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Evaluation of non-domestic energy affordability support schemes

Annex B: Quantitative Impact Report

September 2025

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1. Introduction

To ensure a comprehensive review of the impacts of the schemes, this quantitative impact report provides an examination of first- and second-degree impacts, including an investigation of questions around distribution of impacts and on the timing of the intervention. First-degree impacts are the direct consequences of the scheme; they include changes to uncertainty and changes to the energy bills faced by Non-Domestic Organisations (NDOs). Second-degree impacts encompass the broader, indirect effects of the scheme on the wider economy resulting from first-degree impacts. Second-degree impacts include changes in inflation, energy consumption, market stability, financial health (including redundancies, insolvencies and borrowing behaviour), employment and productivity.

To accommodate issues of data availability and the complexity of impact identification, the analysis in this report followed a layered approach in observing changes to first- and second-degree indicators. Building on the assumption that the support schemes are complementary (i.e., the impacts of each scheme are of different magnitude, but the same direction), the quantitative impact attribution process first examined the support schemes' impacts collectively before identifying the contributions of each scheme individually.

The analyses presented in this report provide evidence of the energy crisis' impact on the first- and second-degree indicators. Establishing the adverse impacts of the energy crisis is a necessary first step before the impact of the schemes can be evaluated and establishes the context with which to interpret observed changes in indicators. While evidence of the impact of the energy crisis is often more readily available than evidence supporting the impact of the schemes, to the extent data is available, for each indicator, the following analyses were performed:

- First, the indicators were analysed, and the theory of expected outcomes were defined.
- Second, a wide set of descriptive statistics were used to evaluate the observed outcomes for these indicators.[1] These provided an overview of how the indicator behaved before the energy crisis, during the energy crisis, and after the implementation of the schemes.
- Third, where data availability allowed, additional modelling and econometric analysis were performed to provide insights on impact attribution. This analysis provided statistically significant findings (which supported stronger conclusions than findings of correlation between trends) and assessed causality.

Three distinct analyses were performed to evaluate the impacts of the schemes and attribute where possible:

- **Econometric analysis of uncertainty**: The first analysis performed was a time series econometric analysis of the impact of the schemes on uncertainty. This analysis involved using an econometric model to capture the dynamic nature of uncertainty, as

[1] All descriptive data presented in this report was last accessed and checked in December of 2024.

recorded in the Economic Policy Uncertainty (EPU) index. The econometric model was used to (a) establish the extent to which the EPU index reacted to changes in energy prices, and (b) whether this relationship with energy prices changed when the schemes were implemented. Vector autoregressive modelling (VAM) was used to measure the change of the correlation of wholesale energy prices and the EPU index over time, to see if these decoupled after the schemes were introduced, such that increases in energy prices did not increase the EPU index as much.

- **Input-Output analysis**: The second analysis was an Input-Output (IO) model that simulated the effect of the energy crisis and the introduction of the schemes across the whole economy, based on static IO tables from 2019 that show the demand of sectors for other sectors' services. This model was used to evaluate the extent to which the schemes were able to mitigate the negative impacts of the crisis, identify the sectors that were most affected, and estimate the total impact on macroeconomic indicators such as employment and output. IO modelling uses static IO tables to model dynamic relationships, and therefore is at risk of overstating benefits. The benefits reported from the IO modelling are upper limits.
- **Meter-level analysis**: The third analysis was a quantitative analysis of firm-level data outlining the amount of discount received by individual NDOs and their financial health at the time. An econometric regression model was developed to estimate the relationship between the support from the schemes and changes to financial performance.

More details on each of these methods can be found in the appendices of this annex.

2. First degree impacts

2.1 Uncertainty

2.1.1 Summary of findings

Uncertainty within the economy was expected to increase during the energy crisis as energy prices and volatility increased, and planning for costs became more challenging. The schemes aimed to provide relief to Non-Domestic Organisations (NDOs) against these price increases so, after their implementation, uncertainty was expected to stabilise and decrease.

The expected responses hold when examining trends in uncertainty both at the economy-wide level and in energy prices reported by NDOs. In the period during the energy crisis but before the implementation of the schemes, there was an increase in the proportion of NDOs that reported energy prices as the main concern for their business, and expectations of unit cost growth started to rise.[2] The EPU index also increased during this time period, indicating rising uncertainty. After the introduction of the schemes, this observed uncertainty decreased, suggesting that the schemes were associated with reducing overall economic uncertainty.

To explore this relationship further, an econometric analysis was performed which showed that the schemes could have contributed to decoupling the impacts of energy prices from uncertainty. During the energy crisis, electricity prices had a statistically significant effect on uncertainty, although it is worth noting that other forces (such as the COVID-19 pandemic) may also have affected uncertainty. After the introduction of the schemes, this relationship weakened, providing evidence that the effect of energy prices on uncertainty may have been mitigated.

2.1.2 Theory of expected impacts of mitigating energy price effects on uncertainty

The announcement and implementation of energy support schemes was expected to reduce uncertainty among NDOs. The schemes were designed to shield eligible NDOs in the UK from increases in wholesale electricity and gas prices (beyond the government-supported price). The schemes were expected to reduce uncertainty through two primary effects:

- **Financial relief**: By reducing overall energy prices and price volatility, NDOs would have been better able to manage energy costs, reducing the financial uncertainty they experienced. The support would have helped NDOs plan and budget more effectively and may have allowed NDOs to resume postponed or cancelled investment plans.
- **Stabilising effect**: Reduced financial uncertainty would be expected to have had a stabilising effect on the market, as the support schemes were expected to provide a clearer picture of future energy costs for NDOs.

[2] Decision Maker Panel data from the Bank of England (Monthly Decision Maker Panel data -December 2024 | Bank of England)

2.1.3 Observed impacts of mitigating energy price effects on uncertainty

Uncertainty reacts to changes to market conditions quickly, but can also be very erratic as current affairs constantly feed into expectations about the future. To offer a comprehensive view of uncertainty, the Uncertainty Analysis (explained in more detail within appendix 3) reviewed two different metrics associated with uncertainty:

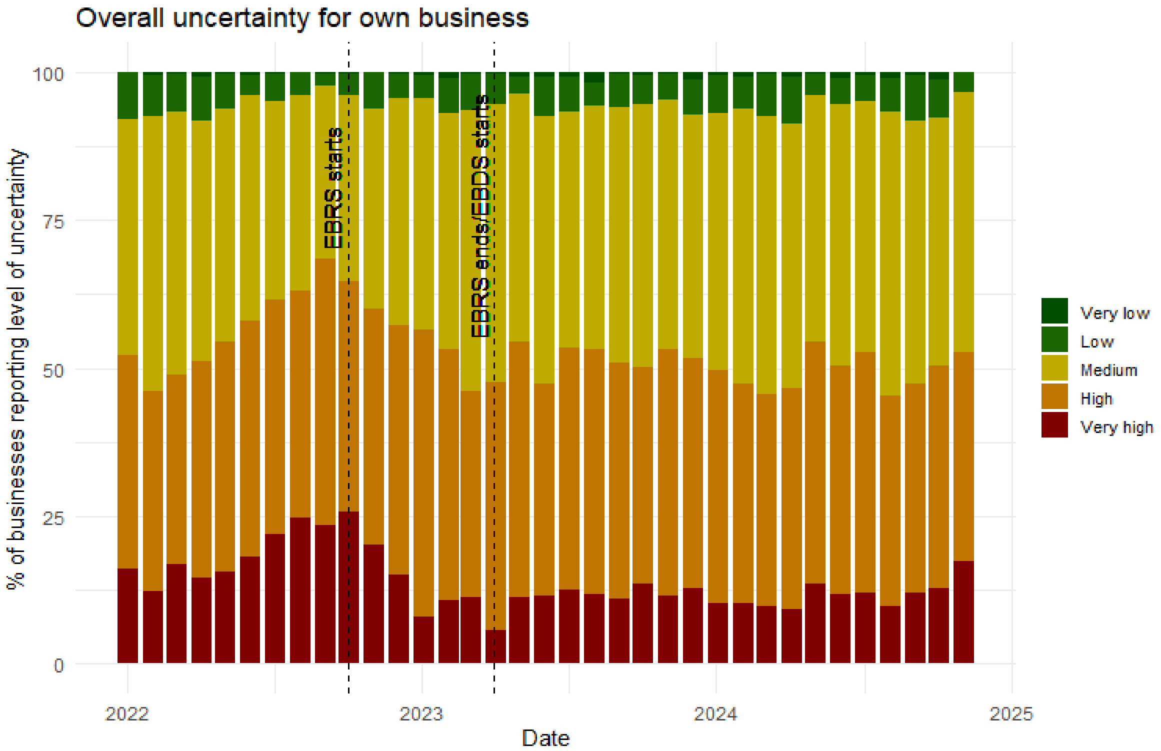
- **NDO-level uncertainty**, based on self-reporting and captured through surveys; this metric reflects the views of NDOs relating to future threats to financial performance.
- **Economic Policy Uncertainty (EPU) index,** based on newspaper articles and social media analytics; this index reflects the way the general public perceives current affairs and the future of the UK economy.

2.1.3.1 Self-reported trends in uncertainty

Decision Maker Panel data from the Bank of England demonstrated self-reported levels of business and organisational uncertainty during the energy price crisis. Organisation-level uncertainty showed a noticeable increase in energy price concerns towards the latter half of 2022, which subsequently stabilised and fell below the levels observed in the initial months of 2022 (see Figure 2.1). Despite the period of high energy prices and higher uncertainty throughout 2022 and 2023 while the schemes were active, the overall trend for energy price concerns declined, indicating that the schemes could have contributed to the observed improvement in future expectations for NDOs.

The implementation of the Energy Bill Relief Scheme (EBRS) may have contributed to the mitigation of concerns related to energy prices. Figure 2.1 shows there was a modest decrease in overall business uncertainty reported close to the launch of the scheme. After the introduction of the EBRS in October 2022, the percentage of respondents reporting 'high' or 'very high' uncertainty dropped to 65% (a decrease of four percentage points from September), and continued to decrease during the EBRS. Shortly after the EBRS came to an end, and the Energy Bills Discount Scheme (EBDS) was introduced, in May 2023, the level of respondents reporting 'high' and 'very high' uncertainty increased by six percentage points, after which it remained relatively stable.

Figure 2.1 Variation in organisation level uncertainty close to schemes launch

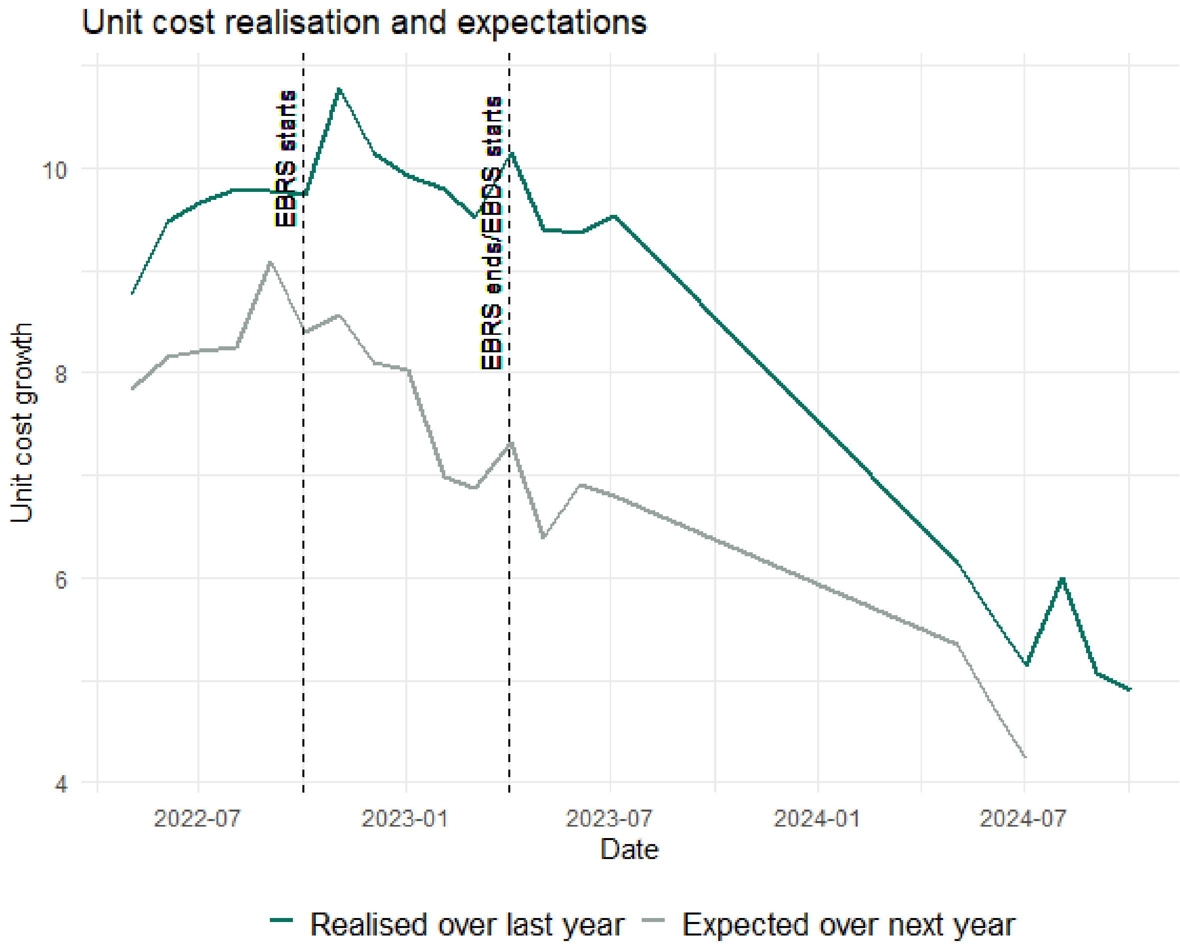


Source: Decision Maker Panel data from the Bank of England (Monthly Decision Maker Panel data -December 2024 | Bank of England)

Expected growth in unit costs (defined as the change in total expenditure incurred to produce one unit of a good or service) exhibited a markedly different pattern. These trends are shown in Figure 2.2, which compares the real average unit cost growth over the past year and the expected (by surveyed NDOs) average unit cost growth for the year ahead. Coinciding with the increase in energy prices around June and July of 2022, the anticipated growth in unit costs rose, reaching a peak in November 2022, shortly after the announcement of the EBRS. After this peak, expectations of unit cost growth begin to subside, suggesting that NDOs reconsidered their 12-month outlook for unit cost growth. Expected unit costs increased sharply in April 2023, as EBRS ended and EBDS began – a substantial adjustment in energy cost expectations during this period, potentially due to concerns over reduced support from the new scheme. This increase in expected costs coincided with the temporary increase in uncertainty present around the EBDS implementation period. It is also important to note, however, that there were other important factors within this period that could have affected unit cost expectations, such as rising interest rates.[3] From July 2023 onwards, unit cost growth expectations decreased consistently, returning to pre-crisis levels. This suggests that despite the initial spike in unit cost growth expectations, the EBDS may have contributed to an improvement in this measure of uncertainty.

[3] See the Bank of England's changes to the Official Bank Rate: Interest rates and Bank Rate | Bank of England

Figure 2.2 Realised vs. expected unit cost growth



Source: Decision Maker Panel data from the Bank of England (Monthly Decision Maker Panel data – December 2024| Bank of England) Note: Realised unit cost growth data are based on the question: "Looking back, from 12 months ago to now, what has been the approximate % change in the average unit cost of your business?". Expected unit cost growth data are based on the question: "Looking ahead, from now to 12 months from now, what approximate % change in your average unit cost would you assign to each of the following scenarios: lowest, low, middle, high, and highest?", with respondents then being asked to assign a probability to each value that would sum to 100%.

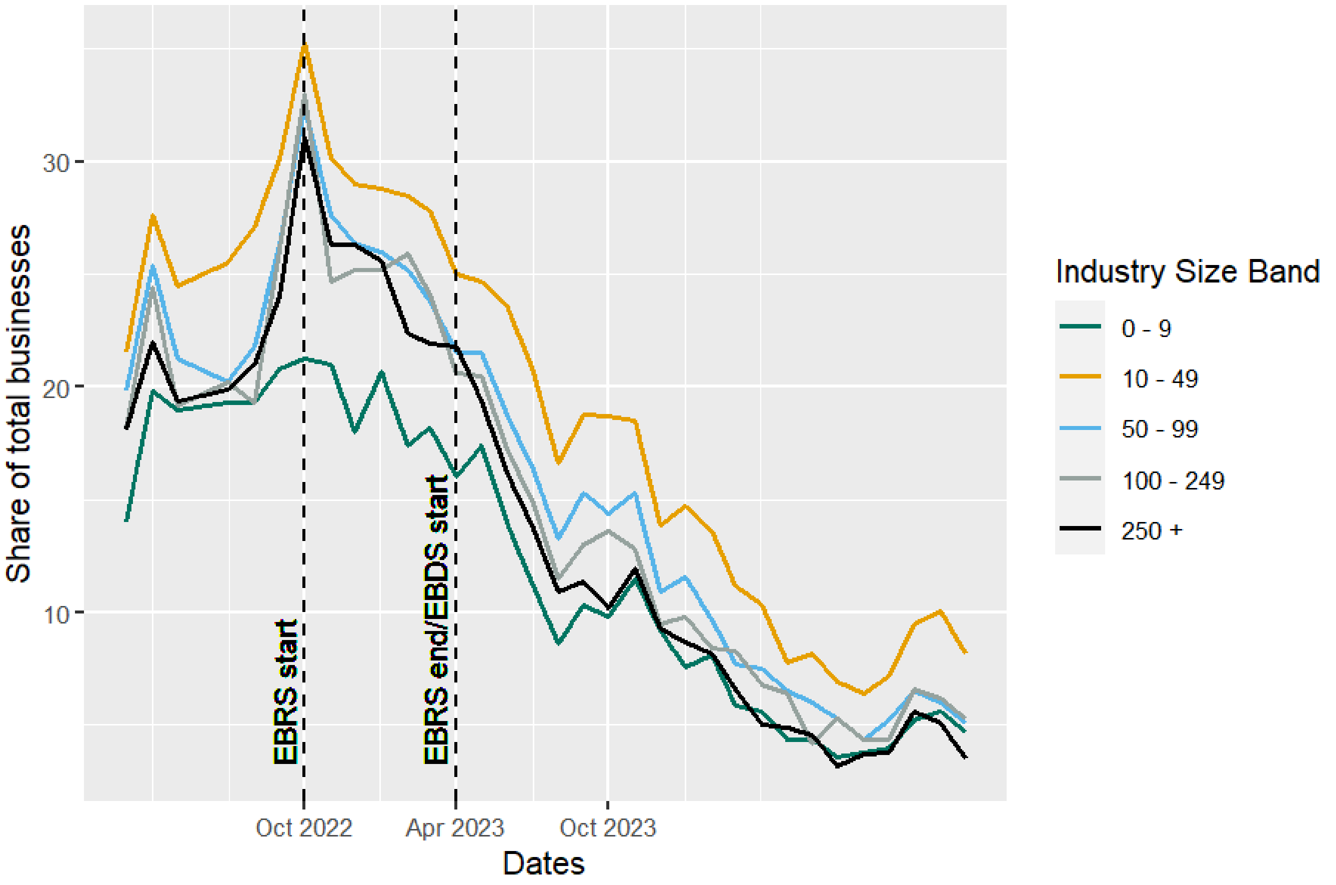
The Business Insight and Conditions Survey (BICS) provided insights into the differences in perceived uncertainty amongst private sector NDOs of various sizes and industries.[4,5] As shown in Figure 2.3, the BICS showed that energy prices were most frequently reported as the main concerns of medium-sized businesses (10-99 employees, as described in appendix 1), taking precedence over other concerns such as competition, interest rates, and decreasing demand. In most cases, reporting of energy price as the main concern peaked at the introduction of the EBRS. After this, the percentage of NDOs reporting energy prices as a primary concern decreased – at first, gradually, but more sharply after the introduction of the EBDS. This suggests that the introduction of the schemes is associated with energy prices

[4] ONS, Business Insight and Conditions Survey (BICS) (Business insights and impact on the UK economy - Office for National Statistics (ons.gov.uk))

[5] BICS includes information on all sectors except agriculture, oil and gas extraction, energy generation and supply, public administration and defence, public provision of education and health, finance and insurance.

being less of a concern across NDOs. The statistical significance of this relationship is explored in more detail within the impact attribution section.

Figure 2.3 Reporting of energy price as the main concern for businesses by size based on number of employees



Source: ONS, Business Insights and Conditions Survey (BICS) (Business insights and impact on the UK economy - Office for National Statistics (ons.gov.uk)) Note: The starting date is 2022-01-01, and the ending date is 2023-12-01. Data gaps emerge in 2022-06-01, 2022-07-01, 2022-09-01, and 2022-10-01.

2.1.3.2 Econometric analysis of uncertainty

Economic uncertainty is captured through the Economic Policy Uncertainty (EPU) index – a publicly available daily index created based on the sentiment of newspaper coverage.[6] In this analysis, the UK-specific index was used, which is created based on the *Times of London* and the *Financial Times*. The index captures concerns about the timing and effects of economic policy decisions, including "non-economic" policy matters like military actions. Articles are identified by keywords related to uncertainty, the economy, and policy.[7] To construct the index,

[6] See Baker et al., 2016

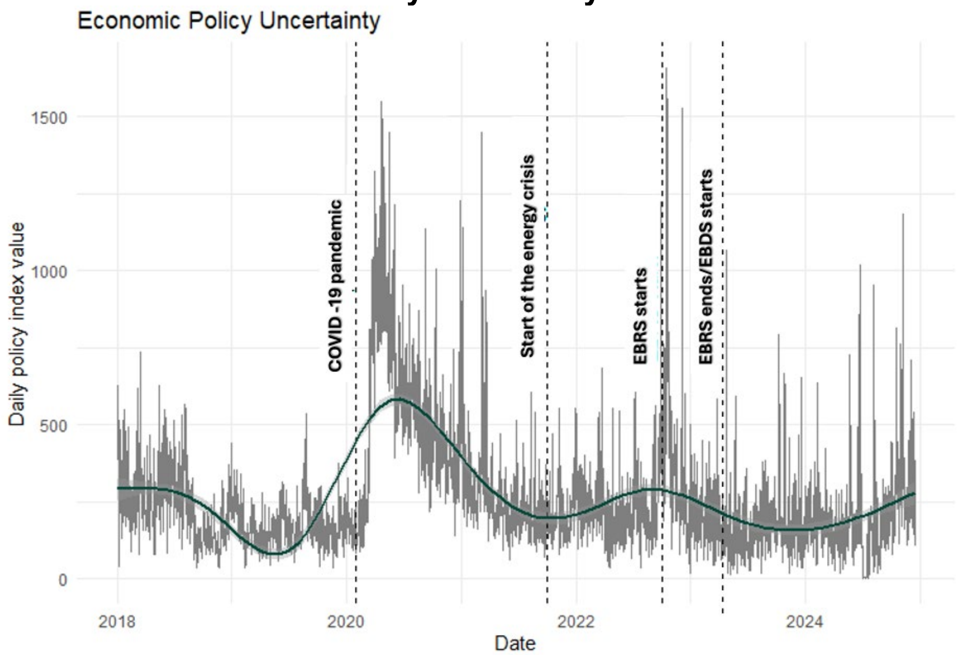
[7] In the case of the UK, the following words were searched for. Economic (E): economic OR economy OR business OR industry OR commerce OR commercial; Policy (P): spending OR policy OR deficit OR budget OR tax OR regulation OR "Bank of England"; and Uncertainty (U) uncertain OR uncertainty. At least one word of all categories should be included in the articles from each category.

raw counts of relevant articles are scaled by total articles in the same period, standardised, and averaged across newspapers.

Economic uncertainty, as measured by the EPU index, remained slightly above its historical (pre-COVID-19) average in the period following the COVID-19 pandemic. As the energy crisis began, the EPU index started to increase again, albeit at a slower rate than during the COVID-19 pandemic. The EBRS was implemented when the EPU index was at its highest – indicating the greatest level of economic uncertainty – since the start of the energy crisis.

The EPU index in the UK remained at high and stable levels throughout most of 2022, with several sharp increases in the latter half of 2022. After the introduction of the EBRS, the EPU index returned to the level it was just before the energy crisis started. Although not causal, the timing could suggest that the schemes contributed to the reduction in economic uncertainty, although other economic factors may also have contributed.

Figure 2.4 Timeline of UK Economic Policy Uncertainty



Source: UK EPU data[8]

2.1.4 Impact attribution for uncertainty

2.1.4.1 Time series correlation analysis

A time series analysis was used to provide insights into the extent to which the schemes impacted uncertainty. This analysis examined the relationship between energy prices (electricity and gas wholesale prices from Independent Commodity Intelligence Services (ICIS) data)[9] and EPU index[10] across various time periods and policy contexts. In the first step, the

[8] Monthly Policy Uncertainty Data

[9] Independent Commodity Intelligence Services (ICIS) is a global provider of market intelligence and data for various sectors. One of its key services is offering detailed information about future prices (known as forward prices) of wholesale gas and electricity. For this analysis, data was drawn from ICIS European Daily Electricity Market report and European Spot Gas Market report.

[10] The Economic Policy Uncertainty Index is measured by UK-specific EPU index from Baker et al., 2016

trends of energy prices and the EPU index were explored using standard univariate time series analysis, such as Autoregressive Integrated Moving Average (ARIMA) modelling.[11] In the second step, the relationship between energy prices and uncertainty was analysed via correlation analysis, which measures the strength and direction of the relationship, and econometric analysis using Vector Autoregression (VAR) modelling.[12] The analysis split the 2007 to 2024 time series into three parts to reveal whether and how the relationship between energy prices and the EPU index changed during the energy crisis and after the introduction of the schemes. This analysis estimated the significance of the schemes' effect on economy-wide uncertainty. The conclusions drawn from this analysis apply to all NDOs, including those in the public, private, and voluntary sectors. More details on the methodology used for this analysis can be found in appendix 3.

In the uncertainty analysis, seven key daily data sources were used: six data series representing the wholesale energy prices of gas and electricity for short-, medium- and long-term fixed-price contracts, and one data series for uncertainty (represented by the EPU index). Fixed-price contracts represent the agreed-upon prices for energy used within a specified time period. These contracts are generally used by energy suppliers or large consumers to lock in a price for energy they will receive later, protecting against potential price fluctuations (especially short-term fluctuations). However, NDOs, including public, voluntary, and private sector organisations, face differing energy prices depending on the conditions under which they contract with the supplier (e.g., system costs, supplier costs, and their market power), which also determined their exposure to short-, medium-, and long-term price fluctuations. Therefore, changes in wholesale energy prices do not translate directly and immediately into price changes for NDOs, but rather more slowly, through changes in the prices of new fixed-price contracts.

Before the energy crisis, the correlation between uncertainty and energy prices was relatively weak. Rolling correlation analysis highlights that the correlation between wholesale energy prices (for both short- and long-term fixed price contracts) and the EPU index was typically under 0.5 in absolute value (see Figure 2.5 and Figure 2.6). A correlation value below 0.5 indicates a relatively weak correlation meaning that uncertainty did not consistently track movements in energy prices during this period; instead, uncertainty was likely driven by other factors extending beyond energy market dynamics.

During the energy crisis, the correlation between uncertainty and energy prices increased, with the two metrics becoming more closely coupled, especially for those prices driven by short term expectations (see Figure 2.5 for gas and Figure 2.6 for electricity). This meant that rather than the negative correlation observed during the COVID-19 pandemic (i.e., increases in uncertainty were associated with decreased energy prices, with a minimum below -0.75), energy prices and uncertainty were now moving in the same direction (the correlation turned to be positive). The rolling correlation steadily increased for short-, medium-, and long-term price contracts. First, the correlation between energy prices and uncertainty returned to

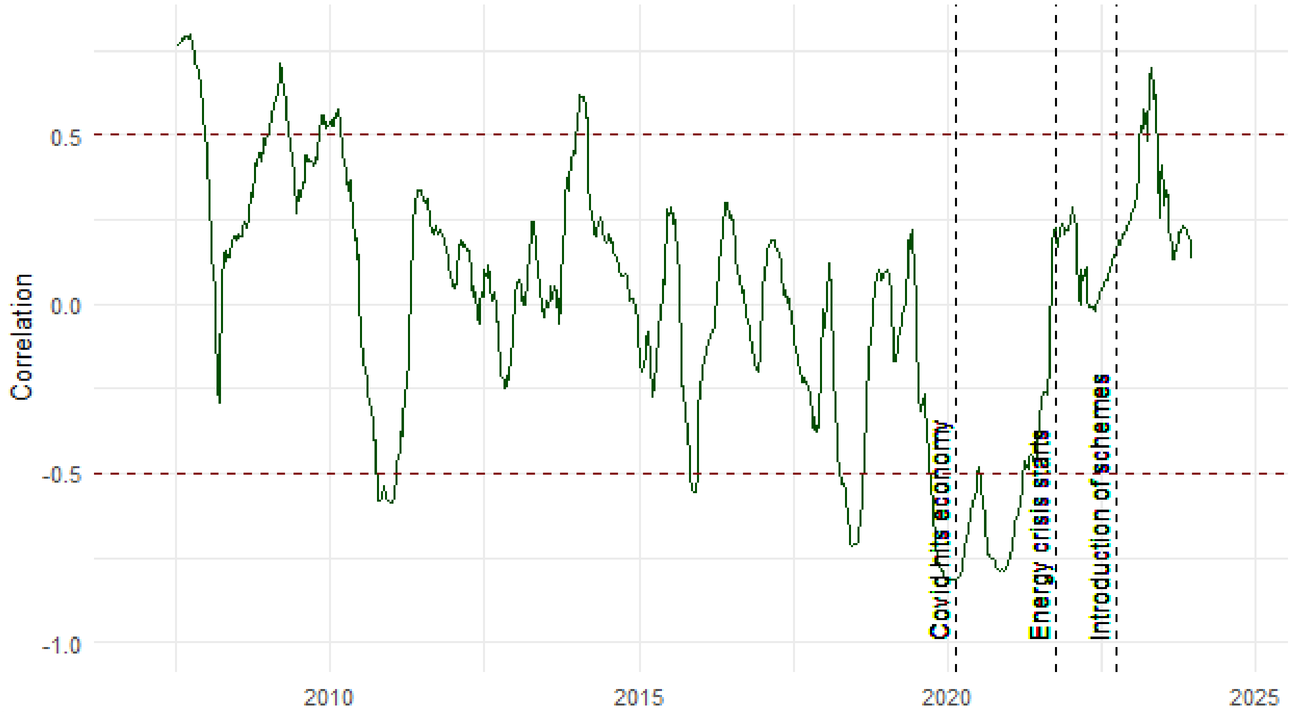
11 ARIMA modelling provides a basic understanding of behaviour and characteristics of time series before more complex econometric methods are applied.

12 VAR models are statistical models that capture the dynamic interactions between multiple time series variables.

the level before the COVID-19 pandemic (a positive but weak correlation of between zero and 0.25), indicating that the two variables were not coupled, reaching a positive peak when the energy crisis started (October 2021). This positive peak could indicate that rising energy prices raised general economic uncertainty – however, the rolling correlation analysis is unable to isolate the impact of energy prices from that of other events, such as policies related to COVID-19 or other political concerns. When comparing different fixed-price contracts, short-term prices (appendix 3 for further details) displayed the largest fluctuations, responding rapidly to immediate shocks, while medium-term prices also showed a strong increase. In contrast, long-term prices exhibited a lower gradual increase in correlation, as they are driven more by long-term market expectations.

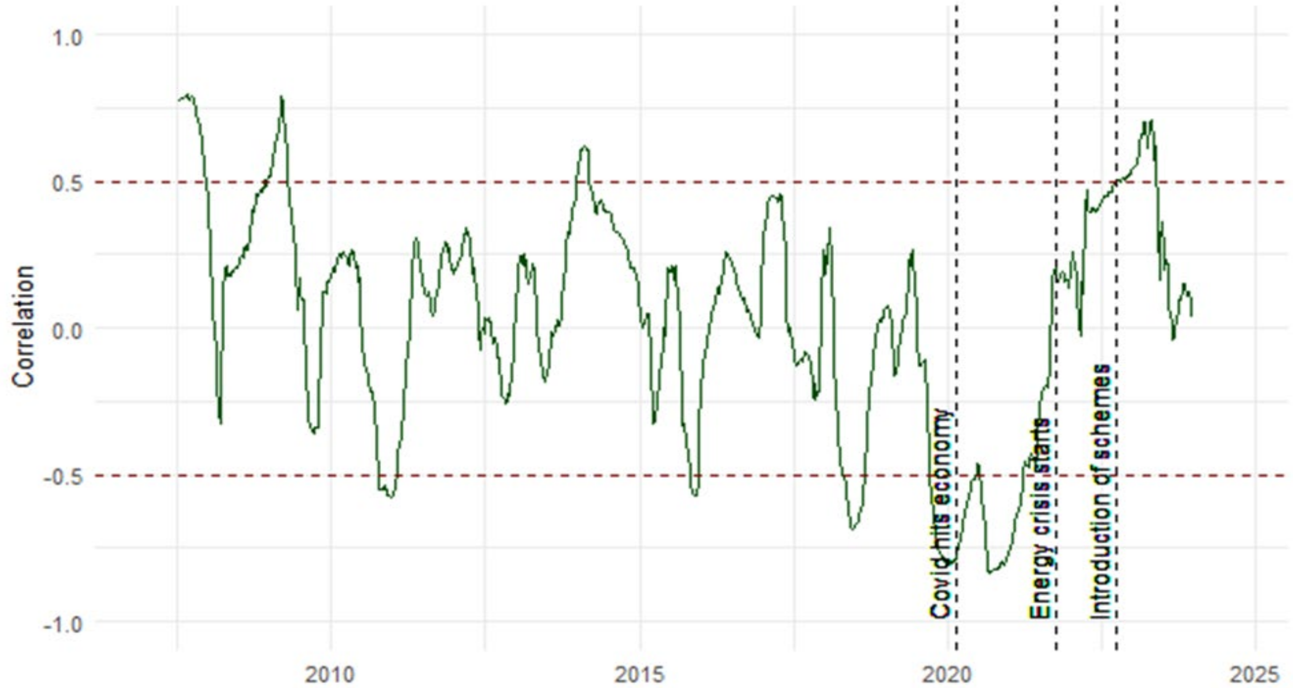
After the introduction of the schemes, with a lag of around two months, the correlation of uncertainty and energy prices started to drop. For all fixed-price contracts, the rolling correlation peaked above 0.5 a few months after the introduction of the schemes. Although there is no agreement on what is considered a high correlation, a correlation above 0.5 is relatively high compared to the rolling correlation between energy prices and uncertainty for the period between 2007 and 2024. This indicates that uncertainty and energy prices were relatively strongly coupled for a short period of time (a few months after the schemes were introduced). The peak mainly reflects the turning point in the increase in energy prices – they started to decrease between late 2022 and early 2023. This was an expected result, as the introduction of the schemes and the reduction of wholesale energy prices were both expected to result in a reduction in uncertainty. The lagged behaviour in the correlation may be explained by the fact that introducing a policy is often unable to reduce uncertainty immediately as it may also create uncertainty regarding how the policy will be implemented or what impact it will have. This uncertainty is likely to decrease within a few months of implementation. Furthermore, many NDOs may not have realised the impact of the schemes unit it appeared on their energy bills, and therefore would have been unable to react to them. VAR modelling (discussed below) also revealed that energy prices and uncertainty explain each other with some lags. As energy prices reduced (but remained higher than before the energy crisis) and EBDS replaced EBRS, the correlation started to weaken. This suggests that the schemes may have had an impact on decoupling energy prices from uncertainty. This motivated further modelling to quantify the extent to which this decoupling occurs.

Figure 2.5 Rolling correlation between uncertainty and short-term fixed gas prices



Source: ICIS wholesale price data and EPU data

Figure 2.6 Rolling correlation between uncertainty and short-term fixed electricity prices



Source: ICIS wholesale price data and EPU data

2.1.4.2 ARIMA and VAR modelling

To explore the relationship of energy prices and uncertainty further, the data was analysed using ARIMA and VAR models. ARIMA modelling is useful to capture dependencies in the time series (i.e., how different time series react to random shocks and to their previous values). VAR models extend this analysis further by considering multiple variables (i.e., different energy time series and the EPU index) and examining their interdependencies over time. This process enables the modelling and analysis of how uncertainty functions as both a dependent and an independent variable within the system, providing deeper insights into its dynamic interactions with energy prices. Additional details on ARIMA and VAR modelling are provided in appendix 3.

Using short-, medium-, and long-term fixed-price contracts, the VAR model analysed the relationship between different energy prices and uncertainty and revealed how it changed in different periods (see Table 2.1). In the period before the energy crisis (between January of 2007 and September of 2021), uncertainty was driven by factors other than energy, and energy prices were not driven by uncertainty.

Table 2.1 Summary of significant variables and their sign in different VAR models by analysed period

Period	Dependent variable	Short-term fixed-price contracts	Medium-term fixed-price contracts	Long-term fixed-price contracts
Pre-crisis Jan 2007 – Sep 2021	Gas	Positive drivers: • Gas (autocorrelation) lag of 1 week • Electricity lag of 1 week	Positive drivers: • Gas (autocorrelation) lag of 1 week • Gas (autocorrelation) lag of 4 weeks	Positive drivers: • Gas (autocorrelation) lag of 1 week
	Electricity	Positive drivers: • Electricity (autocorrelation) lag of 1 week	Positive drivers: • Electricity (autocorrelation) lag of 1 week Negative driver: • Gas lag of 4 weeks	Positive drivers: • Electricity (autocorrelation) lag of 1 week
	Uncertainty	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week • Uncertainty (autocorrelation) lag of 3 weeks	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week
Crisis Oct 2021 – Sept 2022	Gas	White Noise[1]	White Noise[1]	White Noise[1]
	Electricity	Negative drivers: • Uncertainty (autocorrelation) lag of 1 week	White Noise[1]	White Noise[1]
	Uncertainty	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week Negative drivers: • Gas lag of 1 week	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week Negative drivers: • Electricity lag of 1 week	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week Negative drivers: • Electricity lag of 1 week

Period	Dependent variable	Short-term fixed-price contracts	Medium-term fixed-price contracts	Long-term fixed-price contracts
During the schemes Oct 2022 – Jun 2024	Gas	White Noise[1]	White Noise[1]	Positive drivers: • Gas (autocorrelation) lag of 1 week Negative drivers: • Uncertainty lag of 1 week
	Electricity	Positive drivers: • Gas lag of 1 week Negative drivers: • Uncertainty lag of 1 week	White Noise[1]	Positive drivers: • Gas lag of 1 week
	Uncertainty	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week	Positive drivers: • Uncertainty (autocorrelation) lag of 1 week

Source: Uncertainty modelling results.

[1] 'White Noise' represents white noise processes, meaning that the dependent variable has a constant mean, constant variance, and no autocorrelation; in other words, the values are uncorrelated over time, and there are no significant relationships or patterns (including with lagged values of the dependent variable or with explanatory variables) that can explain the dependent variable.
Note: The different rows of the table represent the three time periods by which the equations were estimated. The different columns represent the different equations that were estimated, for the short-, medium-, and long-term fixed-price contracts. The entries within the table show for each dependent variable the variables for which a significant coefficient was found within the respective equation, and 'negative' or 'positive' drivers represent the sign of that coefficient. The lag of the variable represents which lag (or lags) of the dependent and explanatory variables explained the dependent variable. For example, 'Gas lag of 4 weeks' represents the coefficient for gas prices with 4 lags (i.e., 4 weeks before).

During the energy crisis before the schemes were introduced (i.e., between October of 2021 and September of 2022), changes in gas and electricity prices became significant drivers of uncertainty, with electricity prices influencing medium- and long-term expectations and gas prices having a short-term effect. Iin econometric terms, the changes in gas and electricity prices were a significant explanatory factor influencing the level of uncertainty after the energy crisis started, whereas this was not the case before the energy crisis. While the fact that electricity and gas prices were statistically significant drivers of uncertainty is an expected finding (i.e., this finding is consistent with a hypothesis that rising energy prices would have led to rising uncertainty during the energy crisis, but not prior to the energy crisis), the direction of the relationship observed is unexpected. Rather than increasing energy prices having a positive effect on uncertainty, an inverse relationship was observed, in which increases in energy prices corresponded to decreases in uncertainty (in econometric terms: the signs of the coefficients for gas and electricity are negative, as denoted by gas and electricity being classified as “negative drivers” of uncertainty in Table 2.1). This phenomenon may be explained by other factors that have not been accounted for in the analysis, such as recovery after the lifting of COVID-19-related restrictions or other market adjustments, which may have influenced expectations during this period.[13]

The VAR modelling, supported by the rolling correlation analysis, indicates that by protecting NDOs from extreme price fluctuations, the introduction of the schemes may have contributed to decoupling energy prices and uncertainty. Following the introduction of the schemes, the significant relationship between energy prices and uncertainty weakened. The direct impact of energy price changes on uncertainty reduced (in econometric terms: uncertainty was not significantly explained by the change of energy prices). Furthermore, the EPU index remained autocorrelated, meaning it relied more heavily on its past values rather than reacting strongly to energy price fluctuations (in econometric terms: the past values of the EPU index significantly explained its current values). Although the results of the VAR modelling carry a low degree of certainty due to unexpected coefficient signs and potentially omitted variables, the findings still suggest that the schemes could have provided some degree of relief by reducing the volatility of energy prices – and therefore overall economic uncertainty – faced by NDOs.

2.2 Energy bills

2.2.1 Summary of findings

Energy – particularly electricity and gas – is a crucial input for many NDOs, particularly those with premises or which operate in energy-intensive industries. Energy price increases are expected to have negative economic consequences, such as reduced business profitability, increased default risk, and higher inflation. Reductions in energy consumption and energy

[13] The rolling correlation analysis showed that the COVID-19 stringency index was strongly correlated with the EPU index (and also with the energy prices) shortly after the introduction of the schemes. The COVID-19 stringency index is a country-specific indicator representing the stringency of public policies between 2020 and 2022 on a scale of 100, published by the Blavatnik School of Government, University of Oxford (2023).

intensity can mitigate these effects; however, such measures may take longer to implement or result in decreased production, and may not be feasible for some NDOs.

From December 2021 to April 2023 (and especially during 2022), wholesale prices often exceeded the government-supported price threshold set by the EBRS, demonstrating the need for the price relief provided by the scheme.[14] Analysis revealed a delayed impact of rising wholesale prices on NDO electricity tariffs. The data also shows increasing EBRS numbers of support claims over time, indicating more NDOs renewing contracts at higher tariffs, though total payments have increased only slightly as energy prices decreased after peaking in August 2022. In other words, over time, more NDOs started to receive support from EBRS (the number of claims increased), but the amount of support they received decreased as wholesale energy prices, on which the support is calculated, fell.

The quantitative analysis performed for this evaluation revealed that a £1 electricity price discount provided by the EBDS[15] is associated with a 0.0074 full-time equivalent (FTE) job increase in employment and a positive but non-significant impact on turnover. For gas, a £1 price discount provided by EBDS is associated with a 0.03 FTE increase in employment and a non-significant impact on turnover. When looking at the economy as a whole using the IO model, the scheme's reduction in energy prices is estimated to have prevented the loss of 132,000 full-time equivalent jobs and £21.6 billion in total economic output. All this shows that the schemes were effective in reducing energy bills and mitigating the second-degree consequences resulting from higher energy prices.

2.2.2 Theory of expected impacts of mitigating energy price effects on energy bills

The launch of the energy support schemes was expected to have a strong direct impact on the energy bills of NDOs. As shown in Figure 2.7 and Figure 2.8, the support schemes were launched after both gas and electricity prices reached their peak levels, well above what was later defined as an acceptable government supported price by the schemes.

The support schemes were expected to directly impact energy bills through two main channels:

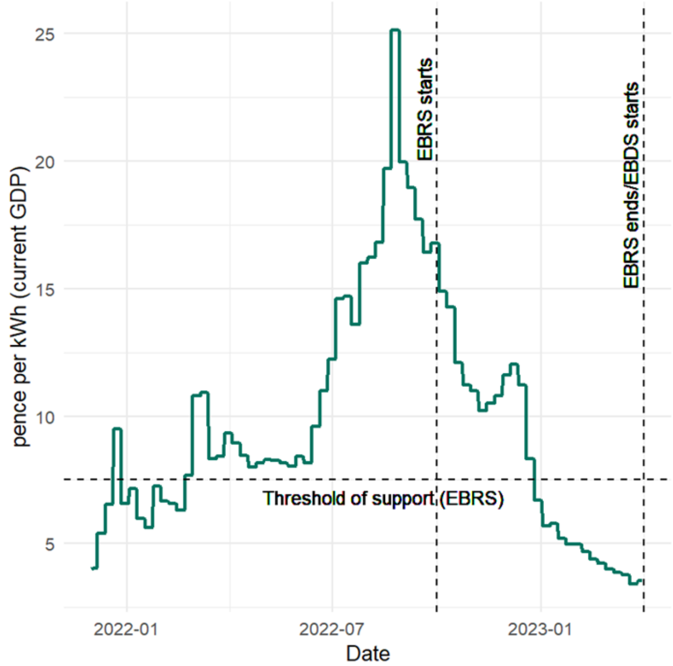
1. **Price decreases:** The support schemes' discounts decreased the electricity and gas tariffs faced by the NDOs, resulting in lower energy bills, and more stable energy expenditures.

2. **Moderating decreases in consumption**: High energy prices were expected to decrease energy consumption (compared to seasonal averages) before the introduction of support schemes. After the introduction of schemes, a rebound to the seasonal average could have occurred due to lower prices. However, the supported energy prices

[14] Wholesale prices are only one component of total cost of energy, accounting for about a third of the total cost of electricity. The share of wholesale energy prices in the total cost of energy also varies by the size of NDOs, as larger NDOs tend to benefit from better rates and varied tariff options.
[15] Modelling was based on EBDS, for which data was more granular and higher quality than EBRS. It is reasonable to assume a similar relationship exists for EBRS.

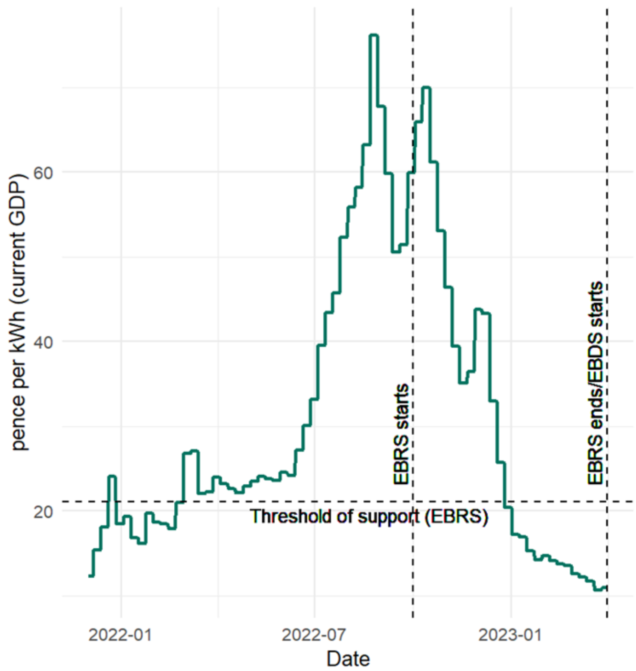
remained higher than pre-crisis levels, which could instead have limited the potential for energy consumption to increase as a result of lower prices. In addition to energy prices, other factors could also have affected energy consumption, such as temperature, adoption of energy efficiency measures, and lower economic activity.

Figure 2.7 Timeline of wholesale gas prices around schemes launch



Source: UK reference wholesale price data from DESNZ (Energy Bill Relief Scheme: discounts for fixed, default and variable contracts and Energy Bills Discount Scheme: discounts for fixed, default and variable contracts)

Figure 2.8 Timeline of wholesale electricity prices around schemes launch



Source: UK reference wholesale price data from DESNZ (Energy Bill Relief Scheme: discounts for fixed, default and variable contracts and Energy Bills Discount Scheme: discounts for fixed, default and variable contracts)

2.2.3 Observed impacts of mitigating energy price effects on energy bills

Trends in electricity and gas prices were analysed to gauge the effectiveness of the price interventions supported by the government. Higher wholesale prices trigger larger discounts for NDOs. Therefore, monitoring wholesale prices is essential to ascertain when the government assistance had the most impact.

Figure 2.7 shows the average monthly reference wholesale gas and electricity prices between December 2021 and April 2023. The "Threshold of Support", shown as a dashed line in each figure, represents the level of the government supported price under the EBRS. The wholesale prices first surpassed the threshold of government supported price level (set later under the EBRS) at the end of December 2021, but only for a few days. Then, between February and December 2022 the wholesale prices remained constantly above the threshold where the government supported price would later be set. After that, the prices stayed below the EBRS supported price.

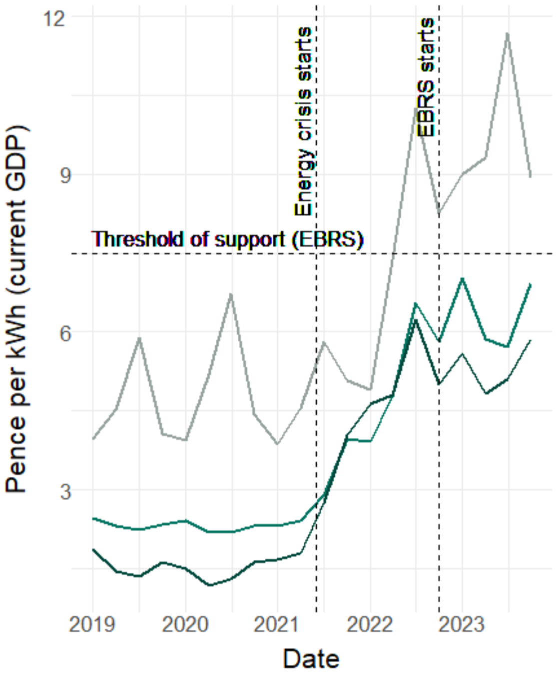
The wholesale price only represents one component of the electricity tariffs. In the UK, wholesale costs, which are the prices paid for energy procured from producers, typically make up around one-third of an electricity tariff. The remaining two-thirds consist of various other charges, including network costs for maintaining the grid infrastructure, government levies related to environmental and social schemes, and operational costs that encompass the energy supplier's business operations.

In the UK, NDOs of varying sizes are likely to encounter different electricity prices due to multiple factors. Larger businesses typically consume more electricity, which may enable them to negotiate better rates. Additionally, they are more likely to benefit from various tariff options, including fixed or flexible tariffs, and time-of-use tariffs, which provide cheaper rates during off-peak hours. In contrast, smaller businesses often lack similar negotiating leverage and may pay higher per-unit costs. Contract length also influences pricing, with longer contracts sometimes offering more favourable rates. Consequently, electricity prices can vary significantly among NDOs of different sizes. DESNZ publishes gas and electricity prices for the non-domestic sector, categorised by the size of organisations based on their consumption, as defined in appendix 1.[16] Figure 2.9 shows the timeline of electricity and gas prices for very small and very large NDOs, which tend to have the highest difference from the average. Data is aggregated to three-month intervals due to data availability; however, the schemes were applied to daily energy prices.

As shown in Figure 2.9, when the energy crisis started, average gas and electricity prices started to increase rapidly. This trend of increasing prices lasted from around December 2021 to April 2023. When the EBRS was introduced, prices had increased by about half of their overall increase over this period, and prices continued to rise for close to a year after EBRS' implementation before showing signs of decreasing.

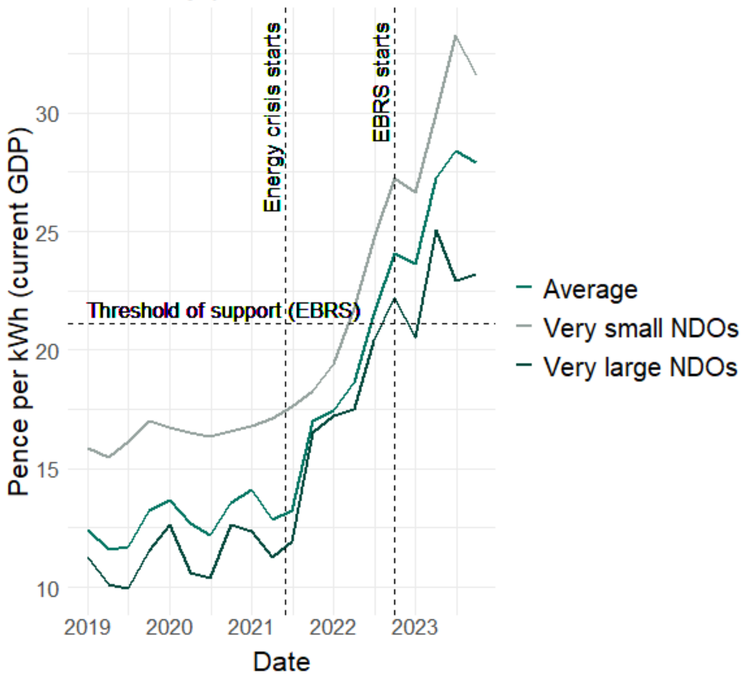
[16] See: Gas and electricity prices in the non-domestic sector - GOV.UK

Figure 2.9 Timeline of retail gas prices around EBRS launch



Source: Detailed UK retail price data were obtained from DESNZ (Prices of fuels purchased by non-domestic consumers in the UK, Table 3.4.1 | DESNZ)

Figure 2.10 Timeline of retail electricity prices around EBRS launch



Source: Detailed UK retail price data were obtained from DESNZ (Prices of fuels purchased by non-domestic consumers in the UK, Table 3.4.1 | DESNZ)

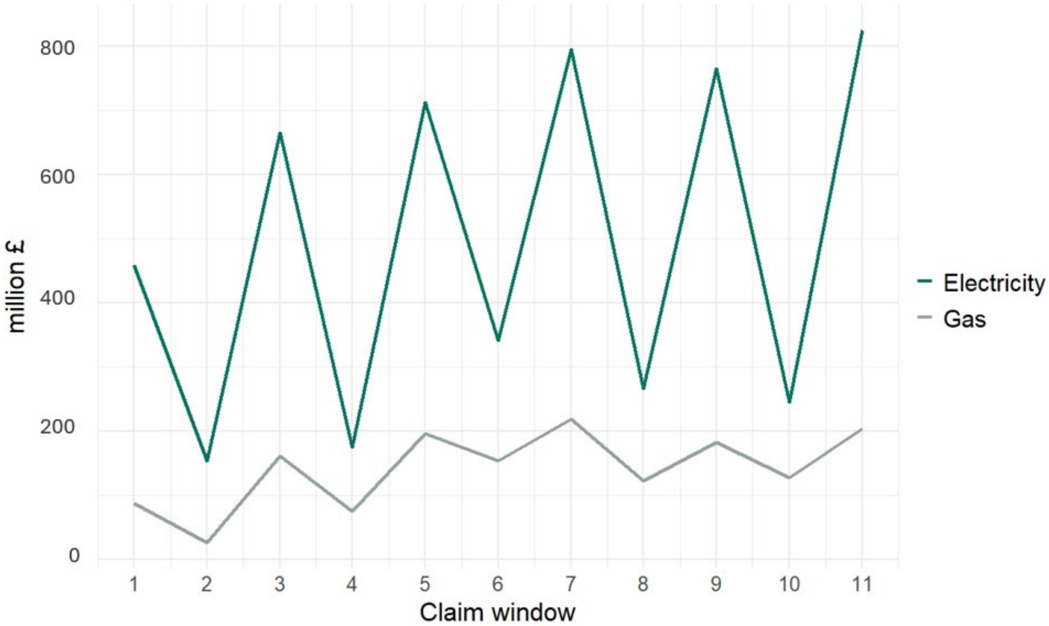
Figure 2.9 and Figure 2.10 show the retail price of energy purchased (i.e., not the wholesale price to which the schemes apply). There are significant differences in these prices depending on the size of NDOs, as classified based on their electricity and gas consumption. Very small NDOs face substantially higher retail energy prices than very large NDOs. Gas prices for very small businesses were well above 7.5 pence per kWh, while average gas prices and prices faced by very large businesses did not reach this level (on average) in any three-month period. While the EBRS may not seem effective for some sizes of NDOs, within each size category there is a proportion of NDOs whose energy tariffs exceeded the government supported prices.

Comparing Figure 2.7 to Figure 2.9, and Figure 2.8 to Figure 2.10, shows a delayed impact of the increase in wholesale prices on the retail price of energy purchased. Wholesale electricity prices peaked in August 2022, while retail electricity prices were still rising from April to June of 2023. Gas prices, on the contrary, stabilised during the initial months of 2023. Fixed-rate contracts between NDOs and suppliers may account for this delay; these NDOs would be protected from the increased prices until they had to renew their contracts. This difference in timing of contract prices can be observed in the average retail energy prices shown in the figures, where retail prices follow wholesale prices with a lag as fixed-price contracts are renewed.

Figure 2.11 and Figure 2.12 provide descriptive information from the meter-level data of NDOs about how the amount of support provided varied through the analysed period. These are presented by claims window. Starting in November 2022, for EBRS, suppliers were able to claim payments for discounts for energy supplied in any of 11 claim windows. They claimed payment from the start of the scheme (1 October) to the end of the claim window (and no later than 31 March 2023). The information presented in these figures represented the net additional payments made in that claim window (for example, in claim window 5, this was payment for any volumes of energy not already claimed in their previous claim). Suppliers did not report in every claim window.

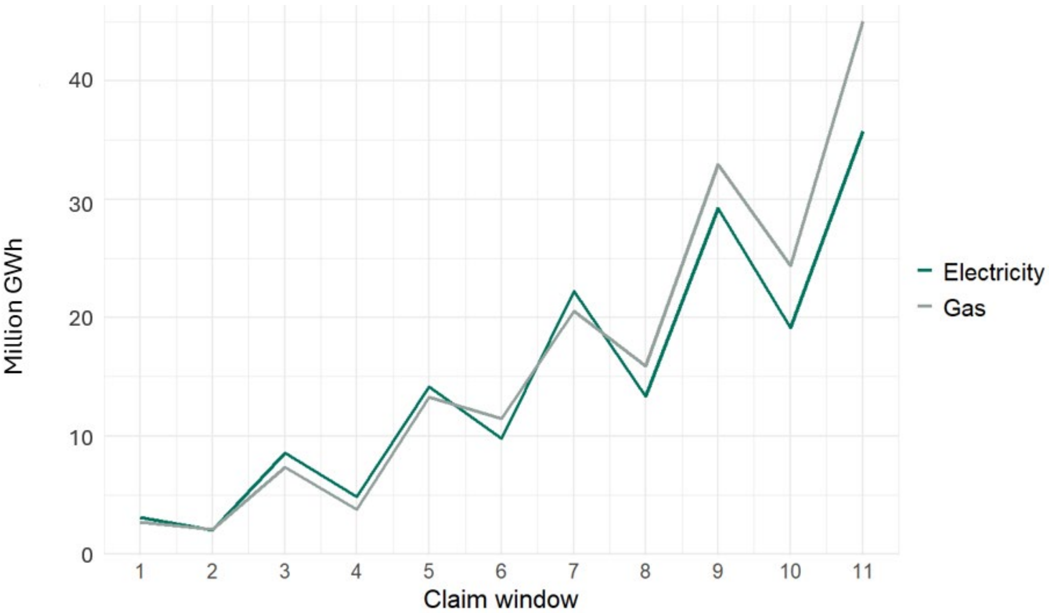
The volume of discounted energy is shown to be steadily rising across the EBRS claim windows, based on payments, volume of energy discounted, and number of contracts discounted under EBRS from DESNZ. This suggests that more NDOs received the discount as they became eligible due to rising energy costs. These figures show trends for payments, energy volumes, and the number of contracts under EBRS starting from October 2022. Despite the intermittency of the series, an increasing trend is visible in all cases, albeit to varying degrees. Although the number of contracts and energy volume sharply increased over time, the total payments made only slightly increased. This is due to two factors. First, this increase can be explained by NDOs who renewed their contracts and faced energy tariffs above the government-supported prices. Second, energy prices peaked in August 2022 and then started to decrease, resulting in a decrease in the support provided to NDOs.

Figure 2.11 EBRS: Payments of energy discounted by energy type and claim window



Source: Payments, volume of energy discounted, and number of contracts discounted under EBRS from DESNZ (EBRS: payments made under the scheme). Claim windows ran approximately every two weeks from 1st October - 21st November 2022 (Claim Window 1) until 26th April 2023 (Claim Window 11)

Figure 2.12 EBRS: Volume of energy discounted by energy type and claim window

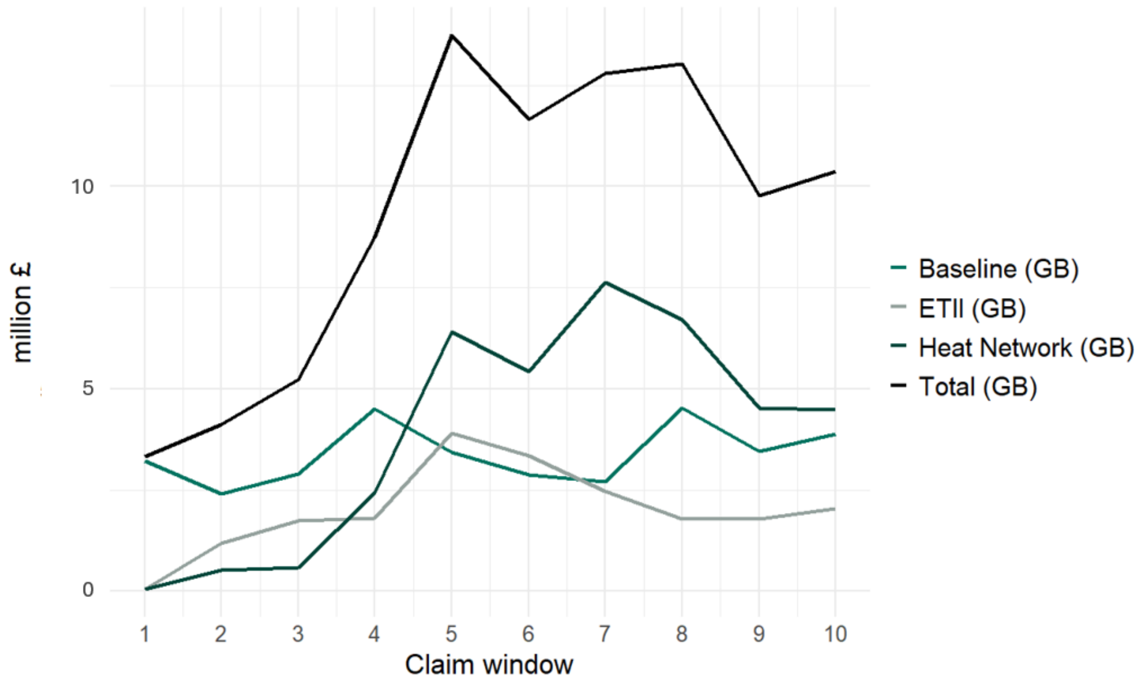


Source: Payments, volume of energy discounted, and number of contracts discounted under EBRS from DESNZ (EBRS: payments made under the scheme)

Figure 2. and Figure 2. show the payments made under the EBDS by claim window and support scheme. After energy prices decreased at the beginning of 2023, new contracts did not have high enough energy costs to qualify for support, and the amount of support paid was substantially reduced.

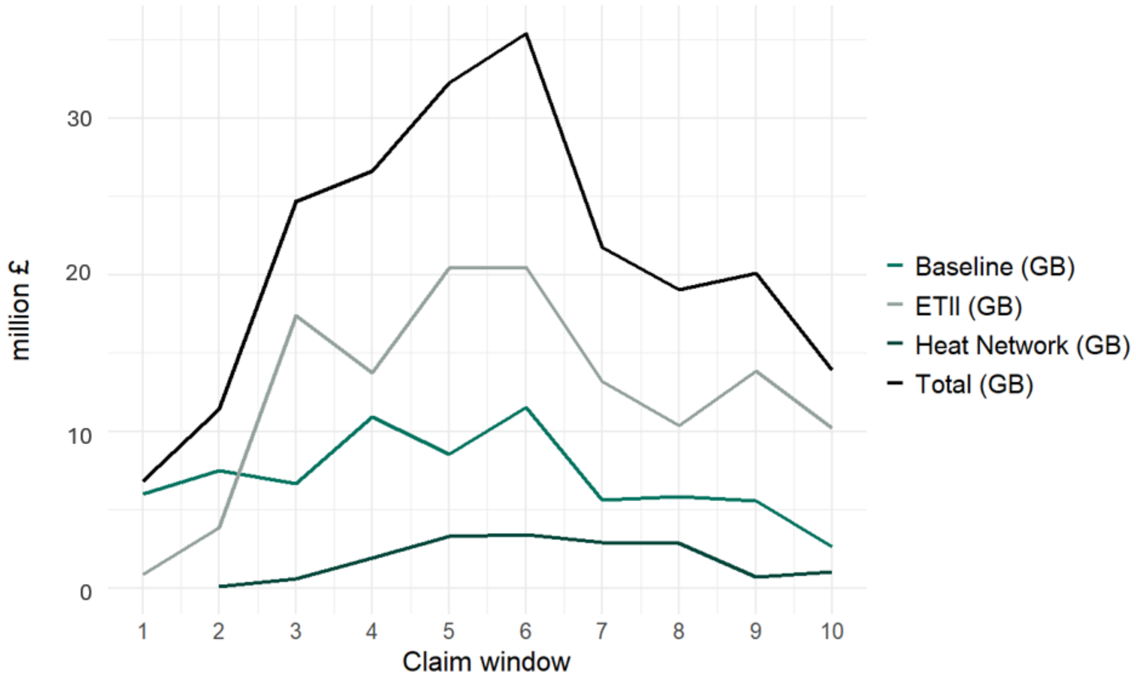
The schemes provided discounts which were applied directly to energy bills, as presented in the meter-level data. The timing and level of support was observed to be in line with the movement of wholesale and retail energy prices, as EBRS is disbursed when energy prices were rising, and EBDS (a lower level of support) when energy prices were declining, but still remained above pre-crisis levels. Energy consumption, which also plays an important role in determining energy bills, is explored later as a second-degree impact.

Figure 2.13 EBDS: Value of payments of energy discounted for gas by claim window



Source: Payments, volume of energy discounted, and number of contracts discounted under EBDS from DESNZ (Payments made to energy suppliers for discounted non-domestic electricity and gas consumption). Claim windows included in this figure ran approximately every month from 1st April - 16th May 2023 (Claim window 1) to 16th January - 14th February 2024 (Claim window 10). Note: The data for Northern Ireland was excluded due to a large proportion of missing values.

Figure 2.14 - EBDS: Value of payments of energy discounted for electricity by claim window



Source: Payments, volume of energy discounted, and number of contracts discounted under EBDS from DESNZ (Payments made to energy suppliers for discounted non-domestic electricity and gas consumption). Note: The data for Northern Ireland was excluded due to a large proportion of missing values.

2.2.4 Impact attribution for energy bills

Establishing the causal impacts of the schemes on energy prices and energy consumption would ideally have been performed through quasi-experimental methods, which can estimate the magnitude and statistical significance of an intervention in quantitative terms. However, these methods depend upon having sufficient data available to create robust counterfactuals (i.e., a scenario identical to the one in which the intervention occurred, but *without* the effect of the intervention itself). After reviewing all secondary data sources and accessing to the most up to data meter-level data (as of October 2024), data limitations led to the conclusion that quasi-experimental methods were not plausible for this evaluation. As an alternative, an econometric analysis of meter-level data matched to Inter-Departmental Business Register (IDBR) data was performed to provide insights on the associated impacts of the schemes. Additionally, Input-Output modelling, which simulated the energy crisis and the discount from the support schemes, was performed to further quantify macroeconomic impacts.

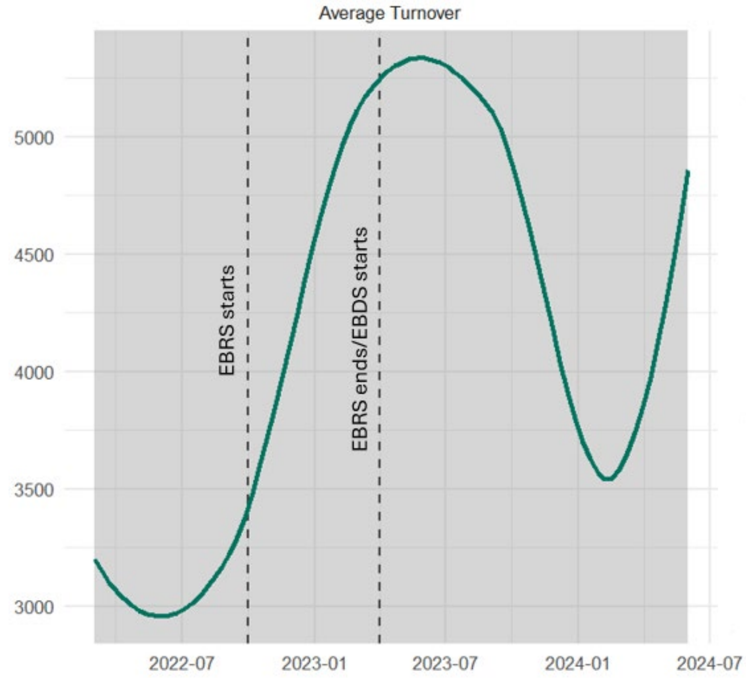
2.2.4.1 Meter-level data

The data employed for this analysis was sourced from ONS and DESNZ. From DESNZ, the meter-level data collected during the schemes was used. This data shows, by meter: the amount of discount NDOs received from each scheme, the recorded energy consumption, the tariff faced, and information about the company in charge of the specific meter. From ONS, the IDBR database was used. This database contains information on organisations that are registered for VAT, including their employment, location, Standard Industrial Classification (SIC) code, and turnover information.

The two different data sources (meter level data and IDBR) were matched using the Company Registration Number, which allowed merging information on financial health, support received, and energy consumption during the schemes for each meter or company. In this matching process, certain organisations had to be dropped from the analysis – e.g., if they were not present in the scheme data or in IDBR. As IDBR does not include charities and may not include smaller sized organisations if they are neither VAT- nor PAYE-registered, these organisations could not be included in the analysis presented in this paper. In total, of the NDOs present in the meter-level data, around 65% were mapped with IDBR.

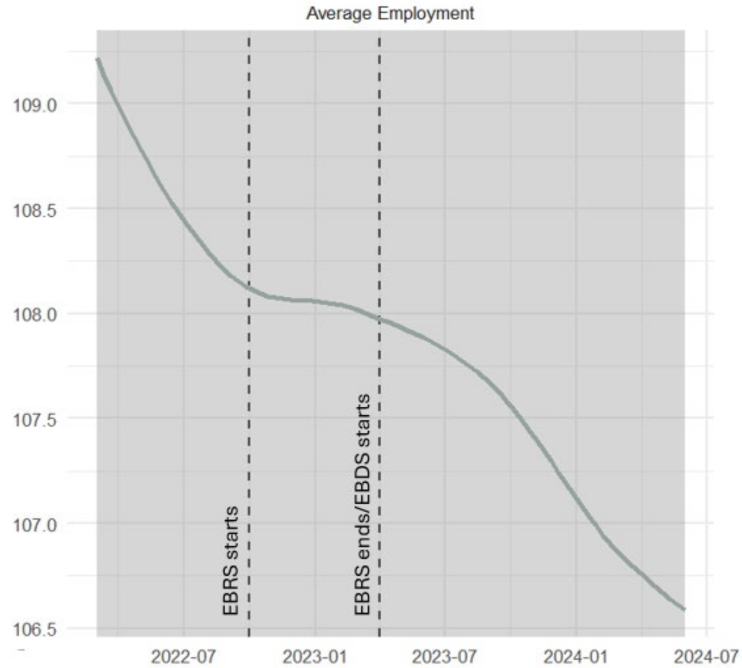
The analysis suggests that the schemes may have contributed to improved financial health of NDOs through reduced energy bills. As seen in Figure 2., NDO's average turnover decreased until the summer of 2022, and started to increase again just before the implementation of EBRS. However, after the implementation of EBRS, the average turnover rate increased sharply, peaking just after EBDS replaced EBRS. This indicates that EBRS may have positively impacted turnover rate (by helping to maintain the positive trend), while EBDS may have lacked the same supportive effect on turnover. Figure 2. shows that after the implementation of the schemes, employment reduction slowed under EBRS but experienced a decline after EBRS ended and EBDS began, although nonetheless at a slower rate than before the schemes. The increase in turnover and the stabilisation of employment indicate some improvement in the financial health across NDOs compared to the periods before EBRS.

Figure 2.15 Average turnover across all organisations



Source: IDBR and meter level data

Figure 2.16 - Average employment across all organisations



Source: IDBR and meter level data

To represent this quantitatively, a series of econometric regressions were performed to isolate the relationship between financial health and the amount of discount received. The regression equations included control variables, such as the tariff, and energy consumption, to avoid omitted variable bias.[17] As a result, the parameter estimates controlled for the relationship between financial health, energy tariffs and consumption, thereby isolating the effect of the discount. The regression equations used to estimate employment and turnover are shown below:

$$\begin{aligned} \Delta Employment_i, (Mar\ 2023 + Sep\ 2023\ -\ Mar\ 2022\ -\ Sep\ 2022) \\ = \alpha \quad + \beta_1 log(Electricity\ Consumption_i(EBDS)) \\ + \beta_2\big(Sum\ of\ NDEA\ Discount_i(EBDS)\big) \\ + \beta_3(ElectricityConsumption_i(EBDS) \times Tariff_i) + \epsilon_i \end{aligned} \tag{1}$$

$$\begin{aligned} \Delta Employment_i, (Mar\ 2023 + Sep\ 2023\ -\ Mar\ 2022\ -\ Sep\ 2022) \\ = \alpha \quad + \beta_1 log(\ Gas\ Consumption_i(EBDS)) \\ + \beta_2\big(Sum\ of\ NDEA\ Discount_i(EBDS)\big) \\ + \beta_3(GasConsumption_i(EBDS) \times Tariff_i) + \epsilon_i \end{aligned} \tag{2}$$

Where:

[17] Omitted variable bias occurs when relevant explanatory variables are excluded from a regression, which alters the estimated coefficients of the includes variables. The excluded variables – if correlated with the included variables and the dependent variable – will influence the parameter estimation and create bias. In this case, the exclusion of the tariff would likely have generated a negative bias (given that it is positively correlated with the discount and negatively correlated with financial performance), and the exclusion of energy consumption would likely have led to a positive bias (given that it is positively correlated with the discount and positively correlated with financial health).

i represents an NDO.

$\Delta \mathrm{Employment}_i$ is the change in employment for NDO i between March and September of 2022 and March and September of 2023.

β_1, β_2, β_3 are fitted coefficients.

α is the constant term

ϵ_i is the error term for NDO i

$$\begin{aligned} \Delta Turnover_i, (Mar\ 2023 + Sep\ 2023\ -\ Mar\ 2022\ -\ Sep\ 2022) \\ = \alpha \quad + \beta_1 log(Electricity\ Consumption_i(EBDS)) \\ + \beta_2 \big(Sum\ of\ NDEA\ Discount_i(EBDS)\big) \\ + \beta_3 (ElectricityConsumption_i(EBDS) \times Tariff_i) + \epsilon_i \end{aligned} \tag{3}$$

$$\begin{aligned} \Delta Turnover_i, (Mar\ 2023 + Sep\ 2023\ -\ Mar\ 2022\ -\ Sep\ 2022) \\ = \alpha \quad + \beta_1 log(\ Gas\ Consumption_i(EBDS)) \\ + \beta_2 \big(Sum\ of\ NDEA\ Discount_i(EBDS)\big) \\ + \beta_3 (GasConsumption_i(EBDS) \times Tariff_i) + \epsilon_i \end{aligned} \tag{4}$$

Where:

i represents an NDO.

$\Delta \mathrm{Turnover}_i$ *is the change in turnover for NDO i between March and September of 2022 and March and September of 2023.*

β_1, β_2, β_3 *are fitted coefficients.*

α *is the constant term.*

ϵ_i *is the error term for NDO i.*

The results of the regression analysis confirmed the positive impact of the schemes on financial health. This econometric analysis found that a £1 increase in the amount of electricity discount received by an NDO from the EBRS or EBDS is associated with a 0.0074 increase in full time equivalent employment. The same holds for the relationship between the electricity discount and turnover, where a £1 increase in the electricity discount was positively associated with turnover, but was not statistically significant at the 95% confidence level.

The estimated impact of the discount received for gas meters shows a larger effect on employment. A £1 increase in the amount of gas discount by an NDO is associated with 0.03 increase in employment. The association between gas and turnover was not statistically significant.

2.2.4.2 Input-Output modelling

Input-Output (IO) modelling was used to understand the economy-wide impacts of the energy crisis and the schemes. This method leverages IO tables, which provide a snapshot of the economy’s structure at a given time, to simulate external shocks to the economy. Specifically, IO tables map economic transactions across sectors through a matrix that shows how industries interact with one another through supply and demand. More detail on IO modelling is provided in appendix 2.

To explore the impacts of the schemes, an IO analysis was conducted of two different scenarios. In the first scenario, only the energy crisis shock was introduced, which showed the impacts of higher electricity and gas prices on output, employment, and Gross Value Added (GVA) across sectors. The second scenario represented the introduction of the schemes, which provided insights into how decreasing energy prices led to changes in the UK economy. By simulating these two scenarios, the incremental impacts of the schemes in mitigating the economic consequences of rising energy costs were isolated and quantified. This analysis estimated the impact on key indicators (such as industrial output, employment, GDP, and GVA) at aggregate and sectoral levels. These findings are summarised in Table 2.2 to Table 2.4 and graphically in Figure 2.17.

Direct impacts refer to the immediate effects of a shock on the sectors. Indirect impacts are the secondary effects that arise as a result of the direct impacts. These include business-to-business purchases within the supply chain. Induced impacts are the broader effects resulting from the spending of income earned by employees in sectors experiencing direct and indirect impacts. Combined impact refers to the total of direct, indirect and induced impacts.

Table 2.2 Net impacts of the total Energy and Discount shocks on Gross Output

Gross output (£ billion)	Energy shock	Discount shock	Net shock
Direct impacts	-16.6	7.9	-8.7
Indirect impacts	-21.4	5.8	-15.7
Induced impacts	-13.1	7.9	-5.2
Combined impacts	-51.2	21.6	-29.6

Source: IO modelling

Table 2.3 Net impacts of the total Energy and Discount shocks on GVA

GVA (£ billion)	Energy shock	Discount shock	Net shock
Direct impacts	-5.5	3.5	-2.0
Indirect impacts	-7.6	2.6	-5.0
Induced impacts	-3.2	1.9	-1.3
Combined impacts	-16.3	8.0	-8.3

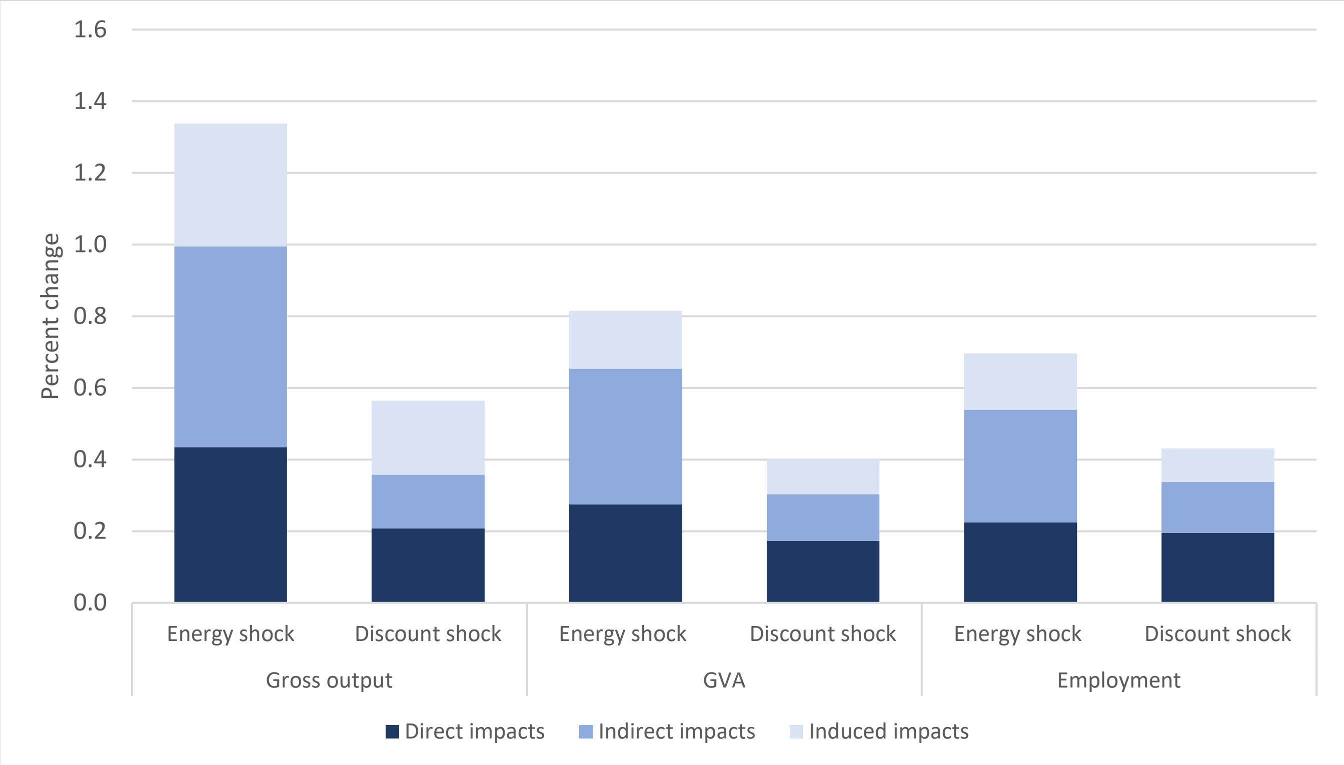
Source: IO modelling

Table 2.4 Net impacts of the total Energy and Discount shocks on Employment

Employment (000s FTE)	Energy shock	Discount shock	Net shock
Direct impacts	-69	60	-9
Indirect impacts	-96	43	-53
Induced impacts	-48	29	-19
Combined impacts	-213	132	-81

Source: IO modelling

Figure 2.1177 Impacts of the Energy and Discount shocks in % changes on Output, GVA and Employment.



Source: IO modelling

The IO modelling finds that the energy crisis led to an estimated direct loss of £16.6 billion in the UK economy, which was partially offset by the schemes, which provided £7.9 billion in support. When accounting for indirect and induced impacts, **the total impact of the energy crisis would have resulted in a decrease in total economic output of £51 billion – a 1.3% loss.** However, **the schemes (as simulated in IO modelling) generated a 0.6% increase in output, covering close to half of these losses.** The schemes helped **preserve up to 132,000 jobs and avoided £21.6 billion in output losses and £8 billion in GVA losses, demonstrating their crucial role in mitigating the adverse effects of the energy crisis**.

These estimates should be taken as an upper bound of the schemes' impacts, as they do not consider potential structural changes in the economy or the time lag between the energy crisis and the schemes deployment. The Input-Output (IO) model is static, meaning it could not account for changes in efficiency. This implies that the amount of input, including energy required to produce one unit of output, remained constant despite the shocks of the energy crisis and support schemes. In the IO model, organisations can respond to shocks by adjusting their level of output, but cannot change structurally. Consequently, if energy prices increased in the model, output decreased – or, if energy prices decreased as with scheme support, output increased. Since the crisis shock was stronger than the support shock, the overall output in the IO model decreased.

The sectors most affected by the energy crisis were energy-intensive industries like construction, retail, and wholesale trade, along with sectors with low-profit margins such as healthcare and education. These sectors saw the largest losses in both output and employment. On the other hand, sectors that are both energy-intensive and trade-exposed, like air transport and manufacturing, benefited most from the schemes relative to their energy crisis impacts. The distribution of support was largely proportional to sectors' energy consumption, though some less energy-intensive sectors with low levels of total output (compared to the average) did not receive as much support relative to their losses.

When looking at the disaggregation across EBRS and EBDS, it is clear that most of the impacts observed occurred within the EBRS period. Of the £21.6 billion of output loss avoided, £20.4 billion occurred during EBRS (see Table 2.5). Of the 132,000 jobs preserved, 125,000 resulted from EBRS (see Table 2.6). Of the £8 billion of GVA loss avoided, £7.6 billion was attributed to EBRS, and £0.4 billion to EBDS (see Table 2.7Table 2.5).

Table 2.5 Net impacts of the Energy and Discount shocks on Gross Output by scheme

Impact	EBRS Energy shock (£ billion)	EBRS Discount shock (£ billion)	EBRS Net shock (£ billion)	EBDS Energy shock (£ billion)	EBDS Discount shock (£ billion)	EBDS Net shock (£ billion)
Direct impacts	-14.6	7.5	-7.1	-2.0	0.4	-1.5
Indirect impacts	-19.0	5.5	-13.6	-2.4	0.3	-2.1
Induced impacts	-11.5	7.5	-4.1	-1.6	0.4	-1.1
Combined impacts	-45.2	20.4	-24.8	-6.0	1.2	-4.8

Source: IO modelling of UK IO table in 2019

Table 2.6 Net impacts of the Energy and Discount shocks on Employment by scheme

Impact	EBRS Energy shock (000s FTE)	EBRS Discount shock (000s FTE)	EBRS Net shock (000s FTE)	EBDS Energy shock (000s FTE)	EBDS Discount shock (000s FTE)	EBDS Net shock (000s FTE)
Direct impacts	-60	57	-3	-9	3	-6
Indirect impacts	-85	41	-44	-11	2	-9
Induced impacts	-42	27	-15	-6	2	-4
Combined impacts	-188	125	-63	-26	7	-19

Source: IO modelling of UK IO table in 2019

Table 2.7 Net impacts of the Energy and Discount shocks on GVA by scheme

Impact	EBRS Energy shock (£ billion)	EBRS Discount shock (£ billion)	EBRS Net shock (£ billion)	EBDS Energy shock (£ billion)	EBDS Discount shock (£ billion)	EBDS Net shock (£ billion)
Direct impacts	-4.8	3.3	-1.5	-0.7	0.2	-0.5
Indirect impacts	-6.7	2.5	-4.2	-0.9	0.1	-0.7
Induced impacts	-2.8	1.8	-1.0	-0.4	0.1	-0.3
Combined impacts	-14.4	7.6	-6.8	-2.0	0.4	-1.5

Source: IO modelling of UK IO table in 2019

When looking at the sectoral targeting of the scheme (i.e. comparing the amount of received discount with respect to the exposure to the energy crisis), EBDS performs slightly better than EBRS, showing a possibility that lessons learned from the first scheme translated into improvements to EBDS. One such lesson is that the EBDS was specifically targeted at Energy and Trade Intensive Industries (ETII), rather than having a broader approach like the EBRS.

Overall, the schemes were effective in reducing the negative impacts of the energy crisis on the economy, particularly for energy-intensive and export-driven sectors. However, the distribution of benefits was not always perfectly aligned with the impact of the energy crisis, as some sectors received more or less support than their share of the crisis warranted.

3. Second degree impacts

3.1 Inflation

3.1.1 Summary of findings

High inflation can have severe implications for an economy, influencing factors beyond the price of goods and services. The Bank of England target inflation rate of two per cent is aimed at fostering economic stability and growth.[18] When inflation exceeds this target, it can introduce uncertainty into the economy. Businesses and consumers start to face unpredictable future price levels, leading to alteration in investment decisions and planning. As the real value of savings and incomes fall, at least until wages catch up to new price levels, purchasing power of consumers is eroded. The erosion of purchasing power associated with high inflation discourages investment and results in negative effects to growth. Moreover, high inflation can impact international competitiveness, making exports relatively more expensive and less demanded in global markets.

Overall, the energy crisis was associated with increases in the Producer Price Index (PPI) and Consumer Price Index (CPI), especially for energy input and output PPI. This suggests that the energy crisis resulted in substantial inflationary pressures, but not all cost increases were passed on to consumers, and were instead likely absorbed by non-domestic organisations. The introduction of the schemes appears to directly mitigate the increase in PPI (particularly moderating the increase in energy input PPI). Therefore, the schemes could indirectly moderate the increase in CPI, reflecting their potential stabilising influence during periods of market volatility. The introduction of the EBRS is aligned with the downward shift in these price indices, suggesting a moderating effect on the rapid price increases seen during the energy crisis. This association indicates that the schemes may have played a positive role in buffering inflationary pressures; however, attributing the impact directly to the schemes was not possible due to data limitations. Moreover, the data available does not enable an analysis of how these effects differ by NDO type.

3.1.2 Theory of energy price effects on inflation

Energy is a crucial component in the production process for a wide range of goods and services. An increase in energy prices would be expected to have a high impact on CPI through changes to the prices of goods and services of NDOs. Based on the price elasticity of demand for the different goods included in the CPI, the impact of rising energy prices on discretionary income may also affect inflation more generally.

The support schemes, especially EBRS, provided substantial discounts on gas and electricity tariffs, safeguarding NDOs from high energy bills, and consequently, from a rapid increase in production costs. By reducing the energy costs of NDOs, the support schemes were expected

[18] The Bank of England has a 2% inflation target: [Inflation and the 2% target | Bank of England]

to limit the need for NDOs to pass on higher costs to consumers, mitigating the increase of output producer prices. The schemes were therefore expected to reduce the increases in the final price of goods and services due to higher energy costs, thereby reducing inflationary pressure on consumer prices.

When demand for goods and services is relatively inelastic, consumers will not substitute or reduce consumption because of high prices. Consequently, even when consumers' income decreases in real terms, they will not cease purchasing these goods and services. As a result, NDOs producing goods and services with inelastic demand can largely pass on increased input prices to consumer prices. Through these industries, it was expected that the support schemes would exert a stronger influence on inflationary pressures, by reducing the impact of the energy crisis on the prices of the goods and services produced.

The cost pass-through of higher energy prices was also expected to vary across NDOs based on the profit orientation of the NDO. Private sector NDOs are more likely than public or voluntary sector organisations to prioritise profitability and pass on additional input costs to consumers if possible (depending on the price elasticity of demand of final goods and services). While maintaining financial health is also important for public and voluntary services, they represent only a small portion of the consumer basket and are less likely to pass on changes in production costs to the price of the goods or services offered.[19,20] As a result, the schemes were expected to reduce inflationary pressures mainly through the support offered to private sector NDOs.

The inflationary pressures were also expected to vary based on whether NDOs were energy-intensive, trade-intensive, or both.[21] NDOs falling under the energy intensive categories (A, B, C, D, and H) of the SIC 2007 industrial code classification were expected to experience the most substantial changes in production costs, a part of which was expected to be passed to consumers. As a result, the schemes were expected to alleviate higher inflationary pressure for energy-intensive industries since they were likely to benefit more substantially from reductions in energy prices.

3.1.3 Observed trends between energy prices and inflation

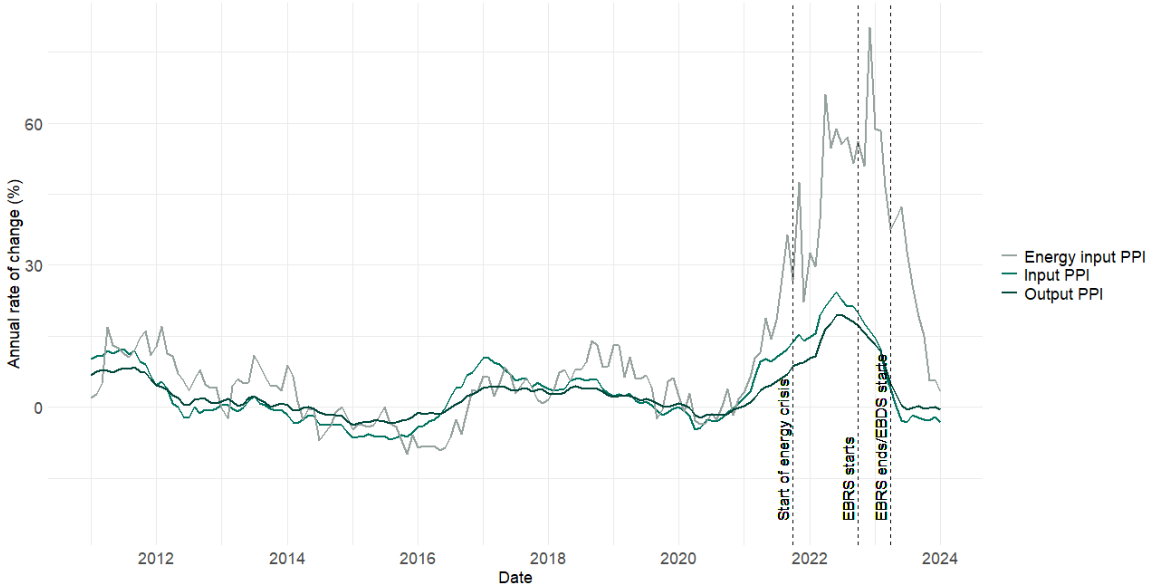
The schemes provided support to NDOs, directly impacting producer price indices (PPIs), and indirectly impacting the consumer price index (CPI). Figure 3.1 below shows the timeline of the input PPI, the energy input PPI, and the output PPI for the manufacturing sector.[22] The input

[19] Public and voluntary organisations frequently offer services that do not have a consumer price, such as public education and healthcare. Consequently, these are not directly included in the consumer basket. The goods and services they provide that are included in the CPI represent only a small portion of the entire basket. Examples include social protection, public transport, and certain administrative fees.
[20] RBB Economics (2014) Cost pass-through: theory, measurement, and potential policy implications. Available at: https://assets.publishing.service.gov.uk/media/5a74a3a940f0b619c86593b8/Cost_Pass-Through_Report.pdf
[21] In the case of energy-intensity, energy as an input represents a higher share in their production, while in the case of trade-intensity, prices cannot always be adjusted due to the price competition with goods and services imported from other regions and countries.
[22] Input PPI: C: Inputs into production of Manufactured products, excluding Climate Change Levy; Energy input PPI: B05_D351TD353: Inputs of Fuel, excluding Climate Change Levy; Output PPI: C: Manufactured products, excluding Duty.

PPI shows how the cost of inputs has changed over time, while the output PPI represents changes in the factory gate prices. The following conclusions can be drawn from the figures:

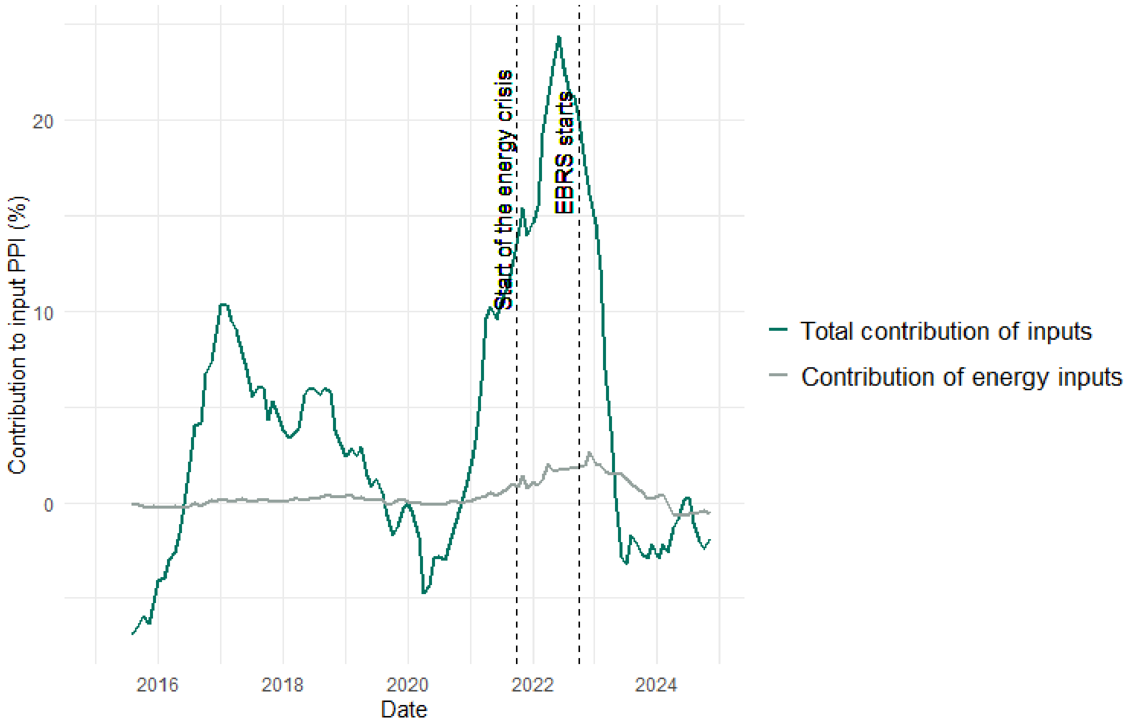
- **Energy input moves together with PPIs.** Between 2010-2011 and 2024, the signs of the annual rate of change of the indices are generally the same (i.e., the indices either decrease together or increase together).
- **Energy input prices are the most volatile.** Energy prices tend to be more volatile than the total input and output producer price indices. From 2011 to 2024, the volatility of energy input prices is much larger. The input and output producer price indices are closely linked, but the output PPI remains in a narrower range (its annual rate of change is smaller).
- **The energy crisis led to a sharp increase in all indices, but especially in the energy input index**. As shown in Figure 3.1, energy input prices started to rise sharply in 2021. Their annual rate of change reached 80% at its peak. The input and output producer price indices show a similar pattern, but their rate of change is lower.
- **Shortly after the introduction of EBRS the indices started to fall, on which the falling wholesale energy prices and the schemes could have a notable impact.** After the introduction of EBRS, energy input prices peaked in December 2022, then began to decline. While producer price indices started to decrease earlier, in mid-2022, a sharp decline occurred in early 2023. After the introduction of the EBDS, the same pattern can be observed, with energy input stabilising after 2024 at pre-crisis levels. The reduction in the energy input PPI can be explained by the sharp decrease in wholesale energy prices starting in the second half of 2022 (see Figure 2.7 in the 'Energy bills' section). It can also be explained by the fact that the schemes mitigated the increase in energy input PPI by providing relief on NDOs' energy bills compared to a 'no schemes' scenario.
- **The contribution of energy prices remained relatively small compared to the overall input PPI** (see Figure 3.1*).* Across all industries, energy has historically been a relatively small share of total inputs. However, the contribution of energy inputs to input PPI increased during the energy crisis, rising to a peak around the time of the introduction of the EBRS; after this point, it began to decrease again, returning to its historical average by 2024. This shows that the schemes in combination with the reduction in wholesale energy prices could have had an impact on reducing the contribution of energy prices to the overall input PPI. This, in turn, could mitigate the increase in output PPI.

Figure 3.1 Timeline of PPI (input, energy and output)



Source: Producer price indices from ONS (Growth rates of output and input producer price inflation (PPI))

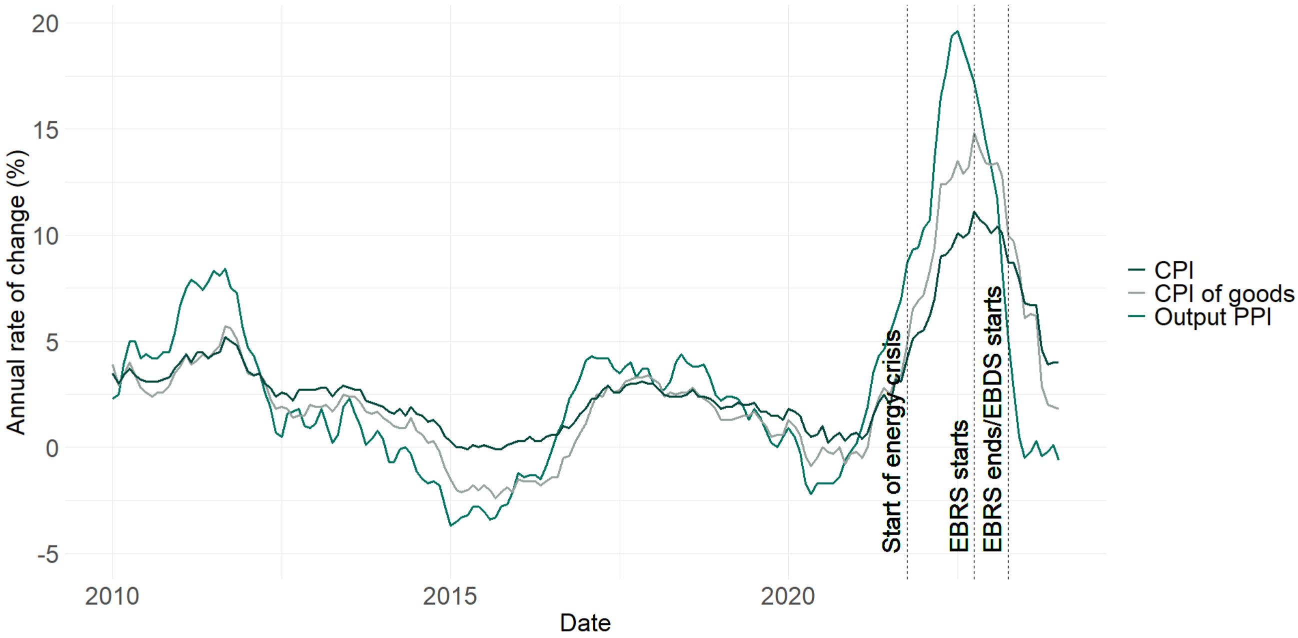
Figure 3.2 Contribution of energy to input PPI as %



Source: Producer price indices from ONS (Growth rates of output and input producer price inflation (PPI))

The output price index has a direct impact on goods, as it reflects factory gate prices (the prices at which goods leave the factory, excluding retail and transportation costs). As a result, it impacts consumer price inflation (CPI). Figure 3.3 compares the annual rate of price change for output producer prices, consumer prices and consumer prices for goods. Over the past 13 years, producer prices have exhibited greater fluctuations, in contrast to the Consumer Price Index (CPI), which has maintained more stability. During the energy crisis, all indices increased, indicating inflationary pressure. Output PPI increased more than CPI and CPI of goods, which likely reflects that a portion of the production cost increases (from increased energy prices) was not passed through to consumers. After the schemes were introduced, the CPI and output PPI indices decreased, indicating that production costs were less volatile, which in turn allowed for more predictable consumer price movements and lower inflationary pressures. Output PPI decreased more rapidly than the other indices, again suggesting that changes in consumer prices were not as responsive.

Figure 3.3 Price index comparison



Source: Producer price and consumer price indices from ONS (Growth rates of output and input producer price inflation (PPI); Consumer price inflation time series - Office for National Statistics)

Beginning in late 2021, output PPI increased more than the CPI for goods; however, the increase was the smallest for the overall CPI. The smaller increase in overall CPI compared to the CPI for goods can be explained by two factors. First, the price increase of services was lower than that of goods. Second, there was a shift in consumer spending patterns, which became less energy intensive. From 2021 to 2024, the goods segment's share of total CPI reverted to near pre-pandemic levels, the services segment's share increased, and the housing and energy segment's share remained relatively unchanged (see Table 3.1). These shifts in the composition of CPI indicate a decreased influence of goods – and thus energy – prices on the overall CPI.

Table 3.1 CPI weights

Expenditure Category	2019	2020	2021	2022	2023	2024
Goods without energy	46%	45%	51%	50%	45%	44%
Services without housing	38%	39%	32%	34%	37%	40%
Housing and energy	17%	16%	17%	17%	17%	16%

Source: Consumer price index weights from ONS (Consumer price inflation tables). Note: The ONS publishes the weights of different categories in the CPI, which reflect changes in the average consumer basket. If the weights of a category increase, this can be interpreted as a relatively higher share of consumer spending for that category.

3.2 Energy consumption

3.2.1 Summary of findings

The total energy consumed by NDOs can depend on several factors, such as the season, temperature, economic activity, energy efficiency improvements, and energy prices. As energy bills increased during the energy crisis, many NDOs temporarily reduced or stopped production and services, or introduced energy saving measures.

Analysis of NDO energy consumption suggests a delayed response to the energy crisis, particularly in natural gas consumption. This analysis finds that the introduction of the schemes led to an increase in energy consumption of 33,700 gigawatt-hours (GWh) compared to a counterfactual of an energy crisis with no scheme support. This increase was more substantial within the time period in which EBRS ran and among energy intensive NDOs. The additional energy consumption during the period the schemes were active did not

3.2.2 Theory of expected impacts of mitigating energy price effects on energy consumption

The support schemes influence energy consumption through two channels:

- Maintaining energy consumption, and thereby sustaining production and service levels, was a core objective of the schemes. The support provided on energy bills may have encouraged NDOs to recover reduced production and service levels, thus increasing energy consumption compared to a scenario without the schemes.
- The support provided on energy bills may have discouraged the continuation or introduction of energy saving measures. However, this is unlikely to be the case due to the level of the government supported price. Even with the support, energy prices faced by NDOs were higher than before the start of the energy crisis.

3.2.3 Observed impacts of mitigating energy price effects on consumption

Figure 3.4 and 3.5 shows how gas and electricity consumption by UK NDOs (final consumption) changed over time. [23] There is a strong seasonality in energy consumption, with higher values in winter and lower values in summer, and a general downward trend in both electricity and gas consumption can be observed over the last 20 years.

[23] Final consumption refers to the energy used directly by end users, excluding energy lost in transformation and distribution processes.

Figure 3.4 Final gas consumption of organisations

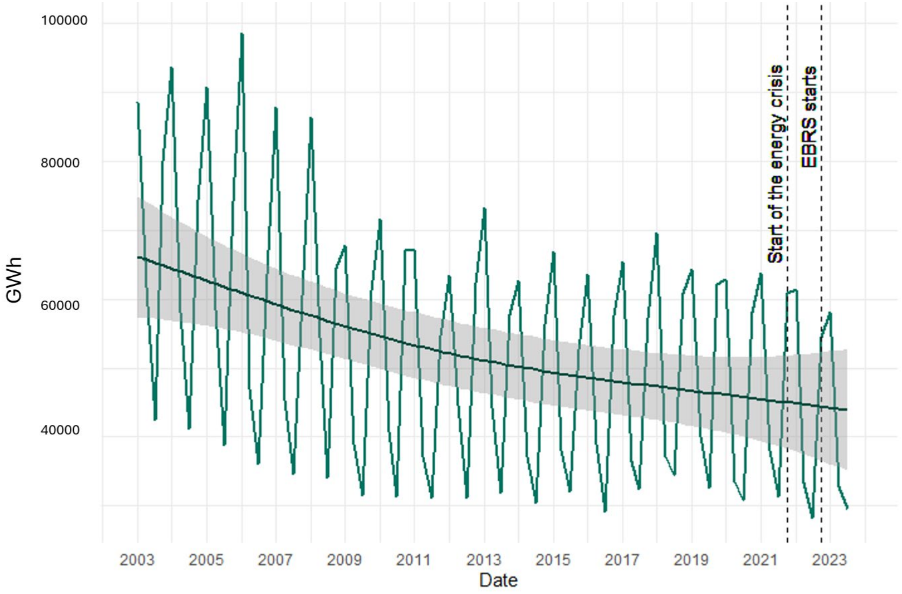
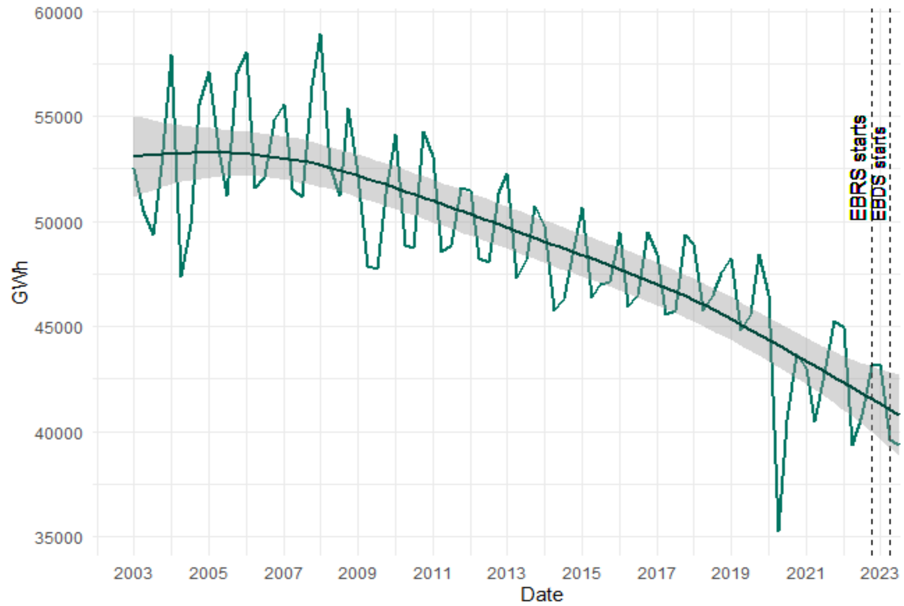


Figure 3.5 Final electricity consumption of organisations



Source: Final gas and electricity consumption of UK NDOs from DESNZ (Energy Trends: UK gas; Energy Trends: UK electricity)

Linear regression can help identify which factors influence energy consumption. In this case, the analysis considered the time of year, the number of heating degree days (HDD – the main measure of heating demand), and overall trends in energy use (which could indicate improvements in energy efficiency or changes in the production of energy-intensive goods and services). This study examined energy consumption trends from 2010 onwards. For gas consumption, only the time of year and the number of HDD had a significant impact, meaning there was no overall trend in gas use. This suggests that either gas-related energy efficiency did not improve, or any gains were offset by more businesses using gas in production. In contrast, electricity consumption was influenced by both the time of year and a general downward trend, indicating significant improvements in energy efficiency or a reduced reliance on electricity for production. These results are used to define the detrending structure shown in

Figure 3.6 and **Error! Reference source not found.**, which presents the energy consumption after removing seasonal components.[24]

Figure 3.6 Detrended gas consumption of organisations

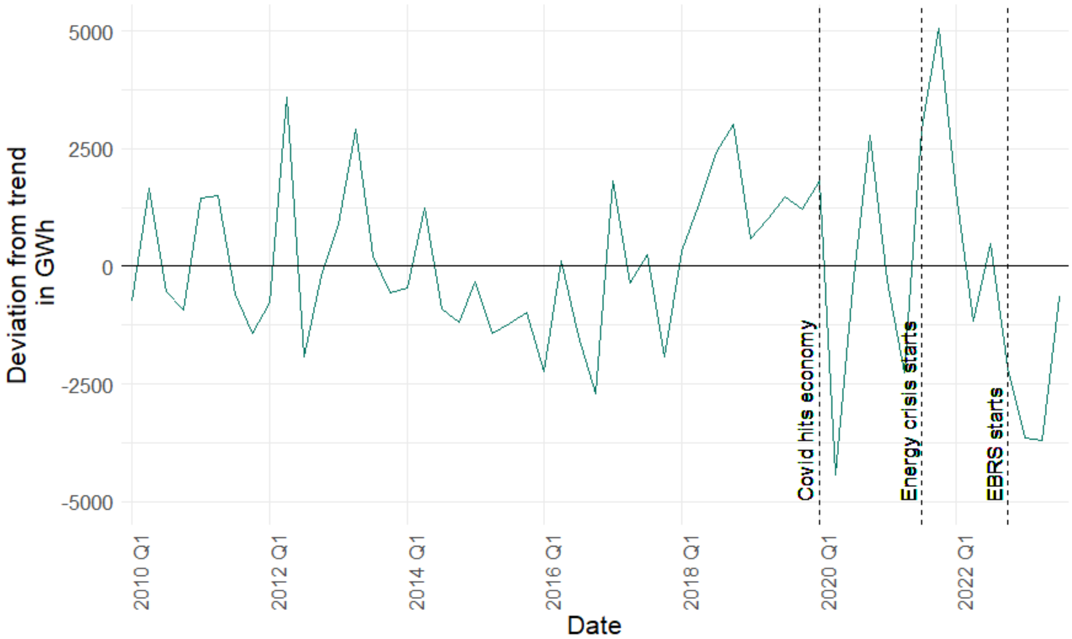
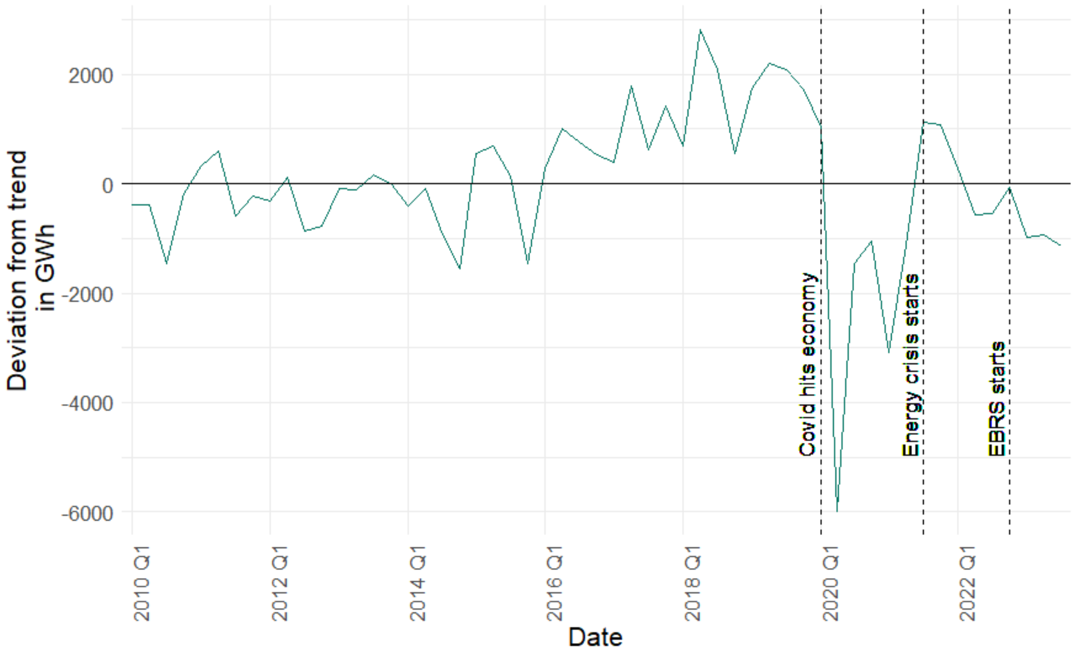


Figure 3.7 Detrended electricity consumption of organisations



Source: Calculation based on final gas and electricity consumption of UK NDOs from DESNZ (Energy Trends: UK gas; Energy Trends: UK electricity)

[24] The final linear regression used for gas included the time of the year (quarterly data, using calendar year quarters) and the number of HDD. In the case of electricity, the time of the year (calendar quarters), the number of HDD and a linear trend was included.

When data was seasonally adjusted and corrected for temperature, energy consumption during the energy crisis did not deviate substantially from the 13-year average trend. At the beginning of the crisis, both natural gas and electricity consumption showed a positive deviation. This can be explained by the rapid recovery period after the COVID-19 shock, which continued into the start of the energy crisis. However, the deviation from the average trend became negative within a few months of the beginning of the energy crisis. For both electricity and gas, deviations from the 13-year trend were not substantial. This could indicate that the energy crisis had a delayed effect on energy consumption, particularly in the case of gas and possibly due to the structure of the NDOs' energy contracts.

After the introduction of the schemes, with some months' lag after the introduction of EBRS, gas consumption began to increase, and electricity consumption stopped decreasing as sharply as it had since the beginning of the energy crisis. This finding reinforces that adjustments to energy consumption lagged behind the corresponding shocks (in this case, the introduction of the schemes). This can be explained by the fact that retail energy prices started to increase several months after wholesale energy prices, due to the delay in renewing fixed-price contracts (compare Figure 2.7 throughFigure 2.10 in the 'Energy bills' section). However, given the lack of data availability in recent periods (as of December 2024), it is not possible to provide further insights on long-term trends after scheme implementation.

3.2.4 Impact attribution for energy consumption

The schemes were associated with an avoided loss of output of £21.6 billion, based on the IO modelling results (see appendix 2 for more details on this methodology). This increase in output is compared to the no-intervention counterfactual, and represents maintaining output closer to levels in a no-crisis scenario. Maintained output resulting from the schemes is associated with a higher level of economic activity, and this increase in economic activity is also associated with higher energy consumption.

This increase in output is associated with a total energy use of 33,678 gigawatt-hours (GWh). This represents 1.65% of UK's total energy consumption in 2022 (however, as EBRS and EBDS lasted for more than one year, this figure may be slightly overstated). To calculate this, energy intensity per sector was calculated using the IO table from 2022,[25] and the sectoral energy use tables from 2022.[26] This sectoral energy intensity was then multiplied by the increase in the sectoral output resulting from the schemes.[27] However, it is important to note that this result assumes the relation between output and energy in the economy remained unchanged during the energy crisis and after the schemes implementation. As a result, it acts as an upper bound estimate.

[25] See: UK input-output analytical tables: industry by industry - Office for National Statistics
[26] See: Energy use: by industry reallocated to final consumer and energy intensity - Office for National Statistics
[27] It is important to note that the sum of the energy use of all sectors does not equal to the total energy use of the UK, as consumer expenditures (i.e., the consumption of fuels and other products by individuals in the UK) are not included (e.g., consumer expenditures on the fuel consumption of road transport). The input-output modelling could not reveal how consumption expenditures changed, therefore the impact on it is not included in this analysis.

Table 3.2 Increase in energy resulting from the schemes

Industry	Output loss avoided through schemes (million £)	Increase in energy use resulting from the schemes (GWh)	% of total increase in emissions
All - Total	16,938	33,678	100%
A - Agriculture, forestry and fishing	348	568	2%
B - Mining and quarrying	335	2,374	7%
C - Manufacturing	4472	9,665	29%
D - Electricity, gas, steam and air conditioning supply	1144	520	2%
E - Water supply; sewerage; waste management and remediation activities	205	290	1%
F - Construction	784	313	1%
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	1477	1,374	4%
H - Transport and storage	1614	15,400	46%
I to T- Services	6559	3,180	9%

Source: IO modelling and sectoral energy use (Available at: Energy use: by industry reallocated to final consumer and energy intensity - Office for National Statistics)

As seen in Table 3.2 above, the sectors with the largest increases in energy use were the manufacturing sector, and the transport and storage sector, which is heavily affected by demand for manufacturing. Although the table only provides a sectoral overview, some sub-sectors show substantial increases in energy use, including industries which are part of the energy supply chain such as extraction of crude petroleum and natural gas, energy-intensive manufacturing industries such as manufacture of industrial gases and fertilisers, manufacture of glass, and manufacture of basic iron and steel, and types of transportation heavily involved in logistics such as water and air transport.

The majority of this impact can be associated with EBRS, as £20.4 billion of the total avoided output loss can be attributed to this scheme. As a result, from the total increase in energy use, 31,900 GWh can be attributed to EBRS, and 1,700 GWh can be attributed to EBDS.

3.3 Market stability

3.3.1 Summary of findings

Energy market stability was analysed by examining the volatility of fixed-price wholesale energy contracts, changes in correlation across time periods of these prices, and the financial health of energy suppliers. Fixed price energy contracts for different periods (e.g., five months vs. two years) represent different expectations in the market. Short-term fixed energy prices tend to be more volatile and reactive to shocks, whereas longer-term prices are expected to be more constant are only fluctuating when structural changes and significant alterations shock the market.

The analysis revealed that the energy crisis led to substantial decreases in market stability, shown by the increase in energy prices and reduction in correlation for all fixed-price contracts, including long-term prices. This correlation suggests market stability was negatively affected by the crisis. The schemes' introduction coincided with an improvement of market stability, as energy prices started to decrease and short- and long-term prices become more correlated. The correlation analysis cannot identify the causal factor(s) behind the observed increase in correlation between short-, medium-, and long-term fixed energy prices. This increase in correlation may have occurred due to the schemes (i.e., through signalling structural stability by restoring market confidence and mitigating uncertainty in the longer horizon), or due to reductions in overall market uncertainty, in which the energy crisis was treated as a systemic issue (i.e., price expectations internalized the effects of the energy crisis). In addition to changes in the correlation between energy prices, energy suppliers also experienced improvements in financial health after the introduction of the schemes, further reinforcing the hypothesis of improved market stability.

3.3.2 Theory of expected impacts of mitigating energy price effects on market stability

A stable energy market both facilitates a predictable (i.e., low volatility) pricing environment and ensures that the supply of energy is sufficient to meet the demand across various sectors. The energy crisis is therefore expected to have negatively affected:

- **Wholesale energy price volatility:** High volatility means that wholesale energy prices fluctuate significantly in a short amount of time, making it difficult for businesses and consumers to predict costs.
- **Retail energy price volatility and energy cost volatility:** Similar to wholesale energy price volatility, retail energy price volatility refers to fluctuations in the retail prices, as faced by NDOs based on their energy contracts. Energy cost volatility is a more complex metric to interpret, since changes may be the result of changes in energy consumption or energy prices.
- **Energy cost affordability:** A market that maintains energy cost affordability ensures that energy expenses do not become a disproportionate burden on the economy or on individual consumers, promoting equitable access to energy resources.

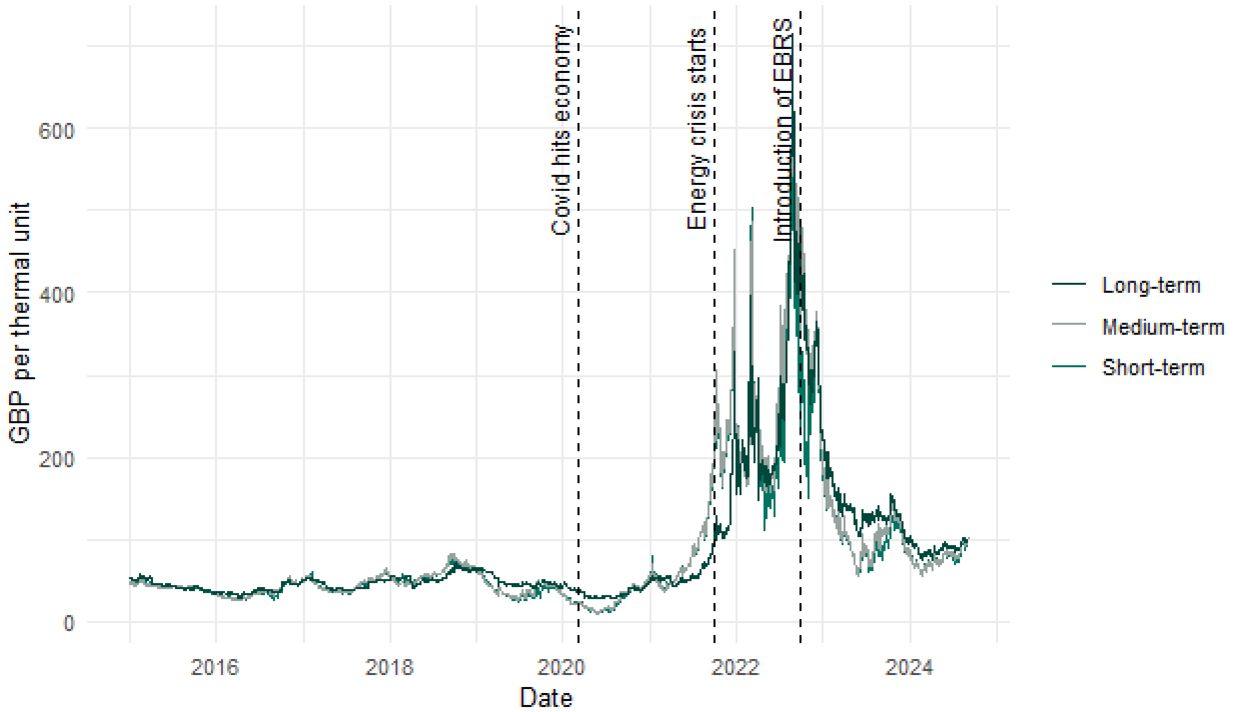
The support schemes were expected to avoid the adverse impacts of rising wholesale energy prices on price and cost volatility and energy cost affordability. Additionally, the schemes were expected to reduce pressures on smaller energy suppliers, thereby reducing the number of energy company insolvencies and promoting overall market stability.

3.3.3 Observed impacts of mitigating energy price effects on market stability

Figure 3.8 and Figure 3.9 below show the movements of the selected short-, medium- and long-term gas and electricity prices. In general, energy prices moved strongly together, and all series had historically high values during the energy crisis. The fact that even long-term prices reached historically high levels suggests that market expectations for future energy costs were higher than before the energy crisis. This indicates a structural adjustment in pricing, reflecting concerns about sustained supply-demand imbalances, geopolitical risks, or anticipated long-term shifts in production costs. More broadly, the higher prices and high degree of volatility point to a decreased market stability during the energy crisis.

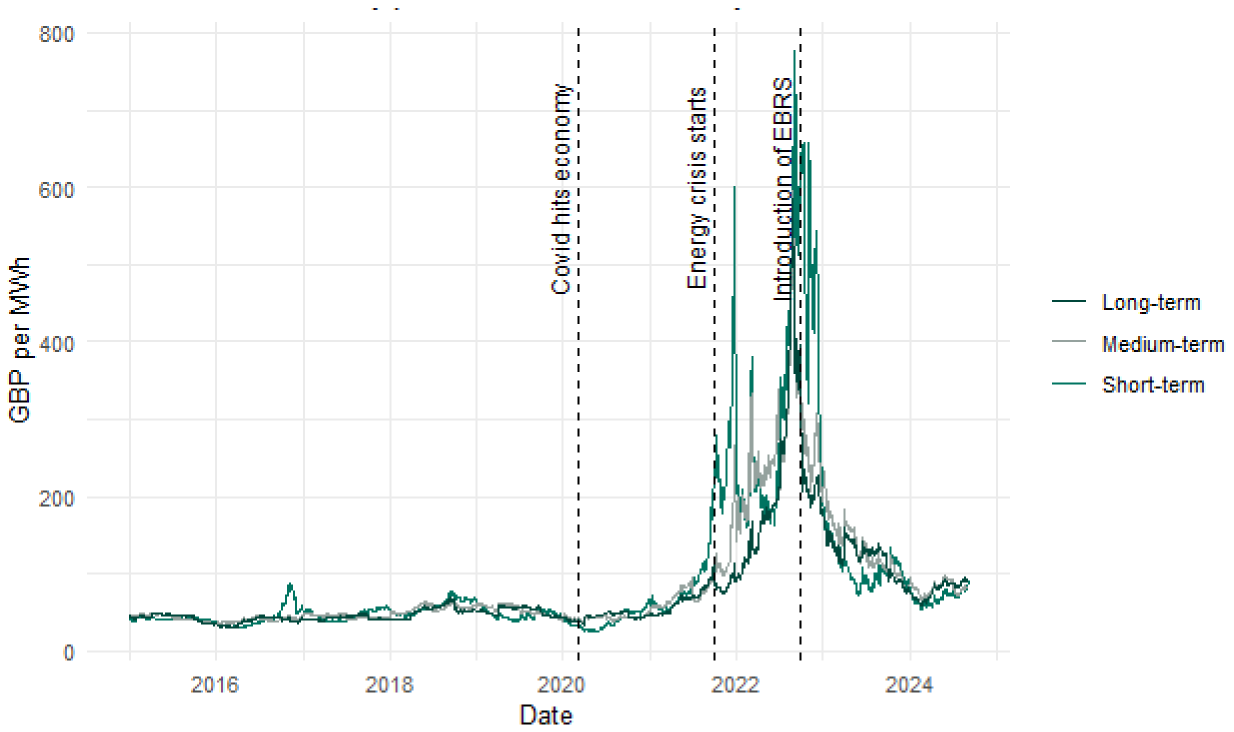
As the schemes were introduced, both gas and electricity prices started to decrease. This was especially the case for long- and medium-term prices, which peaked before the introduction of the schemes, and decreased shortly after. Short-term prices peaked slightly after the introduction of the schemes. This suggests that market stability improved after the schemes were introduced.

Figure 3.8 Timeline of gas prices at different delivery dates



Source: ICIS wholesale gas price data

Figure 3.9 Timeline of electricity prices at different delivery dates



Source: ICIS wholesale electricity price data

The prices used in wholesale energy transactions vary depending on how far in advance it is being forecasted. Using pricing data from ICIS,[28] changes over time in the correlation between energy prices with different time horizons were examined to provide insights into how expectations have changed and how rising energy prices affected the stability of the energy market and were incorporated into market expectations.

Before the support schemes were introduced, fixed energy prices for adjacent delivery periods moved very closely together. For example, prices agreed for the same month and the following month, or for one quarter and the next, often rose and fell in near unison (with correlation coefficients often exceeding 0.8). In contrast, prices for immediate delivery and those set for much later (one year or more ahead) showed a much weaker connection (with correlations around 0.5). This gap suggests that markets saw short-term supply pressures as sharp but unlikely to last into the distant future.

Over this pre-scheme period, the relationship between medium-term and long-term prices grew stronger, reflecting growing concern that elevated costs might persist beyond immediate disruption. At the same time, the relative 'decoupling' of short- and long-term prices highlighted a divergence in expectations: short-term supply shortages led to sharp price increases that markets did not expect to be sustained over the long term.

Once the schemes came into effect, overall relationships between different contract lengths stayed broadly the same. However, the correlation between short-term and long-term prices

[28] Independent Commodity Intelligence Services (ICIS) is a global provider of market intelligence and data for various sectors. One of its key services is offering detailed information about future prices (known as forward prices) of wholesale gas and electricity. For this analysis, data was drawn from ICIS European Daily Electricity Market report and European Spot Gas Market report

did strengthen slightly, suggesting the market began to internalise the crisis's longer-term implications. Prices for delivery in the coming months and those for delivery many months ahead began to move more in step. Medium-term contracts, by contrast, held steady in their alignment with both short- and long-term horizons, showing little change in correlation strength.

Two interrelated factors likely drove these shifts:

- First, as broader disruptions and policy responses became clearer, market expectations were adjusted, signalling a growing view that the crisis would exert sustained upward pressure on prices across all time frames. [29]
- Second, the schemes themselves may have bolstered confidence by reducing uncertainty around future energy costs, thereby synchronizing price movements between the near and distant delivery periods. Together, these influences point to a market increasingly unified in its forward outlook, even as immediate supply challenges remained acute.

3.3.4 Impact attribution for market stability

After the implementation of the schemes, the correlation between short- and long-term expectations became stronger, potentially indicating that the schemes could have contributed to restoring market confidence, although alternative explanations are possible. Soon after the introduction of EBRS, energy prices started to fall, and short- and long-term prices became more strongly correlated with each other. Given the timing of this 'coupling', it could be argued that the schemes played a role by helping to restore market confidence and mitigate uncertainty in the longer term. However, other potential factors influencing this correlation include: the market treating the energy crisis as a systemic issue rather than a temporary shock (i.e., by internalising the effects of the energy crisis into both short- and long-term price expectations), changes in global supply chains, shifts in consumption and production patterns, and other broad macroeconomic changes. The correlation analysis is unable to determine attribution to specific factors.

As detailed in section 2.1, the schemes could have contributed to decoupling energy prices and uncertainty. During the energy crisis, the change in gas or electricity prices were a significant driver of uncertainty.[30] After the introduction of the schemes, however, the link between energy prices and uncertainty was no longer statistically significant, suggesting a decoupling effect. The reduction in uncertainty is likely to have improved market stability by contributing to improved expectations.

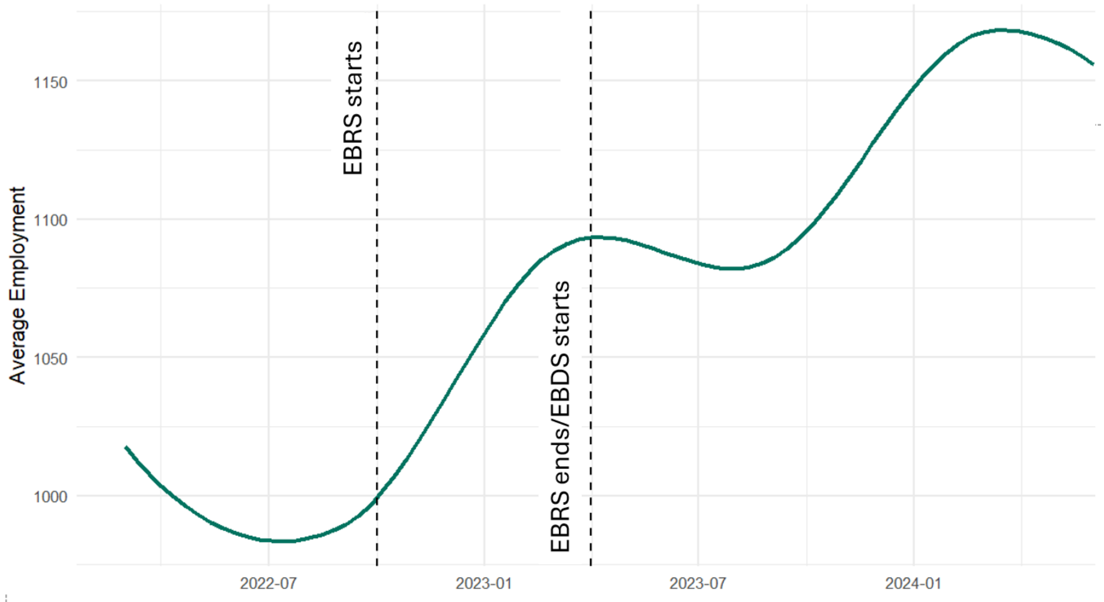
Looking further into the performance and financial health of energy suppliers can also share insights into how market stability was impacted. If energy suppliers suffer from deteriorating financial health and insolvencies, the overall energy market is expected to be negatively

[29] For example, Figure 3.8 and Figure 3.9 show that short-term prices increased sharply at the start of the energy crisis, as the disruption to the gas supply was initially considered to be temporary. However, as the war in Ukraine began and other factors emerged, such as damage to the North Stream gas pipeline), market expectations became more aligned and short-, medium- and long-term prices all increased over time.
[30] However, omitted variables, such as the uncertainty caused by COVID-19 related policies, could have biased the analysis, which is the key limitation of the results presented in the uncertainty analysis.

affected. This analysis of energy suppliers' financial health uses the meter-level data provided by DESNZ, matched with IDBR data.

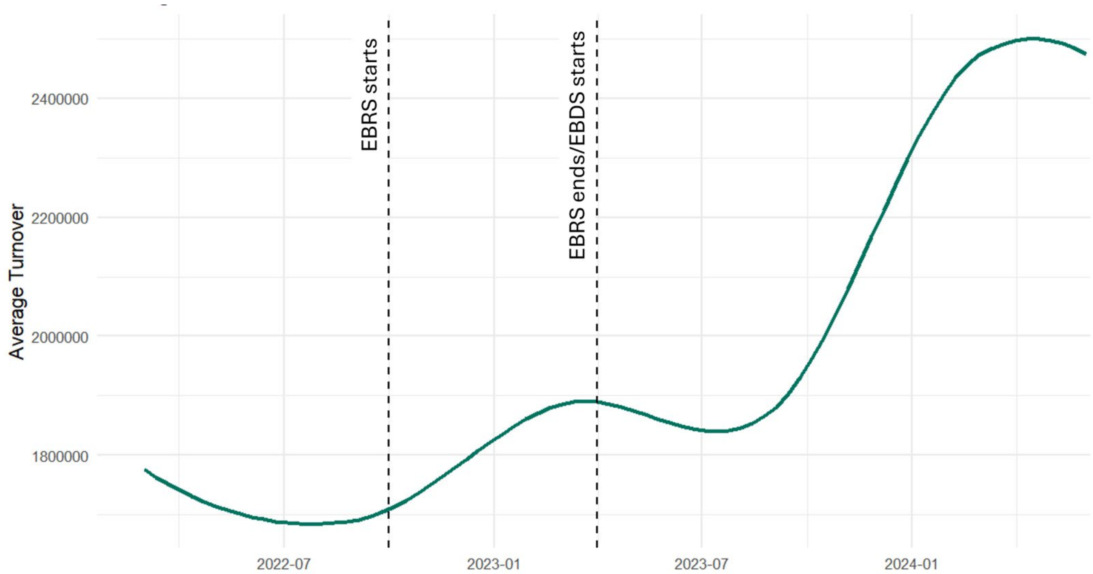
Figure 3.10 below shows the changes of energy suppliers' employment and turnover across the time period of interest. After the introduction of the schemes, energy supplier employment generally increased, with a brief disruption after the introduction of the EBDS. The same trend is observed for turnover, which increased after the implementation of the schemes. The increase in turnover in particular became much more pronounced after the introduction of EBDS, suggesting a potential time lag in realising the impacts of the schemes on turnover.

Figure 3.10 Energy suppliers' average employment over time



Source: IDBR information, and NDOs matched with the DESNZ meter level data

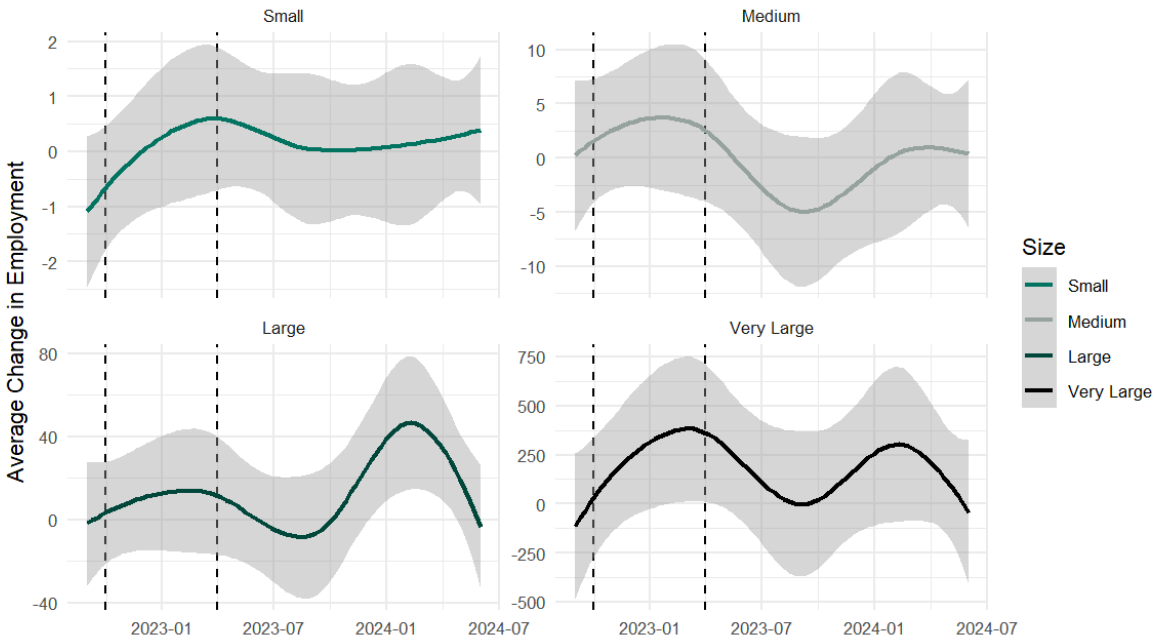
Figure 3.11 Energy suppliers' average turnover over time



Source: IDBR information, and NDOs matched with the DESNZ meter level data

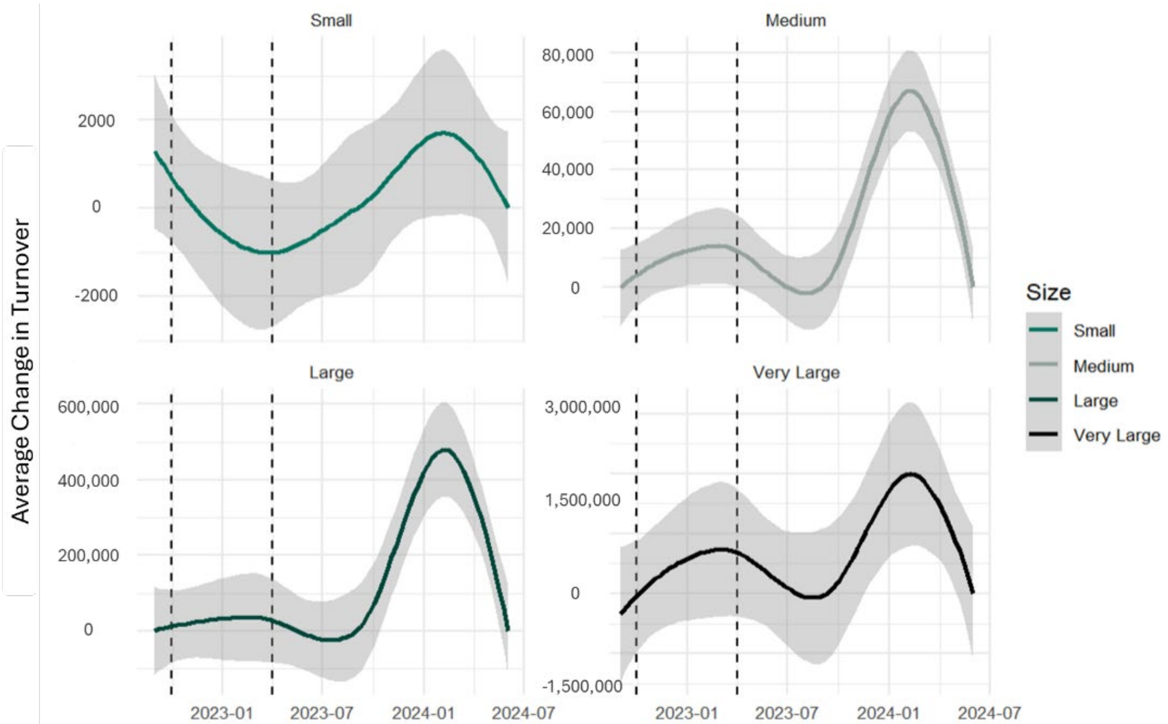
Figure 3.12 and Figure 3.13 below examines trends in employment and turnover across energy supplier size categories. Please note that the axis of these figures has been tailored to the cluster of NDOs analysed. Overall, changes in employment were greater in relative terms (as a % of total employment) for larger energy suppliers, as they had a steeper increasing trend, and a more positive starting point (i.e., the average change before the introduction of the schemes was less negative). The same trend holds for turnover.

Figure 3.12 Average change in employment over time by supplier size



Source: IDBR. Note: Dotted lines represent introduction of EBRS and EBDS. The solid lines shown are linearly fitted lines whereas the grey shaded area represents the standard deviation of the average.

Figure 3.13 Average change in turnover over time by supplier size



Source: IDBR. Note: Dotted lines represent introduction of EBRS and EBDS. The solid lines shown are linearly fitted lines whereas the grey shaded area represents the standard deviation of the average.

3.4 Financial health of non-domestic organisations

3.4.1 Summary of findings

On average, energy costs account for more than ten percent of total costs for nearly one-quarter of UK businesses, and over two per cent of total costs for three-quarters of businesses, with greater exposure amongst small businesses.[31] The energy crisis was therefore expected to have a negative impact on NDOs' financial health, especially for NDOs with: high energy intensity, high competitiveness and trade exposure, low-income elasticity of demand, and smaller size.

Energy-intensive industries are more exposed to high energy prices as these represent a higher proportion of their total production costs. Based on an energy intensity analysis conducted within the IO analysis, this report classifies the following SIC 2007 categories as energy-intensive: A (Agriculture, forestry and fishing), B (mining and quarrying), C (Manufacturing), D (Electricity gas, steam and air conditioning supply), and H (transport and storage).[32] These sectors were expected to have been relatively more affected by the increase in energy prices. NDOs which produce goods and services for which demand is relatively more price elastic and which operate in a competitive market are expected to be in a more vulnerable position due to reduced capacity to transfer production cost increases to consumers. Similarly, smaller NDOs were more vulnerable to the energy crisis than larger NDOs as they tend to face relatively higher energy prices and additional barriers in securing borrowing.

The analysis of financial health included analysis of trend data on insolvencies, redundancies, and borrowing. In addition, BICS responses were used to see how expectations of organisations' performance changed over the time period. Finally, the meter-level data (provided by DESNZ) matched with IDBR data was used to perform simple regression analysis (as described in section 1) to determine the associated impact of the schemes on NDOs turnover and employment.

The energy crisis had a negative impact on NDOs' financial health: business death, insolvencies, and borrowing increased during this period. Smaller organisations were observed to be more at risk, due to their limited access to borrowing. After the introduction of the schemes, there were some signs of improvements in financial health although with a substantial time lag, suggesting weak evidence for the claim that the schemes contributed to improvements in financial health. Expectations of organisations' performance improved after the introduction of EBRS, with fewer NDOs reporting they expected performance to deteriorate

[31] Ari, Anil and Mulas Granados, Carlos. 2023. The Energy Price Shock—Impact, Policy Responses, and Reform Options. IMF Selected Issues Paper (SIP/2023/048). Washington, D. C.: International Monetary Fund.

[32] This analysis calculates energy intensity by dividing the energy use over the total output for each sector. The highest ranked sectors are taken within the analysis to be the "energy intensive" NDOs. Please note this definition is unique to fit the needs of this analysis, and does not correspond 1:1 with other definitions such as the one provided by DESNZ. The data sets used for this classification are: Energy use by industry, source and fuel database from the ONS (Energy use: by industry, source and fuel - Office for National Statistics (ons.gov.uk)), and the United Kingdom Input-Output Analytical Tables of 2019 (UK input-output analytical tables, product by product - Office for National Statistics (ons.gov.uk)) . Total energy use by SIC(2007) category is divided by total output at constant prices for 2019. For more information, please consult appendix 2.

in the next 12 months in BICS waves that took place while EBRS was active (see Figure 3.14). On average, this continued to decline after EBDS was implemented, a chronology consistent with the schemes having a positive impact on financial health. Borrowing also decreased after the introduction of the schemes, further supporting this conclusion. The econometric analysis presented in section 2 above also highlighted the positive effects of the schemes on financial health, estimating that the schemes' discounts (on electricity in particular) are correlated to increased turnover and employment.

Figure 3.14 Share of businesses expecting performance to decrease over the next 12 months

Source: ONS, Business Insight and Conditions Survey (BICS)

3.4.2 Theory of expected impacts of mitigating energy price effects on financial health

The energy crisis was expected to have worsened the financial health of NDOs due to rising energy costs and increased uncertainty about the future economic outlook (as described in section 2). Higher energy prices are expected to have increased production costs, resulting in decreased output, postponed investment, and reduced demand for intermediate goods. In the short term, NDOs may have sought to meet increased costs through additional borrowing to bridge the gap in cash flows.[33] The energy crisis caused lower consumer spending due to higher household energy costs, affecting discretionary income, which would affect businesses selling goods and services. Energy-intensive NDOs, small NDOs, and those in competitive markets were expected to have been particularly vulnerable. These NDOs may have experienced increased production costs, redundancies, and even insolvencies as they struggle to absorb higher energy costs, or pass these on to consumers in the case of businesses.[34]

[33] Bank of England (BoE) (2022) Monetary Policy Report August 2022. Available at: https://www.bankofengland.co.uk/-/media/boe/files/monetary-policy-report/2022/august/monetary-policy-report-august-2022.pdf & Brown, J.R., Gustafson, M.T. and Ivanov, I.T. (2021) 'Weathering Cash Flow Shocks', Journal of Finance, pp. 1731-1771. Available at: https://onlinelibrary.wiley.com/doi/pdfdirect/10.1111/jofi.13024
[34] Ari, Anil and Mulas Granados, Carlos. 2023. The Energy Price Shock—Impact, Policy Responses, and Reform Options. IMF Selected Issues Paper (SIP/2023/048). Washington, D. C.: International Monetary Fund.

Various factors were expected to affect financial health of NDOs, including their energy intensity, market competition, and access to financial resources. Energy-intensive sectors such as manufacturing, agriculture, and transport are more vulnerable to energy price hikes as energy costs comprise a larger portion of their production costs. Smaller NDOs[35] are also more exposed to higher energy prices and face difficulties in securing financing, further aggravating their financial strain. Larger or more creditworthy NDOs may have been able to weather the storm of energy price increases through strategic borrowing, while less financially secure organisations may have been forced into making more drastic operational changes or face insolvency.[36] Moreover, businesses with limited flexibility in adjusting operations (low elasticity) or those already in a fragile financial position before the energy crisis will face heightened risks. [37] The ability of an NDO to adjust its energy consumption and production processes is another key factor in determining its exposure to financial difficulties.

The schemes were expected to alleviate some of the negative effects of the energy crisis on NDOs' financial health. The support is expected to have helped reduce energy costs, providing immediate relief to cash flows and improving liquidity. This was expected to reduce redundancies, insolvencies, and borrowing needs in the short term. The schemes were anticipated to reduce financial distress, especially for energy-intensive NDOs and those in trade-intensive sectors. As energy costs stabilised, long-term financial health was expected to improve due to better access to financing, reduced cost pressures, and improved market confidence.

The effectiveness of the schemes was expected to depend on factors such as sector energy intensity, size of the NDO, and type of NDO (private, public, or voluntary). Private sector NDOs were expected to see the most significant benefits due to their greater representation in energy-intensive sectors and their exposure to competitive pressures. Voluntary and public NDOs may have experienced some relief, but the extent of the impact depended on their access to funding and sectoral exposure.

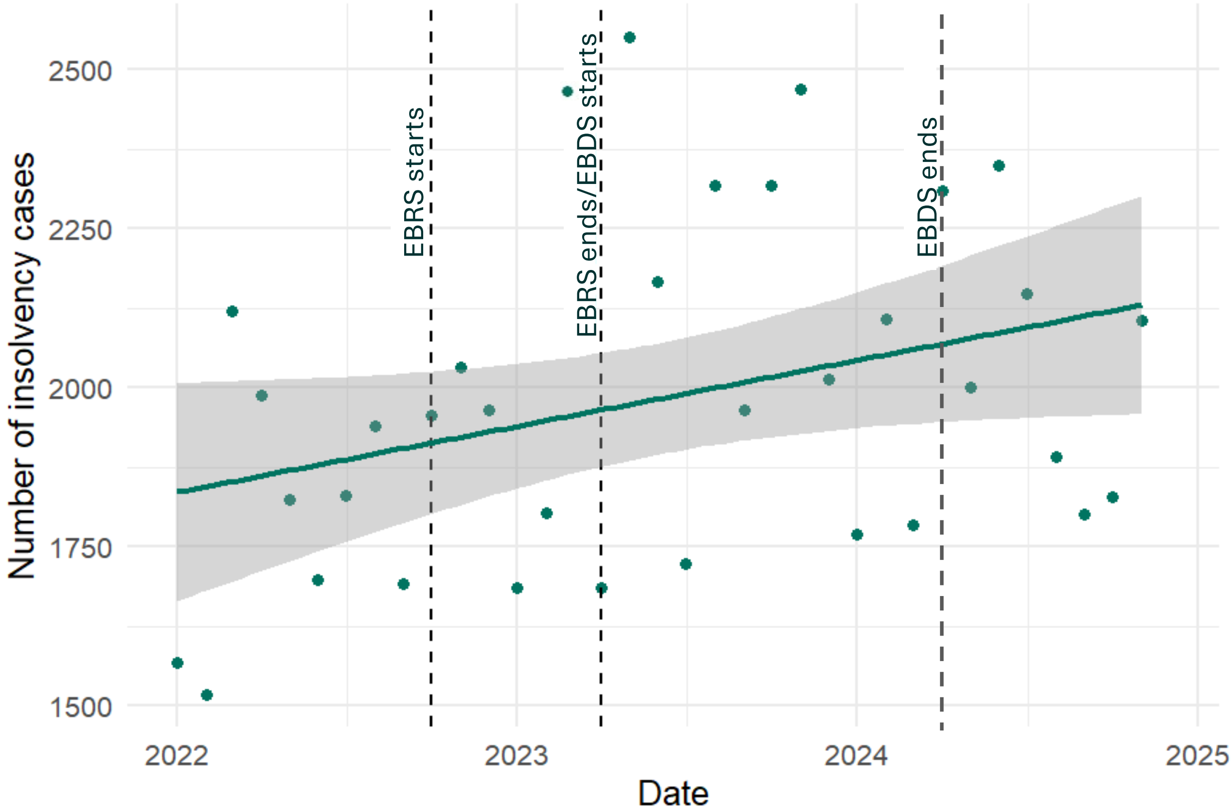
3.4.3 Observed impacts of mitigating energy price effects on financial health

In the latter half of 2022, financial performance across UK NDOs weakened, contrasted by initial improvements in early 2023. However, April 2023 saw a setback in this recovery, associated with rising energy costs (as indicated by survey data).[38] High energy prices in July 2022 could have contributed to a rising fitted trend in insolvencies (Figure 3.1515) and

[35] Small NDOs are categorised as those with 0-9 employees. Size of NDOs is also categorised based on turnover and energy consumption, but in these cases the criteria used will be made explicit. For further details on size definitions please refer to appendix 1 for a full overview of the rankings by different criteria.
[36] Ofgem (2019) *State of the Energy Market 2019 Report*. Available at: https://www.ofgem.gov.uk/sites/default/files/docs/2019/11/20191030_state_of_energy_market_revised.pdf
[37] Elasticity of demand measures the degree of responsiveness of quantity demand for a specific good or service to changes in price. The higher the elasticity the more the quantity changes with price.
[38] Office for National Statistics (ONS). (2024). Business Insights and Conditions Survey (BICS): Financial performance, workforce, prices, trade, and business resilience. https://www.ons.gov.uk/economy/economicoutputandproductivity/output/datasets/businessinsightsandimpactontheukeconomy & Bank of England, 2023. Decision Maker Panel (DMP) survey: November 2023 results. https://edu.bankofengland.co.uk/decision-maker-panel/2023/november-2023

redundancies. Business deaths surged by a quarter (24%) in the late 2022, while redundancies rose by a third (33%) in late 2022.

Figure 3.1515 Insolvencies in England and Wales (with fitted trend line)

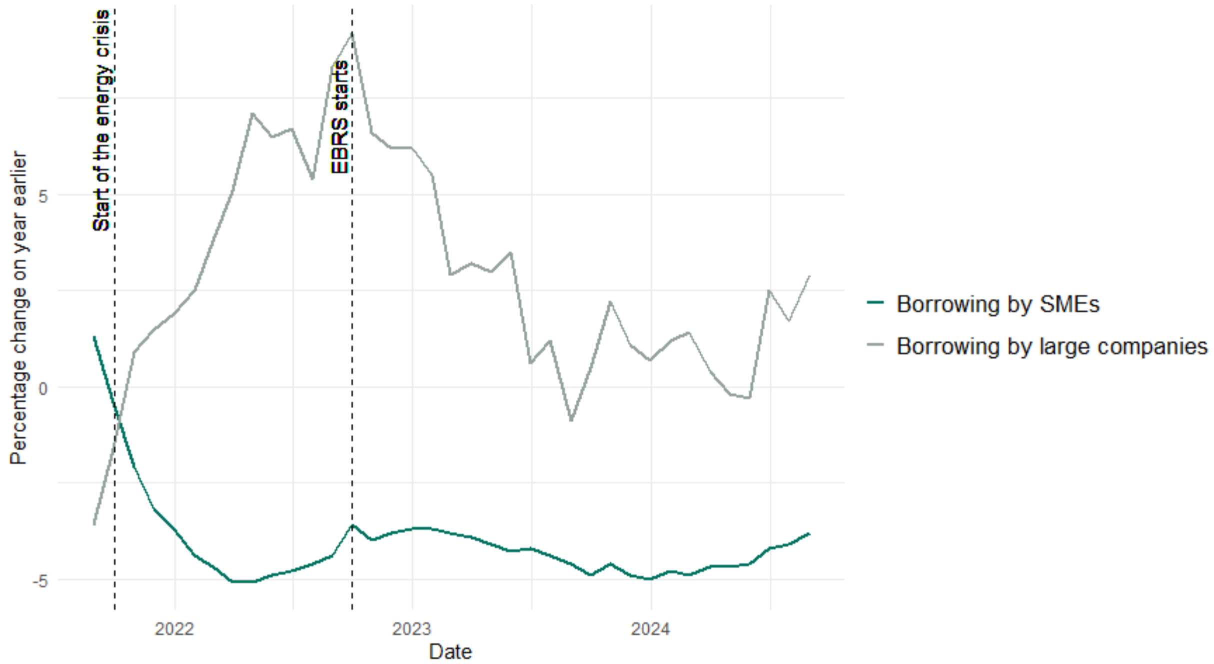


Source: UK Government official statistics (Monthly Insolvency Statistics, December 2024 - GOV.UK).
Note: The fitted line represents a linear fitting of the monthly insolvency levels. It aims to reduce the variance into a clear message, but should not be taken as the actual trend.

As energy prices increased, so did the borrowing needs of organisations, particularly those where energy expenses constituted a larger share of operating costs.

Following the introduction of the energy support schemes, borrowing patterns for large companies decreased substantially, as observed in Figure 3.1616. This finding suggests that the schemes may have eased large companies' need for increased borrowing caused by the energy crisis.

Figure 3.1616 Annual change in borrowing by company size



Source: Bank of England Database (Businesses' finance raised - a visual summary of data | Bank of England)

During the onset of the energy crisis, borrowing by large businesses exhibited an upward trend, whereas borrowing by small and medium-sized enterprises (SMEs) decreased. This divergence could be explained by the issues faced by smaller organisations in securing borrowing under crisis conditions, despite potentially greater need as they were more exposed to the energy crisis, leading to primarily larger organisations accessing additional funds. Following the implementation of EBRS, a decrease in borrowing was observed among large businesses, indicating a potential easing of the pressures that had necessitated increased borrowing during the earlier stages of the energy crisis.

This shift in concerns was most pronounced amongst large industries. However, there was no significant variations observed across different sectors. Following the introduction of the schemes, there was a notable deterioration in expectations regarding future performance over the next 12 months, especially during the EBRS period. This was particularly evident for high and medium energy-intensive sectors,[39] which could partly be explained by lack of awareness of the schemes, or belief that the support was not sufficient to address cost pressures. However, the subsequent implementation of the Energy Bill Discount Scheme (EBDS) coincided with an improvement in expectations.

3.4.4 Impact attribution for improved financial health

These analyses indicate that the schemes were associated with an improvement in financial health. However, as these methods are not quasi-experimental, these strands of analyses alone do not support a conclusion that the schemes directly caused the observed improvements. After the implementation of the schemes, decreases in employment that had occurred during the energy crisis slowed, and turnover improved. An econometric analysis of

[39] SIC 2007 categories ranked with high and medium energy-intensity within the analysis

meter-level data matched to IDBR data (presented in section 2 above) indicated that the schemes' discounts contributed to increases in turnover and employment (particularly for electricity discounts).

As shown in Table 3.3, sectors (by IDBR industry classification) with higher energy intensity experienced the largest improvements in turnover after the implementation of the schemes. The schemes (analysed in aggregate) appear to have contributed towards energy intensive sectors' growth of employment and turnover. This is the case for industries such as forestry, water transport, and mining of coal and lignite, which present some of the highest growth level of employment and turnover among the SIC4 sectors and are energy intensive industries. Some energy intensive industries, such as air transport, nonetheless present low levels of financial recovery. As shown in Table 3.4, less energy intensive sectors, such as publishing and legal services, presented limited improvements in financial health after the introduction of the schemes. It is important to note that the effects on financial health observed could also be caused by other factors such as sector-specific shocks or trends.

Table 3.3 4-digit SIC codes with the largest average turnover growth rate after IO modelling of the schemes

SIC4 code	Average growth rate of turnover
Accommodation	2.19%
Scientific research and development	1.68%
Forestry and logging	1.67%
Water transport	1.61%
Mining of coal and lignite	1.55%
Office administrative, office support and other business support activities	1.52%
Activities of households as employers of domestic personnel	1.47%
Remediation activities and other waste management services.	1.46%
Libraries, archives, museums and other cultural activities	1.45%
Sports activities and amusement and recreation activities	1.44%

Table 3.4 SIC4 codes with lowest turnover average growth rate after 10 modelling of the schemes

SIC4 code	Average growth rate of turnover
Air transport	0.66%
Insurance, reinsurance and pension funding, except compulsory social security	0.75%
Publishing activities	0.87%
Manufacture of beverages	0.94%
Travel agency, tour operator and other related activities	0.96%

SIC4 code	Average growth rate of turnover
Activities auxiliary to financial services and insurance activities	0.96%
Land transport and transport via pipelines	0.99%
Legal and accounting activities	1.00%
Gambling and betting activities	1.00%
Computer programming, consultancy and related activities	1.01%

These findings are generally consistent with the fact that NDOs that experienced worsening financial health during the EBRS period because of high energy prices would receive higher EBDS support, indicating effective targeting of support for more exposed NDOs. Higher EBDS support was in turn associated with stronger turnover growth after the implementation of EBDS.[40] While this analysis does not in and of itself establish a causal link between the schemes' support and NDOs' financial health, these findings are consistent with and reinforce the association between the schemes and improvements in financial health.

3.5 Employment

3.5.1 Summary of findings

Rising energy prices, such as those observed in mid-2022, can present significant financial strain on a company's bottom line. As a response to the rising production costs, NDOs will seek for ways to reduce costs. As labour costs are among the largest components of total production costs, employment was expected to decrease during the energy crisis.

The analysis of the schemes' impact on employment relies on descriptive statistics from analysis of UK employment data and IO modelling. The former reveals that during previous crisis periods, such as the financial crisis and the COVID-19 pandemic, employment declined markedly. When the energy crisis started, employment levels had not fully recovered to pre-COVID-19 levels. However, despite rising energy prices, employment continued to grow until just before the introduction of the schemes, when the effects of the energy crisis started to materialise. After this point, employment decreased until mid-2024, when it began to increase slightly. This analysis of UK employment data does not provide conclusive evidence on the impacts of the schemes on employment, and from this it is unknown whether the schemes had no effect, a negative effect, a lagged positive effect, or cushioned a larger negative effect.

However, IO modelling indicates that the schemes supported employment that would have been lost but for the price support offered under these programs. This conclusion is based on the relationship between input costs and economic activity, including overall economic output and employment. While the energy crisis would have led to employment reductions of up to 213,000 full time equivalent employment (FTEs), this loss was substantially offset by the

[40] Firm-level data indicate that NDOs that received larger total lump-sum of support from the EBDS showed a larger recovery in turnover compared to NDOs that received lower levels of support. This trend does not, however, hold for employment.

schemes, which supported up to 132,000 FTEs. Further details on these calculations are provided below.

3.5.2 Theory of expected impacts of mitigating energy price effects on employment

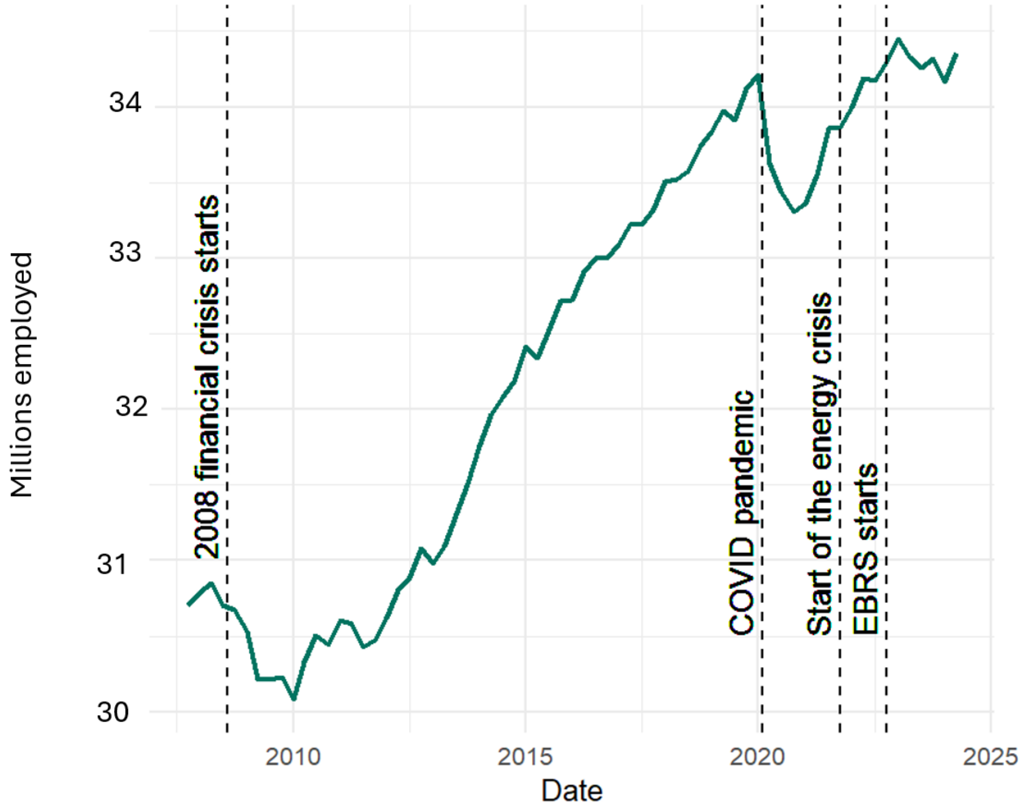
The theory of expected impacts of mitigating energy price effects on employment is consistent with the theory of impacts on overall financial health, as explained in the previous section. Thus, it can be expected that the schemes helped NDOs avoid substantial short-term reductions in employment due to higher energy prices. Additionally, NDOs will not hire new employees until they have confidence in the medium- and long-term growth of their business; therefore, to the extent that the schemes improved this confidence, they may have had a positive effect on employment.

To better understand the changes in employment patterns, the remainder of this section investigates changes over time, as well as employment by sector. The market distortions section provides information on the different types of employment, as well as a decomposition of employment figures to trend, seasonal and residual component. Overall, the expectation was that the period preceding the announcement and launch start of EBRS would be characterised by a slowdown in the growth of employment, due to uncertainty about the impact of rising energy costs on financial health.

3.5.3 Observed impacts of mitigating energy price effects on employment

Examining the changes in employment in the UK over recent decades (as shown in Figure 3.17) reveals several structural breaks that contextualise the impact of the energy crisis and the subsequent energy support schemes. Employment declined during the 2008 financial crisis and the COVID-19 pandemic, disrupting an overall trend towards employment increasing. Following the pandemic, employment levels had not fully recovered to pre-COVID-19 levels when the energy crisis began. However, despite rising energy prices, employment continued to grow until almost mid-2024. While it is not possible to definitively assess the impact of the support schemes on employment in isolation due to the overlapping impacts of the COVID-19 recovery, it is possible that the schemes helped mitigate a potential decline or a slowdown in employment recovery, with a lagged effect. The lag may be explained by the fact that NDOs do not hire new employees when they lack medium- and long-term business confidence and compounded by recruitment processes themselves taking time. The schemes could have increased business confidence by providing more predictable energy prices.

Figure 3.17 A long term overview of employment trends in the UK

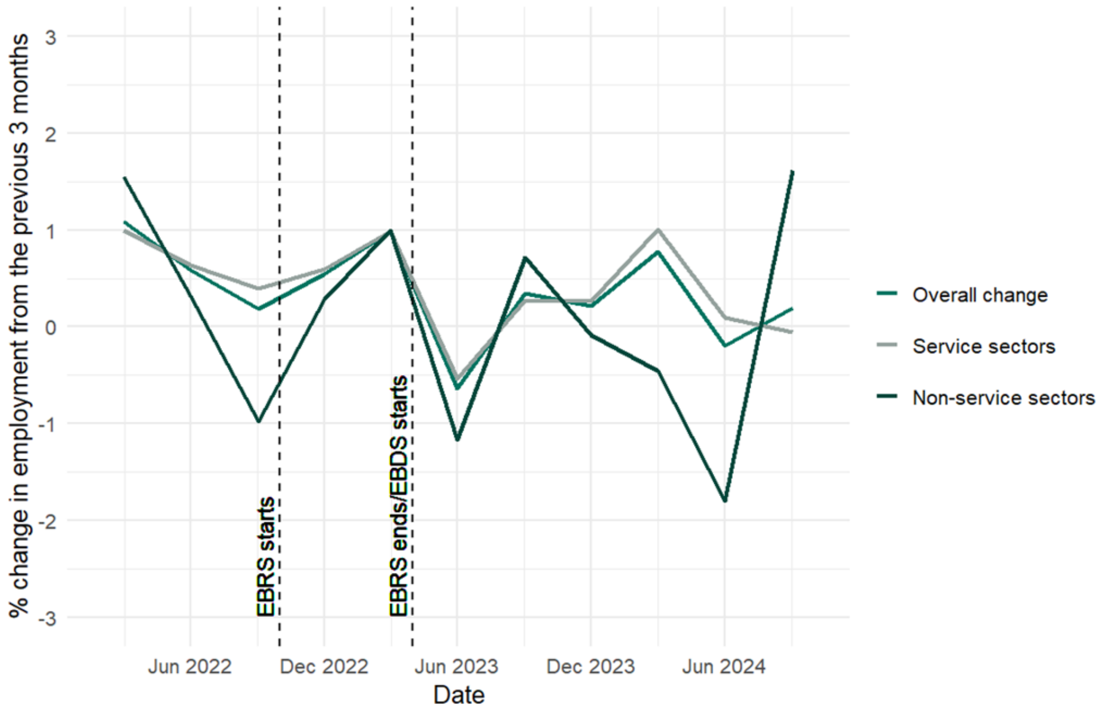


Source: ONS, JOBS02: Workforce jobs by industry (JOBS02: Workforce jobs by industry - Office for National Statistics (ons.gov.uk))

The quarterly employment changes presented in Figure 3.18 align with the long-term trends observed in Figure 3.17, but provide a breakdown of employment by service sector (i.e. sectors G – T) and non-service sector (i.e. sectors A – F).[41] Employment growth slowed around mid-2022, with the growth rate of non-service sectors turning negative by the time the EBRS was announced – however, overall employment continued to rise. Following the introduction of the schemes, employment across all major sectors increased again, reaching pre-crisis growth rates by the beginning of 2023. After the launch of the EBDS, employment declined across both service and non-service sectors before rebounding in late 2023.

[41] For more information on the sectoral breakdown of the NDOs, please see appendix 1.

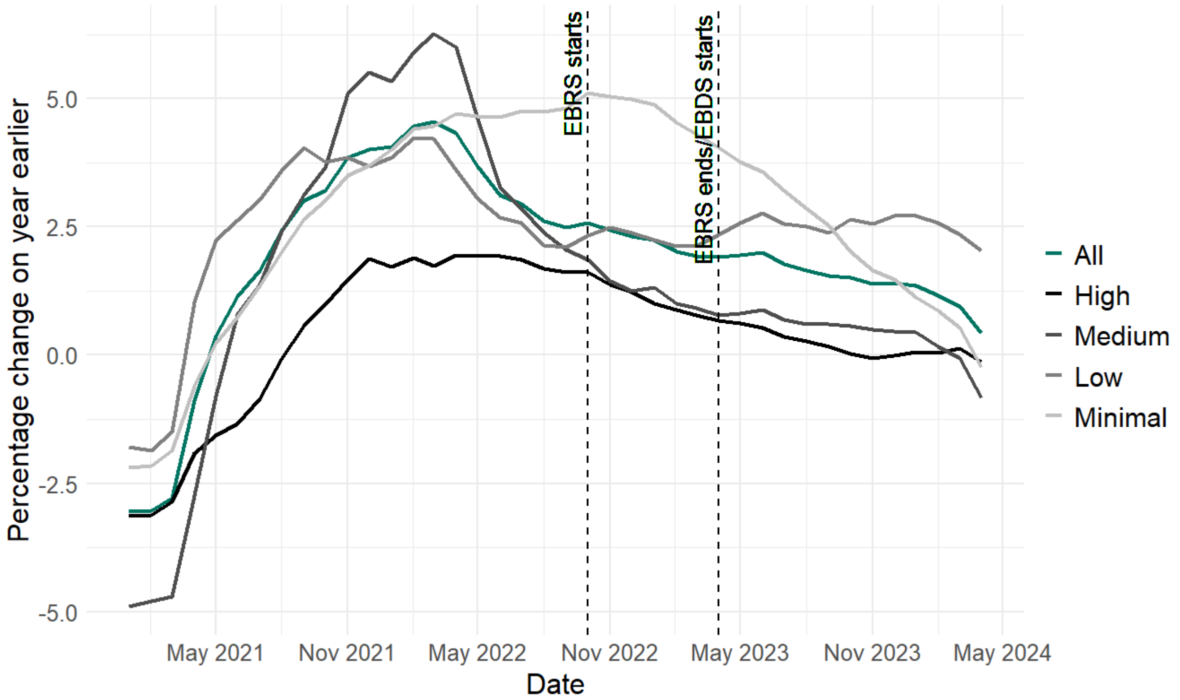
Figure 3.18 Change in employment around the launch of the schemes by sector



Source: Employer surveys, Labour Force Survey and administrative sources
Note: Non-service sectors include sectors A – F, service sectors include sectors G – T (see appendix 1 for more information)

Figure 3.19 presents the growth in employment by business' energy intensity. At the end of 2021, employment growth in high and medium energy-intensive industries initially stagnated and then began to decline, with both remaining below the average growth rate from the second half of 2022 onwards. Despite the introduction of the schemes in October 2022 and March 2023, this downward trend persisted, with the growth rate approaching zero – indicating that employment levels had stabilised – by the end of 2023. The observed improvements in financial health and IO modelling results suggest it is possible that the schemes cushioned a more severe drop. Employment maintained a non-negative growth rate through the end of 2023.

Figure 3.19 Percentage annual growth in employment by the energy intensity of businesses



Source: ONS Labour Market team, HMRC RTI Statistics: Earnings and employment from Pay as You Earn Real Time Information, seasonally adjusted. Note: For more details on the energy intensity rating please refer to the appendix 1.

3.5.4 Impact attribution for employment

IO modelling provides sectoral estimates of the impact of the energy crisis and the schemes on employment. An unmitigated energy crisis (i.e., without the support schemes) was estimated to result in a decrease of up to 213,000 FTEs; the schemes supported up to 132,000 jobs. IO modelling estimates that the schemes prevented over half of the expected impacts of the crisis on employment.

The total impact on employment can be disaggregated by impact category. The direct impact (i.e., the first order impacts of the shock) of the energy crisis was a loss of up to 69,000 FTEs; the direct impact of the schemes was supporting up to 60,000 FTEs. The indirect impacts (which account for how the direct impacts propagate through the economy's supply chains) show that out of a loss of up to 96,000 jobs due to the energy crisis, the schemes supported up to 43,000. The induced impacts, accounting for the impacts on household spending resulting from income adjustments in impacted sectors) estimate that of a loss of up to 48,000 jobs due to the energy crisis, the schemes supported up to 29,000.

Table 3.5 Net impacts of the energy and discount shocks on employment

Impact	Energy shock (000s FTE)	Discount shock (000s FTE)	Net shock (000s FTE)
Direct impacts	-69	60	-9
Indirect impacts	-96	43	-53
Induced impacts	-48	29	-19
Combined impacts	-213	132	-81

Source: IO modelling of UK IO table in 2019

Table 3.6 presents the impacts of the energy crisis and support by scheme. Up to 132,000 FTE jobs supported by the schemes, of which 125,000 were supported by EBRS, and 7,000 by EBDS. EBRS prevented 67% of the impact to employment that would have occurred but for the schemes, while EBDS prevented 27%.[42]

Table 3.6 Net impacts of the energy and discount shocks on employment by scheme

Impact	EBRS Energy shock (000s FTE)	EBRS Discount shock (000s FTE)	EBRS Net shock (000s FTE)	EBDS Energy shock (000s FTE)	EBDS Discount shock (000s FTE)	EBDS Net shock (000s FTE)
Direct impacts	-60	57	-3	-9	3	-6
Indirect impacts	-85	41	-44	-11	2	-9
Induced impacts	-42	27	-15	-6	2	-4
Combined impacts	-188	125	-63	-26	7	-19

Source: IO modelling of UK IO table in 2019

As shown in Table 3.7, high-energy intensity sectors such as manufacture of electricity and gas, retail trade, and construction are amongst the most affected sectors.

Table 3.7 Sectors most affected by the energy crisis in terms of employment

Sector most affected by the energy crisis	Energy shock impact on employment (000s FTE)	% of total impacts in the economy
Electric power generation, transmissions and distribution	-27.8	13%
Retail Trade	-16.6	8%
Construction	-11.0	5%
Food and Beverage Service	-10.3	5%
Manufacture of gas	-8.6	4%

Source: IO modelling of UK IO table in 2019

[42] EBRS: 125÷188=67%. EBDS: 7÷26=27%.

Table 3.8 presents the sectors with the highest level of employment supported by the schemes. The schemes' impact on employment was greatest in many of the same sectors that were most affected by the energy crisis, as shown in Table 3.7 above. While the energy crisis primarily impacted energy-intensive sectors, the discount was largely advantageous for those sectors that are also trade-exposed. Additionally, sectors with very low profit margins and high competition, such as education were significantly impacted. This can potentially be attributed to their relatively higher difficulties in passing additional costs onto consumers.

Table 3.8 Sectors most affected by the schemes in terms of employment

Sector	Employment loss prevented by the schemes (000s FTE)	% of total impacts on the economy
Retail Trade	8.6	7%
Education	7.1	5%
Real estate	6.6	5%
Food and Beverage Service	5.5	4%
Land transport services and transport services via pipelines, excluding rail transport	5.2	4%
Construction	4.9	4%

Source: IO modelling of UK IO table in 2019

3.6 Productivity

3.6.1 Summary of findings

An energy crisis can significantly hamper productivity across industries through various channels including reduced output, higher production costs, supply chain disruptions, resource reallocation, inhibited innovation and investment, and broader macroeconomic effects such as inflation and reduced consumer spending. For this analysis, productivity is defined as Gross Value Added (GVA) per job.[43] The energy crisis and associated schemes were expected to impact both GVA and the number of jobs.

[43] Productivity is commonly measured in two ways: as labour productivity and total factor productivity (TFP). Labour productivity is defined as the output per labour hour or per worker, focusing solely on the efficiency of labour input. This measure is straightforward to quantify using public data such as total output and labour hours from national statistics, but it may not account for changes in other inputs like energy costs, which can distort the picture during an energy crisis. Total factor productivity, on the other hand, measures the output per all-inclusive unit of input (including labour, capital, materials, and energy), attempting to account for the efficiency of all resources in production. Quantifying TFP is more complex due to the difficulty in accurately measuring inputs such as capital and energy, especially with fluctuating prices during an energy crisis. Observing labour productivity can highlight how effectively labour is being used independently of other factors, useful for assessing immediate labour efficiency. In contrast, TFP can provide insights into the overall operational efficiency and technological progress, which is particularly beneficial during an energy crisis to understand how energy cost fluctuations impact the entire production process. It could be beneficial for future evaluations to expand the scope of the productivity analysis to observe changes in TFP, thereby capturing possible technology-side impacts as a result of production factor reallocation.

Productivity levels are evaluated by assessing employment and gross value added (GVA). The data is first adjusted for inflation. despite a sharp increase in nominal productivity after the COVID-19 pandemic, inflation-adjusted figures show that productivity declined since the onset of the energy crisis. Unlike previous crises where productivity eventually stabilised, the energy crisis led to continued decreases in productivity despite stable employment. There was a lagged improvement in productivity after the introduction of the schemes, which only started to materialise after the introduction of the EBDS.

Although the IO modelling provides insights into changes in output and employment by sector, it assumes constant productivity. Therefore, the impact of schemes on productivity is not considered.

3.6.2 Theory of expected impacts of mitigating energy price effects on productivity

The support schemes would be expected to have a positive impact on output, reduce the share of energy inputs in total costs, reduce cost variability and enable better budgeting and financial planning, and reduce the default rate of NDOs (i.e. the proportion of NDOs failing to meet their financial obligations). Similarly, the schemes would be expected to have a positive impact on employment as fewer NDOs would become insolvent.

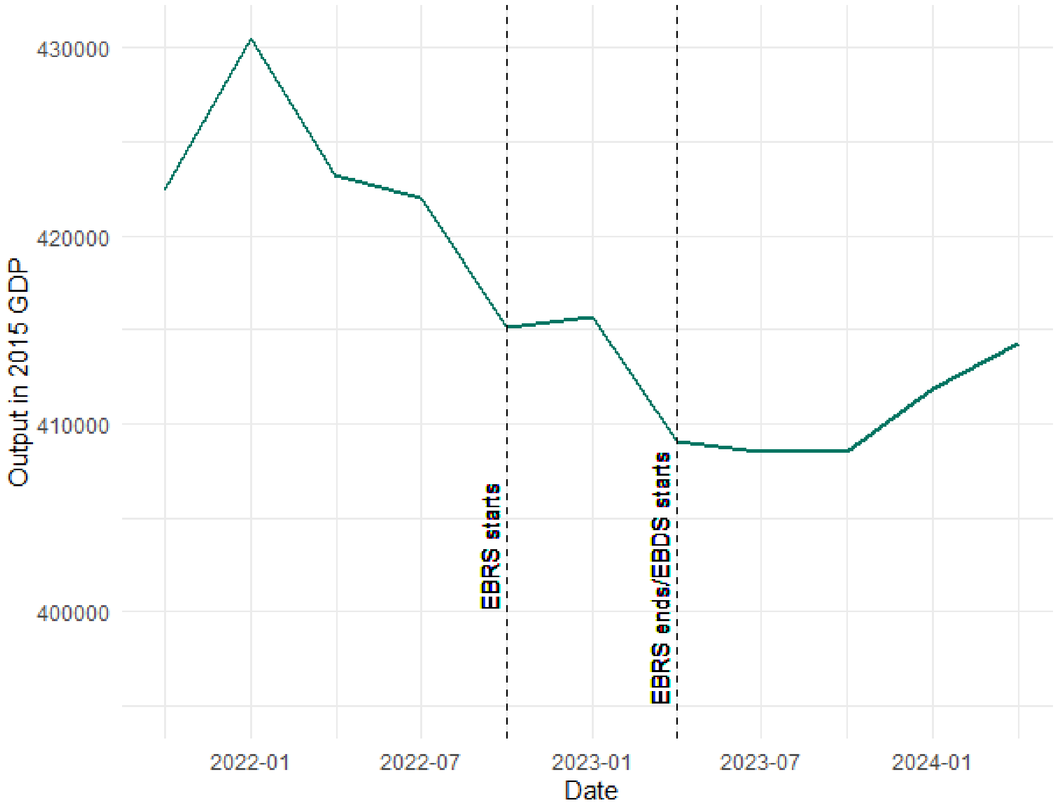
To estimate the schemes' impact on productivity, the schemes' impact on GVA and employment must be estimated in isolation. Generally, output reacts to different economic shocks more quickly than employment. This means that NDOs reduce their margins, increase their output prices, and potentially reduce their production before any redundancies are made. Employment is also slower to rebound after an economic crisis, as NDOs do not hire new employees until they have confidence in the medium- and long-term growth of their business. As a result, it is expected that the energy crisis decreased productivity in the short-term, as GVA would decrease first, and employment would decrease more gradually afterwards. The support schemes were expected to have a positive impact on productivity, as their positive effect on GVA would be realised more quickly than their effect on employment.

The schemes may also have a long-term impact on productivity through energy efficiency. While some self-reported survey data was collected as part of the primary evaluation research, it is more difficult to capture information on energy efficiency through other quantitative means and publicly available data. When an energy crisis occurs, organisations face two opposing forces with respect their behaviour towards energy efficiency improvements. Organisations are expected to face high-cost pressures from the increase in energy prices, which will incentivise energy efficiency improvements and decreased energy consumption. However, the increase in cost pressures is also expected to act as a barrier to increasing investment in energy efficiency. As a result, the disbursement of the schemes, which is expected to alleviate cost pressures, could both reduce incentives to improve energy efficiency and reduce barriers for investment in energy efficiency.

3.6.3 Observed impacts of mitigating energy price effects on productivity

As this report defines productivity as GVA per job, the impact of the energy crisis and the schemes on productivity is estimated by examining changes in both GVA and employment. Figure 3.20 below shows the deflated GVA values from the end of 2021 to the beginning of 2024. As this analysis covers periods with very different macroeconomic environments, controlling for inflation is a necessary step. GVA had been decreasing from the beginning of 2022 and continued to decrease after the introduction of the EBRS. However, by the time the EBDS is implemented, this decreasing trend stabilised, until starting to increase in late 2023. This trend suggests that the schemes were associated with a positive, yet lagged effect on GVA. The lag may be explained by the fact that retail energy prices began to rise several months after wholesale prices increased – when fixed-price contracts were renewed – and the subsequent moderation in wholesale prices took time to appear in NDOs' energy bills. As energy is a key input for many NDOs, high retail energy prices reduced their value added, particularly in energy-intensive industries and when NDOs could not fully pass on higher energy costs to consumers (a constraint exacerbated in a high-inflation environment). The lagged behaviour may also reflect other factors, such as the moderation of inflation in 2023, the reduction in wholesale energy prices, and the improving macroeconomic conditions.

Figure 3.20 Timeline of Gross Value Added



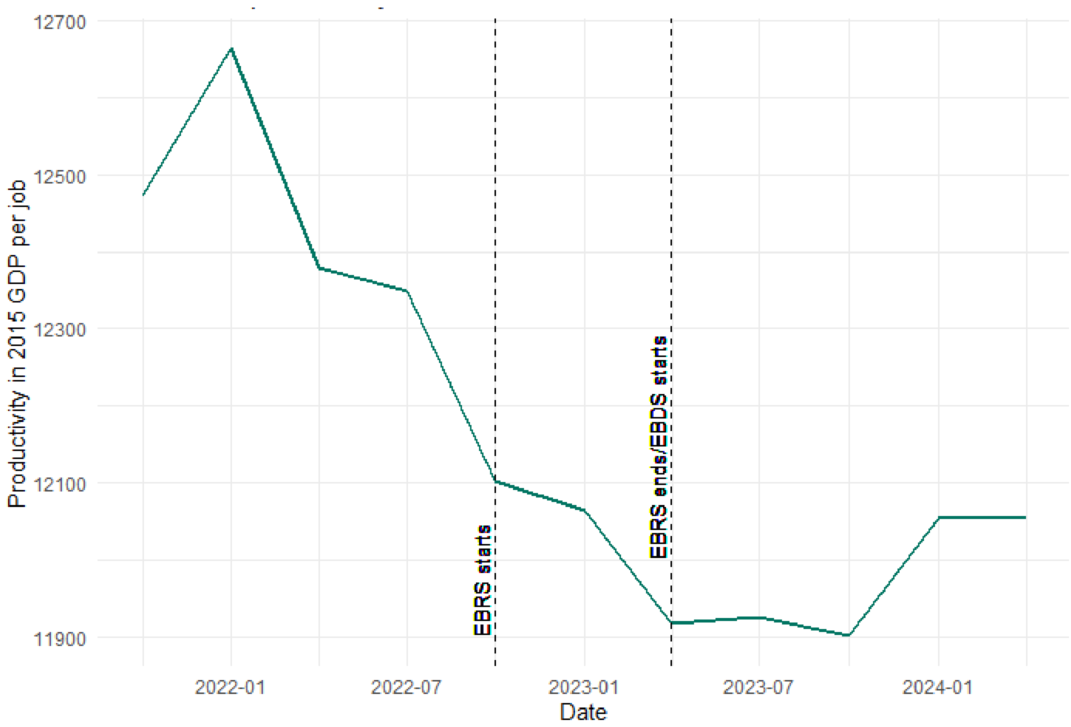
Source: Calculation based on ONS, GDP output approach – low-level aggregates (GDP output approach – low-level aggregates - Office for National Statistics (ons.gov.uk))

Labour productivity, as calculated by the ONS, shows a sharp increase since the COVID-19 crisis. However, reporting labour productivity (i.e. output per job) in current prices does not account for inflation and therefore cannot reflect real changes in the economy.[44] To address

[44] Output per job, UK - Office for National Statistics (ons.gov.uk)

this, labour productivity was recalculated with the deflated GVA results, as shown in Figure 3.21. Unlike the 2008 crisis and COVID-19 pandemic[45] – where productivity declined but showed signs of stabilisation and recovery soon after– the energy crisis led to a continued decline in productivity, even as employment remained stable. This could be caused by the combination of several macroeconomic trends. First, employment did not decrease after the energy crisis began (unlike in 2008 or 2020 – see Figure 3.17 in the 3.5 Employment section). Second, inflation was higher after the energy crisis than in previous periods (see Figure 3.3 in the 3.1 Inflation section) and therefore it reduced nominal output more. Third, high energy prices could have affected energy-intensive sectors more severely, and many of these sectors have higher-than-average productivity. Productivity only stabilised and began to increase starting in late 2023, after the introduction of the EBDS. Around this same time, GVA (in real terms) began to rise, while employment growth plateaued. As productivity is defined as GVA per job, these dynamics led to an improvement in productivity. This trend may suggest that the schemes could have had a positive, yet lagged, effect on productivity; however, this cannot be attributed to the scheme as an impact.

Figure 3.21 Timeline of productivity (deflated using 2015 prices)



Source: Calculation based on ONS, Output per job, UK (Output per job, UK - Office for National Statistics (ons.gov.uk))

3.6.4 Impact attribution for productivity

The effects on productivity described earlier in this chapter cannot be attributed to the schemes, due to the assumptions made in IO modelling.[46] However, it can provide indicative estimates of the size of any potential effects. As described in section 2, the IO analysis

[45] The economic recover after the COVID-19 pandemic may differ slightly from other crises, as the end of the pandemic triggered a particularly high demand for goods and services.
[46] IO modelling assumes constant productivity, and therefore cannot be used to measure the size of any effect on productivity as the result of an intervention.

estimated that the energy crisis resulted in a decrease in Gross Value Added (GVA) of £16.3 billion. The schemes mitigated this shock by avoiding a £8.1 billion loss in GVA, representing 50% of the overall shock. The net impact on GVA when considering both the impacts of the energy crisis and the schemes was a total reduction of £8.2 billion.

As shown in Table 3.9, of the £8.1 billion loss in GVA prevented by the schemes, £7.9 billion was attributed to EBRS, and £0.3 billion to EBDS. This is consistent with the fact that the support distributed under EBRS was much larger in magnitude than under EBDS. EBRS was able to cover 55% of the energy crisis shock, while EBDS covered 15%. As with employment, this implies EBRS was both larger in magnitude and in relative terms.

Table 3.9 Net impacts of the Energy and Discount shocks on GVA by scheme

Impact	EBRS Energy shock (£ billion)	EBRS Discount shock (£ billion)	EBRS Net shock (£ billion)	EBDS Energy shock (£ billion)	EBDS Discount shock (£ billion)	EBDS Net shock (£ billion)
Direct impacts	-4.8	3.4	-1.4	-0.7	0.1	-0.6
Indirect impacts	-11.5	5.9	-5.6	-1.6	0.2	-1.4
Induced impacts	-14.4	7.9	-6.5	-2.0	0.3	-1.7

Source: IO modelling of UK IO table in 2019

Appendices

Appendix 1: Definitions

In this section, the definitions used within the macroeconomic analysis are provided, including approaches for categorising Non-Domestic Organisation (NDO) size; the different types of NDOs; and the definition of an energy-intensive NDO.

1.1 NDO size

NDOs were classified by size based on one of three different variables: (1) the number of employees; (2) turnover; and (3) electricity and gas consumption. Which variable was used was subject to data availability.

NDOs were ranked by size based on the number of employees following the categorisation presented in Table A.1. This ranking was used as the default throughout the analysis, unless explicitly mentioned rankings were based on another methodology. The threshold selection is consistent with the IDBR data.[47]

Table A.1 NDO size ranking by number of employees

No. of employees	Rank	% of total NDOs
0-4	Very Small	77.6%
5-9	Small	11.5%
10-19	Medium	5.8%
20-49	Medium	3.2%
50-99	Medium	1.0%
100-249	Large	0.6%
250+	Large	0.4%

47 UK business; activity, size and location Statistical bulletins - Office for National Statistics. (n.d.). https://www.ons.gov.uk/businessindustryandtrade/business/activitysizeandlocation/bulletins/ukbusinessactivitysizeandlocation/previousReleases?_gl=1*1j31el4*_ga*OTE2MjAyNzk1LjE2OTg2NTY2MjY.*_ga_W804VY6YKS*MTcxNjQ3NzY1MS43MC4wLjE3MTY0Nzc2NTEuNjAuMC4w

NDOs were ranked by size based on turnover using specific threshold ranges from the IDBR data. Table A.2 below presents these turnover rankings.

Table A.2 NDO size ranking by turnover

Turnover in £000's	Rank	% of total NDOs
0-49	Small	16.3%
50-99	Small	20.7%
100-249	Small	31.1%
250-499	Medium	13.5%
500-999	Medium	8.1%
1,000-1,999	Medium	4.5%
2,000-4,999	Large	3.1%
5,000-9,999	Large	1.2%
10,000-49,999	Very large	1.1%
50,000+	Very large	0.3%

NDOs were ranked based on their electricity and gas consumption using thresholds from DESNZ energy price data. The threshold values and their assigned rankings are shown in Table A.3 and Table A.4 below.

Table A.3 NDO size ranking by electricity consumption

Annual electricity consumption (MWh)	Rank
0-20	Very Small
20-499	Small
500-1,999	Small / Medium
2,000-19,999	Medium
20,000-69,999	Large
70,000-150,000	Very Large
150,000+	Extra Large

Table A.4 NDO size ranking by gas consumption

Annual gas consumption (MWh)	Rank
0-278	Very Small
278-2,777	Small
2,778-27,777	Medium
27,778-277,777	Large
277,778-1,111,112	Very Large

1.2 NDO type

This section provides information on the categorisation of NDOs into three types: public, private, and voluntary.[48] IDBR microdata was used to analyse turnover and employment, as this dataset provides a breakdown by NDO type, a level of detail not available in other datasets that typically report at the industry level. To overcome this limitation, impacts on NDO types were approximated based on SIC 2007 codes.

Public NDOs were classified as organisations which operate in the public sector and which deliver services for the benefit of society. They are owned, operated, and financed by government, using money raised from taxes and other sources.

The majority of public NDOs belong to the following SIC 2007 categories:

- O: Public Administration and Defence; Compulsory Social Security – Exclusively public functions.
- P: Education – Includes public schools and universities.
- Q: Human Health and Social Work Activities – Public hospitals and social welfare

Private sector NDOs were classified as organisations which operate in the private sector and are hence held under private ownership. The majority of private sector NDOs belong to the following SIC 2007 categories:

- B: Mining and Quarrying
- C: Manufacturing
- D: Electricity, Gas, Steam, and Air Conditioning Supply
- E: Water Supply; Sewerage, Waste Management, and Remediation Activities
- F: Construction – Largely private sector.
- G: Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles

[48] This terminology is consistently used throughout this annex and the main report, except when data from IDBR or primary (survey) data is directly employed.

- H: Transportation and Storage
- I: Accommodation and Food Service Activities
- J: Information and Communication
- K: Financial and Insurance Activities
- L: Real Estate Activities
- M: Professional, Scientific and Technical Activities
- N: Administrative and Support Service Activities
- R: Arts, Entertainment and Recreation
- S: Other Service Activities

Voluntary NDOs were defined as entities that operate primarily for the benefit of society rather than for profit. These organisations are characterised by their non-profit nature, meaning they do not distribute their surplus funds to owners or shareholders, but instead use these funds to help achieve their goals, which are often related to social, charitable, cultural, educational, or community-oriented objectives. A large amount of voluntary NDOs belong to the following SIC 2007 categories:

- P: Education
- Q: Human Health and Social Work Activities
- R: Arts, Entertainment and Recreation
- S: Other Service Activities
- T: Activities of Households as Employers; Undifferentiated Goods- and Services-Producing Activities of Households for Own Use

1.3 Energy intensive NDOs

To identify which NDOs can be qualified as energy intensive, the following analysis was performed.

- Energy use was summed across each SIC 2007 category, based on the ONS energy use data.[49]
- Total output at constant prices was summed for each SIC 2007 category from the 2019 UK input-output table.[50]
- Sector-specific energy intensity ratios were calculated by dividing energy use by total output (for ease of visual review, this figure was then multiplied by 10,000).

The SIC 2007 categories with the energy intensity ratios were classified as energy intensive using quantile distributions. The results are shown in Table A.5 below. The rankings presented

[49] Data available here: Energy use: by industry, source and fuel - Office for National Statistics (ons.gov.uk)
[50] Data available here: UK input-output analytical tables, product by product - Office for National Statistics (ons.gov.uk)

below do not match the classification of ETIIs used as part of the EBDS scheme, which used ONS data to calculate energy intensity, and additionally considered trade intensity using ONS goods trade data.[51]

Table A.5 SIC 2007 categories classification based on the calculated energy intensity

SIC 2007 Category	Definition	Energy intensity ratio	Energy intensity ranking
A	Agriculture, forestry and fishing	0.656	High
B	Mining and quarrying	1.588	High
C	Manufacturing	0.444	High
D	Electricity, gas, steam and air conditioning supply	1.991	High
E	Water supply, sewerage, waste management and remediation activities	0.136	Medium
F	Construction	0.095	Medium
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	0.115	Medium
H	Transport and storage	1.611	High
I	Accommodation and food service activities	0.103	Medium
J	Information and communication	0.010	Minimal
K	Financial and insurance activities	0.003	Minimal
L	Real Estate Activities	0.010	Minimal
M	Professional, scientific and technical activities	0.021	Minimal
N	Administrative and support service activities	0.055	Low
O	Public administration and defence, compulsory social security	0.100	Medium
P	Education	0.070	Low
Q	Human health and social work activities	0.080	Low
R	Arts, entertainment and recreation	0.063	Low

[51] ETIIs were classified as sectors above the 80th percentile for energy intensity and the 60th percentile for trade intensity across Great Britain and Northern Ireland. Energy intensity was based on electricity and gas consumption as a % of a sector’s GVA using Office for National Statistics (ONS) data. Trade intensity was based on goods trade using ONS data.

SIC 2007 Category	Definition	Energy intensity ratio	Energy intensity ranking
S	Other service activities	0.080	Low
T	Activities of households as employers, undifferentiated goods and services producing activities for households' own use	0.051	Minimal

Using the energy intensity classifications in Table A.5, the distribution of energy intensity across NDOs of different types is presented in Table A.6. Private sector NDOs have the largest proportion of organisations in SIC 2007 categories ranked with high and medium energy intensity (44%), while public and voluntary NDOs have relatively few organisations in the top two energy intensity categories (1% and 11%, respectively).

Table A.6 Percentage of organisations in each energy intensity classification as a proportion of different NDO types

Energy intensity classification	Public	Private	Voluntary	Total
High	1%	9%	2%	14%
Medium	0%	35%	9%	29%
Low	98%	32%	66%	33%
Minimal	1%	24%	23%	24%

Note: This table will be updated once the IDBR data is received by Cambridge Econometrics, to reflect the observed NDO population.

Appendix 2: Input-Output modelling

1.4 Purpose of IO modelling

In order to understand the economy-wide impacts of the energy crisis and the schemes, an Input-Output (IO) modelling analysis was performed. This method leverages 2019 UK IO tables, which provide a snapshot of the economy's structure at a given time to simulate external shocks to the economy.[52] Specifically, IO tables map economic transactions across sectors through a matrix that shows how industries interact with one another through supply and demand.

In an IO table, each column reflects the demand of a particular industry for other industries' products, while each row reflects an industry's supply of goods and services to multiple industries. This dual perspective captures the interconnections between sectors, known as "intermediate demand." These connections enable analyses of how changes in one sector can ripple across other sectors. When aggregating the sum of the rows and columns, economy-wide statistics can be calculated such as total output, and gross value added (GVA). Employment impacts were further calculated using 2019 UK employment data in full-time equivalents (FTE). By combining output and GVA data from the IO model with employment figures, productivity – defined as GVA per employment – can be estimated using historic data on output, GVA, and employment. Assuming productivity remains constant during the shock, the resulting impacts on employment can be calculated. IO modelling is hence commonly used to estimate how an economic "shock" – such as the introduction of an energy support scheme – affects the broader economy in terms of output, employment, and GVA. These impacts are measured both in aggregate terms, to provide insights into how the overall economy is impacted, and at the sector level, to help identify the most affected sectors. Impacts are further broken down into direct, indirect, and induced: direct impacts reflect the immediate consequences on sectors; indirect impacts capture the second degree effects on related industries that supply or demand inputs to the affected sectors; and induced impacts account for the changes in household spending resulting from income adjustments in impacted sectors. This layered view allows IO modelling to reveal not only the primary consequences of a shock but also the wider interdependencies across the economy.

There are some limitations to IO modelling that affect its ability to accurately reflect complex economic changes. One primary limitation is that IO models are inherently static; they provide only a single snapshot of the economy based on historical data, without accounting for how relationships between sectors might evolve. This static nature limits the ability of IO models to predict the dynamic adjustments that industries or consumers might make in response to shocks or policy changes. Furthermore, IO models typically do not account for price changes or capacity constraints, as they assume constant returns to scale and fixed prices. Although there are ways to adjust for price fluctuations, modelling policy changes or shocks with significant price changes necessitates making several analytic assumptions. Finally, IO models

[52] 2019 UK IO tables are available at *UK input-output analytical tables, industry by industry: 2019—Office for National Statistics*. Retrieved from https://www.ons.gov.uk/releases/ukinputoutputanalyticaltablesindustrybyindustry2019

do not consider relations with other countries, and as a result, may fail to capture spillover effects across national borders.

To explore the impacts of the schemes, an IO analysis of two different scenarios was conducted. In the first scenario, only the energy crisis shock was introduced, which allowed to see the impacts of higher electricity and gas prices on output, employment, and GVA across sectors. The Input-Output (IO) model takes sector-specific output changes as input for a shock. Therefore, changes in energy prices had to be translated into a negative output shock for each sector of the UK economy. The literature provides estimates of energy price demand elasticities for broad sectors in the UK economy.[53] Energy price demand elasticity measures the responsiveness of the quantity of energy demanded to changes in its price. Specifically, it is defined as the percentage change in the quantity of energy demanded resulting from a one percent increase in the price of energy, while holding other factors constant. Consequently, the increase in energy prices can be translated into a decrease in intermediate demand for energy in each sector. Using the energy intensity of each sector, the reduced intermediate energy demand is converted into a negative output shock. This shock is then input into the IO model, allowing the impacts on the overall UK economy to be tracked in terms of output, Gross Value Added (GVA), and employment. The second scenario represented the introduction of the schemes, which provided insights into the economy's performance after the introduction of the schemes. For the schemes shock, the total amount of 8.2 billion distributed to support businesses during the crisis was allocated to sectors based on their size, energy intensity, and, under EBDS, their trade exposure. This amount was then directly inputted into the IO model as a positive output shock. By simulating these two scenarios, the aim was to isolate and quantify the incremental effects of the schemes in mitigating the economic impacts of rising energy costs. This analysis estimated the impact on key indicators (such as industrial output, employment, GDP, and GVA) at aggregate and sectoral levels.

Given the lack of natural counterfactual available and the challenges faced with limited granular data availability before and after the scheme (e.g., the meter-level data does not cover pre-scheme periods), IO modelling can serve as an effective tool to quantify impacts of the schemes.

1.5 Theory and expected outcome

This Input-Output analysis was designed to estimate the economic impacts of the energy crisis and assess the extent to which the support schemes might have alleviated these effects.

During the crisis, increased energy prices resulted in reduced intermediate demand (i.e., the demand for goods and services used as inputs in business operations) for energy. Following the effect of the energy crisis, the support schemes played a role in lowering energy prices, which also affected intermediate demand for energy. The impacts of these shocks are categorised in IO modelling as three distinct, but related, impacts:

[53] Labandeira, X., Labeaga Azcona, J. M., & López-Otero, X. (2016). *A Meta-Analysis on the Price Elasticity of Energy Demand* (SSRN Scholarly Paper No. 2768161). Social Science Research Network. https://doi.org/10.2139/ssrn.2768161

- In the case of the energy and discount shocks, all sectors experienced immediate consequences; the immediate impacts on the primary sectors impacted by the shock are termed **direct impacts**.
- Subsequently, the direct impacts on each sector spill over to other sectors that supply and demand inputs. These are the **indirect impacts** through the supply chains.
- Finally, certain sectors would experience **induced impacts** resulting from workers spending less of their wages and salaries in the economy.

Throughout this report, the results will be presented as direct impacts, indirect impacts, and induced impacts

The hypothesis and expected results from this analysis are outlined below across two main areas: (a) the anticipated aggregate impacts of the energy crisis and (b) the expected mitigating effects of the schemes. Additionally, considerations on which sectors were most affected are included, based on energy dependency and interconnections within industries.

At an aggregate level, the energy crisis was expected to produce several broad economic effects as the increase in energy prices flowed through the economy, including:

1. **Output and GVA Reduction**: Higher energy costs increased production expenses across sectors, leading to a reduction in overall economic output. Sectors with high energy consumption, such as manufacturing, transportation, and heavy industries, were expected to be most affected by these increases in costs. As organisations faced pressure to manage higher operating costs, a reduction in output was expected, particularly in energy-intensive industries.
2. **Employment Impacts**: Rising production costs may have led some businesses to reduce their workforce as they attempted to maintain profitability. While some sectors may have been able to cover rising costs by increasing their prices, industries with tight profit margins and providing non-essential goods and services (i.e., sectors that faced very elastic demand) were more likely to reduce employment. Sectors such as manufacturing, logistics, and retail were anticipated to be among the most affected in terms of employment reduction, given their high energy intensity.
3. **Ripple Impacts Across Sectors**: Given the connections across industries, energy costs were likely to flow through across the economy. For example, higher electricity and gas prices in sectors like aluminium or fertilisers production would likely have increased input costs for downstream industries like automotive and food. These ripple effects were expected to have increased the overall impact of the energy crisis.

The schemes are designed to mitigate increasing energy costs for NDOs. This support is expected to partially offset the negative impacts of the energy crisis, although the degree of mitigation will likely vary across sectors. The expected economic effects of the schemes include:

1. **Stabilisation of Output**: By applying reductions on energy bills via energy providers, these schemes aimed to alleviate the burden of rising energy costs for organisations, thereby helping maintain stable output levels in the sectors most impacted. While output reductions

would still be expected, the support should prevent large output reductions in energy-dependent industries, allowing them to maintain closer-to-normal production levels.
2. **Employment Support**: The schemes should enable businesses to retain more employees than they would have otherwise, as they aimed to reduce the immediate need to cut costs through workforce reductions. The theory suggests that sectors with higher energy needs and lower-profit margins, such as manufacturing and logistics, would be expected to benefit most from this support, potentially preserving jobs that would have been at risk without intervention.
3. **Limited Decline in GVA**: The schemes were expected to limit the extent of decreases in GVA. While some reductions in GVA due to the crisis would still be expected even with the schemes, the targeted support could have reduced the impact on both profitability and production levels.
4. **Minimisation of Ripple Impacts**: By avoiding severe output reductions and employment losses in the most affected industries, the schemes could have limited the broader ripple effects across other sectors. This mitigation may have helped reduce the flow of impacts of the energy crisis to interdependent industries.

Certain sectors would have been disproportionately impacted by the energy crisis due to their heavy reliance on energy inputs. These sectors include manufacturing, transportation and logistics, construction, agriculture, and services. Rising energy costs would directly increase production expenses for these sectors.

Additionally, sectors with low-profit margins, intense competition, and limited operational flexibility would be likely to see the largest reductions in employment, as they would face larger pressure to preserve profitable levels of operation. Sectors such as retail, hospitality (accommodation and food), and parts of the manufacturing industry would be vulnerable because their profitability leaves little buffer against sudden increases in operational expenses (for example, retail and hospitality operate with thin margins and competitive pricing structures, making it difficult to pass on increased costs to consumers without risking a loss in market share). These sectors may have reduced employment to contain costs, as labour is one of their most controllable expenses.

1.6 Methodology

In this section, details are provided on the methodology used to conduct the IO analysis, key assumptions, and their implications for the results. Two scenarios were simulated, relative to a baseline: (1) the effect of the energy crisis and (2) the impact of the schemes' support. The results from these two scenarios were compared to assess the impact of the schemes on the UK economy with respect to the energy crisis, focusing on output, GVA, and employment.

The IO analysis consisted of four main steps:

- **Step 1**: Selection of the IO table that will be used

- This analysis was static, using the 2019 input-output table as the basis for the IO modelling.[54]

- **Step 2**: Scenario design of the energy shock
  - Electricity and gas price changes were analysed using DESNZ data
  - Price changes in gas and electricity were assigned to sectors according to their energy intensity and energy mix
  - Sectoral elasticities (without differentiation by energy carrier) were drawn from literature to derive the changes in demand attributed to these energy price changes.[55]
  - The energy crisis shock was calculated using energy intensity and price elasticities of demand for energy to assess the impact of price increases on energy demand and the resulting reduction in output.

- **Step 3**: Scenario design for the energy crisis shock and scheme introduction
  - The discount under the schemes was assigned to industry sectors based on a) meter-level data on the discount received, b) energy intensity analysis, and c) total output of the sector. This is referred to as the “mixed approach” of the discount assignment.
  - The discount shock was calculated as in Step 2.

- **Step 4**: Robustness and sensitivity checks
  - Robustness and sensitivity checks were performed …
    - … on the calculated energy shock
    - … on the coefficients used for assigning the discount
    - … on the split of the shock into EBRS and EBDS.

Selection of IO tables

Given that the analysis focuses on the energy crisis and schemes that occurred from 2022 to 2024, the first step was to select the most appropriate IO table to use. IO tables are static at a specific point in time, and assumptions on the structure of the economy are hence dependent on the year selected. Usually, in this type of analysis, the most recent table is employed, as it portrays an economic structure that is closest to the current situation. As of November 2024, the latest IO table published by the ONS was for 2020. However, the 2020 IO table included the effects of the COVID-19 crisis and as such, the structure of the economy during this period was unlikely to be similar to that of 2022 to 2024. As using the most current IO table was not appropriate. the next most up-to-date table (2019) was used. This implies that the results are influenced by the economic structure of 2019.

The IO analysis was conducted in a static format, meaning that the structure of the economy was assumed to remain constant. In a static IO model, relationships between sectors – such as the proportion of inputs each sector requires from other sectors for producing a given level

[54] 2019 UK IO tables are available at *UK input-output analytical tables, industry by industry: 2019—Office for National Statistics*. Retrieved from https://www.ons.gov.uk/releases/ukinputoutputanalyticaltablesindustrybyindustry2019

[55] Paolo Agnolucci, Vincenzo De Lipsis, Theodoros Arvanitopoulos. Modelling UK sub-sector industrial energy demand. Energy Economics, Volume 67, 2017, Pages 366-374, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2017.08.027

of outputs – are fixed based on historical data, with no adjustments for potential changes over time. Using this static methodology allows for a manageable framework for assessing immediate and short-term impacts. However, this comes with certain limitations, as it is not possible to capture how industries may alter their input mix, adapt their technologies, or change their production processes in response to prolonged shocks or changes in economic conditions.

The COVID-19 pandemic resulted in a fragile economic recovery, which was further disrupted by the war in Ukraine. This conflict drove up energy prices and worsened global inflationary pressures. Additionally, the UK exit from the European Union introduced new trade barriers and regulatory changes, impacting various sectors differently. These factors collectively shaped the overall economic landscape and relative importance of each sector during this period. The results of the IO analysis do not account for these structural changes, which may bias the estimation of the energy shock and discount shock impacts on the economy.

Scenario 1: Energy crisis

The first scenario modelled was the energy crisis without the schemes. This served as the baseline scenario, representing the “counterfactual” world for comparison.

IO tables rely on fixed input-output coefficients that represent the amount of one sector’s output required to produce one unit of another sector's output, assuming constant prices. IO modelling is therefore better suited to capture inter-industry effects in quantity terms, rather than in price terms. Therefore, it was necessary to translate the energy crisis price increases into an output shock that could be used as an input to the IO model.

Performing this conversion required three main steps. First, the magnitude of the energy price increase during the crisis was measured. Second, this increase in energy prices was translated into a change in intermediate demand for energy. Third, using estimates of energy intensity by sector, these changes in energy demand were converted into decreases in output by sector, and input into the IO model. These steps are described in greater detail below.

Step 1: Measure magnitude of energy price increase during the energy crisis

To measure the energy price increase, the wholesale prices reported in the “Energy Bill Relief Scheme – discounts for fixed and default/variable contracts” database released by DESNZ were used.[56]

Each three-month period in the data was assigned to a given period:

- Before energy crisis and before COVID-19: 1st January 2004 up to 31st December 2019
- Before energy crisis and during COVID-19: 1st January 2020 to 30th September 2021
- During energy crisis and before schemes: 1st October 2021 to 30th September 2022
- During energy crisis and during schemes: 1st October 2022 to 31st December 2023

[56] Energy Bill Relief Scheme: discounts for fixed, default and variable contracts - GOV.UK

The mean wholesale energy price was then calculated for each period. The energy price shock was calculated as the percentage change in price between the period before the energy crisis and the period during the energy crisis. To account for the effect of the COVID-19 on the UK economy, the analysis used the period before the energy crisis but during COVID-19 as the baseline for the main results.[57]

Table A.7 Percentage change in energy price due to energy crisis

Energy type	Change in price
Gas	1.41%
Electricity	0.36%

Step 2: Translate energy price changes into change in intermediate demand for energy

Translating the energy price increases into changes in energy quantity demanded relied on findings from two key academic papers, as shown in Table A.8. Agnolucci et al. (2017) modelled industrial energy demand functions for a number of UK industry sectors.[58] They provided evidence on energy demand elasticities with respect to economic activity and energy prices for the most affected sectors. For the other sectors, general UK elasticities were leveraged from Labandeira et al. (2016).[59] This paper reported a meta-analysis of energy price estimates across the literature. It provided average general electricity and gas elasticities, which were assigned as elasticities for the sectors not included in Agnolucci et al. (2017).

Table A.8 Energy-demand price elasticities by sector in the UK

Sectors	Energy Demand Elasticity	Source
C16, C22, C31, C32, C3315, C3316, C33OTHER, E36, E37, E38, E39	-0.0078	Agnolucci et al. (2017)
C244_5	-0.0052	Agnolucci et al. (2017)
C13, C14, C15	-0.0044	Agnolucci et al. (2017)
C17, C18	-0.0034	Agnolucci et al. (2017)

[57] Although the analysis focuses on the post-COVID 19 comparison, since it is most realistic, the results using the pre-COVID-19 comparison are estimated as a sensitivity check.
[58] Paolo Agnolucci, Vincenzo De Lipsis, Theodoros Arvanitopoulos. Modelling UK sub-sector industrial energy demand. Energy Economics, Volume 67, 2017, Pages 366-374, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2017.08.027
[59] Labandeira, Xavier and Labeaga Azcona, José Maria and López-Otero, Xiral, A Meta-Analysis on the Price Elasticity of Energy Demand (April 2016). Robert Schuman Centre for Advanced Studies Research Paper No. RSCAS 2016/25, Available at SSRN: https://ssrn.com/abstract=2768161 or http://dx.doi.org/10.2139/ssrn.2768161

Sectors	Energy Demand Elasticity	Source
C203, C204, C205, C20A, C20B, C20C, C21	-0.0032	Agnolucci et al. (2017)
C254, C25OTHER, C26, C27, C28, C29, C301, C303, C30OTHER	-0.003	Agnolucci et al. (2017)
A01, A02, A03, B05, B06 & B07, B08, B09, C19, C235_6, C23OTHER, C241T243, D351, D352_3, F41, F42 & F43, G45, G46, G47, H491_2, H493T495, H50, H51, H52, H53, I55, I56, J58, J59 & J60, J61, J62, J63, K64, K65.1-2 & K65.3, K66, L683, L68A, L68BXL683, M691, M692, M70, M71, M72, M73, M74, M75, N77, N78, N79, N80, N81, N82, O84, P85, Q86, Q87 & Q88, R90, R91, R92, R93, S94, S95, S96, T97	-0.00235	Labandeira et al. (2016)
C101, C102_3, C104, C105, C106, C107, C108, C109, C1101T1106 & C12, C1107	-0.0017	Agnolucci et al. (2017)

Using the energy intensity of each sector, the decrease in energy demand was converted into a decrease in output, which was used as an input in the IO model to estimate the broader economic impacts of the energy crisis.

Step 3: Translate intermediate demand decrease for energy in output change

Energy intensity figures by sector were used to translate changes in intermediate demand for energy into changes in output. Sectoral energy intensities were computed using data issued by ONS [60] by industry, source and fuel between 1990 and 2022.

Scenario 2: Support schemes

The second scenario modelled reflected the implementation of the support schemes. This scenario was compared against the energy crisis scenario baseline to determine the impact of the schemes. To model this scenario, a sector-level breakdown of the total discount provided by the schemes had to be identified. However, the amount of discount received by each NDO and their sector is neither consistently available nor accurately presented in the meter-level data. Therefore, to determine how the total discount of the schemes was distributed across sectors, a combined approach was used, incorporating information from the meter-level data, the size of each sector (as measured by total output), and the sector's energy intensity. Additionally, it is important to note that the split used to allocate this discount could significantly influence the results.

For the first approach, meter-level data was employed to calculate the discount provided to NDOs by SIC code.[61] This provides firm-level information on the amount of electricity and gas discount a specific NDO received. To perform this analysis, the meter-level data was grouped by SIC code (following the same structure as those in the IO table) and the total discount provided under the EBRS and EBDS schemes was aggregated. Each SIC-level aggregated

[60] Energy use: by industry, source and fuel - Office for National Statistics
[61] Classification ISIC Rev.4

discount was then divided by the total to yield the percentage of discount each sector obtained. This approach assumed that the reported discounts were representative of all the schemes, and that discounts were accurately reported without any biases on the missing values. However, due to gaps in the meter-level data, not all NDOs' discounts were displayed or accurately measured. Therefore, the final distribution of the discount also utilises the findings of two complementary approaches, as described below.

For the second approach, the different industries were ranked based on their energy intensity and the discount was distributed according to this ranking (following the numbers shown in Table A.5). The energy intensity was calculated by dividing the total output of each industry by its total energy use. This approach assumes that the more energy intense an industry is, the greater level of support it receives (which was the case for the volumetric schemes, EBRS and EBDS).

For the third approach, the total output of each sector was extracted and divided by the total output of the economy. The total discount was then distributed across sectors based on each sector's percentage of total output. This approach assumes that greater support is received by industries that produce larger levels of output. This is because sectors with higher levels of production, regardless of their energy intensity, will consume more energy than smaller sized firms with similar activity.

For the EBDS scheme, the trade intensity of sectors was also considered to better align with the scheme design of the ETII support. To do so, we added a fourth approach which considered the trade intensity of sectors to assign the discount, using data from ONS.[62] This ensured that sectors with higher trade exposure received larger discounts, according to the ETII support. The trade intensity is the ratio of exports on output by sector, reported by ONS between 2008 and 2022.

The final estimate of discount by sector used in the IO model was calculated by taking the mean of the discount estimated using the three approaches described above. In the main results, we distribute the discount based on three factors: meter-level data, sector size, and energy intensity. To determine whether our results are driven by any one of these factors (for instance, the meter-level data, which may be of poor quality), we conducted the analysis by distributing the discount using only one of the three factors at a time. The results do not vary significantly, which confirms the robustness of our approach to distribute the discount.

[62] UK trade in goods by industry, country and commodity, exports - Office for National Statistics

Appendix 3: Uncertainty analysis

1.7 Purpose of the uncertainty analysis

The purpose of the uncertainty analysis was to explore the relationship between energy prices and economic uncertainty across different periods and policy landscapes. In this analysis, uncertainty is defined as 'economic policy uncertainty' and reflected by the 'Economic Policy Uncertainty' (EPU) index;[63] additional details on this index are provided in section 1.9 below.

This analysis investigated whether energy prices explain the uncertainty and vice versa, and whether the relationship changed after the energy crisis started and after the schemes were introduced. The methodology relied on the analysis of descriptive statistics (i.e., summary statistics such as mean, median, and standard deviation, as well as time series characteristics assessed through time trend and stationarity tests), on correlation analysis, and univariate Autoregressive Integrated Moving Average (ARIMA) modelling and multivariate time series Vector Autoregression (VAR) modelling. Although the results did not provide evidence of a causal relationship between the schemes and uncertainty, they provided indicative evidence that (1) energy crisis led to an increase in uncertainty and (2) the schemes could have contributed to a reduction in uncertainty. In this analysis, all NDOs were considered as market-wide uncertainty was evaluated (which affects and includes all types of NDOs)

1.8 Theory and expected outcomes

The uncertainty analysis explored several dynamic relationships, including (1) electricity and gas price dynamics and their impact on each other; (2) electricity and gas prices as a driver of uncertainty; (3) uncertainty as a driver of energy prices; and (4) the change of these relationships over time.

Electricity and gas price dynamics

Electricity and gas prices across contract terms (short, medium, and long) can interact dynamically.[64] Short-term prices are typically more volatile and respond to immediate supply-demand conditions, while long-term prices are more stable, reflecting future expectations. Since gas is a key component of the UK's current electricity generation mix, wholesale gas prices would be expected to influence electricity prices, particularly in the short term.

Electricity and gas prices as a driver of uncertainty

The expected impacts of electricity and gas prices on uncertainty depend on the time horizon:

- Short-term fixed price contracts reflect short-term supply-demand dynamics and are the most sensitive to immediate market fluctuations. Any shocks or volatility in short-term prices should immediately impact market sentiment, thus influencing uncertainty.

[63] Baker et al. (2016 and 2024)

[64] The definition of short-, medium- and long-term prices is included in the 'Methodology' section below and is slightly different for the electricity and gas prices.

- Medium-term fixed price contracts reflect a more intermediate outlook, partially capturing near-future expectations without exhibiting the extreme volatility of short-term contracts. As such, changes in medium-term prices contribute to uncertainty, but to a lesser degree than short-term prices.
- Long-term fixed price contracts encapsulate expectations about the overall stability and long-term trends in energy markets and are less affected by immediate shocks. As such, volatility in long-term contract prices should have a lesser impact on uncertainty.

Uncertainty as a driver of energy prices

Economic uncertainty can affect energy prices through multiple channels. During periods of heightened uncertainty, businesses and consumers may adopt a cautious approach – for example, by delaying investments, reducing consumption, or adjusting production levels. This approach may lower energy demand (which is closely linked to overall economic activity), exerting downward pressure on prices. Additionally, geopolitical conflicts and supply chain disruptions contribute to fluctuations in uncertainty. These disruptions can affect the availability and cost of energy resources, increasing price volatility and threatening energy security, which can in turn amplify economic uncertainty.

Uncertainty can also affect energy prices differently depending on the time horizon of energy contracts. In the short term, economic and geopolitical uncertainty can create market volatility, leading to sudden price fluctuations as the market reacts to perceived risks. For instance, concerns about future supply disruptions may drive up short-term prices, even if actual shortages have not yet materialised. Over the long term, uncertainty can influence investment and consumption patterns. If businesses expect prolonged economic instability, they may delay investments in energy infrastructure and efficiency improvements, which can lead to higher long-term energy demand and upward pressure on prices. Similarly, if industrial organisations reduce production due to uncertainty, energy demand may decline, contributing to lower long-term prices. The overall effect of uncertainty on energy prices thus depends on how market participants adjust their behaviour in response to perceived risks and expectations.

Change in parameters over time

Several factors may dynamically influence the expected outcomes described above (i.e., how electricity and gas prices interact, and how the uncertainty and energy prices influence each other). While both uncertainty and energy prices are shaped by various external factors, the interaction between energy prices and uncertainty is not static. Energy price fluctuations may drive changes in uncertainty, and heightened uncertainty can influence energy prices. As a result, the relationship between energy prices and uncertainty may vary over time. At certain times, this relationship may be weak or insignificant, with little observable effect between the two variables. In other periods, when a significant relationship exists, the magnitude and direction of the impact may differ depending on the underlying economic and market conditions.

In this analysis, the period between 2007 and 2024 was separated into three segments, in which the relationship between energy prices and uncertainty is expected to differ:

- The **period before the energy crisis** (January 2007 – September 2021) explored the long-term relationship between energy prices and the EPU index absent the energy crisis. Energy prices would be expected to have had little or no discernible impact on the EPU index in this period.
  - Baker et al. (2016)[65] concluded that the UK-specific EPU index responded to several shocks between 1997 and 2015, such as the Gulf War, the failure of Lehman Brothers, the Eurozone crises, general elections, and the Scottish independence referendum. The EPU index would therefore be expected to be comparatively high at the time of the 2008 financial crisis, the Brexit referendum, and when COVID-19 hit the economy. Since these uncertainty spikes were driven by broader economic and political events rather than energy prices, energy prices would be expected to have had a limited role in shaping uncertainty during this period. While energy price fluctuations may have contributed to overall economic conditions, uncertainty in this timeframe is not expected to have been significantly influenced by energy prices. However, these global and UK-specific events may have had an impact on energy prices (e.g., reduced energy consumption due to stay-at-home regulations during the COVID-19 pandemic[66]), though the magnitude of this impact is expected to be lower than the impact of the energy crisis.
- During the **period with high energy prices before the support of the schemes** (October 2021 – September 2022), energy prices would be expected to have had a significant impact on the EPU index, and uncertainty may have had an impact on energy prices.
  - Energy prices would be expected to have driven uncertainty during the energy crisis, as they had serious impact on households and businesses (e.g., elevated production costs, lower demand for products due to higher domestic energy expenditures, and inflated prices). However, other factors could have simultaneously affected uncertainty and energy prices, such as rising inflation as a result of the high demand due to the recovery of consumption after the COVID-19 pandemic.[67] Conversely, other factors may have reduced uncertainty; for instance, all COVID-19-related restrictions were lifted at the time when the energy crisis started (February 2022), and fears of their return diminished significantly.[68] This may have contributed to greater economic stability, improved business and consumer confidence, and reduced concerns about sudden policy shifts. Taking into account a number of events occurring simultaneously (such as the geopolitical conflict in Ukraine and the inflationary pressures and the end of COVID-19-related policies), the relationship between energy prices and uncertainty is expected to be statistically significant, meaning that energy prices had a direct effect on uncertainty.
  - Uncertainty may also have had an impact on energy prices. When Russia drastically reduced gas exports to Europe, it was unclear what the effects on supply would be. This led to an increase in demand for gas from non-Russian sources, which could also

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[65] Baker et al (2016) Measuring Economic Policy Uncertainty
[66] Energy price developments in and out of the COVID-19 pandemic – from commodity prices to consumer prices
[67] Ukraine brings significant economic uncertainty, Rishi Sunak warns
[68] The rolling correlation analysis showed that the COVID-19 stringency index was strongly correlated with the EPU index (and also with the energy prices) shortly after the introduction of the schemes. The COVID-19 stringency index is a country-specific indicator representing the stringency of public policies between 2020 and 2022 on a scale of 100, published by the Blavatnik School of Government, University of Oxford (2023).

have inflated energy prices.[69] Uncertainty may also have led to a build-up of domestic gas reserves to ensure a stable gas supply during the winter, which may have further contributed to an increase in gas prices.

- Finally, in the **period after the introduction of the schemes** (October 2022 – June 2024), the relationship between energy prices and the EPU index is expected to have weakened.
  - As businesses were sheltered from the high volatility of energy prices through the schemes, associated economy-related uncertainties would have decreased (e.g., organisations would have had less concern over not being able to pay energy bills). Consequently, the schemes were expected to have reduced uncertainty levels compared to the energy crisis period, and to have reduced (or potentially removed) energy prices as a driver of uncertainty.
  - The impact of uncertainty on energy prices during this period was less clear. Protecting non-domestic consumers from high energy prices may have increased their demand for energy, compared to a scenario of high energy prices without the schemes, leading to higher wholesale energy prices. However, the schemes may have improved the financial health of NDOs, enabling them to carry out energy efficiency improvements, such as installing renewable energy sources (e.g., solar PV) or replacing inefficient appliances.
  - As the EPU index is based on analysis of public sentiment as expressed in news articles, any change in uncertainty reflects the impacts of all policies that may have impacted energy prices during this period, including all domestic and non-domestic affordability schemes. In other words, the impact of the schemes on energy prices cannot be separated from other policies, which is a key limitation of the data.
  - It is also worth noting that energy prices remained high for several months after the introduction of the schemes, but significantly decreased in 2024. Other factors may have also significantly affected the EPU index, such as the high inflation rate or the reduction in real income.

1.9 Methodology

The uncertainty analysis examined whether and how energy prices and uncertainty influenced each other, and how this relationship evolved over time. To capture different price dynamics, a selection of time series data representing short-, medium-, and long-term fixed energy prices was used. These data allowed for testing whether uncertainty was primarily driven by, or was a driver of, gas and electricity prices over different time horizons.

In this analysis, uncertainty is defined as 'economic policy uncertainty' and is reflected in the 'Economic Policy Uncertainty' (EPU) index created by Baker et al. (2016 and 2024). The EPU index has a daily frequency and is based on analysis of public sentiment as reflected in newspaper articles. This report uses the UK-specific EPU index, which is created based on the *Times of London* and the *Financial Times*. The EPU index is designed to capture concerns about economic policy decisions, their timing, and effects, including "non-economic" policy

[69] Henderson, J. The Impact of the Russia-Ukraine War on Global Gas Markets. Curr Sustainable Renewable Energy Rep 11, 1–9 (2024). https://doi.org/10.1007/s40518-024-00232-x

matters like military actions. Articles are identified by keywords related to uncertainty, the economy, and policy.[70] To construct the index, raw counts of relevant articles are scaled by total articles in the same period, standardised, and averaged across newspapers. In this analysis, 'uncertainty', 'economic policy uncertainty', and references to the EPU index are used interchangeably and refer to the same measure of uncertainty.

In order to analyse the changes in energy prices, six key daily data sources were used from Independent Commodity Intelligence Services (ICIS) data.[71] These data represent the wholesale energy prices of gas and electricity under fixed price contracts with short, medium, and long terms (see Table A.9 below). Fixed-price contracts represent the agreed-upon price for energy that will be used within a specified time period (e.g., month or calendar quarter). These contracts are generally used by energy suppliers or large consumers to lock in a price now for energy they will use later, protecting against potential price fluctuations (especially short-term fluctuations). However, NDOs face differing energy prices depending on the conditions under which they contract with the supplier (e.g., system costs, supplier costs, and their market power).

To explore the relationship between energy prices and uncertainty, multiple analytical methods were applied:

1. **Descriptive and Correlation Analysis**: Descriptive statistics and correlation analysis were used to identify whether the selected time series data (i.e., energy prices and uncertainty) exhibited potential connections. A rolling correlation analysis was also used to track how the relationship between uncertainty and energy prices changed over time. However, correlation alone does not explain which variable influences the other, nor does it establish causality – external factors may simultaneously affect both energy prices and uncertainty.
2. **Univariate Time Series Analysis**: Stationarity tests and ARIMA modelling were conducted as a prerequisite for more advanced econometric techniques. While these methods allow for some economic interpretation, they do not directly explain the interactions between energy prices and uncertainty.
3. **Multivariate Time Series Analysis (VAR Modelling)**: VAR modelling was used to examine the dynamic relationships between energy prices and uncertainty over time. This method helps assess how a shock to one variable propagates through the system. However, VAR models do not establish causality – they show associations, but cannot determine whether uncertainty drives energy prices or vice versa.

Two additional methods were also considered to explore the causal relationship between energy prices and uncertainty: Vector Error Correction Models (VECM) and Structural VAR (SVAR). VECM was not applicable due to data constraints, as the uncertainty time series was stationary, whereas VECM requires non-stationary (first-integrated) time series. For the SVAR

[70] In the case of the UK, the following words were searched for creating the index. Economic (E): economic OR economy OR business OR industry OR commerce OR commercial; Policy (P): spending OR policy OR deficit OR budget OR tax OR regulation OR "Bank of England"; and Uncertainty (U) uncertain OR uncertainty. At least one word of all categories should be included in the articles from each category.
[71] Independent Commodity Intelligence Services (ICIS) is a global provider of market intelligence and data for different sectors, including detailed information on energy prices of gas and electricity.

model, identification issues arose as it required a structural identification process to separate the endogenous variables. Specifically, a decision had to be made about whether uncertainty causes energy price shocks or energy price shocks cause uncertainty. Since this could not be determined based on the analysis carried out, only VAR models were used instead of SVAR.

Selection of energy time series

Wholesale energy prices for fixed price contracts of gas and electricity were obtained from ICIS data for the period between 2007 and September 2024. The ICIS dataset provides detailed time series of wholesale prices with different contract dates. For gas, prices start from the contract date and last for two years. For electricity, prices start from the contract date and last for two years, divided into four seasons (winter and summer). For this analysis, three representative time series of gas and electricity prices – corresponding to short-, medium- and long-term fixed-price contracts – were selected for detailed analysis.

To select the representative time series, a correlation analysis was carried out for energy prices in different periods. The purpose was to explore the strength of correlation between prices at different contract lengths (e.g., locking in the price for the next-month and two-month-ahead prices) and to identify clusters representing short-, medium-, and long-term periods. This clustering approach facilitated the selection of time series which captured the maximum possible variation from all the available information, while ensuring that the selected series represented distinct time horizons (short, medium, and long-term). The results of the correlation analysis (i.e., the selected gas and electricity prices in different time horizons) are summarised in Table A.9. As the gas and electricity contracts had different lengths (i.e., how far into the future, and for how long, the price could be fixed), and the correlation analysis gave slightly different results (i.e., the strength of the correlation between different time horizons), the selected price time series are slightly different for gas and electricity.

Table A.9 Selected short-, medium-, and long-term wholesale fixed-price gas and electricity contracts

Energy type	Short-term	Medium-term	Long-term
Gas	Month+1 (next month)	Month+6 (half year later)	Quarter+4 (same quarter next year)
Electricity	Month+2 (two months later)	Quarter+3 (three quarters later)	Season+3 (three seasons later) (Each season represents a six-month period, defined as either a summer or winter period)

Source: ICIS data
Note: Quarters are defined as calendar year quarters.

A cross-correlation analysis was also applied to identify the relationship and time lag between the selected short-, medium- and long-term time series. This analysis was implemented to determine how one variable influenced another over time and whether the impact is observed immediately (no time lag) or with a time delay.[72] This process was implemented for prices clustered together (e.g., for all short-term fixed prices) and for different clusters (i.e., comparing short-, medium-, and long-term prices). The results of the cross-correlation analysis show that the immediate correlation is the strongest, meaning that different time series do not lead (or lag) each other, and instead react to random shocks at the same time.

Descriptives and correlation analysis

Rolling correlation measures the dynamic relationship between two variables over time by calculating correlations within a moving window. Unlike static correlation, it reveals how the relationship changes over time, capturing time-varying dynamics, identifying shifts or trends, and smoothing short-term fluctuations. It is useful for detecting changing correlations, assessing lagged effects, and understanding evolving trends. In this analysis, a 52-week rolling window was applied, reflecting the yearly economic cycle, enabling year-on-year comparison, and balancing the impact of the shocks and overall time trends.

If the rolling correlation is higher in some periods (in absolute terms), it indicates a stronger connection between the variables. Additionally, a long-lasting (persistent) change in correlation over time may indicate that the relationship between energy prices and uncertainty has changed. It is important to note that correlation analysis is unable to identify causal relationships, and instead only reflects whether different time series move in the same direction.

ARIMA modelling

After establishing through correlation analysis whether there is evidence that energy prices and uncertainty levels move together (at least temporarily), prices and uncertainty were analysed using an ARIMA model. Using ARIMA modelling before building more complex models can be highly useful, as it provides a foundational understanding of the time series' behaviour and characteristics. ARIMA modelling consists of three main steps:

- **Step 1: Stationarity testing and transformation (Integration component)**: The first step in ARIMA modelling is to test whether the time series is stationary (i.e., it has a constant mean and variance over time). If the series is not stationary, differencing (i.e., subtracting each data point from the previous one to remove trends and stabilise variance) is applied to achieve stationarity. This step corresponds to the 'integrated' ('I') part of ARIMA, and is crucial for the robustness of the ARMA modelling performed in Step 2. However, differencing can lead to information loss, so it should be minimised when possible.
- **Step 2: ARMA modelling (AR and MA components):** After achieving stationarity in the first step, ARMA modelling can be applied to filter out autocorrelation in the data.
    - **Autoregressive (AR) component:** This component examines the relationship between a series' current and past values. The lag parameter shows how many past values affect the present observation, with coefficients indicating the strength of these impacts.

[72] In econometric terms, identifying the number of lags where the correlation is strongest indicates whether one time series leads another time series, follows (lags), or whether the immediate correlation is the strongest.

- **Moving Average (MA) component:** The MA component accounts for past shocks (in modelling, expressed as error terms) and their impact on current values. For instance, in energy prices, significant MA values indicate that past shocks influence current values, capturing the effects of random disturbances.
- **Mixed AR and MA processes (ARMA):** ARMA combines AR and MA components, capturing both past values and past shocks.

- **Step 3: Checking residuals:** If the residuals left after fitting the ARIMA model (after steps 1 and 2) are random and have no pattern (commonly termed 'white noise'), it suggests that the model has captured all systematic information within the series.

Note that while ARIMA modelling is useful in capturing dependencies in time series data (i.e., how different time series react to random shocks and to their previous values), it is unable to explore the relationship between different time series (e.g., energy prices and uncertainty).

VAR modelling

After the structure of the time series was explored through the ARIMA modelling, more complex vector autoregression (VAR) modelling was applied to draw insights on the relationships between prices and uncertainty over time.

Using VAR modelling for multivariate time series analysis: VAR models are a valuable tool for analysing the relationships between multiple time series. Unlike univariate models such as ARIMA, VAR considers several interdependent variables simultaneously, capturing how each variable influences and is influenced by the others over time.

Setting lags and estimating relationships: VAR modelling captures both the direct and lagged impacts among the variables.

- **Lag length selection:** Determining the optimal number of lags (i.e., the number of past observations included in the model as predictors) is crucial, as it defines how far back the model looks to understand dependencies among the variables. In this analysis, one period corresponded to one week, meaning that lags represent data points from previous weeks. Incorporating too few lags may miss significant relationships, while too many lags can overfit the model and reduce model efficiency. This analysis used the Hannan-Quinn information criterion to select the optimal number of lags, which strikes a good balance between avoiding the inclusion of relevant variables and overfitting.[73] However, separate VAR models were estimated with different numbers of lags to ensure the robustness of the results (including the use of the Bayesian Information Criterion – which prefers to include fewer lags) and setting the number of lags to 2, 3, and 4 weeks. This means that, for example, when 2 lags are included, the current values are explained by the values from the previous week (.L1) and the week before that (.L2) for both the dependent and independent variables.

[73] The Hannan-Quinn information criterion is widely used in econometric analysis, first introduced in the late '70s:

- **Dynamic interactions:** Each variable in a VAR model is regressed on its past values and the past values of all other variables in the model. This structure allows the VAR model to capture complex, dynamic interdependencies and feedback effects within a system.

Using short-, medium- and long-term fixed energy prices provided additional information on whether uncertainty was driven by changes in short-, medium-, and long-term energy prices, and whether contract term length had an impact on uncertainty (as described in section 1.8).

Appendix 4: Use of meter-level data and IDBR

The statistics derived from analysis of meter-level data provide an overview of how energy suppliers and NDOs performed (viewed through the lens of the financial health of these entities, as measured by changes in employment and turnover) during the energy crisis and under the schemes. The analysis of financial health based on meter-level data is descriptive only, providing evidence of the impact of both the energy crisis and the schemes on the financial health of NDOs and energy suppliers (as presented in the Contribution Analysis). However, analysis of meter-level data did not provide evidence of a causal relationship between the schemes and financial health.

The data employed for this analysis was sourced from ONS and DESNZ. From DESNZ, the meter-level data collected during the schemes was used. This data summarises, at the meter-level, the amount of discount they received from each scheme, the recorded energy consumption, the tariff (for EBDS only), and information about the company responsible for the specific meter. From ONS, the Inter-Departmental Business Register (IDBR) database was used. The IDBR contains information on organisations that are registered for VAT, including their employment, location, SIC code, and turnover.

These data sources were matched using the Company Registration Number present in both sources. Using this combined data set, the financial health, support received, and energy consumption during the schemes was obtained for each meter/company. Organisations that were not included in the scheme data or in IDBR could not be matched and therefore could not be included in the further analysis. As IDBR does not include charities and smaller sized organisations that are not VAT- or PAYE-registered, these are also not included in the analysis presented above.

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