are known to be hotter than rural areas because of the absorption of heat from materials like concrete, asphalt, and black roofs (Dell *et al.*, 2014).

Average near-surface temperatures (tas) are available at the monthly frequency starting from 1882. I retrieve the monthly time series for each Government Office Region (GOR) in England, as well as for Northern Ireland, Scotland and Wales. Figure 3 displays the official GOR boundaries in 2022 as well as the average size of population over the period 1971 – 2021. Deriving the temperature series at the GOR level allow me to pair the temperature observations with sub-national population estimates, which are reported annually by the Office of National Statistics as well as the National Records of Scotland. Estimates for the mid-year population in each GOR have been reported annually from 1971.

Figure 3: Average Regional Population of the United Kingdom, 1971 – 2021

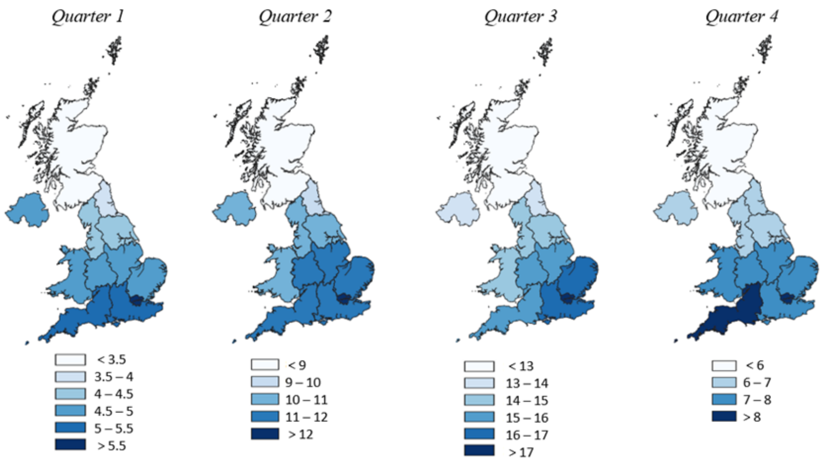


Note: The map shows the average regional mid-year population between 1971 and 2021. Data sources: Population Estimated for Region in England and Wales, Office for National Statistics, National Records of Scotland; Northern Ireland Population Mid-Year Estimates.

I collapse the monthly series from HadUK to a quarterly series by taking the mean temperature over the three months that constitute any given quarter[7]. There are several trivial reasons for working on the quarterly frequency. Firstly, quarters approximately coincide with the calendar seasons, which are somewhat homogeneous in terms of temperatures. This is important, as beliefs (as defined in section 2.2) about certain weather realisations are likely to be contingent on the season of the year. For example, whilst a quarterly average temperature of 5 degrees Celsius is commonplace in the UK in the first quarter (winter), it would be considered exceptionally cold if the same average prevailed in the second quarter (spring). Secondly, because businesses and firms report on the quarterly frequency, economic activity is likely to be more readily observed by quarter. Relatedly, macroeconomic variables are commonly reported on the quarterly frequency, thus facilitating the empirical analysis. Lastly, observing changes over a quarterly horizon is useful for evaluating the potential medium-term effects of a temperature shock. This is consistent with the commonplace view of macroeconomic policy-makers, who tend to be concerned with medium-term inflation rather than month-by-month fluctuations.

Economic activity is assumed to be a function of the population within any given spatial unit. In order for my temperature shock to accurately capture the effect on the UK economy, I use my series of sub-national populations estimates as weights and build a population-weighted temperature series ranging from the first quarter in 1975 to the final quarter in 2021[8]. Figure 4 displays the average quarterly temperature by GOR during the relevant time period.

Figure 4: Average Regional Temperature by Quarter, 1971 – 2021



Note: Average regional temperature between 1971 – 2021 for the United Kingdom, by quarter. Numbers denote the temperature in degrees Celsius (°C). Data sources: HadUK Gridded Climate Observations (McCarthy et al., 2022) and ONS Geography 2020 Boundary Releases, Office for National Statistics.

[7]Each quarter encompasses three consecutive months: Q1 (January – Mars), Q2 (April – June), Q3 (July – September) and Q4 (October – December)

[8]I chose 1975 as the start year of the final series out of convenience, particularly since a number of the outcome variables used in the empirical analysis end at odd years

Average quarterly temperatures vary by both season and location. In general, the south of the UK reports higher quarterly temperatures than the north. Over one calendar year, average quarterly temperatures observed in the GORs range from a little over 17 °C in quarter 3 for London to less than 3.5 °C in quarter 1 in Scotland. Temperatures are lower in Scotland than in the English GMOs, Wales and Northern Ireland throughout the year. Although Scotland is commonly divided into three sub-national regions (North, South and Southwest of Scotland), population estimates at the regional level are only reported from 1981. I thus use the aggregated temperature series at the country level, paired with national mid-year population estimates, to construct a temperature series for Scotland[9]

4.3 Defining a Temperature Shock

Having extracted a series on average quarterly temperatures for each GOR and a series for the associated mid-year population values, I construct a population-weighted temperature shock series. My proposed shock measure is straight-forward: a temperature shock is defined as the difference between the average temperature in the current quarter and average temperature that prevailed in the same quarter over the past five years. Using a rolling average helps the shock measure to better reflect *unanticipated* movements in temperature. The following section formalises this shock measure and delves deeper into the rationale behind it.

Following from Choi, Gao and Jiang (2020) and others, a temperature surprise shock is defined as the difference between realised temperature in the current quarter n and the expected temperature for that same quarter. Drawing on the notation used in Natoli (2022), expectations are formed based on a reference distribution of past temperature realizations $E_{t-1}f(T_t^i)$. That is, the idea that economic agents adjust their beliefs about the weather over a set learning period, L. At the end of each quarter, agents will hold a set expectation on what temperatures should transcend in the same quarter the following year. A country-level temperature shock is thus defined as:

$$\sum_{i=1}^{k} w_t^i [f(T_t^i) - E_{t-1}f(T_t^i)]$$

Where w_t^i is the weight allocated to each sub-national spatial unit i at time t. As discussed above, I define i as a UK Government Office Region (GOR). Every quarter q and year y, the temperature $T_{q,y}^i$ is realized within region i. At the regional level, a temperature shock is thus defined as:

[9] I lack temperature data for the Channel Islands and the Isle of Man, which are consequently excluded from the computation of the temperature shock series. Because of the relatively small population residing on both, I do not anticipate a notable estimation error arising from this exclusion.

$$\text{GOR\_TempShock}^i_{q,y} = T^i_{q,y} - \frac{1}{L}\sum_{n=1}^{L} T^i_{q,y-n}$$

The regional shock represents the abnormality from a rolling average over a set learning period of L prior years. In my main specification, I follow Natoli (2022) and Pankratz and Schiller (2022) in setting the length of the learning period to five consecutive years. In section 4.3, I re-run the results using alternative lengths of the learning period, including the 10-year threshold as used by Choi Gao Jiang (2020). The regional shock is aggregated to the national level by weighting by the mid-year population estimates in the relevant year w^i_y. The weighted rolling temperature abnormality thus forms a UK-wide measure of the temperature abnormality as follows:

$$\text{TempAn\_UK}_{(q,y)} = \sum_{i=1}^{k} w^i_y \left(T^i_{(q,y)} - \frac{1}{L}\sum_{n=1}^{L} T^i_{(q,y-n)} \right)$$

The resulting series is shown in Figure 5. The Ljung-Box Q test suggest that the series is unlikely to suffer from issues of autocorrelation (see appendix C.2). Moreover, the Dickey-Fuller test rejects the null at the 1% level, suggesting that the series is indeed stationary[10]. The distribution of negative (cold) and positive (heat) anomalies is roughly equally distributed throughout the sample period, as shown in table 1 below:

Table 1: Shock Series - Breakdown by Type and Season

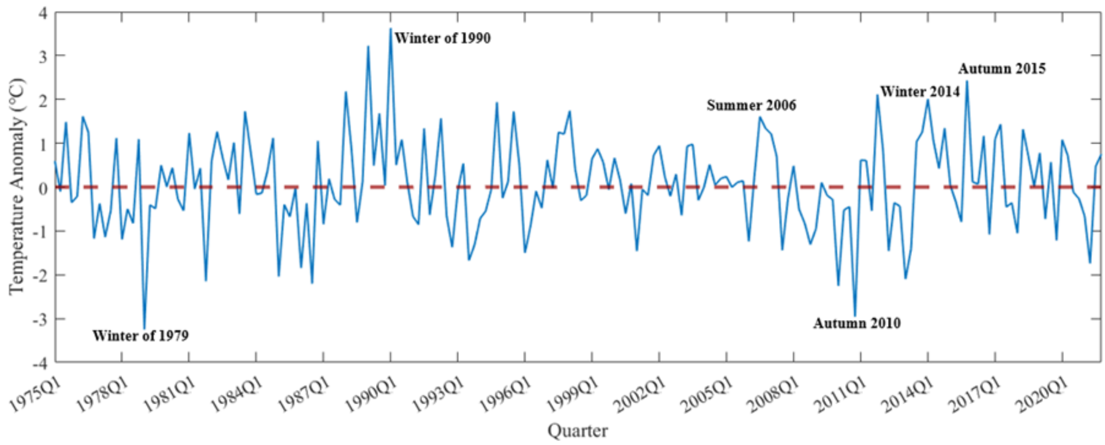
Type	Total	Q1	Q2	Q3	Q4
Positive shocks > 0	96	26	25	21	24
Negative shocks < 0	88	20	21	25	22
Shocks > 1°C	14	10	6	11	11
Shocks < 1°C	10	10	3	3	8
Shocks > 1.5°C	38	5	2	4	3
Shocks < 1.5°C	24	6	0	2	2

A narrative check reveals that outlier values typically coincide with reports of exceptional weather conditions. For example, the first months of 1990 and 2014 are reported to be exceptionally mild across the UK, with a powerful Jet stream driving low pressure systems across the

[10] $Z(t)$ = -12.526 for the full series (1975 - 2021), I therefore reject the null that the series has a unit root, the series does not need to be first-differentiated.

Atlantic (Met Office, 2014). At the end of 2010 the UK experiences the earliest and most widespread snowfall episodes since the early 1990s, driving down average temperatures as a result. During these episodes, most parts of the UK experienced abnormally heavy snowfalls. In the summer of 2006, new temperature records were set in both Wales and the United Kingdom. At the time, July 2006 was the warmest month ever recorded in the Central England Temperature series, which commenced recording temperatures in 1659 (Met Office, 2006). December of 2015 counts as another record-breaking month, with temperatures frequently being closer to what would be expected in April and May, and temperature records where therefore set across the union.

Figure 5: Temperature Shock Series



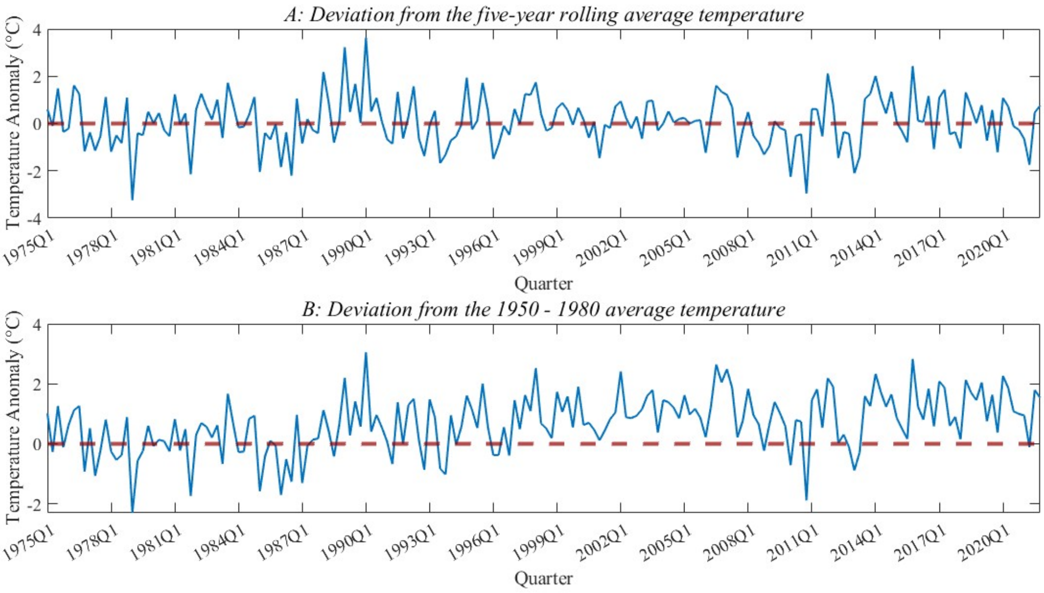
Note: Full temperature shock series, 1975 - 2021.

An alternative approach would be to use the traditional definition of temperature anomaly, that is, set threshold based on a long-term average temperature, thus capturing the long run trend in average warming. By construction, my shock measure captures the effect of unexpected and thus more extreme weather events, rather than absolute increases in average temperatures. In doing so, I make an explicit distinction between climate (changes in the long-run distribution) and weather, as described above. Figure 6 visualises both my constructed shock measure compared to the temperature anomaly series used in the ECB working paper by Faccia, Parket and Stracca (2021) which employs a traditional definition based on the (1950 – 1980) temperature anomaly from 1975q1 – 2021q4. The difference becomes more apparent from the 1990s onward, where the warming of the UK intensifies.

The long-run anomaly incorporates the difference in levels that occurs due to the long-run trend in warming (please refer to appendix C.1 for descriptive statistics). By contrast, my preferred temperature series aims to capture the expectations gap and therefore dismisses the long-run trend, which, following the rationale set out above, agents should be able to anticipate. As seen when comparing panel A to panel B, my shock measure varies around zero.[11]

[11]For my preferred series (Panel A), I fail to reject the null hypothesis that the mean is different from zero.

Figure 6: Temperature Shock Versus Long-Term Temperature Anomaly



Note: Panel A shows my constructed population-weighted temperature anomaly series based on the 5-year rolling average temperature for every quarter. Panel B shows the temperature deviation from the 1950-1980 30-year average temperature for any given quarter, a traditional definition of temperature anomalies.

By construction, zero represents the believes of agents. If the anomaly is zero, the recorded temperature in the current quarter perfectly aligns with the average over the past five years. As such, my proposed shock measure better aligns with the general definition of a macroeconomic surprise as laid forward in Ramey (2016): *"A macroeconomic shock should represent unanticipated movements in economic variables, or some news about future movements in economic variables"*.

5 Empirical Strategy

The following section describes the empirical methodology used to estimate the effect of the temperature shock series on the UK economy. I estimate impulse response functions by local projections, in line with Jordà (2005). Section 5.1 discusses this choice of method and section 5.2 specifies the baseline model. Section 5.2 discusses the potential heterogeneous impact of a temperature shock depending on the season of the year and alters the baseline specification to address this.

That is not true for the long-term anomaly shown in panel B, where I can reject the null at the 1% level, following a simple t-test.

5.1 Impulse Response Analysis

As in any impulse response analysis, the fundamental aim is to pin down empirical patterns in a vector time series. Within a local projections framework, this is done by estimating linear regressions locally for each of the increasingly distant time horizons. For this purpose, I run a loop of linear regressions for each of the time horizons included in the analysis. The choice of time horizons h to include in the analysis is left to the econometrician, with the obvious caveat that a greater h results in a loss in observations at the end of the sample period. At a conceptual level, impulse responses can be defined as the difference between two forecasts, that when a system is hit by a one period shock and the counterfactual. Drawing on the notation laid forward in Jordà (2005) this can be expressed as:

$$IR(t, s, \boldsymbol{d_i}) = E(\boldsymbol{y_{t+s}} \mid \boldsymbol{v_t} = \boldsymbol{d_i}; \boldsymbol{X_t}) - E(\boldsymbol{y_{t+s}} \mid \boldsymbol{v_t} = \boldsymbol{0}; \boldsymbol{X_t}) \text{ for } s = 0, 1, 2, \ldots$$

Where vectors are marked in bold. $\boldsymbol{y_t}$ is a $K \times 1$ random vector, $\boldsymbol{X_t} = (\boldsymbol{y_{t-1}}, \boldsymbol{y_{t-2}}, \ldots)$, $\boldsymbol{0}$ is a zero vector of dimensions $K \times 1$, and $\boldsymbol{v_t}$ is a $K \times 1$ vector of random disturbances. Suppose that between t and $t+n$, the system is hit by a single shock, $\boldsymbol{v_t} = \boldsymbol{d_i}$[12]. The goal of the analysis is that the impulse response function thus represents the effect of this one-period shock to the system at time $t+n$ (provided that no other shocks hit the system at time t). At the conceptual level, the impulse response function thus represents the difference between the shock scenario $\boldsymbol{v_t} = \boldsymbol{d_i}$ and the counterfactual scenario of no shock $\boldsymbol{v_t} = \boldsymbol{0}$.

Unlike a traditional VAR framework, local projections (LPs) do not require any assumptions to be made with regards to the true underlying multivariate dynamic system. This follows naturally from the locality of the estimates. In a local projections analysis, a regression estimated for one time horizon is independent of that estimated for other time horizons, thus not dependent of estimations of intermittent time periods[13]. In applied analysis, the is generally a trade-off in that LPs more robust to mis-specification, whereas VAR frameworks are more efficient in estimating precise estimates, given that the system has been well specified (see for example Nakamura and Steinsson 2018, pg 81).

Identification in an LP analysis relies on the pre-requisite that the shock series is exogenous with regards to the outcome variable of interest (Nakamura and Steinsson 2018, pg. 81). In a sense, the previous two sections of this thesis have been largely dedicated to laying out this

[12] Formally, Jordà (2005) defines $\boldsymbol{D}$ as an $K \times K$ random matrix, where the columns $\boldsymbol{d_i}$ contain the relevant shocks.

[13] It is important to note that VARs and LPs are not conceptually different methods in that they both attempt to estimate the same underlying impulse responses to a shock. It has indeed been shown that both methods of estimation produce equivalent estimates when controlling flexibly for lagged data (Plagborg-Møller and Wolf, 2021).

argument. In order to further improve the *precision* of the LP estimates, I introduce a set of control variables in the specification. It is important to emphasize that control variables included in the local projections do not alter the overall shape of the impulse response functions. That is, the point estimates are derived solely from the (exogenous) variation in the temperature shock series. Furthermore, the control variables included in a local projections model are determined prior to the shock materialises (pre-treatment controls). The next section specifies the model and discusses the choice of controls.

5.2 Baseline Specification

For the baseline results, the impulse responses are retrieved from the following set of $s \in \{0, \ldots, h\}$ linear regressions:

$$y_{t+s} = \alpha^s + \beta^s \text{TempAn}_{\text{UK},t} + \delta^s D_Q^s + \gamma^s(L)X_{t-1} + \varepsilon_{t+s} \quad \text{for } s = 0, 1, 2, \ldots, h$$

Each quarter is represented by the subscript t. The coefficient of interest β^s is interpreted as the response of the outcome variable y to a temperature anomaly ($\text{TempAn}_{\text{UK},t}$) in quarter t at time $t + s$. I set the forecast horizon h to 16 quarters (four years), meaning that h runs from 0 to 16 quarters. Note that the baseline specification is simply concerned with the effects of a one-unit (1 °C) deviation from the five-year rolling average temperature each quarter. To allow for this interpretation, I estimate the model using the *absolute value* of the temperature shock series[14]. I use a log transformation of all outcome variables but the long rate and policy rate. A detailed overview of the data can be found in Appendix D.

On the right-hand side of the equation, a tight set of controls are included to increase the precision of the estimates. I include quarter dummies, D_Q^s, to account for differences in quarterly economic activity over the calendar year (quarter fixed effects). This becomes particularly useful when estimating the impulse response of official CPI components, which are not seasonally adjusted. X_t is an additional vector of controls[15]. In the main results, I follow Natoli (2021) by including up to eight lags of both the outcome and the shock series, as well as linear, quadratic, and cubic time trends. This follows a standard rationale: Including a lag of the shock variable aims to eliminate any dynamics due to past weather shocks, whereas the lagged outcome variable is similarly included to better account for any autoregressive structure with regards to past values. Time trends are included to control for long-term trends in the dependent variable. All regressions are estimated with Neway-West standard errors, where the

[14] I perform the the Dickey-Fuller test of the absolute transformation, which return the test statistic Z(t) = -15.571. I can therefore reject the null that the series has a unit root, suggesting that the absolute series is stationary.

[15] The purpose of the parenthesis (L) is used to clarify that some of the controls are lagged

lag length is chosen to increase with the value of the time horizon s[16] (Newey and West, 1987). In section 6.3, I test a number alternative specifications.

5.3 Seasonal Heterogeneity

It is reasonable to assume that a temperature shock will have different effects depending on the season of the year. For example, an exceptionally hot summer can have different effects on the economy compared to an exceptionally mild winter. An advantage of using data at the quarterly frequency is that I can account for such potential seasonal heterogeneity. I can thus differentiate between the effect of exceptional temperatures during the different parts of the year. To shed light on the potential heterogeneous impact of the various seasonal shock, I interact the temperature shock with quarter numbers, which as previously discussed are assumed to correspond to calendar seasons:

$$y_{t+s} = \alpha^s + \sum_{j=1}^{4} \beta_j^s \mathrm{TempAn}_{\mathrm{UK},t} \times D_j + \delta^s D_Q^s + \gamma^s(L)X_{t-1} + \varepsilon_{t+s} \quad \text{for } s = 0, 1, 2, \ldots, h$$

Where $J \in \{1, 2, 3, 4\}$ such that D_j is a dummy variable that takes on the value of 1 depending on the calendar season (which is assumed to coincide with the four quarters). The model is otherwise identical to the baseline specification drawn up in section 3.2 above.

6 Results

Following the rationale set out in the above sections, this section presents the impulse responses from a temperature shock on the UK economy. It begins by discussing the baseline specification, that is, without distinguishing between seasons, or the direction at which temperatures affect prices. After establishing the general effect of a temperature shock, I show the results for each quarter separately. At the end of the section, I discuss the robustness of the results, showing that the reported estimates persist across different time spans, for alternative formulation of temperature series as well as different specifications of my baseline model.

Two additional appendices compliment this section: appendix E presents some additional results discussed throughout the section, whereas appendix F shows a number of additional robustness checks. The impulse response functions are estimated for the log transformation of all outcome variables, except for the long rate and the policy rate. In the main results section,

[16] For example, the lag is set to 1 for a time horizon of 0, 2 for a time horizon of 1, and to *h+1* for horizon h.

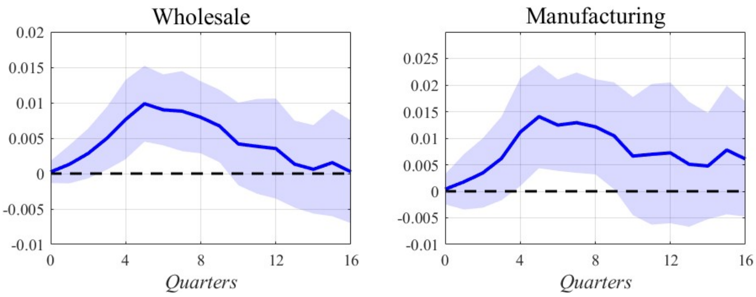
I run the impulse response functions on the 30-year period between 1985 – 2015 [17]. Results for the full sample period (1975 - 2021) can be found in appendix E.1.

6.1 Baseline Specification

Price Effects. Estimates from the baseline specification on aggregate producer and consumer prices are shown in figures 7 – 8 below. The solid line shows the point estimates whereas the shaded area is the 95% confidence band estimated using Newey-West standard errors. A temperature shock causes to a persistent increase in both the producer- and consumer price indices over a four-year time span. In both cases, the response appears with some lag. As expected from the relative sickness of consumer prices, this lagged response is somewhat more pronounced for CPI, suggesting that producers eventually pass on some proportion of the price increase to consumers.

As shown in figure 7, both wholesale and manufacturing PPI increases persistently in the quarters following a 1-degree C deviation from the expected temperature. For overall wholesale prices, this increase amounts to a peak of 0.98 percent after five quarters, after which is successively declines. The effect size is greater for manufacturing prices, which peak at 1.4 percent after five quarters. This evident increase in producer prices seem to place upward pressure on aggregate CPI. The findings are similar when running the shock episode on a longer time span (1975 – 2021), as shown in appendix E.1.

Figure 7: Producer Price Index: Impulse Response to a Temperature Shock



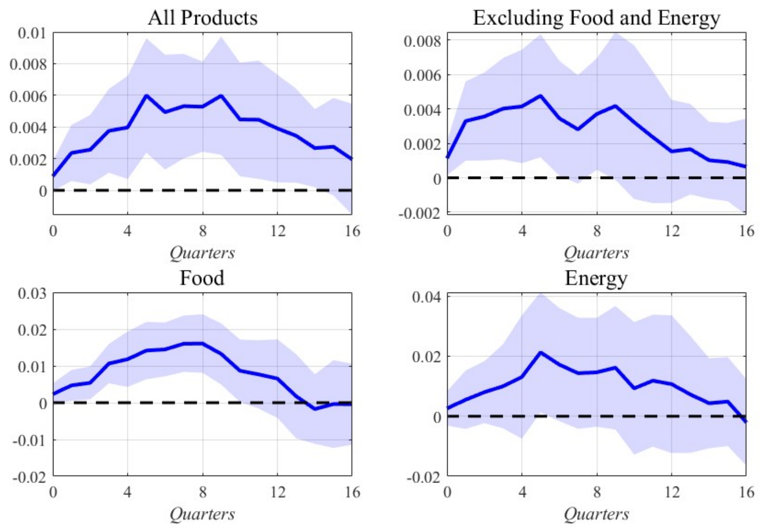
Note: Aggregate (wholesale) Producer Price Index as well Manufacturing Producer Price Index for the United Kingdom. The impulse response from a 1 °C deviation from the five year-rolling quarterly average temperature estimated using data from 1985 – 2015. The solid line is the point estimates, the shaded area denotes the 95% confidence band.

Figure 8 displays the impulse response of aggregate CPI as well as a broad decomposition into its core components (all items excluding food and energy) as well as the typically more

[17] Because the series for the outcome variables are available at different time spans, notably the components of GDP which only start in 1990, I present the main results for a shorter time span (for which all outcome variables are available) to ensure comparability between the panels in the main analysis.

volatile headline components stemming from food and energy prices. Aggregate consumer prices increase persistently in the quarters following a temperature anomaly, peaking at 0.7 percent increase in inflation 9 quarters following the initial stress episode. That is, my estimates suggest that the effect of unexpected temperature stresses may lead to a persistent response in consumer prices, potentially making it difficult for central banks to see through the price impact of abnormal temperatures.

Figure 8: Consumer Price Index: Impulse Response to a Temperature Shock



Note: Consumer Price Index as well as its main components, with 2015 = 100. The impulse response from a 1 °C deviation from the five-year rolling quarterly average temperature estimated using data from 1985 – 2015. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

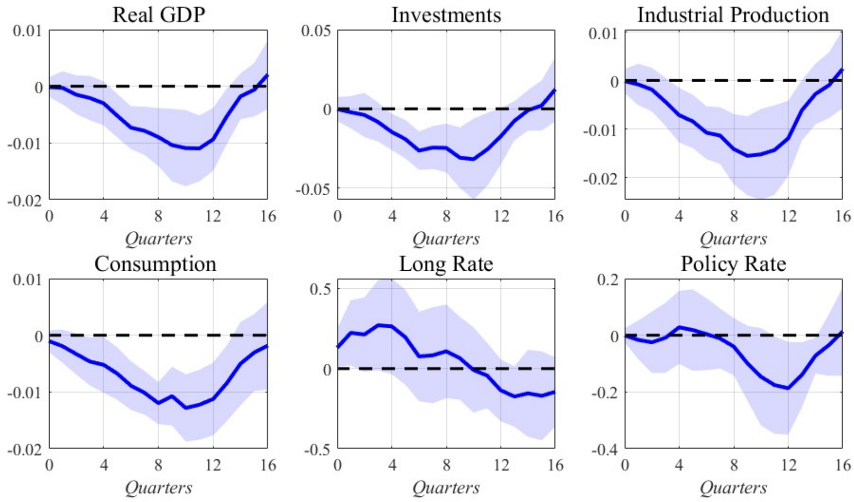
Food and energy prices react more strongly to temperature stresses than the core (non-food and energy) component. Three quarters following a temperature shock, food prices are estimated to have gone up by 1.06 percent, reaching a peak of 1.6 percent by quarter 8. Energy price inflation evolves in a similar manner following the shock, though with wider confidence bands. Notably, the effect of energy prices is not significant at the 95% level (though effects from quarter 0 – 8 are significant at 90% confidence level). Four quarters following the initial impact, energy CPI has increased by 1.3 percent, where the estimated coefficients peak at 2.12 percent after five quarters. I document a significant but smaller response to core CPI, which reaches 0.6 percent five quarters following the initial temperature shock. These findings are largely similar when running the shock episode on a longer time span (1975 – 2021), as shown in Appendix E.1. However, in the long-sample, core CPI respond more strongly to a temperature shock. The detailed decomposition of the CPI index is published by the office of national statistics (ONS) on both a monthly and a quarterly basis, starting from 1988. In Appendix E.2, I run the baseline model on the 12 aggregated categories available in the latest release of the CPI index decomposition. The results are largely consistent with the ones reported in figure 8, with positive response of both food inflation, as well as some service categories, such as house repairs and transportation services.

Aggregate indicators of the business cycle. As established above, abnormal temperature stresses seem to place upward pressure on consumer and producer prices in the United Kingdom. In order to shed light on the possible underlying channels of transmission, I run the baseline specification on a set of macroeconomic aggregates, including GDP and the BoE policy rate. Figure 9 displays the impulse responses for a selection of aggregate indicators of the business cycle. Consistent with the common finding in the climate-economy literature, adverse temperatures depress Real GDP and industrial production. The response is, however, not immediate upon impact, but appears with a lag in the data. Real GDP has fallen by 0.5 percent by the fifth quarter following a shock, reaching its peak of a 1.1 percent fall after 10 quarters. The index for industrial production falls by 0.84 percent five quarters after impact and is down at most 1.19 percent after twelve quarters.

Looking beyond GDP, my estimates show an hike in the long rate (10-year treasury yield) by 13 basis points after four quarters, decreasing rapidly after impact. These effects are not significant at the 95% level. Temperature stresses are also associated with cuts in the BoE policy rate, although this response is observed with a notable lag of approximately eleven quarters and broad confidence brands. The policy rate falls at most by 17.6 basis points twelve quarters after impact, suggesting that temperature anomalies may be associated with some downturn in the business cycle.

I also record a significant and notable fall in investment and consumption expenditures. The fall in consumption expenditures is both significant and effects are observed in the quarters following a temperature shock. By this measure, consumption expenditures have declined by 0.52 percent four quarters after the initial impact, with the estimated coefficients dropping to at most 1.28 percent ten quarters after the shock. Equally, investments drop to at most 3.17 percent ten quarters after the shock. These findings could provide support for the narrative suggest that temperature stresses may also affect the economy though demand side channels of impact, consistent with recent empirical findings for the United States (Natoli 2022).

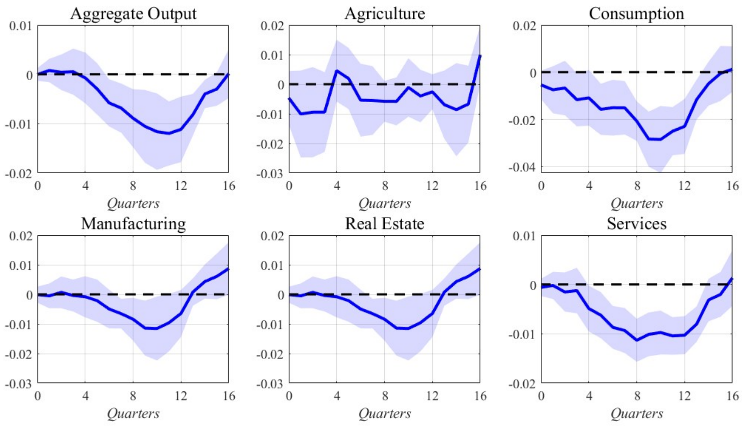
Figure 9: Macroeconomic Aggregates: Impulse Responses to a Temperature Shock



Note: The effect of a temperature shock on the log transformation of macroeconomic aggregates. All variables expressed in real terms. The impulse response from a 1 °C deviation from the five year-rolling quarterly average temperature estimated using data from 1985 – 2015. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

Output by Sector. To better understand the dynamics behind this lagged response to real output, I use the detailed decomposition of gross domestic product into sectorial output, which is available as an index (2015 = 100) through the Office for National Statistics (ONS). This sectorial breakdown is shown in figure 10. Whilst the series only commences in the year 1990, the effect on aggregate output is not affected greatly by the omission of the years 1985 – 1989 from the series. As seen in the top panel, the response of both agricultural output and consumption is immediate upon impact, though not outside the range of the 95% confidence band. Reading directly from the point estimates, agricultural output drops by 0.46 percent immediately upon impact, reaching 1 percent drop the quarter following the initial shock, though the estimated response is not significant at neither the 95 nor the 90 percent level. Output from consumption drops by 0.5 percent immediately, reaching at most a 2.85 percent drop ten quarters after impact. The second panel shows the evolution of manufacturing, real estates and services following a temperature anomaly. The drop in both real estate and manufacturing activity largely mirrors the drop in the aggregate GDP index, dropping by approximately 1 percent by the tenth quarter following a temperature shock. Output from services drops relatively quicker, amounting to at most 1.13 percent eight quarters following a temperature shock.

Figure 10: Real GDP, Breakdown by Sector: Impulse Response to a Temperature Shock



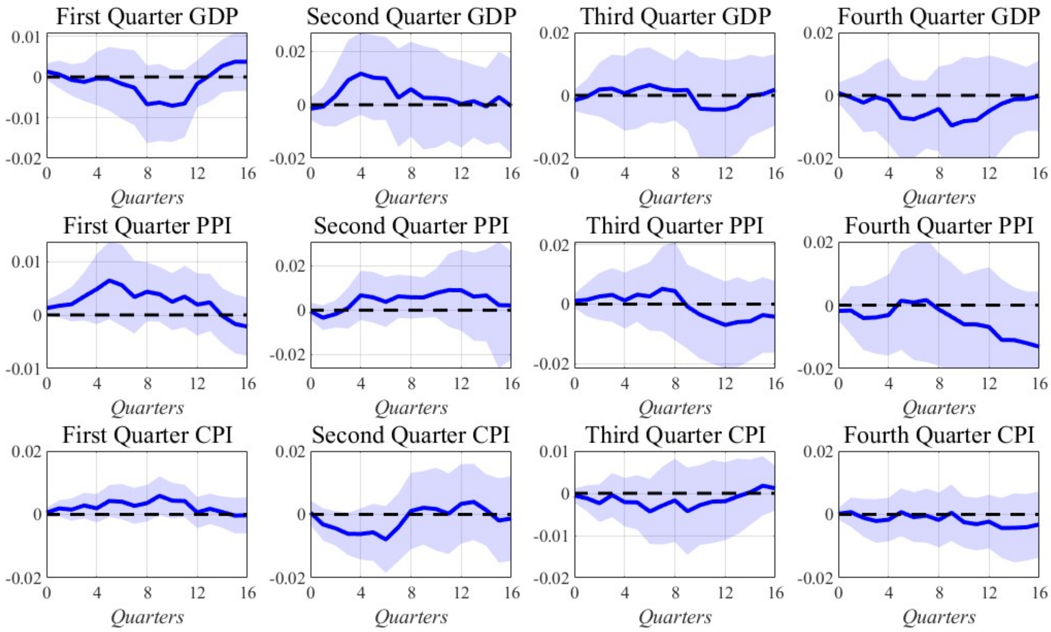
Note: The effect of a temperature shock on aggregate output, breakdown by sector. All variables expressed in real terms. The impulse response from a 1 °C deviation from the five year-rolling quarterly average temperature estimated using data from 1990 – 2015. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

6.2 Shock by Season

The baseline model does not distinguish between neither the timing of the temperature shock throughout the calendar year nor the direction of the shock. To shed light on these potentially disparate effects, I present the impulse response for each season and type of shock separately. More specifically, Figures 11 and 12 display the impulse responses from heat and cold shocks in each quarter throughout the year. As discussed in Section 5.3, the 'seasonal' shock is interacted with a dummy variable that takes on the value of 1 for each respective quarter of the year.

As shown in Figure 11, a one-degree Celsius increase from the expected temperature does not generate significant effects on real GDP, producer prices, or consumer prices. The size and direction of the point estimates for Quarter 1 are consistent with the results reported above, though no significant effects are detected at the 95% confidence level. Notably, a heat shock in the warmer parts of the calendar year (Quarters 2 and 3) does not generate any notable effects on either aggregate quantities or prices.

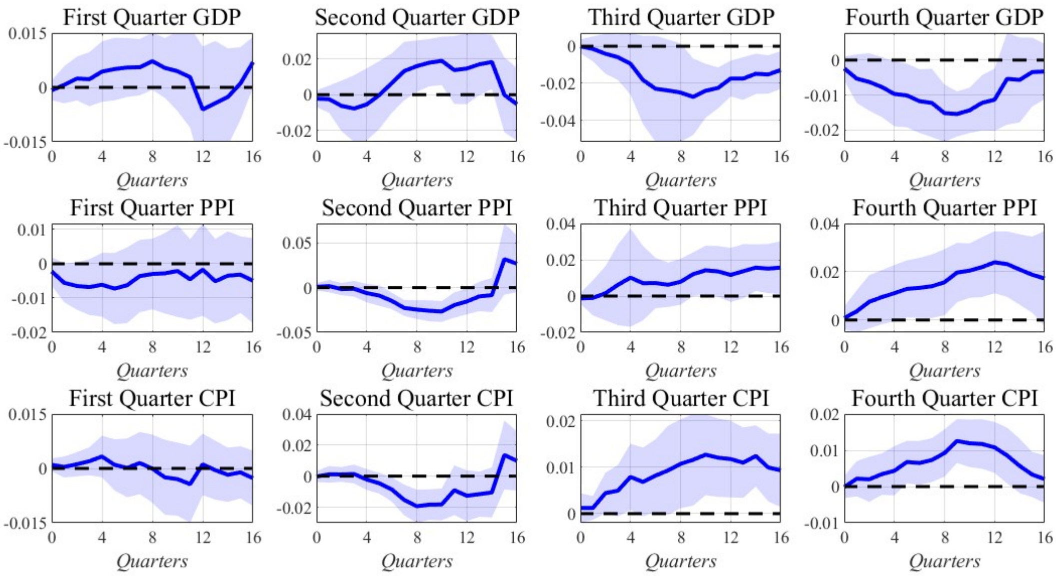
Figure 11: Heat Shock by Quarter



Note: Effects of a 1 °C *positive* deviation from the rolling five-year average temperature, by quarter. The sample runs on the quarterly frequency between 1985 – 2015. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

Figure 12 illustrates the effects of a cold shock, representing a negative deviation from the quarterly temperature norm. In this scenario, significant effects are observed for all quarters except the first quarter of the year. A cold shock in the third and fourth quarters, corresponding to the latter part of the calendar year, is linked to a decline in real GDP and positive effects on producer and consumer prices.

Figure 12: Cold Shock by Quarter



Note: Effects of a 1 °C *negative* deviation from the rolling five-year average temperature, by quarter. The sample runs on the quarterly frequency between 1985 – 2015. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

Following a cold shock in the second quarter of the year, output peaks at 1.9 percent after ten quarters. As discussed in previous sections, it is possible that abnormal temperatures occurring in a specific season of the year could have opposite effects on the economy, potentially even stimulating economic activity. The timing of a temperature shock throughout the calendar year may, therefore, impact how the shock propagates through the economy. To understand the price-temperature dynamics, econometric and theoretical models may need to account for this apparent heterogeneity. However, it remains true that the overwhelming finding in the sections above is that the aggregate effect of a temperature shock places upward pressure on prices and depresses aggregate economic activity. In the coming section, I subject these estimates to a number of robustness tests to further assess the precision and relevance of the estimated coefficients.

6.3 Robustness

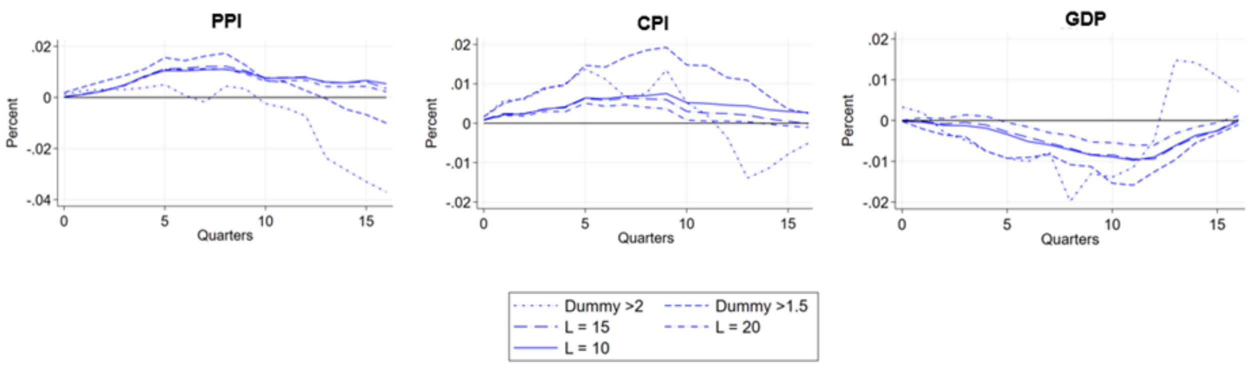
This sub-section discusses the robustness of the results presented above. I show that the reported estimates are consistent across different time spans, alternative formulations of the temperature series and different lag structure. Furthermore, I run the main outcomes on the monthly frequency to establish whether the holds for monthly temperature stresses. Wherever appropriate, the section is complimented by appendix F.

Sample Period. An inherent advantage with the research design is that both data on macroeconomic aggregates and temperatures have been accurately measured at high frequencies for long time spans. There are, however, some potential issues to be raised with regards to the time periods included in the main estimations. If the UK economy changes its response to unexpected weather stresses over the chosen time horizon, results could differ depending on the periods included in the estimation. To address this, I estimate the local projections on the two separate time horizons running from 1975 – 1994 and 1995 – 2015. As noted in section 3 above, the choice of estimating by local projections relied crucially on the length and frequency of my data series. Running the impulse responses on shorter time periods therefore come at the cost of compromising the accuracy of the estimated coefficients.

Figure 13 in Appendix F.1 shows the results of a 1 °C temperature anomaly on real GDP as well as aggregate consumer-and producer prices, with the left-hand column showcasing the results for the years 1975 – 1994 and the wright-hand column showing the period 1995 – 2015. The point estimates for both GDP and PPI follow a similar trajectory across both time periods. Whilst I do not detect any effect on aggregate CPI and Energy CPI in the later time sample, food inflation exhibit consistent positive effects, in line with the main results, during both time periods (see Appendix F.1 for discussion and results).

Alternative shock definitions. Figure 13 shows the point estimates of five alternative formulations of the temperature shock series. The first two formulations compute the temperature series as binary, with the shock variable taking on the value of one when the absolute value of my baseline series exceeds 1.5°C and 2°C, respectively. The subsequent three formulations recalculate the baseline shock when the learning period L is set to 10, 15, and 20 years.

Figure 13: Impulse Response to Various Definitions of Temperature Shocks



Note: The figures show the point estimates of various alternative formulations of the temperature shock series. All temperature shocks are computed on quarterly temperature estimates between the years 1985 – 2015.

Changing the length of the learning period L does not appear to alter the estimates to a notable extent. The reported point estimates remain similar to the estimated baseline learning period of five years. Longer meaning period is associated with a somewhat more muted effect of CPI and GDP, thought the estimated effect of producer prices remain similar irrelevant of the chosen value for L. Specifying a binary shock result in similar estimates. A binary shock that takes on the value of 1 if the anomaly (from the rolling average) exceeds a certain treshold (1.5°C or 2isolates more 'extreme' weather events, potentially explaining the greater effects Changing the length of the learning period L does not appear to alter the estimates to a notable extent. The reported point estimates remain similar to the estimated baseline learning period of five years. Longer meaning period is associated with a somewhat more muted effect of CPI and GDP, thought the estimated effect of producer prices remain similar irrelevant of the chosen value for L. Specifying a binary shock result in similar estimates. Naturally, a binary shock that takes on the value of 1 if the anomaly (from the rolling average) exceeds a certain threshold (1.5°C or 2 °C in this case) isolates more 'extreme' weather events.

Lag Structure. In the baseline model, lags of up to eight years are introduced for both the outcome and the shock variable. The model accommodates these lags effectively due to its relatively long sample period, avoiding the power problem outlined in Jordà (2005). While the shock variable often exhibits significant lags in the baseline model, the lagged outcome variable shows comparatively less significance in the models run on CPI, PPI, and real GDP.

To address this, I determine the optimal number of lags for the outcome variable using both the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) for each time horizon (s). The lag results from this exercise can be found in table 8 (Appendix F.2). While the AIC supports the lag structure chosen for the main model, the BIC results suggest 1–4 lags, varying by period. In Appendix F.2, I present results using four instead of eight lags for the outcome variables, which align closely with those presented above.

Monthly shock. The quarterly frequency impulse response functions reveal that temperature stresses exert pressure on energy and food prices while dampening output. Does this relationship persist when estimating temperature stresses at the monthly frequency? Using data on temperature stresses and macroeconomic aggregates at the monthly frequency allows me to investigate the effect of a monthly temperature shock. These results are shown in Appendix F.3.

7 Discussion

In this thesis, I set out to research the effects of unexpected temperature changes on economic activity and prices, with a focus on the UK economy. My evidence consisted of temperature stress episodes affecting the UK over the past five decades. I built a unique population-weighted temperature shock series using geospatial temperature data and official population estimates. My findings relate to the idea of extensive and intensive margin adaption as defined in Affhaumer (2016). In particular, the significant and negative effects on aggregate output following a temperature shock suggest that at least in the short run, economic agents hold a limited ability to mitigate the effect of adverse temperature shocks though intensive margin adaption. Coupled with the upward pressure recorded for consumer and producer price indices, the effects are consistent with the expected transmissions of adverse supply-side disruptions.

In contrast to the stylized predictions presented by the Basic New Keynesian model in Figure 1, a consistent finding in the data is that the response is lagged for most variables, rather than immediate upon impact. Because this thesis is limited to an empirical investigation, central mechanisms such as the heterogeneous weather exposure of firms or climate adaptation are not integrated into an explicit theoretical framework. Instead, standardized theoretical notions are employed for the purpose of hypothesizing about the channels. When observing the real data, additional mechanisms are likely to come into play to explain the dynamics. For example, the lagged response could support the theoretical proposition that climatic shocks induce economic agents to engage in after-the-event (*ex-post*) adaptation that accumulates dynamically after the initial shock (Lemonie, 2021; Fankhauser *et al.*, 1999; Mendelsohn, 2000)[18]

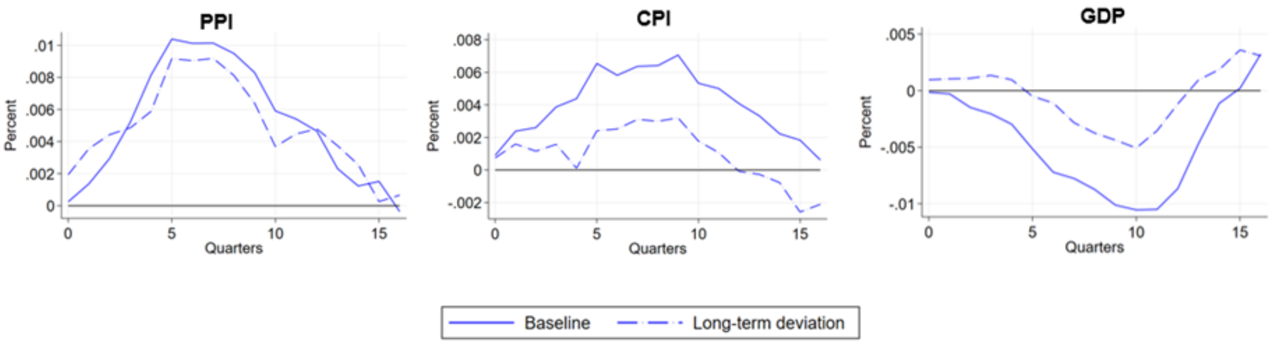
By defining a temperature shock in relation to a rolling average, I follow a recent set of empirical studies in reconciling my empirical estimates with the idea of Bayesian learning in the theoretical literature on climate adaption (Moore, 2017). Following this approach has two main advantages. Firstly, the validity of empirical evaluations based on historical weather data has been questioned with regards to their validity in estimating future climate change (Hsiang, 2016). This has been an explicit goal of the climate-economy literature, where an overarching purpose has been to inform the economic damage functions, which maps climate change to economic outcomes. By reconciling empirical definition of temperature anomaly with the idea of expectations and adaption, estimates are made more robust to this criticism. Secondly, by looking at the temperature deviation from a rolling average temperature, I capture a crucial dimension of future climate change, namely the prevalence of extreme or abnormal weather events, which are associated with the increasing tail-risk of the weather distribution. The constructed shock series therefore makes a clear distinction between weather and climate, drawing on the longstanding rationale *"climate is what you expect, and weather is what you get"* [19]. Consequently, the constructed series pick up on sudden and unexpected weather events, rather than long-term climate changes.

To emphasize the importance of this point, it is helpful to reflect on the interpretation of my estimates in contrast to alternative measures prevalent in the related literature. For example, Figure 14 displays impulse response functions for temperature shocks in relation to a longer-term historical average.

[18]For example, such adaptive responses may include firm's production responses to price signals following a weather event (Lemonie, 2021).

[19]See Jhon Hebertson (1901) *Outlines of of Physiography.*

Figure 14: Baseline Series Compared to the Deviation From the 1950-1980 Average Temperature



Note: The solid line show the point estimates of a 1 °C temperature anomaly from the rolling five-year average quarterly temperature (the baseline series). The dashed line shows the point estimates for a 1 °C temperature anomaly from the long-term average quarterly temperature (1950 – 1980). Impulse responses are estimated using data from 1985 – 2015.

Unexpected weather events have a notably greater aggregate impact on consumer prices and output in my baseline case than in the alternative definition using long-run temperature averages. This aligns with the concept that my series identifies unexpected, and consequently more severe, weather events.

As a final step in the analysis, I subject the impulse response functions to an array of robustness checks. I construct a number of alternative temperature shock series, using longer learning periods as well as re-defining the shock series as binary in order to isolate more severe weather events. The overall effects from these reformulations are largely consistent with the baseline shock series. On the aggregate, adverse temperatures depress output and puts upward pressure on inflation. In addition, the main findings hold up against alternative specifications of the lag structure and are consistent across different sample periods.

I demonstrate that the effect of a temperature shock naturally depends on the direction and timing of the shock. At the aggregate level, however, I observe that unexpected temperature fluctuations influence prices and quantities in different directions, potentially leading to challenging trade-offs for monetary policy. These findings can inform policy discourse, particularly in line with the narrative that physical risks may give rise to adverse supply-side shocks (Cœuré, 2018). The central goal for central banks, especially those with flexible inflation-targeting regimes, is to stabilize inflation around the targeted level . The tendency to 'see through' transitory supply shocks becomes increasingly challenging with the rising duration and magnitude of the shock. Persistent supply shocks pose a risk of de-anchoring inflation expectations, potentially resulting in suboptimal policy outcomes (Kabundi *et al.,* 2022). The crucial question then becomes the extent to which these adverse supply-side disruptions are transitory, and to what extent their effects may persist into the medium- and longer-term horizon. My results show a lag in the data—key indicators such as CPI and PPI are positive and significant after 2–3 years. Understanding the dynamic response of prices to extreme weather events becomes crucial, especially if extreme weather events do become more common and severe , which is why there is growing scope for climate scenario analysis at central banks around the world (Brainard, 2021).

7.1 Validity and Limitations

There are also a number of limitations to the analysis presented in this thesis. Firstly, my empirical strategy rests fundamentally on the identifying assumption that the temperature shock series is exogenous to any economic activity. A critical reader could raise arguments to challenge this statement. One possible problem is that observational weather data is not orthogonal to economic outcomes due to accessible public weather forecasts (Hisang, 2018). If agents possess some information before a weather event materializes, one could question whether the weather shocks picked up by the temperature series are truly exogenous. This point could be addressed relatively easily using data on day-ahead forecasted temperatures to define the shock series, a robustness test that has fallen outside the scope of this thesis due to limited data accessibility. In any case , weather forecasts are inherently uncertain for time periods exceeding 10 days ahead of forecasted weather events, limiting the possibilities for economic agents to adapt ex-ante (UK Met Office, 2023). Indeed, this might help to explain why I found investment expenditure to be more sensitive to temperature shocks than consumption expenditure (See Figure 9 again.) A second possible challenge is that climate change is fundamentally induced by human activity, indicating that long-run changes in the climate may not be fully endogenous to economic outcomes (Carleton and Hsiang, 2016). However, whilst this may be true for long-term changes in the weather distribution, short-term weather variations are unlikely to be a direct result of human activity. Hence, endogeneity issues with regards to human-induced climate change should therefore be mitigated by the fact that I make a sharp distinction between weather and climate.

In the second part of the thesis, I present the results from the impulse response analysis. These empirical estimates come with a few potential limitations. Firstly, the impulse response analysis relies on linear estimation, indirectly imposing the assumptions that the relationship between the weather shock series and the economic outcomes is linear. Other functional forms are not considered explicitly in the analysis. Secondly, the empirical analysis focuses on aggregated price indices and broad macroeconomic indicators related to the business cycle. This restricts the granularity of the analysis, making it challenging to precisely identify the transmission mechanisms affecting prices. A temperature shock is plausibly two-fold, giving rise to both supply-side price pressures and demand-side effects. The direction of impact is ambiguous because different channels of impact may push prices in different directions. Consequently, some of the empirical estimates presented in this thesis are aggregates that encompass several, potentially conflicting, price pressures. Classic economic theory provides useful frameworks to hypothesize about the channels at play in the data, as discussed further in section 3.2. However, to adequately observe of the specific transmissions' channels, more granular price data would be useful. Questions with regards to the specific channels of impact are therefore left for future research.

Finally, relating to the discussion in section 3, the choice of estimating impulse responses using local projections compared to a traditional VAR model comes with a potential loss of precision. To further improve the precision of the LP estimates, I introduce a set of control variables in the specification. The problem of precision does not change the shape of the point estimates but makes it more difficult to detect potentially significant effects. Because some of the macroeconomic variables treated in this thesis are highly volatile by nature, temperature shock would intuitively account for only a small part of this total fluctuation, thus yielding a low signal-to-noise ratio. Throughout the decades long sample period, aggregate prices in the UK will have been affected by a multitude of macroeconomic shocks and supply-side disturbances, contributing to this potential problem (see Känzig (2021) for a similar discussion). In my context, both temperature data and outcome variables are available at high frequencies at generous time spans, which I argue prove a good foundation to produce impulse responses at a reasonable precision (and without imposing additional structures on the system).

7.2 Avenues for Future Research

The temperature shock series developed in this thesis may offer some useful perspectives for future research efforts in this area. Gridded climate observations are readily available at a global scale. Coupled with regional population estimates, my shock definition could be applied to the investigate the impact of temperatures across a range of other contexts and countries, thus contributing to the growing literature focusing explicitly on the price effects from weather shocks. Relatedly, future empirical studies may draw on the idea of Bayesian updating in the context of climate change. Defining the shock series in relation of a rolling average temperature may help researchers make explicit distinction between weather and climate. This approach has recently been adapted by (Choi *et al.*, 2020) in the context of studying investor behaviour in financial markets and has been proposed by (Natoli, 2022) for studying the effects of temperature shock on prices.

The choice to focus solely on the UK economy has been motivated in the previous section. However, utilizing a one-country case study comes with the inherent limitation of external validity for the estimated coefficients. Seminal works in the climate-economy literature has highlighted the dichotomy between developed and emerging economy with regards to their vulnerability to extreme temperatures (Dell *et al.*, 2012). Previous studies examining historical time series data in advanced economies have uncovered further asymmetric channels of impact on prices across countries with distinct economic structures (Ciccarelli and Marotta, 2021). Whilst the estimates may vary depending on the context of study, the UK case study may still offer insights to other advanced economies, particularly countries in northern Europe. Nonetheless, future studies may want to expand the shock series to a cross-country setting.

Finally, this thesis focuses explicitly on temperatures rather than alternative weather indicators. As noted in section three, this follows the rationale that temperatures are indicative of other weather events. Whilst the temperature series may be useful in indicating the occurrence of such events, it follows that this thesis has left the task of disentangling the impact of specific weather events, such as heavy rain, storms, or snowfalls, to the future literature.

8 Conclusion

Central banks around the world are becoming increasingly concerned with physical risks to financial and macroeconomic stability. The purpose of this thesis has been to estimate the effects of unexpected temperature stresses on price stability within an advanced economy context, directly addressing one of the core mandates of monetary policy. To achieve this, a temperature shock series is constructed using geospatial temperature observations and official population estimates from the United Kingdom spanning several decades. The shock series is designed to capture unexpected components of weather realizations, rather than long-term and predictable changes in climate. In a second step, this series is used to estimate the impulse responses to a temperature shock on both producer and consumer prices, following the local projections method (Jordà, 2005).

The results indicate that temperature stresses that fall outside the bounds of recent experience can have significant effects on the UK economy in the short and medium term. Unexpected temperatures overwhelmingly place upward pressure on aggregate price indices, although the effect may vary depending on the timing and direction of the temperature shock. The headline components of the official consumer price index, especially food prices, are particularly susceptible to temperature shocks. The response is typically not immediate upon impact but appears with a lag in the data. Producer prices respond quicker and more strongly than consumer prices, suggesting that producers pass-though some of the weather-related costs to consumers. At the same time, a temperature shock is also associated with the negative effects on aggregate indicators of the business cycle, depressing key indicators such as output, industrial production and consumption. Consequently, the aggregate effects closely align with the effects of traditional adverse supply shocks, potentially leading to challenging trade-offs for monetary policy.

This thesis contributes to filling an increasingly pressing gap in the empirical climate-economy literature, specifically addressing the need to understand the propagation of physical risks on prices. It has demonstrated how historical weather fluctuations can help economists shed light on the potential effects of unexpected weather events on price stability. As unprecedented weather events become more frequent in the decades to come, the findings for the UK underscore the necessity for further assessment into the possible effects in other advanced economy contexts.

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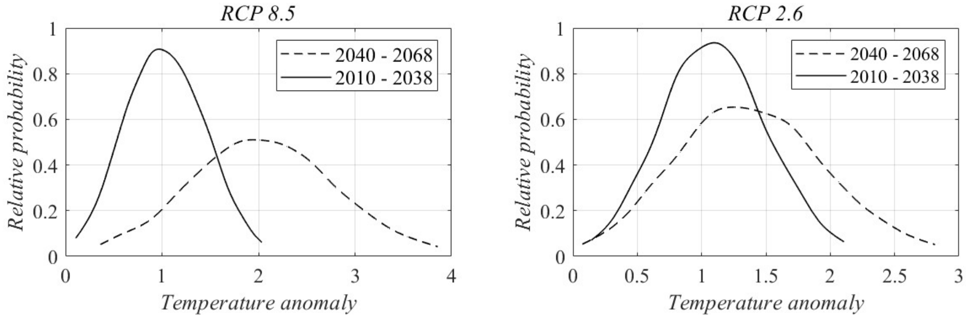
A Appendix: UK Climate Distribution

Figure 15 shows the cumulative climate distribution in the United Kingdom for two Representative Concentration Pathways (RCPs): the more lenient RCP 2.6 and the more extreme RCP 8.5. A Representative Concentration Pathway (RCP) consists of a set of assumptions made around the physical, economic, and social factors that will determine the nature of future climate changes. Each RCP specifies the concentration of greenhouse gases in the atmosphere that will result in total radiative forcing increasing by a target amount by the year 2100. For example, in RCP 2.6, the target level of radiative forcing has been set to 2.6 watts per square meter, resulting in an average increase of approximately 1.6 degrees Celsius by 2100 relative to the pre-industrial average temperature (1850 - 1900). In the case of RCP 8.5, global temperatures are projected to increase by approximately 4.3 degrees Celsius by 2100 (UK Met Office, 2018). The RCP simulations below are specific to the United Kingdom and are produced by the Hadley Center at the UK Met Office. Comparing the dashed line (2040 - 2068) to the solid line (2010 - 2038), one can see that future climate change is going to be associated with both higher average temperatures (a right shift of the curve) as well as increased tail risks (flattening of the curve). As discussed extensively in the sections above, this thesis specifically focuses on the tail-risk aspect of future climate change.

Figure 15: Cumulative Probability Distributions: Annual Average Mean air Temperature Anomaly in the United Kingdom



Note: Average annual temperature anomaly, relative to the 1961 - 1990 average temperature. The left hand side shows the forecasted distribution under Representative Concentration Pathways (RCP) 8.5 and 2.6, respectively. The solid line denotes the 30-year distribution between 2010 and 1938, the dashed line denotes the 30-year distribution between 2040 - 2068. Data Source: Met Office Hadley Center.

B Appendix: Complimentary notes on Section 3

B.1 Belief effects, Hsiang (2016)

The Jacobian matrices can be written as:

$$\frac{\partial c}{\partial C} = \begin{bmatrix} \frac{\partial c_1}{\partial C_1} & \cdots & \frac{\partial c_1}{\partial C_K} \\ \vdots & \ddots & \vdots \\ \frac{\partial c_K}{\partial C_1} & \cdots & \frac{\partial c_K}{\partial C_K} \end{bmatrix} \qquad \frac{\partial b}{\partial C} = \begin{bmatrix} \frac{\partial b_1}{\partial C_1} & \cdots & \frac{\partial b_1}{\partial C_K} \\ \vdots & \ddots & \vdots \\ \frac{\partial b_K}{\partial C_1} & \cdots & \frac{\partial b_K}{\partial C_K} \end{bmatrix}$$

B.2 The Basic New Keynesian Model, Galí (2008)

The Keynesian framework used in section 3 is based on 'The Basic New Keynesian model' from chapter 3 in *Monetary Policy, Inflation, and the Business Cycle* by Jordi Galí. Log-linearization is a simplification that transforms the model into a linear system of equations, thus yielding an approximate solution. The log-linearized version of Galí's Basic New Keynesian model yields a three-equation system (based on the production function, the labour market equilibrium condition and the resource constraint) that can be solved numrically in Dynare. I draw the parameter values directly from Galí (2008).

Table 2: Parameters Values, Galí (2008) Ch. 3

Parameter	**Long Name**	**Value**
α	Capital Share	0.25
β	Discount Factor	0.99
ρ_a	Autocorrelation Technology Shock	0.9
ρ_ν	Autocorrelation Monetary Policy Shock	0.5
ρ_z	Autocorrelation Monetary Demand Shock	0.5
σ	Inverse EIS	1
φ	Inverse Frisch Elasticity	5
ϕ_π	Inflation Feedback Taylor Rule	1.5
ϕ_y	Output Feedback Taylor Rule	0.125
η	Semi-Elasticity of Money Demand	3.77
ϵ	Demand Elasticity	9
θ	Calvo Parameter	0.75

C Appendix: Diagnostics

C.1 Comparative Descriptive Statistics

Table 3: Comparative Descriptive Statistics

	5-year rolling average	Long-term average
Mean	0.078	0.597
Standard Deviation	1.045	1.033
Min	-3.25	-2.54
Max	3.63	3.35
p10	-1.24	-0.739
p90	1.27	1.88

C.2 Ljung-Box Q Test

The identifying assumption underpinning the empirical methodology in this paper is that temperature realizations over time are exogenous to economic activity. Because weather conditions vary randomly over time as a result of meteorological processes, my temperature series should exhibit little autocorrelation. To formalise this argument and assure that my series indeed does exhibits empirically desirable characteristics, I conduct a narrative analysis on the series and run the Ljung Box-Q test. The results for the Ljung Box-Q test using 1, 4, 8, 12 and 20 lags are shown in table 4 (Appendix A1). In all five cases I fail to reject the null hypothesis that residuals are independently distributed (i.i.d), suggesting that autocorrelation is indeed unlikely to be an issue.

Table 4: Ljung Box-Q Test

Lags	Q-statistic	Prob $> \chi^2$
1	0.73	0.39
4	2.52	0.64
8	5.71	0.68
12	9.79	0.63
16	13.34	0.65
20	17.07	0.65

D Appendix: Data

Table 5: Data Overview: Temperature Shock Series

Long Name	Short Name	Frequency	Source	Sample Period
Near-Surface Temperature	tas	monthly	Met Office	1836 - 2021
Mid-Year Population, England and Wales	pop	Annual	ONS	1971 - 2022
Mid-Year Population, Northern Ireland	pop	Annual	NISRA	1971 - 2022
Mid-Year Population, Scotland	pop	Annual	NRS	1971 - 2022

Note: ONS, Office of National Statistics. NISRA, Northern Ireland Statistics and Research Agency. NRS, National Records of Scotland.

Table 6: Data Overview, Empirical Analysis

Long Name	Short Name	Frequency	Source	Sample Period	Adjusted
Bank of England Policy Rate	Policy rate	Quarterly	FRED	1695 - 2016	no
Consumer Price Index	CPI	Quarterly	FRED	1960 - 2023	no
Consumer Price Index, Energy	CPI Energy	Quarterly	FRED	1970 - 2023	no
Consumer Price Index, Excl. Food and Energy	CPI Core	Quarterly	FRED	1971 - 2023	no
Consumer Price Index, Food	CPI Food	Quarterly	FRED	1960 - 2018	no
Industrial Production Index	Industrial Production	Quarterly	BoE	1960 - 2023	no
Long-Term Government Bond Yields: 10-Year	Long Rate	Quarterly	FRED	1960 - 2023	no
Producer Price Index, Manufacturing	PPI Manufacturing	Quarterly	FRED	1960 - 2022	no
Real Consumption Expenditures	Consumption	Quarterly	BoE	1960 - 2023	no
Real Gross Domestic Product	Real GDP	Quarterly	FRED	1955 - 2023	yes
Real Output, Agriculture	Agriculture	Quarterly	ONS	1990 - 2015	no
Real Output, Consumption	Consumption	Quarterly	ONS	1990 - 2015	no
Real Output, Manufacturing	Manufacturing	Quarterly	ONS	1990 - 2015	no
Real Output, Real Estate	Real Estate	Quarterly	ONS	1990 - 2015	no
Real Output, Services	Services	Quarterly	ONS	1990 - 2015	no
Wholesale (Producer) Price Index	PPI	Quarterly	FRED	1790 - 2016	no

Note: BoE, Bank of England. FRED, Federal Reserve Bank of St. Louis. ONS, Office for National Statistics.

Table 7: Data Overview, Official CPI by Category

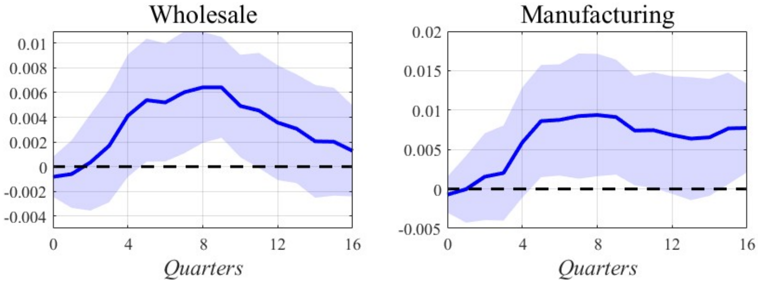
Long Name	ONS Category	Frequency	Source	Sample Period	Adjusted
All Items	D7BT	Quarterly	ONS	1988 - 2015	no
Clothing and Footware	D7BW	Quarterly	ONS	1988 - 2015	no
Communication	D7C3	Quarterly	ONS	1988 - 2015	no
CPI: Alcoholic Beverages, Tobacco and Narcotics	D7BV	Quarterly	ONS	1988 - 2015	no
Education	D7C5	Quarterly	ONS	1988 - 2015	no
Food and Non-Alcoholic Beverages	D7BU	Quarterly	ONS	1988 - 2015	no
Furniture, HH. Equipment, and Routine Repairs	D7BY	Quarterly	ONS	1988 - 2015	no
Health	D7BZ	Quarterly	ONS	1988 - 2015	no
Hotels, Cafes and Restaurants	D7C6	Quarterly	ONS	1988 - 2015	no
Housing, Water and Fuels	D7BW	Quarterly	ONS	1988 - 2015	no
Miscellaneous Goods and Services	D7C8	Quarterly	ONS	1988 - 2015	no
Recreation and Culture	D7C4	Quarterly	ONS	1988 - 2015	no
Transport	D7C2	Quarterly	ONS	1988 - 2015	no

Note: ONS, Office for National Statistics.

E Appendix: Additional Results

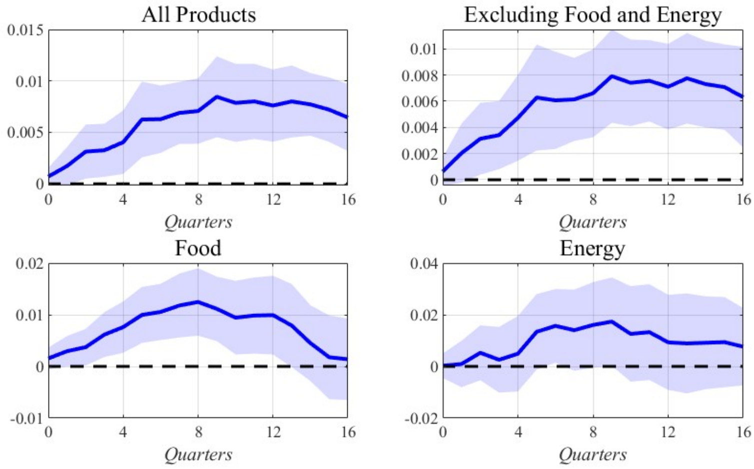
E.1 Long sample period

Figure 16: PPI: Impulse Response to a Temperature Shock (Long sample)



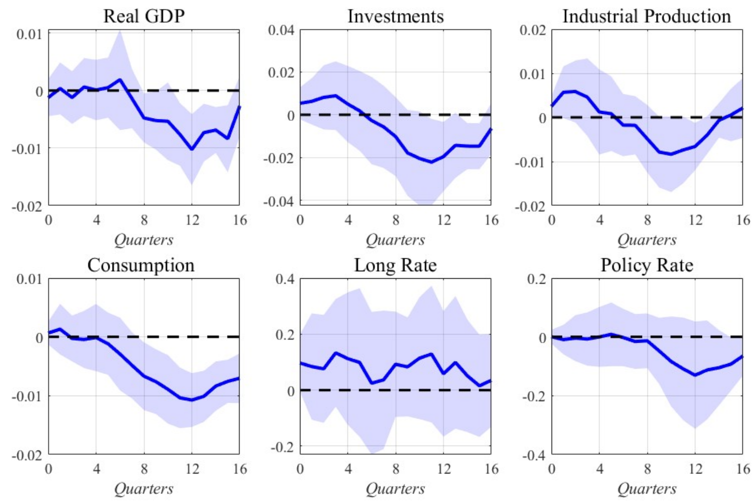
Note: Effects of a 1 °C negative deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1975 - 2021 (1975 - 2018 for food CPI).

Figure 17: CPI: Impulse Response to a Temperature Shock (Long sample)



Note: Effects of a 1 °C negative deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1975 - 2021 (1975 - 2018 for food CPI).

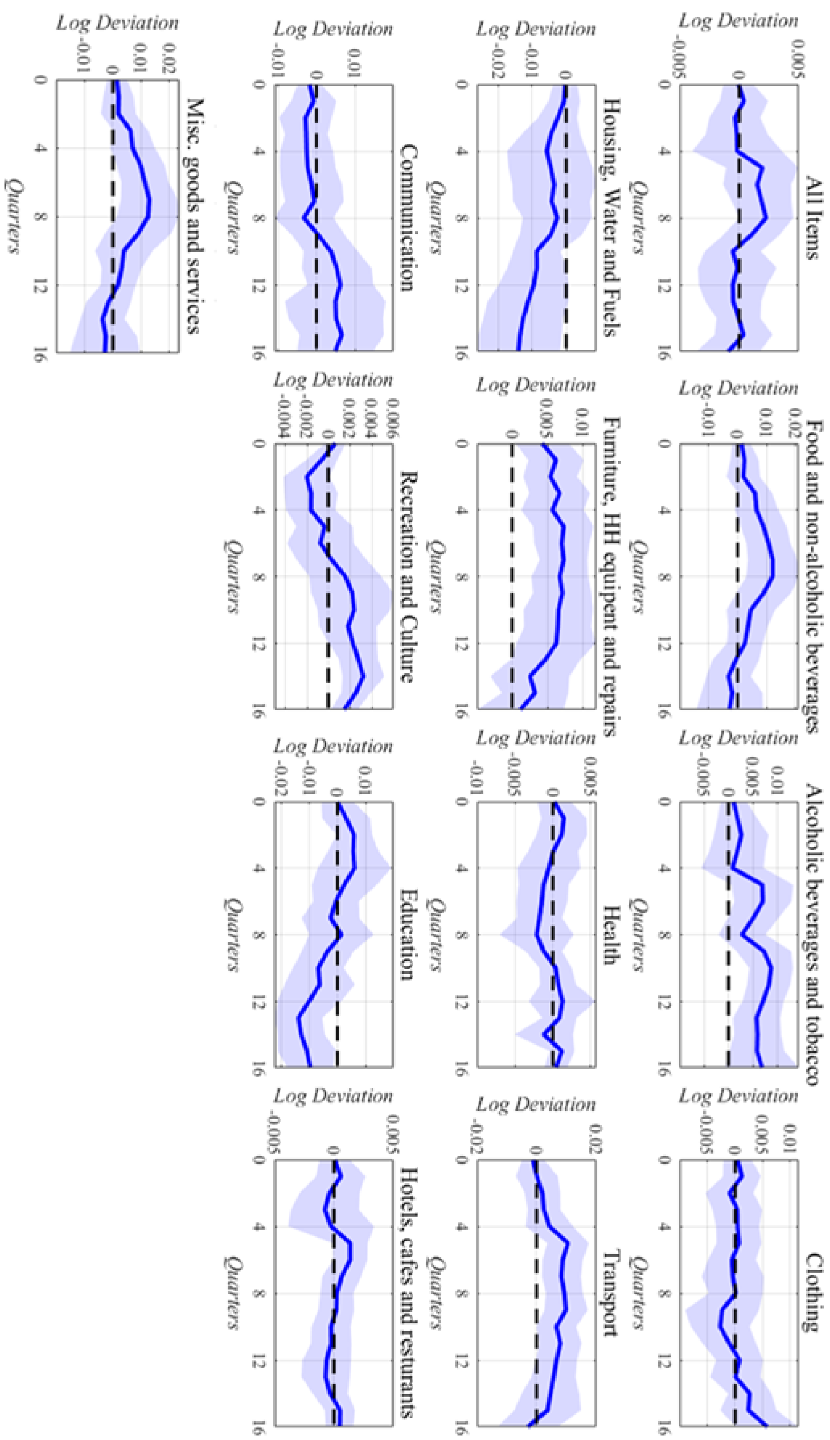
Figure 18: Macroeconomic Aggregates: Impulse Response to a Temperature Shock (Long sample)



Note: Effects of a 1 °C negative deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1975 - 2021 (1975 - 2018 for food CPI).

E.2 CPI: Breakdown by ONS Category

Figure 19: CPI: Impulse Response to a Temperature Shock, by ONS Category



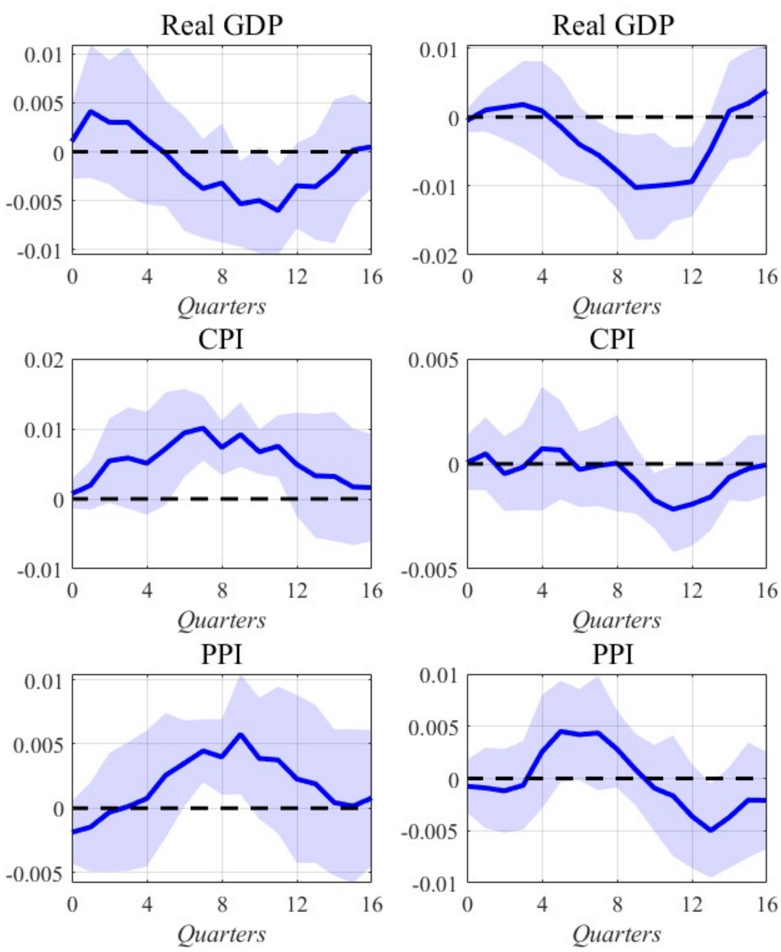
Note: Effects of a 1 °C negative deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1985 - 2015.

F Appendix: Robustness

F.1 Temporal Comparison: CPI Breakdown

Figure 20 shows the results of a 1 °C temperature anomaly on real GDP as well as aggregate consumer-and producer prices, with the left-hand column showcasing the results for the years 1975 – 1994 and the wright-hand column showing the period 1995 – 2015. The point estimates for both GDP and PPI follow a similar trajectory across both time periods. As in the baseline model, the effect in the data appears with some lag. For the producer price index, the effect is insignificant at the 95% level for most of the estimated time periods in the later sample. The drop in GDP is notably larger in the 1995 – 2015 sample, reaching at most a 1 percent drop two years after impact.

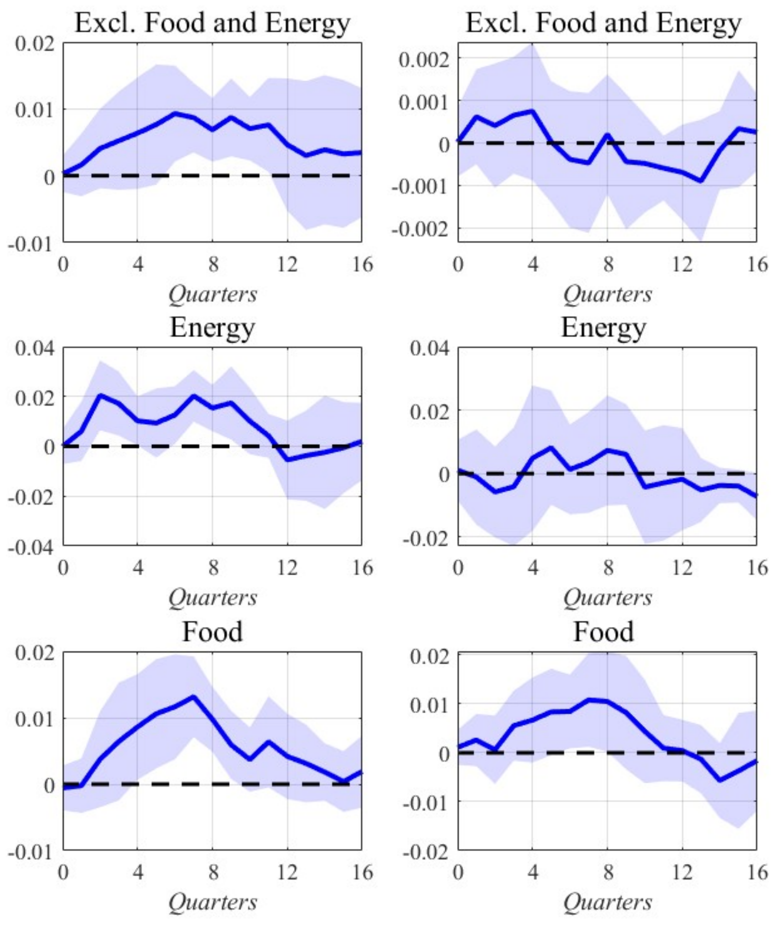
Figure 20: Temporal Comparison, 1975 – 1994 and 1995 – 2015



Note: Effects of a 1 °C negative deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

I do not find any effects on consumer prices when running the baseline model between 1995 – 2015, although the 1975 – 1994 sample largely aligns with the trajectory reported for the full sample in Appendix D.1. To further explore the effects on consumer prices in the split sample, I run the same exercise for the main components of the CPI index, as shown in figure 21. Consistent with the estimates reported for the baseline model, I find that a temperature shock places upward pressure on energy and food prices in both time periods, though the effect on energy prices remains insignificant in the later sample. However, I record an increase in core inflation for the period 1975 – 1994. Given the relative weight of core inflation compared to the food and energy components alone, it is probable that the effect of a temperature shock on aggregate prices in the early time period is driven by this hike in core inflation.

Figure 21: CPI Temporal Comparison, 1975 – 1994 and 1995 – 2015



Note: Effects of a 1 °C negative deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band.

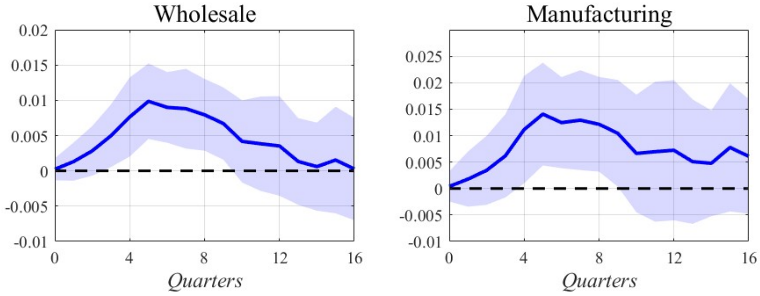
F.2 Lag Structure

To determine the optimal number of lags of the dependent variable, I compute the AIC and BIC criterion for each regression, and compute the optimal number of lags. Table 8 shows the resulting BIC and AIC optimal lag structure for the time horizons included on the estimation (0 - 16).

Table 8: BIC and AIC Criterion, Baseline Model

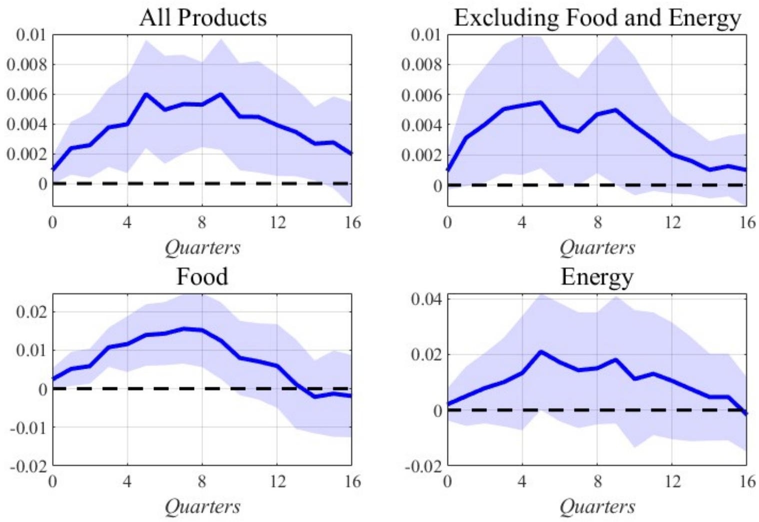
	BIC			AIC		
	PPI	CPI	Real GDP	CPI	PPI	Real GDP
0	2	2	2	5	2	3
1	1	2	2	8	4	6
2	1	2	2	8	8	6
3	1	2	2	8	8	5
4	1	2	3	8	8	8
5	1	1	3	8	8	8
6	1	1	2	8	8	8
7	1	1	2	8	8	8
8	1	1	2	8	8	8
9	1	1	1	8	8	8
10	1	1	1	8	8	8
11	1	1	1	8	8	8
12	1	2	1	8	8	8
13	1	2	1	8	8	8
14	1	1	1	8	8	8
15	1	1	1	8	8	8
16	1	1	1	8	8	8

Figure 22: PPI: Impulse Response to a Temperature Shock, Alternative lag



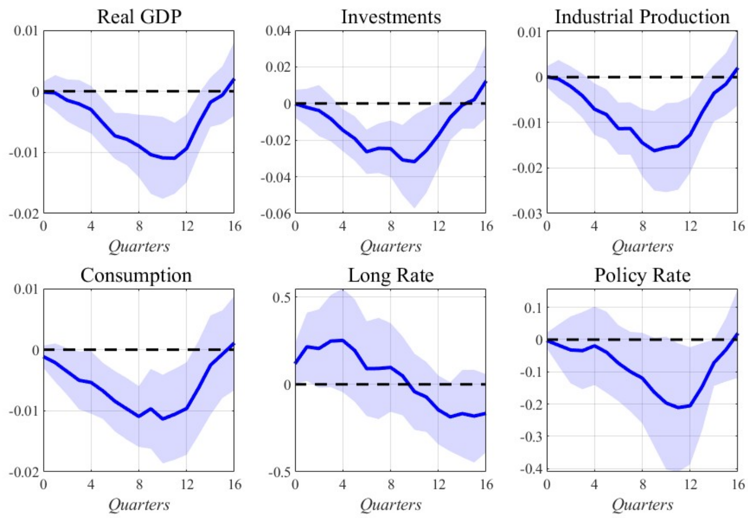
Note: Effects of a 1 °C deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1985 - 2015).

Figure 23: CPI: Impulse Response to a Temperature Shock, Alternative lag



Note: Effects of a 1 °C deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1985 - 2015).

Figure 24: Macroeconomic Aggregates: Impulse Response to a Temperature Shock, Alternative lag

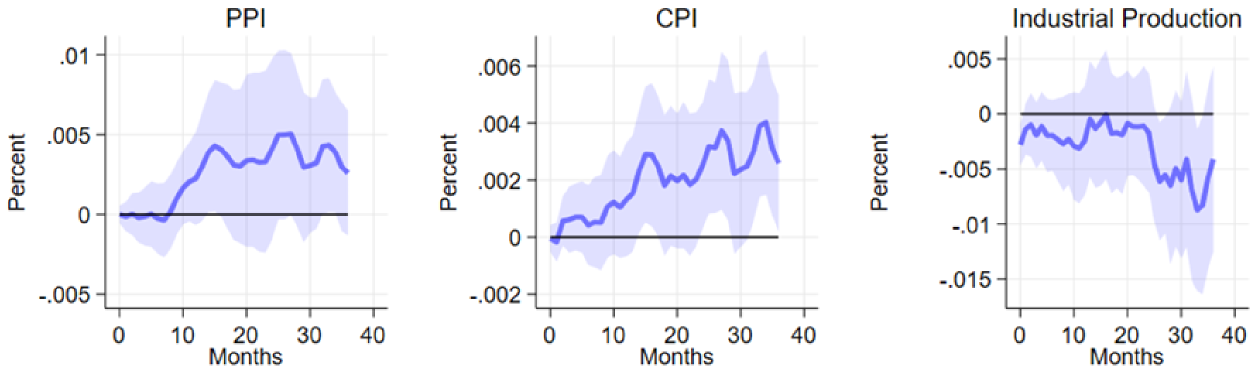


Note: Effects of a 1 °C deviation from the rolling five-year average temperature, by quarter. The solid line is the point estimates, while the shaded area denotes the 95% confidence band. The estimation includes the years 1985 - 2015).

F.3 Monthly shock

Because month-to-month fluctuations in temperatures are likely to be less persistent than an anomaly aggregated over the full quarter, I use a binary variable to identify months where the temperature has exceeded 1.5 °C compared to the five-year rolling average. Figure 25 shows the impulse response function derived from a binary temperature shock, thus capturing months where temperatures have been exceptionally low or high compared to the same month in the previous five years. As real GDP figures are reported on quarterly and annual frequencies, Figure 25 displays the UK index for industrial production, which is available on a monthly level.

Figure 25: Impulse Responses to a Monthly Temperature Shock

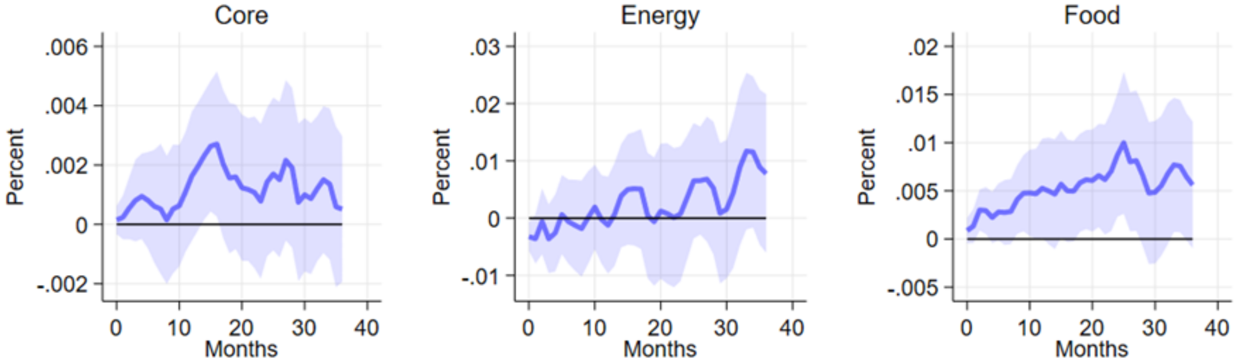


Note: The impulse response from a 1.5 °C deviation from the five year-rolling monthly average temperature estimated using data from 1985 – 2015. The solid line is the point estimates, while the shaded area denotes the 90% confidence band.

A monthly temperature shock places pressure on both consumer and producer prices, yet the impact on the Producer Price Index (PPI) remains statistically insignificant across all estimated time horizons. Real industrial production experiences a decline of up to 0.7 percent, which similarly remains statistically insignificant for the majority of estimated time horizons. This decline becomes notably observable approximately two years after the initial shock, consistent with the documented lag in the quarterly series.

Figure 25 illustrates the effects on the primary components of the Consumer Price Index (CPI). In line with previous findings, the impact is more pronounced for food and energy prices compared to core inflation. However, no significant effects are observed for the energy CPI. Following the shock, food prices begin to rise in the subsequent months, reaching a peak of 1% after two years, although the lower 90% confidence band closely approaches zero across most time horizons.

Figure 26: CPI Breakdown: Impulse Responses to a Monthly Temperature Shock



Note: The impulse response from a 1.5 °C from the five year-rolling monthly average temperature estimated using data from 1985 – 2015. The solid line is the point estimates, while the shaded area denotes the 90% confidence band.