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Energy Prices and Adjustments in European Industrial Sectors

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Title:

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Abstract:

This thesis replicates Marin and Vona (2019) and adopts a common framework to examine adjustments to predicted energy-price exposure beyond employment. The sample covers European industrial sectors over 1995–2019. The empirical framework relies on national end-use energy prices, fixed fuel shares, first differences, and controls for structural transformations. The findings show limited aggregate employment adjustment, alongside increases in the shares of technicians and professionals and a decline in the share of manual workers. Labor productivity and real value-added experience short-lived increases, yet the effects weaken over later periods. Aggregate investment shows a delayed negative response, whereas the effects on total investment and its composition do not remain robust when I use revised or extended data. Common-sample comparisons suggest that the weaker productivity results are mainly associated with later years, whereas the investment results are also sensitive to data revisions.

Keywords:

energy prices, occupational composition, labor productivity, capital investment, European industrial sectors

Název práce:

Ceny energií a přizpůsobení evropských průmyslových odvětví

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Abstrakt:

Tato práce replikuje studii Marina a Vony (2019) a používá společný rámec ke zkoumání přizpůsobení predikované expozici cenám energií nad rámec zaměstnanosti. Vzorek zahrnuje evropská průmyslová odvětví v období 1995–2019. Empirický rámec vychází z národních koncových cen energií, fixních podílů paliv, prvních diferencí a kontrolních proměnných pro strukturální transformace. Výsledky ukazují omezené přizpůsobení agregátní zaměstnanosti spolu s růstem podílů techniků a odborných pracovníků a poklesem podílu manuálních pracovníků. Produktivita práce a reálná přidaná hodnota krátkodobě rostou, avšak v pozdějších obdobích tyto účinky slábnou. Agregátní investice vykazují opožděnou negativní reakci, zatímco výsledky pro celkové investice a jejich strukturu nezůstávají robustní při použití revidovaných nebo rozšířených dat. Porovnání na společném vzorku naznačují, že slabší výsledky produktivity souvisejí především s pozdějšími roky, zatímco výsledky investic jsou citlivé také na revize dat.

Klíčová slova:

ceny energií, profesní struktura, produktivita práce, kapitálové investice, evropská průmyslová odvětví

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Introduction

Higher energy-price exposure and climate-policy exposure can raise production costs in energy-intensive industrial sectors. Affected sectors may respond through different margins, including employment, occupational composition, output, productivity, capital investment, and investment composition. However, the net adjustment remains unclear. Higher energy prices may increase costs, harming competitiveness and reducing production and employment. Nevertheless, higher energy prices could also encourage polluting sectors to adopt clean technologies, thereby increasing efficiency and reducing energy use and employment. Therefore, the main restructuring may occur through other adjustments, while the aggregate employment response might be limited.

Existing studies generally report limited aggregate employment alongside statistical changes happening at the worker, occupation, plant, firm, and sector levels. Moreover, evidence on productivity is mixed, and previous studies mostly suggest adjustments in aggregate investment, environmental investment, and capital deepening. However, existing literature provides limited evidence on how employment effects coexist with changes in output and productivity. Consequently, there is insufficient research examining whether changes in productivity come from changes in real output or hours worked, and how price movements matter. Furthermore, studies on investment address aggregate and environmental investment responses, while reallocation across detailed standard fixed-capital asset categories, particularly ICT and non-ICT assets and their components, remains underexplored. Moreover, there is insufficient research on whether the adjustments persist over longer periods, across sector reclassifications, and despite data revisions. Last but not least, few studies appear to examine employment composition, productivity decomposition, and investment composition within one consistent empirical framework.

Building on previous studies, my objective is to analyze industrial adjustments

to predicted energy price exposure beyond aggregate employment. Therefore, I aim to answer four sets of questions in this thesis. First, can the employment and occupational composition results documented by Marin and Vona (2019) be replicated and adapted to other adjustments? Second, are higher predicted energy prices associated with higher labor productivity, and does higher productivity operate through higher output or lower hours worked? In turn, do nominal value added or the value-added deflator mainly account for the changes in real value added? Third, are higher energy prices associated with changes in aggregate investment or with reallocation across asset categories, such as ICT and non-ICT, and with their detailed components? Fourth, do the productivity and investment relationships with predicted energy-price exposure persist through a longer period, and are changes across periods associated with sector reclassification, data revisions, or the inclusion of later years?

To answer the questions listed above, I first replicate the results on employment and occupational composition reported by Marin and Vona (2019) and use them later as a verified benchmark for my extensions. The identification relies on the movements in national tax-inclusive energy prices weighted by fixed energy-use shares. The regressions are in first differences to isolate unobserved fixed characteristics. Country-year and sector-year fixed effects account for national and sectoral shocks, while initial cluster controls account for overlapping structural transformations. Standard errors are clustered at the country-sector level to account for heteroskedasticity and within-pair serial correlation. The replication sample covers 15 sectors in 14 European countries over 1995–2011. Later, I adapt the framework to examine how labor productivity and investment respond to predicted energy price exposure during 1995–2011 and 1995–2007, respectively. To extend these two analyses through 2019, I harmonize sectors classified under the NACE Rev. 2 back to NACE Rev. 1. Samples differ slightly across analyses due to data availability. To assess whether the main source of changes is additional periods, sector reclassification, or data revisions, I also apply common-sample

comparisons for the estimates on labor productivity and investment.

The replication analysis reproduces limited adjustment in aggregate employment along with noticeable occupational restructuring. Both higher observed and predicted energy prices are associated with increases in the shares of technicians and professionals and with reductions in the share of manual workers. Labor productivity analysis during 1995–2011 shows that higher predicted energy price exposure is associated with higher productivity and real value added, with limited responses in total employment. The decomposition of real value added also suggests that price movements account for more of the changes in real value added. Therefore, productivity adjustment is short-lived and does not provide clear evidence of innovation or efficiency improvements. During the extended period, the positive contemporaneous productivity effects persist but weaken. The coefficients for real value added and the value-added deflator lose significance. These changes over the later period suggest that the efficiency mechanism might be overly optimistic.

Additionally, the investment analysis for 1995–2007 provides some evidence of subsequent reductions in total investment and only a weakly significant short-lived reallocation towards IT investment. The extension to later years substantially changes the adjustment in total investment. Reallocation is not visible across broad and detailed ICT and non-ICT shares. Such mixed results support the importance of the common-sample comparisons. Weaker labor productivity results are mainly due to additional years, whereas differences in investment results already appear when the revised EU KLEMS outcome data are used. Sector harmonization does not seem to be the primary driver of the changes in either analysis.

This thesis contributes to existing literature in several ways. First, I use a single consistent empirical framework to study industrial adjustments, including employment, output, productivity, aggregate investment, and its composition. This helps me connect labor, capital, and production responses to predicted energy-price exposure. Second, I extend the analysis of labor productivity by

decomposing it into real value added and hours worked to analyze whether higher productivity is due to higher production or lower hours worked. In the same logic, I decompose real value added into nominal value added and the value-added deflator to examine the role of price movements. The decomposition methods help avoid the false attribution of positive productivity automatically to the efficiency mechanism. Third, I examine whether predicted energy-price exposure is associated with reallocation across standard fixed-capital asset categories rather than focusing mainly on environmental investment as in most studies. Finally, I harmonize the NACE Rev. 2 sectors back to NACE Rev. 1, extend the productivity and investment analyses to more recent years, and implement common-sample comparisons for each analysis. The comparison helps me assess whether the differences in results between the original and extended sample periods are due to additional years, sector reclassification, or data revisions.

The remainder of the thesis is organized as follows. Chapter 1 reviews the related literature. Chapter 2 describes the data sources and sample coverage, while Chapter 3 presents the descriptive statistics. Chapter 4 explains the methodology of Marin and Vona (2019) and the adaptations introduced in this thesis. Chapter 5 presents the replication results and extends the original analysis to labor productivity, value added, aggregate investment, and investment composition. Chapter 6 extends the labor-productivity and investment analyses through 2019. Chapter 7 reports the harmonized common-sample comparisons, and the Conclusion chapter concludes the thesis.

1 Literature Review

High energy-price exposure may increase compliance and production costs, reducing hours worked, productivity, and investment. However, it can also encourage highly exposed entities to innovate to save energy and reallocate labor, capital, and even location to reduce costs. Therefore, the overall employment effects of higher energy prices may be limited, while the main adjustments may occur at more disaggregated levels, such as workers, plants, firms, and sectors.

The Pollution Haven and the Porter hypotheses emphasize these opposing channels. The Pollution Haven hypothesis claims that strict environmental regulation may raise production costs and reduce competitiveness for emission-intensive sectors. This may encourage them to relocate to countries with less strict policies, thereby decreasing domestic output and potentially employment (Levinson; Taylor, 2008). The weak version of the Porter hypothesis explains a contrasting but related mechanism: strict environmental policies motivate emission-intensive sectors to innovate and adopt green equipment and practices, hence saving energy (Porter; Linde, 1995). These hypotheses provide only a basis for interpretation, but the empirical analyses in this thesis do not directly examine mechanisms of relocation or innovation. Empirical studies help identify how these mechanisms operate and appear at different levels and in different ways.

Empirical studies generally identify some employment adjustment but do not reveal substantial job losses at the aggregate level. To begin with, Martin et al. (2014) examine the consequences of carbon taxation for UK manufacturing plants by comparing plants paying the full tax rate with those paying a discounted rate and instrumenting the tax rate with eligibility for the discount. They document considerable reductions in energy intensity and electricity use but no statistically significant changes in employment, revenue, or exit. Their results indicate that environmental taxation may cause plant-level adjustments in energy use without necessarily reducing employment. Similarly, Marin and Vona (2021)

provide another establishment-level analysis. They explore the impacts of energy prices, used as a proxy for carbon taxes, on French manufacturing plants over 1997–2015. They employ a shift-share instrument based on initial energy-use shares and national tax-inclusive fuel-specific prices. The authors note that higher energy prices reduce energy use and emissions while producing modest declines in employment and productivity. Highly exposed plants experience larger employment responses and show some evidence of a shift towards technicians and away from manual workers. These estimates are consistent with Marin and Vona (2019) and are particularly relevant to this thesis in terms of the construction of energy-price exposure and the analyses of employment dynamics and productivity.

Firm-level and sector-level studies provide similar results. Dussaux (2020) uses a fixed-weight energy price index as an instrumental variable for firm-level data for French manufacturing over 2001–2016. The results show that higher energy prices reduce energy use and shift production and employment from energy-intensive firms towards more energy-efficient firms. However, the net industry-level employment response is negligible. This evidence supports the argument that overall employment responses can remain limited although adjustment may occur at a more disaggregated level. In addition, Yamazaki (2017) documents similar results for employment in energy-intensive sectors. Using province–industry-level data for British Columbia’s revenue-neutral carbon tax over 2007–2013, Yamazaki (2017) adopts the difference-in-differences method. The author notes employment losses in carbon-intensive and trade-exposed industries alongside gains in cleaner industries, providing evidence of sectoral redistribution consistent with the firm-level redistribution reported by Dussaux (2020). The aggregate estimates indicate a slight increase in employment, suggesting that higher employment in cleaner industries and, more importantly, the recycling of tax revenues may offset losses in more exposed industries (Yamazaki, 2017).

The results described above provide important evidence that the employment response to higher energy prices usually operates through several channels rather

than a single, consistent effect across plants, firms, or sectors. Therefore, Hille and Möbius (2019) decompose the employment response to energy prices into demand, cost, and factor-shift channels, using country–sector-level data over 1996–2009. They identify significant positive employment impacts for the economy as a whole, although manufacturing sectors do not show a significant net response. These estimates indicate that modest employment changes in more-exposed manufacturing sectors may reflect offsetting adjustment mechanisms, including negative demand effects, positive cost effects, and shifts among labor, capital, and energy inputs.

Overall, this part of the literature does not support substantial job destruction from higher energy prices or environmental taxation. Negative impacts are more noticeable among polluting entities, whereas aggregate employment remains broadly stable. Instead, the evidence points to labor reallocation and some production shifts across plants, firms, and sectors. Similarly, as Marin and Vona (2021) reported, the results become more visible in labor composition.

The following studies help understand the effects on labor composition and unemployment at the worker level. To examine the effects of British Columbia’s revenue-neutral carbon tax, Yip (2018) uses worker-level data over 2001–2015 and the difference-in-differences method. The author reports that medium- and low-skilled workers experience higher unemployment rates and tend to work part-time jobs until they become discouraged and leave the labor force entirely. This suggests that studying aggregate effects alone may overlook how employees may experience different working conditions based on their skills. Wei and Yip (2025) also analyze the labor market effects of British Columbia’s revenue-neutral carbon tax through worker-level data. Using the difference-in-differences approach, they document gradually lower wage rates and only temporary increases in unemployment rates. High unemployment occurs mainly through increases in job-separation rates and decreases in job-finding rates, but the increase in unemployment is not persistent. In general, the findings suggest that while aggregate employment remains broadly

unchanged, the effects of environmental taxation may operate through hiring conditions and labor turnover. These papers further motivate the analysis of occupational effects of energy prices, which are examined in detail by Marin and Vona (2019) and Marin and Vona (2021).

As previously discussed, Marin and Vona (2021) briefly reported that energy prices, used as a proxy for carbon taxes, may benefit technicians and harm manual workers, despite a limited aggregate response. In their earlier article, *Climate policies and skill-biased employment dynamics: Evidence from EU countries*, Marin and Vona (2019) use country- and sector-level data over 1995–2011 to analyze skill-biased employment adjustment. They study the impacts of energy prices, a proxy for climate policies, across 15 industrial sectors in 14 European countries. Their identification methodology relies on a shift-share instrumental variable, constructed as national fuel-specific prices weighted by initial energy-use shares. They also control for initial exposure to emissions, green innovation, globalization, and automation. They report no significant adjustment in aggregate employment, with positive effects for technicians and negative effects for manual workers. They argue that the effects of climate policies resemble the skill-biased adjustment associated with automation and globalization. The results support this idea and move further, showing that the strongest effects are concentrated among technicians Marin and Vona (2019).

To sum up, this literature, with worker- and sector-level analyses of labor composition, further supports the view that aggregate employment alone is not sufficient to assess industrial adjustments to energy prices or climate policies. In fact, disaggregated analyses can reveal how energy prices change unemployment risk and occupational demand. This motivates replicating the baseline estimates of total employment and labor composition reported by Marin and Vona (2019). The replication will enable me to conduct a parallel analysis of occupational and investment composition, which is explained in more detail later.

In addition to employment and labor composition, Marin and Vona (2019) also

briefly report the impacts of energy prices on labor productivity, finding short-lived positive adjustments. However, the labor-productivity analysis only receives limited discussion and does not decompose productivity into real value added and hours worked or real value added into nominal value added and the value-added deflator. Therefore, labor productivity deserves more detailed examination, which I build on the methodology used by Marin and Vona (2019). Yamazaki (2022) also studies the effects of environmental taxes on labor productivity. The author uses a propensity-score-weighted difference-in-differences method to analyze plant-level data for British Columbia’s revenue-neutral carbon tax. The results indicate that the tax may reduce productivity, while recycling the tax revenue may offset some productivity losses, with the effect becoming positive for some plants. This finding reveals that productivity adjustment may be affected not only by energy prices or carbon taxes but also by the design of the tax reform. Albrizio et al. (2017) provide another aspect to explore. They analyze the effects of the OECD Environmental Policy Stringency Index on firm- and industry-level productivity in OECD countries from 1990 to 2009 to test the strong version of the Porter hypothesis. They report that industrial productivity increases in technologically advanced countries. In addition, the positive effects are stronger for industries closer to the technological frontier, while the firm-level results differ. Most (least) productive firms experience a short-lived productivity boost (slowdown).

Overall effects are more mixed for labor productivity. Because labor productivity is measured as real value added per hour worked, its decomposition into total hours worked and real value added may help assess whether it reflects output rather than employment changes. The decomposition of real value added into nominal value added and the value added deflator may further distinguish changes in nominal activity from price movements.

Investment is another possible adjustment to higher energy prices. Marin and Vona (2021) also report that the capital–labor ratio rises at the firm level, indicating that capital deepening may represent an important adjustment mecha-

nism. Dlugosch and Koźluk (2017) provide a firm-level examination of the effects of energy prices and environmental policies on investment in 30 OECD economies over 1995–2011. The authors report that higher energy-price inflation is associated with a modest reduction in aggregate investment. However, they also note that investment appears to increase among firms in energy-intensive sectors. This suggests that investment may be another adjustment mechanism of energy-price exposure. Leiter et al. (2011) analyze the impacts of environmental regulation on several investment types, such as tangible goods, buildings, machinery, and productive investment net of pollution-abatement investment, using country-sector data from 1998 to 2007. They find that environmental regulation is positively associated with each type of gross investment, although the relationship diminishes. Colmer et al. (2025) examine specifically how the European Union Emissions Trading System (EU ETS) affects emissions and investment using administrative data. They show that this market-based climate policy caused targeted cleaner-production investment, which contributed to a decline in emissions. They distinguish different types of environmental investment rather than analyzing standard fixed-capital asset categories. Gray and Shadbegian (1998) also distinguish pollution-abatement investment from productive investment to analyze whether plants shift toward environmental investment and away from productive capital investment. They find that plants’ environmental and productive investments are negatively related and that new mills are less likely to choose dirtier technologies after stricter environmental regulation.

The existing literature primarily suggests that investment restructuring may be a potential adjustment to higher energy prices despite limited or modest impacts on aggregate investment. Current studies mainly focus on aggregate investment, capital deepening, and environmental investment. However, the question of whether standard fixed-capital formation may be reallocated across detailed asset categories, such as ICT equipment, software, transport equipment, machinery, and construction, has received less attention. Therefore, examining asset shares allows

me to analyze whether higher energy prices are associated with a redistribution of capital investment across asset categories.

All in all, the existing literature on energy prices and environmental policies suggests limited aggregate employment responses, along with adjustments in occupational composition, production, capital, and technology. This motivates the application of a common framework provided by Marin and Vona (2019) to analyze the effects of predicted energy price exposure on employment composition, productivity decomposition, aggregate investment, and capital asset composition.

2 Data

This thesis combines multiple datasets for the replication and extension exercises. To replicate the results reported by Marin and Vona (2019), I use a country-sector-year-specific dataset that the authors cleaned and merged. To extend the authors' original analysis to more recent years and to estimate the effects of energy price exposure on additional outcomes, I also use supplementary datasets. In the following subsections, I first describe the main sources and the sample coverage used in the original analysis to estimate the effects of energy price exposure on employment and occupational composition. Then, I describe the sources and the sample coverage I use for the extension analysis. While the authors' dataset follows the NACE Rev. 1 (ISIC Rev. 3) sector classification, the datasets I employ to extend the analysis follow the NACE Rev. 2 (ISIC Rev. 4) classification.

2.1 Data Used by Marin and Vona (2019)

The dataset provided by Marin and Vona (2019) combines information from several sources, including the World Input-Output Database (WIOD), the International Energy Agency (IEA), the European Labour Force Survey (EU-LFS), EU KLEMS, OECD STAN, and OECD REGPAT.

The World Input-Output Database provides the core year-specific country-sector-level data. The database includes Socio-Economic Accounts and Environmental Accounts and has two releases, published in 2013 and 2016. The authors use the 2013 release to obtain total hours worked, energy use by source (coal, oil, natural gas, and electricity), greenhouse gas emissions, value added, and the value-added deflator. Meanwhile, the International Energy Agency provides tax-inclusive national energy prices by source, which are used as a proxy for climate policy exposure. More precisely, the IEA provides industrial end-use prices for light fuel oil, steam coal, natural gas, and electricity.

The European Labour Force Survey is another key source, providing country-sector-year-level data on hours worked by employees across different occupational groups. The selected occupational groups are managers, professionals, technicians, and manual workers. The authors exclude clerical and service occupations from the analysis, as they represent only a small share of employment, specifically 10.6% of the average industry workforce (Marin; Vona, 2019).

The authors use EU KLEMS to obtain year-specific country-sector-level stocks of ICT and non-ICT capital per hour worked. Moreover, OECD STAN provides year-specific country-sector-level import penetration, as imports divided by apparent domestic consumption, where apparent domestic consumption equals output plus imports minus exports. Finally, OECD REGPAT provides patent applications at the European Patent Office.

2.2 Original Sample Coverage

The original sample examined in the replication analysis is restricted to a balanced panel of 14 European countries and 15 industrial sectors during the 1995–2011 period, due to data availability limitations. In particular, the EU KLEMS data are not available for Bulgaria, Cyprus, Estonia, Greece, Latvia, Lithuania, Malta, Poland, Portugal, Romania, and Slovakia. Furthermore, OECD STAN does not provide import penetration for Luxembourg, and the OECD Environmental Policy Stringency index, used only for robustness analysis by Marin and Vona (2019) but not included in the baseline estimation that I replicate, is missing for Slovenia. Thus, the original sample countries are limited to Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, the Netherlands, Spain, Sweden, and the United Kingdom, for which the required variables are consistently available. Nevertheless, Marin and Vona (2019) state that the selected countries account for 73.7% of employment and 92.3% of value added among the EU27 countries, covered in the WIOD 2013 release. The authors use these coverage shares to justify the restriction.

Moreover, the selected 15 sectors comprise 13 manufacturing sectors, “Mining and Quarrying” and “Electricity, Gas, and Water Supply”. The authors aggregate two manufacturing sectors, namely “Textiles and Textile Products” and “Leather and Footwear”, into one manufacturing sector in the final dataset to harmonize sectors across the sources used. Additionally, they exclude the “Construction” sector from the analysis, as it is less exposed to international competition, measured by import penetration, and automation, measured by ICT and non-ICT capital intensities. Marin and Vona (2019) also explain that the “Construction” sector has extreme values for employment.

The original sample period covers the years from 1995 to 2011, as the main data source, the WIOD 2013 release, provides information only for this period. Although data on ICT and non-ICT capital stocks and import penetration are available through 2007 and 2009, respectively, only their initial-period values are used in the study, allowing the analysis to cover 1995–2011.

2.3 Data Sources and Sample Coverage for Extensions

In addition to the dataset provided by Marin and Vona (2019), I use several additional datasets. I obtain data from the EU KLEMS releases based on NACE Rev. 1 and NACE Rev. 2 industry classifications, for which the classification concordance and harmonization procedures are explained later in Section 6.1. First, I employ the earlier EU KLEMS data released in 2011, from which I obtain gross fixed capital formation, both in aggregate and by asset category. I also use the new EU KLEMS data released in 2025, from which I obtain hours worked by employees, chain-linked volume measures of value added, nominal value added, the value-added deflator, and gross fixed capital formation, both in aggregate and by asset category. For energy prices, I use the IEA’s 2019 and 2020 Statistics reports, *Energy Prices and Taxes for OECD Countries*, from which I obtain industrial

end-use fuel-specific energy prices for 2010–2019.

For the labor-productivity analysis during 1995–2011, I rely on the dataset provided by Marin and Vona (2019). The earlier EU KLEMS data are only used to estimate the effects of energy price exposure on total investment and asset shares during 1995–2007 for the restricted investment subsample. By contrast, the new EU KLEMS data are used to extend the analysis of labor productivity and investment to cover the period 1995–2019.

For the labor-productivity analysis during 1995–2011, the sample countries are the same as in the replication exercise. For the investment analysis during 1995–2007, the only available countries are Austria, the Czech Republic, Denmark, Finland, Germany, Italy, the Netherlands, Spain, Sweden, and the United Kingdom, because of limitations in the NACE Rev. 1 EU KLEMS data. With the recent EU KLEMS release, I analyze a larger investment sample by extending the sample period through 2019. The available countries for the extension of the labor-productivity analysis are Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, the Netherlands, Spain, and the United Kingdom. For the extension of the investment analysis, the available countries are Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden, and the United Kingdom.

The labor-productivity analysis during 1995–2011 and the investment analysis during 1995–2007 cover the same sectors as in the original analysis. The sectors examined in the extension analysis are 13 harmonized sectors. As EU KLEMS does not provide data at the same level of sectoral detail, the corresponding NACE Rev. 1 sectors ‘Wood and Products of Wood and Cork’ and ‘Pulp, Paper, Printing and Publishing’ are reported together in the recent EU KLEMS release, as are ‘Rubber and Plastics’ and ‘Other Non-Metallic Mineral Products’. Tables 2.1 and 2.2 describe country and sector coverage, respectively, for each exercise implemented in this thesis.

Table 2.1 Country coverage by empirical exercise

Empirical exercise	Period	Countries	No.
Replication of employment and occupational composition Original-period labor-productivity analysis	1995–2011	AT, BE, CZ, DE, DK, ES, FI, FR, HU, IE, IT, NL, SE, UK	14
Original-period investment analysis Investment common-sample comparison	1995–2007	AT, CZ, DE, DK, ES, FI, IT, NL, SE, UK	10
Extended labor-productivity analysis Labor-productivity common-sample comparison	1995–2019 1995–2011	AT, BE, CZ, DE, DK, ES, FI, FR, HU, IT, NL, UK	12
Extended investment analysis	1995–2019	AT, BE, CZ, DE, DK, ES, FI, FR, IT, NL, SE, UK	12

Table 2.2 Sector coverage by empirical exercise

Original 15-sector sample	Harmonized 13-sector sample
Replication and labor productivity: <i>1995–2011</i> Investment analysis: <i>1995–2007</i>	Labor-productivity and investment extensions: <i>1995–2019</i> Labor-productivity comparison: <i>1995–2011</i> Investment comparison: <i>1995–2007</i>
C: Mining and Quarrying	C: Mining and Quarrying
15t16: Food, Beverages and Tobacco	15t16: Food, Beverages and Tobacco
17t19: Textiles, Textile Products, Leather and Footwear	17t19: Textiles, Textile Products, Leather and Footwear
20: Wood and Products of Wood and Cork	20t22: Wood, Paper and Printing
21t22: Pulp, Paper, Printing and Publishing	
23: Coke, Refined Petroleum and Nuclear Fuel	23: Coke, Refined Petroleum and Nuclear Fuel
24: Chemicals and Chemical Products	24: Chemicals and Chemical Products
25: Rubber and Plastics	25t26: Rubber, Plastics and Other
26: Other Non-Metallic Mineral Products	Non-Metallic Mineral Products
27t28: Basic Metals and Fabricated Metal Products	27t28: Basic Metals and Fabricated Metal Products
29: Machinery, Nec	29: Machinery, Nec
30t33: Electrical and Optical Equipment	30t33: Electrical and Optical Equipment
34t35: Transport Equipment	34t35: Transport Equipment
36t37: Manufacturing, Nec; Recycling	36t37: Manufacturing, Nec; Recycling
E: Electricity, Gas and Water Supply	E: Electricity, Gas and Water Supply

3 Descriptive Statistics

Table 3.1 shows descriptive statistics for the labor productivity sample during 1995–2011 and the investment sample during 1995–2007. Table 3.2 shows descriptive statistics for the extended labor productivity and investment samples during 1995–2019. Samples differ across exercises due to data availability. The descriptive tables confirm the accounting decompositions of labor productivity growth and real value added growth. ICT and non-ICT shares mirror each other, as expected.

Table 3.1 shows that on average, predicted energy-price exposure increases annually by 0.019 units in the labor productivity sample and by 0.016 in the investment sample. The average labor productivity growth is 2.27%, with 0.55% growth in real value added and -1.72% growth in hours worked. Nominal value added and the value-added deflator increase by 1.79% and by 1.24%, respectively, on average. Real investment experiences annual growth of 2.28%, yet its standard deviation of 14.84% shows substantial variation. Asset shares change only slightly, whereas the ICT investment share grows by 0.41 percentage points on average. The increase in the ICT investment share appears to be driven by large positive changes in the software share.

Table 3.2 shows that annual growth in predicted energy-price exposure becomes smaller (0.006) in the extended periods, whereas the average lagged exposure level is higher in both samples. The average labor productivity growth remains similar at 2.18%, but its composition has changed. The growth in the value-added deflator also becomes smaller. Average real investment growth falls to 0.92%, while its standard deviation rises. Average asset changes remain close to zero. The average increase in the ICT investment share is smaller, at 0.16 percentage points. The increase in the ICT investment share again seems to be driven by positive changes in the software share. Overall, asset share changes are more volatile in the extended period.

Table 3.1 Descriptive statistics for the original-period analyses

Variable	<i>N</i>	Mean	SD	Median	Min.	Max.
<i>Panel A: Productivity and value added, 1995–2011</i>						
Δ Predicted energy-price exposure	3,360	0.019	0.066	0.012	-0.317	0.313
Predicted energy-price exposure ($t - 1$)	3,360	0.460	0.208	0.415	0.000	1.281
Annual labor-productivity growth (%)	3,360	2.274	9.549	2.259	-237.025	256.865
Annual real-value-added growth (%)	3,360	0.550	9.461	0.660	-242.155	276.754
Annual hours-worked growth (%)	3,360	-1.724	5.620	-1.282	-74.153	92.975
Annual nominal-value-added growth (%)	3,360	1.788	8.711	1.984	-164.178	129.346
Annual value-added-deflator growth (%)	3,360	1.237	7.075	1.071	-222.221	274.952
<i>Panel B: Investment, 1995–2007</i>						
Δ Predicted energy-price exposure	1,796	0.016	0.048	0.009	-0.176	0.193
Predicted energy-price exposure ($t - 1$)	1,796	0.412	0.166	0.377	0.000	1.004
Annual real-investment growth (%)	1,796	2.276	14.844	2.722	-154.902	168.546
Annual change in ICT investment share	1,796	0.410	2.752	0.152	-19.221	21.831
Annual change in non-ICT investment share	1,796	-0.410	2.752	-0.152	-21.831	19.221
Annual change in IT investment share	1,796	-0.026	1.348	-0.010	-14.657	15.698
Annual change in communication-equipment share	1,796	-0.061	0.632	-0.019	-6.376	4.270
Annual change in software investment share	1,796	0.497	2.143	0.163	-21.922	19.912
Annual change in transport-equipment share	1,796	-0.036	2.050	0.000	-31.631	28.928
Annual change in other-machinery share	1,796	-0.164	4.884	0.031	-48.072	98.381
Annual change in other-construction share	1,796	-0.211	4.337	-0.102	-116.604	48.696

Notes: Statistics are calculated using the exact estimation samples and are weighted by initial hours worked in 1995. First differences of logarithmic outcomes are multiplied by 100 and reported as approximate percentage changes. Changes in investment shares are multiplied by 100 and reported in percentage points. Predicted energy-price exposure is measured in constant US dollars per kilogram of oil equivalent.

Table 3.2 Descriptive statistics for the extended-period analyses

Variable	<i>N</i>	Mean	SD	Median	Min.	Max.
<i>Panel A: Productivity and value added, 1995–2019</i>						
Δ Predicted energy-price exposure	3,717	0.006	0.070	0.002	-0.415	0.421
Predicted energy-price exposure ($t - 1$)	3,717	0.527	0.246	0.498	-0.002	1.364
Annual labor-productivity growth (%)	3,717	2.184	7.321	1.899	-179.111	181.055
Annual real-value-added growth (%)	3,717	1.158	7.864	1.440	-178.787	176.240
Annual hours-worked growth (%)	3,717	-1.026	4.321	-0.448	-57.818	26.906
Annual nominal-value-added growth (%)	3,717	2.080	7.340	2.265	-151.565	129.053
Annual value-added-deflator growth (%)	3,717	0.922	5.730	0.876	-131.194	211.567
<i>Panel B: Investment, 1995–2019</i>						
Δ Predicted energy-price exposure	3,744	0.006	0.071	0.004	-0.415	0.421
Predicted energy-price exposure ($t - 1$)	3,744	0.541	0.239	0.515	-0.002	1.364
Annual real-investment growth (%)	3,744	0.921	16.443	1.669	-241.199	224.786
Annual change in ICT investment share	3,744	0.162	4.081	0.033	-115.542	73.660
Annual change in non-ICT investment share	3,744	-0.162	4.081	-0.033	-73.660	115.542
Annual change in IT investment share	3,744	-0.055	1.242	-0.029	-17.969	13.480
Annual change in communication-equipment share	3,744	-0.015	0.820	-0.014	-16.025	16.538
Annual change in software-and-databases share	3,744	0.232	3.899	0.038	-132.760	78.834
Annual change in transport-equipment share	3,744	-0.002	2.376	0.043	-49.405	60.544
Annual change in other-machinery share	3,744	-0.214	5.254	-0.139	-67.790	101.970
Annual change in other-construction share	3,744	0.053	4.157	0.111	-113.793	84.615

Notes: Statistics are calculated using the exact estimation samples and are weighted by fixed 1995 hours worked. First differences of logarithmic outcomes are multiplied by 100 and reported as approximate percentage changes. Changes in investment shares are multiplied by 100 and reported in percentage points. Predicted energy-price exposure is measured in constant US dollars per kilogram of oil equivalent.

4 Methodology of Marin and Vona (2019)

This section presents the empirical design of Marin and Vona (2019), which provides the common methodological framework for the replication and extension exercises in this thesis. The authors' objective is to assess the effects of climate policies, proxied by energy-price exposure, on total employment and occupational composition. My objective is to adopt their methodology as a benchmark and adapt it to additional adjustment mechanisms in production and capital. In particular, I analyze whether energy prices are also associated with labor productivity and its decomposition into real value added and hours worked, the decomposition of real value added into nominal value added and the value-added deflator, and total investment and investment composition. These additional outcomes are suitable, as these adjustments may still coexist with limited aggregate employment effects.

The methodology of Marin and Vona (2019) is relevant to the additional outcomes I adopt, as it provides a common framework for country–sector-level exposure to energy price movements. It also accounts for relevant overlapping shocks, such as green technological capacity, automation, and import penetration. I therefore first replicate their employment and labor composition results across European country–sector pairs over 1995–2011 to use as a verified benchmark for my extension exercises. Then, I exclude initial emission intensity as a separate control and examine predicted exposure directly in a reduced-form specification, which I use consistently for additional outcomes and extensions through 2019. For extended-period analyses, I reconstruct initial energy-use shares and cluster-composition shares using data provided by the authors for the harmonized sectors from rev 2 to rev 1. I later introduce common-sample comparisons for production and capital analyses to assess whether differences in results are due to an extension of the sample period coverage or due to revisions to classification and vintage. The

following subsections explain the elements of the authors’ methodology required for these adaptations.

4.1 Energy-Price Measure and Instrument

To begin with, Marin and Vona (2019) use energy prices as a proxy for climate policy exposure, since strict climate policies tend to increase the cost of energy use through compliance costs. The energy-price measure is the weighted average of country-year industrial end-use prices for steam coal, light fuel oil, natural gas, and electricity from the IEA, where the weights are country-sector-year energy-source shares of total energy use from the WIOD. Raw IEA energy prices vary only by country, year, and source, but not by sector; therefore, energy shares are necessary to create sectoral variation. In addition, the energy-price measure is deflated to make prices comparable over time and scaled down by 1,000 to make the coefficients easier to read.

The authors address potential endogeneity in observed energy prices by using an instrumental-variable specification. First, demand shocks may affect both employment and energy prices, for example, through quantity discounts or negotiated price reductions. Second, unobserved technological changes may affect both labor demand and observed energy prices through the sector’s energy mix, as observed energy prices are weighted by a time-varying energy mix. Therefore, the authors instrument energy prices using a Bartik shift-share logic, which is the interaction of time-varying national end-use energy prices for each source with the initial shares of coal, oil, natural gas, and electricity use by each country-sector pair. The idea is that the instrument keeps the energy-use shares fixed in the initial period of 1995 to identify the energy-price exposure; thus, later changes in energy-use shares cannot affect the instrument. While the annual change in energy prices is instrumented by the annual change in the shift-share energy price, the lagged energy price is instrumented by the lagged shift-share energy price. The inclusion of initial cluster dummies also makes the exclusion restriction assumption more

plausible by controlling for overlapping structural labor-market changes.

4.2 Initial Structural Exposure and Cluster Controls

Marin and Vona (2019) identify two distinct and potentially opposing measures of exposure to climate policies: emission intensity and environmental patent intensity. The intuition is that climate policies may not only impose costs on dirty sectors; they may also create opportunities for sectors involved in green technologies. More precisely, the rising compliance cost may reduce competitiveness and destruct jobs. Yet it may lead to job creation, as the increased demand for green goods and services increases labor demand for highly skilled workers in sectors engaged in green activities Marin and Vona (2019). These two concepts are related to the Pollution Haven hypothesis and the weak version of the Porter hypothesis. Thus, emission intensity captures the cost-side of energy-policy exposure, whereas environmental patent intensity captures the opportunity-side of energy-price exposure.

First, emission intensity is measured as greenhouse gas emissions divided by real value added, where greenhouse gas emissions include direct and indirect greenhouse gas emissions. It accounts for exposure to climate-policy costs. Direct greenhouse gas emissions are generated directly by each sector and are the sum of CO₂, CH₄, and N₂O, measured in CO₂-equivalent tons. Indirect greenhouse gas emissions are embodied in the electricity sold by the “Electricity, Gas, and Water Supply” sector to the examined sectors and are calculated by Marin and Vona (2019) based on input-output estimates retrieved from the WIOD. The reason for the inclusion of indirect emissions is that electricity generation also leads to greenhouse gas emissions.

Second, environmental patent intensity is the stock of climate-related patent applications at the European Patent Office divided by hours worked. It accounts

for exposure to green comparative advantage, which may favor workers with skills suitable for working with green technologies. Marin and Vona (2019) construct it using data on the stock of EPO applications from OECD REGPAT. The authors identify climate-related technologies through the IPC-CPC taxonomy developed by the OECD ENV-TECH Indicator and later assign them to the sample sectors that produce green technologies using the IPC-ISIC concordance table by Lybbert and Zolas (2014).

The authors construct initial cluster dummies to account for several overlapping structural transformations and to isolate the employment effect of climate policies, proxied by energy-price changes, from other structural transformations. In their descriptive analysis, Marin and Vona (2019) observe an unusual correlation between emission intensity and employment dynamics: sectors that become cleaner over time hire more routine or manual workers, while the demand for skilled workers, such as technicians, declines. Thus, country-sector pairs are grouped into different clusters based on their combined degree of exposure to emission intensity, environmental patent intensity, ICT capital intensity, non-ICT capital intensity, and import penetration, which are the clustering variables.

Cluster analysis is adopted because climate policies may overlap with other structural labor-market transformations, including automation and globalization. ICT and non-ICT capital intensities, measured as the respective capital stocks per hour worked, control for automation, digital technological change, and broader capital deepening, whereas import penetration controls for trade, globalization pressure, and import competition. The intuition is that sectors with higher exposure to automation tend to favor skilled workers while laying off routine or manual workers. Similar reasoning applies to import penetration, where sectors open to trade may outsource routine workers to low-income countries, or domestic sectors producing low-skill-intensive goods may face competition from cheaper imports, reducing production and hence routine or manual workers.

The initial cluster dummies used in the replication were constructed by Marin

and Vona (2019); however, I briefly summarize their construction process. As the clustering variables have outliers and skewed distributions, the authors first transform them into percentile ranks. Marin and Vona (2019) state that they use two-step average-linkage clustering: hierarchical clustering to find the optimal number of clusters and non-hierarchical clustering to reassign country-sector pairs to the generated clusters based on their homogeneous attributes. This method aims to minimize the distance between observations within a cluster and maximize the distance between observations across different clusters. Cluster dummies are fixed at their 1995 values to avoid endogeneity problems related to cluster switching, where cluster membership itself may depend on energy-price changes or employment dynamics. The result is six distinct clusters: ‘Brown Global Low-tech’, ‘Brown Medium-tech’, ‘Green Global High-tech’, ‘Exposed to Automation’, ‘Black Exposed to Multiple Drivers’, and ‘Black High-tech’. Marin and Vona (2019) compare time-varying lagged clustering variables with lagged cluster dummies and find that initial cluster dummies have greater explanatory power. Therefore, the clusters enter the regression as initial dummy variables and control for multiple structural shocks that may occur simultaneously with climate-policy exposure.

4.3 Baseline Estimating Specifications

Marin and Vona (2019) estimate the regressions using two main specifications: OLS and a just-identified baseline IV specification. The authors also include an overidentified IV specification in which the instrument is decomposed by energy source, such as coal, oil, natural gas, and electricity, and the conclusions remain mainly robust. Given this robustness, I do not discuss or replicate the overidentified specification in this thesis. The baseline estimation equation is as follows:

$$\Delta y_{ijt} = \beta_1 \Delta p_{ijt}^E + \beta_2 p_{ij,t-1}^E + \gamma \ln\left(\frac{GHG}{VA}\right)_{ij,1995} + \phi_{ij,1995}^c + \mu_{it} + \theta_{jt} + \varepsilon_{ijt}. \quad (4.1)$$

The variable Δy_{ijt} is the annual change in the relevant outcome variable in country i , sector j , and year t . For total hours worked, $y_{ijt} = \ln(Y_{ijt})$, so $\Delta y_{ijt} = \Delta \ln(Y_{ijt})$. For occupational shares, $y_{ijt} = s_{ijt}$, so $\Delta y_{ijt} = \Delta s_{ijt}$. The main explanatory variable is energy price, p_{ijt}^E , in country i , sector j , and year t , which is constructed as described earlier by combining the vector of country-year energy-source prices with the vector of country-sector-year energy-use shares for observed energy-price exposure. Energy prices are also instrumented using initial energy-use shares.

The regression includes both the annual change in energy prices (Δp_{ijt}^E) and the lagged level of energy prices ($p_{ij,t-1}^E$). The change in energy prices captures the short-term adjustment to current price movements, while the lagged level captures the persistent effect of past energy-price movements. Therefore, the joint inclusion of these two variables allows the authors to distinguish between the immediate and cumulative effects of energy prices on employment (Marin; Vona, 2019).

The variable $\ln(GHG/VA)_{ij,1995}$ is the initial emission intensity in country i , sector j , and year 1995. Initial emission intensity enters the specification twice: first indirectly through the initial cluster dummies and second directly as a separate logarithmic variable. Marin and Vona (2019) prefer this additional control because it helps further isolate the effect of energy prices from persistent labor-market trends in emission-intensive sectors, which behave differently from other sectors. However, as its separate inclusion barely changes the results, I later simplify the specification by excluding initial emission intensity as a separate control.

While μ_{it} and θ_{jt} are country-year and sector-year fixed effects, $\phi_{ij,1995}^c$ is the initial cluster dummy in country i , sector j , and year 1995. Year-specific country

dummies control for national shocks affecting all sectors within a country in a given year, such as national policy changes, debt crises, and recessions. Year-specific sector dummies, on the other hand, account for sectoral shocks affecting the same sector across countries in a given year, such as international demand shocks and commodity-price changes. Lastly, the initial cluster dummies help control for overlapping structural transformations, as discussed earlier.

The authors estimate the regression in first differences to remove time-invariant unobserved country-sector characteristics, keeping variation only within country-sector pairs over time. In addition, the regression is weighted by hours worked in 1995, so that larger sectors receive greater importance in the estimation while avoiding weights that respond to later labor-market movements.

5 Replication and Extension to Additional Adjustments

This section first clarifies the replication procedure and reports my replication of the baseline employment results studied by Marin and Vona (2019). I then apply two simplifications to the original specifications and extend the analysis to additional outcomes, using the replication results as a verified benchmark. In particular, I examine labor productivity and value added, as well as total capital investment and investment composition, while the authors briefly examine only labor productivity, but not real value added or its decomposition. Finally, I extend the labor-productivity and investment analyses to a later period in Chapter 6 using the harmonized data described in Section 2.3. Thus, the sections following the replication results constitute the main extensions relative to the original study. They represent distinct industrial adjustments to energy-price exposure and help assess whether these structural responses exhibit a coherent pattern.

The first extension is the labor-productivity analysis, which examines the production-side counterpart of the employment results. In other words, I analyze how higher energy prices affect labor productivity and its relevant decompositions. The expected relationship is ambiguous, as higher energy prices may increase cost pressures but could also motivate efficiency and innovation to save energy. Although aggregate hours worked do not respond significantly, production and labor productivity may still change alongside the observed adjustment in occupational composition. In particular, labor productivity is measured as real value added per hour worked. Thus, positive productivity responses could be associated with lower hours worked, higher real value added, or both at the same time. Likewise, positive real value-added changes might be associated with changes in nominal activity, prices, or both simultaneously. I therefore examine the associations between predicted energy-price exposure and labor productivity, real value added,

the value-added deflator, and nominal value added. These outcomes help assess whether the estimated patterns are more consistent with cost pressures associated with the Pollution Haven hypothesis or with efficiency enhancement emphasized by the strong version of the Porter hypothesis.

The second extension is the investment analysis, which investigates another aspect of technological and structural adjustment. On the one hand, higher energy price exposure may increase costs and reduce expected profitability, discouraging investment. On the other hand, it may also encourage investment in energy-saving capital. Total investment alone cannot capture the changes across asset categories, especially if the aggregate response is limited. However, broad ICT and non-ICT investment shares, along with their detailed components, could help identify whether capital formation is reallocated across asset categories. This analysis also complements the analysis of occupational composition. In particular, comparing these patterns with occupational composition allows me to explore whether the increase in the technician share documented by Marin and Vona (2019) occurs alongside a reallocation toward ICT-related assets. However, this comparison is exploratory rather than causal.

5.1 Replication Procedure

The replication materials are obtained from the authors, specifically the cleaned and merged dataset and the Stata code. Using these replication materials, I re-estimate the baseline OLS and just-identified IV specifications. Therefore, I do not copy the estimates from the published table; instead, I execute the regression using the authors' code. The estimates reported in Table 5.1 match the published results precisely after rounding.

Table 5.1 Replication of baseline estimates for total hours worked and occupational composition

	$\Delta \log$ Hours worked	Δ Managers	Δ Professionals	Δ Technicians	Δ Manual
<i>Panel A: OLS estimates</i>					
Δ Energy price	0.0432 (0.0480)	-0.00172 (0.0111)	-0.0139 (0.0107)	-0.000731 (0.0178)	0.0241 (0.0243)
Energy price ($t - 1$)	-0.0122 (0.0162)	-0.00167 (0.00251)	0.00587** (0.00252)	0.0130** (0.00548)	-0.0102 (0.00661)
Log of GHG intensity (1995)	-0.000527 (0.00305)	-0.0000252 (0.000334)	-0.000135 (0.000408)	0.000137 (0.000535)	0.000327 (0.000671)
Joint-test p -value	0.394	0.790	0.0189	0.0576	0.121
Joint F -statistic	0.934	0.236	4.046	2.893	2.137
R^2	0.495	0.437	0.441	0.372	0.313
Observations	3360	3360	3360	3360	3360
<i>Panel B: Just-identified IV estimates</i>					
Δ Energy price	-0.0205 (0.0877)	0.00365 (0.0197)	-0.0109 (0.0195)	0.0630** (0.0313)	-0.0599 (0.0407)
Energy price ($t - 1$)	-0.0305 (0.0217)	-0.00163 (0.00302)	0.00807** (0.00322)	0.0141** (0.00573)	-0.0135** (0.00621)
Log of GHG intensity (1995)	-0.000835 (0.00281)	-0.0000202 (0.000316)	-0.000102 (0.000394)	0.000203 (0.000519)	0.000214 (0.000663)
Joint-test p -value	0.370	0.827	0.0260	0.0207	0.0704
Joint χ^2 -statistic	1.986	0.380	7.302	7.757	5.308
Weak-ID statistic	58.31	58.31	58.31	58.31	58.31
Observations	3360	3360	3360	3360	3360

Notes: Regressions are weighted by hours worked in 1995 and include year-specific country dummies, year-specific sector dummies and initial (1995) cluster dummies. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

5.2 Replication of Baseline Employment Results

Table 5.1 presents the replicated baseline OLS and IV estimates for total hours worked and the occupational shares of managers, professionals, technicians, and manual workers. Each occupational share is measured as hours worked by the relevant group divided by total hours worked in a country-sector pair.

5.2.1 OLS Results

The OLS results indicate that a one-unit increase in the annual change in energy prices, where the unit is 1 US dollar per kilogram of oil equivalent, is associated with approximately 4.32% higher annual growth in total hours worked. In contrast, a one-unit increase in lagged energy prices corresponds to 1.22% lower annual growth in total hours worked. However, this finding cannot be interpreted as evidence of a robust relationship, as the coefficients are neither individually nor jointly statistically significant.

The results are more mixed across occupational groups, reflecting possible workforce restructuring effects of energy-price movements. A one-unit increase in the annual change in energy prices is associated with a 0.17 percentage-point decrease in the annual change in the manager share of total hours worked, a 1.39 percentage-point decrease in the annual change in the professional share, a 0.07 percentage-point decrease in the annual change in the technician share, and a 2.41 percentage-point increase in the annual change in the manual-worker share. However, none of these coefficients is statistically significant.

The effects of lagged energy prices are more pronounced. A one-unit higher lagged energy price corresponds to a 0.17 percentage-point decrease in the annual change in the manager share of total hours worked, a 0.59 percentage-point increase in the annual change in the professional share, a 1.30 percentage-point increase in the annual change in the technician share, and a 1.02 percentage-point decrease in the annual change in the manual-worker share. The effects on professionals and technicians are statistically significant at the 5% level, whereas the effects

on managers and manual workers are statistically insignificant. The energy-price coefficients are jointly significant at the 5% and 10% levels for professionals and technicians, respectively.

The effects of initial emission intensity are close to zero and statistically insignificant for every outcome. Overall, the OLS results indicate suggestive patterns, but the specification does not allow a causal interpretation because of the potential endogeneity of observed energy prices.

5.2.2 IV Results

The IV specification in Table 5.1 shows that both energy-price coefficients are negative and individually and jointly insignificant for total hours worked, unlike the OLS specification, in which the contemporaneous coefficient is positive. A one-unit increase in the annual change in energy prices and a one-unit increase in lagged energy prices are associated with approximately 2.05% and 3.05% lower annual growth in total hours worked, respectively.

A one-unit increase in the annual change in instrumented energy prices is associated with a 0.37 percentage-point increase in the annual change in the manager share of total hours worked, a 1.09 percentage-point decrease in the annual change in the professional share, a 6.30 percentage-point increase in the annual change in the technician share, and a 5.99 percentage-point decrease in the annual change in the manual-worker share. The coefficient is statistically significant only for technicians at the 5% level. This differs from the OLS results, in which the contemporaneous coefficient for the technician share is statistically insignificant.

A one-unit higher lagged instrumented energy price corresponds to a 0.16 percentage-point decrease in the annual change in the manager share of total hours worked, a 0.81 percentage-point increase in the annual change in the professional share, a 1.41 percentage-point increase in the annual change in the technician share, and a 1.35 percentage-point decrease in the annual change in

the manual-worker share. The effects on professionals, technicians, and manual workers are statistically significant at the 5% level, whereas the effect on managers remains statistically insignificant. Unlike the OLS results, the IV results indicate a statistically significant effect on the manual-worker share. The energy-price coefficients are jointly significant at the 5% level for professionals and technicians and at the 10% level for manual workers.

The coefficients on initial emission intensity are close to zero and statistically insignificant for every outcome, as in the OLS specification. Table 5.1 also reports a weak-identification statistic of 58.31, indicating strong instrument relevance.

Overall, the results suggest that aggregate employment, measured by total hours worked, does not respond significantly to energy prices. While total employment remains largely unchanged, the occupational composition of employment may experience meaningful restructuring that is not captured by the aggregate outcome. This motivates extending the analysis to additional adjustment margins. While the labor-productivity and value-added analyses examine whether production changes despite relatively stable aggregate hours worked, the investment analysis tests whether firms change their fixed capital formation or investment composition.

5.3 Specification Simplifications

Table 5.2 presents the baseline results after excluding initial emission intensity as a separate control. The coefficients on initial emission intensity in the replicated baseline specification are close to zero and statistically insignificant for every outcome. I therefore estimate the baseline OLS and IV specifications without this additional control variable. This simplification is motivated by quantitative robustness. The estimated energy-price coefficients, standard errors, significance levels, and model fit remain broadly unchanged, suggesting that initial emission intensity as a separate control has only marginal effects in the model. Initial emission exposure is also partly accounted for through the initial cluster dummies.

Table 5.2 Baseline estimates after excluding initial emission intensity

	$\Delta \log$ Hours worked	Δ Managers	Δ Professionals	Δ Technicians	Δ Manual
<i>Panel A: OLS estimates</i>					
Δ Energy price	0.0434 (0.0478)	-0.00171 (0.0111)	-0.0138 (0.0106)	-0.000783 (0.0178)	0.0240 (0.0243)
Energy price ($t - 1$)	-0.0119 (0.0160)	-0.00166 (0.00252)	0.00594** (0.00250)	0.0130** (0.00550)	-0.0104 (0.00660)
Joint-test p -value	0.403	0.793	0.0172	0.0606	0.116
Joint F -statistic	0.912	0.232	4.143	2.842	2.180
R^2	0.495	0.437	0.441	0.372	0.313
Observations	3360	3360	3360	3360	3360
<i>Panel B: Just-identified IV estimates</i>					
Δ Energy price	-0.0200 (0.0876)	0.00366 (0.0197)	-0.0108 (0.0194)	0.0629** (0.0313)	-0.0600 (0.0407)
Energy price ($t - 1$)	-0.0299 (0.0217)	-0.00161 (0.00298)	0.00815** (0.00317)	0.0139** (0.00571)	-0.0136** (0.00611)
Joint-test p -value	0.387	0.826	0.0228	0.0211	0.0615
Joint χ^2 -statistic	1.898	0.383	7.565	7.717	5.577
Weak-ID statistic	58.63	58.63	58.63	58.63	58.63
Observations	3360	3360	3360	3360	3360

Notes: Regressions are weighted by hours worked in 1995, exclude initial log GHG intensity and include year-specific country dummies, year-specific sector dummies and initial (1995) cluster dummies. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The conclusions are therefore unaffected by the exclusion of initial emission intensity as a separate control.

As a second simplification, I apply the reduced form of the IV analysis, again excluding initial emission intensity as a separate control. I use the reduced form to maintain a consistent energy-price exposure measure across the original and extended periods and to avoid introducing breaks from combining sectoral energy-use data based on different sources, classifications, and accounting definitions. The WIOD, which is used by Marin and Vona (2019) to construct time-varying country-sector-level energy-use shares, had its most recent release in 2016, limiting its use for my extension through 2019. I therefore directly regress the outcome variables on predicted energy-price exposure. This changes the interpretation to some extent: rather than estimating the effect of observed energy-price exposure instrumented by predicted exposure, the reduced-form specification estimates the direct effect of predicted energy-price exposure on the outcomes. In the 1995–2011

sample, the IV and reduced-form specifications produce the same qualitative conclusions for employment, which supports the use of the reduced form in the subsequent extensions.

Table 5.3 Reduced-form employment estimates without initial emission intensity

	$\Delta \log$ Hours worked	Δ Managers	Δ Professionals	Δ Technicians	Δ Manual
<i>Reduced-form estimates</i>					
Δ Predicted energy price	-0.0115 (0.0746)	0.00304 (0.0163)	-0.00945 (0.0161)	0.0467* (0.0243)	-0.0445 (0.0327)
Predicted energy price ($t - 1$)	-0.0224 (0.0176)	-0.00131 (0.00241)	0.00647** (0.00259)	0.00928** (0.00470)	-0.00912** (0.00448)
Joint-test p -value	0.443	0.849	0.0426	0.0248	0.0559
Joint F -statistic	0.818	0.163	3.204	3.764	2.924
R^2	0.495	0.437	0.440	0.372	0.313
Observations	3360	3360	3360	3360	3360

Notes: Regressions are weighted by hours worked in 1995, exclude initial log GHG intensity and include year-specific country dummies, year-specific sector dummies and initial (1995) cluster dummies. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5.3 shows that the coefficient signs and joint-significance classifications remain unchanged in the reduced-form specification. The individual significance levels also remain broadly unchanged, except for the contemporaneous technician-share coefficient, whose significance changes from the 5% level in the IV specification to the 10% level in the reduced form. However, this does not indicate a weaker effect because the reduced-form and two-stage IV specifications estimate different quantities. They convey the same qualitative pattern; I therefore use the reduced-form specification in the subsequent analyses.

5.4 Labor Productivity and Value Added

This section estimates the associations between predicted energy-price exposure and labor productivity, real value added, hours worked, nominal value added, and the value-added deflator during 1995–2011. Marin and Vona (2019) also estimate the effects on labor productivity and report the results in their appendix.

Still, they do not examine real value added, nominal value added, and the value-added deflator separately. They use country and sector fixed effects, whereas I use country-year and sector-year fixed effects to maintain the same model setup across analyses. Their coefficients are based on observed energy-price exposure, although the coefficients and statistical-significance classifications are close to the coefficients I report.

All of these outcome variables that I analyze are expressed in logarithms, so their first differences approximate annual percentage changes. Labor productivity is measured as real value added per hour worked. Therefore, its annual growth can be decomposed into the annual growth of real value added and the annual growth of total hours worked, as shown below:

$$LP_{ijt} = \frac{VA_{ijt}^R}{H_{ijt}}, \quad (5.1)$$

$$\ln(LP_{ijt}) = \ln(VA_{ijt}^R) - \ln(H_{ijt}), \quad (5.2)$$

$$\Delta \ln(LP_{ijt}) = \Delta \ln(VA_{ijt}^R) - \Delta \ln(H_{ijt}), \quad (5.3)$$

where LP_{ijt} denotes labor productivity, VA_{ijt}^R denotes real value added, and H_{ijt} denotes total hours worked. Accordingly, for the contemporaneous and lagged predicted energy-price exposure, the estimated labor-productivity coefficient can be decomposed, as shown below:

$$\hat{\beta}^{LP} = \hat{\beta}^{VA^R} - \hat{\beta}^H. \quad (5.4)$$

Table 5.4 shows that the contemporaneous coefficient satisfies the accounting decomposition:

$$0.229 \approx 0.217 - (-0.0115) = 0.2285 \quad (5.5)$$

Table 5.4 Reduced-form estimates for labor productivity and value added in 1995–2011

	$\Delta \log$ Labor productivity	$\Delta \log$ Real value added	$\Delta \log$ Hours worked	$\Delta \log$ Nominal value added	$\Delta \log$ Deflator
<i>Reduced-form estimates</i>					
Δ Predicted energy price	0.229** (0.115)	0.217** (0.110)	-0.0115 (0.0746)	0.0310 (0.0855)	-0.186** (0.0733)
Predicted energy price ($t - 1$)	-0.0386 (0.0284)	-0.0610** (0.0308)	-0.0224 (0.0176)	-0.0313* (0.0183)	0.0297 (0.0299)
Joint-test p -value	0.0457	0.00916	0.443	0.235	0.00867
Joint F -statistic	3.132	4.800	0.818	1.457	4.857
R^2	0.435	0.528	0.495	0.604	0.394
Observations	3360	3360	3360	3360	3360

Notes: The sample period covers 1995–2011. Regressions are weighted by hours worked in 1995, exclude initial log GHG intensity and include year-specific country dummies, year-specific sector dummies, and initial (1995) cluster dummies. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Similarly, the lagged coefficient satisfies:

$$-0.0386 = -0.0610 - (-0.0224) \quad (5.6)$$

A one-unit increase in the annual change in predicted exposure is associated approximately with 22.9% higher annual labor-productivity log growth, and the result is statistically significant at the 5% level. Likewise, a one-unit increase in the annual change in predicted energy-price exposure is associated with approximately 21.7% higher annual real-value-added log growth at the 5% significance level. The short-term effect on total hours worked is weak and statistically insignificant. The estimated effects on real value added and labor productivity are also very close, indicating that the positive labor-productivity coefficient is accounted for mainly by the positive real-value-added coefficient rather than by lower hours worked.

The effects of lagged predicted energy-price exposure are more mixed. A one-unit higher lagged predicted energy-price exposure is associated approximately with 3.86% lower annual labor-productivity growth, but the coefficient is statistically insignificant. Lagged predicted energy-price exposure is also associated approximately with 6.1% lower annual real-value-added growth at the 5% sig-

nificance level. This suggests that the positive contemporaneous effect on real value added is short-lived. Nevertheless, there is no clear relationship between lagged energy-price exposure and labor productivity. Annual growth in total hours worked also appears to decline, although the lagged coefficient is statistically insignificant.

The regressions on nominal value added and the value-added deflator help clarify the effects on real value added. Together, their coefficients provide the accounting decomposition of the real-value-added coefficient. A one-unit increase in the contemporaneous change in predicted exposure is associated approximately with 3.10% higher annual nominal-value-added growth, but the coefficient is statistically insignificant. The contemporaneous effect of predicted energy-price exposure is also associated approximately with 18.6% lower annual log growth in the value-added deflator at the 5% significance level. This decomposition shows that the contemporaneous positive coefficients for labor productivity and real value added primarily reflect a decline in the value-added deflator rather than an increase in nominal value added. This weakens the interpretation of the estimates as evidence of the innovation and efficiency mechanisms emphasized by the Porter hypothesis.

Lagged predicted energy-price exposure is associated approximately with 2.97% higher annual growth in the value-added deflator and 3.13% lower annual nominal-value-added growth. However, the coefficient for the value-added deflator is statistically insignificant, whereas the coefficient for nominal value added is statistically significant at the 10% level. This suggests that the delayed effect on real value added may reflect both an increase in the value-added deflator and a decline in nominal value added. These results are more consistent with cost-pressure and competitiveness mechanisms associated with the Pollution Haven hypothesis.

The effects of predicted energy-price exposure are jointly significant for labor productivity at the 5% level and for real value added and its deflator at the 1%

level. Nevertheless, they are not jointly significant for hours worked or nominal value added. Overall, Table 5.4 indicates that energy-price exposure has no robust relationship with hours worked or nominal value added. The short-run productivity pattern is qualitatively consistent with the finding in Table 5.3 that predicted energy-price exposure is associated with an increase in the technician share. One possible interpretation is that greater demand for skilled workers capable of adopting new technologies and practices may contribute to higher efficiency and productivity. However, the results for the value-added deflator and the longer-term effects on labor productivity and real value added indicate that these patterns are neither stable nor conclusive. Despite the positive lagged employment effects for professionals and technicians, persistent energy-price exposure may eventually suppress real activity.

5.5 Capital Investment and Asset Composition

This section examines the effects of predicted energy-price exposure on real total investment and on the shares of ICT and non-ICT capital investment at both aggregate and disaggregated levels. To ensure compatibility between the old and new EU KLEMS releases, all asset shares use a common denominator that includes IT equipment, communication equipment, software, transport equipment, other machinery, and other construction. I do not include residential structures, residual other assets, cultivated assets, R&D, and other intellectual property products because their availability varies across the series.

For the selected assets, two country-sector-year observations have negative total investment values; thus, the first-difference analysis loses four observations. Although such values are economically meaningful, they cannot be transformed into logarithms, and asset shares are not interpretable when total investment is non-positive. The affected investment outcomes are therefore treated as missing, and these observations are omitted from the corresponding regressions, resulting in a total of 1,796 observations across the regressions. I preserve non-positive

values for asset categories because they remain interpretable.

The analysis uses the restricted investment subsample, which covers 10 countries during 1995–2007, rather than the full 14-country sample covering 1995–2011. It examines the same sectors as in Marin and Vona (2019). To determine whether differences in the investment results may reflect this sample restriction, I also re-estimate the employment outcomes using the same investment subsample. As Table 5.3 shows, energy-price exposure is associated with a higher technician share and a lower manual-worker share in the full sample. The analysis of investment by asset category examines whether investment composition displays a parallel pattern and whether any reallocation is consistent with the employment findings.

Table 5.5 shows that the contemporaneous coefficient for total hours worked remains negative and similar in magnitude to the estimate for the original full sample, while the lagged coefficient becomes (-0.0558), increasing substantially in absolute magnitude. It also becomes statistically significant at the 5% level, which differs from the original full-sample result in Table 5.3. Among the occupational outcomes, only the positive lagged coefficient for professionals remains statistically significant at the 5% level across both samples. The contemporaneous coefficient for professionals changes sign from negative to positive.

Although the contemporaneous coefficients for technicians and manual workers are statistically insignificant in the investment subsample, their magnitudes remain relatively close to those in the original full sample. However, the lagged coefficients for technicians and manual workers decrease in absolute magnitude and lose statistical significance, while the lagged coefficient for manual workers changes sign from negative to positive. The lagged coefficient for managers remains broadly unchanged and statistically insignificant, although the contemporaneous coefficient changes sign from positive to negative. The coefficients are jointly significant at the 10% level for total hours worked and at the 5% level for professionals, but they are not jointly significant for managers, technicians, or manual workers. Overall, some features of the original estimates persist, but the occupational results are

Table 5.5 Reduced-form estimates for investment and employment composition in the 1995–2007 investment subsample

<i>Panel A: Aggregate and ICT investment outcomes</i>					
	$\Delta \log$ Real investment	Δ ICT share	Δ IT share	Δ CT share	Δ Software share
Δ Predicted energy price	-0.141 (0.234)	-0.000494 (0.0451)	0.0500* (0.0271)	-0.000401 (0.0114)	-0.0501 (0.0340)
Predicted energy price ($t - 1$)	-0.0993** (0.0495)	0.0209 (0.0149)	0.00631 (0.00482)	0.00279 (0.00376)	0.0118 (0.0105)
Joint-test p -value	0.115	0.368	0.119	0.613	0.162
Joint F -statistic	2.192	1.007	2.156	0.492	1.844
R^2	0.403	0.361	0.352	0.479	0.364
Observations	1796	1796	1796	1796	1796
<i>Panel B: Selected non-ICT investment outcomes</i>					
	Δ Non-ICT share	Δ Transport equipment share	Δ Other machinery share	Δ Other construction share	
Δ Predicted energy price	0.000494 (0.0451)	-0.0407 (0.0380)	-0.0584 (0.117)	0.0996 (0.125)	
Predicted energy price ($t - 1$)	-0.0209 (0.0149)	-0.00233 (0.00503)	-0.00785 (0.0209)	-0.0108 (0.0154)	
Joint-test p -value	0.368	0.418	0.835	0.573	
Joint F -statistic	1.007	0.878	0.180	0.558	
R^2	0.361	0.404	0.299	0.252	
Observations	1796	1796	1796	1796	
<i>Panel C: Employment outcomes</i>					
	$\Delta \log$ Hours worked	Δ Managers	Δ Professionals	Δ Technicians	Δ Manual
Δ Predicted energy price	-0.0184 (0.0744)	-0.0154 (0.0228)	0.0314 (0.0237)	0.0622 (0.0421)	-0.0518 (0.0491)
Predicted energy price ($t - 1$)	-0.0558** (0.0228)	-0.00149 (0.00374)	0.00964** (0.00412)	0.00386 (0.00552)	0.000963 (0.00650)
Joint-test p -value	0.0527	0.786	0.0445	0.334	0.544
Joint F -statistic	3.003	0.241	3.177	1.105	0.612
R^2	0.586	0.246	0.199	0.275	0.248
Observations	1796	1796	1796	1796	1796

Notes: The subsample covers 1995–2007 and 10 of the focus countries. Regressions are weighted by hours worked in 1995, exclude initial log GHG intensity and include year-specific country dummies, year-specific sector dummies, and initial (1995) cluster dummies. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

less stable in the restricted investment subsample. Section 6.5.2 later examines whether the patterns persist in a larger sample.

According to Table 5.5, a one-unit increase in the annual change in predicted energy-price exposure is associated approximately with 14.1% lower annual log growth in real total investment, but the coefficient is statistically insignificant. Thus, it does not provide robust evidence of a short-run decline in fixed capital formation. The relationship between aggregate capital investment and lagged predicted energy-price exposure is more pronounced. A one-unit higher lagged predicted energy-price exposure is associated approximately with 9.93% lower annual investment log growth at the 5% significance level. This result is consistent with a cost-pressure mechanism related to the competitiveness channel emphasized by the Pollution Haven hypothesis, as persistent energy-price exposure may reduce expected profitability and discourage investment. It also suggests that persistent energy-price exposure may eventually weaken fixed capital formation. However, the two energy-price coefficients are not jointly significant, so the evidence remains suggestive.

The annual change in the ICT investment share is negatively associated with the annual change in predicted energy-price exposure and positively associated with lagged predicted energy-price exposure. The corresponding coefficients for the non-ICT investment share are equal in magnitude and opposite in sign. This symmetry is expected because the two shares are complementary. However, the coefficients are neither individually nor jointly statistically significant and therefore provide no robust evidence of a broad reallocation between ICT and non-ICT investment. The contemporaneous effects for both are also close to zero, suggesting no clear change in the broad investment shares.

Among individual assets, only the IT investment share provides exploratory evidence. A one-unit increase in the annual change in predicted energy-price exposure is associated approximately with a 5.00 percentage-point increase in the annual change in the IT investment share at the 10% significance level. The lagged

coefficient is also positive but statistically insignificant, and the contemporaneous and lagged coefficients are jointly insignificant. Therefore, the result provides only suggestive evidence of a potential reallocation toward IT investment.

The positive IT coefficient is qualitatively consistent with the occupational-composition results, but the evidence is not strong enough to establish a clear connection between the two adjustment margins. For communication equipment and software investment shares, the contemporaneous coefficients are negative and the lagged coefficients are positive, but all are statistically insignificant. For transport equipment and other machinery investment shares, both coefficients are negative, whereas the other construction investment share has a positive contemporaneous coefficient and a negative lagged coefficient. However, the coefficients for all these shares are individually and jointly insignificant. The later-period extension examines whether the additional observations alter these results or improve their precision.

6 Extension to Recent Years

In this chapter, I extend the original labor-productivity and investment analyses from 1995–2011 and 1995–2007, respectively, through 2019 to examine whether the results during the original periods persist in more recent years. Considering the later period is important because it shows whether the estimated relationships are specific to the original sample periods or remain relevant under more recent economic and policy conditions. However, because the IEA national end-use energy prices are available only through 2019, the extended-period analyses end in 2019.

To extend the analysis, I gather information from EU KLEMS under NACE Rev. 2 and from the IEA’s 2019 and 2020 Statistical Reports, as discussed in Section 2.3. I then describe how I address the new industry classification and missing data for labor productivity, investment, and energy prices.

6.1 Sector Harmonization

Due to the revision of the industry classification, the sectors covered by Marin and Vona (2019) are not directly comparable to those used in the extended-period analysis implemented in the following sections. However, the ISIC Rev. 3–ISIC Rev. 4 concordance table provided by Gouma et al. (2018) allows me to map the new sectors back to the old sectors studied by Marin and Vona (2019).

Because I use the initial energy-use quantities and initial cluster dummies provided by the authors, I apply a back-classification procedure. The new EU KLEMS release provides information for all relevant activities; however, some are reported together rather than at a detailed level. Therefore, I obtain 13 sectors instead of the 15 sectors used in the original full sample.

While several sectors have strong correspondence under the new industry classification, the sectors “Pulp, Paper, Printing and Publishing”, “Machinery, Nec”, “Electrical and Optical Equipment”, “Manufacturing, Nec; Recycling”,

and “Electricity, Gas and Water Supply” show relatively weaker correspondence (**un2008isic**).

Table 6.1 summarizes the sector-harmonization procedure and the sector-boundary changes reported by **un2008isic**. Publishing activities are not included in the sector corresponding to the old “Pulp, Paper, Printing and Publishing” sector. Instead, they were transferred from manufacturing to the information and communication sector.

Because publishing is reported alongside other activities that were not included in the old “Pulp, Paper, Printing and Publishing” sector, the corresponding sector analyzed over the extended period excludes publishing activities. Activities related to the repair and installation of machinery and equipment, which were previously included in “Machinery, Nec”, were also transferred to a separate sector.

Due to limitations in the EU KLEMS data structure, these activities are accounted for within the corresponding “Manufacturing, Nec; Recycling” sector. The corresponding “Manufacturing, Nec; Recycling” sector in the extended-period analysis excludes recycling activities that were part of the old sector.

The corresponding “Electricity, Gas and Water Supply” sector now also includes waste and remediation activities, most of which correspond to the old recycling activities included in the old “Manufacturing, Nec; Recycling” sector. Some activities within “Electrical and Optical Equipment” were also transferred to several new sectors, but the corresponding sector retains relatively good correspondence.

Table 6.1 Harmonization of the NACE Rev. 2 sectors to the original NACE Rev. 1 sectors

Harmonized sector	Original NACE Rev. 1 sector(s)	NACE Rev. 2 sector(s) used	Correspondence and treatment
C: Mining and Quarrying	C: Mining and Quarrying	B: Mining and quarrying	<i>Strong</i>
15t16: Food, Beverages and Tobacco	15t16: Food, Beverages and Tobacco	C10–C12: Food products, beverages and tobacco	<i>Strong</i>
17t19: Textiles, Textile Products, Leather and Footwear	17t19: Textiles and Textile Products; Leather and Footwear	C13–C15: Textiles, wearing apparel, leather and related products	<i>Strong</i>
20t22: Wood, Paper, and Printing	20: Wood and Products of Wood and Cork; 21t22: Pulp, Paper, Printing and Publishing	C16–C18: Wood and paper products; printing and reproduction of recorded media	<i>Imperfect</i> Two original sectors are reported jointly. Publishing activities are excluded.
23: Coke, Refined Petroleum and Nuclear Fuel	23: Coke, Refined Petroleum and Nuclear Fuel	C19: Coke and refined petroleum products	<i>Strong</i>
24: Chemicals and Chemical Products	24: Chemicals and Chemical Products	C20–C21: Chemicals and chemical products; basic pharmaceutical products and pharmaceutical preparations	<i>Strong</i>
25t26: Rubber, Plastics and Other Non-Metallic Mineral Products	25: Rubber and Plastics; 26: Other Non-Metallic Mineral Products	C22–C23: Rubber and plastics products; other non-metallic mineral products	<i>Strong</i> Two original sectors are reported jointly.
27t28: Basic Metals and Fabricated Metal Products	27t28: Basic Metals and Fabricated Metal	C24–C25: Basic metals and fabricated metal products, except machinery and equipment	<i>Strong</i>

Continued on the next page

Table 6.1 continued from the previous page

Harmonized sector	Original NACE Rev. 1 sector(s)	NACE Rev. 2 sector(s) used	Correspondence and treatment
29: Machinery, Nec	29: Machinery, Nec	C28: Machinery and equipment n.e.c.	<i>Imperfect</i> Repair and installation activities previously included in the old sector are classified under C33 and therefore enter harmonized sector 36t37.
30t33: Electrical and Optical Equipment	30t33: Electrical and Optical Equipment	C26–C27: Computer, electronic and optical products; electrical equipment	<i>Relatively strong</i> Some activities were transferred to other NACE Rev. 2 sectors.
34t35: Transport Equipment	34t35: Transport Equipment	C29–C30: Transport equipment	<i>Strong</i>
36t37: Manufacturing, Nec; Recycling	36t37: Manufacturing, Nec; Recycling	C31–C33: Other manufacturing; repair and installation of machinery and equipment	<i>Imperfect</i> Recycling activities are excluded, while repair and installation activities are transferred from old sector 29.
E: Electricity, Gas and Water Supply	E: Electricity, Gas and Water Supply	D–E: Electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities	<i>Imperfect</i> The harmonized sector is broader because it includes waste-management and remediation activities, many of which correspond to activities previously included under recycling in old sector 37.

Notes: The harmonized sector codes preserve the original NACE Rev. 1 coding convention. “Strong” indicates close correspondence in activity coverage. “Relatively strong” indicates that the main activities correspond, although some activities were reclassified. “Imperfect” indicates that activities were transferred across sectors or that the NACE Rev. 2 aggregate is broader or narrower than the original sector.

6.2 Treatment of Missing Observations

For the labor-productivity analysis, no data are available for Ireland and Sweden. For the investment analysis, data for Hungary and Ireland are missing. Due to the data structure and the scattered pattern of missing observations, I cannot reconstruct missing values for these countries.

Among the remaining sample countries in the extended period, hours worked by employees are missing for 11 Hungarian manufacturing sectors from 1995 to 2009, resulting in 165 missing observations. The observations for “Mining and Quarrying” and “Electricity, Gas and Water Supply” are available and remain unchanged.

Investment data for the corresponding “Chemicals and Chemical Products” sector in Sweden are completely missing. I use different methods to fill these missing observations.

6.2.1 Missing Hungarian Employee Hours

For the missing observations on hours worked by employees in Hungary, I use the number of employees reported by the new EU KLEMS release and multiply it by reconstructed average annual hours per employee.

Let AHE denote average annual hours per employee, H denote hours worked by employees, and E denote the number of employees. Superscripts K , W , and MV refer to the new EU KLEMS release, the WIOD 2016 release, and the dataset provided by Marin and Vona (2019), respectively.

I first scale the WIOD average annual hours per employee to the 2010 level reported by the new EU KLEMS release:

$$\widetilde{AHE}_{j,t}^W = AHE_{j,2010}^K \left(\frac{AHE_{j,t}^W}{AHE_{j,2010}^W} \right), \quad t = 2000, \dots, 2010. \quad (6.1)$$

Here j denotes the sector and t denotes the year. The tilde indicates the rescaled series. Equation (6.1) preserves movements in the WIOD series while

making its level consistent with the new EU KLEMS series in the 2010 anchor year.

Because the WIOD 2016 series does not cover 1995–1999, I extend the reconstructed series backward using average annual hours per employee from the dataset provided by Marin and Vona (2019). I scale this earlier series to the reconstructed WIOD value in 2000:

$$\widetilde{AHE}_{j,t}^{MV} = \widetilde{AHE}_{j,2000}^W \left(\frac{AHE_{j,t}^{MV}}{AHE_{j,2000}^{MV}} \right), \quad t = 1995, \dots, 2000. \quad (6.2)$$

Thus, 2010 is the anchor year between the WIOD 2016 and new EU KLEMS series, while 2000 is the anchor year between the dataset provided by Marin and Vona (2019) and the reconstructed WIOD series.

I calculate the missing Hungarian employee hours as follows:

$$\widehat{H}_{j,t}^K = E_{j,t}^K \begin{cases} \widetilde{AHE}_{j,t}^{MV}, & 1995 \leq t \leq 1999, \\ \widetilde{AHE}_{j,t}^W, & 2000 \leq t \leq 2009. \end{cases} \quad (6.3)$$

The hat indicates a reconstructed value. Equation (6.3) is applied only to the 11 Hungarian manufacturing sectors with missing hours worked by employees. The observed values for “Mining and Quarrying” and “Electricity, Gas and Water Supply”, as well as all observed new EU KLEMS values from 2010 onward, remain unchanged.

6.2.2 Missing Swedish “Chemicals and Chemical Products”

For the missing Swedish “Chemicals and Chemical Products” observations, I first reconstruct additive investment variables.

Let X represent additive variables, such as total gross fixed capital formation at current and previous-year prices and gross fixed capital formation by asset category. M indicates the aggregate manufacturing sector reported by the new EU

KLEMS release, while c indicates the missing “Chemicals and Chemical Products” sector. The notation j represents the 10 observed manufacturing sectors, and $\mathcal{O}$ denotes the set of these sectors.

$$X_{M,t} = X_{c,t} + \sum_{j \in \mathcal{O}} X_{j,t}, \quad |\mathcal{O}| = 10. \quad (6.4)$$

The reconstruction logic for additive variables follows from the accounting identities below. The notations $q_{M,t}$ and $p_{M,t}$ represent the quantity and price of investment for total manufacturing M in year t . Current-price and previous-year-price gross fixed capital formation for total manufacturing satisfy:

$$q_{M,t}p_{M,t} = \sum_{j \in \mathcal{O}} q_{j,t}p_{j,t} + q_{c,t}p_{c,t}, \quad (6.5)$$

$$q_{M,t}p_{M,t-1} = \sum_{j \in \mathcal{O}} q_{j,t}p_{j,t-1} + q_{c,t}p_{c,t-1}. \quad (6.6)$$

The first identity values year- t quantities at year- t prices and corresponds to current-price gross fixed capital formation. The second identity values year- t quantities at year- $t - 1$ prices and corresponds to previous-year-price gross fixed capital formation.

Using the relevant measures provided by the new EU KLEMS release, I express these identities as:

$$CP_{M,t} = \sum_{j \in \mathcal{O}} CP_{j,t} + CP_{c,t}, \quad (6.7)$$

$$PYP_{M,t} = \sum_{j \in \mathcal{O}} PYP_{j,t} + PYP_{c,t}. \quad (6.8)$$

Here CP represents gross fixed capital formation at current prices, and PYP corresponds to gross fixed capital formation at previous-year prices.

I rearrange the accounting identities to retrieve the missing current-price and previous-year-price gross fixed capital formation for the Chemicals sector as

residuals:

$$CP_{c,t} = CP_{M,t} - \sum_{j \in \mathcal{O}} CP_{j,t}, \quad (6.9)$$

$$PYP_{c,t} = PYP_{M,t} - \sum_{j \in \mathcal{O}} PYP_{j,t}. \quad (6.10)$$

Because these values are additive across sectors, I subtract the sum of the 10 available non-overlapping manufacturing sectors from total manufacturing to recover the missing values for Swedish “Chemicals and Chemical Products” over 1995–2020. I apply the same residual method to recover nominal current-price fixed capital formation for each asset category.

Because chain-linked volume measures are non-additive across sectors, I cannot simply subtract the observed sectoral chain-linked values from total manufacturing to recover the missing sector values. Instead, I calculate the annual real growth factor using the recovered current-price and previous-year-price values:

$$\frac{Q_{c,t}^{CL}}{Q_{c,t-1}^{CL}} = \frac{PYP_{c,t}}{CP_{c,t-1}}. \quad (6.11)$$

Here $PYP_{c,t}$ measures current-year investment at previous-year prices, while $CP_{c,t-1}$ measures previous-year investment at the same previous-year prices. Their ratio therefore captures the change in investment volume between $t - 1$ and t .

Let Q^{CL} indicate chain-linked gross fixed capital formation. I first set the chain-linked value equal to the current-price value for 2020, the base year. I then reconstruct the preceding values backward:

$$\begin{aligned} Q_{c,2020}^{CL} &= CP_{c,2020}, \\ Q_{c,t}^{CL} &= Q_{c,t+1}^{CL} \left(\frac{CP_{c,t}}{PYP_{c,t+1}} \right), \quad t = 2019, \dots, 1995. \end{aligned} \quad (6.12)$$

6.3 Extension and Imputation of Energy Prices

To extend the national end-use fuel-specific energy prices, I apply several techniques. First, I retain the values from 1995 to 2009 as provided by Marin and Vona (2019). I update the values for 2010 and 2011 using the IEA’s 2019 and 2020 Statistical Reports, as these reports were released after Marin and Vona (2019) published the paper.

I then extend the series through 2019 using observed values from the IEA. I deflate the observed nominal prices using the country-specific World Bank GDP deflator rebased to 1995.

The missing observations consist of steam-coal prices for the Czech Republic, Denmark, Germany, Hungary, Ireland, Italy, the Netherlands, Spain, and Sweden from 2012 to 2019, as well as for France in 2019. Light-fuel-oil prices for Hungary are also missing from 2012 to 2019.

As suggested by Sato et al. (2019), I impute the missing observations using the IEA fuel-specific real industrial price indices for OECD Europe. Using a common OECD Europe index may reduce country-sector variation in the imputed price series.

Although their first and second suggestions are the fuel-country-specific real price index and the country-specific real industrial energy-price index, respectively, the IEA no longer publicly provides these indices.

For each country-fuel observation, I calculate a scaling factor by dividing the observed real price in the most recent available anchor year by the corresponding OECD Europe real industrial fuel-price index in that year:

$$S_{cf} = \frac{P_{cf,a}^{R,obs}}{I_{f,a}^R}. \quad (6.13)$$

Here $P_{cft}^{R,obs}$ denotes the observed real price for country c , fuel f , and year t . I_{ft}^R denotes the IEA real industrial fuel-price index for OECD Europe. S_{cf} denotes the country-fuel-specific scaling factor, and a denotes the most recent observed

anchor year before the missing period.

I carry this scaling factor forward and multiply it by the corresponding OECD Europe real industrial fuel-price index in each missing year:

$$\hat{P}_{cft}^R = S_{cf} I_{ft}^R = P_{cf,a}^{R,obs} \left(\frac{I_{ft}^R}{I_{f,a}^R} \right). \quad (6.14)$$

The observed country-specific price level in the anchor year is therefore combined with subsequent movements in the OECD Europe real industrial fuel-price index. A hat denotes an imputed value.

Thus, 2011 is the anchor year for observations missing from 2012 to 2019, while 2018 is the anchor year for the missing French steam-coal price in 2019. Choosing 2011 as the anchor year may be a limitation because some of the 2011 values used as anchors may themselves have been imputed by the authors.

Nevertheless, to ensure continuity in the energy-price series, I use the last available values as anchors. The observed price values remain unchanged. I divide the reconstructed energy-price-exposure variables by 1,000 to make the coefficients easier to read.

6.4 Reconstruction of Predicted Energy-Price Exposure and Initial Cluster Controls

To reconstruct predicted energy-price exposure and the initial cluster controls, I use the initial energy use and cluster dummies provided by Marin and Vona (2019). I reconstruct predicted energy-price exposure using the observed and imputed fuel-specific energy prices and the fixed initial energy-use shares.

For the aggregate sectors under NACE Rev. 2, I calculate their combined initial fuel-specific shares by summing the initial fuel quantities of their component sectors and dividing each fuel quantity by their combined total four-fuel energy use:

$$\tilde{s}_{cjt,1995} = \frac{\sum_{k \in \mathcal{K}(j)} U_{ckf,1995}}{\sum_g \sum_{k \in \mathcal{K}(j)} U_{ckg,1995}}. \quad (6.15)$$

Here c , j , and f denote country, harmonized sector, and fuel, respectively. $\mathcal{K}(j)$ denotes the set of original sectors combined into harmonized sector j , while $U_{ckf,1995}$ denotes the initial quantity of fuel f used by original sector k in 1995. A tilde denotes a harmonized value.

I reconstruct predicted energy-price exposure by weighting the current observed or imputed real fuel prices by the fixed initial fuel shares:

$$\hat{P}_{cjt}^E = \frac{1}{1000} \sum_f \tilde{s}_{cjt,1995} P_{cft}^R. \quad (6.16)$$

Here t denotes the year and P_{cft}^R denotes the observed or imputed real fuel price. A hat denotes a reconstructed value. The resulting predicted energy-price exposure is divided by 1,000 to make the coefficients easier to read. The initial fuel shares for the directly matched sectors remain unchanged.

For the cluster assignment, I weight the initial cluster dummies by initial hours worked in the dataset provided by Marin and Vona (2019):

$$\tilde{C}_{cjm} = \frac{\sum_{k \in \mathcal{K}(j)} H_{ck,1995} C_{ckm}}{\sum_{k \in \mathcal{K}(j)} H_{ck,1995}}. \quad (6.17)$$

Here $H_{ck,1995}$ denotes initial hours worked and C_{ckm} denotes the original dummy for cluster m . For an aggregate sector, the original cluster dummies are therefore weighted by the initial hours worked of its component sectors.

For aggregate sectors under NACE Rev. 2, this converts the initial cluster dummies into initial cluster-composition shares, while the initial cluster dummies for the remaining sectors remain unchanged. Their purpose and logic remain the same as those of the original cluster controls.

The weighted cluster-composition shares preserve the relative structural composition of the original component sectors that are reported as aggregates in the new EU KLEMS release.

6.5 Results for the Extended Period

This section presents the extension of the labor-productivity and investment analyses through 2019 for the 13 harmonized sectors. The aim is to examine whether the estimated effects persist over a longer sample period.

6.5.1 Labor Productivity and Value Added

Table 6.2 Reduced-form estimates for labor productivity and value added in 1995–2019

	$\Delta \log$ Labor productivity	$\Delta \log$ Real value added	$\Delta \log$ Hours worked	$\Delta \log$ Nominal value added	$\Delta \log$ Deflator
<i>Reduced-form estimates</i>					
Δ Predicted energy price	0.1702* (0.0913)	0.1127 (0.0958)	-0.0575 (0.0460)	0.0245 (0.0856)	-0.0882 (0.0788)
Predicted energy price ($t - 1$)	-0.0177 (0.0201)	-0.0184 (0.0175)	-0.0007 (0.0128)	-0.0037 (0.0148)	0.0146 (0.0171)
Joint-test p -value	0.132	0.259	0.330	0.898	0.377
Joint F -statistic	2.052	1.364	1.118	0.107	0.982
R^2	0.424	0.523	0.640	0.586	0.452
Observations	3717	3717	3717	3717	3717

Notes: The sample period covers 1995–2019 and includes 12 countries and 13 harmonized sectors, excluding Ireland and Sweden. Regressions are weighted by fixed 1995 EU KLEMS hours worked by employees, exclude initial log GHG intensity, and include year-specific country dummies, year-specific sector dummies, and five initial cluster-composition controls, with cluster 4 omitted as the reference category. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The regressions in Table 6.2 are estimated in first differences. Because some values are non-positive, they cannot be transformed into logarithms. Twenty-seven country-sector-year changes are therefore treated as missing and omitted from the regressions, resulting in the same total of 3,717 observations across all outcomes.

A one-unit increase in the annual change in predicted exposure is associated with approximately 17.02% higher annual labor-productivity log growth. The result is statistically significant at the 10% level, down from the 5% level in the 1995–2011 sample.

All other coefficients that were statistically significant during the 1995–2011 sample period become insignificant, and none of the effects is jointly significant. However, all contemporaneous and lagged coefficients retain the same signs as in

the 1995–2011 results.

6.5.2 Capital Investment and Asset Composition

Table 6.3 Reduced-form estimates for investment outcomes in 1995–2019

<i>Panel A: Aggregate and ICT investment outcomes</i>					
	$\Delta \log$ Real investment	Δ ICT share	Δ IT share	Δ CT share	Δ Software share
Δ Predicted energy price	0.0983 (0.1841)	-0.0333 (0.0538)	0.0104 (0.0089)	0.0013 (0.0082)	-0.0449 (0.0506)
Predicted energy price ($t - 1$)	0.0231 (0.0234)	0.0007 (0.0046)	-0.0011 (0.0012)	-0.0009 (0.0009)	0.0027 (0.0043)
Joint-test p -value	0.475	0.824	0.355	0.610	0.593
Joint F -statistic	0.748	0.194	1.042	0.496	0.524
R^2	0.393	0.299	0.454	0.288	0.281
Observations	3744	3744	3744	3744	3744
<i>Panel B: Selected non-ICT investment outcomes</i>					
	Δ Non-ICT share	Δ Transport equipment share	Δ Other machinery share	Δ Other construction share	
Δ Predicted energy price	0.0333 (0.0538)	-0.0174 (0.0212)	0.0130 (0.0679)	0.0377 (0.0672)	
Predicted energy price ($t - 1$)	-0.0007 (0.0046)	-0.0033 (0.0036)	-0.0013 (0.0056)	0.0039 (0.0045)	
Joint-test p -value	0.824	0.571	0.953	0.619	
Joint F -statistic	0.194	0.563	0.049	0.480	
R^2	0.299	0.349	0.344	0.297	
Observations	3744	3744	3744	3744	

Notes: The sample period covers 1995–2019 and includes 12 countries and 13 harmonized sectors, excluding Hungary and Ireland. Regressions are weighted by fixed 1995 EU KLEMS hours worked by employees, exclude initial log GHG intensity, and include year-specific country dummies, year-specific sector dummies, and five initial cluster-composition controls, with cluster 4 omitted as the reference category. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

I estimate the regressions in first differences. Table 6.3 shows that the contemporaneous coefficient for real investment changes from negative to positive and remains statistically insignificant.

The lagged coefficient for real investment changes from negative and statistically significant at the 5% level to positive and statistically insignificant. The contemporaneous coefficient for the IT investment share, which was statistically significant at the 10% level in the 1995–2007 subsample, remains positive but becomes insignificant.

All other coefficients are also statistically insignificant, none of the effects is jointly significant, and some coefficients change sign. Overall, the results provide no clear evidence of investment reallocation among the selected asset categories in the extended sample.

7 Harmonized Common-Sample Diagnostic Comparison

To inspect whether the changes in the results for the extended-period analyses are due to differences in country and period coverage and the use of 13 harmonized sectors instead of the original 15 sectors, I apply several restricted regressions using the old data. I first reconstruct predicted energy-price exposure and initial cluster-composition shares for the old data used in the labor-productivity and investment analyses, following the same logic as in the respective extended analyses. For additive old outcome variables, I simply sum the values across the component sectors. For the labor-productivity analysis, I aggregate real value-added growth using a Törnqvist index. For the investment analysis, I first derive previous-year-price gross fixed capital formation in year t for each original sector from the old EU KLEMS release. I then sum gross fixed capital formation at current prices and previous-year prices across the component sectors and calculate real investment growth using these aggregated values. Investment shares are calculated after aggregating the underlying asset values.

7.1 Labor Productivity and Value Added

This section compares the new EU KLEMS data under the NACE Rev. 2 classification with the harmonized original data under the NACE Rev. 1 classification provided by Marin and Vona (2019) for the labor-productivity analysis. Table 7.1 reports the results for 1995–2011 using the same 12 countries, excluding Ireland and Sweden due to missingness, and the same 13 harmonized sectors. The corresponding strong-sector comparison and the comparison excluding Hungary are reported in the Appendix. The results show broadly similar patterns across both panels, allowing me to analyze the role of data revision separately

from the effect of extending the sample period.

Table 7.1 Labor Productivity and Value-Added: Exact Common Sample Comparison, 1995–2011

	$\Delta \log$ Labor productivity	$\Delta \log$ Real value added	$\Delta \log$ Hours worked	$\Delta \log$ Nominal value added	$\Delta \log$ Deflator
<i>Panel A: New data outcomes</i>					
Δ Predicted energy price	0.2425** (0.0997)	0.1874* (0.1029)	−0.0551 (0.0533)	0.0219 (0.0952)	−0.1655** (0.0755)
Predicted energy price ($t - 1$)	−0.0539* (0.0273)	−0.0519* (0.0283)	0.0020 (0.0181)	−0.0278 (0.0207)	0.0241 (0.0213)
Joint-test p -value	0.011	0.032	0.458	0.393	0.020
Joint F -statistic	4.652	3.520	0.784	0.940	4.004
R^2	0.458	0.567	0.674	0.629	0.484
Observations	2,483	2,483	2,483	2,483	2,483
<i>Panel B: Harmonized old data outcomes</i>					
Δ Predicted energy price	0.3125** (0.1577)	0.2904** (0.1260)	−0.0221 (0.0843)	0.1175 (0.1092)	−0.1729* (0.0892)
Predicted energy price ($t - 1$)	−0.0321 (0.0325)	−0.0484 (0.0361)	−0.0163 (0.0214)	−0.0286 (0.0223)	0.0198 (0.0318)
Joint-test p -value	0.079	0.013	0.734	0.305	0.072
Joint F -statistic	2.582	4.484	0.309	1.196	2.679
R^2	0.464	0.555	0.536	0.633	0.410
Observations	2,483	2,483	2,483	2,483	2,483

Notes: The sample period covers 1995–2011 and includes 12 countries and 13 harmonized sectors, excluding Ireland and Sweden. Panel A is weighted by fixed 1995 EU KLEMS employee hours. Panel B is weighted by harmonized Marin–Vona initial hours. Regressions include year-specific country dummies, year-specific sector dummies, and five initial cluster-composition controls, with cluster 4 omitted as the reference category. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The main difference in Panel B of Table 7.1 is that the analysis covers 12 countries and 13 harmonized sectors during 1995–2011, whereas Table 5.4 shows results for the full set of 14 countries and 15 sectors during 1995–2011. Nonetheless, both tables report results based on the old data. Across both sets of estimates, the contemporaneous coefficients for labor productivity and real value added remain positive and significant. The contemporaneous coefficient also remains insignificant for hours worked and negative and significant for the value-added deflator, at least at the 10% level. However, the lagged coefficient for real value added loses significance in Panel B but remains negative. The results generally show a broadly stable pattern in labor productivity across the original and new harmonized structures. This supports the conclusion that sector harmonization

and smaller country coverage may not substantially affect the robustness of the results.

To move forward, I compare Panel A to Panel B of Table 7.1 to assess whether the changes in the results may reflect data revisions. I use the same 12 countries and 13 harmonized sectors during 1995–2011, but Panel A examines new outcomes, while Panel B examines old outcomes. I use initial hours worked from the respective data release as weights for each panel. I also re-estimated both panels using the old initial hours worked as weights, but the results generally remained unchanged, implying that weighting does not substantially change the interpretation. Thus, I do not report those results in this thesis. Across both panels, the contemporaneous coefficient for labor productivity remains positive and significant. For real value added, it remains positive and significant, but at the 10% level, down from the 5% level in Panel B. The contemporaneous coefficient also remains insignificant for hours worked and negative and significant for the value-added deflator at the 5% level, compared with the 10% level in Panel B. Interestingly, the lagged coefficients for labor productivity and real value added in Panel A gain significance at the 10% level and remain negative. The results show broadly similar signs and qualitative patterns across the original and new data releases. Especially, the short-run productivity responses remain broadly stable, although some magnitudes and significance levels change. This suggests that differences in data vintage may have only a limited impact on the qualitative conclusion.

Finally, I compare the results in Panel A of Table 7.1 with those in Table 6.2, both of which use the new data and harmonized sectors. The only difference is that Table 6.2 extends the period covered by Panel A of Table 7.1 through 2019. Across both tables, the contemporaneous coefficient for labor productivity remains positive, but its significance falls from 5% to 10% in the extended period. The contemporaneous coefficient for hours worked remains insignificant. The positive real-value-added coefficient and the negative value-added-deflator coefficient retain

their signs but become insignificant. The lagged coefficients for labor productivity and real value added are no longer significant. The remaining lagged coefficients become smaller, and none of the effects is jointly significant in the extended period. These results imply that the main weakening occurs when the years 2012–2019 are added.

Overall, the intermediate comparisons in Table 7.1 suggest that the weakening coefficients in the extended period are driven mostly by differences in the association during the post-2011 period rather than by sector reclassification or data revisions alone. Positive short-run productivity responses to energy-price exposure seem to persist across the original and new structures and the old and new data releases during 1995–2011. Nonetheless, the coefficients become insignificant or less significant when the analysis is extended to recent years.

7.2 Capital Investment and Asset Composition

This section compares the new EU KLEMS capital-account data with the harmonized old EU KLEMS data for the investment analysis. Tables 7.2 and 7.3 report the results for 1995–2007 using the same 10 countries and the same 13 harmonized sectors. The corresponding strong-sector comparison and the comparison excluding Sweden are reported in the Appendix. The results differ more substantially across both panels, especially for real total investment, suggesting that the extended-period investment results should be interpreted with caution. The differences in the results may reflect data-vintage revisions and a longer sample period.

Table 5.5 studies 15 sectors during 1995–2007, whereas Panel B estimates in Tables 7.2 and 7.3 report 13 harmonized sectors during 1995–2007. Both regressions include the same 10 countries and use the old data release. Under the new harmonized structure, the lagged coefficient for aggregate investment remains negative and becomes more significant at the 1% level. On the other hand, the contemporaneous coefficient for aggregate investment becomes positive

Table 7.2 Aggregate and ICT Investment Outcomes: Exact Common Sample Comparison, 1995–2007

	$\Delta \log$ Real investment	Δ ICT share	Δ IT share	Δ CT share	Δ Software share
<i>Panel A: New data outcomes</i>					
Δ Predicted energy price	0.2123	−0.0622	0.0288	0.0027	−0.0936*
	(0.5294)	(0.0514)	(0.0268)	(0.0149)	(0.0486)
Predicted energy price ($t - 1$)	0.0536	0.0022	−0.0011	−0.0021	0.0053
	(0.0472)	(0.0079)	(0.0028)	(0.0018)	(0.0074)
Joint-test p -value	0.428	0.456	0.541	0.495	0.126
Joint F -statistic	0.854	0.790	0.618	0.707	2.101
R^2	0.354	0.366	0.542	0.333	0.321
Observations	1,556	1,556	1,556	1,556	1,556
<i>Panel B: Harmonized old data outcomes</i>					
Δ Predicted energy price	0.0225	−0.0346	0.0267	−0.0038	−0.0575
	(0.2503)	(0.0486)	(0.0266)	(0.0123)	(0.0408)
Predicted energy price ($t - 1$)	−0.1244***	0.0206	0.0070	0.0023	0.0113
	(0.0473)	(0.0137)	(0.0046)	(0.0038)	(0.0097)
Joint-test p -value	0.033	0.231	0.242	0.612	0.197
Joint F -statistic	3.495	1.483	1.434	0.494	1.643
R^2	0.416	0.373	0.359	0.486	0.377
Observations	1,556	1,556	1,556	1,556	1,556

Notes: The sample period covers 1995–2007 and includes 10 countries and 13 harmonized sectors. The exact common sample contains 1,556 observations. Panel A is weighted by fixed 1995 EU KLEMS employee hours. Panel B is weighted by harmonized Marin–Vona initial hours. Regressions include year-specific country dummies, year-specific sector dummies, and five initial cluster-composition controls, with cluster 4 omitted as the reference category. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7.3 Selected Non-ICT Investment Outcomes: Exact Common Sample Comparison, 1995–2007

	Δ Non-ICT share	Δ Transport equipment share	Δ Other machinery share	Δ Other construction share
<i>Panel A: New data outcomes</i>				
Δ Predicted energy price	0.0622	−0.0602*	0.0978	0.0247
	(0.0514)	(0.0352)	(0.1059)	(0.0964)
Predicted energy price ($t - 1$)	−0.0022	−0.0072*	0.0062	−0.0012
	(0.0079)	(0.0041)	(0.0128)	(0.0110)
Joint-test p -value	0.456	0.080	0.626	0.960
Joint F -statistic	0.790	2.577	0.469	0.041
R^2	0.366	0.501	0.424	0.294
Observations	1,556	1,556	1,556	1,556
<i>Panel B: Harmonized old data outcomes</i>				
Δ Predicted energy price	0.0346	−0.0396	−0.0734	0.1477
	(0.0486)	(0.0421)	(0.1342)	(0.1384)
Predicted energy price ($t - 1$)	−0.0206	−0.0028	0.0077	−0.0255*
	(0.0137)	(0.0052)	(0.0195)	(0.0152)
Joint-test p -value	0.231	0.476	0.793	0.161
Joint F -statistic	1.483	0.746	0.232	1.855
R^2	0.373	0.435	0.311	0.269
Observations	1,556	1,556	1,556	1,556

Notes: The sample period covers 1995–2007 and includes 10 countries and 13 harmonized sectors. The exact common sample contains 1,556 observations. Panel A is weighted by fixed 1995 EU KLEMS employee hours. Panel B is weighted by harmonized Marin–Vona initial hours. Regressions include year-specific country dummies, year-specific sector dummies, and five initial cluster-composition controls, with cluster 4 omitted as the reference category. The regressors are the annual change and lagged level of predicted energy-price exposure. Standard errors clustered by country-sector pair are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

but remains insignificant. The positive contemporaneous coefficient for the IT investment share decreases and becomes insignificant. For other detailed ICT asset shares and the broad ICT investment share, the contemporaneous and lagged coefficients retain their signs and remain insignificant. For the detailed non-ICT asset shares and the broad non-ICT investment share, both the contemporaneous and lagged coefficients preserve their signs, except for the lagged coefficient for the other machinery share. It becomes positive but close to zero. They all remain insignificant, while the lagged coefficient for the other construction share becomes significant at the 10% level. The comparison results indicate that sector harmonization does not account for the main changes observed in the extended-period estimates.

Comparing the results in Panel A with those in Panel B of Tables 7.2 and 7.3 allows me to assess whether data revisions between the old and new EU KLEMS releases account for the changes in the extended-period analysis. Panel A and Panel B estimates cover the same 10 countries and 13 harmonized sectors during 1995–2007. However, Panel A uses revised data for the outcome variables. I also re-estimated both panels using the old initial hours worked as weights, but the results did not change much, so I do not report them in this thesis. The results become more mixed with the new data. The contemporaneous and lagged coefficients for aggregate investment substantially increase, and the lagged coefficient becomes positive and loses significance. The contemporaneous and lagged coefficients for the broad ICT and non-ICT investment shares retain their signs, while their magnitudes change modestly. The coefficients for the detailed asset shares are more mixed; some change sign and become significant or insignificant. These results indicate that the investment analysis is more sensitive to data revisions, unlike the labor-productivity analysis. While the changes in the labor-productivity responses arise mainly after extending the sample period, the investment estimates change substantially even before the later years are added.

Finally, I compare the results in Panel A of Tables 7.2 and 7.3 with those in

Table 6.3. Both estimates use the new data and harmonized sectors. The difference is that Table 6.3 extends the sample period in Panel A of Tables 7.2 and 7.3 by adding the years 2008–2019. The contemporaneous and lagged coefficients for aggregate investment become smaller and remain positive and insignificant during the extended period. The coefficients for the broad and detailed asset shares generally retain their signs, except for the lagged coefficients for the other machinery and other construction shares. All coefficients are individually and jointly insignificant during the extended period. Extending the analysis to later years further weakens the estimates.

Overall, the intermediate comparisons in Tables 7.2 and 7.3 indicate that data revisions and the extension to recent years substantially change the results for aggregate investment and some asset-share outcomes. Thus, the investment estimates are more sensitive across data releases and sample periods and cannot be presented as robust evidence of aggregate investment adjustment or asset reallocation.

Conclusion

In conclusion, I replicated the baseline OLS and IV estimates of total employment and occupational composition by Marin and Vona (2019) for 1995–2011 across 15 industries in 14 European countries. I simplified it by excluding initial emission intensity and using it in a reduced form. Then I adapted it as a verified benchmark for additional industrial adjustments, such as labor productivity, real value added, capital investment, and the composition of capital investment. I also extended the additional adjustments, along with aggregate employment, through 2019 using the new EU KLEMS release, which includes data revisions and sector classification changes. The common-sample diagnostic comparison helped me to separate the roles of sector harmonization, data revision, and additional years in the differences between original and extended periods. In general, total hours worked show limited response to predicted energy-price exposure. However, occupational composition changes more considerably: the shares of technicians and professionals generally seem to grow, while the share of manual workers declines. Therefore, studying aggregate employment alone is insufficient to capture the full picture of labor market adjustment, particularly given potential occupational restructuring. Furthermore, predicted energy-price exposure is positively associated with labor productivity and real value added in the short run during 1995–2011. Hours worked responses remain insignificant, implying they do not explain most of the positive changes in labor productivity. The delayed hours worked response shows some losses. However, the decomposition of real value added to nominal value added and the deflator shows that price movements mainly drive the short-run positive changes in real value added. Thus, the short-lived positive productivity coefficient is not clear evidence of efficiency improvements. The effects weaken over the extended period from 1995 to 2019, suggesting they may not be persistent over a longer period. The common-sample diagnostic comparison also shows that labor productivity effects remain more stable despite sector harmonization and data

revision. Moreover, the investment analysis during 1995–2007 suggests a delayed decline in aggregate capital investment. I find only weak evidence of a short-lived increase in the share of IT investment. Nevertheless, the results do not provide a robust reallocation of investment shares between ICT and non-ICT or detailed asset categories. The investment effects also weaken when the sample period is extended. However, unlike the labor productivity effects, which are mainly sensitive to additional years, the investment effects are also sensitive to data revisions. Additional years further weaken the investment effects. However, sector harmonization does not appear to account for differences across sample periods. Thus, investment adjustment and asset reallocation are not robust findings. The overall results indicate that industrial adjustments appear to be compositional rather than aggregate. In addition, the effects are mostly short-lived, and several adjustments do not persist over a longer period. The exercises do not suggest large and robust employment losses, long-lasting productivity improvements, or a clear reallocation of capital between assets. My decomposition results imply that productivity should be examined and interpreted alongside real value added and hours worked, and that price movements also matter. I leave the examination of capital investment composition to future research, as it is sensitive to data revision and should be reassessed using more comparable data.

Shrnutí v češtině

Tato práce replikuje základní OLS a IV odhady celkové zaměstnanosti a profesní struktury podle Marin and Vona (2019) pro 15 odvětví ve 14 evropských zemích v období 1995–2011. Původní metodologie je zjednodušená a následně využita k analýze produktivity práce, reálné přidané hodnoty, kapitálových investic a jejich struktury. Vybrané analýzy jsou pomocí nových dat EU KLEMS rozšířeny do roku 2019.

Výsledky ukazují pouze omezenou reakci celkového počtu odpracovaných hodin, avšak výraznější změny profesní struktury, zejména růst podílů odborníků a technických pracovníků a pokles podílu manuálních pracovníků. Krátkodobý pozitivní vztah mezi predikovanou expozicí cenám energií, produktivitou práce a reálnou přidanou hodnotou je z velké části spojen s cenovými pohyby a v delším období slábne.

Investiční analýza naznačuje opožděný pokles celkových kapitálových investic, neposkytuje však robustní důkazy o přerozdělení mezi jednotlivými druhy aktiv. Srovnání na společném vzorku ukazuje, že rozdíly mezi původním a rozšířeným obdobím jsou způsobeny především zahrnutím dodatečných let a v případě investic také revizemi dat, zatímco harmonizace odvětví hraje pouze omezenou roli.

Celkově jsou průmyslová přizpůsobení převážně kompoziční, krátkodobá a v delším období často nepřetrvávají.

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