# Russia-Ukraine War: A Note on Short-Run Production and Labour Market Effects of the Energy Crisis

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# Russia-Ukraine War: A Note on Short-Run Production and Labour Market Effects of the Energy Crisis*

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**Abstract:** We provide first causal evidence of effects of the energy crisis on Germany, representing a major European economy. Combining cost structure data, national accounts and administrative labour market data, we identify effects in a sectoral panel setting using sector-specific energy intensity as "bite" variable. The results show that via the channel of energy intensity, monthly production and real turnover decreased by 4.1 and 2.6 percent, respectively, after the onset of the Russian war against Ukraine. Instead of layoffs, firms safeguarded employment via short-time work with 24.1 percent additional applications. Vacancy posting was reduced by 10.2 percent.

**JEL classification:** E23, H56, J63, Q43

**Keywords:** Russia-Ukraine war, energy, production, labour market, Germany

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# 1 Introduction

With Russia's war against Ukraine and the imposed sanctions, global economic conditions have changed abruptly in February 2022. Manufacturing worldwide is coming under pressure especially due to rising energy prices. Europe is particularly exposed because of its energy supply relationships with Russia (compare McWilliams et al. (2023)). In this note, we provide first causal evidence of economic effects of the energy crisis in Germany, representing a major European economy. Our study addresses effects via the exposure of industries, which comes in addition to effects on households via cost increases (e.g. Kröger et al. (2023)).

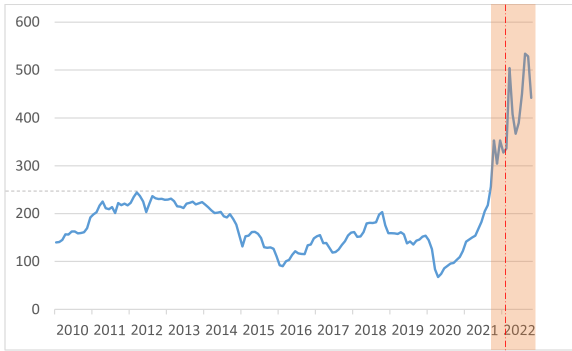
We focus on monthly key indicators: production, real turnover, new vacancies, unemployment entries and short-time work. This mirrors the consequences on output and the labour market. Considering short-time work is important in view of recent evidence that this instrument has been used extensively to buffer the effects of the COVID-19 crisis in both Germany (Gehrke and Weber (2020)) and Europe (e.g. Giupponi et al. (2022)).

Early simulation studies for the war in Ukraine projected considerable economic effects due to spikes in energy prices (e.g. Wolter et al. (2022)). The HWWI Energy Raw Materials index shown in Figure 1 surpassed previous highs in September 2021. This marked the beginning of an energy "crisis", whereas until then, prices had been still rather comparable to strong years in the recent decade. With the onset of the war, however, the surge in energy prices sped up even further.

We make use of energy intensity of manufacturing industries as a treatment variable. Combining cost structure data, national accounts and administrative labour market data, we identify causal effects in a sectoral panel setting.

Our study relates to several strands of literature. The negative output effects of increasing energy (especially oil) prices are analysed in studies such as Baumeister and Hamilton (2019), Kilian (2008) or Carstensen et al. (2013). Lee and Ni (2002) investigate the sectoral effects via supply and demand channels. Ordonez et al. (2011) focus on the labour market dynamics following oil price shocks. Belin and Hanousek (2021) and Crozet and Hinz (2020), amongst others, investigate the economic effects of sanctions in the countries concerned. Labour market

Figure 1: HWWI Energy Raw Materials index




Notes: HWWI Energy Raw Materials index. Monthly time series from January 2010 to October 2022. Unit: index (2020=100). Source: HWWI. The previous all-time high (dashed horizontal line) was exceeded in September 2021. According to our definition, this is when the energy crisis begins (orange area). The red vertical line marks the onset of the war (24th February 2022).

reactions and robustness to economic fluctuations are studied, for instance, in Giupponi et al. (2022) and Klinger and Weber (2020).

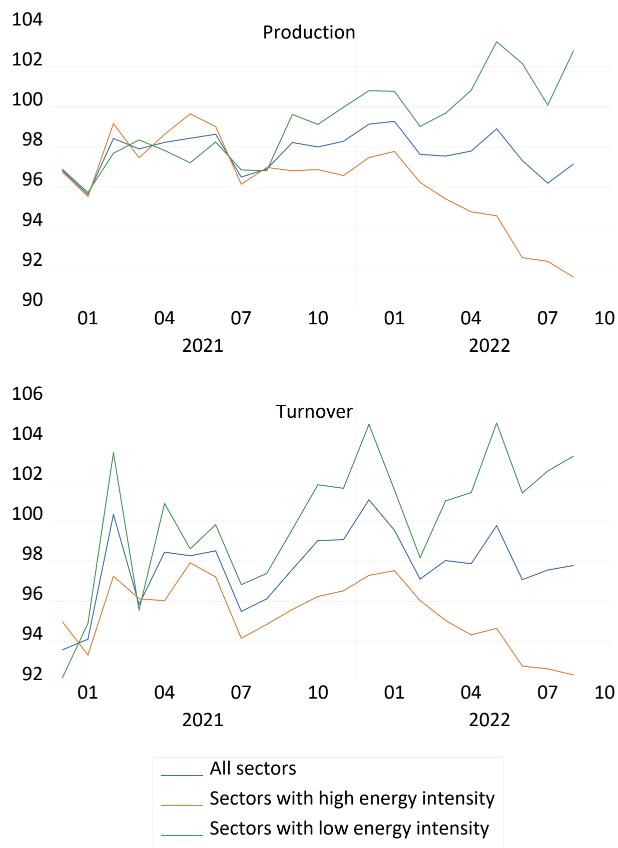
# 2 Data

For our analysis, we combine cost structure data, national accounts and administrative labour market data on a sectoral level. Indices of production and real turnover (2015=100) are obtained from the German Statistical Office (destatis). New vacancies, unemployment entries from employment in the primary labour market, and short-time work notifications[1] are taken from the Statistics of the Federal Employment Agency. Energy intensity is defined as energy usage in 2019 divided by gross output value and is obtained from the destatis cost structure statistics (Kostenstrukturerhebung).

All variables are combined in the dimension of economic sectors. Disaggregation at the 2-digit level yields 24 different sectors of the manufacturing industry. We focus on sectors of manufacturing for several reasons. Firstly, the cost structure data is not available for the service

[1]Before short-time work can begin, a notification is required. During short-time work, the employees receive wage replacement benefits from the unemployment insurance for the reduced working time. While high energy prices as such do not justify short-time work, an induced loss of orders due to the need to raise sales prices would be sufficient.

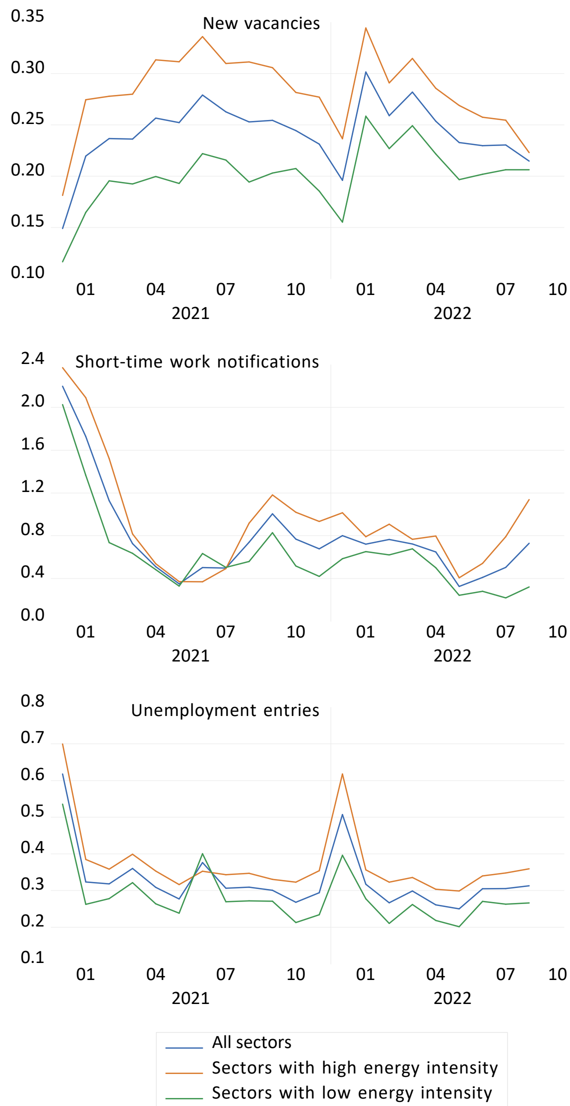
Figure 2: Production and turnover




Notes: Average production and real turnover among 24 sectors in the manufacturing industry together with the means among the 12 sectors with highest and lowest energy intensity, respectively. Unit: index (2015=100). Observation period: January 2021 to September 2022. Source: destatis.

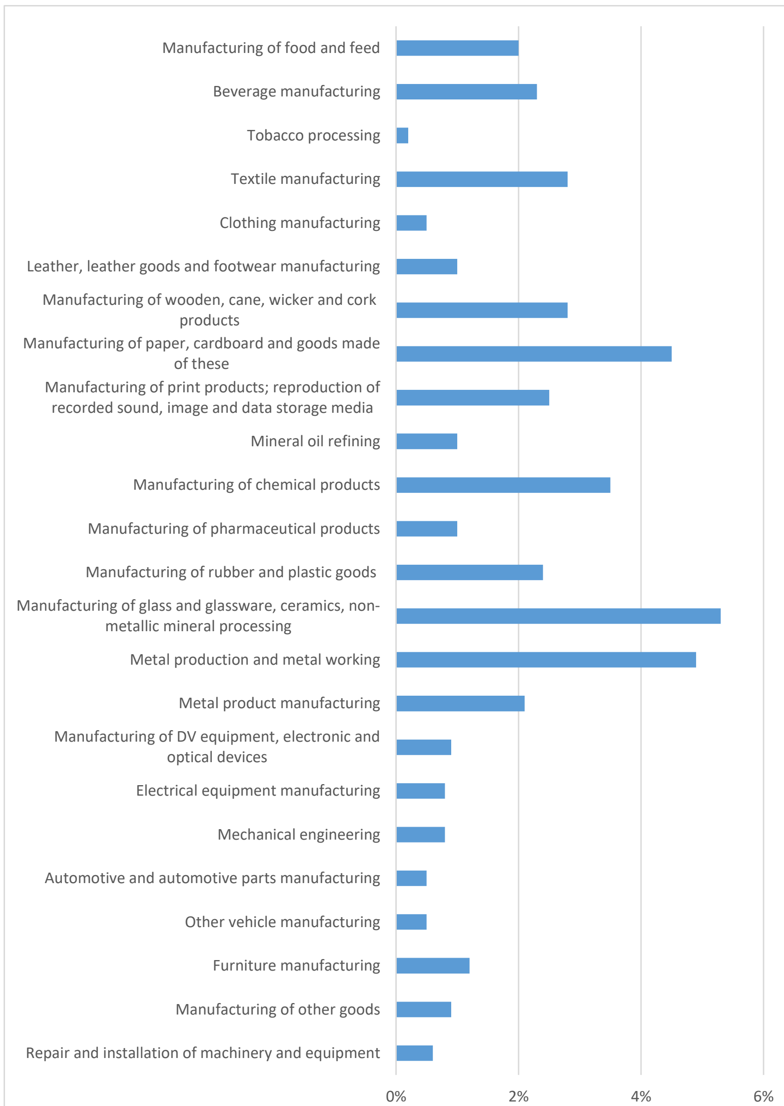
sector. Secondly, energy intensive firms usually belong to manufacturing. Thirdly, parallel pre-treatment trends, i.e. the identifying assumption in a difference-in-difference approach, are likely to hold within manufacturing. In contrast, the recovery from the recent corona waves could lead to diverging trends especially in contact-intensive service sectors.

Figure 3: Labour market variables




Notes: Average number of new vacancies, short-time work notifications, and unemployment entries from employment in the primary labour market among 24 sectors in the manufacturing industry together with the means among the 12 sectors with highest and lowest energy intensity, respectively. All variables are divided by the number of employees subject to social security contributions. Unit: percent. Observation period: January 2021 to October 2022. Source: Statistics of the Federal Employment Agency.

Figure 4: Energy intensity




Notes: Energy intensity defined as energy usage in 2019 divided by gross output value. Source: destatis.

Figure 4 shows the energy intensity for 24 sectors in the manufacturing industry. We exploit the strong differences for identifying effects of the energy crisis. Figure 2 shows the development of the production index and the turnover index, while Figure 3 displays new vacancies (upper panel), short-time work notifications (middle panel), and unemployment entries from employment in the primary labour market (lower panel). The labour market variables are divided by the number of employees subject to social security contributions.

The observation period of all variables starts in January 2021 and ends in September or October 2022, depending on the publication lag of the respective variables. After a rather stable development in 2021, production has recently fallen significantly whereas aggregate turnover stayed at its pre-war level with some fluctuations. New vacancies have been decreasing in 2022, unemployment entries remained close to pre-war levels on aggregate and short-time work notifications began to rise in the most recent months. In all graphs, we show the overall mean and the means of the sample halves with higher and lower energy intensity. With the beginning of the energy crisis in autumn 2021, especially production and turnover in high-energy sectors started to differ from the low-energy sectors.

# 3 Methodology

We estimate the effects of the energy crisis in a sectoral panel model. As explained above, we define the crisis by its start point in September 2021 and the acceleration by the Ukraine war. For the purpose of identification, we make use of differences in energy intensity across sectors. The combination of the time and sector dimensions yields 504 to 528 observations in our panel setting, depending on data availability.

The dependent variables are production, real turnover, new vacancies, unemployment entries, and short-time work notifications. The explanatory variable is given by energy intensity, interacted with a dummy for the energy crisis and another one for the Russia-Ukraine war. We use sector-fixed effects to control for general sector differences. Time-fixed effects take into account specifics of the months including seasonal effects. This also captures the fact that all sectors alike may be affected by weakened demand when higher energy prices reduce effective purchasing power (Lee and Ni (2002)). The panel model is shown in Equation (1):

$$y_{it} = c_0 + c_1 x_i \times d_{1t} + c_2 x_i \times d_{2t} + \mu_i + \gamma_t + \epsilon_{it}, \tag{1}$$

where $c_0$ to $c_2$ are the coefficients, $y$ is the outcome (unemployment entries, vacancies, short-time work notifications, production, turnover), $x$ is the treatment variable (energy intensity), $d_1$ the energy crisis dummy, $d_2$ the war dummy, $\mu_i$ the sector fixed effects, $\gamma_t$ the time fixed effects and $\epsilon_{it}$ the error terms. The index for the sectors is denoted by $i$ and the time index by $t$.

The first energy crisis dummy $d_1$ is 1 from September 2021, the month in which the HWWI surpassed its previous highs of the past decade, and 0 otherwise. The second energy crisis dummy $d_2$ is 1 after the onset of the war, and 0 otherwise. For production, turnover, and short-time work notifications, the cut-off date for measurement is the end of a month. As the war began on 24th February 2022, February already contains five post-treatment days. Hence, for the estimations of these three variables, $d_2$ is zero until January 2022, $\frac{5}{28}$ in February 2022, and 1 afterwards. By contrast, unemployment entries and new vacancies are measured between the two cut-off dates around the mid of a month. Therefore, we set $d_1$ to zero until August 2021, to $\frac{1}{2}$ in September 2021, and to 1 afterwards. In case of March 2022, unemployment entries and new vacancies are measured between February 14 and March 14. Hence, the March values contain 9 pre-war days, and we set $d_2$ to zero until February 2022, to $\frac{28-9}{28}$ in March 2022, and to 1 thereafter in these estimations.

Effects of the energy crisis can be presumed if energy intensity has an additional effect on the outcome variable during the respective treatment periods. This procedure can be seen as a type of a difference-in-difference approach with September 2021 and 24th February 2022 as treatment dates. We use a special application of this approach by replacing the binary treatment by the "bite", i.e. different energy intensities. We borrow this procedure from the literature that is concerned with the measurement of the effects of a nationwide minimum wage on employment; see, for instance, Card (1992) or recent applications in Bauer and Weber (2021) and Caliendo et al. (2018). In the appendix, we also show the results for a classic difference-in-difference estimation with binary treatment variable.

# 4 Results

Table 1 shows the results for the treatment interaction effects. From September 2021 to the beginning of the war, one additional percentage point in energy intensity decreased production and real turnover by 0.48 and 0.53 index points, respectively, where the latter effect can be estimated only imprecisely. However, the main effect of the energy crisis occurred after the onset of the war, affecting production and real turnover by -2.16 and -1.35 index points, respectively ($c_1 + c_2$). This suggests that the peak in energy prices has dampened economic activity, especially in energy-intensive sectors. Due to sales from stock, turnover did not fall as much as production.

The labour market results show that one additional percentage point in energy intensity leads to 0.113 additional short-time work applications per 100 employees already from the beginning of the energy crisis in September 2021. During the war, the effect increases only slightly to 0.134; as Figure 3 shows, this is due to the fact that applications in energy-intensive sectors picked up only during summer when considerable production losses occurred. By contrast, the energy crisis affects new vacancies both before and even more strongly during the war, with one additional percentage point in energy intensity leading to 0.013 fewer new vacancies per 100 employees. Put into context, 0.902 short-time work applications per 100 employees and 0.239 new vacancies per 100 employees could be expected on average per month in a typical 2-digit sector of the manufacturing industry during the pre-war period. Entries to unemployment did not react significantly. Evidently, firms are safeguarding employment via short-time work and reducing their hiring activities. This is in line with the negative effects on production, the relevant determinant for labour demand.

As an illustration, we quantify the overall effects following from our estimations in a counterfactual scenario. For the 24 sectors considered, we calculate a hypothetical development without the energy crisis and the war, i.e. $d_1$ and $d_2$ in Equation (1) remain zero.[2] We find

[2] An alternative interpretation would be that energy intensity is zero for all sectors.

Table 1: Estimated treatment interaction effects

| | Dependent variable | | | | |
|---|---|---|---|---|---|
| | Production | Turnover | New vacancies | Short-time work | Unemploy-ment entries |
| Effects from 2021m09 | -0.481 | -0.533 | -0.005 | 0.113 | 0.018 |
| (p-value) | (0.007) | (0.155) | (0.045) | (0.001) | (0.298) |
| Effects from 2022/02/24 | -2.157 | -1.348 | -0.013 | 0.134 | -0.001 |
| (p-value*) | (0.000) | (0.001) | (0.000) | (0.002) | (0.881) |
| Observations | 504 | 504 | 528 | 528 | 528 |

Notes: Estimated treatment interaction effects following Equation (1). Effects from 2021m09: $c_1$. Effects from 2022/02/24: $c_1 + c_2$. Estimation period: 2021:1 to 2022:9 (production, turnover) or to 2022:10 (labour market variables). White cross-section (period cluster) standard errors and covariance were used to calculate p-values. *: p-values from Wald-tests testing $c_1 + c_2 = 0$.

that during the pre-war energy crisis period, the energy channel leads to an average monthly production and turnover loss of 0.9% and 1.0%, respectively, compared to the counterfactual levels. After the onset of the war, these monthly losses increase substantially to 4.1% (production) and 2.6% (turnover). Furthermore, we estimate 83,800 (or 20.3%) additional short-time work applications and 3,700 (or 4.0%) fewer vacancy postings during the pre-war energy crisis period, and another 140,200 (or 24.1%) additional short-time work applications and 12,500 (or 10.2%) fewer vacancy postings after the onset of the war.

We check the validity of our results in view of the nature of the energy crisis. A crucial assumption of our identification strategy is that the sectors underwent parallel trends during the pre-treatment period, independently of the energy intensity. Figures 2 and 3 show that before September 2021, the target variables reveal largely parallel trends for sectors with higher and lower energy intensity. In general, the parallel-trends assumption can be considered fulfilled. While there are occasional outliers, e.g. for real turnover in the beginning of 2021, there are no persistent deviations from the common trend. This also supports our timing of the beginning of the treatment period.

Economic pressure came not only from rising energy prices, but also from supply chain bottlenecks. If these bottlenecks are correlated with energy intensity, this may bias our estimates. Therefore, we include two additional variables in the regressions, namely the change of material shortages interacted with each of the treatment dummies $d_1$ and $d_2$. Data are obtained from a survey of the ifo institute in which firms are asked about a lack of primary and intermediate products. Here, only 19 of the 24 sectors at the 2-digit level are available. Therefore, we repeat the baseline estimation with the smaller sample and report the difference of the coefficients from the models with and without the bottleneck variable in the second bottom panel of Table 2. Reassuringly, the results remain stable.

Moreover, besides supply-side effects, sectors could be indirectly affected by reduced demand due to dampened economic activity in other sectors (Guerrieri et al. (2022)). Therefore, an input-output matrix (obtained from the destatis national accounts) capturing the demand linkages between the sectors is pre-multiplied to the energy intensity variable. We add this new control variable to Equation (1) and repeat the regression. Again, only 19 sectoral units are available after matching them to the product groups of the input-output matrix. Hence, the bottom panel of Table 2 shows the difference of the coefficients from the models with and without the control variable. Again, the results do not change.

Table 2 reports several more robustness checks. Firstly, we define $d_1$ and $d_2$ as conventional binary dummies in all equations, i.e. being 0 until August 2021 and 1 from September 2021 ($d_1$) and being 0 until February 2022 and 1 from March 2022 ($d_2$). Secondly, we shorten the pre-treatment period to 2021:4 to exclude the second corona lockdown in Germany. Thirdly, mineral oil refining has a rather low energy intensity in our data. This is due to the fact that the sector mainly only converts energy commodities but the cost structure data measures energy intensity where energy (e.g. fuel) is actually consumed. We conduct a robustness check by leaving out mineral oil refining. Finally, potential dynamic effects are taken into account by including a lag of the endogenous variable in a GMM estimation with two further lags as instruments. In general, the results do not change substantially compared to our baseline estimations.

Table 2: Robustness checks and additional control variables

| | Dependent variable | | | | |
|---|---|---|---|---|---|
| | Production | Turnover | New vacancies | Short-time work | Unemployment entries |
| | Estimation with binary dummies $d_1$ and $d_2$ | | | | |
| Effect from 2022/02/24 (p-value*) | -2.166 (0.000) | -1.364 (0.001) | -0.012 (0.000) | 0.136 (0.002) | -0.001 (0.880) |
| Observations | 504 | 504 | 528 | 528 | 528 |
| | Estimation with shortened pre-treatment period | | | | |
| Effect from 2022/02/24 (p-value*) | -2.201 (0.000) | -1.452 (0.001) | -0.015 (0.000) | 0.127 (0.002) | 0.012 (0.115) |
| Observations | 432 | 432 | 456 | 456 | 456 |
| | Estimation without mineral oil refining | | | | |
| Effect from 2022/02/24 (p-value*) | -1.987 (0.000) | -1.309 (0.001) | -0.013 (0.006) | 0.139 (0.002) | -0.001 (0.892) |
| Observations | 483 | 483 | 506 | 506 | 506 |
| | GMM estimation of dynamic panel | | | | |
| Effect from 2022/02/24 (p-value**) | -2.443 (0.000) | -1.187 (0.000) | -0.015 (0.000) | 0.143 (0.024) | 0.007 (0.521) |
| Observations | 456 | 456 | 480 | 480 | 480 |
| | Controlling for supply chain bottlenecks | | | | |
| Difference of effects | +0.017 | +0.016 | +0.000 | +0.000 | +0.000 |
| Observations | 399 | 399 | 418 | 418 | 418 |
| | Controlling for demand linkages between sectors | | | | |
| Difference of effects | -0.028 | -0.014 | +0.000 | -0.001 | +0.000 |
| Observations | 399 | 399 | 418 | 418 | 418 |

Notes: Estimated treatment interaction effects $(c_1 + c_2)$ following Equation (1). GMM estimation: total effects that result as $(c_1 + c_2)/(1 - \alpha)$, where $\alpha$ is the coefficient of the lagged $y$. Bottom two sections: Differences of coefficients from models with and without the respective control variables. *: p-values from Wald-tests testing $c_1 + c_2 = 0$. **: p-values from Wald-tests testing $c_1 + c_2)/(1 - \alpha) = 0$.

## 5 Conclusion

We present first causal evidence for economic effects of the Russia-Ukraine war. Using data for economic sectors in Germany, we estimate short-run consequences of the energy crisis.

Via the identification channel of sectoral energy intensity, we find that the energy crisis has already had a sizeable impact on industrial production and real turnover in the short run. This is notable as macroeconometric studies such as Kilian (2008) estimate GDP effects to amplify over several quarters after the shock has hit. The drop in production can cause further harm over time and eventually affect the labour market, too. Energy-intensive industries, such as metal, chemistry, or glass, usually stand at the beginning of production chains, which implies macroeconomic relevance. Indeed, supply bottlenecks had already reached a significant level due to Corona (e.g. Krolikowski and Naggert (2021)) and were exacerbated by the Ukraine war. Hummel et al. (2023) show that supply bottlenecks on the labour market are primarily compensated for by short-time work and only lead to job losses to a limited extent.

In energy crises, besides short-run measures in energy markets (e.g. Kotek et al. (2023)), economic policy instruments could be considered that support sustaining production instead of buffering losses of working hours, as short-time work does (Weber (2022)). At the same time, policy should support the ecological transition in the direction of decarbonisation and energy efficiency, which can also boost economic and employment growth (Diaz et al. (2019), Lehr et al. (2012)). Future research, in addition to the short-run effects investigated in this note, could treat long-run consequences of the energy crisis (compare Yoon and Ratti (2011)). For instance, this could concern investment or energy intensity itself.

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# A Estimation with binary treatment variable

While our baseline approach uses the full range of energy intensity for identification, we also conduct a classic binary difference-in-difference estimation. There, the 12 sectors with highest energy intensity are allocated to the group of treated ($x_i = 1$ in Equation (1)), whereas the 12 sectors with lowest energy intensity are considered as untreated ($x_i = 0$). The average energy intensity for the untreated is 0.73%, that of the treated is 3.03%. Table 3 shows the results.

With the onset of the war, the treated sectors experienced an average production and turnover loss of 7.7 and 5.9 index points, respectively, compared to the untreated sectors. As in the baseline models, the effects are substantially smaller in the pre-war period of the energy crisis, in which they amount to -2.7 and -2.8 index-points, respectively. Furthermore, the more energy-intensive sectors suffered from 0.049 fewer new vacancies per 100 employees during the war period compared to their less energy-intensive counterparts. We also find a positive effect on short-time work, which is, however, less precisely estimated than in the baseline model.

Table 3: Effects estimated with binary treatment variable

| | **Dependent variable** | | | | |
|---|---|---|---|---|---|
| | Production | Turnover | New vacancies | Short-time work | Unemploy-ment entries |
| Effects from 2021m09 | -2.749 | -2.849 | -0.010 | 0.156 | 0.038 |
| (p-value) | (0.007) | (0.024) | (0.209) | (0.247) | (0.238) |
| Effects from 2022/02/24 | -7.676 | -5.911 | -0.049 | 0.236 | 0.012 |
| (p-value*) | (0.000) | (0.000) | (0.000) | (0.195) | (0.549) |
| Observations | 504 | 504 | 528 | 528 | 528 |

Notes: Classic difference-in-difference approach: Estimated treatment interaction effects following Equation (1) with $x_i$ defined as binary variable. Effects from 2021m09: $c_1$. Effects from 2022/02/24: $c_1 + c_2$. Estimation period: 2021:1 to 2022:9 (production, turnover) or to 2022:10 (labour market variables). White cross-section (period cluster) standard errors and covariance were used to calculate p-values. *: p-values from Wald-tests testing $c_1 + c_2 = 0$.