Greenwich Papers in Political Economy

Do recessions accelerate routine-biased technological change in Western Europe?

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This version: June 9, 2025

No: GPERC98

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Keywords: employment, routine tasks, technological change, great recession, job polarisation, routine-biased technological change, labour market regulation

Acknowledgements: We are grateful to Ozlem Onaran, Rafael Wildauer, Miriam Rehm, Yannis Dafermos, Maria Nikolaidi, Cem Oyvat, Hannah Hasenberger, and Ben Tippet for their comments. The usual disclaimers apply.

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Abstract

The decline of routine employment is a well-documented feature of labour markets in high-income economies, commonly attributed to routine-biased technological change (RBTC). This study examines the impact of the Great Recession on RBTC in Western Europe. Leveraging industry-level variations in the severity of the Great Recession in a difference-in-difference analysis, we reveal that employment in routine jobs has increased in industries that were severely affected by the recession, compared to those less affected. Additionally, severely affected industries show a decline in investment and a decrease in routine task content. These findings suggest that the Great Recession led to a slowdown in RBTC - contrasting sharply with evidence from the US, where recessions have accelerated RBTC. We demonstrate that variation in labour market regulation can help explain these differences: routine employment declines more sharply in less regulated labour markets compared to those with stricter regulation, likely because hiring and firing costs decrease more substantially in unregulated labour markets during recessions.

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1 Introduction

Over the past decades, the decline in routine jobs has been one of the most critical labour market trends in high-income countries. Previous research has shown that the main driver of this trend is routine-biased technological change (RBTC), where computers and automation replace human labour in routine tasks (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014). As these tasks are typically performed by workers in the middle of the distribution, RBTC has been associated with the hollowing of middle-income jobs, also referred to as job polarisation (Goos and Manning, 2007; Goos et al., 2014). Until recently, RBTC and the decline in routine jobs were considered gradual processes. However, a long-standing economic argument, dating back to Schumpeter's *creative destruction* (Schumpeter, 2005), suggests that technological change is not smooth but cyclical. Indeed, recent empirical studies show that recessions have accelerated RBTC and the decline in routine jobs in the US (Jaimovich and Siu, 2020; Hershbein and Kahn, 2018)

RBTC, even when gradual, places considerable strain on routine workers who are particularly at risk of job loss. These strains are exacerbated when RBTC accelerates during recessions, resulting in sudden shifts in labour demand. Key concerns include a rapid and concentrated increase in unemployment for a subset of routine workers, reduced time for retraining, a high burden on social safety nets, and jobless recoveries (Jaimovich and Siu, 2020). Moreover, research has highlighted the psychosocial effects of job loss and unemployment, such as decreased well-being, lower happiness, and deteriorating mental health (Darity and Goldsmith, 1996; Tella et al., 2003; Hussam et al., 2022).

This article provides the first analysis of the impact of recessions on RBTC in Western Europe. We contrast two opposing hypotheses. The first hypothesis posits that recessions accelerate technological change, based on *pitstop* theories of the business cycle (Davis and Haltiwanger, 1992; Aghion and Saint-Paul, 1998; Berger, 2012). The main explanation is that in boom times, the opportunity costs of changing production processes might be too high. However, recessions lower the opportunity costs of restructuring, for example, because they reduce the costs of layoffs (Berger, 2012; Jaimovich and Siu, 2020; Hershbein and Kahn, 2018) and drive out unprofitable firms or old techniques, which frees up resources for more productive uses (Caballero and Hammour, 1994). The key implication from this hypothesis is that recessions accelerate the pace of technological adoption and the decline in routine employment. We will refer to this line of argument as the *Schumpeter hypothesis*, as it aligns with Schumpeter's (2005) view of *cleansing* the economy of unprofitable firms or technologies during economic downturns.[1]

A contrasting hypothesis suggests that recessions slow technological change, based on the idea that economic downturns lead to increased uncertainty and subdued demand. Several mechanisms can account for this effect. First, the Kaldor-Verdoorn law posits that high demand stimulates investment, which in turn drives innovation and accelerates technological adoption (Kaldor, 1957, 1966; Verdoorn, 1949; Deleidi et al., 2023). Accordingly, periods of low demand, like recessions, slow the adoption of new technology. Second, recessions increase uncertainty, which results in slower technological progress. This is formalised in the 'real options' framework, which emphasises the strategic importance of delaying investment decisions in the face of uncertainty (Dixit and Pindyck, 1994). Moreover, Keynesian theory posits that heightened uncertainty reduces business expectations, resulting in increased liquidity preference and lower investment (Dafermos, 2012). We will refer to this as the *Kaldor-Keynes hypothesis*[2], due to the link with the Kaldor-Verdoorn law and Keynes's 2018 emphasis on fundamental uncertainty.

Previous research has shown that recent recessions accelerated RBTC in the US (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). However, this relationship has not been explored outside the US context. Theoretically, it is ambiguous whether firms respond more strongly to cost incentives, according to the Schumpeter hypothesis, or factors such as (expected) demand and uncertainty, in line with the Kaldor-Keynes hypothesis. Which of these channels dominates is ultimately an empirical question, and may vary across countries with different institutional settings. We hypothesise that a key institutional determinant is the degree of labour market regulation. A core premise of the Schumpeter hypothesis suggests that recessions make it cheaper for firms to hire and fire workers, due to lower costs of restructuring their labour inputs

[1] We use this label for ease of reference and because reference to Schumpeter is prominent in (Hershbein and Kahn, 2018), an influential study finding evidence for this hypothesis. However, Schumpeter himself has not commented on RBTC or pitstop theories, and his *cleansing* argument is only a subset of the mechanism that form part of this hypothesis, as discussed in more detail in Section 2.

[2] Again, this label is used for ease of reference and it is not claimed that all mechanisms that form part of this hypothesis were developed by or are consistent with Kaldorian or Keynesian theory.

compared to normal times (Hershbein and Kahn, 2018; Berger, 2012). This could explain why the Great Recession has accelerated RBTC in the US, a country with a low degree of labour market regulation. However, in countries with more regulated labour markets and strict employment protection, such as many European countries, this mechanism may be hindered because labour adjustment costs remain high during recessions. In such a context, stagnant demand or increased uncertainty may be more significant in shaping the relationship between recessions and technology adoption.

We begin our empirical analysis by examining routine job trends in Western Europe, using individual-level survey data from the European Union Statistics on Income and Living Conditions (EU-SILC) alongside task content data from the Occupational Information Network (O*NET). Our findings confirm the ongoing decline in routine employment between 2003 and 2018 across 15 Western European countries. This shift in job composition is consistent with the adoption of routine-biased technologies (Autor et al., 2003; Brynjolfsson and McAfee, 2011).

To investigate the effect of the Great Recession on employment in routine jobs, we employ a difference-in-differences framework and leverage industry-level variations in the severity of the Great Recession, measured through value-added shocks. We find that the decline in routine jobs has decelerated in industries that suffered a more severe decline in value added over the Great Recession compared to those with less severe crisis shocks. Our preferred estimates suggest that moving from the tenth to the ninetieth percentile in the recession shock increases annual employment growth in routine jobs by around 2 percentage points. This effect persists over the post-crisis period. To validate the causal interpretation of our estimates, we demonstrate parallel pre-trends in routine jobs across industries. Additionally, we employ an instrumental variable approach based on value-added shocks in U.S. industries to mitigate concerns about potential confounders, such as other simultaneous industry- or country-specific shocks.

If the recession shock slows RBTC, we expect to observe a simultaneous decrease in technology adoption in severely affected industries. Using our difference-in-difference design, we demonstrate that capital investments and information technology (IT) investments decrease in severely affected industries, compared to those less affected. Additionally, we examine how the Great Recession has affected the task content of jobs. Recent research has shown that RBTC simultaneously reduces routine employment and increases the routine task content of remaining jobs along with the use of computers in the workplace (Fernández-Macías et al., 2022). Our analysis confirms that in industries severely impacted by the recession, we find a fall in repetitive and standardised task content, as well as a corresponding decline in computer usage. These findings further support the notion that the Great Recession has decelerated RBTC.

Our findings contrast with those in the US, where the Great Recession accelerated RBTC. To shed light on this puzzle, we examine whether labour market regulation moderates the effect of recessions on the decline in routine jobs. Our analysis indicates that countries with less flexible labour markets experienced faster declines in routine jobs during the Great Recession compared to those with more flexible labour markets. This finding is consistent with the argument that in countries with less regulated labour markets, such as the US, hiring and firing costs tend to decrease during economic downturns. In contrast, in countries with more regulation, this effect is less pronounced. Consequently, our analysis suggests that variations in labour market regulation help explain the discrepancy between our findings and those pertaining to the US.

Overall, our analysis provides three novel contributions. First, we introduce the Kaldor-Keynes hypothesis to the literature on RBTC and the cyclicality of technology adoption. Second, we are the first to test two contrasting hypotheses regarding the effect of recessions on RBTC in Europe, using a difference-in-difference design. We reveal that severely affected industries in Europe experience a slowdown in RBTC, in line with the Kaldor-Keynes hypothesis, and in contrast to the Schumpeter hypothesis. Third, we examine the relevance of the institutional environment in explaining differences in the effect of recessions on RBTC across different countries. We show that the degree of labour market regulation moderates the effect of recessions on changes in the employment composition. This corroborates research that highlights the importance of the institutional context for technological change (e.g., Fernández-Macías and Hurley (2016)) and further cautions against treating RBTC as a near-universal phenomenon in high-income countries. In producing our main results, we also establish that the secular decline in routine jobs continues across Western Europe, extending earlier work by Goos et al. (2014) to a more recent period.

The article is organised as follows. We review the literature and outline our hypotheses in Section 2. Section 3 introduces the data used in our study. Section 4 outlines the empirical methodology. We present our empirical findings in Sections 5 and 6. Section 7 concludes.

2 Recessions and the decline in routine employment

Routine-biased technological change (RBTC) has been identified as the primary driver of the decline in routine employment (Autor et al., 2003; Acemoglu and Autor, 2011; Autor et al., 2008; Goos et al., 2014)[3]. Evidence for RBTC, the decline in routine jobs and job polarisation abounds in empirical studies on the US, (Autor et al., 2006; Autor and Dorn, 2013; Firpo et al., 2011; Wright and Dwyer, 2003), Japan (Ikenaga and Kambayashi, 2016), Germany (Dustmann et al., 2009; Spitz-Oener, 2006), the United Kingdom (Goos and Manning, 2007), Sweden (Adermon and Gustavsson, 2015), Portugal (Fonseca et al., 2018) and South Korea (Kim et al., 2019). In a leading study, Goos et al. (2014) demonstrate that the decline in routine jobs was pervasive in Western Europe between 1993 and 2010. Yet, for Italy, both Guarascio et al. (2018) and Basso (2020) find mixed evidence. For an expansive survey of this literature, see Mondolo (2022). Some studies have linked differences in routine employment trends or job polarisation to differences in institutional settings across countries (Fernández-Macías and Hurley, 2014, 2016), but they do not quantitatively test these institutional arguments. In addition, some studies have highlighted that RBTC not only results in occupational change but also alters the task content of jobs themselves (Fernández-Macías et al., 2022). Yet, empirically, only a few studies have focused on the latter, possibly due to data limitations.

2.1 The Schumpeter hypothesis

Economists have typically viewed RBTC and the decline in routine jobs as gradual processes. However, theoretical literature, beginning with Schumpeter's concept of creative destruction (Schumpeter, 2005), suggests that adjustments to technological

[3]The rise of offshoring has been proposed as another driver of the decline in routine jobs and job polarisation. However, empirical evidence finds less support for this hypothesis especially in Europe (Goos et al., 2014). Nonetheless, we use measures for offshorable tasks in robustness tests in our empirical analysis in Section 5

changes are episodic. This notion has been formalised in 'pitstop' theories of the business cycle (Davis and Haltiwanger, 1992; Hall, 2005; Berger, 2012). The core idea is that in boom times, high opportunity costs and adjustment costs hinder the optimal allocation of input factors in response to new technologies. However, recessions produce shocks large enough to overcome these costs (Hall, 2005) and accelerate RBTC (Hershbein and Kahn, 2018). Several mechanisms account for this. First, recessions can lower the costs for firms to lay off workers, making it cheaper for firms to fire workers (Berger, 2012; Jaimovich and Siu, 2020). Similarly, Kudlyak et al. (2025) find that because the outside options for workers are limited, a crisis presents an opportune time for employers to lay off less productive workers or reorganise production. Laying off workers during recessions is more acceptable from a fairness perspective; it is argued that it is fairer for an employer to respond to an exogenous shock than to take the initiative and cause harm (Charness and Levine, 2000).

Second, recessions reduce the opportunity cost of restructuring production inputs due to low demand. This induces firms to improve productivity and alter their labour inputs (Hall, 2005). Third, recessions increase the risk of firm closure and prompt a shift in managerial focus from growth to efficiency, resulting in adjustments of the employee composition (Koenders and Rogerson, 2005). Lastly, recessions drive Schumpeterian cleansing (Schumpeter, 2005), in which less productive firms exit and resources are reallocated to more productive firms with newer production technologies (Caballero and Hammour, 1994; Mortensen and Pissarides, 1994). All these mechanisms imply that recessions accelerate RBTC and the decline in routine jobs. We will refer to this hypothesis, which posits that recessions accelerate RBTC and, consequently, the decline in routine employment, as the *Schumpeter hypothesis*.

2.2 The Kaldor-Keynes hypothesis

A contrasting line of argument posits that recessions slow technological change. The core idea is that recessions depress demand and increase uncertainty, which hamper investment and, thereby, technological change. Accordingly, recessions decelerate the decline in routine employment. We will refer to this hypothesis as the *Kaldor-Keynes hypothesis*. Several mechanisms can account for this effect. First, literature based on the Kaldor-Verdoorn law links technological change and technology adoption to high demand (or output) growth (Kaldor, 1957, 1966; Verdoorn, 1949; Deleidi et al., 2021, 2023). This is largely due to dynamic economies of scale, derived from specialisation between firms (division of labour effects) and increased efficiencies resulting from learning-by-doing effects. Additionally, higher demand and growth often incentivise investment which embodies new technology (Kaldor, 1957; Robinson, 1956). A substantial body of empirical literature has found evidence for the Kaldor-Verdoorn law based on country-, regional- and firm-level data (see Deleidi et al. (2021) and Deleidi et al. (2023) for a review). The corollary of the Kaldor-Verdoorn effect is that recessions - periods of stagnant demand or growth — slow technology adoption.

A second mechanism links recessions and lower investment through an increase in uncertainty. Uncertainty significantly increases during recessions, prompting firms to delay decisions, which in turn leads to notable declines in hiring, investment, and output (Bloom, 2009). The strategic significance of postponing investment decisions in the face of uncertainty has also been formalised in the "real options" framework by Dixit and Pindyck (1994) and Bernanke (1983). Similarly, Keynesian theory argues that heightened uncertainty affects business expectations, leading to increased liquidity preference and reduced investment (Dafermos, 2012). Empirical evidence from various studies supports the hypothesis that uncertainty further depresses economic activity (Christiano et al., 2014; Alexopoulos and Cohen, 2015). Bloom et al. (2007) demonstrates that firms temporarily halt their investment and hiring in response to an increase in uncertainty, which also diminishes productivity, as this interruption in activity freezes reallocation across units. Fajgelbaum et al. (2017) finds that greater uncertainty about fundamentals discourages investment. Lastly, Disney et al. (2020) demonstrate that stagnant demand and uncertainty were the primary factors inhibiting UK firms' investment after the Great Recession, resulting in an investment slump.

A third mechanism of the Kaldor-Keynes hypothesis is that recessions increase firms' financial constraints, mainly if they rely on external financing (Stein, 2003; Fee et al., 2009). These constraints might hamper investment in new technologies. For example, Babina et al. (2020) have demonstrated that disruptions in access to financing can largely explain why areas more severely affected by the Great Depression experienced substantial and persistent declines in patenting activity in the United States.

These related mechanisms suggest that recessions lower investment, which decelerates RBTC and slows the decline in routine jobs. Given the presence of two hypotheses with opposing predictions for our research question, it is also plausible that findings will differ across countries, depending on whether investment and technology adoption is more sensitive to changes in (opportunity) costs during recessions (as highlighted by the Schumpeter hypothesis), or factors like (expected) demand, uncertainty and financing conditions (as highlighted by the Kaldor-Keynes hypothesis).[4]

2.3 Empirical evidence

Empirical studies on the US demonstrate that recent recessions have accelerated RBTC in line with the Schumpeter hypothesis. Jaimovich and Siu (2020) demonstrate that, over the 1980-2017 period in the US, employment declines in routine jobs are concentrated around recessions. Their results hold at the national and state levels. Similarly, Hershbein and Kahn (2018) investigate the effect of the Great Recession in the US using regional variation in the Great Recession shock as an identification strategy. Using job vacancy postings, they demonstrate that skill requirements have become less routine in areas more severely affected by the Great Recession—indicative of a restructuring of production in line with RBTC, towards more skilled workers, and away from routine skills. They also demonstrate that increases in skill requirements accompany increases in capital investments, in line with faster RBTC. However, they do not discuss changes in the occupational composition, such as trends in routine jobs, directly. Moreover, none of these studies focus on the industry-level variation of the Great Recession shock , despite the industry-level being a key dimension for analysing the decline in routine employment and occupational change.[5]

To the best of our knowledge, no analysis on the impact of the Great Recession on RBTC or routine employment exists in Europe. Goos et al. (2014) document the decline in routine employment in Western European countries from the 1990s to 2010 but don't discuss the impact of the Great Recession. Jaimovich and Siu (2020) highlight the employment decline during the early stages of the recovery from the Great Recession in European countries but don't examine routine employment. Herrero (2024) provides descriptive evidence of heterogeneous patterns of changes in

[4] The question of whether demand or cost factors determine investment is a crucial and well-researched issue in economics. Microeconometric studies on firm-level investment behaviour have demonstrated that demand conditions are more relevant than cost factors for investment (in fixed capital stock) in the European context (Tori and Onaran, 2022, 2020).

[5] Autor et al. (2003) and Acemoglu and Autor (2011) demonstrate that the shift away from routine jobs within industries is a more important factor for occupational employment trends than shifts in industrial composition (away from routine-intensive towards nonroutine-intensive industries).

the employment composition after the Great Recession across 18 European countries and Anghel et al. (2014) demonstrate employment polarisation in Spain between 1997 and 2012, with managers, professionals, and technicians expanding more than those related to non-qualified services. However, neither of these studies discuss routine employment or test the impact of the recession shock. Finally, Moawad (2023) argue that the Great Recession increased the earnings gap between the working and upper-middle classes, using EU SILC data, but the study does not examine employment outcomes or the impact on routine occupations.

Considering these studies, we lack a comprehensive understanding of how the Great Recession affected RBTC and specifically routine employment in Western Europe. Moreover, no study has specifically examined industry-level variation in the severity of the Great Recession, despite the industry level being a key focus in the literature on the decline in routine employment and the broader literature on occupational change (Autor et al., 2003; Goos et al., 2014). Another gap in the RBTC literature is that the Kaldor-Keynes hypothesis has been overlooked despite empirical evidence supporting several mechanisms of this hypothesis, as discussed above.

Because of the focus of the empirical literature on the effect of recessions on RBTC in a single country – the US – we also lack an understanding of how distinct institutional settings, like labour market regulation, moderate the effect of recessions on RBTC. However, the institutional context may interact with technology and produce distinct outcomes for RBTC and changes in the employment structure (Fernández-Macías and Hurley, 2016). Understanding the role of institutions is also important because institutional settings underpin several mechanisms of the Schumpeter and Kaldor-Keynes hypotheses. For example, the former posits that recessions reduce the costs of layoffs, thereby making it cheaper for firms to restructure their labour inputs us (Hershbein and Kahn, 2018; Berger, 2012). This assumes that recessions lead to lower hiring and firing costs. However, while not explicitly discussed in the literature, the validity of this assumption critically depends on the level of labour market regulation, including factors such as hiring and firing regulations, the cost of worker dismissal, or centralised collective bargaining. In countries with unregulated labour markets, such as the US, this assumption is plausible. However, in countries with stricter labour market regulation - such as many European countries - these arrangements prevent a fall in hiring and firing costs during recessions and the mechanism of falling labour adjustment costs may be impeded. In such a context, other mechanisms, like demand constraints or uncertainty, may exert a greater influence on the decision of firms during recessions in Europe.[6] Our multi-country study enables us to examine how differences in labour market regulations across European countries during the Great Recession moderate the effect of recessions on RBTC.

2.4 Research hypotheses

We derive two hypotheses with opposing signs on the effect of the Great Recession on RBTC and the decline in routine jobs.

Hypothesis 1a) The Schumpeter Hypothesis: Recessions accelerate RBTC and the decline in routine jobs through faster RBTC.

Hypothesis 1b) The Kaldor-Keynes Hypothesis: recessions decelerate RBTC and the decline in routine jobs.

We will test these hypotheses by leveraging industry-level variation in economic conditions over the Great Recession in Section 5. Our main analysis focuses on employment in routine jobs as the outcome variable. In auxiliary analyses, we also test the effects of recession shocks on investment and routine task content (see, e.g. Fernández-Macías et al. (2022)).

In a separate step, we investigate if labour market regulation moderates the effect between recessions and routine employment. Based on the aforementioned literature, we hypothesise that recessions accelerate RBTC more substantially in less-regulated labour markets (like the US) than in more-regulated ones (like many European countries).

Hypothesis 2: The impact of recessions on RBTC is influenced by labour market regulation: recessions accelerate the decline of routine jobs more substantially in less-regulated labour markets.

[6] Consistent with this idea there is evidence that before the 1980s, when US labour markets were more regulated due to higher union presence (Berger, 2012), recessions did not accelerate RBTC (Jaimovich and Siu, 2020).

3 Data

3.1 Employment

Our main analysis focuses on the effect of the Great Recession on employment in routine jobs. To measure employment, we use repeated cross-sectional individual-level data from EU SILC. Our analysis encompasses 15 Western European countries from 2003 to 2015, comprising over 1.5 million worker observations, including both full-time and part-time workers with assigned occupations. We aggregate employment hours at the job level, defined as an occupation-industry-country group, for each year, resulting in approximately 32,000 job-level observations. We use weekly hours worked in a job as the measure of employment[7], following Goos et al. (2014). EU SILC provides two-digit International Standard Occupational Classification (ISCO) codes, and one-digit industry codes based on the Classification of Economic Activities in the European Community (NACE). Due to changes in occupational and sectoral classifications over time, we adjust and link various definitions to maintain consistency in our analysis, as discussed in Appendix A.

3.2 Routine index

Job tasks are routine when they are repetitive, standardised, and follow well-defined procedures. These characteristics make them susceptible to automation or computerisation. In the empirical literature on routine employment, the measure for routine tasks is typically an off-the-shelf measure of the task content of jobs (Autor et al., 2003; Goos et al., 2014; Firpo et al., 2011; Acemoglu and Autor, 2011). Our measure is based on the Firpo et al. (2011)[8], who updated the routine index of Autor et al. (2003). We use the Occupational Information Network (O*NET) database provided by the Bureau of Labour Statistics to generate this measure. O*NET provides expert-coded task categorisations for occupations, ensuring accuracy and relevance in occupational task profiles. This database is widely used in U.S. and international

[7]Looking at the number of employed workers can be misleading, as hours worked vary significantly across workers.

[8]An alternative measure is the Routine Task Intensity (RTI) index by Autor et al. (2003). However, it is based on the discontinued Dictionary of Occupational Titles (DOT) database, which has been since been replaced by the O*NET. Therefore, we use the Firpo et al. (2011) measure, which closely follows the initial RTI index, but adapted to use more detailed and recent task content data. We use O*NET version 20.1, published in 2015, to construct our measure.

studies (Firpo et al., 2011; Acemoglu and Autor, 2011; Goos et al., 2014). Our routine index uses the following task content variables from O*NET:

- 4.C.3.b.2 Degree of Automation
- 4.C.3.b.7 Importance of repeating the same tasks
- 4.C.3.b.8 Structured v. Unstructured work (reverse)
- 4.C.3.d.3 Pace Determined by Speed of Equipment
- 4.C.2.d.1.i Spend Time Making Repetitive Motions

We combine the variable scores additively and average them to create a single index value for each occupation. The resulting index measure is continuous and time-invariant, in line with leading studies (Autor et al., 2003; Firpo et al., 2011)[9]. Drawing on linking practices from earlier studies (Acemoglu and Autor, 2011; Autor et al., 2013; Hardy et al., 2018) we run several crosswalks to align the O*NET classifications with 2-digit ISCO08 and ISCO88 groups in EU SILC. We provide additional details on this mapping process in Appendix A. The routine index is standardised with a mean of zero and a unit standard deviation, where higher values indicate greater routineness. Appendix Table A1 shows the resulting routine index scores for ISCO08 occupations. The index is highest at 2.41 for stationary plant and machine operators and lowest at -1.52 for chief executives, senior officials, and legislators. The most routine occupations are concentrated in the middle of the wage distribution (Figure 1). Consequently, falling demand for routine jobs would result in job polarisation, with relatively faster employment growth at the top and bottom of the wage distribution.

Figure 2 shows that a higher value on the routine index is associated with slower employment growth during our sample period, providing descriptive evidence for RBTC. A linearly fitted line suggests that a job one standard deviation higher on the routine index is related to 1.2 percentage points slower annual employment growth.

[9] Some studies categorise occupations into groups like routine manual, routine cognitive, and non-routine rather than using a continuous task index (e.g., Jaimovich and Siu (2020); Holman and Rafferty (2018)). However, we prefer a continuous measure of routine task intensity because it captures variations in routine task content more accurately.

3.3 The Great Recession

To measure the severity of the Great Recession shock, we leverage industry-level changes in value added from 2007 to 2009, spanning its peak-to-through period[10], using OECD Structural Analysis (STAN) data. The impact of the Great Recession is heterogeneous across industry-country groups, varying from a +10 to a -30 log point change in value-added across these groups (Figure 3). The figure also includes data for US industries, which we use as an instrument for two-stage least squares (2SLS) estimations in Sections 5 and 6.

3.4 Investment

To assess the impact of the Great Recession on investment in Section 6, we utilise data on industry-level capital investment and IT investment, measured as the share of value added, from the EU KLEMS (Appendix Table A3).

3.5 Task content and computer use

To investigate how the recession has affected changes in the task content of work, we use survey data from EWCS. We use three variables to measure time-varying routine task content: i) repetitive tasks, ii) standardised tasks and iii) computer use. The index measures, based on Fernández-Macías et al. (2022), rely on self-reported individual-level worker information on how repetitive and standardised worker perceive their tasks as well as their computer use - key proxies for RBTC. EWCS data is available every five years, and for the purpose of our analysis, we aggregate it at the industry-country level (see Appendix Tables A3 and A4 for details on variable construction and descriptive statistics).

3.6 Other employment determinants

In robustness checks, we include demographic variables, such as age, education levels (classified into five ISCED levels), gender, and migrant status, from EU SILC

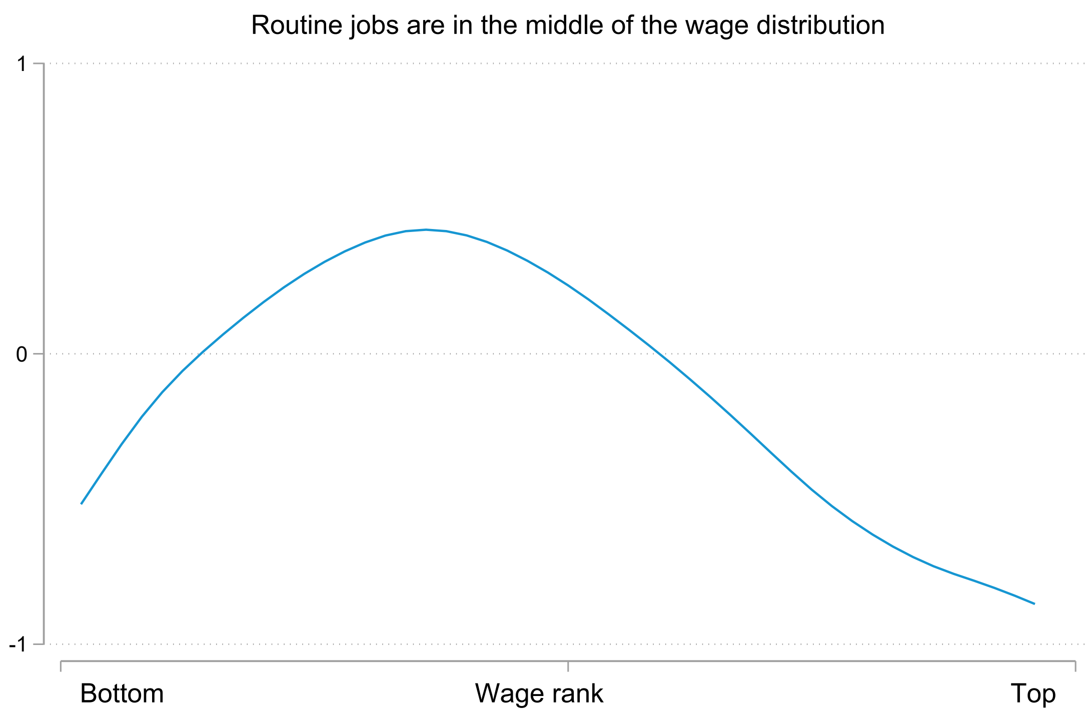
[10] Ireland was the first European country to dip into recession from Q2-Q3 2007. But no other country has been affected in 2007. In some European countries, the Great Recession induced downturn was extended by the Euro crisis. Yet, the highest proportion of the drop in value added across industries happened between 2007 and 2009.

(Appendix Table A2). In addition, we construct a measure for offshorable tasks, previously highlighted as an alternative driver of routine-employment trends, based on Acemoglu and Autor (2011) and using O*NET data (see Appendix A for details).

3.7 Labour market regulation

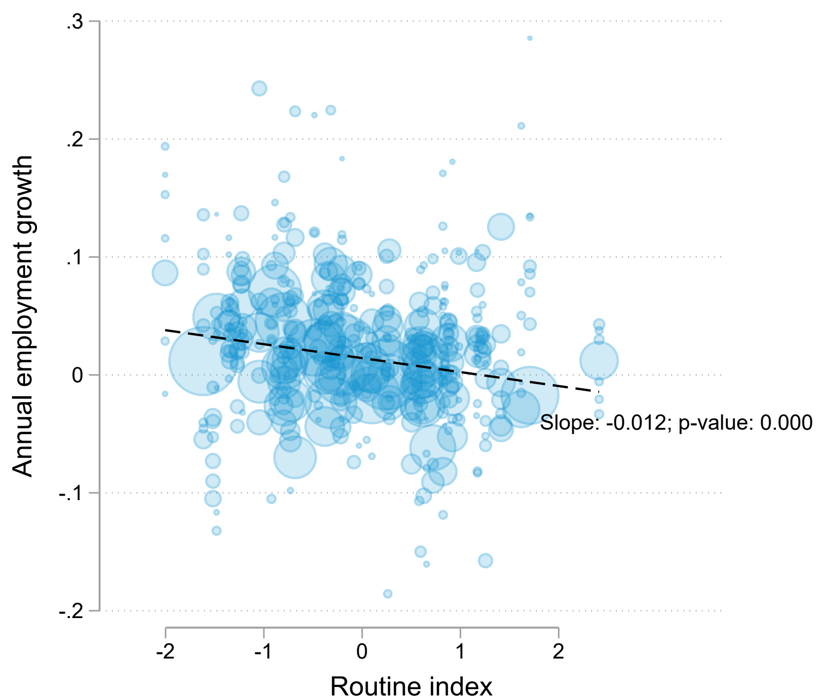
To explore how differences in labour market regulation moderate the impact of the recession on routine jobs, we first utilise the Labor Market Regulation Index from the The Fraser Institute (2024). This index measures the market versus institutional orientation of economies. Specifically, we focus on the labour market component (5B) of the index, which is designed to assess the extent to which restraints on market forces are present. A high index score in this component means that a country allows market forces to determine wages and establish the conditions for hiring and firing of workers. The index comprises five categories: (i) hiring regulations and minimum wage, (ii) hiring and firing regulations, (iii) centralised collective bargaining, (iv) hours regulations, and (v) mandated costs of worker dismissal. We present the index values for 2007 in Appendix Table A5. The index ranges from 0 to 100; the least regulated labour market in our sample is Denmark (99.9), and the most regulated is Portugal (41.5), followed by Germany (44.2).

Figure 1: Routine jobs are in the middle of the wage distribution



Source: EU SILC and O*NET, own calculations.
The horizontal axis ranks the average wage of jobs in 2005. The vertical axis displays the routine index, measured in standard deviations. The blue dotted line represents the LOWESS smoothed curve, highlighting the relationship between autonomy and wage ranks.

Figure 2: Routine job growth, 2003 to 2018



Source: EU SILC and O*NET, own calculations.
Each circle refers to an job group. Circle sizes represent employment shares of job cells. The linear fit is weighted by employment shares.

Figure 3: Crisis shock: measured as change in value-added from 2007 to 2009, in log points

	AT	BE	CH	DE	DK	ES	FI	FR	IE	IT	NL	NO	PT	SE	UK	US
Manufacturing and mining	-0.128	-0.092	-0.065	-0.190	-0.134	-0.116	-0.253	-0.101	-0.146	-0.196	-0.080	-0.045	-0.096	-0.268	-0.075	-0.087
Construction	-0.113	-0.006	0.041	-0.038	-0.071	-0.095	-0.105	-0.075	-0.377	-0.122	-0.007	-0.061	-0.162	-0.056	-0.216	-0.255
Retail, repair and trade	-0.002	-0.006	0.044	-0.064	-0.091	-0.006	-0.031	-0.032	-0.189	-0.082	-0.057	-0.002	-0.004	-0.018	-0.131	-0.107
Hotels and restaurants	0.029	-0.100	-0.025	-0.117	-0.090	-0.041	-0.109	-0.019	-0.089	0.006	-0.142	-0.037	-0.025	-0.006	-0.080	-0.115
Transport, information and communication	-0.058	0.041	0.035	-0.001	-0.127	-0.024	-0.067	-0.037	0.080	-0.030	-0.036	-0.050	-0.009	0.018	0.021	-0.000
Finance	0.069	-0.089	-0.116	-0.057	0.045	-0.014	-0.037	0.078	-0.052	-0.014	0.054	0.015	0.055	0.010	-0.047	0.015
Business services and professional activities	0.016	0.014	0.043	-0.026	-0.008	0.040	0.007	-0.024	-0.109	-0.027	0.009	0.016	0.023	-0.017	-0.010	-0.011
Other services	0.044	0.028	0.093	0.082	0.047	0.061	0.016	0.051	0.069	0.009	0.091	0.036	0.008	0.049	-0.039	0.079

Source: Own calculations with OECD.Stan data. The figure shows the log point change in value added from 2007 to 2009 in an industry-country cell. Darker cells mark industries with a more substantial decline in value added. The figure includes all countries in our sample plus the US values, which will serve as instruments in our analysis.

4 Methodology

Our analysis consists of several steps. As a preliminary analysis, we examine the trajectory of routine jobs in Europe, following the approach from Goos et al. (2014). The relationship between employment growth and routineness is modelled as:

$$ln(\text{emp})_{jkct} = \beta_0 e^{(\beta_1 R_j)\text{t}} \tag{1}$$

where *emp* represents the log of total hours (in thousands) worked in an occupation j, industry k, country c, in year t. Employment growth is a function of the routine index R_j. We convert equation 1 to a logarithmic form to obtain our baseline estimation equation, based on Goos et al. (2014):

$$ln(\text{emp})_{jkct} = \beta_0 + \beta_1(R_j \times \text{t}) + \lambda_{kjc} + \theta_{kct} + \mu_{jkct} \tag{2}$$

$R_j \times \text{t}$ represents the interaction of the time-invariant routine index R_j with a linear time trend. We include occupation-industry-country fixed effects λ_{kjc} to control for pre-existing employment level differences. Additionally, we include industry-country-year fixed effects θ_{kct} to control for industry- or country-specific employment trends. Our empirical strategy consists of estimating equation 2 by OLS and weighting our aggregated job cell by the population represented in each job cell relative to the country's population and cluster standard errors at the job level.

In equation 2, the coefficient β_1 indicates how a standard deviation difference in our routine index (R_j) relates to a percentage point (pp) annual deviation of occupational employment growth from the average industry-country employment growth. If β_1 equals -1, it implies that an occupation with a routine score one standard deviation above the mean is associated with a one pp relative annual employment decline. In some specifications, we will include a variable offshorable tasks, to isolate changes in routine employment from other labour demand determinants, and demographic variables to adjust for sampling variation. If a sample period includes more women, it may impact employment trends since women differ in their distribution between routine and non-routine jobs compared to men. Thus, by including demographic variables, we can more accurately estimate the relations between routineness and employment growth.

We extend equation 2 to estimate the effect of the Great Recession on routine jobs, leveraging the varied impact of the recession across industry-by-country groups:

$$
\begin{aligned}
ln(\text{emp})_{jkct} = \delta_0 + \delta_1(R_j \times \text{t}) + \delta_2\text{Post}_t + \delta_3\text{Crisis}_{kc} + \delta_4(R_j \times \text{t} \times \text{Post}_t) + \\
+ \delta_5(R_j \times \text{t} \times \text{Crisis}_{kc}) + \lambda_{jkc} + \theta_{kct} + \mu_{jkct}
\end{aligned} \tag{3}
$$

Our dependent variable is the log of employment hours within a job (occupation-industry-country group) by year ($ln(\text{emp})_{jkct}$). On the right-hand side of equation 3, we include an indicator $Post_t$ for the post-recession period (1 for $t > 2009$, 0 otherwise)[11]. The coefficient δ_1 follows the interpretation of β_1 above. We measure the effect of the Great Recession with a continuous variable equal to the value-added shock at the industry-level $Crisis_{kc}$, fixed at the industry-country level for post-recessions years. To ease interpretation, we invert-normalise this variable so that a one-unit change in this crisis shock measure represents the difference between the tenth and ninetieth percentile, following Hershbein and Kahn (2018)[12]. A greater positive value in $Crisis_{kc}$ corresponds a more severe (negative) value-added shock.

Our main coefficient of interest is δ_5, linked to the interaction term $R_j \times t \times Crisis_{kc}$. This coefficient is our difference-in-differences estimate that indicates the difference in the employment growth gap between a highly-routine job ($R_j = 1$) and an average-routine job with $R_j = 0$, across industries with varying crisis shocks $Crisis_{kc} = 0$ and $Crisis_{kc} = 1$. If δ_5 is negative, it implies that the routine jobs decline faster in hard-hit industries, compared to less-hard hit industries. We also include job fixed effects λ_{jkc}, to account for pre-existing employment level differences across jobs. In addition, we include year fixed effects to account for overall employment trends, and in some specifications industry-country-year fixed effects (θ_{kct}) to nonparametrically control for other factors influencing employment trends at the industry or country level. In these specifications, the coefficients for δ_2 and δ_3 will be omitted due to collinearity with the added fixed effects. As above, we include controls for offshorable tasks and

[11] We exclude all observations in the shock period (2007 to 2009) from our regression analyses as they fall in the middle of our treatment period.

[12] The difference between the tenth and ninetieth percentile is 0.178 log points in value added.

for demographic variables in some specifications. Because the recession shock varies at the industry level, we cluster standard errors at this level (Abadie et al., 2022).

Our research design fits within the difference-in-difference framework. Each job (in each industry) is treated in period t, but treatment intensity - the crisis shock - varies at the industry-level. This setup echoes other studies where a macro-level shock affects micro-level units differently (e.g., Alsan and Wanamaker (2018); Charles et al. (2018); Clemens et al. (2018); Goodman-Bacon (2018). The difference-in-differences analysis relies on two critical assumptions. First, the parallel trends assumption requires that in the absence of the Great Recession, routine jobs would have grown similarly across industries, regardless of how severely these industries were affected. Second, the 'no anticipation assumption' requires that firms did not adjust their demand for routine jobs in anticipation of the Great Recession. Given the unexpected nature of the Great Recession, it is unlikely that firms altered their job composition in anticipation of the shock.

We validate these assumptions with the help of event-study specifications. These specifications are based on equation 3 and include a comprehensive set of time dummies for each year, interacted with the shock measure Crisis_{kc}:

$$\begin{aligned} ln(\text{emp})_{jkct} = \delta_0 + \delta_1(R_j \times \text{t}) + \sum_{t=2003}^{2015} \delta_{0,t} D_t + \sum_{t=2003}^{2015} \delta_{1,t}(R_j \times D_t) + \\ + \sum_{t=2003}^{2015} \delta_{2,t}(\text{Crisis}_{kc} \times D_t) + \sum_{t=2003}^{2015} \delta_{3,t}(R_j \times \text{Crisis}_{kc} \times D_t) + \lambda_{kjc} + \theta_{kct} + \varepsilon_{jict} \end{aligned} \tag{4}$$

The coefficients of interest are δ_3, t. For t $>$ 2009, these coefficients capture the dynamic effect of the recession shock. For t $<$ 2007, these pre-treatment coefficients function as a placebo or falsification test (Miller, 2023). If the pre-treatment coefficients are statistically indistinguishable from zero and show no trend over time, it suggests that the parallel trends and 'no anticipation assumption' holds. Yet, even if we can validate this assumption, estimates for the recession impact could still be confounded by simultaneous shocks during the Great Recession that affect both the demand for routine jobs (our outcome variable) and value-added (our treatment variable). For instance, if many routine workers retire simultaneously as the recession hits, the resulting labour supply shock would bias our estimates for the effect of the Great Recession. To address this concern, we employ an instrumental variable approach using two-stage least squares (2SLS) estimations of equations 3 and 4. We instrument the shock variable with recession shocks in U.S. industries, a method previously applied in recession impact studies (Cette et al., 2020). In our study, the first stage is to regress local industry specific recession shocks on the US specific shock[13]. This approach enables us to isolate variation in industry-level recession shocks in European countries from potential other local shocks, such as labour supply shocks.

5 Results

Section 5.1. shows findings for routine employment trends, while Section 5.2. shows our main results of the impact of the Great Recession on routine employment, using industry-level variation.

5.1 Results: employment growth of routine jobs

We find that the decline in routine jobs continued from 2003 to 2018 (Table 1). Our point estimates suggests that employment hours in a job with one standard deviation more intense in routine tasks grow approximately 0.8-0.9 percentage points slower annually, compared to a job with an average routine intensity, ceteris paribus. This result extends the finding of Goos et al. (2014), who, using the same method, showed that routine jobs have declined at a similar magnitude in Western Europe between 1993 and 2010. Specification 1 is our most parsimonious bivariate specification with unit and year fixed effects. Our result is robust to including demographic variables, which account for potential outliers in the sample composition (Specification 2)[14],

[13]The US industry-level shock accounts for percent in explaining the variation of local industry shocks, with an F-statistic of 45. See Appendix Table B1

[14]The coefficient for the relationship between age suggests a negative correlation between employment and the age structure in a job. An increase in the average age in a job by one year is correlated with 0.013 percentage points slower employment growth. Similarly, an increase in the women's share by one percentage point is associated with slower employment growth. The migrant share and employment growth in a job are positively correlated. This could mean that migrants are sorting into growing jobs or that jobs with more migrants are growing faster, perhaps because of lower wages due to migrants' lower bargaining power or higher productivity of skilled migrants. The correlation between average education and employment growth is negative, holding other variables fixed. Another interpretation of these coefficients is that they account for potential outliers in the sample composition, as discussed in Section 4. We do not have strong priors about these

and to including the offshorable task index (Specification 3).[15] From Specification 4 we include industry-country-year (ICY) fixed effects (FE) θ_{kct} to control for other industry-country specific employment trends to isolate within-industry occupational change, following Goos et al. (2014). The interpretation of the coefficient for routine tasks from Specifications 4 is that routine employment grows approximately 0.8 percentage points slower than the average routine job in the same industry-country group. Specification 5 additionally includes demographic variables, which does not affect our result. Specification 6 additionally includes the offshorability task measure. (see the values for this index in Appendix Table A1). The coefficient is small and statistically insignificant. Crucially, our coefficient for routine tasks remains unchanged and is very similar across all specifications.

5.2 Results: the impact of the Great Recession on routine jobs

Next, we tackle our main research question by examining whether the Great Recession accelerated RBTC. Our difference-in-difference analysis demonstrates a relative increase in routine employment in industries that suffered a more severe crisis shock compared to those with less severe shocks, in line with the Kaldor-Keynes hypothesis. Specifications 1-4 in Table 2 show our OLS estimates based on equation 3. The economic interpretation of our difference-in-differences estimate (δ_5 in equation 3, labelled as $R_j \times \text{t} \times \text{Crisis}_{kc}$ in Table 2) is that moving from the tenth to the ninetieth percentile in the crisis shock increases the relative employment growth of routine jobs by approximately 1.5 pp. In other words, if routine employment declines annually by one per cent in the less affected industry (10th percentile), it increases by 0.5 percent (=-1+1.5pp) in the severely affected industry (90th percentile). This difference-in-differences estimate is significant at the 95 percent level. This finding is robust to including industry-country-time fixed effects θ_{kct} (specification 2)[16]. Our findings are also robust to adding the offshorability index (specification 3) and demographic control variables to account for variation in the observed sample composition

demographic correlations and are careful not to overstate their importance.

[15]Our findings here confirm earlier research on Western European countries, with offshoring risk unable to predict employment declines (Goos et al., 2014).

[16]In this specification, the effect of the Great Recession (Crisis_{kc}) and the variable Post on employment is absorbed by $\theta_k ct$. These coefficients are omitted in rows 2 and 4 of Table 2

Table 1: Employment growth of routine jobs (2003 - 2018)

	(1) Ln employment	(2) Ln emp	(3) Ln emp	(4) Ln emp	(5) Ln emp	(6) Ln emp
Routine	-0.926***	-0.877***	-0.873***	-0.805***	-0.787***	-0.790***
	(0.175)	(0.172)	(0.173)	(0.146)	(0.145)	(0.145)
Education		-0.057***	-0.057***		-0.037***	-0.037***
		(0.012)	(0.012)		(0.010)	(0.010)
Women share		-0.141***	-0.141***		-0.159***	-0.159***
		(0.043)	(0.043)		(0.032)	(0.032)
Age		-0.017***	-0.017***		-0.017***	-0.017***
		(0.001)	(0.001)		(0.001)	(0.001)
Migrant share		0.292***	0.292***		0.312***	0.312***
		(0.030)	(0.030)		(0.029)	(0.029)
Offshorable			-0.187			-0.117
			(0.145)			(0.123)
Observations	43182	43182	43182	43182	43182	43182
FE	Year	Year	Year	ICY	ICY	ICY
r2	0.970	0.971	0.971	0.975	0.976	0.976

Notes: Standard errors in parentheses. All specifications include job (occupation-industry-country) fixed effects. Specifications 1 to 3 include year fixed effects, and specifications 3 to 5 include industry-country-year (ICY) fixed effects to account for industry-specific employment trends. Standard errors are clustered at the job-level to account for serial correlation within jobs over time. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(specification 4).

To support a causal claim for this finding and address potential concerns that other simultaneous shocks (e.g. labour supply shocks) confound our estimates, we include the industry-specific recession shocks in the US as an instrument, and present 2SLS regressions in Specifications 5 to 8. These corroborate our finding that routine employment relatively increases in hard-hit industries, compared to less-hit industries, but the estimates increase in size. The interpretation from our preferred estimate in Specification 8, which includes industry-country-year fixed effects and a set of control variables, is that routine employment does not decline in the less affected industry (10th percentile), and increases by 1.973 pp in the severely affected industry (90th percentile).[17]

[17]Our results are not sensitive to the choice of the exact time period to calculate the recession shock. Appendix Table B2 shoes that our results are robust to using alternative start and end dates for the shock: 2006 to 2009, 2006 to 2010, 2006 to 2012 and 2007 to 2012.

Table 2: The effect of the Great Recession, industry-level analysis

	(1) Ln emp	(2) Ln emp	(3) Ln emp	(4) Ln emp	(5) Ln emp	(6) Ln emp	(7) Ln emp	(8) Ln emp
Routine	-1.349***	-0.177	-0.153	-0.176	-1.408***	-0.190	-0.165	-0.190
	(0.359)	(0.341)	(0.357)	(0.350)	(0.344)	(0.337)	(0.353)	(0.347)
Post	0.078***				0.106**			
	(0.029)				(0.043)			
Post $\times$ Routine	-0.549	-0.825*	-0.824*	-0.799*	-1.112	-1.388**	-1.401**	-1.404**
	(0.575)	(0.446)	(0.446)	(0.439)	(0.729)	(0.586)	(0.582)	(0.576)
Crisis	-0.062				-0.139*			
	(0.048)				(0.073)			
Routine $\times$ Crisis	1.475**	0.689*	0.835**	0.823**	2.769***	1.760**	1.935***	1.973***
	(0.581)	(0.373)	(0.395)	(0.404)	(0.971)	(0.678)	(0.692)	(0.699)
Offshorable			0.130	0.129			0.147	0.145
			(0.252)	(0.247)			(0.253)	(0.248)
Offshorable $\times$ Crisis			0.343	0.305			0.215	0.122
			(0.270)	(0.275)			(0.373)	(0.363)
Post $\times$ Offshorable			-0.025	0.029			0.054	0.133
			(0.260)	(0.262)			(0.311)	(0.310)
Education				-0.034***				-0.033***
				(0.010)				(0.010)
Women share				-0.145***				-0.147***
				(0.045)				(0.045)
Age				-0.017***				-0.017***
				(0.001)				(0.001)
Migrant share				0.316***				0.317***
				(0.035)				(0.035)
Observations	38343	38343	38343	38343	38343	38343	38343	38343
Estimator	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
ICY	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: Standard errors in parentheses. All specifications include job fixed effects. Industry-country-year fixed effects (ICY) are inlcuded where indicated. Standard errors are clustered at industry-country level to account for serial correlation within these groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Estimating the event-study equation (4) sheds further light on potential pre-trends and post-recession dynamics. Figure 4 plots the difference-in-differences estimates $\delta_{3,t}$ and 95 percent confidence-interval bars, estimated by 2SLS.[18] They capture the employment growth rate difference for a job one standard deviation more routine than the average in a given year t, for a hard-hit industry (ninetieth percentile) compared to a less hard-hit industry (tenth percentile). The point estimates demonstrate that the employment growth effect is persistent over the post-2010 period.[19] Lastly, and crucially for validating the parallel trend and no anticipation assumption, pre-event leads are insignificant. This implies that routine employment trends are similar across industries before the crisis, regardless of the size of the crisis shock they will face. Against the backdrop of a secular decline in routine jobs (Goos et al. (2014), and Section 5.1.), our results suggest that the Great Recession slowed RBTC.

6 Discussion

To corroborate and contextualise our findings, next we analyse the effect of the recession on investment (6.1) and on routine task content (6.2). In Section 6.3, we examine how labour market regulation mediates the impact of the recession on routine employment to assess why results differ between the US and Europe.

6.1 The Great Recession and RBTC: investment

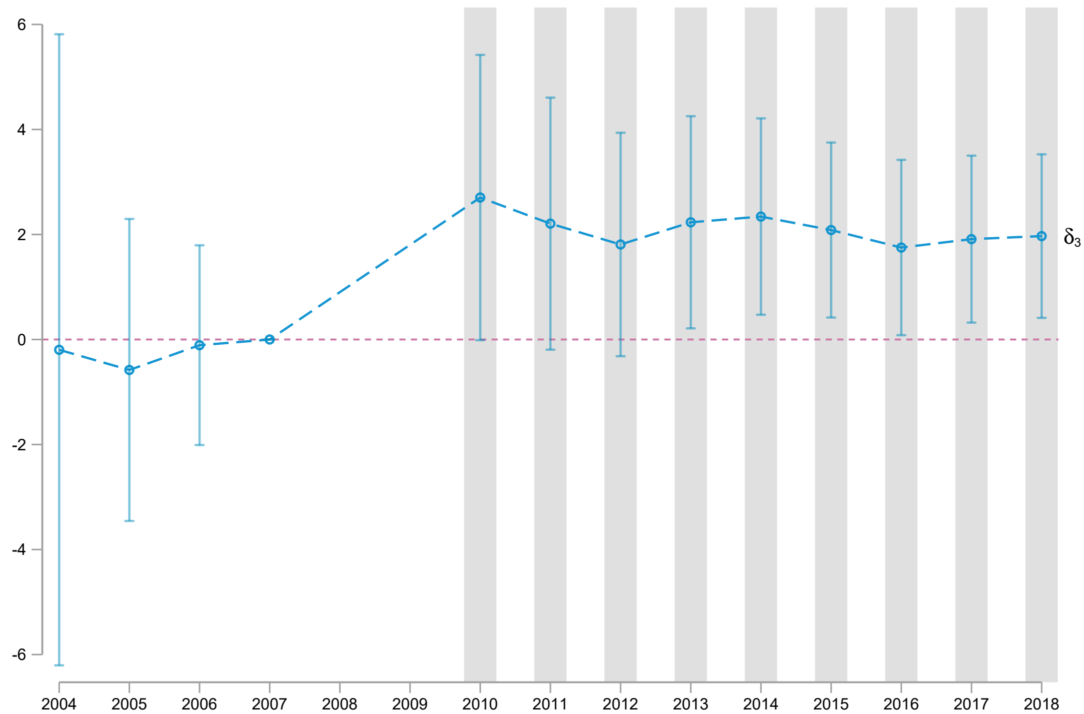
We have shown that the decline in routine jobs has slowed in severely-affected industries, compared to those less affected. If RBTC has indeed slowed in severely-affected industries, then we also expect a decline in investment in these industries. We can investigate this by estimating the following equation:

$$\text{outcome}_{kct} = \sum_{t=2003}^{2015} \alpha_{0,t} D_t + \sum_{t=2003}^{2015} \alpha_{1,t} (\text{Crisis}_{kc} \times D_t) + \varepsilon_{kct} \tag{5}$$

[18] We present the regression coefficients for Figure 4 also in Appendix Table B3, Specification 1. We present the OLS estimates in Appendix Figure B1 and Appendix Table B3, Specification 2).

[19] In Appendix B, we also present a specification of the effect of the Great Recession on overall employment. Appendix Figure B2 presents the findings and shows a decline in overall employment in several affected industries during and after the recession. However, in 2014, point estimates have converged between severely and less severely affected industries, highlighting the recovery period from the crisis.

Figure 4: Event study plot for the crisis shock on routine job growth, 2SLS estimation



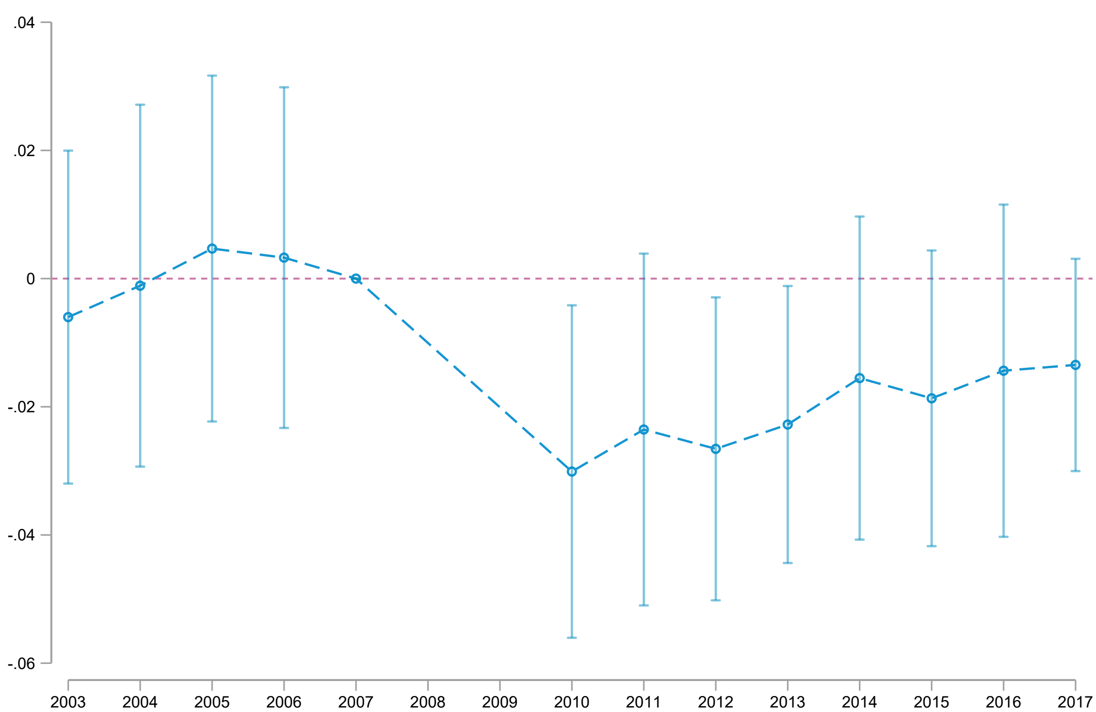
Notes: The regression includes occupation-industry-country and industry-country year effects. These effects ensure that the coefficient is identified purely from variation in employment growth across distinct jobs within a given industry. The caps mark the 95% confidence interval. The horizontal line at 0 marks the relative trend of routine job growth in an industry at the 10th percentile of the Great Recession shock. The blue dots plot the coefficient, denoting the relative trend of routine job growth in an industry at the 90th percentile of the Great Recession shock compared to the trend at the 10th percentile.

Where outcome$_{kct}$ is the growth in industry level capital stock and IT capital stock, which are often considered a key routine-biased technology (Michaels et al., 2014), between 2007 and year t. We regress these variables on a complete set of industry-value added shock-by-year interactions (Crisis$_{kc} \times D_t$) and control for year fixed effects (D_t) for each year. $\alpha_{1,t}$ represent difference-in-differences estimates: the difference in capital stock growth between 2007 and a given year t, for a hard-hit industry (ninetieth percentile) relative to a less hard-hit industry (tenth percentile).

We plot the coefficients $\alpha_{1,t}$ and the 95 per cent confidence-interval bars in Figure 5 and find a fall in investment. The point estimate of -0.03 in 2010 indicates that a one-unit change in the crisis shock (going from the 10th to the 90th percentile) is associated with an additional 3 log-point drop in the capital stock growth rate in this year. The fall in capital stock growth rates is statistically signficant until 2013. We also present the coefficients in Appendix Table B4. We can also observe that capital stock growth (relative to that in 2007) is similar across industries early in the decade, regardless of the size of the shock they will eventually face in the Great Recession.

For IT capital stock growth as the outcome variable, we find an episodic decline. The estimated effects are large, but only the estimate in 2012 is statistically significant at the 10 percent level (Results in Appendix Figure B3 and Appendix Table B4). The point estimate of -.1 in 2012 indicates that a one-unit change in the crisis shock is associated with a 10 log-point lower IT capital stock growth rate in 2012. Afterwards, IT capital stock growth rates converge again across industries. The figure also shows that IT capital stock growth is more erratic across industries before the crisis.

Figure 5: The effect of the Great Recession on capital stock growth, in log points



Notes: We regress the change in industry-level capital stock variables on a complete set of industry-value added shock-by-year interactions and controlling for year fixed effects, using the 2SLS estimator. The figures plot the coefficients on the interaction between the recession shock and year, relative to their 2007 value. We also plot 95 percent CI bars. We cluster standard errors by industry to address possible serial correlation within an industry.

6.2 The Great Recession and RBTC: routine task content

Consistent with a slowdown of RTBC in severely affected industries, we also expect a fall in routine task content (Fernández-Macías et al. (2022), see Section 2). We estimate equation 6 to examine the impact of the recession shock on task content measures:

$$\begin{aligned} \text{Routine task content}_{kct} = \beta_1 Post_t + \beta_2 \text{Crisis}_{kc} + \\ \beta_3 \text{Crisis}_{ct} \times Post_t + \text{FE}_t + \mu_{kct} \text{ for each } t \in \{1995, 2000, 2005, 2010, 2015\} \end{aligned} \tag{6}$$

We include three measures of worker self-reported routine task content, all aggregated at the industry-level: a) the degree of repetitiveness and b) standardisation of workers' tasks and c) the share of computer users. These data are available in five-year steps.

Table 3 presents difference-in-difference coefficients β_3 from equation 6. Specification 1 shows the OLS estimate that the crisis shock has resulted in a decline in repetitiveness of tasks. The 2SLS estimate is also negative but not statistically significant. Specifications 3 and 4 demonstrate that task have become less standardised due to the crisis shock, in OLS and 2SLS estimations, respectively. Lastly, for computer use, the OLS estimate are negative but significant (specification 5), but the 2SLS estimate suggests that the crisis shock reduces computer uses (Specification 6). These findings suggest that the recession shock made task content less routine and reduced computer use, providing further evidence of the slowdown in RBTC, which aligns with our findings in the preceding sections.

Taken together, we have shown that the more severely affected industries in the recession have experienced i) a relative increase in employment in routine jobs, ii) lower capital stock and IT capital stock growth, and iii) a decrease in routine task content and computer use. These results jointly point in a consistent direction: the Great Recession shock has slowed RBTC, in line with the Kaldor-Keynes hypothesis (Hypothesis 1b), suggesting that recessions affect technological change mainly due to suppressed demand, higher uncertainty or financial constraints. These results contrast with the US, where the recent recession has accelerated RBTC, as discussed in Section 2. Next, we aim to shed some light on this difference by examining labour market regulation as a factor that shapes the effect of recessions on RBTC.

Table 3: The effect of the Great Recession on routine task content

	(1) Repetitive	(2) Repetitive	(3) Standardised	(4) Standardised	(5) Computer use	(6) Computer use
Crisis shock	-0.027**	-0.011	-0.038***	-0.058**	-0.012	-0.077**
	(0.012)	(0.019)	(0.013)	(0.026)	(0.014)	(0.033)
Observations	520	520	520	520	520	520
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: Standard errors in parentheses. All regressions include industry-country and year fixed effects. Standard errors are clustered at the industry level to account for serial correlation within units. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.3 The Great Recession and RBTC: the role of labour market regulation

As discussed in Section 2, differences in labour market regulation might help to reconcile our findings with earlier studies that have found that recessions accelerate RBTC in the US (Jaimovich and Siu, 2020) (Hershbein and Kahn, 2018). We test if labour market regulation moderates the relationship between recessions and RBTC (Hypothesis 2) by adding a triple-interaction term between our routine task measure, the recession shock and measures for labour market regulation to equation 7. The estimation equation becomes:

$$\begin{aligned} \ln(\text{emp})_{jkct} = \alpha + \delta_1(R_j \times t) + \delta_2\text{Post}_t + \delta_3\text{Crisis}_{kc} + \delta_4(R_j \times t \times \text{Post}_t) + \\ \delta_5(R_j \times t \times \text{Crisis}_{kc}) + \delta_6(R_j \times t \times \text{Crisis}_{kc} \times \text{LMI}_c) + \lambda_{jkc} + \text{FE}_t + \mu_{jkct} \end{aligned} \tag{7}$$

Our main measure for labour market regulation is the labour freedom index by the The Fraser Institute (2024). A higher value on this index indicates less regulated labour markets. We include industry-country-year fixed effects, which results in all time-variant industry and country-specific coefficients to drop.

We find that in countries with less regulated labour markets, the recession results in a faster decline in routine jobs compared to countries with more regulation (Table 4, specification 1), in line with Hypothesis 2. In Specification 2, we employ the 2SLS estimator with US industry-level recession shocks as instruments, which confirms our results.

This finding hints at a potential explanation for different findings between the US and Europe. Even within Europe, the recession has resulted in a relative acceleration of the decline in routine jobs in countries with less regulated labour markets, compared to more regulated ones. The US has a highly flexible labour market, more so than any European country except Denmark (Appendix Table A5). This might explain why the decline in routine jobs accelerated over the recession, in line with the argument that the costs of layoffs have decreased in severely affected parts of the economy.

Table 4: Interaction with Labor Freedom Index

	(1) Ln emp	(2) Ln emp
Routine	0.205	0.222
	(0.272)	(0.267)
Post $\times$ Routine	-1.225***	-1.859***
	(0.279)	(0.368)
Routine $\times$ Crisis	1.790***	3.086***
	(0.690)	(0.685)
Routine $\times$ Crisis $\times$ Labor Freedom	-1.870*	-2.106**
	(0.978)	(0.846)
Observations	41017	41017
Estimator	OLS	2SLS
r2	0.975	0.003

Notes: Standard errors in parentheses. All regressions include occupation-industry-country (OIC) fixed effects and industry-country-year fixed effects (ICY) where indicated. Standard errors are clustered at the job (occupation-industry-country) level to account for serial correlation within units. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

This study presents new evidence on the effect of the Great Recession on RBTC in Western Europe. Our difference-in-difference analysis uses the varied impact of the Great Recession across industries and establishes a set of new findings. First, we show that routine employment relatively increased in severely affected industries compared to those less affected by the Great Recession. Second, in auxiliary analyses, we show that more severely affected industries have also experienced a decline in investment, a decrease in computer use, and a fall in repetitive and standardised task content. These findings suggest that the recession slowed RBTC. Our results differ from earlier studies that found that RBTC accelerated during the Great Recession in the US. We argue that differences in labour market regulation help explain this finding, and show that in countries with more regulated labour markets, the Great Recession relatively increases routine employment compared to less regulated labour markets.

Our findings are crucial for the literature on the determinants of RBTC and, more broadly, on the socio-economic determinants of technological change. The established hypothesis that recessions accelerate RBTC (Hershbein and Kahn, 2018) does not hold for Western Europe. In contrast, our evidence aligns with the Kaldor-Keynes hypothesis: more severely affected industries experience a slowdown in RBTC. Our results caution that neither hypothesis can be assumed to hold a priori, but that institutional settings mediate their relevance. Although determining the specific contribution of each mechanism discussed in our hypotheses, such as decreased demand, increased uncertainty, and poorer financing conditions, is beyond this article's scope, this is a promising avenue for future research, potentially using firm-level data.

Our analysis underscores the importance of adopting nuanced approaches to managing recessions. On the one hand, our findings mitigate concerns about episodic increases in unemployment for routine workers during recessions in Europe. On the other hand, they suggest that European firms are less likely than US firms to capitalise on potential opportunities for restructuring that arise during recessions. This suggests that the imperative for countercyclical measures is potentially even stronger in Europe relative to the US.

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Appendix A

Employment data

EU SILC provides two-digit International Standard Occupational Classification (ISCO) codes and one-digit industry codes based on the Classification of Economic Activities in the European Community (NACE). The ISCO classification organises occupations into a clearly defined set of groups based on the tasks performed in the occupation. After excluding public sector, military and agricultural occupations, following the approach by Goos et al. (2014), our analysis includes 21 ISCO-88 sub-major group (two-digit) occupations until 2010. For 2010 and later, the classification shifted to the ISCO-08 system, leaving us with 34 occupations in our analysis (Appendix Table A1). Notably, 2010 features both ISCO classifications, so we can consistently estimate the 2009 to 2010 employment growth based on ISCO-88 groups, and the 2010 to 2011 employment growth based on ISCO-08 groups. Additionally, there was a shift in the NACE industry classification during our sample period from NACE Rev.1 to NACE Rev.2. To ensure consistency in our analysis, we categorise industries into eight groups: manufacturing and mining; construction; retail, repair and trade; hotels and restaurants; transport, information and communication; finance; business services and professional activities; and other services.

Routine index

Job tasks are routine when they are repetitive, standardised, and follow well-defined procedures. These characteristics make them susceptible to automation or computerisation. In the empirical literature on routine employment, the measure for routine tasks is typically an off-the-shelf measure of the task content of jobs (**?**Goos et al., 2014; Firpo et al., 2011; Acemoglu and Autor, 2011). Our measure is based on the Firpo et al. (2011)[20], who updated the routine index of **?**. We use the Occupational Information Network (O*NET) database provided by the Bureau of Labour Statistics to generate this measure. O*NET provides expert-coded task categorisations

[20] An alternative measure is the Routine Task Intensity (RTI) index by Autor et al. (2003). However, it is based on the discontinued Dictionary of Occupational Titles (DOT) database, which has been since been replaced by the O*NET. Therefore, we use the Firpo et al. (2011) measure, which closely follows the initial RTI index, but adapted to use more detailed and recent task content data. We use O*NET version 20.1, published in 2015, to construct our measure.

for occupations, ensuring accuracy and relevance in occupational task profiles. This database is widely used in U.S. and international studies (Firpo et al., 2011; Acemoglu and Autor, 2011; Goos et al., 2014). Our routine index uses the following task content variables from O*NET:

- 4.C.3.b.2 Degree of Automation
- 4.C.3.b.7 Importance of repeating the same tasks
- 4.C.3.b.8 Structured v. Unstructured work (reverse)
- 4.C.3.d.3 Pace Determined by Speed of Equipment
- 4.C.2.d.1.i Spend Time Making Repetitive Motions

In O*NET data, occupations are coded using the O*NET-SOC classification, whereas EU SILC employs the ISCO classification. Estimating the task content for ISCO occupations requires several crosswalk steps. First, we map O*NET variables to the corresponding occupations in SOC, utilising the crosswalk from Acemoglu and Autor (2011). The Stata do-files for O*NET to SOC mapping can be found on David Autor's website at https://economics.mit.edu/people/faculty/david-h-autor/data-archive. We then link SOC to ISCO using the official ILO crosswalk, drawing upon the code provided by Hardy et al. (2018). The .zip package containing crosswalks is available at https://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/. The SOC and ISCO classifications have undergone several revisions in recent years, with a significant one occurring in 2010 when ISCO-88 was revised and replaced by the newer ISCO-08. EU SILC data provides both classifications for this year. Lastly, we collapse our index at the 2-digit occupational level for the respective periods of ISCO-08 and ISCO-88 classifications.

We combine the selected task content variables into a single index, following the approach by Acemoglu and Autor (2011). The resulting index equals the sum of each variable scale, giving each variable equal weighting. The index is standardised with a mean of zero and a unit standard deviation, where higher values indicate greater occupational autonomy. Appendix Table A1 shows the resulting routine task scores for 2-digit ISCO08 occupations.

Table A1: Occupation-level index measures: routine and offshorable

Occupation	ISCO 08	Routine index	Offshorable index
Chief executives, senior officials and legislators	11	-1.52	-.77
Administrative and commercial managers	12	-1.35	.14
Production and specialized services managers	13	-1.27	-1.1
Hospitality, retail and other services managers	14	-.73	-1.31
Science and engineering professionals	21	-1.22	.37
Health professionals	22	-1.48	-1.28
Business and administration professionals	24	-1.23	.79
Information and communications technology professionals	25	-.03	1.44
Legal, social and cultural professionals	26	-1.36	.67
Science and engineering associate professionals	31	.58	-.77
Health associate professionals	32	-.2	-1.2
Business and administration associate professionals	33	-.21	.79
Legal, social, cultural and related associate professionals	34	-.92	.25
Information and communications technicians	35	-.08	.4
General and keyboard clerks	41	.5	2.06
Customer services clerks	42	1.23	1.19
Numerical and material recording clerks	43	.88	1.29
Other clerical support workers	44	.82	1.48
Personal services workers	51	-.34	-.21
Sales workers	52	-.8	1.14
Personal care workers	53	-.89	-.37
Protective services workers	54	-.22	-1.36
Building and related trades workers (excluding electricians)	71	.05	-1.15
Metal, machinery and related trades workers	72	.59	-.55
Handicraft and printing workers	73	.66	.03
Electrical and electronics trades workers	74	-.44	-1.76
Food processing, woodworking, garment and other craft and workers	75	1.17	.39
Stationary plant and machine operators	81	2.41	.05
Assemblers	82	1.26	-.21
Drivers and mobile plant operators	83	.89	-1.06
Cleaners and helpers	91	.26	.98
Labourers in mining, construction, manufacturing and transport	93	1.16	-.77
Food preparation assistants	94	.98	.95
Refuse workers and other elementary workers	96	.84	-.55

Notes: Index values generated with O*NET data and mapped onto 2-digit ISCO08 occupational classification. All index measures are standardised with zero mean and unit standard deviation. Routine: a higher value means higher intensity of routine tasks. Offshorable: a higher value means that tasks in the occupation are more offshorable.

Other variables

Table A2: Summary Statistics for EU-SILC Variables

	Mean	Median	Std. Dev.
Job Hours	1.70e+06	311246.58	4.69e+06
Job Education (ISCED level)	3.49	3.39	0.91
Job Gender (share of hours worked by women in %)	0.39	0.34	0.34
Job Migrant share (in %)	0.14	0.06	0.20
Job Age (years)	41.66	41.49	6.47

Table A3: Summary Statistics for Industry-Level Variables

	(1)			
	Mean	Median	Std. Dev.	Obs.
Repetitiveness of tasks (Index 0-1)	0.44	0.43	0.11	520
Standardisation of tasks (Index 0-1)	0.57	0.57	0.12	520
Computer use (in %)	0.40	0.36	0.22	520
Number of persons employed (in thousands)	1201.93	512.01	1619.45	1560
Capital stock net (in million EUR)	386688.31	96815.00	830293.09	1528
IT Capital stock (in million EUR)	1928.03	818.00	2664.38	1304

Table A4: Tasks indices from European Working Conditions Survey (EWCS) 2015

Index	EWCS question	Text of the survey questions
Routine: repetitiveness	48b	Please tell me, does your job involve short repetitive tasks of less than 10 min?
	53d	Generally, does your main paid job involve monotonous tasks?
	30e	Please tell me, using the same scale, does your main paid job involve repetitive hand or arm movements?
Routine: standardisation	50c	On the whole, is your pace of work dependent on numerical production targets or performance targets?
	53a	Generally, does your main paid job involve meeting precise quality standards?
Technology: computers	30i	Please tell me, using the same scale, does your main paid job involve working with computers, laptops, smartphones, etc.?

Table A5: Labour market regulation

Country	Labor Freedom Index (2007)
AT	70.1
BE	70.8
CH	77.0
DE	44.2
DK	99.9
ES	49.3
FI	45.6
FR	56.1
IE	80.6
IT	74.4
NL	62.7
NO	49.0
PT	41.5
SE	65.0
UK	79.0

Source: Fraser Institute (2024). The table shows the Labor Freedom Index for each country in 2007. Higher values represent less regulated labour markets.

Appendix B

Table B1: First stage regression

	(1) Crisis
Crisis (US-industry)	0.428***
	(0.064)
Constant	0.231***
	(0.052)
Observations	120
F	45.298
r2	0.277

Notes: Standard errors in parentheses. This table presents the first stage regression of the industry-country specific change in value added from 2007 to 2009 (in log points) on the US-industry specific change.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Robustness: alternative crisis periods

	(1) 2007-2009	(2) 2006-2009	(3) 2006-2010	(4) 2006-2012	(5) 2007-2012
Routine	-0.190	-0.132	-0.160	-0.209	-0.255
	(0.347)	(0.348)	(0.349)	(0.349)	(0.350)
Post × Routine	-1.404**	-1.657**	-1.579**	-1.531**	-1.357**
	(0.576)	(0.661)	(0.638)	(0.635)	(0.574)
Routine × Crisis	1.973***	2.446***	2.518***	2.544**	2.417***
	(0.699)	(0.885)	(0.944)	(0.984)	(0.919)
Offshorable × Crisis	0.122	0.214	0.220	0.257	0.199
	(0.363)	(0.466)	(0.448)	(0.448)	(0.411)
Offshorable	0.145	0.142	0.131	0.119	0.121
	(0.248)	(0.252)	(0.251)	(0.249)	(0.246)
Post × Offshorable	0.133	0.081	0.069	0.047	0.087
	(0.310)	(0.352)	(0.334)	(0.323)	(0.297)
Education	-0.033***	-0.033***	-0.033***	-0.032***	-0.032***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Women share	-0.147***	-0.146***	-0.147***	-0.146***	-0.146***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Age	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Migrant share	0.317***	0.317***	0.317***	0.317***	0.317***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Observations	38343	38343	38343	38343	38343
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS
ICY	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. All specifications are versions of Specification 8 in Table 2, with variations in the time period over which the crisis shock is measures. Speficication 1 measures the crisis shock from 2007 to 2009. Specification 2 measures the crisis shock from 2006 to 2009. Specification 3 measures the crisis shock from 2006 to 2010. Specification 4 measures the crisis shock from 2006 to 2010. Specification 5 measures the crisis shock from 2006 to 2010. All specifications include job fixed effects. Industry-country-year fixed effects (ICY) are inlcuded where indicated. Standard errors are clustered at industry-country level to account for serial correlation within these groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B3: The effect of the Great Recession on routine jobs: event study estimates

	(1) Ln employment	(2) Ln emp
Routine × Crisis × 2004	-0.943	-0.196
	(1.641)	(3.066)
Routine × Crisis × 2005	-0.928	-0.580
	(1.061)	(1.467)
Routine × Crisis × 2006	-0.401	-0.108
	(0.804)	(0.970)
Routine × Crisis × 2010	1.260	2.703*
	(0.834)	(1.386)
Routine × Crisis × 2011	1.263*	2.207*
	(0.723)	(1.224)
Routine × Crisis × 2012	0.882	1.810*
	(0.591)	(1.086)
Routine × Crisis × 2013	1.132*	2.232**
	(0.586)	(1.031)
Routine × Crisis × 2014	1.178**	2.341**
	(0.545)	(0.954)
Routine × Crisis × 2015	1.051**	2.085**
	(0.498)	(0.850)
Routine × Crisis × 2016	0.861*	1.751**
	(0.502)	(0.852)
Routine × Crisis × 2017	0.829*	1.912**
	(0.480)	(0.811)
Routine × Crisis × 2018	0.942*	1.969**
	(0.477)	(0.795)
Observations	41649	41649
Estimator	OLS	2SLS

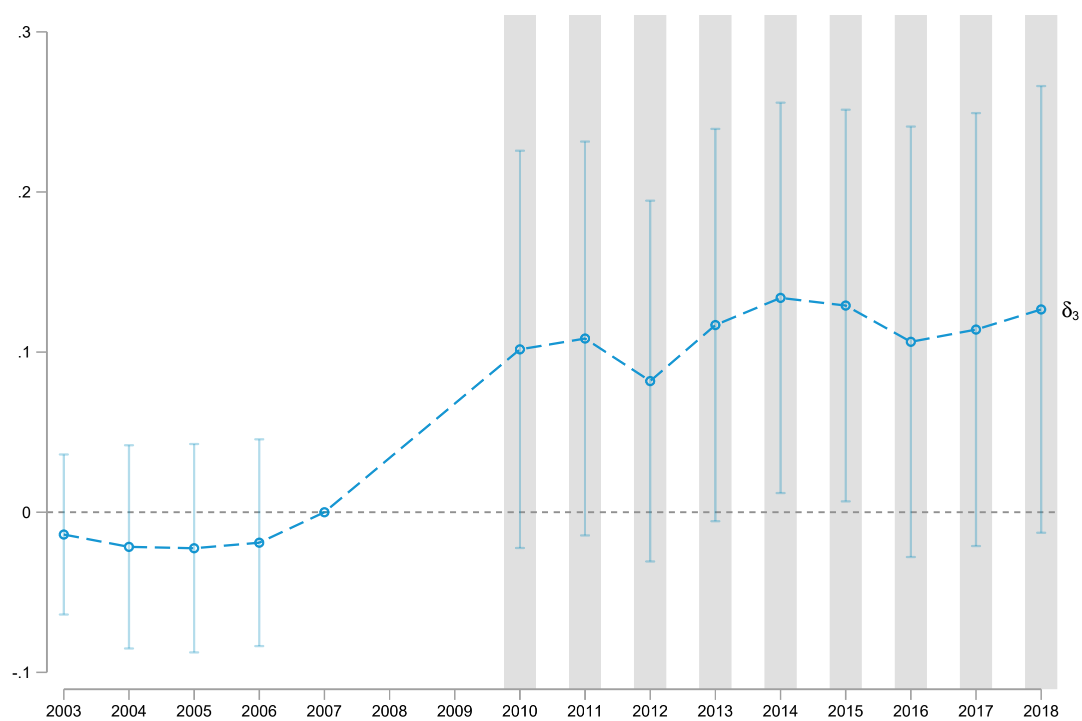
Notes: The table reports the coefficients of an event study on the effect of the Great Recession on routine jobs. The coefficients are estimated using OLS in column (1) and 2SLS in column (2). Standard errors are clustered at the industry-country level and reported in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01.

Table B4: The effect of the Great Recession on investment: event study estimates

	(1) Capital stock growth rate	(2) IT capital stock growth rate
Crisis × 2003	-0.006	-0.038
	(0.013)	(0.073)
Crisis × 2004	-0.001	0.078
	(0.014)	(0.081)
Crisis × 2005	0.005	-0.081
	(0.014)	(0.055)
Crisis × 2006	0.003	-0.038
	(0.014)	(0.045)
Crisis × 2010	-0.030**	-0.054
	(0.013)	(0.071)
Crisis × 2011	-0.024*	-0.072
	(0.014)	(0.051)
Crisis × 2012	-0.027**	-0.095*
	(0.012)	(0.056)
Crisis × 2013	-0.023**	-0.056
	(0.011)	(0.038)
Crisis × 2014	-0.016	0.003
	(0.013)	(0.063)
Crisis × 2015	-0.019	-0.012
	(0.012)	(0.072)
Crisis × 2016	-0.014	-0.043
	(0.013)	(0.058)
Crisis × 2017	-0.013	-0.019
	(0.008)	(0.043)
Observations	1527	1304
Estimator	2SLS	2SLS

Notes: The table reports the coefficients of an event study on the effect of the Great Recession on investment.

Figure B1: Event study plot for the crisis shock on routine job growth, OLS estimation



Event study regressions based on equation 4. The caps mark the 95% confidence interval.

Figure B2: The effect of the Great Recession on employment growth, in log points

Notes: We regress industry-level employment growth variables on a complete set of industry-value added shock-by-year interactions and controlling for year fixed effects. The figures plot the coefficients on the interaction between the recession shock and year, relative to their 2007 value, estimated by 2SLS. We also plot 95 percent CI bars. We cluster standard errors by industry to address possible serial correlation within an industry. Employment variables are from EU KLEMS. Annual employment growth is around 10 pp lower in 2010 in a hard-hit industry compared to a less hard-hit one. In 2014, employment growth has converged across these industries.

Figure B3: The effect of the Great Recession on IT capital stock growth, in log points

Notes: We regress the change in industry-level capital stock variables on a complete set of industry-value added shock-by-year interactions and controlling for year fixed effects. The figures plot the coefficients on the interaction between the recession shock and year, relative to their 2007 value, estimated by 2SLS. We also plot 95 percent CI bars. We cluster standard errors by industry to address possible serial correlation within an industry.